Advances in Concrete Construction, *Vol. 9, No. 4* (*2020*) *337-343*
DOI: https://doi.org/10.12989/acc.2020.9.4.337

Bayesian demand model based seismic vulnerability assessment of a concrete girder bridge

M. Bayat*[1], M. Kia[2], V. Soltangharaei[1], H.R. Ahmadi[3] and P. Ziehl[1]

[1]*Department of Civil and Environmental Engineering, University of South Carolina, Columbia, SC, USA*
[2]*Department of Civil Engineering, University of Science and Technology of Mazandaran, Behshahr, Iran*
[3]*Department of Civil Engineering, Faculty of Engineering, University of Maragheh, Maragheh P.O. Box 55136-553, Iran*

(*Received September 28, 2019, Revised February 15, 2020, Accepted February 21, 2020*)

Abstract. In the present study, by employing fragility analysis, the seismic vulnerability of a concrete girder bridge, one of the most common existing structural bridge systems, has been performed. To this end, drift demand model as a fundamental ingredient of any probabilistic decision-making analyses is initially developed in terms of the two most common intensity measures, i.e., PGA and Sa (T_1). Developing a probabilistic demand model requires a reliable database that is established in this paper by performing incremental dynamic analysis (IDA) under a set of 20 ground motion records. Next, by employing Bayesian statistical inference drift demand models are developed based on pre-collapse data obtained from IDA. Then, the accuracy and reasonability of the developed models are investigated by plotting diagnosis graphs. This graphical analysis demonstrates probabilistic demand model developed in terms of PGA is more reliable. Afterward, fragility curves according to PGA based-demand model are developed.

Keywords: Bayesian Interface; Finite Element Modeling (FEM); Fragility Function Methodology; Probabilistic Seismic Demand Analysis (PSDA)

1. Introduction

The seismic risk stem of US highway structures has been one of the main concerns for a long time. Although seismic resilience of the US highway system has been improved in recent decades, not all existing highway infrastructure has been retrofitted; therefore, some seismic risks to the U.S. highway structures remain. There is no national database for seismic risk to U.S. highway infrastructure. Different approaches have been taken to deal with the vulnerability of existing highway structures such as replacing, retrofitting, and abandoning.

In the straight highway bridges, the longitudinal and transverse responses are decoupled, since the superstructure and substructural centerlines are perpendiculars. Since the approach of seismic design codes has switched from deterministic to probabilistic, fragility function methodology has become a significant decision-making tool to assess the condition of existing structures and design new structures. There are two main methods to derive fragility curves; empirical and analytical. In the former method, the fragility curves were developed based on the data of historical earthquakes. In the analytical method, nonlinear dynamic analyses apply to structures using a limited number of ground motion to generate fragility curves. One of the main drawbacks attributed to the empirical method is a need for a large amount of damage data for a specific class of structure, which is usually not available.

Wang *et al*. (2018) analyzed twenty-six intensity measures to propose the optimal intensity measure of probabilistic seismic demand analysis of the pile-shaft-supported bridges in liquefied and laterally spreading ground. Jeon *et al*. (2019) developed the work on the seismic fragility curves for California concrete bridges. They considered structural uncertainties such as material and geometric in the generation of the fragility curves. Dukes *et al*. (2018) used a multi-parameter demand model to estimate the fragility curves. They applied Monte Carlo simulation to determine the fragility of the bridge components. Cui *et al*. (2018) tried to conduct the fragility analysis for the high-speed railway continuous-girder bridge by considering different modeling parameters and damage states.

Recent works related to the empirical and analytical fragility curves can be found in the open literatures (Cimerallo *et al.* 2010, Muntasir Billah *et al*. 2015, Parghi *et al*. 2017, Cui *et al*. 2019, Duke *et al*. 2018, Wang *et al*. 2018, Jeon *et al*. 2017, 2019, Haukaas *et al*. 2008, Kia *et al*. 2018, 2016, Jalayer *et al*. 2015, Alam *et al*. 2017, 2019, Soltangharaei *et al*. 2019, Hwang *et al*. 2001, Kwang *et al*. 2017, Bai *et al*. 2011, Choe *et al*. 2008, Gkatzogias *et al*. 2015, O'Reilly *et al*. 2018, Sisi *et al*. 2018, Chen *et al*. 2016).

In this paper, regression-based demand models with a linear formulation in the logarithmic space are proposed to predict the maximum drift ratio for bridge columns of concrete girder highway bridges. A concrete girder bridge was modeled in SAP 2000 V.14.2.4 finite element software.

