Engineering Structures 160 (2018) 85–94

Contents lists available at ScienceDirect

Engineering Structures

journal homepage: www.elsevier.com/locate/engstruct

Classification of failure mode and prediction of shear strength for reinforced concrete beam-column joints using machine learning techniques

Sujith Mangalathu[a], Jong-Su Jeon[b,*]

[a] Department of Civil and Environmental Engineering, University of California, Los Angeles, CA 90095, USA
[b] Department of Civil Engineering, Andong National University, Andong, Gyeongsangbuk-do 36729, Republic of Korea

ARTICLE INFO

Keywords:
Beam-column joints
Joint shear failure
Failure mode
Machine learning
Probabilistic models

ABSTRACT

Beam-column joints are one of critical components that control the oveerall performance of reinforced concrete building frames under seismic loadings. To identify the response mechanism, including the classification of failure mode and the prediction of associated shear strength, of beam-column joints, this paper introduces the application of machine learning techniques. The efficiency of various machine learning techniques is evaluated using extensive experimental data from 536 experimental tests, all of which exhibited either non-ductile joint shear failure prior to beam yielding or ductile joint shear failure after beam yielding. It has been seen from the comparison that lasso regression has a better efficiency and reasonable accuracy in the classification and prediction. The suggested formulations as a function of influential input variables can be easily used by structural engineers to provide an optimal rehabilitation strategy for existing buildings and to design new structures.

1. Introduction

Earthquake reconnaissance studies have highlighted the significance of beam-column joint responses on the overall seismic performance of reinforced concrete (RC) frames [1,2]. Under strong seismic events, beam-column joints, one of key components to maintain their structural integrity of structural systems, may experience large deformations and significantly reduce their lateral and gravity load-carrying capacity, leading to partial damage or global collapse to the structure. Typically, this lateral instability and collapse have been observed in non-ductile RC frames with inadequate design details. To explore the main reasons of this non-ductile failure and to evaluate the seismic performance of these frames, numerous experiments have been performed for unreinforced joints (no joint transverse reinforcement) with poor design details [3,4]. Results of these researches resulted in the requirements for an amount of joint transverse reinforcement and anchorage in modern building design codes [5–7]. These seismic design codes have adopted strong column-weak beam philosophy to ensure the elastic response of joints and the formation of plastic hinges in beams at large deformations rather than in columns. However, the significant loss of strength and stiffness has been observed for joints designed on the basis of the seismic design code requirements [8,9]. In addition, Shin and LaFave [10] stated that the joint panel zones in modern RC frames are not essentially rigid, but experience considerable shear deformations and strength reductions that contribute greatly to global flexibility.

As mentioned above, the inelastic response of beam-column joints is one of the most critical failure mechanisms influencing the overall structural performance. Thus, a realistic simulation of the inelastic joint action in the numerical model of frames is required to more accurately evaluate the performance of existing structures and design new structures. Such a reliable estimation depends on capturing an accurate prediction of the failure mode of beam-column connections and its associated beam-column joint capacity. However, existing beam-column joint models used for the probabilistic assessment of frames [11–13] were developed regardless of failure mode. The failure mode dependent computational model is very complicated and computationally intensive due to use of continuum-based finite element models. To efficiently assess the failure mode classification, Mitra et al. [14] suggested a binominal logit model to predict the likelihood of joint failure in RC frames: non-ductile joint shear failure prior to beam yielding or ductile failure that initiates with beam yielding. The authors used 110 laboratory tests of interior beam-column joint sub-assemblages, and the logit model was a function of the joint design variables such as nominal joint shear stress demand, average bond stress demand, the ratio of joint transverse reinforcement strength to joint shear stress demand, column axial load ratio, and the ratio of beam top to bottom longitudinal reinforcement strength. However, logit model estimates often have low bias but large variance, and prediction accuracy can be sometimes improved by removing some of regression coefficients [15].

* Corresponding author.
E-mail addresses: sujithmangalath@ucla.edu (S. Mangalathu), jsjeon@anu.ac.kr (J.-S. Jeon).

https://doi.org/10.1016/j.engstruct.2018.01.008
Received 7 September 2017; Received in revised form 30 November 2017; Accepted 4 January 2018
0141-0296/

This paper explores the various machine learning techniques such as logistic, lasso logistic, discriminant, *k*-nearest neighbors, support vector machines, decision trees, and random forests to identify the failure mode of RC beam-column joints. The current study employs an extensive and comprehensive database consisting of 536 experimental tests of beam-column joints and uses 12 input variables that may affect the joint response. To evaluate the relative efficiency of various techniques the data is split into a training set and test set. The training set is used to establish the classifier and its efficiency is evaluated using the test set. Although these machine learning techniques have been used widely in the field of statistics [15–17], the application of machine learning techniques has not been yet fully explored to the classification of failure mode for RC beam-column joints and this paper is the initial step in that direction. Additionally, most of existing studies [13,18] developed joint shear strength prediction models for all collected data without classifying the failure mode. However, such an estimation cannot provide a more reliable basis for the performance evaluation of structures to design new structures and rehabilitate existing structures to ensure the ductile behavior of beam-column joints.

