

Bayesian Updating of Pole-Cable Systems for Damage Quantification after Sequential Extreme Events

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ABSTRACT

Strong earthquakes can significantly damage electrical distribution infrastructure, causing prolonged outages and challenging recovery. Sequential extreme events, such as earthquake mainshocks followed by aftershocks, further complicate recovery by requiring repeated damage assessments and repairs. Utilities need real-time tools that combine physics-based modeling with power-infrastructure monitoring to assess damage and prioritize repairs during disaster response. This paper presents a Bayesian inference approach that updates the nonlinear structural properties of pole-cable systems after each hazard sequence using time-history response data. We demonstrate the method using a sequence of earthquakes with no intermediate repairs. First, we developed a high-fidelity finite-element model of a cable-connected pole system that captures material and geometric nonlinearities and the progressive damage that develops under sequential earthquake loading. Second, we implement Bayesian inference to sequentially update the nonlinear parameters of the cable-connected pole model using recorded time-history data after each earthquake. We introduce an energy-based log-likelihood function for Bayesian inference of pole properties and employ the Teleport Markov Chain Monte Carlo algorithm to improve exploration and mixing of the chains in the complex multidimensional space. Finally, we track the degradation of power pole strength that may trigger repairs. The proposed framework can provide utilities with real-time information on damage states of individual poles, supporting prioritization of inspections and repairs during sequential earthquake events.

1. INTRODUCTION

Earthquakes can cause significant damage to power systems, leading to cascading power failures. For example, the 2022 Ferndale Earthquake caused a power outage affecting more than 70,000 customers in Humboldt County, California [1]. Utilities are often prepared to respond to low-intensity, frequent events, such as recloser failures caused by vegetation, but struggle to respond to cascading failures [2]. The situation is further exacerbated during sequential hazards, such as aftershocks following a mainshock, which can further damage already weakened infrastructure. Such events can further stress the already affected infrastructure systems, increasing their vulnerability to subsequent events. During the 2011 Christchurch earthquake, aftershocks caused more damage to the infrastructure than the mainshock [3].

Furthermore, manual visual inspection of individual poles after an earthquake can require several days of field effort [4]. In practice, utility-pole inspection programs are often conducted on multi-year cycles, meaning that only a fraction of the pole inventory is inspected each year [5]. Still, structural damage may remain undetected because degradation in pole capacity can occur without visible residual displacement [6]. The utilities require a tool that could provide a virtual representation of the system that evolves with changes in structural condition across sequential events, enabling continuous assessment of its reliability [7–9]. Bayesian inference can update uncertain structural parameters by integrating sensor observations with physics-based models [10–13]. The updated model can then be used in forward analyses to estimate damage [14], helping utilities identify and prioritize the most severely affected poles for inspection and repair.

When assessing the risk to distribution systems from natural disasters, most studies focus on the structural response and failure of individual components, such as utility poles [15–17]. However, coupled systems, such as two pieces of electrical equipment connected by a cable, can exhibit strong dynamic interaction. The cable introduces time-varying geometric stiffness as the connected components move relative to one another, adding significant geometric nonlinearity to the coupled system and potentially amplifying the structural response [18]. This paper presents a Bayesian framework for estimating the structural parameters of nonlinear coupled pole–cable systems and subsequently assessing damage to wooden distribution poles using damage-index calculations [19].

Previous research has applied Bayesian inference to structural health monitoring applications [20–23]. However, existing studies largely focus on systems with well-defined modal properties, such as shear buildings, using natural frequencies and mode shapes for model updating [10, 24]. For pole–cable systems, modal characteristics can vary during ground

shaking because changes in cable slackness and tension alter the system stiffness. As the cable transitions from slack to taut, its stiffness can increase abruptly, producing a time-varying system stiffness and shifting the dominant frequencies and mode shapes. This makes modal-property-based updating more challenging than for systems with relatively stable modal characteristics.

Research on Bayesian inference using nonlinear dynamic analyses under earthquake loading is also relatively limited. In [25], Bayesian inference was performed for a bridge pier subjected to earthquake excitation. However, the study focused on updating a single model parameter and did not consider the simultaneous updating of multiple uncertain parameters. The strength and nonlinear response of a wooden pole are governed by multiple parameters in both tension and compression. Therefore, jointly updating these parameters is important for accurately characterizing the structural behavior and damage state.

Bayesian updating has also been applied to utility poles during wind events to assess structural failure [26]. However, poles may experience structural damage or degradation without complete failure, highlighting the need to estimate intermediate damage states in addition to failure. Bayesian updating using Markov Chain Monte Carlo (MCMC) can employ either single-chain or multi-chain sampling strategies. High-dimensional updating of pole parameters can be challenging for traditional single-chain algorithms, such as Metropolis—Hastings, because of slow exploration and poor mixing in complex parameter spaces. Multi-chain methods have demonstrated improved exploration in structural engineering applications [27–29].

To this end, this paper establishes a Bayesian inference framework for coupled pole–cable systems, enabling nonlinear updating of structural parameters under sequential earthquake events. We investigate multiple log-likelihood formulations for Bayesian inference. To improve exploration and mixing in complex parameter spaces, we employ the ensemble Teleport Markov Chain Monte Carlo algorithm [30]. Multi-chain methods such as DREAM MCMC and Transitional MCMC improve exploration by evolving multiple chains or samples and sharing information across the population [27, 28]. The cloning mechanism in Teleport MCMC enables direct transfer of walker states across the ensemble, allowing walkers to relocate between separated regions of the posterior without relying solely on local transitions. This can accelerate exploration, reduce trapping in individual modes, and improve mixing in complex or multimodal parameter spaces.

The rest of the paper is arranged as follows. Section 2 introduces Bayesian inference for DT applications. Section 3 provides further details on parameter updates during earthquakes and the selection of the log-likelihood function along with the teleport MCMC

algorithm. Bayesian updating for a single wooden pole is established in Section 4. Furthermore, a coupled wooden pole-cable system is presented in Section 5. The paper is concluded in Section 6.

2. BAYESIAN INFERENCE FOR DISTRIBUTION POWER SYSTEMS

The primary purpose of this Bayesian approach is to provide a dynamic virtual representation of the physical power systems. This would allow us to quickly assess damage to the physical system, providing utilities with the necessary information to expedite repair and recovery decisions. The Bayesian framework (Figure 1) requires a connection between the virtual representation, a finite element model, and the physical power systems. Bayesian inference establishes this connection by updating the model's uncertain parameters using observed structural-response data. In practical applications, these observations may be obtained from accelerometers or other structural monitoring sensors. In the numerical demonstrations presented in this study, the observations are generated using the high-fidelity finite-element model and are used to update the corresponding low-fidelity virtual model.

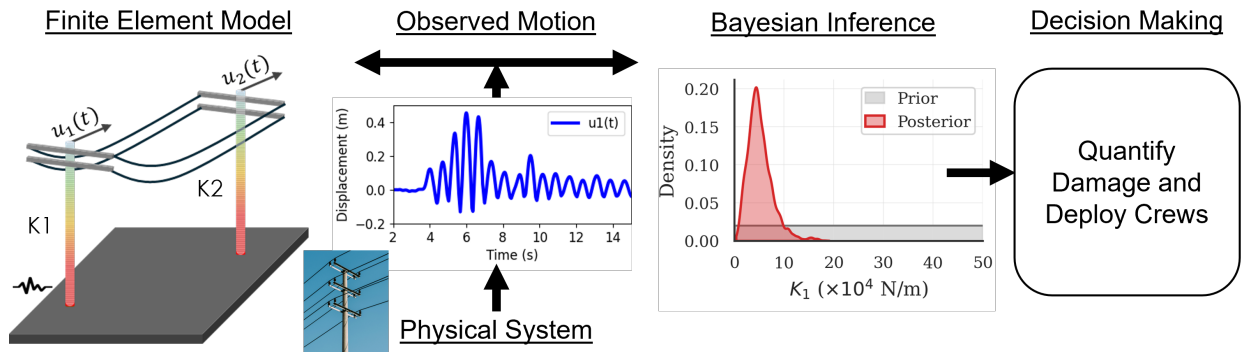


Fig. 1. Bayesian updating framework for coupled pole-cable system models. Displacement time histories from the physical system are assimilated into the OpenSees model through Bayesian inference to update uncertain structural parameters. The posterior parameter samples are subsequently in this study, we generate observations using the high-fidelity finite-element model and use them to estimate the probability distribution of the damage index and quantify structural damage.

In reliability engineering, structural failure is typically defined as the demand exceeding the capacity [31]. A structure initially designed to withstand a target hazard level, such as the maximum considered earthquake, may experience strength degradation and capacity loss due to damage from subsequent events, highlighting the need for continuous assessment of its evolving structural state [25, 32]. This paper focuses on identifying the evolving

structural state and quantifying changes in key parameters, such as strength degradation, resulting from the accumulation of damage.

Bayesian inference enables the estimation of posterior distributions of structural model parameters by combining prior knowledge with observations from the physical system [28, 33–35]. It has been widely applied in structural engineering and structural health monitoring applications for model updating using experimental and sensor measurement data [24, 36–39]. Let $\mathcal{D}$ denote the set of measurement data, such as sensor recordings, and $\mathcal{M}$ represent the virtual structural models. Through Bayesian updating, the observational data $\mathcal{D}$ are used to update the prior knowledge about the possible structural states represented by the virtual finite element model ($\mathcal{M}$), yielding a posterior distribution that reflects updated belief about the structure’s current condition.

