Available online at www.eccomasproceedia.org
Eccomas Proceedia COMPDYN (2025) 570 -571

ECCOMAS
Proceedia

COMPDYN 2025
10th ECCOMAS Thematic Conference on
Computational Methods in Structural Dynamics and Earthquake Engineering
M. Papadrakakis, M. Fragiadakis (eds.)
Rhodes Island, Greece, 15-18 June 2025

SEISMIC DAMAGE LIMIT STATE MODELS FOR CORRODED RC BUILDING FRAMES USING MACHINE LEARNING

M. K. Athul Nath[1], and Needhi Kotoky[2*]

[1] Research Scholar, Department of Civil Engineering, National Institute of Technology Meghalaya, Saitsohpen, Sohra, 793108, India
e-mail: p21ce003@nitm.ac.in

[2*] Assistant Professor, Department of Civil Engineering, National Institute of Technology Meghalaya, Saitsohpen, Sohra, 793108, India
needhikotoky@nitm.ac.in

Abstract

Reinforced concrete (RC) buildings situated in coastal areas are under constant exposure of chloride-induced corrosion. Corrosion deterioration can lead to a considerable decrease in the cross-sectional area of reinforcing steel, along with various secondary effects including concrete spalling, and strength and ductility loss in reinforcement bars causing significant engineering and economic challenges. Moreover, a considerable number of aged RC buildings are in high seismicity regions and are susceptible to damage under earthquakes due to low-ductility properties. There is an inadequacy of available literature studying the influence of corrosion on RC frame global behavior and estimating seismic damage limit states considering deterioration in columns, beam-columns joints, and potential change in failure mechanisms. The present study demonstrates a framework to develop a machine-learning-based model capable of predicting the damage limit states of low-ductility corroded RC frames conditioned on material, structural, and deterioration modeling parameters. A finite-element model is developed by accounting for the nonlinear behavior of different components, low-ductility properties and deterioration effects such as non-uniform corrosion of columns including concrete cracking effects and joints corrosion. Inter-story drift ratios are estimated at various damage states using pushover analyses. The RC frame inter-story drift ratios are mapped on the pushover curve by monitoring reinforcement and concrete strain limits, shear failure of columns, and joint failure, among others. Finally, damage state predictive expressions are developed for the corroded RC frames using modern machine learning algorithms.

Keywords: RC Buildings; Corrosion Deterioration; Earthquakes; Damage Limit States; Machine Learning.

ISSN:2623-3347 © 2025 The Authors. Published by Eccomas Proceedia.
Peer-review under responsibility of the organizing committee of COMPDYN 2025.
doi: 10.7712/120125.1284 .25108

1 INTRODUCTION

The recent adoption of performance-based seismic design has provided an efficient and reliable approach that aims to understand the risks and losses in reinforced concrete (RC) buildings, which may incur against future earthquakes. Performance-based design enables good prediction accuracy in the performance of RC buildings over earthquakes, along with contributing to the improvement in functionality post-earthquake. The performance-based design uses various quantifiable performance objectives specified as damage levels that the RC building should resist under seismic risk. Prediction of various damage states of an RC building post-earthquake supports the restoration and retrofitting process. Damage states are levels of structural and non-structural damage corresponding to a predefined performance criterion. Damage states are quantified through engineering demand parameters, such as displacement, inter-story drift ratio, or curvature. Recent studies have considered residual drift [1], as well as material strains [2], to estimate and map damage states.

Buildings constructed before the introduction of seismic codes and regulations are low ductility in nature with inadequate reinforcement detailing, such as the absence of transverse reinforcement or with large spacing between stirrups, poor anchorage, limits the ductility as well as energy dissipation capacity under seismic exposure. Low-ductility RC buildings are prone to brittle failure mechanisms, such as bond-slip failure, shear, or flexure-shear failure, causing sudden collapse due to the loss of strength and stiffness. Non-ductile RC buildings constructed prior to the implementation of seismic codes, as well as constructed flouting the rules and regulations, are still in service and in good numbers in areas of high seismicity, posing a major threat. Significant damages incurred due to the recent earthquakes in Turkey and Morocco has underlined the risk of low-ductility RC buildings against seismic forces. RC buildings with existing risks, when exposed to multiple environmental stressors, the associated risk is increased multifold due to further deterioration. RC buildings in coastal areas are subjected to chloride-induced corrosion deterioration, undergoing loss of area [3], strength, and ductility [4] in the reinforcement bars, decreasing the confining effect of the concrete and other associated secondary losses. Chloride-induced corrosion can alter the failure mechanisms, such as flexure failure in column members to flexure-shear or pure shear failure [5]. Experimental studies have observed a reduction in the capacity of lateral load resistance in beam-column joints due to corrosion [6]. Various researchers have carried out analytical and experimental studies to propose empirical methods to estimate the damage states. The change in behavior of the components due to corrosion further affects the damage states. While analyzing the elements and the whole structure, considering a single failure mode is not convincing [7], and different potential failures need to be considered for accurate prediction of the global behavior of RC frames.

