Material Parameter Estimation in Distributed Plasticity FE Models using the Unscented Kalman Filter

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ABSTRACT: This paper describes a novel framework that combines advanced mechanics-based nonlinear (hysteretic) finite element (FE) models and a nonlinear stochastic filtering technique, the unscented Kalman filter (UKF), to estimate unknown time-invariant parameters of nonlinear inelastic material models used in the FE model. The proposed framework updates the nonlinear FE model of the structure using input-output data recorded during earthquake events. The updated model can be directly used for damage identification. A two-dimensional 3-bay 3-story steel moment-resisting frame is used to verify the convergence, robustness, and accuracy of the proposed methodology. The steel frame is modeled using fiber-section beam-column elements with distributed plasticity and is subjected to a ground motion recorded during the 1989 Loma Prieta earthquake. The results indicate that the proposed framework provides accurate estimation of the unknown material parameters of the nonlinear FE model.

1. INTRODUCTION

System identification (SID) and damage identification (DID) have become important fields in the structural engineering community. With the aim of implementing accurate and robust DID methodologies, research on structural health monitoring (SHM) for civil structures has increased significantly during the last years. Many efforts have focused on vibration-based DID methods for civil structures based on changes in identified modal properties or quantities derived therefrom (e.g., Doebling et al. 1996, Housner et al. 1997); however, this approach has been applied to real structures or full-scale structural specimens subjected to damage induced by realistic sources of dynamic excitation only in the last years (e.g., Moaveni et al. 2011, Ji et al. 2011, Astroza et al. 2013).

Because modal properties are related to global properties of the structure and because actual response of structures is nonlinear from the onset of loading, some researchers have objected the use of modal parameters for DID purposes. Considering the relevance of nonlinearities in the dynamic response of civil structures, SID and DID for nonlinear structures have also been the subject of intense research (e.g., Masri and Caughey 1979, Yun and Shinozuka 1980, Corigliano and Mariani 2004, Chatzi and Smyth 2009). Nevertheless, these studies have used highly idealized structural models, localizing the modeling of nonlinear behavior in a few prescribed elements defined by nonlinear hysteretic force-deformation laws not traditionally used in state-of-the-art modeling of civil structures.

Finite element (FE) model updating (Friswell and Mottershead 1995, Marwala 2010), which can be defined as the process of calibrating a FE model to minimize the discrepancy between the FE predicted and measured response of a structure, has emerged as a powerful method that enables the use of more realistic models for SID and DID purposes. Recently, Bayesian techniques have been used for FE model updating of linear and nonlinear structures, for both static and dynamic loading (e.g., Ching et al. 2006, Huang et al. 2010, Nasrellah and Manohar 2011, Simoen et al. 2013). In the case of nonlinear hysteretic response, previous studies employed highly simplified nonlinear models (e.g., lumped plasticity, shear building, empirical-based nonlinear material models) which are not able to properly characterize the behavior of large and complex civil structures.

This paper presents a novel framework that combines advanced mechanics-based nonlinear FE models and a nonlinear Bayesian filter, referred to as the unscented Kalman filter (UKF) (Julier and Uhlmann 1997, Wan and van der Merwe 2000), to estimate unknown time-invariant parameters of nonlinear inelastic material models used in the FE model. In the implementation of the framework, the software *OpenSees* is used to model the structure and simulate its response to earthquake excitation.

