Bayesian updating: Reduction of epistemic uncertainty in hysteretic degradation behavior of steel tubular structures

Sifeng Bi[1], Yongtao Bai[2,*], Xuhong Zhou[2]

1 School of Aerospace Engineering, Beijing Institute of Technology, Beijing, China
2 School of Civil Engineering, Chongqing University, Chongqing, China
Corresponding Author: Yongtao Bai (bai.yongtao@cqu.edu.cn)

Abstract: This paper proposes a probabilistic framework for updating the governing parameters in the hysteretic constitutive model for tubular steel with strength degradation. The hysteretic constitutive model is formulated to track the strength degradation due to local buckling of square hollow steel beam-columns imposed by cyclic loadings with large elasto-plastic deformation. Despite various hysteretic laws have been proposed to model the steel tubular strength degradation, a limited number of studies have proposed well-calibrated parameter values in numerical implementation. The parameters are generally obfuscated by the inevitable epistemic uncertainties from material and geometric properties. The updating process of the material parameters is performed within the Bayesian framework employing the Markov chain Monte Carlo algorithm. The epistemic uncertainty involved in the computational procedure is initially represented as pre-defined intervals of the uncertain parameters. The proposed Markov chain Monte Carlo (MCMC) algorithm can generate samples from the posterior distributions of the parameters according to the experimental results. The epistemic uncertainty is hence significantly reduced by the Bayesian updating process such that the updated model is feasible to predict the degradation behavior of square hollow steel beam-columns subjected to cyclic loadings. The example with benchmark data indicates that the proposed method can improve the model accuracy and efficiency concerning the real measurement by reducing the errors from epistemic uncertainty.

Keywords: Strength degradation, Steel structures, Constitutive model, Modeling uncertainty, Hysteretic behavior, Bayesian updating.

Introduction

Damage modeling and evaluation of steel beam-columns provide valuable information for estimating the real-time condition and remaining seismic capacity of structural systems subjected to ground motions exceeding the design level (Wenchuan earthquake 2008). For the special steel moment-resisting frames designed to prevent earthquake-induced collapse, collapse mechanism is usually identified as the exceedance of critical deformation capacity, such as the strength degradation due to local buckling of beam-columns at lower stories. Although the definition of collapse is at a global level of structural system, the local failure in members accelerates the reduction of lateral rigidity and force redistribution in buildings (Lin et al. 2018). Thus, providing efficient and accurate models with the updating algorithm of the degradation parameters are primary concerns regarding collapse prevention.

Strength and stiffness degradation of steel beam-columns results in complete failure to sustain the prescribed axial load (Nakashima and Liu 2005). For accurately capturing the degradation behavior of steel structures under seismic excitations, it is important to determine the critical parameters in the constitutive models of the materials for finite element analyses. The detailed finite element model can visually demonstrate buckled shapes, whereas detailed meshes with large number of elements may bring difficulties in performing nonlinear dynamic simulations on large-scale frames. Contrarily, the use of fiber and spring elements concentrated at component ends is simple and efficient to implement strength and stiffness degradation into structures (Ibarra et al. 2005, Lignos et al. 2011, Bai et al. 2012, Bai et al. 2016). Although the fiber element model possesses the advantage of simple mesh discretization, there are limitations in explicitly incorporating out-of-plane deformations to fibers layers that are caused by local buckling. From the point of view of uncertainty, on the one hand, the numerical implementation and mesh discretization lead to modeling uncertainty to the fiber element model. On the other hand, the model parameters such as buckling strength, degradation ratio etc., cannot be exactly determined due to the lack of knowledge of local instability, leading to inevitable uncertainties. Both the modeling errors and parameter uncertainty, also known as epistemic uncertainty, lead to a discrepancy between the numerical simulation and practical measurement, which obstructs further application for reliable performance-based seismic design and analysis of steel structures (Birrell et al. 2021, Song 2020, Pourreza et al. 2021). Hence, an updating procedure to reduce the epistemic uncertainty within the framework of numerical model is thus critical but challenging since such work has not been fully investigated in the field of post-local buckling strength degradation modeling for steel and composite steel-concrete structures (Mou et al. 2020).