*Corresponding author, Ph.D.
E-mail: mbayat@mailbox.sc.edu,
mbayat14@yahoo.com

ISSN: 2287-5301 (Print), 2287-531X (Online)

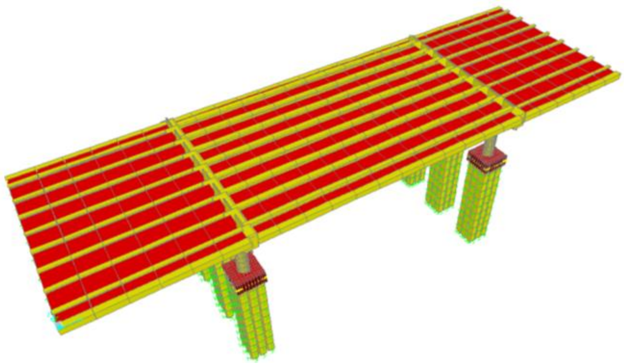

Fig. 1 A scheme of the three dimension of the bridge

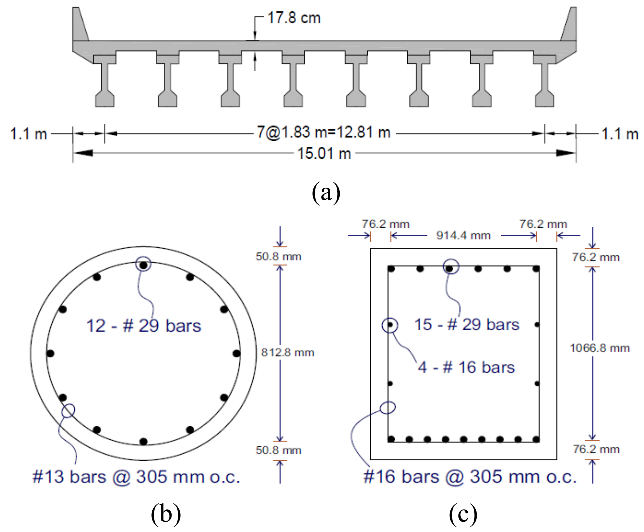

Fig. 2 Concrete member reinforcing layout (a) Deck detail (b) Column (c) Bent beam (Bayat *et al*. 2015b)

A full incremental dynamic analysis has been conducted on the bridge. PGA is chosen as an intensity measure (IM), and column drift ratios as an engineering demand parameter (EDP). The different performance levels of the bridge are considered through slight, moderate and extensive levels. Bayesian regression analysis has been utilized to develop a probabilistic demand model to predict damages in the bridge. In the Bayesian regression, the uncertainty resulted due to incomplete sample populations (statistical uncertainty) is directly addressed by standard deviation σ and regression coefficients, which are random variables, rather than constant variables.

Analytical fragility curves have been developed for a typical bridge class of Central and Southeastern United States (CSUS) region. The CSUS is a moderate seismic zone which the seismic risk mitigation efforts are inevitable. The main objective of this paper is to assess the bridge seismic vulnerabilities using a probabilistic demand model developed using the Bayesian interface framework. Seismic fragility curves are developed, considering both the uncertainties from the hazard and the capacity of the bridges. A numerical modeling of the bridge is presented for the investigation on the seismic response and risk assessment of the most common bridge types in the Central and Southeastern US.

Table 1 Damage States (DS) for concrete columns (Zhang *et al*. 2009)

Component/ Damage	Slight (DS=1)	Moderate (DS=2)	Extensive (DS=3)	Collapse (DS=4)
Column	Cracking and spalling	Moderate cracking and spalling	Degradation *w/o* collapse	Failure leading to collapse
	μ>1	μ>2	μ>4	μ>7
	θ>0.007	θ>0.015	θ>0.025	θ>0.050

2. Numerical modelling

The model used in this study is derived from a non-skewed model developed by Nielson (2005). The bridge characteristics are based on the data obtained from a survey of numerous bridge plans of CSUS region. Fig. 1 shows a three-dimensional finite-element of the considered bridge in SAP2000 software. The bridge has a total length of 48 m with three spans, and a total width of 15.01 m with eight AASHTO-type prestressed girders. Frame elements were used to model the prestressed concrete girders and cap beams and columns were modeled by nonlinear frame elements. Two joint link elements were used to model the elastomeric pads between the cap beams and girders. The bridge deck was modeled by shell elements. The lateral stiffness of soil was modeled by spring elements.

The detail of the bridge components is shown in Fig. 2. More details of this bridge can be found in (Bayat *et al*. 2015a, b, Choi 2002). A bilinear plastic element is used to model the place of plastic hinges that are likely to form. Abutments and the column boundary conditions are fixed-free in the longitudinal direction and fixed-fixed in the transverse direction. The bearings are elastomeric pads and their behavior are modeled with an elastic-perfectly plastic material. The first period of the bridge was 0.59 seconds with 5% damping.

3. Damage states for IDA

In this paper, column drift ratios were utilized to define the performance levels as tabulated in Table 1.

4. Seismic fragility analysis

Seismic fragility is defined as the probability of exceeding a specific threshold value of d in the condition of *IM* equals to *x*, which is computed as follows

$$P[D(\mathrm{Im},\Theta)\geq d\mid \mathrm{Im}=x]\cong\left[1-\varphi\left(\frac{Ln(d)-\lambda_{Ln(D|IM)}}{\sigma_{Ln(D|\mathrm{Im})}}\right)\right] \quad (1)$$

Where $\lambda_{Ln(D|IM)}$ and $\sigma_{Ln(D|Im)}$ are the median and standard deviation of the seismic demand given