2. BAYESIAN APPROACH FOR STATE AND PARAMETER ESTIMATION OF DYNAMIC SYSTEMS

Consider a nonlinear state-space model with additive zero-mean white Gaussian noises:

$$\begin{aligned}\mathbf{x}_{k+1} &= \mathbf{f}_k\left(\mathbf{x}_k, \mathbf{u}_k\right) + \mathbf{w}_k \\ \mathbf{y}_{k+1} &= \mathbf{h}_{k+1}\left(\mathbf{x}_{k+1}, \mathbf{u}_{k+1}\right) + \mathbf{v}_{k+1}\end{aligned} \tag{1}$$

where $\mathbf{x}_k \in \mathbb{R}^{n_x}$, $\mathbf{u}_k \in \mathbb{R}^{n_u}$, and $\mathbf{y}_k \in \mathbb{R}^{n_y}$ are the state vector (defined as the smallest subset of variables needed to completely characterize the system at time $t_k = k\Delta t$, where Δt = time step), input vector (deterministic and known), and measurement vector at time t_k, respectively. The components of the process and measurement noises, $\mathbf{w}_k$ and $\mathbf{v}_{k+1}$ respectively, are assumed to be mutually uncorrelated and uncorrelated between sampling times Gaussian processes. Noise processes $\mathbf{w}_k$ and $\mathbf{v}_{k+1}$ have zero-mean and covariance matrices $\mathbf{Q}_k$ and $\mathbf{R}_{k+1}$, respectively. The terms $\mathbf{f}_k$ and $\mathbf{h}_{k+1}$ are deterministic and known nonlinear vector-valued functions. The objective of a filtering technique is to recursively estimate at least the first two statistical moments of the state vector using the measured input and noisy measurement vectors up to the current time (Haug 2005). If modeling parameters are unknown, the state vector can be augmented to contain both state variables and unknown parameters ($\boldsymbol{\theta}_{k+1}$). For the special case that all system dynamics are contained in the measurement equation, a parameter-only estimation problem can be set up (Haykin 2001), i.e., only $\boldsymbol{\theta}_{k+1}$ is present in the state equation, Eq. (1).

The UKF can be used to solve the nonlinear state-space model in Eq. (1). It is based on the assumptions that the posterior *PDF* of the state at time t_k, $p(\mathbf{x}_k \mid \mathbf{y}_{1:k})$ (where $\mathbf{y}_{1:k} = [\mathbf{y}_1^T, \mathbf{y}_2^T, \ldots, \mathbf{y}_k^T]^T$), and the *PDF* $p(\mathbf{x}_{k+1} \mid \mathbf{y}_{1:k})$ are approximated by Gaussian distributions. Then, the posterior *PDF* of the state at time t_{k+1}, $p(\mathbf{x}_{k+1} \mid \mathbf{y}_{1:k+1})$, can be approximated as Gaussian with mean vector and covariance matrix estimates given by:

$$\begin{aligned}\hat{\mathbf{x}}_{k+1|k+1} &= \hat{\mathbf{x}}_{k+1|k} + \mathbf{K}_{k+1}\left(\mathbf{y}_{k+1} - \hat{\mathbf{y}}_{k+1|k}\right) \\ \hat{\mathbf{P}}^{\mathbf{xx}}_{k+1|k+1} &= \hat{\mathbf{P}}^{\mathbf{xx}}_{k+1|k} - \mathbf{K}_{k+1}\hat{\mathbf{P}}^{\mathbf{yy}}_{k+1|k}\mathbf{K}^T_{k+1}\end{aligned} \tag{2}$$

where $\hat{\mathbf{x}}_{k+1|k+1}$ and $\hat{\mathbf{P}}^{\mathbf{xx}}_{k+1|k+1}$ denote estimates of the mean and covariance matrix of $\mathbf{x}_{k+1}$ given $\mathbf{y}_{1:k+1}$, $\hat{\mathbf{y}}_{k+1|k}$ is the estimate of the mean of $\mathbf{y}_{k+1}$ given $\mathbf{y}_{1:k}$ and the Kalman gain matrix, $\mathbf{K}_{k+1}$, is defined as

$$\mathbf{K}_{k+1} = \hat{\mathbf{P}}^{\mathbf{xy}}_{k+1|k}\left(\hat{\mathbf{P}}^{\mathbf{yy}}_{k+1|k}\right)^{-1} \tag{3}$$

