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ADDRESSING STATISTICAL UNCERTAINTY IN A SURROGATE MODEL FRAMEWORK FOR PERFORMANCE-BASED RISK OPTIMIZATION OF STRUCTURES SUBJECTED TO SEISMIC ACTIONS

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Abstract. Integrating risk-based optimization into Performance-Based Earthquake Engineering (PBEE) is challenging due to the high computational cost of evaluating consequences and the uncertainties inherent in seismic performance assessments. Statistical variability, for instance, arises from the inherent uncertainty in estimating Engineering Demand Parameters (EDPs) using statistical estimators based on a limited number of Nonlinear Time History Analyses. In a Performance-Based Risk Optimization framework, such variability becomes a critical factor that must be carefully addressed. This study proposes a metamodeling framework that incorporates statistical variability as regression noise and uses Kriging to estimate the median and standard deviation of EDPs, assuming a lognormal distribution. This integration allows the surrogate models to accurately represent and propagate statistical uncertainty within the optimization process. A practical application is presented in which expected repair and construction costs of a steel structural frame are minimized through multi-objective optimization, adopting the FEMA P-58 methodology within the PBEE framework. The results demonstrate that the proposed approach significantly reduces computational costs while preserving accuracy. The main contribution of this work is the development of a Gaussian Process-based surrogate modeling framework that efficiently estimates joint lognormal EDP parameters, directly addressing statistical variability and enabling robust, performance-based design optimization.

1 INTRODUCTION

Performance-Based Engineering (PBE) has emerged as a framework for predicting and assessing a structure's performance with sufficient confidence, allowing for informed decision-making based on potential losses and the development of strategies to mitigate consequences and reduce the impact of disasters [1, 2, 3]. Specifically for earthquakes, Performance-Based Earthquake Engineering (PBEE) focuses on designing, evaluating, and constructing buildings to meet community needs and objectives during seismic events, relying on a probabilistic description of hazards. Among the various PBEE frameworks available, FEMA P-58 [4] stands out as a modern and comprehensive methodology for assessing structures within the PBEE framework and has gained significant recognition in recent research studies [5, 6].

PBEE methodologies commonly rely on Nonlinear Time History Analysis (NLTHA) to estimate the structural response of buildings subjected to seismic events. This response is quantified through Engineering Demand Parameters (EDPs), which are measures that reflect the demand on structural and non-structural components during an earthquake, such as interstory drifts or floor accelerations. In an ideal setting, to properly account for uncertainty and capture the variability in structural behavior, thousands of NLTHAs would be conducted using a comprehensive set of ground motion records. The results from this large ensemble would produce estimates of probabilistic distributions that are minimally affected by statistical variability, thereby enabling a robust evaluation of seismic consequences. However, the computational effort required for such an extensive number of simulations is often prohibitive. Consequently, EDP samples are typically derived from a limited set of ground motions, from which probabilistic measures, such as medians, dispersions, and correlation coefficients, are inferred for the EDPs of interest. This reliance on limited data inevitably introduces statistical variability, i.e., the uncertainty in estimating the probabilistic parameters (or distributions) from finite sample sets.

While ensuring satisfactory seismic performance, a fundamental criterion of PBEE techniques, it is equally important to achieve economically efficient designs. This can be addressed by integrating risk-based optimization (RO) problems into the PBEE framework. Referred to herein as Performance-Based Risk Optimization (PBRO), in this type of problem the objective function typically involves minimizing expected losses, such as repair or replacement costs. A central difficulty in solving PBRO problems lies in the need to evaluate probabilistic objective functions or constraints within the optimization loop, which demands repeated assessment of decision variables and imposes a significant computational burden [8, 9, 10, 11]. This challenge is compounded by the fact that the statistical distributions of the EDPs depends on the design variables themselves. As a result, statistical variability plays a critical role, since optimization is often performed based not on the true distribution parameters, but on inferred distribution parameters that carry their own uncertainty in the form of statistical variability.

This study presents a PBRO framework designed to identify optimal structural designs under seismic demands. The proposed approach employs a metamodeling strategy to estimate the joint lognormal distributions of EDPs, explicitly incorporating the statistical variability that arises from limited ground motion datasets. A noisy Kriging technique is adopted, where the surrogate model reduces the computational cost of optimization, and the noise component models the uncertainty associated with parameter inference. The optimization problem is formulated in a multi-objective context, aiming to minimize both construction costs and expected seismic repair costs. The main contribution of this framework lies in its use of Gaussian Process-based surrogates to efficiently represent and propagate statistical variability, enabling robust and computationally tractable seismic risk optimization.