Machine learning-based algorithms have been a prominent technique recently, which makes use of data to learn about patterns and make possible predictions. Machine learning has emerged as a reliable and efficient technique to predict various aspects across various fields including structural and earthquake engineering. Researchers have utilized machine learning approaches to develop fragility curves [8], classify failure modes [9], and estimate column drift capacity [10]. Hamidia et al. [11] has proposed machine learning based prediction models to identify damages in non-ductile beam-column joints correlating to drift ratios. Bhatta and Dang [12] have considered structural and seismic parameters to predict the seismic damage in RC frames using machine learning models. Xu et al. [13] has adopted various machine learning based algorithms to identify failure modes in corroded bridge columns. Machine learning techniques have been recently adopted for prediction of damages in deteriorated RC bridges, yet there is a lack of studies predicting the damage in deteriorated RC frames considering change in failure modes. Rapid damage detection in RC frames post-earthquake with high accuracy is possible with the help of ML techniques, without performing complex time-consuming numerical analyses.

Addressing the mentioned research gaps, the present study aims to develop simplified expressions with the ability to predict various performance levels of a low-ductility RC building subjected to chloride-induced corrosion. A large set of data requirements to train the models through experimental study is unfeasible and hence analytical study with the finite element models are carried out. A robust experimentally validated finite-element model is developed by accounting for the nonlinear behavior of different components and deterioration effects. Deteriorated RC frames are modelled considering the corrosion effects such as non-uniform corrosion of beams and columns including concrete cracking effects and joints corrosion, decrease in the cross-sectional area of reinforcing steel, and various secondary effects including concrete spalling, and steel rebars strength and ductility loss to vary along with the deterioration level. Seismic damage limit state data is produced considering the influence of material and deterioration parameters. Nonlinear static pushover analyses are carried out to mark the performance levels based on strain limits and shear failure in column members. The set of damage limit states obtained from the analyses is utilized to fit polynomial response surface models. The fitted model can predict seismic damage limit state at various levels of deterioration and change in material parameters. The study provides efficient models for performance level identification and rapid prediction of damages in the RC frames without incurring heavy computational efforts. The outcome of the study also supports the restoration and rehabilitation efforts post-earthquakes**.**

2 METHODOLOGY FOR DEVELOPING DAMAGE STATES

To assess the RC building performance, prediction of various damage levels against ground motions is required. The demand obtained from nonlinear time history analysis against ground motions is usually compared with the capacity of critical components such as columns and joints to obtain the failure probability of the RC frames. Past literature assesses the vulnerability of RC buildings at specific levels of structural damage defined as discreet damage states (DS) based on qualitative and quantitative parameters [14]. Corrosion deterioration alters the behavior of critical components consequently altering the performance levels. Reduction in strength and deformability of columns is observed in experimental studies and is found to reduce the strength and drift limits under deterioration [5][15]. Past studies often ignore the change of behavior while estimating the damage in the structure [16]. To accurately predict the change in behavior under chloride-induced corrosion, deterioration aspects need to be included in the estimation of various performance levels.

The performance levels used in this study are adopted from Freddi et al. [17], which is mapped to maximum inter-story drift ratio (*MIDR*). Considering inter-story drift as an engineering demand parameter is observed to be effective in examining the behavior of RC frames [18]. Estimation of *DS*s using drift can be observed in HAZUS [19] as well. The considered performance levels are yielding column rebar, spalling of concrete cover, and column shear failure. Table 1 lists the qualitative description of the Slight, Moderate, Extensive, and Complete *DS* along with the corresponding failure criterion. The yielding of the longitudinal reinforcement of columns is correlated with the Slight *DS*. This first performance level is obtained by marking the point at which the critical yielding strain limit is crossed for at least half of the column members at the same storey. The spalling of cover concrete is correlated with the second performance level denoted as Moderate *DS*. Experimental studies have observed the cover concrete spalling to initiate when the compressive strain crosses 0.004 [20]. The initiation of spalling of cover concrete in at least half of the columns at a single-storey level is mapped by measuring the critical strain limits.