Covariance matrices $\hat{\mathbf{P}}^{\mathbf{xx}}_{k+1|k}, \hat{\mathbf{P}}^{\mathbf{xy}}_{k+1|k}$, and $\hat{\mathbf{P}}^{\mathbf{yy}}_{k+1|k}$ require the computation of multi-dimensional integrals that seldom can be evaluated in closed-form; therefore, the unscented transformation (UT) can be alternatively used to approximate them. The UT defines a set of deterministically selected sample points (referred as sigma points or SPs) to represents a random vector **z** such that the sample mean and sample covariance matrix obtained from the SPs match exactly the true mean and covariance matrix of the random vector **z**. When the SPs are propagated through a nonlinear function, they capture the true mean and covariance matrix up to the second order of the Taylor series expansion of the nonlinear function. In this paper, the scaled unscented transformation (Wan and van der Merwe 2000) with parameters α=0.01, κ=0, and β=2 is adopted. More details about the UKF and scaled UT can be found elsewhere (Wan and van der Merwe 2000).

3. MECHANICS-BASED NONLINEAR FINITE ELEMENT MODELS OF FRAME-TYPE STRUCTURES

Different approaches have been proposed over the years to model and simulate the nonlinear response of frame-type structures subjected to earthquake loading. Global models, structural FE models, and continuum FE models have been developed for this purpose. The simplest are global models, which concentrate material nonlinearities at global degrees of freedom, however they lack accuracy and resolution in predicting the nonlinear response of real structures. Structural FE models describe the structure by an assembly of interconnected frame elements. Lumped or concentrated plasticity and distributed plasticity are two categories within structural FE models. Finally, continuum FE models are the most sophisticated but computationally expensive, since they discretize the members of frame-type structures into 3D solid FEs with 3D nonlinear material constitutive models.

Structural FE models with distributed plasticity have shown to provide accurate results in matching experimental data. In addition, their formulation is simple and computational cost is feasible. Therefore, these types of models have been broadly employed in research and engineering practice. In this type of FE models, material nonlinearity can take place at any numerically monitored cross section (integration point) along the element, and the element behavior is obtained by numerical integration of the section response along the element. Element cross-sections are discretized in longitudinal fibers, which permit to simulate the section nonlinear response using uniaxial material constitutive laws for the fibers (Figure 1). This formulation accounts for the interaction between bending and axial force at the section level, while the interaction with the shear force occurs at the element level. It is noted that a uniaxial material model depends on a set of physical and/or empirical set of parameters. More details about these type structural FE modeling techniques can be found in Taucer et al. (1991).

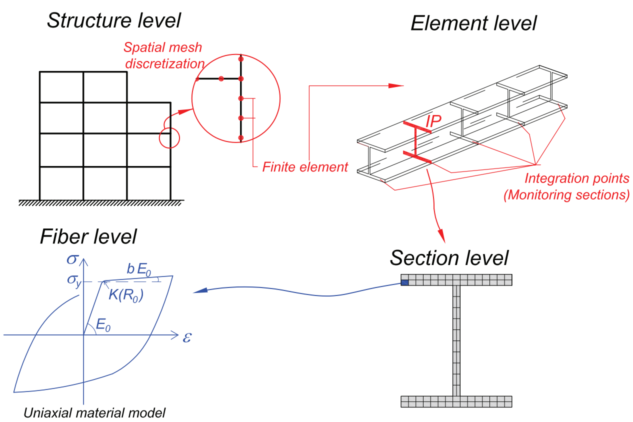

Figure 1: Distributed plasticity FE model of frame-type structures.