Im in the logarithmic space. φ indicates cumulative standard normal distribution function. According to Eq. (1), probabilistic demand model is vital component of probabilistic decision-making analyses such as seismic fragility analysis. These models are commonly developed based on observations obtained from experimental tests and/or numerical analyses. It should be noted that a model that matches past observations would not necessarily predict future events. Therefore, both aleatory and statistical uncertainty should be explicitly embedded within the predictive demand models. To this end, linear model with random parameters in the logarithmic space have been employed to describe relation between overall maximum drift as the bridge structural demand parameter (D) and earthquake intensity, the spectral acceleration at the fundamental period Sa (T_1) or peak ground acceleration (PGA). The logarithmic transformation is also utilized to approximately satisfy the normality assumption (i.e., model error has normal distribution) and homoscedasticity assumption (i.e., Standard deviation of model error is constant). This mathematical expression conforms to the perceptional of a structural performance curve (IDA curve). Eq. (2) illustrates general form of the predictive model considered in this study

$$Ln\left(D\right)=a+b\times Ln\left(Sa\left(T_1\right)or\ PGA\right)+u \tag{2}$$

where D represents the target response (overall maximum drift), Ln function denotes natural logarithm, u is a term reflecting model error and is supposed to be a normal random variable with zero mean and unknown standard deviation equals σ, and $\Theta=(a, b)$ is a vector of unknown normal random model parameters. It is worthy noted the above-mentioned relation is also written as follows

$$Ln\left(D\right)=a+b\times Ln\left(Sa\left(T_1\right)or\ PGA\right)+\sigma\varepsilon \tag{3}$$

In practice, estimating the statistical characteristics of the model parameters a, b and σ require collecting a large quantity of observations, including: appropriate ground motion records selection, Incremental Dynamic Analysis, and statistical inference, which are explained in the following.

5. Ground motion records selection

Twenty ground motion records were selected according to criteria proposed by FEMA-P695 (2003). The records are listed in Table 2 and the criteria are presented as follow:

- Peak Ground Acceleration (PGA)>0.2 g and Peak Ground Velocity (PGV)>15 cm/sec. Earthquake magnitude is larger than 6.5 M.
- Epicenters are larger than 10 km.
- Soil shear wave velocity, in upper 30m of soil, greater than 180 m/s.
- Lowest useable frequency<0.25 Hz.
- Strike-slip and thrust faults.

6. Incremental Dynamic Analysis (IDA)

In this paper, the spectral acceleration at the fundamental period Sa (T_1) and peak ground acceleration (PGA) were employed to represent earthquake intensity. In addition, Overall maximum drift (θ_{max}) is also considered as a demand of interest to evaluate seismic performance of the bridge. All records were scaled to 1 g and applied to the bridge with 0.1 g intervals. In each step, full nonlinear time history analysis is conducted (Vamvatsikos *et al*. 2002). The scale started from 0.1 g and increased until the collapse state of the bridge.

Table 3 Characteristics of the earthquake ground motion histories (FEMA 2009)

ID No	M	Earthquake			Recording station	
		PGA(g)	Year	Name	Name	owner
1	7.0	0.48	1992	Cape Mendocino	Rio Dell Overpass	USGS
2	7.6	0.21	1999	Chi-Chi, Taiwan	CHY101	CWB
3	7.1	0.82	1999	Duzce,Turkey	Bolu	ERD
4	6.5	0.45	1976	Friuli, Italy	Tolmezzo	------------
5	7.1	0.35	1999	Hector Mine	Hector	SCSN
6	6.5	0.34	1979	Imperial Valley	Delt	UNAMUCSD
7	6.5	0.35	1979	Imperial Valley	El Centro Array#1	USGS
8	6.9	0.38	1995	Kobe, Japan	Nishi-Akashi	CUE
9	6.9	0.51	1995	Kobe,Japan	Shin-Osaka	CUE
10	7.5	0.24	1999	Kokaeli,Turkey	Duzce	ERD
11	7.3	0.36	1992	Landers	Yemo Fire Station	CDMG
12	7.3	0.24	1992	Landers	Coolwater	SCE
13	6.9	0.42	1989	Loma Prieta	Capitola	CDMG
14	6.9	0.53	1989	Loma Prieta	Gilory Arrey#3	CDMG
15	7.4	0.56	1990	Manjil	Abbar	BHRC
16	6.7	0.55	1994	Northridge	Beverly Hills-Mulhol	USC
17	6.7	0.44	1994	Northridge	Canyon Country-WLC	USC
18	6.6	0.36	1971	San Ferando	LA-Hollywood Stor	CDMG
19	6.5	0.51	1987	Superstition Hills	El Centro Imp.Co	CDMG
20	6.5	0.52	1987	Superstition Hills	Poe Road (temp)	USGS

A comprehensive structural data-base is established due to these extensive nonlinear dynamic analyses. The database is divided into two parts, collapse and non-collapse data. The non-collapse data is applied to develop probabilistic demand model according to Eqs. (4) or (5).