The uncertainty in the structural model is represented through probability distributions over the model parameters, denoted by Θ . The posterior distribution of the model parameters Θ conditioned on the observations $\mathcal{D}$ and the model $\mathcal{M}$ is given by Bayes theorem as:

$$p(\Theta|\mathcal{D}, \mathcal{M}) = \frac{p(\mathcal{D}|\Theta, \mathcal{M})p(\Theta|\mathcal{M})}{p(\mathcal{D}|\mathcal{M})}, \quad (1)$$

where $p(\Theta|\mathcal{M})$ denotes the prior probability distribution of the model parameters Θ before observing the data $\mathcal{D}$ for a given structural model $\mathcal{M}$. The prior distribution $p(\Theta|\mathcal{M})$ can be specified as either non-informative or informative, depending on the available prior knowledge of the model parameters. The likelihood function, $p(\mathcal{D}|\Theta, \mathcal{M})$, represents the probability (density) of observing the measurements $\mathcal{D}$ given the structural model $\mathcal{M}$ and a particular set of model parameters Θ . The term $p(\mathcal{D}|\mathcal{M})$ is the normalizing constant, defined as $\int p(\mathcal{D}|\Theta, \mathcal{M})p(\Theta|\mathcal{M}) d\Theta$, which represents the probability of observing the data $\mathcal{D}$ integrated over all possible parameter values of the structural model. The explicit dependence on $\mathcal{M}$ indicates that the prior and posterior distributions depend on the choice of the underlying structural model. For simplicity, the dependence on $\mathcal{M}$ is omitted in subsequent formulations, with the understanding that all parameter distributions are conditioned on the selected structural model.

Since the normalizing constant $p(\mathcal{D}|\mathcal{M})$ is typically intractable, the posterior distribution is often expressed up to a proportionality constant as [21]:

$$p(\Theta|\mathcal{D}) \propto p(\mathcal{D}|\Theta)p(\Theta). \quad (2)$$

Using Eq. 2, Markov Chain Monte Carlo (MCMC) methods [40, 41] are commonly employed to sample from the posterior distribution, enabling an empirical Bayesian

132 updating of model parameters.

133 **A. Metropolis Hastings Algorithm**

134 The Metropolis-Hastings (MH) algorithm [42, 43] provides a straightforward approach for
135 generating samples from the posterior distribution, as it only requires evaluation of the
136 posterior distribution up to a proportionality constant (Eq. 2). In the MH algorithm, suc-
137 cessive samples are generated as states of a Markov chain whose equilibrium distribution
138 matches the target posterior distribution over the parameter space.

139 To generate the next sample in the Markov Chain, a candidate state Θ' is sampled from
140 a proposal distribution $q(\cdot|\Theta)$, which is conditional on the current state Θ . The candidate
141 is accepted with the probability:

$$\min \left(1, \frac{p(\Theta' | \mathcal{D})q(\Theta|\Theta')}{p(\Theta | \mathcal{D})q(\Theta'|\Theta)} \right). \quad (3)$$

142 If the candidate is rejected, the chain takes the previous Θ as its current state. In this
143 paper, we use an isotropic Gaussian proposal centered at the current state. Its parameters
144 are adjusted to obtain an acceptance rate ranging between 20% and 50% depending on
145 the dimensionality of the parameter space [44, 45]. The likelihood function is detailed in
146 Section 3.

147 **B. Teleport MCMC**

148 Due to the interacting components of a coupled structural system, the posterior distribu-
149 tions arising in structural model updating can be challenging to sample using a single local
150 random-walk Markov chain. Strong parameter correlations or limited information about
151 some parameters can lead to slow mixing and highly correlated samples. A conventional
152 MH chain with a single walker can remain trapped in a single region for many iterations
153 because transitions between modes require traversing low-posterior-probability regions,
154 leading to poor mixing and slow convergence [27, 46].

155 To improve exploration, we use the teleport MCMC algorithm, which evolves an ensem-
156 ble of interacting walkers rather than a single Markov chain [30]. Each walker performs lo-
157 cal Metropolis updates, while teleportation moves allow information from high-probability
158 regions discovered by one walker to be shared with the rest of the ensemble. This mecha-
159 nism improves the ability of the sampler to move through the posterior distribution and
160 reduces dependence on the initial condition of any one chain. During a teleportation
161 step in the algorithm, a selected walker is duplicated and moved to a new location in the
162 parameter space, while another walker is removed to maintain a constant ensemble size.

163 Consider an ensemble of N walkers. First, a walker $j \in \{1, 2, \dots, N\}$ is selected uni-

formly at random, and a candidate state x is sampled from the proposal distribution $q(\cdot|\Theta_j)$, where Θ_j is the current state for the j th walker. Next, a walker i is selected for deletion, and its state in the ensemble is replaced by x . For example, with $N = 3, j = 2$, and $i = 3$, the proposed ensemble transition is $\{\Theta_1, \Theta_2, \Theta_3\} \rightarrow \{\Theta_1, \Theta_2, x\}$. Also see Figure 2 for an illustration of the Teleport MCMC algorithm. The walker i is selected based on the importance weights

$$w_i(\Theta, x) = \frac{q(\Theta_i|x) + \sum_{m \neq i}^N q(\Theta_i|\Theta_m)}{p(\Theta_i | \mathcal{D})} / Z(\Theta, x), \quad (4)$$

$$Z(\Theta, x) = \sum_{l=1}^N \frac{q(\Theta_l|x) + \sum_{m \neq l}^N q(\Theta_l|\Theta_m)}{p(\Theta_l | \mathcal{D})}, \quad (5)$$

where $w_i(\Theta, x)$ assigns larger deletion probabilities to walkers located in low-density regions of the target posterior distribution that are also close to the proposed state x or to other walkers in the ensemble. For $N > 1$, the state of the walker selected for cloning at each iteration is retained in the posterior sample sequence, ensuring the same number of posterior samples across different ensemble sizes. For example, for an ensemble of size ($N = 3$), if walker ($j = 2$) is selected for cloning, its state (Θ_2) is retained as the posterior sample for that iteration. Let Θ' denote the proposal ensemble after the replacement. The proposed teleportation move is accepted according to the Metropolis-Hastings acceptance probability

$$\min \left(1, \frac{Z(\Theta, x)}{Z(\Theta', \Theta_i)} \right).$$

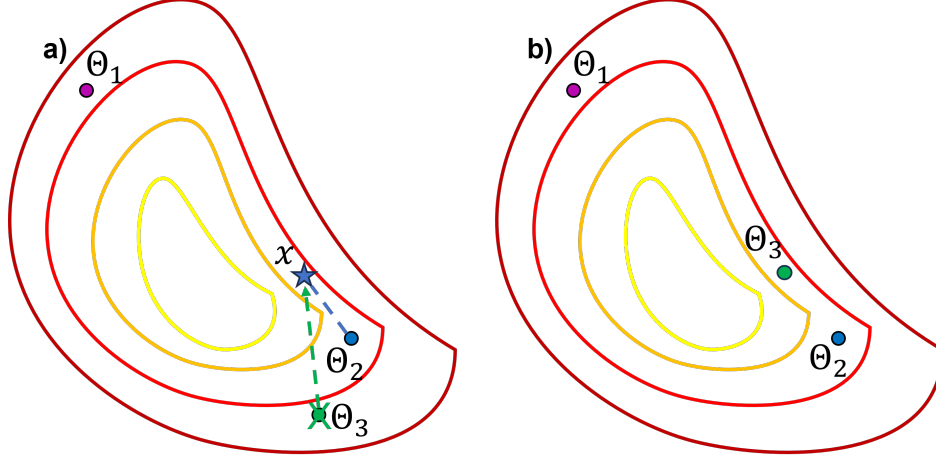


Fig. 2. Conceptual illustration of a Teleport MCMC update using three walkers. Walker 2 is selected for cloning, and a candidate state x is generated from the proposal distribution centered at walker 2. Walker 3 is then selected for deletion according to the importance weights, which assign higher deletion probabilities to walkers located closer to the cloned walker (Eq. 4) and its position in the ensemble is replaced by x .

Further details and derivation of this acceptance probability are provided in [30]. Notably, the MH algorithm converges to the target distribution under ergodic conditions, but it may require a large number of likelihood evaluations to obtain well-mixed posterior samples. For structural model updating, where each likelihood call relies on computationally intensive simulations, this slow mixing becomes a bottleneck. The advantage of teleport MCMC therefore extends beyond multimodal posteriors. For multimodal distributions, teleportation helps walkers move between separated modes. For unimodal but poorly mixing distributions, the ensemble improves decorrelation and produces more effective samples for the same number of model evaluations. We can quantify the sampling efficiency of MH and teleport MCMC algorithms using the integrated autocorrelation time (IAT) [47], which measures the correlation between successive MCMC samples and provides an estimate of the number of correlated samples required to obtain the equivalent of one independent posterior sample. Theoretically, for a stationary MCMC sequence, the IAT τ_{int} is defined as

$$\tau_{\text{int}} = 1 + 2 \sum_{\ell=1}^{\infty} \rho_{\ell},$$

where ρ_{ℓ} is the true autocorrelation at lag ℓ . In practice, given a finite MCMC sequence of length L , the infinite sum is truncated at a cutoff lag $M \ll L$ to suppress high-variance noise in sample autocorrelations at large lags. The estimated integrated autocorrelation

time $\hat{\tau}_{\text{int}}$ is computed as

$$\hat{\tau}_{\text{int}} = 1 + 2 \sum_{\ell=1}^M \hat{\rho}_{\ell},$$

where $\hat{\rho}_{\ell}$ represents the sample autocorrelation at lag ℓ . The truncation parameter M can be determined adaptively using an automated windowing scheme (e.g., Sokal's method, setting M such that $M \geq 5\hat{\tau}_{\text{int}}$). A sampler with faster autocorrelation decay and a smaller τ_{int} is considered to have better mixing. When likelihood evaluations dominate the computational cost, a smaller IAT also corresponds to fewer model evaluations required per effectively independent posterior sample.

3. LIKELIHOOD FORMULATION AND NUMERICAL EVALUATION

For a pole–cable system, the recorded motion of the poles can be used through Bayesian inference to update uncertain structural properties, such as stiffness. For a given set of model parameters, the likelihood function quantifies the agreement between the recorded structural response and the response predicted by the virtual structural model. In this study, we consider time-, frequency-, and energy-based likelihood formulations.

A. Likelihood functions

A.1. Time-domain likelihood function

Assume that the discrepancies between the measured and predicted response trajectories across time points and sensors are i.i.d. Gaussian with zero mean and standard deviation ϵ ; the likelihood function is given by:

$$p(\mathcal{D}|\Theta) \propto \prod_{p=1}^S \prod_{q=1}^L \exp \left(-\frac{(u_p(t_q) - \tilde{u}_p(t_q; \Theta))^2}{2\epsilon^2} \right), \quad (6)$$

where $u_p(t_q)$ and $\tilde{u}_p(t_q; \Theta)$ denote the recorded and simulated responses, respectively, at the p^{th} sensor and the q^{th} time step.