4. PROPOSED FRAMEWORK

The discrete-time equation of motion of a FE model of a structure can be expressed as:

$$\mathbf{M}(\boldsymbol{\theta})\ddot{\mathbf{q}}_{k+1}(\boldsymbol{\theta})+\mathbf{C}(\boldsymbol{\theta})\dot{\mathbf{q}}_{k+1}(\boldsymbol{\theta})+\mathbf{r}_{k+1}\left[\mathbf{q}_{k+1}(\boldsymbol{\theta}),\boldsymbol{\theta}\right]=\mathbf{f}_{k+1} \tag{4}$$

where $\boldsymbol{\theta} \in \mathbb{R}^{n_\theta}$ = vector of unknown time-invariant modeling parameters, $\mathbf{q}$, $\dot{\mathbf{q}}$, $\ddot{\mathbf{q}} \in \mathbb{R}^n$ = nodal displacement, velocity, and acceleration vectors, $\mathbf{M} \in \mathbb{R}^{n\times n}$ = mass matrix, $\mathbf{C} \in \mathbb{R}^{n\times n}$ = damping matrix, $\mathbf{r}[\mathbf{q}(\boldsymbol{\theta}),\boldsymbol{\theta})] \in \mathbb{R}^n$ = history-dependent internal resisting force vector, $\mathbf{f} \in \mathbb{R}^n$ = dynamic load vector, and the subscript indicates the time step. For the case of rigid base earthquake excitation the dynamic load vector takes the form $\mathbf{f}_{k+1} = -\mathbf{M}\,\mathcal{L}\,\ddot{\mathbf{u}}^g_{k+1}$, where $\mathcal{L} \in \mathbb{R}^{n\times r}$ = influence matrix and $\ddot{\mathbf{u}}^g \in \mathbb{R}^{r\times 1}$ = input ground acceleration vector with r = number of base excitation components (in the general case r = 6, i.e., 3 rotations and 3 translations base excitation components). The structural response can be recorded using different types of sensors (e.g., accelerometers, GPS) and at time $t_{k+1} = (k+1)\Delta t$, with k = 0,1,… and Δt = time step, can be expressed as

$$\mathbf{y}_{k+1} = \hat{\mathbf{y}}_{k+1} + \mathbf{v}_{k+1} \tag{5}$$

where $\mathbf{y} \in \mathbb{R}^{ny}$ = vector of recorded structural response quantities, $\hat{\mathbf{y}} \in \mathbb{R}^{ny}$ = predicted response of the structure from the FE model, $\mathbf{L}_y \in \mathbb{R}^{ny\times 3n+r}$ = output matrix (known), and $\mathbf{v} \in \mathbb{R}^{ny}$ = output measurement noise vector assumed to be white Gaussian with zero-mean and covariance matrix $\mathbf{R}_k$, i.e., $\mathbf{v}_k \sim \mathcal{N}(\mathbf{0},\mathbf{R}_k)$. From Eqs. (4) and (5), the vector of recorded response quantities at time t_{k+1}, $\mathbf{y}_{k+1}$, can be expressed as a nonlinear function of the modeling parameters ($\boldsymbol{\theta}$), input ground acceleration time histories ($\ddot{\mathbf{U}}^g_{k+1}$), and initial conditions ($\mathbf{q}_0$, $\dot{\mathbf{q}}_0$) of the FE model, i.e.,

$$\mathbf{y}_{k+1} = \mathbf{h}_{k+1}\left(\boldsymbol{\theta}, \ddot{\mathbf{U}}^g_{k+1}, \mathbf{q}_0, \dot{\mathbf{q}}_0\right) + \mathbf{v}_{k+1} \tag{6}$$

Here $\mathbf{h}_{k+1}(\cdot)$ is a nonlinear response function of the nonlinear FE model at time t_{k+1} and $\ddot{\mathbf{U}}^g_{k+1} = [(\ddot{\mathbf{u}}^g{}_1)^T, (\ddot{\mathbf{u}}^g{}_2)^T, \ldots, (\ddot{\mathbf{u}}^g{}_{k+1})^T]^T$ is the input ground acceleration time history from time t_1 to t_{k+1}. At rest initial conditions are assumed henceforth, i.e., $\mathbf{q}_0 = \dot{\mathbf{q}}_0 = \mathbf{0}$.