Damage State	Description
Slight	Yielding of 50% of columns at any one storey (outermost tension reinforcement crossing yielding strain)
Moderate	Spalling/crushing of concrete in 50% of column at one storey (compression side of the column crossing strain limit of 0.004)
Extensive	Average of moderate and complete damage states
Complete	Shear failure in 50% of columns at any one storey (exceeding shear strength/ drift limit of column)

Table 1: Qualitative description and corresponding failure criteria were used to identify the *DS*s in RC frames.

The Complete *DS* is defined based on shear failure in at least 50% of the column members in a particular storey. The shear capacity based on shear strength and drift for as built and corroded columns is adopted from Vu et al. [15]. Figure 1 illustrates a graphical representation of flexure-shear and shear failure modes of the RC column once either the strength limit curve or drift limit curve is reached. A performance level in between the Moderate and Complete *DS*s is considered as Extensive *DS*. The discussed Slight, Moderate, Extensive, and Complete *DS*s are mapped against *MIDR* through nonlinear static pushover analysis of the entire building frame.

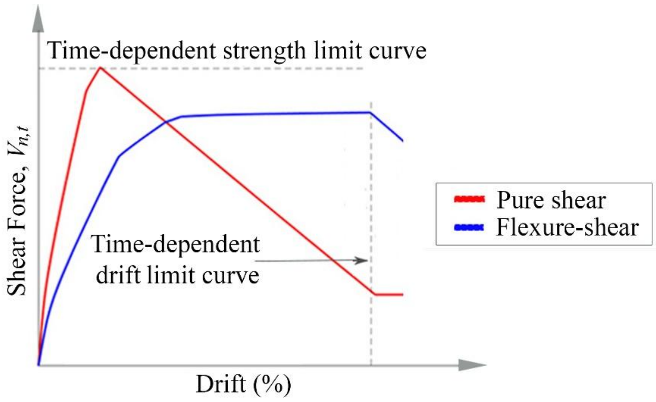

Figure 1: Graphical representation of pure shear and flexure-shear failure modes of RC columns

3 CASE-STUDY FRAME AND FINITE ELEMENT MODELING

To assess the behavior of a low-ductility RC building, a two-dimensional frame representing a typical residential building found in Indian subcontinent is adopted for the present study [21]. The frame is assumed to be designed based on basic thumb rules without considering any ductile detailing provisions and built under moderate supervision. The rectangular frame has three storeys with a floor height of 3 m. The two-dimensional frame is adopted at the side with a bay width of 4 m. The RC slabs at the floors and the roof has a thickness of 120 mm. Columns are square sections with 300 mm depth at both the sides. Beam members have a depth of 400 mm and a width of 300 mm throughout the frame. The compressive strength of concrete is 26 MPa and grade 415 steel is used in both reinforcements. The present study adopts the FE modeling strategy proposed by Freddi et al. [17] based on component level and global level validation. Figure 2 shows the case study frame and its column and beam sections along with its numerical modeling representation with the column, beam and joint components.

A Finite Element (FE) model of the RC frame is developed using the OpenSees software framework [22]. The response of the column member is modeled using the *nonlinearBeamColumn* element considering the spread of the plasticity across the column member. Beam responses are simulated using *beamWithHinges* element considering plastic hinges at both the ends and an elastic section in the middle. Concrete properties are assigned to the modeling elements using fiber sections. Concrete properties are defined using the *Concrete04* material and reinforcement properties as per *Hysteretic* steel material model which considers the pinching behavior as well as the unloading stiffness degradation. Core concrete and cover concrete properties are assigned separately considering the confining effects adopted from Mander et al. [23]. A *Zerolength* shear spring element modeled using *limistate* material is attached to the top of the column element to capture the shear failure in the RC column. Shear failure is recorded when the predefined shear strength or drift limit parameters are exceeded during the flexure, flexure-shear or shear failure happening in the column. The change is implemented in the source code of OpenSees by changing the shear *limitcurve* object. Beam column joints are modeled as *zerolength* rotational spring elements using moment-rotation parameters [24] developed from constitutive shear stress-strain relations [25]. The beam and column elements are connected to *zerolength* elements along with rigid link offsets. Gravity loads are assumed to be spread over the beam components as uniformly distributed load and the concentrated masses on the joint component. The effects of chloride-induced corrosion deterioration in the FE model are incorporated into the material parameters. Reduction in the material strength of cover concrete and core concrete properties are defined through *concrete04* material.