2 PROBLEM SETTING

The foundation of PBEE is the framework developed by researchers at the Pacific Earthquake Engineering Research Center (PEER) [12], represented by the following integral [13]:

$$\lambda\left(DV > dv\right) = \int_{im}\int_{dm}\int_{edp} G\left(dv|dm\right) dG\left(dm|edp\right) dG\left(edp|im\right) \left|d\lambda\left(im\right)\right| \quad (1)$$

where im denotes the intensity measure; edp represents the engineering demand parameters (e.g. interstory drift ratios); dm indicates the damage measure; dv denotes a decision variable (e.g. repair costs or repair time); $\lambda\left(DV > dv\right)$ indicates the mean annual rate of events $\{DV > dv\}$; $\lambda\left(im\right)$ represents the mean annual rate of exceeding a given value of the seismic intensity measure, also known as the hazard curve; $G\left(x|y\right)$ indicates the conditional cumulative distribution function (CDF) of a random variable X given a particular outcome $Y = y$ of the random variable Y.

Given the complexity of solving the multi-level integral in Equation 1, even for relatively simple systems, several implementations of the PBEE framework have been proposed in the literature [12, 14, 13]. In this work, the methodology developed by Yang et al. (2009) [13] is adopted, where a Monte Carlo simulation is used to numerically evaluate the integral.

While a comprehensive probabilistic assessment would ideally rely on demand data obtained from thousands of NLTHAs, such an approach is computationally prohibitive. To overcome this limitation, distribution parameters are statistically inferred from a limited number of NLTHAs, including the median values $\hat{\mu}_{i,edp}$, dispersions $\hat{\sigma}_{i,edp}$, and correlations $\hat{\rho}_{ij,edp}$ of the EDPs, and used to generate a statistically consistent set of simulated demands. A joint lognormal distribution is adopted in this work to generate the simulated set, as suggested in FEMA P-58 [4]. A schematic representation of this process is provided in Figure 1.

The inferred parameters are approximations of the true values, inherently affected by uncertainty. Three sources of uncertainty are associated with these estimates: (1) intrinsic uncertainty, arising from the randomness of the physical phenomenon; (2) statistical variability, resulting from the limited precision of parameter estimation based on a small sample size; and (3) model uncertainty, introduced by assumptions within the modeling framework. It is assumed that the intrinsic uncertainty is adequately represented by the reduced ground motion set used in the NLTHAs [4]. However, when only a small number of simulations are available, statistical variability remains present and can only be mitigated through an increased number of analyses [7, 15].

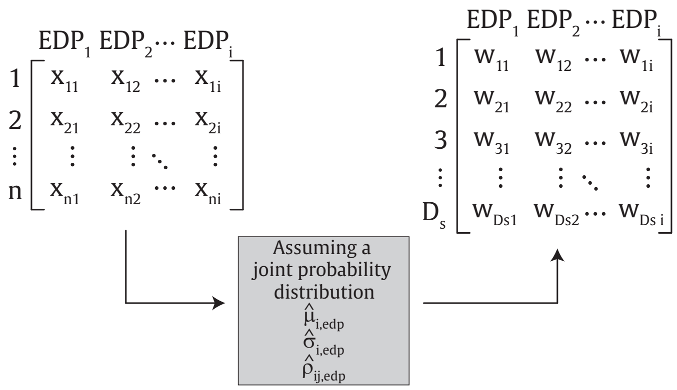


Figure 1: Generation of the synthetic simulated demand set.

With the main goal of comparing design alternatives and identifying the most cost-effective solutions, optimization techniques can be naturally integrated into the PBEE framework. The problem referred to herein as PBRO, which seeks to achieve an economical balance between construction costs and expected repair costs, is formulated as:

$$\begin{gathered} \text{Find } \mathbf{x^*} = \{x_1, ..., x_n, ...x_N\}^T \\ \text{to minimize } W(\mathbf{x}) = C_{cons}(\mathbf{x}) + C_{exReCo}(\mathbf{x}) \\ \mathbf{x}_n \in \mathcal{X}_n \;\text{ with } n = 1, ..., N \end{gathered} \tag{2}$$

where $\mathbf{x}^*$ is a design variable vector with parameters that define the structural system; W indicates the cost function, given by the initial construction cost $C_{cons}(\mathbf{x^*})$ and the expected annual repair cost $C_{exReCo}(\mathbf{x^*})$, which includes the repair, demolition and collapse costs of the building and is dependent on the mean annual rate of events $\lambda(DV > dv)$; $\mathcal{X}_n$ represents the design space from which all the components of $\mathbf{x}$ can be chosen.