Numerous studies have demonstrated the significant advantages of the Bayesian updating approach for the explicit treatment of the modeling uncertainty and quantification of the parametric uncertainty in civil engineering problems. This work consequently simulates the strength degradation behavior of steel beam-columns after local buckling according to the fiber element model, based on which the Bayesian updating approach is proposed to reduce the epistemic uncertainty in this model, such that the feasibility and precision of the developed model can be further improved. Model updating has been developed as a mature technique in the field of structural dynamics simulation to calibrate the value of uncertain parameters specifically for finite element models (Mottershead et al. 2011, Luque and Straub 2016, Bi et al. 2019). However, the application of model updating in the current scene of buckling degradation simulation has more challenging features than the typical structural dynamics simulation, such as the higher sensitivity of the uncertain parameters, the more complex output features, and the higher nonlinearity between the parameters and the model features. To deal with these challenges, this paper employs the Transitional Markov Chain Monte Carlo (TMCMC) algorithm to overcome the complicated relationship between the parameters and features, by iteratively generating random samples from the posterior distributions of the true parameters. The Bayesian updating framework based on the TMCMC algorithm is demonstrated to be efficient and feasible for the developed fiber element model for buckling degradation simulation in the example part, where practical measurement data is provided to validate the model.

The remaining parts of this paper are organized as follows. Section 2 proposes the principle of the fiber element modeling where the nonlinear uniaxial constitutive law is proposed to predict the degradation behavior. In Section 3, the hysteretic curves are then compared between experiment and simulation results to calibrate the proposed constitutive model. The Bayesian model updating framework combined with the TMCMC algorithm is proposed in Section 4 to reduce epistemic uncertainty in the parameters of the constitutive model. Section 5 presents the case study on the hysteretic curves of a square hollow steel tube with strength degradation, which is utilized to demonstrate the effectiveness of the proposed MCMC-based Bayesian updating approach for estimating degradation parameters in the constitutive model for steel tubular structures in engineering practice.

Fiber element model with strength degradation

Element discretization for beam-column members

The concept of a fiber discretized model of beam-column members is illustrated in Fig. 1. A member section is subdivided into finite block layers, each of which is represented by a fiber element. Fig. 1(b) shows the discretization of a section that is subject to an axial force and bending moment along the x-axis. The stress fiber is defined to be located at the centroid of an element and to have the sectional area of the elements. Fig. 2(a) shows the fiber discretization for a section of a square hollow steel member under an axial force and bending moment about the x-axis. The fiber element analysis program is employed to carry out the nonlinear analysis of various structural members under dynamic loading procedures (Kawano and Sakino 2003, Bai et al. 2015). The relation between generalized stress and strain is briefly introduced as follows. The plane assumption of the section satisfies as shown in Fig. 1. The sectional stiffness is integrated by dividing the section into a finite number of fiber layers, the stress of which is defined by a stress-strain relation. The axial force and bending moment can be derived by summing the stress of all-fiber layers in the element section.

Geometric nonlinearity is investigated using an updated Lagrangean formula with a local coordinate axis for each element, which moves along with the element within the global coordinate axis system. The element stiffness is evaluated by the means of Gaussian numerical integrals using three Gaussian points (sections).

Rectangular sectional members could be subdivided into block fiber elements. The stress fiber is defined to be located at the centroid of each element and to accumulate the sectional areas. Considering the modeling simplicity and time-consuming for dynamic analysis of large-scale structures, the cross-section is divided with a finite number of parallel layers for tubular walls. In particular, the fiber discretization for the rectangular hollow steel tubular and CFT sections and the H-shaped steel section is demonstrated in Fig. 2, respectively. Where B is the outer width of steel tubes, t is the thickness of steel tubes.

The plastic deformation may be thought to concentrate at the regions of beam ends and/or column ends in high-rise multi-story buildings. The beam-column element at the plastic region should have an appropriate length so that the degradation behavior occurs only within the length of the element. Ideally, the length of the element should vary according to the sectional shape, a kind of material, and the structural system (i.e. H-shaped steel section, square steel tubular section, circular steel tubular section, square CFT section, circular CFT section), because the mechanism of the strength degradation, that is the size of local unstable deformation region, are widely different from each other (i.e., local buckling of a steel plate element, crushing of concrete, and confining effect between concrete and steel). It is well known that the axial force ratio affects the size of the local unstable deformation region as well. After having considered these complexities enough, the length of an element in the plastic region is assumed as large as the depth of the member cross-section D. In other words, the stress-strain relation models of various cross-sections and various axial force ratios are calibrated to express the strength degradation in structural members and frames under the condition of the element length of D as shown in Figs. 3-4.