7. Bayesian statistical inference

Consider $h(x)$ as a vector of explanatory functions formulated in terms of independent variables collected in vector x. y is a response variable predicted by

$$y=\theta_1 h_1\left(x\right)+\theta_2 h_2\left(x\right)+\dots\dots\dots+\theta_k h_k\left(x\right)+\sigma\varepsilon \tag{4}$$

where $\theta_i s$ are called model parameters, ε is a standard normal random variable and σ is standard deviation of model error. Traditionally, classical regression is applied to compute point estimation of model parameters (θ, σ). It is clear that point estimation based on information obtained from a finite-size sample population is incomplete and uncertain. Conversely, Bayesian linear regression can express our uncertainty about (θ_i, σ) by considering model

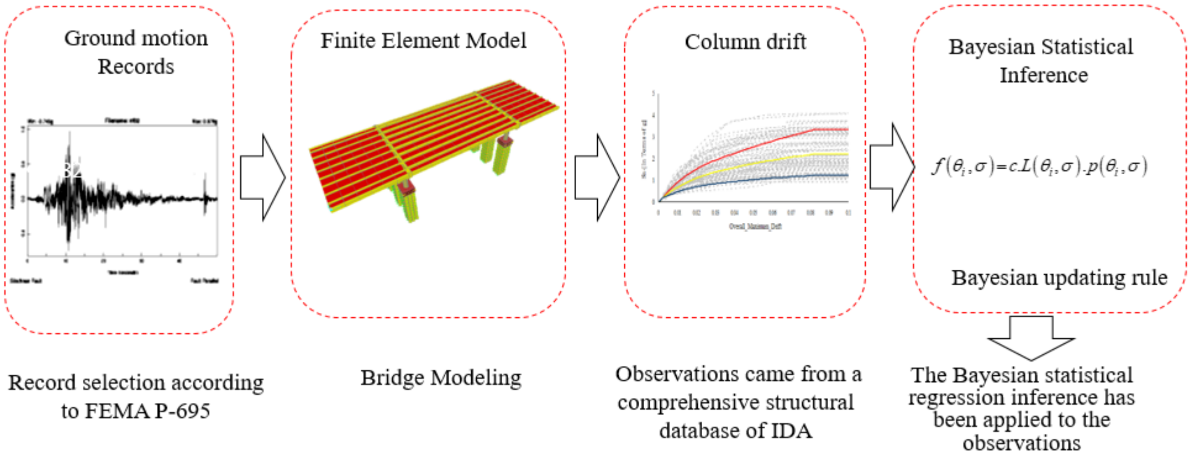

Fig. 3 Procedure of developing regression-based demand model

Table 4 Posterior statistics of the model parameters implemented in Eq. (3)

	a		b		σ	
$Ln(D)=a+b\times Ln(PGA)+\sigma\varepsilon$	Mean	C.O.V %	Mean	C.O.V %	Mean	C.O.V %
	-4.072	0.5894	0.893	2.772	0.298	0.0459
	a		b		σ	
$Ln(D)=a+b\times Ln(Sa(T_1))+\sigma\varepsilon$	Mean	C.O.V %	Mean	C.O.V %	Mean	C.O.V %
	-4.602	0.2586	0.952	1.6355	0.1855	0.0459

parameters as random variables and determines probability distribution of the coefficients using the Bayesian updating rule (Box and Tiao 2011)

$$f(\theta_i,\sigma)=c.L(\theta_i,\sigma).P(\theta_i,\sigma) \tag{5}$$

Where $f(\theta_i, \sigma)$ denotes posterior distribution representing our updated knowledge about the coefficients, $L(\theta_i, \sigma)$ indicates the likelihood function representing the objective information on (θ_i, σ) gained from a set of observations, $p(\theta_i, \sigma)$ denotes the prior distribution reflecting our knowledge about parameters prior to obtaining observations and c is a normalizing factor . In the case that lower bound data and/or upper bound data are not available such as data collected in this study, and the probabilistic model of interest is formulated as a linear function of θ, closed-form solution can be found for Eq. (6) (Gardoni *et al*. 2002). Under the normality assumption on ε and a non-informative priors, Box and Tiao (2011) show that the posterior distributions of θ and σ^2, denotes vector of model parameters θ, are a multivariate t distribution and an inverse chi-square distribution respectively.

$$f(\theta)=\frac{\Gamma\left(\frac{1}{2}(\nu+k)\right).s^{-k}\sqrt{|H^TH|}}{\left[\Gamma\left(\frac{1}{2}\right)\right]^k\Gamma\left(\frac{\nu}{2}\right)\left(\sqrt{\nu}\right)^k}\left[1+\frac{(\theta-\hat{\theta})^T H^T H(\theta-\hat{\theta})}{\nu s^2}\right]^{\frac{\nu-k}{2}}$$

$$f\left(\sigma^2\right)=\nu s^2\chi_\nu^{-2} \tag{6}$$

$$\hat{\theta}=\left(H^TH\right)^{-1}H^TY \ \ ,\nu=n-k,$$

$$s^2=\frac{1}{\nu}\left(Y-\hat{Y}\right)^T\left(Y-\hat{Y}\right),\ \hat{Y}=H\hat{\theta}$$

Where H is a n-by -k dimensional matrix which contains all n observations of explanatory functions. Also, Y is the n-dimensional vector of response variable observations. Once posterior distribution is known, mean vector M_θ and covariance matrix $\sum\theta\theta$ can be computed as follows