A.2. Frequency-domain likelihood function

Previous studies in structural health monitoring have employed frequency-based likelihood functions. However, most of these studies have focused on lumped-mass models, which typically exhibit only two to four dominant vibration modes [24, 48]. Consequently, the likelihood function is often constructed by comparing the structural response at these dominant modal frequencies. In contrast, the dynamic responses of utility poles with distributed cable masses can span a broader frequency range. Similar to the time-domain formulation, assuming i.i.d. Gaussian discrepancies in the frequency domain, the likeli-

hood function can be expressed as

$$p(\mathcal{D}|\Theta) \propto \prod_{p=1}^S \prod_{q=1}^L \exp \left(- \frac{(A_p(\omega_q) - \tilde{A}_p(\omega_q; \Theta))^2}{2\epsilon^2} \right), \quad (7)$$

where $A_p(\omega_q)$ and $\tilde{A}_p(\omega_q)$ denote the Fourier transform of recorded and simulated responses, respectively, at the p^{th} sensor and the q^{th} frequency point.

A.3. Cumulative energy-based likelihood function

We propose a new likelihood function based on the cumulative spectral energy of the structural response. Compared with the previous time- and frequency-domain likelihood functions, the proposed energy-based likelihood provides a smoother likelihood landscape over the parameter space, where the accumulation process reduces the influence of noisy, local details in response trajectories. This smoother landscape facilitates exploration by MCMC algorithms and improves convergence toward the high probability regions of the structural parameters. The proposed likelihood function is presented as:

$$p(\mathcal{D}|\Theta) \propto \prod_{p=1}^S \prod_{q=1}^L \exp \left(- \left(\frac{\sum_{i=1}^q A_p(\omega_i) \Delta\omega}{\sum_{j=1}^L A_p(\omega_j) \Delta\omega} - \frac{\sum_{i=1}^q \tilde{A}_p(\omega_i; \theta) \Delta\omega}{\sum_{j=1}^L \tilde{A}_p(\omega_j; \theta) \Delta\omega} \right)^2 / 2\epsilon^2 \right). \quad (8)$$

In the following section, we evaluate the performance of these likelihood functions in identifying structural parameters for a pole-cable system.

B. Selection of likelihood functions

B.1. Pole-cable model

To evaluate the proposed likelihood functions and demonstrate the application of Teleport MCMC, we perform numerical simulations on a pole-cable system from literature [18], shown in Figure 3. The cable tension and the dynamic responses of the poles are influenced by the slackness ratio. A smaller slackness ratio leads to higher cable forces and stronger interaction between the poles. These coupling effects cannot be captured when the poles are analyzed independently.

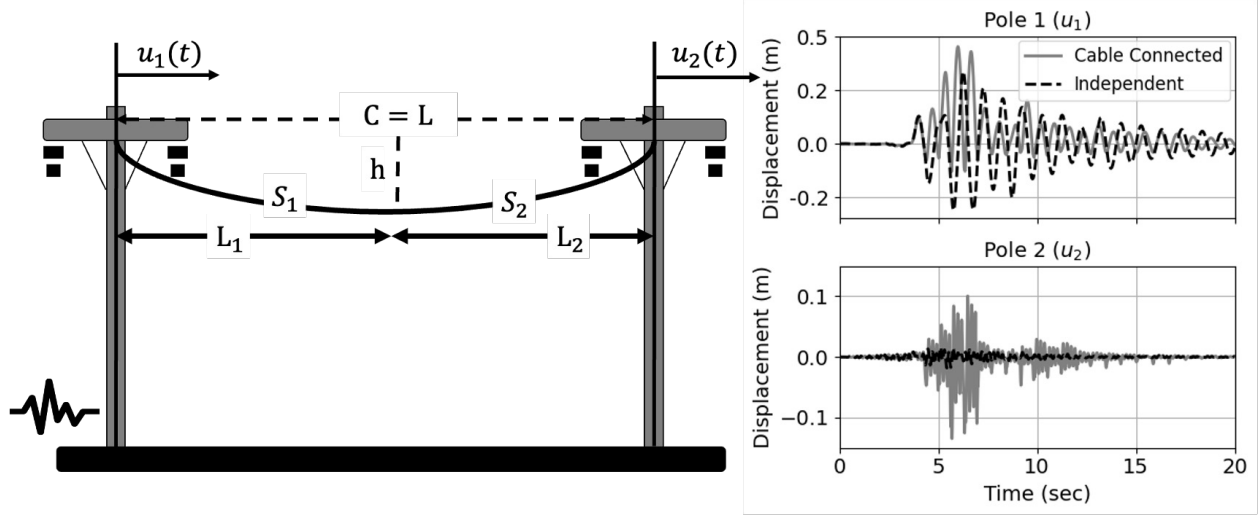


Fig. 3. Schematic representation of the coupled utility pole–cable system used for numerical simulations. (Left panel) The model consists of two utility poles interconnected by a suspended cable subjected to ground excitation. The horizontal displacements at the tops of the poles are denoted by $u_1(t)$ and $u_2(t)$, while L_1 , L_2 , S_1 , S_2 , C , and h define the cable geometry. (Right panel) Comparison of the response of the electrical equipment to the 1994 Northridge earthquake when the components are connected by a cable and when they are modeled independently without cable coupling.

The initial material and geometric properties of the poles and cables are adopted from [18] and are summarized in Table 1. To investigate the effect of dynamic interaction, the dynamic response of the coupled system is compared with that of the corresponding standalone poles under the ground motion recorded at the Newhall–County Fire Station (Station CE24279) during the 1994 Northridge earthquake, obtained from the Center for Engineering Strong Motion Data (CESMD) [49]. Details on cable-coupling equations are described in [18]. We modeled the electrical equipment and the connecting cable using the analytical equations in [18], implemented in Python. Due to the cable coupling, the left pole exhibits a maximum displacement amplitude that is 1.35 times greater than that of the standalone left pole, while the right pole exhibits a maximum displacement amplitude that is 6.38 times greater than that of the standalone right pole (Figure 3).

B.2. Bayesian inference of stiffness

We use the top pole responses ($u_1(t)$ and $u_2(t)$ in Figure 3) to the Northridge earthquake obtained from the numerical model as the observed responses for Bayesian inference. Non-informative uniform prior distributions are assigned to the stiffness parameters of the two structures. Specifically, the stiffness of the left pole is assumed to follow $K_1 \sim U(0.02, 5) (\times 10^5 N/m)$, while the stiffness of the right pole is assumed to follow

Parameter	Description	Value
<i>Cable properties</i>		
A	Cable cross-sectional area	$1.96 \times 10^{-3} \text{ m}^2$
E	Cable elastic modulus	$7.0 \times 10^{10} \text{ Pa}$
w	Cable self-weight per unit length	52.2 N/m
L_0	Initial horizontal span length	5.0 m
S_0	Initial cable arc length	5.033 m
L_1/L_0	Cable segment length ratio	0.5
S_1/S_0	Cable segment arc-length ratio	0.5
H	Vertical offset between supports	0.0 m
<i>Pole properties</i>		
m_1	Mass of pole 1	1000 kg
m_2	Mass of pole 2	500 kg
f_1	Natural frequency of pole 1	1.0 Hz
f_2	Natural frequency of pole 2	5.0 Hz
ζ_1	Damping ratio of pole 1	0.02
ζ_2	Damping ratio of pole 2	0.02
$K_1 = m_1(2\pi f_1)^2$	Implied stiffness of pole 1	$3.95 \times 10^4 \text{ N/m}$
$K_2 = m_2(2\pi f_2)^2$	Implied stiffness of pole 2	$4.93 \times 10^5 \text{ N/m}$

Table 1. Model parameters used for the two-pole cable-coupled dynamic response simulation.

$$K_2 \sim U(0.01, 1.6) (\times 10^6 N/m).$$

We perform Bayesian inference using the Metropolis–Hastings algorithm to estimate the posterior distributions of K_1 and K_2 based on the three log-likelihood functions: time-domain-based likelihood (Eq. 6), frequency-based likelihood (Eq. 7), and energy-based likelihood (Eq. 8). For each case, 20,000 posterior samples are generated with 10 walkers, with the proposal distribution tuned to achieve an acceptance rate of approximately 20% – 50%. The posterior distribution of samples is presented in Figure 4. Among the three likelihood formulations, the cumulative energy-based likelihood provides the most accurate estimates of the true stiffness parameters K_1 and K_2 .

The energy-based likelihood predicts the mean value of K_1 with a 35% error relative to the true value, compared with 160% and 59% for the time- and frequency-based likelihoods, respectively. Similarly, the error in K_2 is 15% for the energy-based likelihood, compared with 68% and 74% for the time- and frequency-based likelihoods, respectively. The time- and frequency-based likelihood functions clearly identify K_1 , but K_2 is less well identified, particularly when the response amplitudes differ substantially between the two poles. In contrast, the energy-based likelihood provides more accurate estimates of both K_1 and K_2 . Additionally, Supplementary Figure S1 provides a heatmap of the different log-likelihood functions over a grid of K_1 and K_2 values. The energy-based formulation exhibits a more regular high-likelihood region around the reference parameter values.