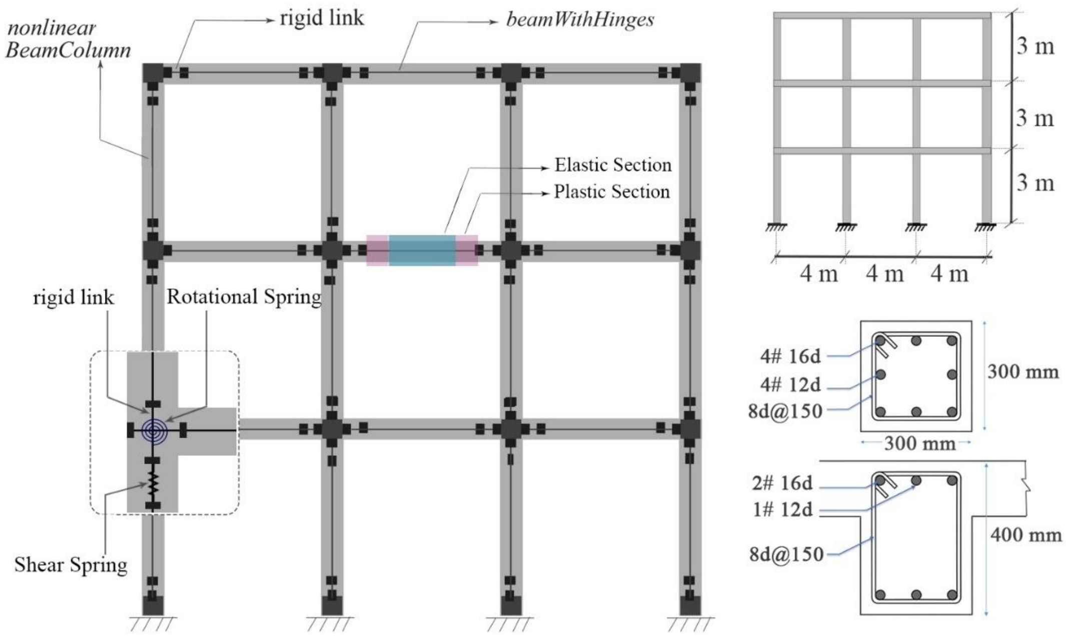

Figure 2: Numerical representation of case study frame with elevation, column, and beam section view

Cross-sectional area loss and associated secondary losses in the reinforcement are considered in the mechanical properties of the *Hysteretic* material. The cross-sectional area loss in the transverse reinforcement is estimated based on the relationship proposed by Dai et al. [26]. Cover concrete and core concrete strength reduction is considered by updating the properties in *Concrete04* material based on Biondini and Vergani [27]. Shear strength and drift limit based on deterioration in the column is adopted from Vu et al. [15]. The shear stress-strain envelope model considering deterioration in joints proposed by Zhang and Li [28] is adopted for the beam-column joint modeling.

4 SELECTION OF INPUT PARAMETERS AND MODELING DESIGN OF EXPERIMENTS

The variation in the parameters as well as deterioration levels has a significant influence over the performance levels of RC frames. Design of Experiments (DOE) approach is adopted to facilitate the identification of parameters that have significant impact on the output responses [29]. Based on the approach, the present study takes account of the variation in material parameters such as concrete compressive strength and reinforcement yield strength, as well as variation in deterioration in the form of mass loss in the reinforcement. To study the impact of modeling parameter variation in the performance of RC frames subjected to various ground motions, a large set of input parameters needs to be generated. An experimental design matrix for the three input parameters is generated for 5000 simulations using a Quasi-random sequence. The experimental design matrix is of order $m \times n$, where m and n denote the number of simulations and input parameters respectively. An upper and lower limit is considered to generate the input parameters in the range. The set of parameters for the concrete compressive strength as well as yield strength of the reinforcement are generated based on the Indian code [30]. The percentage mass loss in the longitudinal reinforcement (ψ_{corr}) is assumed to range from 0% to 35%. Table 2 lists the lower and upper bounds of the input parameters considered for DOE. The associated input parameters for further analysis are generated based on the three main input parameters.

Parameters	Unit	Lower Limit	Upper Limit
Compressive strength, f_c	MPa	22	31
Reinforcement strength, f_y	MPa	404	527
Mass Loss, ψ_{corr}	%	0	35

Table 2: Input parameters chosen for design of experiments (DOE) and their lower (5th) and upper bounds (95th).