Table 5 Correlation matrix of regression coefficients implemented in model in terms of PGA

	a	b
a	1	0.604
b	0.604	1

Table 6 Correlation matrix of the regression coefficients implemented in model in terms of Sa (T_1)

	a	b
a	1	-0.0085
b	-0.0085	1

$$\mu_\theta=\hat{\theta} \qquad \sum\nolimits_\theta\frac{\nu}{\nu-2}s^2\left(X^TX\right)^{-1}$$

$$\mu_\sigma=\sqrt{\frac{\nu}{\nu-2}s^2} \qquad \sigma_\sigma^2=\frac{s^2}{2(\nu-2)(\nu-4)} \tag{7}$$

According to above description and those presented in the previous section, the procedure implemented in the present study to develop demand model is graphically exhibited in the following

8. Developed regression-based demand model

According to the above description, maximum drift demand model in terms of PGA in the form of Eq. (3) is developed. Table 4 demonstrates model parameters

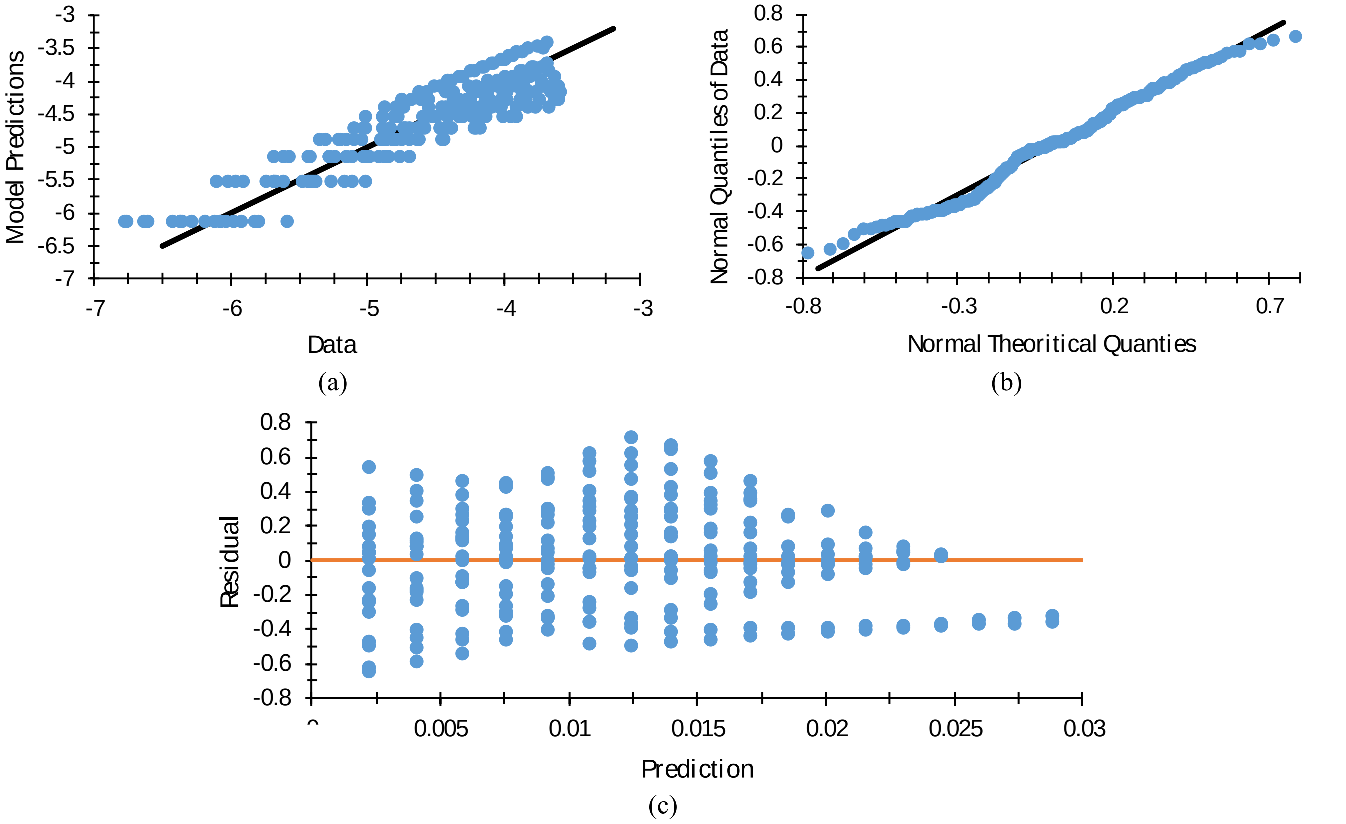

Fig. 4 Graphical diagnoses of the demand model developed in terms of PGA; (a) Prediction model plot; (b) Quantile-Quantile plot to assess the normality; (c) Residual plot to assess homoscedasticity