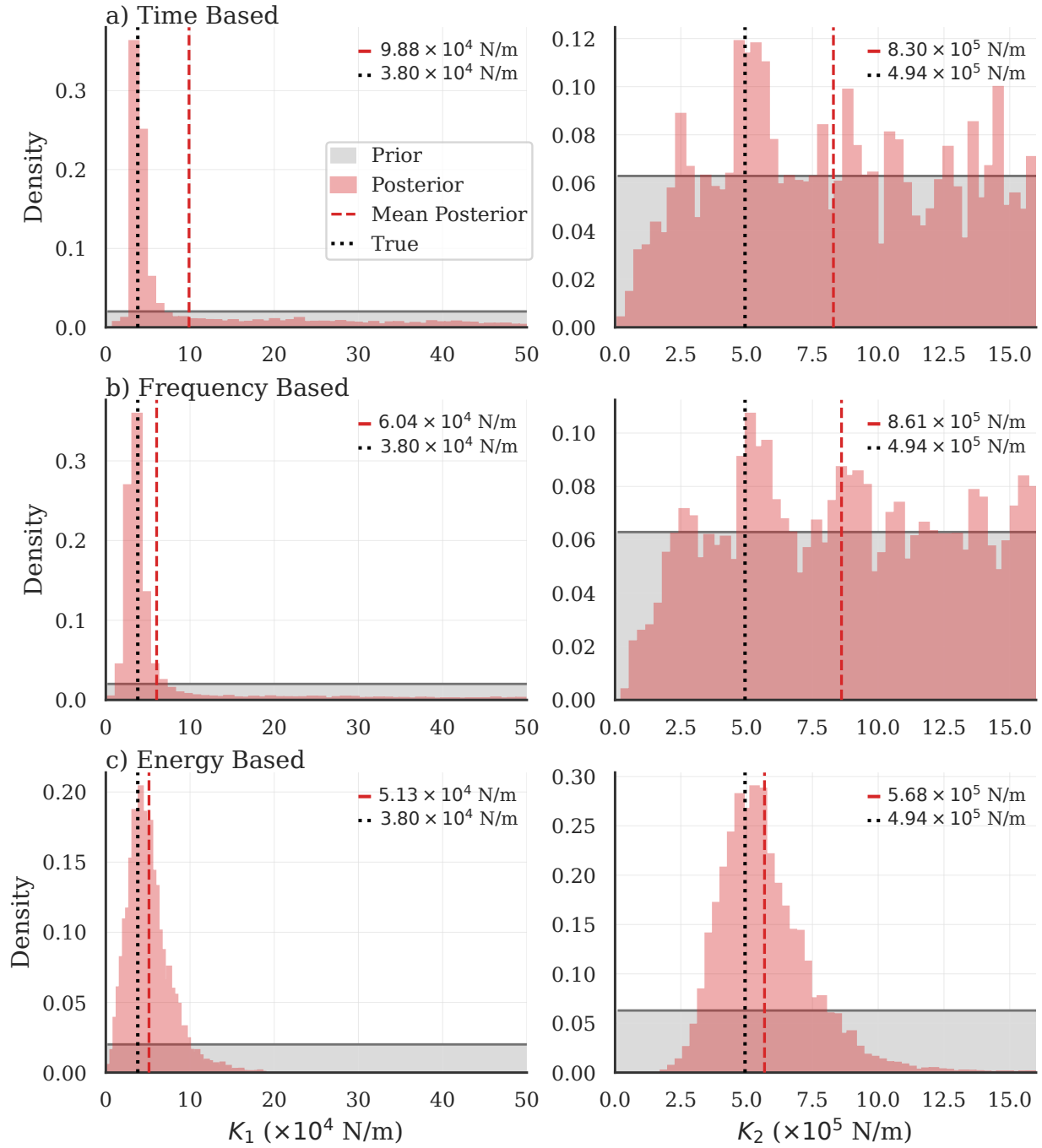


Fig. 4. Kernel density estimates of the posterior samples obtained using teleport MCMC with 10 walkers for the two-pole system. The rows correspond to likelihoods defined in the time, raw frequency, and energy domains, respectively. The left and right columns show the marginal posterior distributions of K_1 and K_2 . Solid black vertical lines indicate the posterior sample means, while dashed red vertical lines indicate the true parameter values used to generate the synthetic response.

C. Efficiency of the sampling algorithm

We assess Teleport MCMC sampling efficiency for different ensemble sizes using the integrated autocorrelation time (IAT). For each ensemble size, the algorithm is run for 22,000 iterations with the first 2,000 steps discarded as burn-in steps. At each iteration, only one walker which is selected for cloning is retained as a sample, and one new candidate state is generated. Hence, the number of new log-likelihood evaluations is the same across ensemble sizes. For $N > 1$, only the cloned walker is retained in the posterior sample sequence, ensuring a consistent number of samples across cases.

Figure 5 shows the IAT as a function of the number of walkers with 20,000 samples each. The IAT decreases substantially as the number of walkers increases and approaches $\tau_{int} \approx 1$ for ensembles with 10 or more walkers. Thus, for the same number of log-likelihood evaluations, larger ensembles produce posterior samples with lower serial correlation and a higher effective sample size.

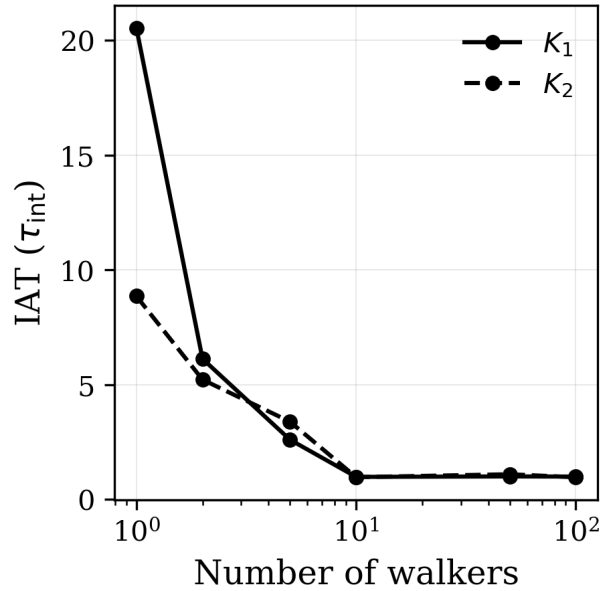


Fig. 5. Integrated autocorrelation time (IAT) for different numbers of walkers.

D. Bayesian inference with limited information

In the previous example, we assumed that the sensor measurements were available at the tops of both poles. In practice, however, only a limited number of sensors are available for monitoring large-scale infrastructure systems, making it necessary to infer the structural state from sparse measurements.

Here we assume that only the left pole response is used to infer the parameters of both poles. We use the energy-based log-likelihood estimator with MCMC sampling to learn the

stiffnesses K_1 and K_2 . Figure 6 shows the posterior distributions of K_1 and K_2 . The posterior distribution of K_1 accurately identifies the true parameter value, with both the posterior mean and median lying close to the ground truth. For K_2 , the posterior mean and median deviate slightly from the true value due to the limited sensor information. Nevertheless, the posterior distribution remains centered around the true value and exhibits a clear peak near the ground truth.

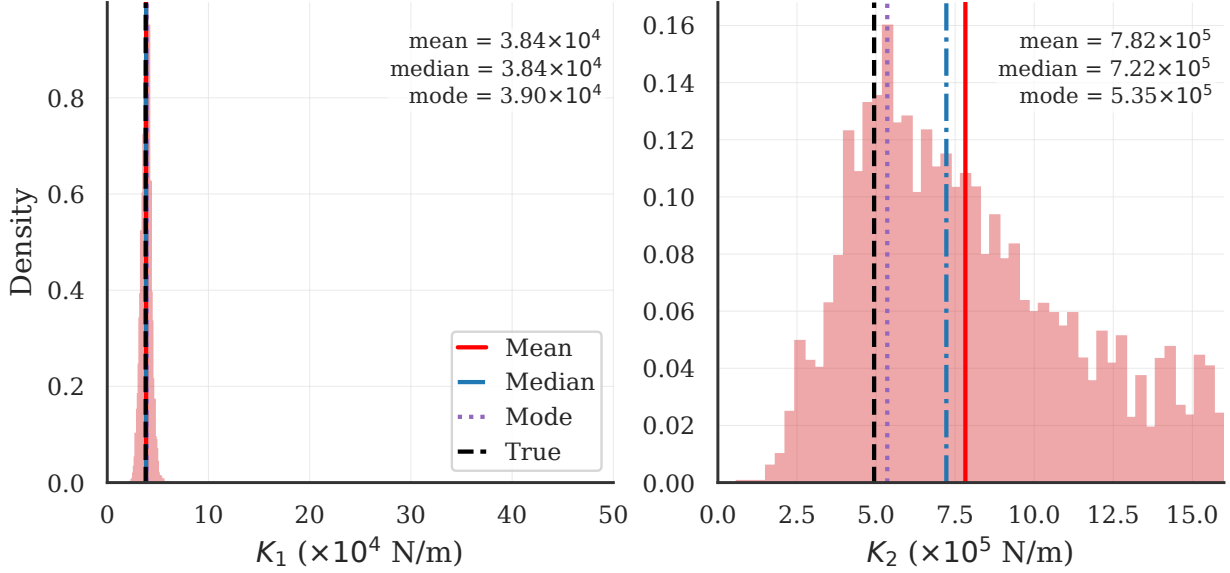


Fig. 6. Posterior distribution of K_1 and K_2 using information available from the motion of the left pole (u_1) only.

In the previous example, the cable is relatively taut, resulting in strong dynamic interaction between the two poles. Consequently, the response of the left pole contains information about the characteristics of the right pole, even when the likelihood is computed using measurements from only the left pole. To investigate the effect of cable tautness on parameter identification, we increase the slackness ratio by changing the slackness parameter S from 5.033 m to 5.1 m to imitate variable real-world conditions. Next, we performed numerical simulations of the K_1 stiffness at the left pole and the K_2 stiffness at the right pole, using only limited information from the left pole's dynamics. The results are presented in Supplementary Figure S2, which shows the posterior distributions for K_1 and K_2 . Increasing cable slackness weakens the dynamic coupling between the poles, thereby limiting information about K_2 in the left pole's response. Consequently, K_2 is identified with much greater uncertainty than in the case of a smaller slackness ratio.

4. BAYESIAN DAMAGE INFERENCE FOR WOODEN POLES

Next, we apply the proposed framework to utility wooden power poles. Relatively few studies have investigated the seismic vulnerability of wooden utility poles. In [50], the authors conducted a seismic vulnerability analysis of timber piles and substructures and performed material characterization tests on wooden telephone poles. Owing to the limited availability of material data for utility power poles, we assume that the material properties reported for the tested telephone poles are representative of utility wooden power poles because of their similar wood species and structural applications.