5 DAMAGE STATE THRESHOLD MAPPING USING NONLINEAR STATIC PUSHOVER ANALYSES

The limits for the damage states are influenced by variation in material parameters and deterioration levels. Performance level of the RC frame diminishes along with the level of deterioration in the frame. To estimate the variation in the limits of damage states in the FE models, nonlinear static pushover analysis is carried out. Pushover analysis is conducted using a displacement control strategy where the top node of the frame is subjected to a lateral push with gradual increment to a targeted displacement while recording the reactions at the base of the frame. The strain limits to estimate the performance levels are achieved by carrying out a target drift of 4 % during the pushover analysis. FE models equal to the number of simulations (n) are generated using the input parameters through experiment design matrix. The associated parameters are calculated based on the average mass loss and are incorporated in the FE models as discussed in section 3. The set of FE models are subjected to nonlinear static pushover analysis and the resulting damage states are recorded at their corresponding maximum inter-storey drift levels. The discussed damage states denoted yielding of column, spalling of cover concrete, and flexure-shear failure in column are recorded for each of the simulations.

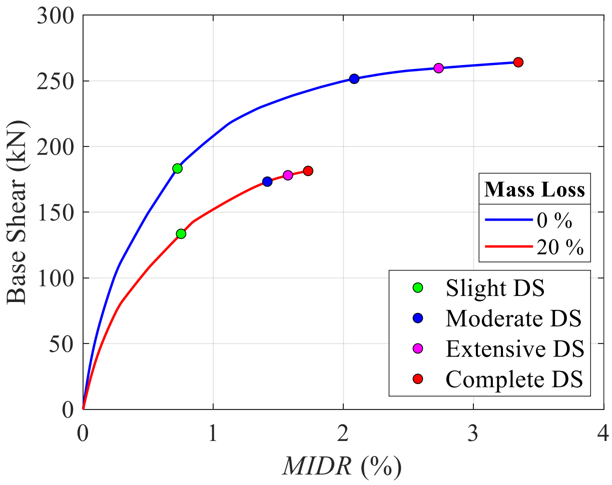

Figure 3: Capacity curves of the RC frame showing the *DS*s corresponding to different levels of deterioration

Figure 3 shows the sample capacity curves plotting base shear reaction against maximum inter-storey drift ratios (*MIDR*) of the RC frame at varying levels of deterioration (0%, and 20%) mapped with the resulting damage states. The other material parameters for this depiction are assumed to be at the mean strength (yield strength of the reinforcement and compressive strength of concrete). The performance limits corresponding to the Slight, Moderate, Extensive, and Complete *DS*s are identified for each of the deterioration levels and are plotted on the curve. A reduction in every level can be observed along with the deterioration of RC frame.

6 DEVELOPMENT OF DAMAGE STATE PREDICTIVE EXPRESSIONS

The global level capacities of the RC frames defined by maximum inter-storey drift ratios mapped to various damage states are noted during the nonlinear static pushover analyses, which facilitates the identification of performance levels. Polynomial response surface models have been adopted to predict the capacity in various studies including bridge piers which are adopted in the present study. The input parameters and the output values in terms of *MIDR* are fitted in polynomial response surface models (PRSM) at each of the provided damage states followed by an accuracy check. The cross validation of the fitted model was carried out using an 80% and 20% split for training and testing respectively. The training process was carried out fifteen times over random permutations of the input parameters of design matrix avoiding repetition of same training data set. The test data set is used to validate the goodness of fit of the prediction models using the adjusted R square and normalized root mean square errors. The estimated *MIDR* at various levels of *DS*s are compared with the predicted data.

The fitted PRSMs can be used to predict the performance levels in terms of *MIDR* of the RC frame for varying levels of material strength and deterioration levels. Table 3 lists the fitted first order PRSMs allowing the prediction of *MIDR* for Slight, Moderate, Extensive, and Complete *DS*s using the input parameters (concrete compressive strength, yield strength and mass loss of the reinforcement). The observations drawn from the predictive expressions show that the increase in percentage mass loss of longitudinal reinforcement reduces the *MIDR* of the damage states. Table 3 also lists the adjusted R^2, showing how well the fitted models explain the observed data, along with the normalized root mean square error (nRMSE) for each of the predictive expressions. The adjusted R^2 for the *MIDR* on all the DSs stays above 0.85, showing a good correlation between the predicted and the real values of *MIDR*. The nRMSE shows the same correlation with *MIDR* for all the DSs stays below 0.38 depicting a less margin of error for the prediction.