The plastic deformation and strength degradation can be reasonably assumed to concentrate at the local regions near the column ends. Fig. 5 shows a schematic of longitudinal localization for a fiber element model. The local region needs a fine mesh with an appropriate length. For incorporating the degradation behavior associated with local buckling, this length shall be corresponding to the length of local buckling. Based on the theory of buckling in plate elements, the length of the local region with a simple boundary condition can be determined as large as the total depth of the cross-section.

Stress-strain model for post-local buckling degradation behavior

A uniaxial stress-strain material model incorporating the strength and stiffness degradation after local buckling is developed. This model utilizes a Giuffré-Menegotto-Pinto (M-P) model with isotropic strain hardening (Bai et al. 2012, Birrell et al. 2021). Fig. 6 shows the hysteresis curve of the developed stress-strain model where, E is Young's modulus, and σ_y and σ_u are yields and ultimate stresses of steel material. The R_{ini} and R_u are roundness factors for the elastic and post-yielding skeleton curves in the model: the recommended values for these two factors are 10.0 and 0.9.

The onset of local buckling triggers a negative slope in the skeleton curve at a critical stress σ_{lb}. For compact HSS members subjected to bending moment with constant axial force, the critical stress σ_{lb} should be larger than yielding stress σ_y, so it can be determined by its associated strain ε_{lb}, which means a limit state where strength degradation occurs. The negative slope after local buckling is bilinear with two defining factors, τ_{lb} and τ_{re}. The value of the second negative slope τ_{re} should be a small negative value, for instance, -0.005 times Young's modulus to keep some amount of residual strength considering contact between severely buckled plate elements.

Numerical prediction of degradation behavior

Cyclic experiment of hollow steel sectional beam-columns

Severe local buckling occurs reversely in terms of the folding along yielding lines such as thin-walled tubes and deployable origami structures (Chen et al. 2020, Ahmed et al. 2020). A series of cyclic tests on square hollow steel beam-columns was conducted with various width-to-thickness ratios and axial load ratios as test parameters (Kurata et al. 2005). The fiber element model with degradation effect due to local buckling was applied to a series of cyclic tests on the square hollow steel beam-columns subjected to cyclic loadings with constant axial load applied by electro-hydraulic servo actuators with the capacity of 1000 kN. Fig. 7 shows the configuration of the specimens and the schematic of the modeling process developed for the specimens. The section of the beam-column specimen is 200 mm by 200 mm and the height is 1221 mm. The width-to-thickness ratios B/t of 17, 22, and 33 represent the compact, FA, and FB rank, in the Japanese design codes. The axial load ratios P/P_y of 0.3 and 0.1 correspond to the lower and middle stories in high-rise buildings, respectively. Fig. 7(a) shows the test setup of the specimen and loading system. The deformation at the top of the beam-column specimen was controlled by a quasi-static loading system. The horizontal cyclic loadings were controlled by displacement, which was up to extremely large deformation levels. The experimental results of displacements and forces are measured respectively by the Linear Variable Differential Transformer (LVDT) and electro-hydraulic servo actuators. The measurement uncertainty can be neglected because the accuracy of LVDT can be ensured by precisely recording an increment of 0.01 mm at smallest, and the precision of actuators is similarly high as well (0.1% tolerant error).

In the fiber element model, the local region was defined as large as the depth of the column. The web in the square hollow steel section was subdivided into eight layers, and the flange was subdivided into two layers. The geometric coefficient greatly affects degradation behavior in terms of hysteretic curves, but this influence is not due to the value uncertainty but the sensitivity. For instance, the specimens with the width-to-thickness ratios of 17, 22, and 33 demonstrate great sensitivity to the degradation parameters as presented in Table 1.