Multidisciplinary Center for Earthquake Engineering Research (MCEER) [50] characterized the material properties of the wooden poles using the well-established Mander constitutive model. Table 2 summarizes the mechanical properties adopted for the wooden poles. Supplementary Figure S3 illustrates the corresponding stress–strain relationship for the wood fibers. We modeled the wooden poles in OpenSees using the Mander constitutive model [51] and displacement-based beam-column elements with a fiber discretization of 20 radial and 32 circumferential fibers. In addition, we modeled the cable as a Catenary Cable element in OpenSees [52, 53] with the properties mentioned in Table 1.

Description	Symbol	Value
Modulus of elasticity in compression	E_c	10,000 MPa
Modulus of elasticity in tension	E_t	9,000 MPa
Compressive strength	F_c	31 MPa
Tensile strength	F_t	40 MPa
Strain at peak compressive stress	ε_{co}	0.004
Strain at peak tensile stress	ε_{to}	0.005

Table 2. Material properties of the timber pole.

Once the material properties of a power pole have been identified, we then quantify the damage induced by earthquake loading. Damage indices provide a quantitative measure of structural deterioration based on the hysteretic response under cyclic loading [54, 55]. By accounting for the cumulative effects of repeated loading and unloading in both the positive and negative directions, these indices provide a measure of the accumulated seismic damage sustained by the component. We use the Kratzig Damage Model [56], which is based on the dissipated energy during earthquake loading and the maximum energy under monotonic loading. The maximum energy points are analytically derived

using the pushover analysis with OpenSees. The ultimate failure point is defined by crushing of the wood fibers.

The Kratzig damage model [56] quantifies structural damage based on the primary and follower half-cycles of the hysteretic response. Primary half-cycles are loading excursions that establish a new maximum displacement envelope, whereas follower half-cycles remain within the previously established displacement envelope and have smaller amplitudes. The Kratzig damage index for the positive and negative loading directions is given by

$$DI^{+/-} = \frac{\sum E_{si}^{+/-} + \sum E_i^{+/-}}{E_u^{+/-} + \sum E_i^{+/-}}. \quad (9)$$

where E_{si} is the energy in the primary half cycle, E_u is the ultimate energy in the monotonic loading and E_i is the energy in the follower half cycles. A complete failure of the component occurs when the accumulated energy dissipated during the primary half-cycles exceeds the ultimate energy capacity. The damage index (DI) that combines both the negative and positive cycles is given by:

$$DI = DI^+ + DI^- - DI^+ DI^- \leq 1. \quad (10)$$

A. Bayesian inference of damage in utility poles

Most of the structural damage in wooden utility poles accumulates near the groundline, where bending moments are typically the largest. This concentration of nonlinear behavior motivates a low-fidelity representation for repeated MCMC evaluations. Rather than repeatedly evaluating a computationally expensive fiber-based finite element model for each sampled parameter set, we model the dominant groundline nonlinearity using a rotational spring at the pole base with a hysteretic material model in OpenSees [57].

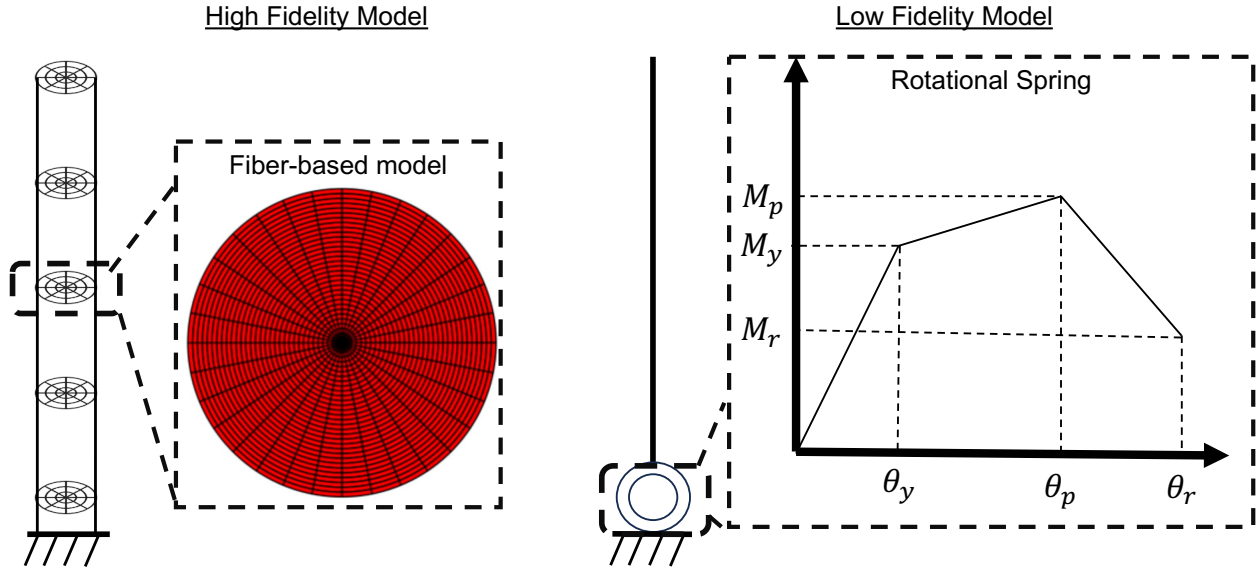


Fig. 7. The left panel shows the high-fidelity fiber-based model of the wooden pole, with the cross-section discretized into fibers in the radial and circumferential directions. The right panel shows the low-fidelity representation, in which the nonlinear response is concentrated at the pole base and modeled using a hysteretic material in OpenSees. This simplified representation substantially reduces the computational cost of repeated log-likelihood evaluations during Bayesian inference. The rotational spring parameters are updated after each earthquake event based on the observed structural response.

Figure 7 illustrates the low-fidelity equivalent representation of the high-fidelity fiber-based finite element model. The rotational spring is characterized by six parameters: three characteristic moments, namely the yield moment M_y , plastic moment M_p , and residual moment M_r , and three corresponding rotation values, namely the yield rotation θ_y , plastic rotation θ_p , and residual rotation θ_r . Failure of the pole is assumed once the residual rotation θ_r is reached. The portion of the pole above the rotational spring is modeled as a linear elastic member, while all nonlinear deformation and damage are represented by the rotational spring at the base of the low-fidelity model.

A.1. Single Pole Example

To demonstrate that the proposed low-fidelity representation can accurately capture earthquake-induced damage in a utility pole, we consider a single utility pole subjected to earthquake excitation. The response generated by the high-fidelity fiber-based finite element model is treated as the measured structural response, while Bayesian inference is used to update the parameters of the low-fidelity virtual model. The damage index predicted by the updated low-fidelity model is then compared with that of the high-fidelity model to assess the accuracy of the proposed approach.

We selected utility pole dimensions representative of those reported in [50], ensuring that the simulated structural response is qualitatively consistent with that observed in the literature. The wooden pole is assumed to be 2.43 m tall with a diameter of 120 mm. The pole is modeled in OpenSees using a displacement-based beam-column element with five integration points. The circular cross-section is discretized into 20 circumferential and 32 radial fibers.

Many wooden utility poles in electrical distribution systems have been in service for more than 40 years. As a natural material, wood is susceptible to degradation over time. Environmental factors such as temperature fluctuations, moisture, and fungal decay can progressively reduce the strength and stiffness of wooden utility poles. In this study, material deterioration is represented by a reduction in the pole’s effective cross-sectional depth due to decay. As an illustrative example, we consider a wooden pole with a 10% reduction in cross-sectional depth subjected to the 1994 Northridge ground motion recorded at the Newhall station scaled by a factor of 3.

A.2. Bayesian inference of pole properties

For the simplified two-pole example in Section 3, we assumed non-informative uniform priors for the two stiffness parameters. In the low-fidelity rotational-spring model, however, six nonlinear parameters must be inferred: three moment parameters and three corresponding rotational-capacity parameters. Assigning broad non-informative priors to all six parameters would substantially enlarge the parameter space to be explored, potentially requiring a large number of likelihood evaluations and slowing convergence. To reduce the computational cost of the Bayesian updating, we therefore define informative prior distributions using parameter estimates obtained from the pushover curve, which can be evaluated at substantially lower computational cost.

We match the pushover response of the undamaged high-fidelity pole model to that of the simplified rotational-spring model. A grid search is performed over the six spring parameters, M_y , M_p , M_r , θ_y , θ_p , and θ_r , to identify parameter values that approximately reproduce the pushover response. These values are then used as the means of the prior distributions. For simplicity, we assume normal prior distributions for the six rotational-spring parameters, each with a coefficient of variation of 50%. Supplementary Figure S4 shows the match between the pushover curves for the simplified low-fidelity and high-fidelity fiber models. The initial prior means are specified as $\mu_{M_{y,0}} = 73.52 \text{ kN} \cdot \text{m}$, $\mu_{M_{p,0}} = 77.64 \text{ kN} \cdot \text{m}$, $\mu_{M_{r,0}} = 25.47 \text{ kN} \cdot \text{m}$, $\mu_{\theta_{y,0}} = 0.002688 \text{ rad}$, $\mu_{\theta_{p,0}} = 0.01622 \text{ rad}$, and $\mu_{\theta_{r,0}} = 0.13741 \text{ rad}$.

To perform Bayesian updating of the simplified model parameters, we used the Teleport

MCMC algorithm with 20 walkers to generate a total of 20,000 posterior samples after 2,000 burn-in steps. Figure 8 shows the posterior distribution of parameters for the low-fidelity representation of the wooden poles. For comparison, we also performed MCMC sampling with a single walker to evaluate the effect of the ensemble size on sample mixing. The samples generated with 20 walkers exhibit improved mixing and lower integrated autocorrelation times (IATs) than those obtained using a single walker. For example, the M_y samples generated with 20 walkers have an IAT of 1.57, compared with 36.98 for the single-walker case. Similarly, the posterior samples of θ_y have an IAT of 87.37 with 20 walkers, compared with 287.16 using a single walker. These results indicate that increasing the ensemble size substantially improves sampling efficiency and reduces IAT in the posterior chains. Supplementary Figures S4 and S5 present trace plots of the posterior samples with 1 walker and 20 walkers, respectively.