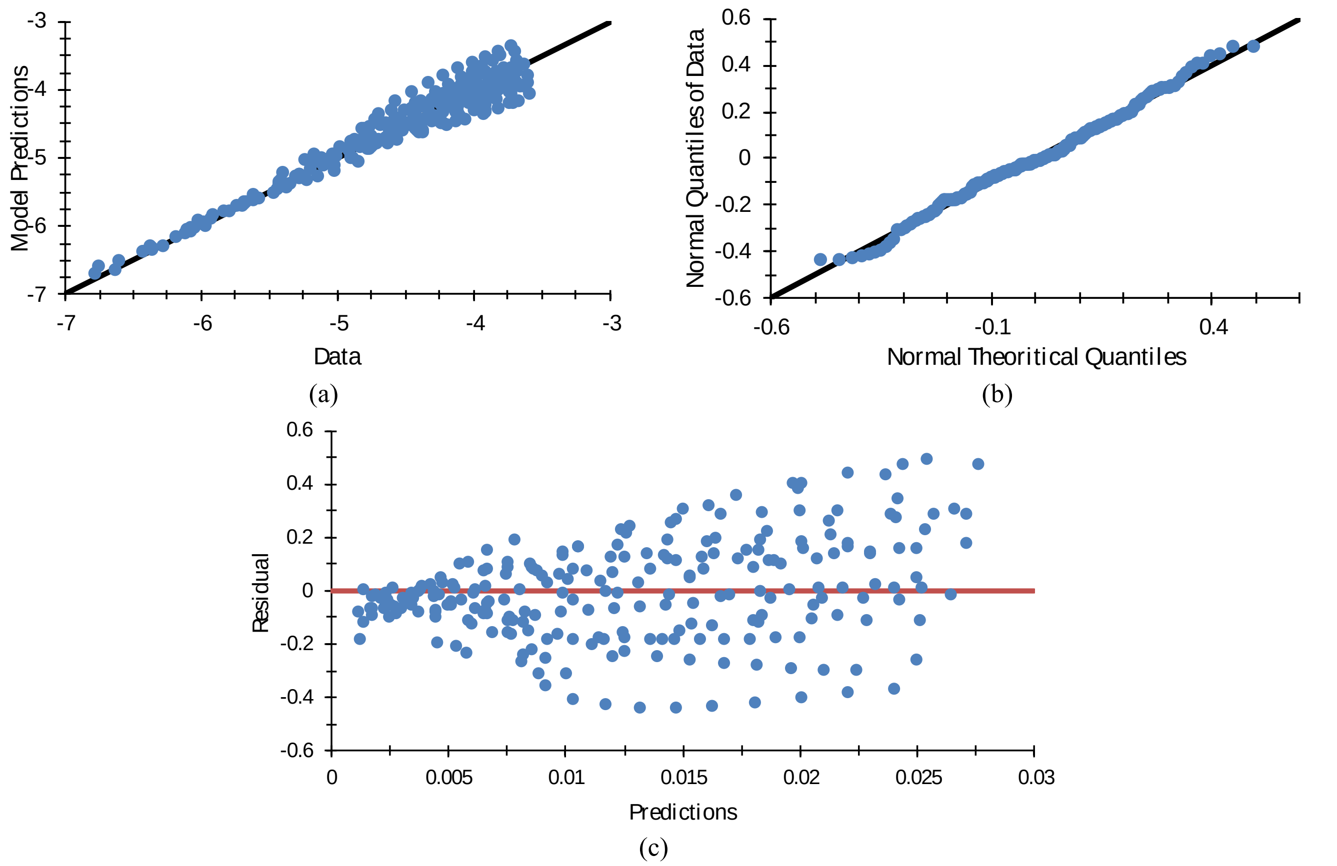

Fig. 5 Graphical diagnoses of the demand model developed in terms of PGA; (a) Prediction model plot; (b) Quantile-Quantile plot to assess the normality; (c) Residual plot to assess homoscedasticity

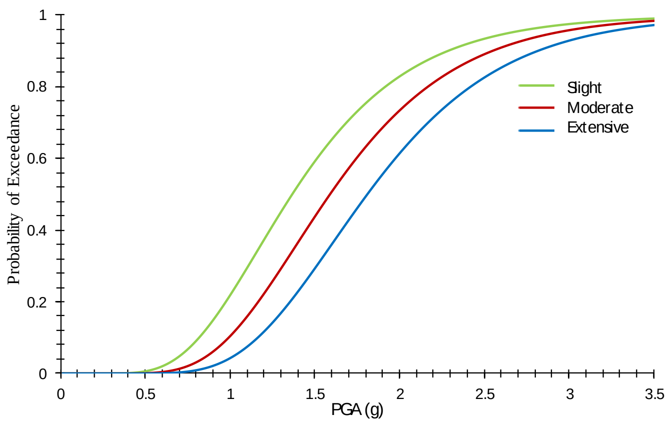

Fig. 6 Fragility curves of the bridge pier respect to PGA

computed based on IDA and Bayesian regression analysis.

The posterior correlation coefficients were calculated between the regression coefficients (model parameters a, b) are also presented in Tables 4 and 5.

In addition, a graphical diagnosis of regression demand models is illustrated in Figs. 4 and 5 to investigate the performance of model. The assessment proceeded with plotting the model predictions against observed data, the model residuals versus the predicted values of the dependent variable and quantiles of the model residual against normal theoretical quantiles. The latter which is known as Q-Q plot depicts the residual values against the value of inverse normal cumulative distribution function (CDF) at *u/n* point, where *u* is the number of the residual in ordered vector of residuals and *n* is the number of observations. In the case of normally distributed residuals, the points align with a 45° line. Similarly, the degree to which plotted prediction data align with a 45° line implies the quality of the model. In addition, the proposed regression model is acceptable regarding the heteroscedasticity if the residuals fall within fairly horizontal lines on both sides of the zero axes. Further information about regression diagnosis techniques can be found in technical texts.