The probabilistic evaluation of the expected repair cost, nested within the optimization loop defined in Equation 2, poses a significant challenge. For each new point in the design space of the design variable, $C_{exReCo}(\mathbf{x})$ must be reevaluated. When considering high-fidelity finite element (HFFE) models in estimating repair costs, the associated computational effort can become prohibitive. Indeed, the following responses obtained from the HFFE model are functions of the design variable $\mathbf{x}$: (1) the fundamental period of the structure; (2) the statistical estimates of the distribution parameters inferred from a limited number of NLTHAs. As a result, the optimization problem is not solved using the true values of the distribution parameters of the ESPs, but rather their statistical estimates. In this work, we address this limitation by employing a noisy Kriging approach. The Kriging metamodel reduces the computational burden of solving the optimization problem, while the noise term explicitly captures the statistical variability present in the estimated descriptors.

3 PROPOSED APPROACH

According to the description of the calculation of $C_{exReCo}(\mathbf{x})$, a nonlinear HFFE model needs to be evaluated with NLTHA to infer the statistical distributions of the EDPs, which are dependent on $\mathbf{x}$. In other words, the expected repair cost is dependent on the following parameters obtained with a high-fidelity finite element model:

- First mode period of the structure $\bar{T}(\mathbf{x})$, obtained through a modal analysis.
- Inferred distribution parameters of the EDPs, represented by a joint lognormal distribution characterized by the median $\hat{\mu}_{i,edp}(\mathbf{x})$, standard deviation $\hat{\sigma}_{i,edp}(\mathbf{x})$, and correlation matrix $\hat{\rho}_{ij,edp}(\mathbf{x})$ of the EDPs.

The expected repair cost can be written in terms of a general implicit nonlinear function, g_{NL}, as:

$$C_{exReCo}(\mathbf{x}) = g_{NL}\left(\bar{T}(\mathbf{x}), \hat{\mu}_{i,edp}(\mathbf{x}), \hat{\sigma}_{i,edp}(\mathbf{x}), \hat{\rho}_{ij,edp}(\mathbf{x})\right) \tag{3}$$

where $i = 1, 2, ..., N_p$, $j = 1, 2, ..., N_p$, and N_p indicates the number of EDPs considered.

This work proposes to replace the evaluation of the high-fidelity Finite Element model necessary to obtain the described parameters with a Kriging metamodel, considering the associated statistical variability as the noise term. The main goal of the metamodels is to infer the true population values of the distribution parameters. Kriging aims to utilize the outcomes $y = \mathcal{M}(x)$ of a complex computational model $\mathcal{M}$ at a limited set of sampling points to construct a predictive model $\tilde{\mathcal{M}}$ estimating the results at any other point within the domain [16, 17]. Kriging operates under the assumption that $\tilde{\mathcal{M}}$ represents a Gaussian process across the **x** space. In general, noise will be observed in the responses at the limited set of sampling points. This noise ε is often assumed to follow a zero-mean Gaussian distribution, and it is added to the Kriging interpolation $\tilde{\mathcal{M}}(\mathbf{x})$ as:

$$\hat{Y}(\mathbf{x}) = \tilde{\mathcal{M}}(\mathbf{x}) + \varepsilon \simeq \mathbf{f}(\mathbf{x})^T \beta + Z(\mathbf{x}) + \varepsilon \tag{4}$$

where $\mathbf{f}(\mathbf{x})^T\beta$ is the deterministic part, defined by a linear regression model and which represents the mean value of the approximation [16]; $Z(\mathbf{x})$ is a homogeneous stochastic Gaussian field with zero mean and autocovariance function represented by $\sigma_z^2 \mathbf{R}(x_j, x_k, \theta)$; $\mathbf{R}$ represents the correlation function calibrated to the hyperparameters θ [18]; ε is the noise, following a Gaussian distribution with zero-mean and covariance matrix $\sum_n$ ($\varepsilon \sim \mathcal{N}(0, \sum_n)$).

Due to the nature of statistical inference, a single experiment will yield estimates of the parameters of the joint lognormal distribution of the EDPs - $\hat{\mu}_{i,edp}(\mathbf{x})$ and $\hat{\sigma}_{i,edp}(\mathbf{x})$. Therefore, the noise term in the metamodel is expected to capture the estimation error, ϵ, resulting from the statistical variability introduced by the limited number of NLTHA performed at each support point.