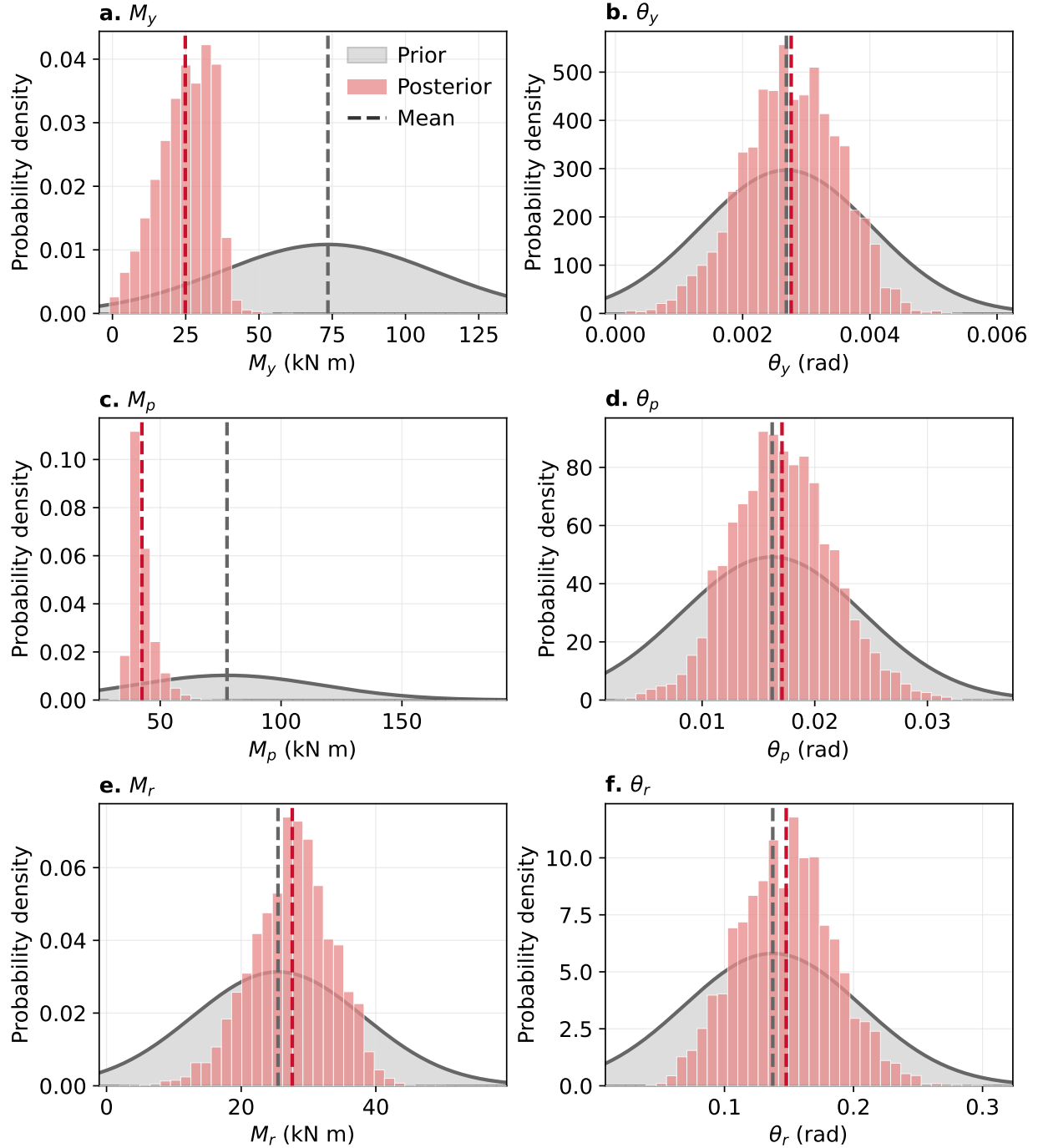


Fig. 8. Prior and posterior distributions of parameters of the simplified low-fidelity representation of the wooden pole.

The posterior distributions of M_y and M_p shift toward lower values relative to their prior distributions, indicating a reduction in rotational spring capacity consistent with earthquake-induced damage (Figure 8). In addition, the posterior distributions of the model parameters are narrower than their corresponding priors, reflecting reduced uncer-

tainty after incorporating the observed structural response.

Figure 9 compares the hysteresis response of the reference fiber-section pole model with that of the spring-based pole model evaluated using the posterior mean parameter values. The two responses are in close agreement, indicating that the updated simplified model captures the reference model's hysteretic behavior well. Small differences in the top-displacement response may arise from differences in how structural nonlinearity is represented: in the low-fidelity model, nonlinearity is concentrated at the pole base, whereas in the high-fidelity fiber model it is distributed along the member. Because the Kratzig damage index is derived from the cyclic hysteretic response, we next assess whether the updated low-fidelity model can reproduce the damage estimated by the reference high-fidelity model.

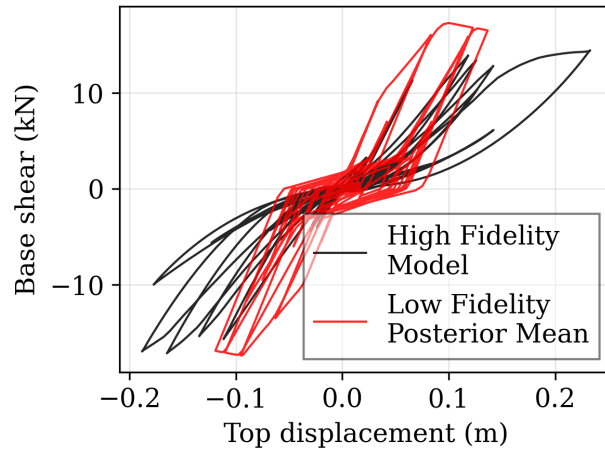


Fig. 9. Hysteresis responses of the high-fidelity 10%-damaged fiber model (black) and the low-fidelity zero-length model evaluated using the Teleport MCMC posterior-mean parameters (red) under the three-times-scaled Northridge ground motion.

A.3. Damage index of single pole example

We calculated the Kratzig damage index (DI) using the posterior samples of the pole parameters (Figure 10). The simplified model with posterior parameters yields a mean DI of 0.68, compared with the reference DI of 0.58. For comparison, using the prior mean parameters gives a DI of 0.40, which underestimates the actual level of damage. An underestimation of damage may provide a false sense of structural reliability when the pole has, in fact, experienced significant damage. Such underestimation could lead to an overly optimistic assessment of the pole condition and may delay inspection or repair decisions.

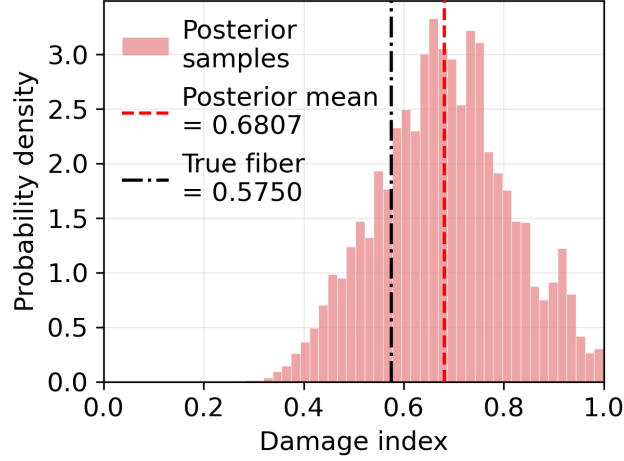


Fig. 10. Comparison of the damage-index distribution obtained from the low-fidelity representation with the reference high-fidelity fiber-based model.

5. BAYESIAN UPDATING UNDER SEQUENTIAL EARTHQUAKES

We set up numerical experiments involving two identical wooden poles, each 9 m high with a constant radius of 0.14 m, approximately corresponding to a Class 4 pole under the ANSI wood-pole classification [58]. The poles are connected by a conductor cable with the properties listed in Table 1, over a span of 22.86 m. Each pole has a lumped translational mass of $0.273 \text{ kN s}^2/\text{m}$ (273 kg) at its top. Gravity loading is represented by a concentrated axial load of 2.68 kN at the pole top and a uniformly distributed vertical line load of 0.31 kN/m along the pole height, corresponding to a total distributed pole weight of 2.79 kN. Second-order geometric effects are included through a P-Delta transformation, so the axial gravity and cable forces generate additional overturning moments as the poles displace laterally.

Similar to the single-pole example in Section 4, each wooden pole is represented in the Bayesian updating framework using the simplified rotational-spring model. The nonlinear behavior of each pole is characterized by six parameters: the yield, plastic, and residual moments, M_y , M_p , and M_r , and their corresponding rotations, θ_y , θ_p , and θ_r . The parameter vector for each pole is therefore defined as

$$\Theta = [M_y, M_p, M_r, \theta_y, \theta_p, \theta_r]^T.$$

As in the single-pole example, the initial prior means are obtained by matching the pushover response of the simplified model to that of the high-fidelity fiber-based model. For each parameter Θ_i , the initial prior distribution is defined as

$$\Theta_i \sim \mathcal{N}(\mu_{i,0}, \sigma_{i,0}^2), \quad i = 1, \dots, 6.$$

A coefficient of variation of 50% is assumed for each parameter, such that

$$\sigma_{\Theta_{i,0}} = 0.5 \mu_{\Theta_{i,0}}.$$

Bayesian updating is performed after each earthquake event so that information obtained from the response to one event informs the subsequent update. The posterior distribution obtained after each earthquake is used to construct the prior distribution for the next event. In addition, the complete loading history through the current event is retained in the structural analysis to preserve the accumulated stresses, deformations, and residual structural state. For example, during the second earthquake, the analysis includes the complete ground-motion history from the first through the second event so that residual stresses and structural deformations from the first event are retained.