Performance Levels	β_0	β_1	β_2	β_3	Adjusted R^2	nRMSE
Slight *DS*	1.5 x10^{-1}	-5.1 x10^{-2}	1.2 x10^{-2}	-2.2 x10^{-3}	0.983	0.127
Moderate *DS*	8.3 x10^{-1}	5.2 x10^{-2}	8.4 x10^{-3}	-8.4 x10^{-3}	0.857	0.377
Extensive *DS*	2.0 x10^{0}	9.9 x10^{-3}	4.1 x10^{-3}	-3.5 x10^{-2}	0.947	0.228
Complete *DS*	3.2 x10^{0}	-2.6 x10^{-2}	-3.6 x10^{-4}	-6.4 x10^{-2}	0.961	0.198
Note: $MIDR = \beta_0 + \beta_1(f_c) + \beta_2(f_y) + \beta_3(\psi_{corr})$						

Table 3: Expressions to predict various *DS*s fitted to polynomial response surface models (PRSMs)

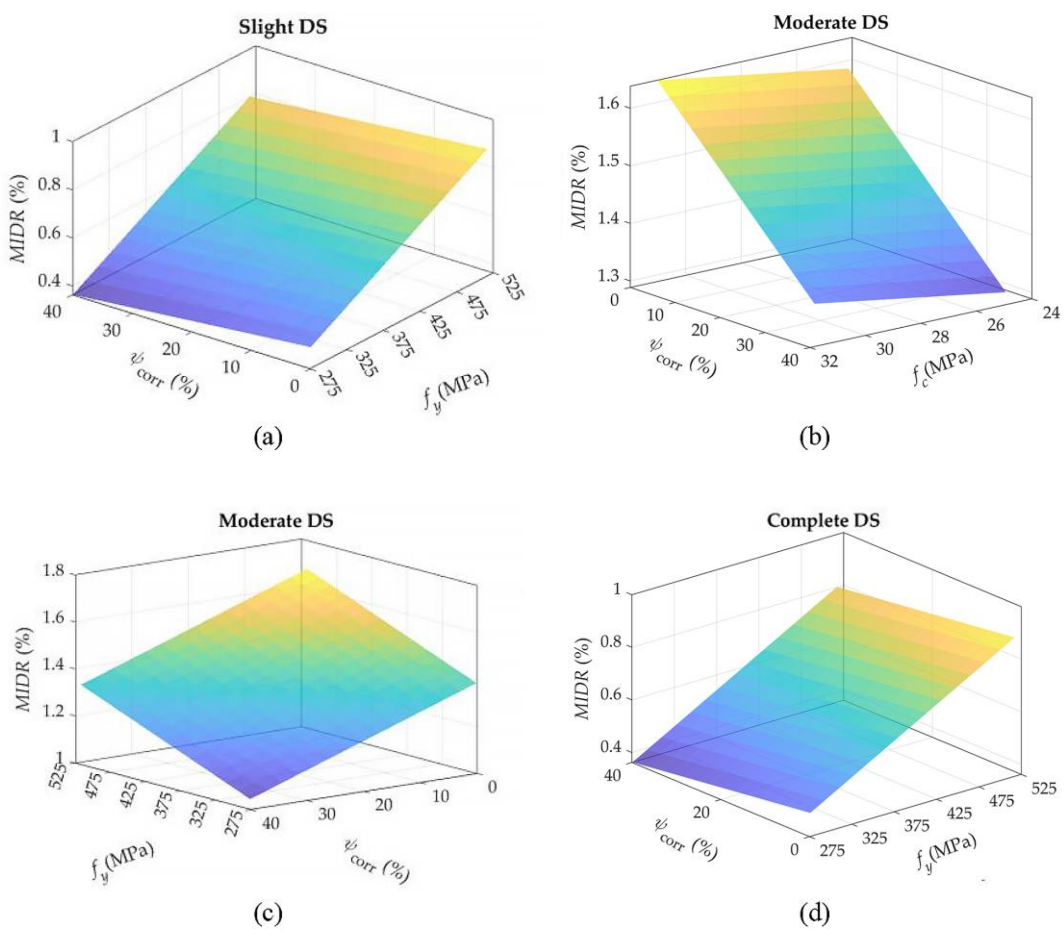

Figure 4: Influence of yield strength and percentage mass loss of longitudinal reinforcement on (a) Slight *DS*, (c) Moderate *DS* and (d) Complete *DS*, and influence of concrete compressive strength on (b) Moderate *DS*

Figure 4 (a) to (d) shows the surface response plots of the RC frame represented at global level maximum inter-storey drift ratio of various performance levels, such as representing yielding of 50% of column member in a single storey, cover concrete spalling at 50% of column member in a single storey, and shear failure of 50% of column member in a single storey. The surface response plots represent *DS*s and the influence of variation in percentage mass loss of the longitudinal reinforcement (ψ_{corr}), concrete compressive strength (f_c), and reinforcement yield strength (f_y). While comparing the variation in percentage mass loss and concrete compressive strength (Figure 4 a & b), the yield strength is assumed to be at mean value, and vice versa.