If the unknown time-invariant modeling parameter vector, $\boldsymbol{\theta}$, is modeled as a stationary process according to the Bayesian approach, the evolution of which is characterized by a random walk process, the nonlinear parameter estimation problem at time t_{k+1} (k = 0, 1, 2, …) can be formulated as

$$\begin{cases} \boldsymbol{\theta}_{k+1} = \boldsymbol{\theta}_k + \boldsymbol{\gamma}_k \\ \mathbf{y}_{k+1} = \mathbf{h}_{k+1}\left(\boldsymbol{\theta}_{k+1}, \ddot{\mathbf{U}}^g_{k+1}\right) + \mathbf{v}_{k+1} \end{cases} \tag{7}$$

where $\boldsymbol{\gamma}_k$ and $\mathbf{v}_{k+1}$ are called process noise and measurement noise, respectively, and are assumed to be independent Gaussian white noise processes with zero mean vectors and diagonal covariance matrices $\mathbf{Q}_k$ and $\mathbf{R}_{k+1}$, respectively, i.e., $\boldsymbol{\gamma}_k \sim \mathcal{N}(\mathbf{0},\mathbf{Q}_k)$ and $\mathbf{v}_{k+1} \sim \mathcal{N}(\mathbf{0},\mathbf{R}_{k+1})$. Eq. (7) represents a nonlinear state-space model like Eq. (1), therefore it can be used to estimate the modeling parameter vector, $\boldsymbol{\theta}$, using the UKF as summarized in Figure 2. More information about the formulation of the parameter estimation problem for frame-type distributed-plasticity FE models using the UKF is discussed elsewhere (Astroza et al. 2014).

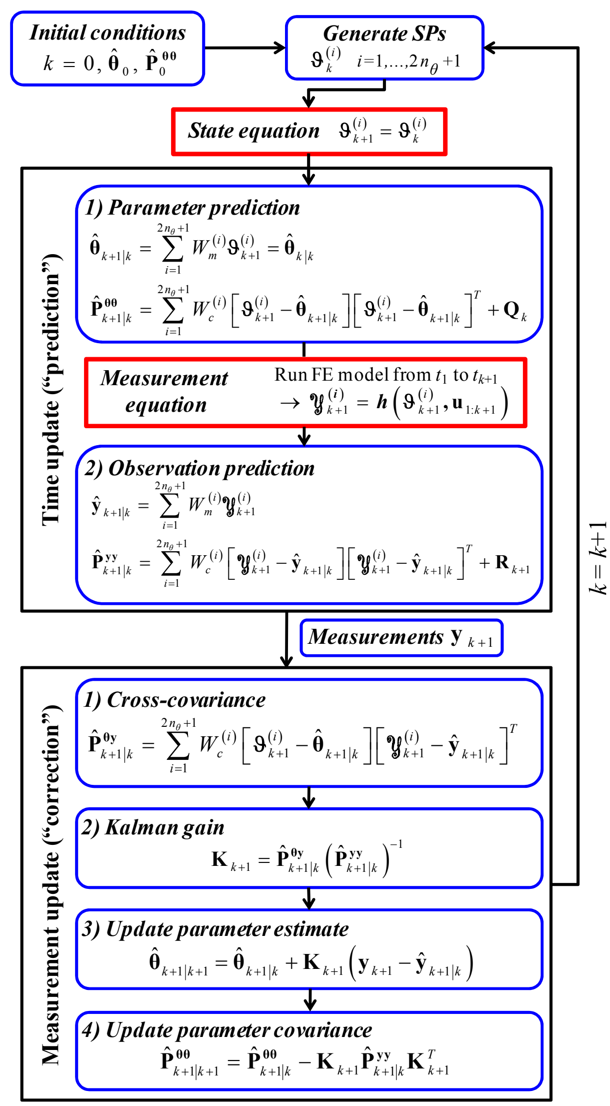

Figure 2: Proposed framework for nonlinear FE model updating.