To examine the accuracy and feasibility of the numerical model, the cyclic M-θ curves from numerical and experimental results are compared. Fig. 8 shows the analytical and experimental results of the M-θ curve and ε-θ curve for the specimens S2201 and S1703. In Fig. 8(a)and (b), the initial stiffness and maximum bending strength are accurately predicted by the numerical model with errors smaller than 5% to the experimental results. The end rotation for the S2201 is 6% and the ductility ratio is around 12. In contrast, the end rotation of S1703 is 8% with a ductility ratio of 16. Post-buckling strength degradation is reasonably predicted well even with large deformation because of the instability followed by the local buckling. The post-buckling degradation ratios τ of the S2201 and S1703 are similar to each other. This means that the post-buckling degradation ratio is both sensitive to axial force ratio and width-to-thickness ratio. The validated results on the maximum bending strength, post-capping degradation behavior, and axial contraction between experiment and simulation are verified as summarized in Table 2.

Furthermore, as an important indicator for the collapse of HSS beam-columns, axial contraction ratio δ after local buckling can be calculated as the axial deformation normalized by the localized length L_p. As shown in Fig. 8(c), the axial contraction ratio ε has significantly grown when the bending rotation θ_c exceeds 0.05 where the local buckling is already initiated. This indicates that the post-buckling strength degradation followed by local buckling is significantly related to the axial contraction.

Fig. 9 presents the influence of post-peak strength degradation on the remaining strength capacity compared with the conventional full-plastic simulation results of specimen S1701, which is specified by compact section and low level of axial force. It can be seen that the sectional stress distribution in terms of the full-plastic constitutive law presents symmetric and nonlinear distribute along the both sides of neutral axis. With regard to the strain distribution,the whole section remains in compression resulting in unilateral hysteresis behavior as shown in Fig. 9(a).

Hysteretic curves

Fig. 10 shows the comparisons for the hysteresis curves of test results with those of simulation results without and with degradation effects for the specimens with a width-thickness ratio of 17. The strength started deteriorating at the rotation of 0.04 rad for the two specimens with different axial load ratios, 0.1 and 0.3. However, the negative slope after the onset of local buckling was steeper with a larger axial load. The specimen with the width-to-thickness ratio of 17 and the axial load ratio of 0.3, i.e., S-1703, lost its axial-load carrying capacity at a rotation of 0.06. Although equations are available to determine the value of various parameters in the stress-strain model, those parameters still need to be tuned to achieve satisfactory accuracy for numerical simulation concerning the degradation of stiffness and strength during the development of local buckling. The deteriorated stress-strain model should be employed in fiber elements to predict the collapse condition following the onset of local bucking. The strength degradation along with the increase in deformation amplitudes up to extremely large deformation at approximately 8-10 times the yielding rotation. Compared to the level of post-local buckling degradation in strength, the reloading stiffness degradation is minor due to the limited reduction in the second moment of inertia of the buckled sections. Moreover, the simulation results using the fiber element model with and without strength degradation are significantly different. It indicates that the quantification of the strength degradation due to local buckling is very important for evaluating the seismic behavior of damaged steel structures.

Propagation of axial contraction

Large axial contraction after the onset of local buckling occurs due to the excessive flexural deformations along the mountain and valley lines in origami structures as observed in the experiment (see Fig. 7). Two end-points of local buckling nearly contact with each other at the web and flange of hollow steel sections. In the seismic design of steel structures, the axial force-bending moment interaction indicates the ultimate strength capacity of beam-columns under a constant axial load. However, the strain-softening tends to accelerate the development of axial deformation at the column base where local buckling is explicitly related to the sidesway collapse (Lignos et al. 2011).

The number of axial contractions in S1701and S1703 are compared in Fig. 11. The strength degradation had a close relationship with the increase of axial contraction. The simulation without degradation failed to track the axial contraction in the tests. By appropriately accounting for the degradation in stiffness and strength in the strain-stress relationship, the fiber element model successfully tracked the increase in axial contraction. Note that the parameters in the strain-stress relation were tuned to degradation in strength and stiffness but axial contraction. These results illustrated the strong potential of the developed fiber element model with a degrading constitutive model for collapse simulation of steel buildings.