A negative correlation can be observed for percentage mass loss on all *DS*s with *MIDR* of the RC frame. It aligns with the trends in past studies showing a reduction in the performance levels of RC frames with the rise in corrosion deterioration [31]. Figure 4 (b) shows an increase in concrete compressive strength corresponds to rise in the levels of *MIDR* for the *DS* depicting cover concrete spalling. Figure 4 (a) and (c) shows an increase in the yield strength if the reinforcement bar corresponds to increase in the *MIDR* levels for column yielding and cover concrete spalling. Yields strength has a negative correlation with the mass loss in the reinforcement, yet a positive correlation of the yield strength shows that the usage of an initially higher strength reinforcement can be better performing at damages. Figure 4 (d) shows a negative correlation of percentage mass loss with the failure of column in shear; however, the yield strength is showing a minimal correlation with the shear failure in column due to the drift-based damage limit [15] adopted for the study.

7 CONCLUSIONS

This study presented a framework to develop predictive expressions for seismic damage limit states for RC frames subjected to chloride-induced corrosion. The framework developed simplified predictive expressions that can identify various performance levels of the deteriorated RC frame under earthquake with good efficiency and reliability. Local level damage corresponding to the global level damage states in RC frames is estimated by following performance levels of column yielding, cover concrete spalling and shear failure in columns. An input parameters dataset for the deteriorated RC frame is generated through the design of experiments strategy. OpenSees platform is used to generate the numerical models. A past literature-based FE model of a low-ductility RC frame is developed, and nonlinear static pushover analysis is carried out across the dataset. The maximum inter-storey drift ratios (*MIDR*) obtained from the pushover analysis is mapped with occurrence of various damage states in the RC frame. The obtained *MIDR* values at all the damage states are utilized to fit the polynomial response surface models. The predictive expressions are able to generate *MIDR* values corresponding to the various damage states. Prediction models demonstrated a robust fit with a minimum adjusted R^2 of 0.85 and a maximum normalized root mean square of 0.38. The proposed framework can assist in the service life prediction of RC buildings in coastal areas subjected to chloride-induced corrosion to support risk mitigation strategies as well as retrofitting process. The future work of this study will consider multiple uncertainties in the materials and modeling of a deteriorated RC frame, as well as utilize advanced machine learning algorithms for developing the prediction models.

REFERENCES

[1] A. H. M. Billah and M. S. Alam. "Performance-based seismic design of shape memory alloy–reinforced concrete bridge piers. I: Development of performance-based damage states." *Journal of Structural Engineering,* vol. 142, no. 12, 2016.

[2] Goodnight, C. Jason, M. J. Kowalsky, and J. M. Nau. "Strain limit states for circular RC bridge columns." *Earthquake Spectra*, vol. 32, no. 3, 2016.

[3] R. Capozucca, "Damage to reinforced concrete due to reinforcement corrosion." *Construction and Building Materials,* vol. 9, no. 5, 1995.

[4] L. Di Sarno and F. Pugliese. "Numerical evaluation of the seismic performance of existing reinforced concrete buildings with corroded smooth rebars." *Bulletin of Earthquake Engineering,* vol. 18, no. 9, 2020.

[5] N.S. Vu, and B. Li. "Seismic performance assessment of corroded reinforced concrete short columns." *Journal of Structural Engineering,* vol. 144, no. 4, 2018.

[6] X. Zhang and B. Li. "Seismic performance of interior reinforced concrete beam–column joint with corroded reinforcement." *Journal of Structural Engineering,* vol. 148, no. 2, 2022.

[7] D. D'ayala, A. Meslem, D. Vamvastikos, K. Porter, T. Rossetto, H. Crowley, and V. Silva. "Guidelines for analytical vulnerability assessment of low/mid-rise Buildings—Methodology. Vulnerability Global Component project." 2014.

[8] Y. Pang, X. Dang, and W. Yuan. "An artificial neural network based method for seismic fragility analysis of highway bridges." *Advances in Structural Engineering*, vol. 17, no. 3. 2014.

[9] S. Mangalathu and J. Jeon. "Classification of failure mode and prediction of shear strength for reinforced concrete beam-column joints using machine learning techniques." *Engineering Structures*, vol. 160, 2018.