5. VERIFICATION EXAMPLE

A 2D steel building frame is considered as application example. The steel fibers are modeled using the modified Giuffre-Menegotto-Pinto (G-M-P) material constitutive model (Filippou et al. 1997). One input earthquake motion is considered to simulate recorded response data, which are then contaminated by measurement noise for the estimation phase. Gravity loads are applied quasi-statically before running the dynamic analysis. The Newmark-β average acceleration method is used to integrate the equations of motion in time using a time step $\Delta t = 1/f_s$, where f_s is the sampling rate of the input earthquake motion. The Newton algorithm is used to solve the set of coupled nonlinear algebraic equations resulting from the equations of motion. The framework presented above is used to identify the material parameters and update the nonlinear FE model. The same FE model is used to simulate the response and to estimate the material parameters, i.e., effects of modeling uncertainty are not considered here. The ground motion recorded at the Los Gatos station during the 1989 Loma Prieta (Mw=6.9) is selected as input motion (Figure 3). The peak ground acceleration is 0.45g and the sampling rate is f_s = 50 Hz.

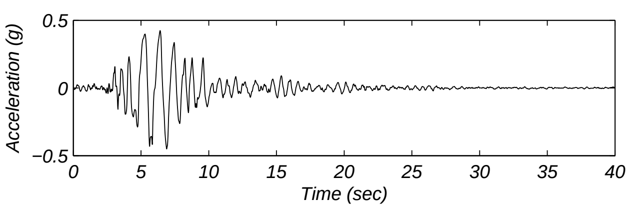

Figure 3: Ground acceleration recorded at the Los Gatos station during the 1989 Loma Prieta earthquake.

The structure is a 3-story steel moment resisting frame structure studied under the SAC venture, known as the SAC-LA-3 story building (FEMA 2000) (Figure 4). The modeled 2D frame has 3 stories and 3 bays, with a story height of 3.96 m and a bay width of 9.14 m. Exterior and interior columns are made of A572 steel with W14×257 and W14×311 cross-sections, respectively. Second, third, and roof level beams are made of A36 steel with W33×118, W30×116, and W24×68 cross-sections, respectively. Beam-column joints are assumed to be fully restrained, and rigid end zones are modeled at the ends of beams and columns. Frame elements are modeled using one force-based element for each beam and column. Numerical integration over the length of the elements is performed by using Gauss-Lobatto quadrature with 6 and 7 IPs for columns and beams, respectively. Column webs are discretized into 6 fibers along their length and one fiber across their width, while a single fiber is used to represent each flange of the cross-section. The webs of the second, third, and roof level beams are discretized into 16, 14, and 11 fibers along their length, respectively, and one fiber across their width. A single fiber is used to represent each flange of the cross-section. A linear elastic section shear force-deformation model is aggregated with the inelastic coupled flexure-axial behavior at the section level and along the element. The flexure-axial behavior is uncoupled from the shear behavior at the section level.

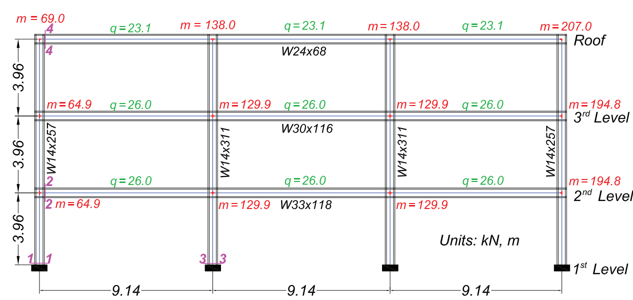

Figure 4: 2D steel frame building model.