Bayesian updating methodology

The above-developed fiber element model demonstrates efficiency and good applicability to accurately predict the post-local buckling strength degradation. However, the numerical modeling procedure contains approximations and simplifications concerning the physical system, and thus the epistemic uncertainty is inevitable for the model. More specifically, the parameters in stress-strain relation cannot be fully determined by physical theories but only assigned with a pre-defined interval because of the lack of knowledge for the mechanical behavior correlated with those parameters. Therefore, an additional training procedure is critical before practical application to reduce the pre-defined intervals of the parameters according to the measured experimental data. This procedure is known as model updating to estimate the value of the parameter such that the model simulation can be automatically tuned towards the realistic condition. Among a wide range of techniques for model updating, the Bayesian updating approach possesses the superiorities such as low calculation cost and applicability for the limited database (Li et al. 2018).

In this study, the Bayesian updating approach in association with the Transitional Markov Chain Monte Carlo (TMCMC) is employed in this section.

The Bayesian model updating approach is based on the Bayes' theorem

$$P(\mathbf{x}|\mathbf{y}_{exp}) = \frac{P_L(\mathbf{y}_{exp}|\mathbf{x})P(\mathbf{x})}{P(\mathbf{y}_{exp})}, \tag{1}$$

where $P(\mathrm{x})$ is the prior distribution of the parameters x determined based on the prior knowledge of the system and expert experience; $P(\mathrm{x}|\mathrm{y}_{exp})$ is the posterior distribution of the parameters conditional to the experimental measurements y_{exp}; $P(\mathrm{y}_{exp})$ is the normalization factor ensuring the integral of the posterior PDF of the parameter $P(\mathrm{x}|\mathrm{y}_{exp})$ equal to one; $P_L(\mathrm{y}_{exp}|\mathrm{x})$ is known as the likelihood function, which is theoretically defined as the probability of the experimental data conditional to each instance of the parameters. The posterior distribution $P(\mathrm{x}|\mathrm{y}_{exp})$ refers to the outcome of the updating procedure, which will be utilized to estimate the updated value of the parameters whereby leading the likelihood function to reach the maximum.

As mentioned above, the original definition of the likelihood $P_L(\mathrm{y}_{exp}|\mathrm{x})$ is the probability of the existing measurement data. The evaluation of the probability requires the PDF of the output feature, which requires a large of random samples, i.e. a large number of model evaluations, leading to a huge calculation burden. It is consequently suggested to utilize the approximated likelihood, instead of the original likelihood function, based on simple functions such as the Gaussian function:

$$P_L\left(\mathrm{y}_{exp}|\mathrm{x}\right) = \frac{1}{\sigma\sqrt{2\pi}} exp\left\{-\frac{\left(y_{sim}-y_{exp}\right)^2}{2\sigma^2}\right\}, \tag{2}$$

Where $y_{sim} = f(x)$ is the simulation result obtained from the fiber element model $f(\mathrm{x})$; σ is known as the "width coefficient" controlling the degree of the centralization of the post-distribution curve of the parameter. The width coefficient is not a fixed value but case-depended. A smaller width coefficient would lead to a more peaked posterior distribution, which makes it easier to estimate the optimal value. But a too-small width coefficient requires more iterations before the updating procedure reaches convergence, and for some extreme cases, even leads the convergence to be prohibitive. The effect of the width coefficient will be illustrated in the case study (Section 5).

Another important component of the Bayes' theorem in Eq. (1) is the normalization factor $P\ (y_{exp})$. A direct evaluation of the factor requires integral processes on the PDFs of the target parameters and the posterior distribution of the parameters, which lead to intractable difficulties in the overall Bayesian procedure. Hence, the TMCMC algorithm is proposed in this work by introducing a series of intermediate PDFs of the inputs, which gradually converge to the posterior distribution, and thus avoiding the direct evaluation of the integral (Beck and Au 2002, Ching and Chen 2007).

The TMCMC algorithm is essentially a directional random sampling approach from a given probability distribution by generating Markov chains for each intermediate samples. It is consequently critical to determine how many steps are required before a stationary distribution can be converged with acceptable error. One of the most common methods for generating and selecting intermediate samples is the Metropolis-Hastings algorithm, which generates samples based on an arbitrary distribution by introducing dependence among samples and rejecting the Markov chains according to a proposed probability. For clarity, detailed information of TMCMC and Metropolis-Hastings algorithms is omitted, but more information can be referred from the fundamental work by Ching and Chen (2007) and the tutorial paper by Lye, Cicirello and Patelli (2021). More applications of the TMCMC algorithm in the field of structure simulation engineering can be found, for example, in the stochastic model updating and structural health monitoring (Rocchetta et al. 2018).