Let $\mathcal{D}_s$ denote the recorded structural response associated with earthquake event E_s , and let $\mathcal{D}_{1:s} = \{\mathcal{D}_1, \dots, \mathcal{D}_s\}$ denote the observations available through event E_s . Assuming that the structural parameters stay constant between earthquake events, the posterior distribution after earthquake event E_s is obtained recursively as

$$p_s(\Theta) = p(\Theta \mid \mathcal{D}_{1:s}, \mathcal{M}) \propto p(\mathcal{D}_s \mid \Theta, \mathcal{M}) p_{s-1}(\Theta), \quad s = 1, 2, 3.$$

Here, $\mathcal{M}$ denotes the virtual structural model. For $s > 1$, $p_{s-1}(\Theta)$ represents the prior distribution transferred from the posterior obtained after the previous earthquake event.

In implementation, following each event, the MCMC posterior samples are approximated using independent marginal normal distributions. These fitted marginal distributions are then used as the prior distributions for the subsequent earthquake event. We performed Bayesian inference to estimate the pole parameters using two measurement configurations: (1) response information available from both poles and (2) response information available only from the left pole. For reference, the observed structural response was generated using a high-fidelity fiber-based finite-element model of the poles implemented in OpenSees.

A. Bayesian updating with information on both poles

We present the results of Bayesian updating of the multidimensional parameter space when response measurements are available from both poles. To investigate cumulative damage under sequential seismic loading, the coupled pole-conductor system is subjected consecutively to the 1994 Northridge earthquake record at Newhall station scaled to 100%,

200%, and 300%. For sequential analysis, we added 40 seconds of zero padding to the ground motion to allow the structure to come to rest before starting the dynamic analysis for the next event.

Figure 11 shows the posterior updates for M_y and θ_y after each earthquake event, while Supplementary Figure S7 presents the corresponding results for all parameters of both poles. Among the six parameters, M_y and θ_y exhibit the most noticeable shifts in their posterior distributions across the sequential events. The remaining parameters show relatively small changes in their posterior means; however, their uncertainties are reduced after Bayesian updating.

We observe a shift in M_y toward lower values after each event, indicating a reduction in the moment capacity associated with yielding and suggesting progressive strength degradation as damage accumulates. The posterior distribution of θ_y , which represents the rotation at the onset of yielding, also evolves across the sequential events. Changes in θ_y reflect a modification of the deformation threshold at which the pole transitions from elastic to nonlinear behavior. Unlike M_y , however, the direction of change in θ_y does not provide a direct monotonic measure of damage because it is jointly identified with the other nonlinear spring parameters. Instead, its evolution reflects changes in the shape of the inferred hysteretic backbone as the pole's structural state changes.

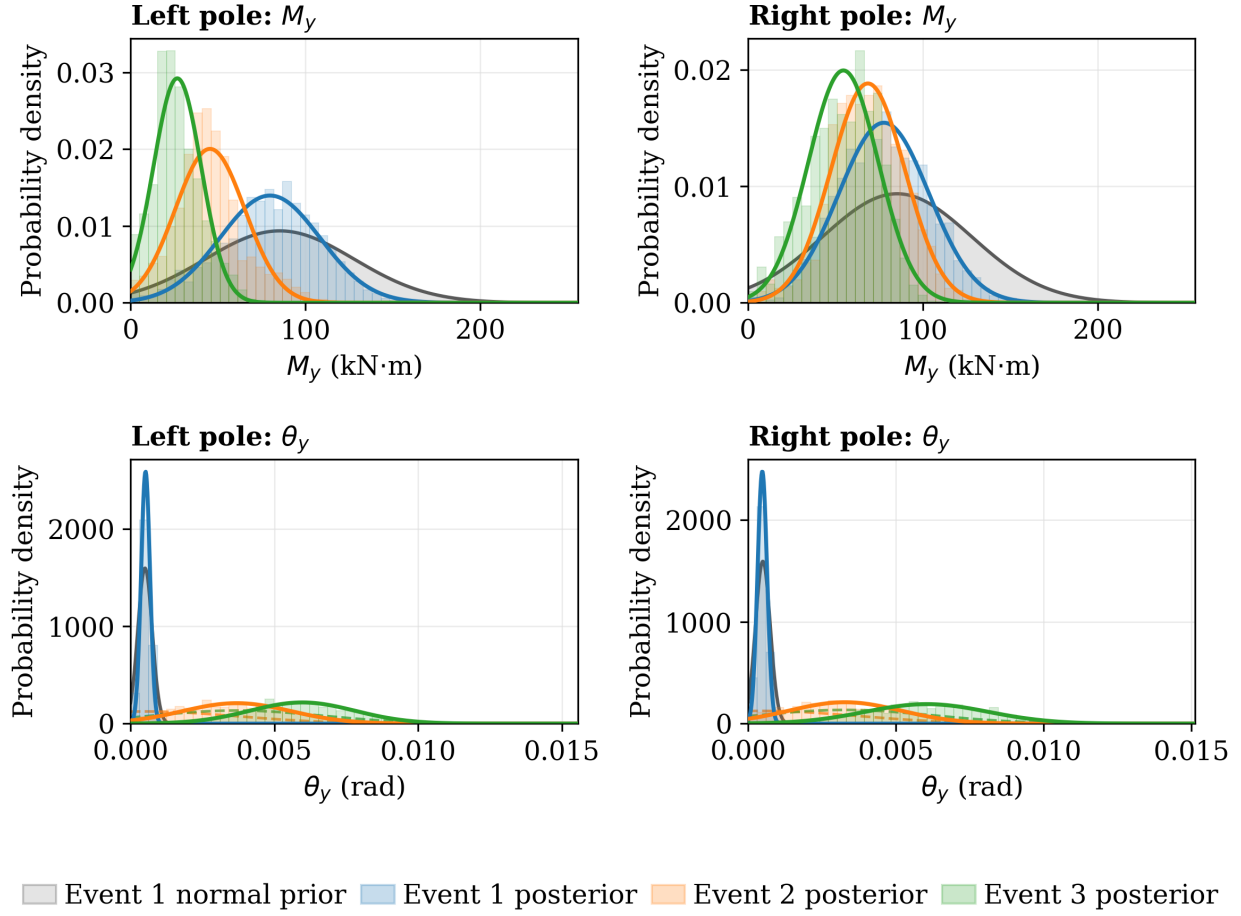


Fig. 11. Parameter distribution for the poles after three earthquake events. Events 1, 2, and 3 are 100%, 200%, and 300% of the 1994 Northridge earthquake.

Figure 12 presents the damage index calculated from the posterior samples after each earthquake event for both poles. We observe an increase in damage after each event. Our model is able to capture the progressive damage during the events.

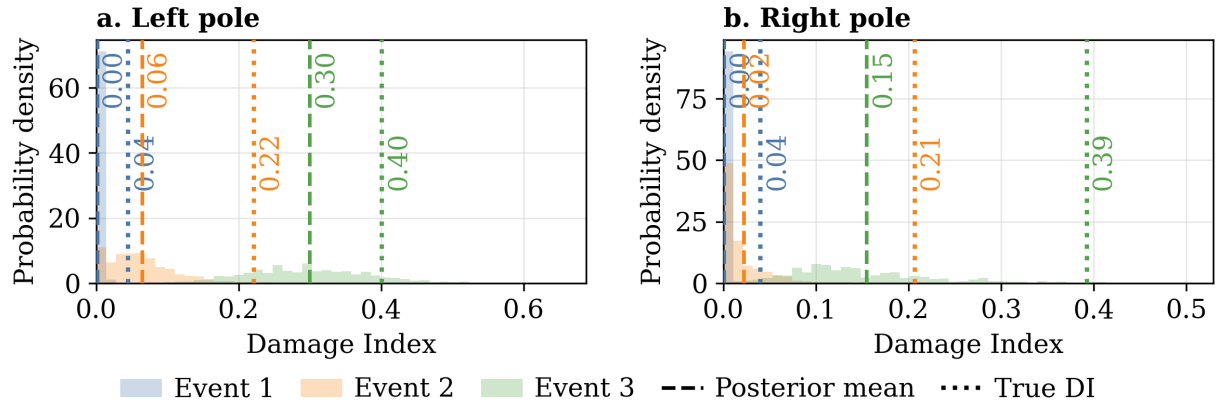


Fig. 12. Damage indices for both poles after sequential ground motions scaled to 100%, 200%, and 300% of the motion recorded at Newhall Station during the 1994 Northridge earthquake.

To further evaluate the proposed approach's ability to characterize the damage state of power poles, we subjected the poles sequentially to 200% of the ground motion recorded at the previously selected Newhall Station, followed by 250% of the ground motion recorded at Rinaldi Station. We observe trends similar to those in the previous analysis, including a reduction in M_y , indicating progressive degradation in yield-moment capacity (see also Supplementary Figure S8). Figure 13 shows that our proposed approach can capture progression in damage during different earthquake events.

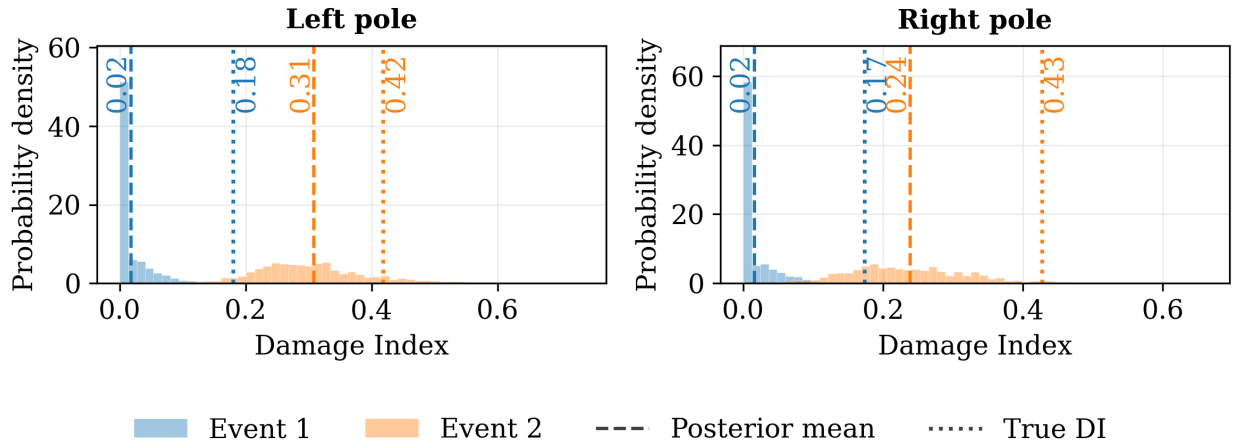


Fig. 13. Damage indices for both poles after sequential ground motions, first 200% of the motion recorded at Newhall Station and followed by 250% of the motion recorded at Rinaldi Station during the 1994 Northridge earthquake.