The uniaxial G-M-P material model with primary parameters $\theta^{true} = [E_0^{col}, \sigma_y^{col}, b^{col}, R_0^{col}, E_0^{beam}, \sigma_y^{beam}, b^{beam}, R_0^{beam}]^T$ = [200 GPa , 345 MPa , 0.08 , 20 , 200 GPa , 250 MPa , 0.05 , 18]^T is used to model the axial behavior of the fibers of the cross sections of beams and columns and to simulate the true dynamic response of the frame structure to earthquake excitation. Nodal masses and distributed gravity loads on beams are computed from the design dead and live loads as reported in FEMA-355C and are shown in Figure 4. The sources of energy dissipation beyond hysteretic energy dissipated through nonlinear material behavior are modeled using mass and tangent stiffness-proportional Rayleigh damping assuming a critical damping ratio of 2% for the first two initial natural periods (after application of the gravity loads), T_1 = 1.06 sec and T_2 = 0.35 sec.

In the material parameter identification process, the UKF algorithm requires 17 SPs (=2×8+1) and it is assumed that only one horizontal acceleration response is measured at each level (at the left column). The initial estimates of the material parameters to be identified are taken as 140% of their true values, $\hat{\boldsymbol{\theta}}_0 = 1.4\boldsymbol{\theta}^{true}$, and the initial covariance matrix $\hat{\mathbf{P}}_0^{\theta\theta}$ is assumed diagonal with terms computed assuming a coefficient of variation of the initial parameter estimates (with $\hat{\boldsymbol{\theta}}_0$ as initial mean) of 15% for E_0^{col} and E_0^{beam} and 25% for σ_y^{col}, b^{col}, R_0^{col}, σ_y^{beam}, b^{beam}, and R_0^{beam}. An output measurement noise with 5% RMS noise-to-signal-ratio (NSR) is considered. It is assumed that the process noise $\boldsymbol{\gamma}_k$ and measurement noise $\mathbf{v}_k$ are zero-mean Gaussian white noise processes with time-invariant diagonal covariance matrices **Q** and **R**, respectively. A coefficient of variation of 1×10^{-4} is assumed for the initial estimates of the material parameters ($\boldsymbol{\theta}_0$) to construct the process noise covariance matrix **Q**. A standard deviation (or RMS) of the measurement noise $\mathbf{v}_k$ of 7×10^{-2} of the RMS of the corresponding simulated measurements (horizontal acceleration at the 2nd, 3rd, and roof levels) is assumed in the measurement noise covariance matrix **R**.

Time histories of the mean ($\hat{\mu}$) and standard deviation ($\hat{\sigma}$) estimates of the material parameters for SAC-LA-3 building frame subjected to Los Gatos earthquake motion are shown in Figure 5. The eight parameters are accurately identified and the standard deviation estimates of all these parameters decrease asymptotically to zero. The stiffness related parameters E_0^{col} and E_0^{beam} quickly converge to their true values after a few time steps, the strength or yield related parameters σ_y^{beam} and σ_y^{col} converge to their true values soon after the strong motion phase of the earthquake begins and some steel fibers have yielded, and the post-yield related parameters b^{beam}, b^{col}, R_0^{beam}, and R_0^{col} converge to their true values after the strain ductility demand of enough steel fibers has increased sufficiently.

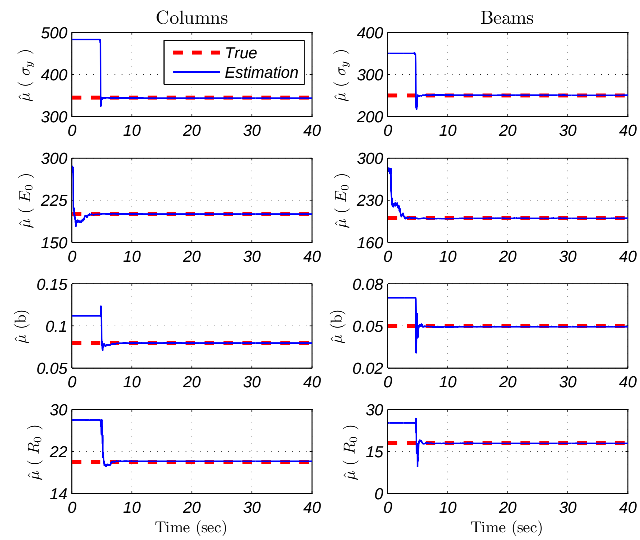

Figure 5: Mean estimates of the material parameters of beams and columns of the frame building.