Illustration of the Bayesian updating process

Problem description

The square hollow steel tube with local buckling process is proposed here to demonstrate the feasibility of the fiber element modeling and Bayesian model updating approaches to simultaneously calibrate multiple degradation parameters, in the presence of complicated and strong nonlinear relation between the parameters and the output features. In particular, four critical parameters for local buckling (Bai et al. 2015), which are the strain to initiate local buckling ε_{lb}, post-buckling stiffness ratio of negative slope τ_{lb}, the factor for strength degradation following local buckling r_{spm}, and the ratio of moving strain value ϕ, are chosen as the input parameters to be updated for model calibration, as listed in Table 3. Intervals of these parameters are pre-defined to represent the epistemic uncertainty due to the occurrence of local buckling and the sequential strength degradation. The purpose of model updating is to find the "true values" from the intervals, such that the numerical results of hysteresis behavior can satisfactorily agree with that of the measured experimental results. However, the measurement from experimental results is not able to indicate the critical parameters as aforementioned in the fiber element model. Alternatively, the “simulated measurement” data is utilized in the example, which is generated by assigning a set of “target values” to the input parameters, as shown in Table 3, and substituting to the model to calculated the output features.

The assigned target values for those parameters are assigned to the stress-strain relation in the fiber element model, which has been calibrated to accurately predict the hysteresis curves of the tested specimens, as shown in Fig. 9. As shown in the 4th column of Table 3, the initial values of the parameters are purposedly assigned to be different from the target values. Using these initial parameter values in stress-strain relation, the fiber element analysis is further performed to obtain the initial simulation result as shown in Fig. 12. Because the initial parameters and target parameters are different, clearly their corresponding hysteresis curves show significant disagreement in the strength degradation corresponding to the local buckling. The direct comparison between these two hysteresis curves cannot provide a quantitative value. It is then suggested to utilize the poles of the curve, and the relative error between the positions of the two sets of poles is proposed as the indicator to measure the difference between the target and initial hysteresis curves.

Updating results and discussion

The MCMC algorithm converged after 6 iterations, where 100 samples are generated in each iteration. The histogram of the 100 samples in the last iteration is illustrated in Fig. 13. The histograms of the prior samples (following uniform distribution) are also presented in this figure as a comparison with the posterior ones. The posterior distributions of the parameters are estimated based on these 100 posterior samples. The posterior distributions are calibrated to be much more centralized to a certain range of values. These values are extracted as the “Updated values” as shown in Table 4, which are obtained by taking the horizontal axis values of the maximal poles as illustrated in Fig. 13. Note that, in this example, the width coefficient σ in Eq. (2) is set as 0.01. A smaller width coefficient would lead to a more centralized posterior distribution, however, with more iterations and calculation consumed.

The relative errors of the initial and updated values for each parameter, compared with the target values as summarized in Table 4. It is shown that the absolute mean error of the four parameters are dramatically reduced from 659.3 % to 130.7 %, which means that the updating procedure is clearly feasible in this case to search for "true values" of the parameter within a very wide pre-defined interval. It is necessary to explain that, the absolute mean error of the updated parameter, 130.7 %, is still large for engineering application. This large error is mainly caused by the tiny target value of x_3 (τ_{lb}), -0.0096. Generally, a nearly zero value would lead the relative error to be very sensitive. Nevertheless, the relative error of x_3 is significantly reduced from 1983% to 466.7% in this case, and the absolute errors caused by the other two dominant parameters, the strain at local buckling x_2 (ε_{lb}) and strength reduction rate x_4 (r_{spm}), are effectively reduced by the Bayesian updating process.