B. Bayesian updating with information only from the left pole

Here we report Bayesian parameter updates using response information from only the left pole as the reference measurement for the 1994 Northridge earthquake record at Newhall Station, scaled to 100%, 200%, and 300%. Figure 14 shows the posterior distributions of M_y and θ_y for both the left and right poles. As in the case with measurements from both poles, the posterior distributions of M_y and θ_y shift for both poles. In particular, the progressive reduction in M_y indicates degraded pole-moment capacity and is consistent with accumulated structural damage.

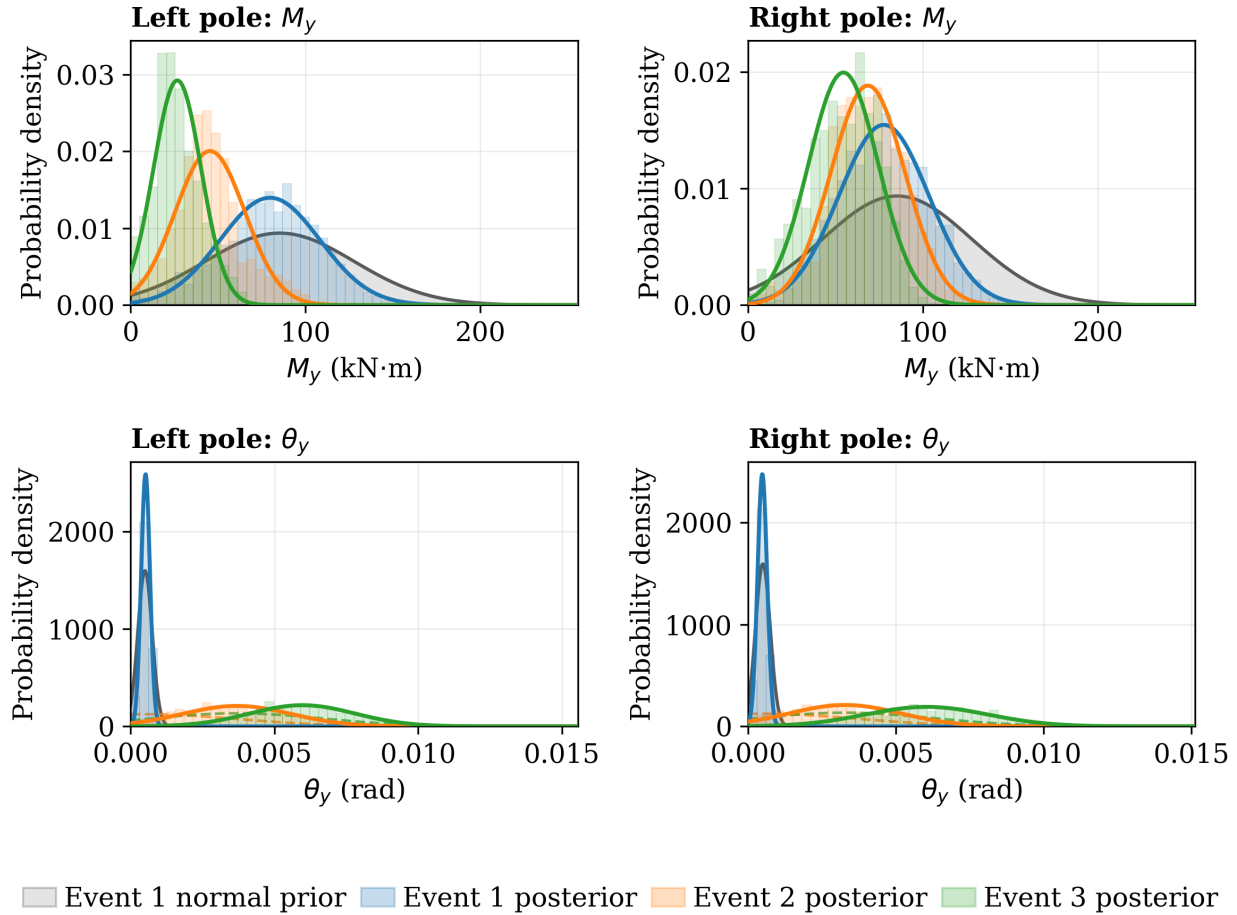


Fig. 14. Parameter distributions for both poles after three earthquake events using response information from only the left pole. Events 1, 2, and 3 are 100%, 200%, and 300% of the 1994 Northridge earthquake.

Figure 15 presents the damage indices calculated from the posterior samples for both poles. Although the inferred damage to the right pole shows a greater discrepancy from the reference value, its progressive degradation can still be tracked using measurements from the left pole alone.

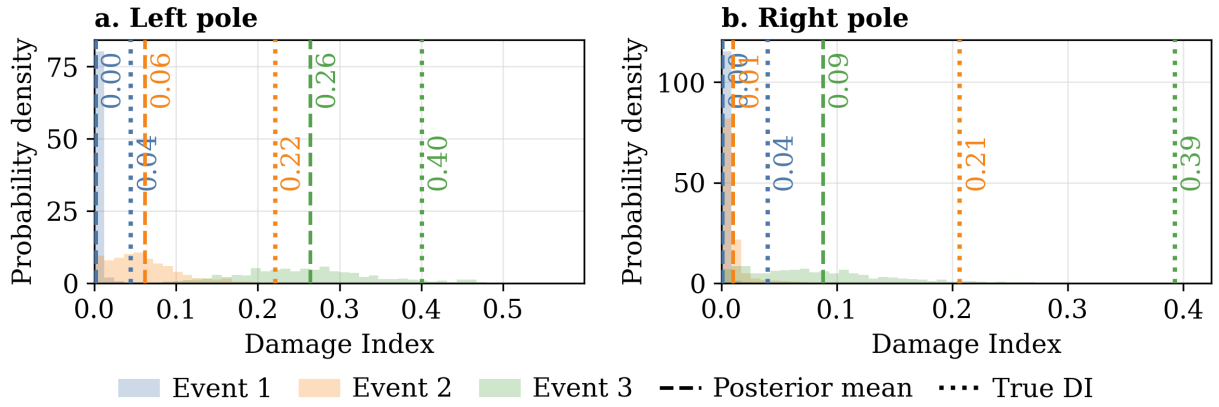


Fig. 15. Damage indices for both poles after each earthquake event using only the recorded motion of the left pole for Bayesian updating.

6. CONCLUSION

This paper develops a Bayesian approach to update and assess the evolving condition of cable-connected wooden utility poles subjected to sequential events. The presented study combines dynamic response measurements with a virtual structural model to update uncertain nonlinear parameters and quantify damage from subsequent earthquakes. Unlike structures with relatively stable modal properties, such as shear buildings, cable-connected pole systems exhibit time-varying geometric stiffness due to changes in cable tension. This interaction introduces additional nonlinearity relative to standalone poles and can amplify their dynamic response.

First, we investigated several likelihood formulations for Bayesian updating of a coupled pole–cable system. The proposed energy-based likelihood function can better infer the posterior distributions from the observed measurements when the coupled electrical equipment exhibits substantially different response amplitudes. In addition, the Teleport MCMC algorithm improved posterior exploration and sampling efficiency, as indicated by reductions in the integrated autocorrelation time (IAT). For the two-pole example, where the stiffness parameters of the electrical equipment were inferred within the nonlinear cable-coupled system, the IAT approached 1 for ensemble sizes of 10 or more walkers.

Second, to reduce the computational cost of likelihood evaluations in Bayesian inference for a high-fidelity model of wooden poles, we employ a low-fidelity representation of the power pole. Through numerical simulations, we demonstrate that the low-fidelity model captures the essential nonlinear response associated with damage progression while substantially reducing computational cost. For the single-pole scenario, the low-fidelity

model yields a mean damage index of 0.68 from the posterior samples, which is comparable to the reference value of 0.58 from the fiber model.

Finally, we perform Bayesian updating for cable-connected wooden poles subjected to sequential earthquakes. The posterior distributions captured progressive changes in key nonlinear parameters, including a reduction in the yield moment M_y , consistent with accumulating structural damage. The updated model parameters more accurately represent the infrastructure's current condition and expected performance. We further quantify the damage state of the updated structure using the Kratzig Damage Model. The developed Bayesian inference framework can track damage progression in connected systems. For instance, when the system was sequentially subjected to 200% of the Newhall ground motion followed by 250% of the Rinaldi ground motion, the posterior-mean damage index increased from approximately 0.02 to 0.31 for the left pole and from 0.02 to 0.24 for the right pole. The framework also demonstrated that the condition of both poles could be tracked using measurements from only the left pole, although the inferred damage of the unmonitored right pole exhibited greater uncertainty.

These results demonstrate the potential of Bayesian updating to provide timely information on the evolving structural condition of coupled distribution-system components and support post-event inspection and repair prioritization. In digital twin applications, sensor measurements could be assimilated into the virtual model as new observations become available.

This study assumes a fixed base at the bottom of the pole. However, the poles are directly embedded into the soil. Thus, the poles can also fail due to soil backfill failure. Future studies could also examine soil backfill failure by integrating soil-based springs into structural models [59]. Additionally, the present study demonstrates the framework using sequentially scaled instances of the Newhall record and an additional sequence involving the Newhall and Rinaldi ground motions. Future studies will evaluate the robustness of the inferred parameters and damage estimates across a broader suite of ground motions with different frequency contents and intensity measures.

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DATA AND CODE AVAILABILITY

All data and codes are available from the corresponding author upon reasonable request.

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