Figure 6 compares different global and local responses of the frame obtained using the true material parameter values ($\boldsymbol{\theta}^{true}$), the initial estimate of the parameters ($\hat{\boldsymbol{\theta}}_0$), and the final estimate of the parameters ($\hat{\boldsymbol{\theta}}_N$). The following responses are plotted: absolute horizontal acceleration response history at the roof level (A_{roof}), base shear (V) versus roof drift ratio (Δ), moment (M_{1-1}) versus curvature (κ_{1-1}) hysteretic response at the base of the left column (section 1-1 in Figure 4), and stress (σ_{3-3}) versus strain (ε_{3-3}) hysteretic response at one of the extreme fibers at the base of the central-left column (section 3-3 in Figure 4). All the responses computed using the final estimates of the material parameters are in excellent agreement with the simulated true responses and the correct updating of the nonlinear FE model is clear from the comparison of the true responses with the responses obtained using the initial and final material parameter estimates.

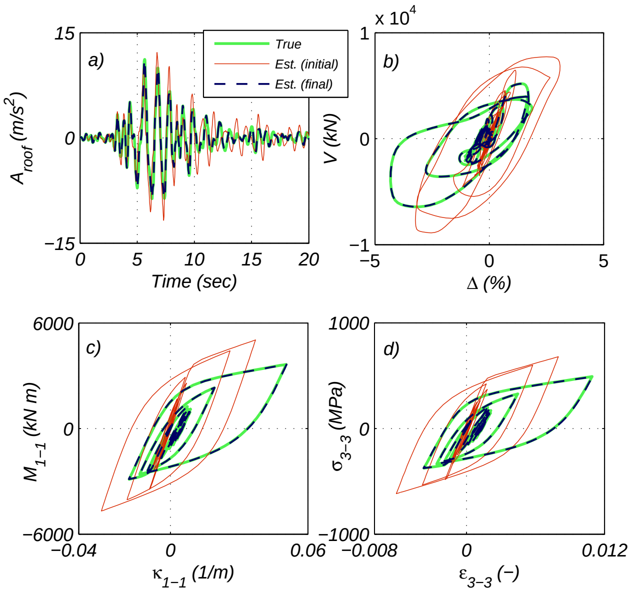

Figure 6: Comparison of true and estimated responses of the frame building.

6. CONCLUSIONS

This paper proposes and verifies, using numerically simulated data, a novel methodology to estimate unknown time-invariant parameters of nonlinear inelastic material models in frame-type structures subjected to earthquake excitation. The method combines state-of-the-art nonlinear finite element (FE) models and the unscented Kalman filter (UKF) as the estimation tool. The methodology formulates the nonlinear state-space model considering the unknown time-invariant modeling parameters in the state equation and the responses of the nonlinear FE model corresponding to the measured response quantities are used in the measurement equation. A 2D 3-story, 3-bay steel frame subjected to a ground acceleration recorded at the Los Gatos station during the 1989 Loma Prieta earthquake is used to verify the proposed methodology. The simulated responses of the building are contaminated by white noise to analyze the robustness of the identification scheme. The proposed method is able to accurately estimate the unknown time-invariant material parameters of the nonlinear FE model. True and estimated time histories of various global and local response quantities are compared to confirm the effectiveness of the proposed nonlinear FE model updating approach. The proposed framework provides a powerful tool for model updating of advanced mechanics-based nonlinear FE models, even when a limited number of measurement data are available.

7. ACKNOWLEDGMENTS

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