Conclusions

This study presents a strength degradation model trained by Bayesian updating approach for the post-local buckling behavior of square hollow steel beam-columns in high-rise buildings. A nonlinear stress-strain model that incorporates the post-buckling strength degradation is built to predict hysteresis behavior and axial contraction of hollow steel sectional beam-columns at very large deformation around 10 % of rotational ratio. The model is first validated using the quasi-static cyclic loading test results of HSS beam-columns with various width-to-thickness ratios and axial load ratios. It is demonstrated that the simulation reasonably predicted the tested behavior up to extremely large deformation at approximately 8-10 times the yielding rotation.

As a further step to enrich the feasibility of the model training framework, the Bayesian updating procedure is performed on the developed model to reduce the epistemic uncertainty of the numerical model. The illustration results show that the Bayesian updating approach is capable of handling the complicated and strong nonlinear relation between the buckling parameters and the critical feature of the fiber element model. This is found as a great advantage of the developed fiber element model to significantly generalize its applicability. Thus, the developed constitutive model with local buckling is expected to be effective in the simulations of the seismic collapse of steel buildings with rare data and severe uncertainties.

One point which has not been addressed in this work is the treatment of the measurement uncertainty since only one set of measurement data is used as the reference in the example. If the measurement uncertainty is going to be investigated in a stochastic model updating procedure, multiple measurements are required. It will be the further step of this work to appropriately extract enough uncertainty information from the limited experimental data, and subsequently to ensure the robustness of the model prediction in the presence of measurement uncertainty.

Last, prediction and monitoring on the strength and stiffness degradation of steel structures remain a big challenge even with the support of the state-of-the-art sensors or monitoring techniques in the field of structural earthquake engineering. On the other hand, numerical simulations cannot be directly adopted for condition assessment. Therefore, based on a reasonable number of databases combined with the model training technique might be effective for seismic damage assessment.

Data availability statement

All data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgment

This work is supported by the National Natural Science Function of China (grant no. 12102036) and the and the Stateful Support Project of Science and Industry Bureau of China (grant no. HTKJ2019KL502011). The first and the corresponding authors appreciate the support of the Alexander von Humboldt Stiftung/Foundation (award No. 1193706 and No. 1196752). The corresponding author is grateful to professor emeritus Masayoshi Nakashima and Dr. Masahiro Kurata from Kyoto University for providing the original experimental data.

References

Ahmed, M., Liang, Q. Q., Patel, V. I., and Hadi, M. N. S., 2020, "Computational Simulation of Eccentrically Loaded Circular Thin-Walled Concrete-Filled Double Steel Tubular Slender Columns," Eng. Struct., **213**.

Bai, Y., Kawano, A., Odawara, K., and Matsuo, S., 2012, "Constitutive Models for Hollow Steel Tubes and Concrete Filled Steel Tubes Considering the Strength Deterioration," J. Struct. Constr. Eng., **77**(677), pp. 1141–1150.

Bai, Y., and Lin, X., 2015, "Numerical Simulation on Seismic Collapse of Thin-Walled Steel Moment Frames Considering Post Local Buckling Behavior," Thin-Walled Struct., **94**, pp. 424–434.

Bai, Y., Lin, X., and Mou, B., 2016, "Numerical Modeling on Post-Local Buckling Behavior of Circular and Square Concrete-Filled Steel Tubular Beam Columns," Int. J. Steel Struct., **16**(2), pp. 531–546.

Beck, J. L., and Au, S.-K., 2002, "Bayesian Updating of Structural Models and Reliability Using Markov Chain Monte Carlo Simulation," J. Eng. Mech., **128**(4), pp. 380–391.

Bi, S., Broggi, M., and Beer, M., 2019, "The Role of the Bhattacharyya Distance in Stochastic Model Updating," Mech. Syst. Signal Process., **117**, pp. 437–452.

Birrell, M., Astroza, R., Carreño, R., Restrepo, J., Araya-Letelier, G., 2021, Bayesian parameter and joint probability distribution estimation for a hysteretic constitutive model of reinforcing steel, Structural Safety, **90**, pp. 102062.

Chen, Y., Yan, J., Sareh, P., and Feng, J., 2020, "Feasible Prestress Modes for Cable-Strut Structures with Multiple Self-Stress States Using Particle Swarm Optimization," J. Comput. Civ. Eng., **34**(3).