9. Results and discussions

By comparison these two sets of graphs according to above mentioned explanations (accuracy and reasonability), it is concluded:

Both models are acceptable according to normality and accuracy criteria, but only the demand model developed in terms of PGA is acceptable and reliable regarding the homoscedasticity criterion.

Thus, the demand model in terms of PGA is implemented in the following to perform fragility analysis. To this end, it is only required to substitute probabilistic demand model in Eq. (1) as follow

$$P[D(PGA,\Theta(a,b))\geq d \mid PGA=x]\cong$$
$$\left[1-\varphi\left(\frac{Ln(d)-(\lambda_{Ln(D|IM)}=a+b\times Ln(PGA=x))}{(\sigma_{Ln(D|\mathrm{Im})}=\sigma)}\right)\right]$$

$$=\left[1-\varphi\left(\frac{Ln(d)-(-4.072+0.893\times Ln(x))}{0.298}\right)\right] \quad (8)$$

Now Fragility curves are developed for three different limit-state named Slight, Moderate, and Extensive prevention by assigning different values to the PGA. (Fig. 6). It is worthy noted, the above mention formulation could only reflect aleatory uncertainties raised from nature of the phenomena, and variability in the models parameters is neglected to simplify calculation.

10. Conclusions

In this study, the seismic vulnerability of a detailed three-dimensional bridge is completely investigated by developing probabilistic demand model in terms of the two most used intensity measures, i.e. PGA and Sa (T_1) based on incremental dynamic analysis and Bayesian inference. After developing demand models, a graphical diagnosis of the models is extracted. According to these graphs not only accuracy and reasonableness of the models are investigated, but also the authors are capable of answering which intensity measure is suitable for this type of bridge. This methodology is different from those commonly employed in the technical text to evaluate the sufficiency and efficiency of different intensity measures. Next, the PGA based- demand model is employed in a fragility analysis to assess the seismic vulnerability of the bridge.

Acknowledgment

This research is partially supported by the South Carolina Department of Transportation (SCDOT) under Project SPR 739.

References

Alam, J., Kim, D. and Choi, B. (2017), "Uncertainty reduction of seismic fragility of intake tower using Bayesian Inference and Markov Chain Monte Carlo simulation", *Struct. Eng. Mech.*, **63**(1), 47-53. https://doi.org/10.12989/sem.2017.63.1.047.

Alam, J., Kim, D. and Choi, B. (2019), "Seismic risk assessment of intake tower in Korea using updated fragility by Bayesian inference", *Struct. Eng. Mech.*, **69**(3), 317-326. https://doi.org/10.12989/sem.2019.69.3.317.

Bai, J.W., Gardoni, P. and Hueste, M.B.D. (2011), "Story-specific demand models and seismic fragility estimates for multi-story buildings", *Struct. Saf.*, **33**(1), 96-107. https://doi.org/10.1016/j.strusafe.2010.09.002.

Bayat, M., Daneshjoo, F. and Nisticò, N. (2015a), "Probabilistic sensitivity analysis of multi-span highway bridges", *Steel Compos. Struct.*, **19**(1), 237-262. http://dx.doi.org/10.12989/scs.2015.19.1.237.

Bayat, M., Daneshjoo, F. and Nisticò, N. (2015b), "A novel proficient and sufficient intensity measure for probabilistic analysis of skewed highway bridges", *Struct. Eng. Mech.*, **55**(6), 1177-1202. http://dx.doi.org/10.12989/sem.2015.55.6.1177.

Box, G.E. and Tiao, G.C. (2011), *Bayesian Inference in Statistical Analysis*, Vol 40, John Wiley & Sons

Chen, L. and Chen, S. (2016), "Seismic fragility performance of skewed and curved bridges in low-to-moderate seismic region", *Earthq. Struct.*, **10**(4), 789-810. https://doi.org/10.12989/eas.2016.10.4.789.

Choe, D.E., Gardoni, P., Rosowsky, D. and Haukaas, T. (2008), "Probabilistic capacity models and seismic fragility estimates for RC columns subject to corrosion", *Reliab. Eng. Syst. Saf.*, **93**(3), 383-393. https://doi.org/10.1016/j.ress.2006.12.015.

Choi, E. (2002), "Seismic analysis and retrofit of mid-America bridges", School of Civil and Environmental Engineering, Georgia Institute of Technology.

Cimerallo, G.P., Reinhorn, A.M. and Bruneau, M. (2010), "Framework for analytical quantification of disaster resilience", *Eng. Struct.*, **32**(11), 3639-3649. https://doi.org/10.1016/j.engstruct.2010.08.008.

Cui, S., Guo, C., Su, J., Cui, E. and Liu, P. (2019), "Seismic fragility and risk assessment of high-speed railway continuous-girder bridge under track constraint effect", *Bull. Earthq. Eng.*, **17**(3), 1639-1665. https://doi.org/10.1007/s10518-018-0491-9.

Dukes, J., Mangalathu, S., Padgett, J.E. and DesRoches, R. (2018), "Development of a bridge-specific fragility methodology to improve the seismic resilience of bridges", *Earthq. Struct.*, **15**(3), 253-261. https://doi.org/10.12989/eas.2018.15.3.253.