Jeon et al. [18] proposed a probabilistic joint shear strength model using regression techniques such as multivariate adaptive regression splines (MARS) and symbolic regression. However, the authors have not identified the failure mode of beam-column joints. This paper further extends their work through the application of machine learning techniques such as lasso, ridge, elastic net, stepwise, and random forest to the prediction of beam-column joint capacity depending on the failure mode. These machine learning techniques perform better compared to the traditional regressions [15] and recent researches in civil engineering have been exploring the application of these techniques [18,19].

This research aims to (1) compare the efficiency of various machine learning techniques in identifying the failure mode (ductile or non-ductile) and shear strength of beam-column joints with transverse reinforcement, (2) suggest an easy-to-use equation to identify the failure-mode and shear strength as a function of the geometric, material, and structural properties of beam-column joints, and (3) identify the relative importance of various uncertain input parameters on the shear strength of beam-column joints. The paper is outlined as follows. The experimental database is described in detail in Section 2, and the review of various machine learning techniques used for classification and regression is given in Section 3. The comparison of various machine learning techniques in estimating the failure mode and joint capacity is provided in Section. The paper is concluded in Section 5 with the salient points noted in the current study.

2. Experimental database

2.1. Description of database for RC beam-column joint sub-assemblages

To identify the failure mode of reinforced concrete beam-column connection sub-assemblages and to develop their failure-related strength model, this research uses the database consisting of 536 test specimens. Extensive experimental results on beam-column joints from various scientific literatures published in USA, Japan, New Zealand, Europe and Korea are used to construct the database. The database of 516 specimens with transverse reinforcement is reported in Jeon et al. [18]. The database consists of beam-column joint failures before and after member (beam or column) yielding during the experiment. Among the database, 186, 318, and one specimens failed in joint shear prior to member yielding (J failure mode, hereafter), joint shear after beam yielding (BJ failure mode, hereafter), and joint shear after column yielding (CJ failure mode, hereafter), respectively. One specimen exhibiting CJ failure is excluded in this research to assess a reliable estimate of failure mode and associated joint shear strength. Typically, the response of the sub-assemblages exhibiting J failure is governed by the joint response (leading to a sudden loss of lateral load-carrying capacity and thus brittle failure) while the behavior of the sub-assemblages with BJ failure is controlled by beam yielding (ductile failure). The original database includes exterior and interior specimens with and without transverse beams and with and without floor slab. The detailed description of the specimens can be found in Jeon et al. [18] and Jeon [20]. In addition to the reported data [18,20], the authors collect 21 additional experimental data for knee-joint types [21–27], as presented in Table 1. Among these knee connections, 10 and 11 specimens experienced joint shear failure, respectively, prior to and after beam yielding. All knee specimens do not have transverse beams. Fig. 1 shows the constituents of the reinforced beam-column joint sub-assemblage database (536 specimens = 294 interior + 221 exterior + 21 knee) used in this research. In the figure, for example, BJ-TB0 indicates the specimens with no transverse beams exhibiting BJ failure and J-TB2 indicates the specimens with two transverse beams exhibiting J failure.

Table 1
Experimental database for knee beam-column joints.

First author	Specimen	Failure mode	f_c (MPa)	$\tau_{exp}/f_c^{0.5}$ (MPa$^{0.5}$)
Shimonoka [21]	L-U	J	32.0	0.872
Tabata [22]	L-BH1	J	25.6	0.630
	L-BH2	J	25.6	0.681
	L-BU	J	25.6	0.885
McConnell [23]	KJ5	BJ	31.5	0.858
	KJ6	BJ	33.0	0.842
	KJ7	BJ	32.9	0.842
	KJ8	BJ	36.3	0.658
	KJ9	BJ	38.5	0.642
	KJ10	BJ	37.9	0.650
	KJ11	BJ	35.0	0.700
	KJ12	BJ	32.9	0.717
	KJ13	BJ	31.7	0.725
Mazzoni [24]	2-hoop	J	42.1	0.656
	4-hoop	J	42.1	0.664
Choi [25]	L-1	J	27.2	0.549
	L-2	J	27.2	0.425
Kramer [26]	Joint 4	BJ	34.6	0.493
Megget [27]	1	BJ	27.8	0.486
	5	J	33.6	0.415
	8	J	40.4	0.400

Note that f_c is the compressive strength of concrete and τ_{exp} is the experimental joint shear strength.

2.2. Brief description of input variables affecting beam-column joint response

The current study employs the candidate input variables for the reinforced joint database constructed by Jeon et al. [18], which was used to develop the joint shear strength models via MARS approach. These input variables were determined by examining influential variables affecting the joint response such as joint shear strength, failure mode, and ductility from the review of existing experimental results, statistical observations, mechanics theories, and design specifications. The input variables are 12 such as the concrete compressive strength (f_c), joint transverse reinforcement (ρ_j), design joint shear stress (τ_d), in-plane joint geometry (JP), out-of-plane joint geometry (TB), ratio of beam depth to column depth (h_b/h_c), joint eccentricity parameter (e_c), ratio of beam width to column width (b_b/b_c), column axial load ratio (q), beam-bar bond parameter (χ), column-to-beam flexural moment strength ratio (M_R), and column intermediate longitudinal reinforcement factor (θ). Fig. 2 shows the distribution of 12 input variables used for the reinforced joint database. Because a detailed description of the input variables was already provided in Jeon et al. [18], the current study briefly describes the definition of input variables used here. The joint transverse reinforcement (ρ_j) is defined as the ratio of the area of