Ching, J., and Chen, Y.-C., 2007, "Transitional Markov Chain Monte Carlo Method for Bayesian Model Updating, Model Class Selection, and Model Averaging," J. Eng. Mech., 133(7), pp. 816–832.

Hackl, J., Kohler, J., 2016, "Reliability assessment of deteriorating reinforced concrete structures by representing the coupled effect of corrosion initiation and progression by Bayesian networks," Structural Safety, **62**, pp. 12-23.

Ibarra, L. F., Medina, R. A., and Krawinkler, H., 2005, "Hysteretic Models That Incorporate Strength and Stiffness Deterioration," Earthq. Eng. Struct. Dyn., **34**(12), pp. 1489–1511.

Kawano, A., and Sakino, K., 2003, "Seismic Resistance of CFT Trusses," Eng. Struct., **25**(5), pp. 607–619.

Kurata, M., Nakashima, M., and Suita, K., 2005, "Effect of Column Base Behaviour on the Seismic Response of Steel Moment Frames," J. Earthq. Eng., **9**(SPEC. ISS. 2), pp. 415–438.

Li, X, Kurata, M. 2018, "Probabilistic updating of fishbone model for assessing seismic damage to beam-column connections in steel moment-resisting frames." Computer-Aided Civil and Infrastructure Engineering, **34**(9), pp. 790–805.

Lignos, D. G., Krawinkler, H., Whittaker, A. S., 2011, "Prediction and validation of sidesway collapse of two scale models of a 4-story steel moment frame," Earthquake Engineering and Structural Dynamics, **40**, pp. 807–825.

Lin, X., Kato, M., Zhang, L., and Nakashima, M., 2018, "Quantitative Investigation on Collapse Margin of Steel High-Rise Buildings Subjected to Extremely Severe Earthquakes," Earthq. Eng. Eng. Vib.

Luque, J., and Straub, D., 2016, "Reliability analysis and updating of deteriorating systems with dynamic bayesian networks," Structural Safety, **62**, pp. 34-46.

Lye, A., Cicirello, A., Patelli, E., 2021, "Sampling methods for solving Bayesian model updating problems: A tutorial", Mechanical Systems and Signal Processing. **159**, p. 107760.

Ma, Y., Zhang, J., Wang, L., and Liu, Y., 2013, "Probabilistic prediction with bayesian updating for strength degradation of RC bridge beams," Structural Safety, **44**, pp. 102-109.

Mou, B., Bai, Y., and Patel, V., 2020, "Post-Local Buckling Failure of Slender and over-Design Circular CFT Columns with High-Strength Materials," Eng. Struct., **210**, pp. 110197.

Mottershead, J. E., Link, M., and Friswell, M. I., 2011, "The Sensitivity Method in Finite Element Model Updating: A Tutorial," Mech. Syst. Signal Process., **25**, pp. 2275–2296.

Bayesian updating: Reduction of epistemic uncertainty in hysteretic degradation behavior of steel tubular structures

Nakashima, M., and Liu, D., 2005, "Instability and Complete Failure of Steel Columns Subjected to Cyclic Loading," J. Eng. Mech., **131**(6), pp. 559–567.

Pourreza, F., Mousazadeh, M., Basim, C., "An efficient method for incorporating modeling uncertainties into collapse fragility of steel structures," Structural Safety, **88**, pp. 102009.

Rocchetta, R., Broggi, M., Huchet, Q., and Patelli, E., 2018, "On-Line Bayesian Model Updating for Structural Health Monitoring," Mech. Syst. Signal Process., 103, pp. 174–195.

Song, X., 2020, "Parameterized fragility analysis of steel frame structure subjected to blast loads using bayesian logistic regression method," Structural Safety, **87**, pp. 102000.

List of figure captions

large deformation

Fig. 10 Comparisons of hysteresis curves between test and various models: (a) S1701 without degradation; (b) S1701 with degradation; (c) S1703 without degradation; and (d) S1703 with degradation.

Fig. 11 Normalized moment vs. axial contraction relationships from test specimen and numerical model: (a) S1701 without degradation; (b) S1701 with degradation; (c) S1703 without degradation; and (d) S1703 with degradation.

Fig. 12 The target and initial hysteresis curves based on fiber element analysis

Fig. 13 The initial and updated PDFs of the parameters