FEMA (2003), HAZUS-MH MR1: Technical Manual, Federal Emergency Management Agency Washington, DC.

FEMA (2009), Quantification of Building Seismic Performance Factors, FEMA P695, Washington, DC.

Gardoni, P., Der Kiureghian, A. and Mosalam, K.M. (2002), "Probabilistic capacity models an and d fragility estimates for reinforced concrete columns based on experimental observations", *J. Eng. Mech.*, **128**(10), 1024-1038. https://doi.org/10.1061/(ASCE)0733-9399(2002)128:10(1024).

Gkatzogias, K.I. and Kappos, A.J. (2015), "Deformation-based seismic design of concrete bridges", *Earthq. Struct.*, **9**(5), 1045-1067. https://doi.org/10.12989/eas.2015.9.5.1045.

Haukaas, T. (2008), "Unified reliability and design optimization for earthquake engineering", *Prob. Eng. Mech.*, **23**(4), 471-481. https://doi.org/10.1016/j.probengmech.2007.10.008.

Hwang, H., Liu, J.B. and Chiu, Y.H. (2001), "Seismic fragility analysis of highway bridges", Mid-America Earthquake Center CD Release 01-06.

Jalayer, F., De Risi, R. and Manfredi, G. (2015), "Bayesian cloud analysis: Efficient structural fragility assessment using linear regression", *Bull. Earthq. Eng.*, **13**(4), 1183-1203. https://doi.org/10.1007/s10518-014-9692-z.

Jeon, J.S., Choi, E. and Noh, M.H. (2017), "Fragility characteristics of skewed concrete bridges accounting for ground motion directionality", *Struct. Eng. Mech.*, **63**(5), 647-657. https://doi.org/10.12989/sem.2017.63.5.647.

Jeon, J.S., Mangalathu, S. and Lee, S.Y. (2019), "Seismic fragility curves for California concrete bridges with flared two-column bents", *Bull. Earthq. Eng.*, **17**(7), 4299-4319. https://doi.org/10.1007/s10518-019-00621-4.

Kia, M. and Banazadeh, M. (2016), "Closed-form fragility analysis of the steel moment resisting frames", *Steel Compos. Struct.*, **21**(1), 93-107. http://dx.doi.org/10.12989/scs.2016.21.1.093.

Kia, M., Banazadeh, M. and Bayat, M. (2018), "Rapid seismic vulnerability assessment by new regression-based demand and collapse models for steel moment frames", *Earthq. Struct.*, **14**(3), 203-214. https://doi.org/10.12989/eas.2018.14.3.203.

Kwag, S., Oh, J., Lee, J.M. and Ryu, J.S. (2017), "Bayesian-based seismic margin assessment approach: Application to research reactor", *Earthq. Struct.*, **12**(6), 653-663. https://doi.org/10.12989/eas.2017.12.6.653.

Muntasir Billah, A. and Alam, M.S. (2015), "Seismic fragility assessment of concrete bridge pier reinforced with super elastic shape memory alloy", *Earthq. Spectra*, **31**(3), 1515-1541. https://doi.org/10.1193/112512EQS337M.

Nielson, B.G. (2005), "Analytical fragility curves for highway bridges in moderate seismic zones", Georgia Institute of Technology.

O'Reilly, G.J. and Sullivan, T.J. (2016), "Fragility functions for eccentrically braced steel frame structures", *Earthq. Struct.*, **10**(2), 367-388. https://doi.org/10.12989/eas.2016.10.2.367.

Parghi, A. and Alam, M.S. (2017), "Seismic collapse assessment of non-seismically designed circular RC bridge piers retrofitted with FRP composites", *Compos. Struct.*, **160**, 901-916. https://doi.org/10.1016/j.compstruct.2016.10.094.

Sisi, A.A., Erberik, M.A. and Askan, A. (2018), "The effect of structural variability and local site conditions on building fragility functions", *Earthq. Struct.*, **14**(4), 285-295. https://doi.org/10.12989/eas.2018.14.4.285.

Soltangharaei, V., Razi, M. and Gerami, M. (2016), "Comparative evaluation of behavior factor of SMRF structures for near and far fault ground motions", *Periodica Polytechnica Civil Eng.*, **60**(1), 75-82. https://doi.org/10.3311/PPci.7625.

Vamvatsikos, D. and Cornell, C.A. (2002), "Incremental dynamic analysis", *Earthq. Eng. Struct. Dyn.*, **31**(3), 491-514. https://doi.org/10.1002/eqe.141.

Wang, X., Shafieezadeh, A. and Ye, A. (2018), "Optimal intensity measures for probabilistic seismic demand modeling of extended pile-shaft-supported bridges in liquefied and laterally spreading ground", *Bull. Earthq. Eng.*, **16**(1), 229-257. https://doi.org/10.1007/s10518-017-0199-2.

Zhang, J. and Huo, Y. (2009) "Evaluating effectiveness and optimum design of isolation devices for highway bridges using the fragility function method", *Eng. Struct.*, **31**(8), 1648-1660. https://doi.org/10.1016/j.engstruct.2009.02.017.

CC