[10] H. Luo and S. G. Paal. "A locally weighted machine learning model for generalized prediction of drift capacity in seismic vulnerability assessments." *Computer‐Aided Civil and Infrastructure Engineering*, vol. 34, no. 11, 2019.

[11] M. Hamidia, S. Mansourdehghan, A. H. Asjodi, and K. M. Dolatshahi. "Machine learning-based seismic damage assessment of non-ductile RC beam-column joints using visual damage indices of surface crack patterns." *Structures*, vol. 45, pp. 2038-2050. Elsevier, 2022.

[12] S. Bhatta and J. Dang. "Seismic damage prediction of RC buildings using machine learning." *Earthquake Engineering & Structural Dynamics*, vol. 52, 2023.

[13] B. Xu, X. Wang, C. W. Yang, and Y. Li. "Machine Learning–Aided Rapid Estimation of Multilevel Capacity of Flexure-Identified Circular Concrete Bridge Columns with Corroded Reinforcement." *Journal of Structural Engineering*, vol. 150, no. 3, 2024.

[14] S. Shekhar, F. Freddi, J Ghosh, and D. Lad. "Influence of corrosion on failure modes and lifetime seismic vulnerability assessment of low‐ductility RC frames." *Earthquake Engineering & Structural Dynamics*, vol. 52, no. 15, 2023.

[15] N.S. Vu, B. Yu, and B. Li. "Prediction of strength and drift capacity of corroded reinforced concrete columns." *Construction and Building Materials*, vol. 115, 2016.

[16] R. Yu, L. Chen, D. Zhang, and Z. Wang. "Life cycle embodied energy analysis of RC structures considering chloride-induced corrosion in seismic regions." *Structures*, vol. 25, pp. 839-848. Elsevier, 2020.

[17] F. Freddi, J. Ghosh, N. Kotoky, and M. Raghunandan. "Device uncertainty propagation in low‐ductility RC frames retrofitted with BRBs for seismic risk mitigation." *Earthquake Engineering & Structural Dynamics*, vol. 50, no. 9, 2021.

[18] C. Caruso, R. Bento, and J. M. Castro. "A contribution to the seismic performance and loss assessment of old RC wall-frame buildings." *Engineering Structures*, vol. 197, 2019.

[19] HAZUZ -MH MR5, Federal Emergency Management Agency, D.C, 2013.

[20] M.J. Priestley, M.J. Nigel, F. Seible, and G. M. Calvi. *Seismic design and retrofit of bridges*. John Wiley & Sons, 1996.

[21] S. C. Dutta, L. Halder, and R. P. Sharma. "Seismic vulnerability assessment of low to mid-rise RC buildings addressing prevailing design and construction practices in the Northeastern region of the Indian subcontinent: A case study based approach." *Structures*, vol. 33, pp. 1561-1577. Elsevier, 2021.

[22] F. McKenna, L. G. Fenves, and M. H. Scott. "Open system for earthquake engineering simulation." University of California, Berkeley, CA, 2000.

[23] J. B. Mander, M. J. N Priestley, and R. Park. "Theoretical stress-strain model for confined concrete." *Journal of structural engineering*, vol. 114, no. 8, 1988.

[24] O. C. Celik, and B. R. Ellingwood. "Modeling beam-column joints in fragility assessment of gravity load designed reinforced concrete frames." *Journal of Earthquake Engineering*, vol. 12, no. 3, 2008.

[25] S. Alath. "Modeling inelastic shear deformation in reinforced concrete beam-column joints." 1995.

[26] K. Dai, X. Yu, and L. Da-Gang. "Phenomenological hysteretic model for corroded RC columns." *Engineering Structures*, vol. 210, 2020.

[27] F. Biondini, and M. Vergani. "Deteriorating beam finite element for nonlinear analysis of concrete structures under corrosion." *In Design, Assessment, Monitoring and Maintenance of Bridges and Infrastructure Networks*, pp. 107-120. Routledge, 2020.

[28] X. Zhang and B. Li. "Shear-strength capacity assessment of corroded reinforced concrete beam-column joints." *Journal of Performance of Constructed Facilities*. vol. 32, no. 5, 2018.

[29] D. C. Montgomery, *Design and analysis of experiments*. John wiley & sons, 2017.

[30] IS: 10262 (2009). Indian standard for concrete mix proportioning – Guidelines, New Delhi, India: Bureau of Indian Standards.

[31] E. A. Dizaj, R. Madandoust, and M. M. Kashani. "Probabilistic seismic vulnerability analysis of corroded reinforced concrete frames including spatial variability of pitting corrosion." *Soil Dynamics and Earthquake Engineering*, vol. 114, 2018.