The metamodels for the true values of the parameters of the joint lognormal distributions of the EDPs are denoted by $\hat{Y}_{\mu_{i,edp}}$ and $\hat{Y}_{\sigma_{i,edp}}$. Since it is not affected by the stochastic nature of the seismic inputs, the first-mode period of the structure is approximated using Kriging interpolation without noise, represented by $\tilde{\mathcal{M}}_{\bar{T}}(\mathbf{x})$. Additionally, the correlation matrix $\rho_{ij,edp}$ is assumed to be weakly dependent on **x**. The assumption made herein is that the point $\mathbf{x}_0$ represents the mean of all the support points considered. Thus, the correlation matrix $\rho_{ij,edp}$ approximates the correlation at all the support points, denoted as $\bar{\rho}$. With the proposed metamodels, the objective function of the optimization problem is now calculated without any calls to the HFFE model, which significantly reduces the computational time required for the optimization problem.

Additionally, once the metamodels have been trained to provide estimates of the true probabilistic parameters of the structural responses required for computing the expected annual repair cost throughout the design domain, $C_{exReCo}(\mathbf{x})$ is also approximated by a Kriging metamodel, $\tilde{C}_{exReCo}$, to further reduce the computational burden. Since the true values of the probabilistic parameters are already embedded in the intermediate metamodels used to compute C_{exReCo}, this final metamodel encapsulates their effect, enabling the direct estimation of the repair cost. As a result, instead of sequentially evaluating several intermediate metamodels within the optimizer, generating the expanded synthetic demand set, and performing a Monte Carlo simulation to calculate the expected repair cost for each candidate design variable, only the final surrogate $\tilde{C}_{exReCo}$ is queried, significantly reducing the computational time. Equation 3 can now be rewritten as:

$$\tilde{C}_{exReCo}(\mathbf{x}) = \tilde{\mathcal{M}}_{\tilde{g}_{NL}}\left(\tilde{\mathcal{M}}_{\bar{T}}(\mathbf{x}), \hat{Y}_{\mu_{i,edp}}(\mathbf{x}), \hat{Y}_{\sigma_{i,edp}}(\mathbf{x}); \bar{\rho}\right) \tag{5}$$

To start training the metamodels considered in this work, an initial Design of Experiments (DoE) with S support points is created considering the Latin Hypercube Sampling (LHS). For each support point, let us assume that a set of N_e ground motion records is randomly selected from a Stochastic Ground Motion Model, and scaled to be consistent with the target hazard spectrum at $S_a(\bar{T})$. An experiment is then performed at each support point, consisting of N_e NLTHAs used to estimate the parameters of the lognormal distribution. These expermients yield the inferred parameters: the median $\hat{\mu}_{i,edp}(\mathbf{x})$ and standard deviation $\hat{\sigma}_{i,edp}(\mathbf{x})$ of each EDP.

To capture the true population values of the parameters of the lognormal distribution, this work proposes conducting N_s repetitions of the proposed experiment, each using a different set of ground motions with different seismic inputs. The goal is to build a sample distribution of the statistical parameters, resulting in multiple estimates for the median and standard deviation of each EDP distribution. The distribution of these estimated probabilistic parameters tends toward a normal distribution as N_s becomes sufficiently large [15]. From the normal distribution obtained for each statistical parameter across the N_s experiments, the estimated variance $\hat{\sigma}_\epsilon^2$ quantifies the magnitude of the error ϵ. This variance is then incorporated as the noise term (ε) in the Kriging regression represented in Equation 4, such that $\sum_n = \hat{\sigma}_\epsilon^2$.

Nevertheless, performing repeated experiments at every support point to capture the population values of the distribution parameters would reintroduce the original challenge of excessive computational time, making the solution impractical. To address this, the proposed approach limits the N_s experiment repetitions to the central point of the DoE. Assuming that the variance of the error is homogeneous across the design space, the estimated variance $\hat{\sigma}_\epsilon^2$ obtained at the central point is extended to all other support points. Under this assumption of homogeneity, the noise in the Kriging regression is treated as homoscedastic.

In summary, the proposed approach is presented in the flowchart of Figure 2. Branch (a) illustrates the process for estimating the statistical variability $\hat{\sigma}_\epsilon^2$. Branch (b) details the methodology for predicting structural responses while incorporating the evaluated noise in the EDP parameters.

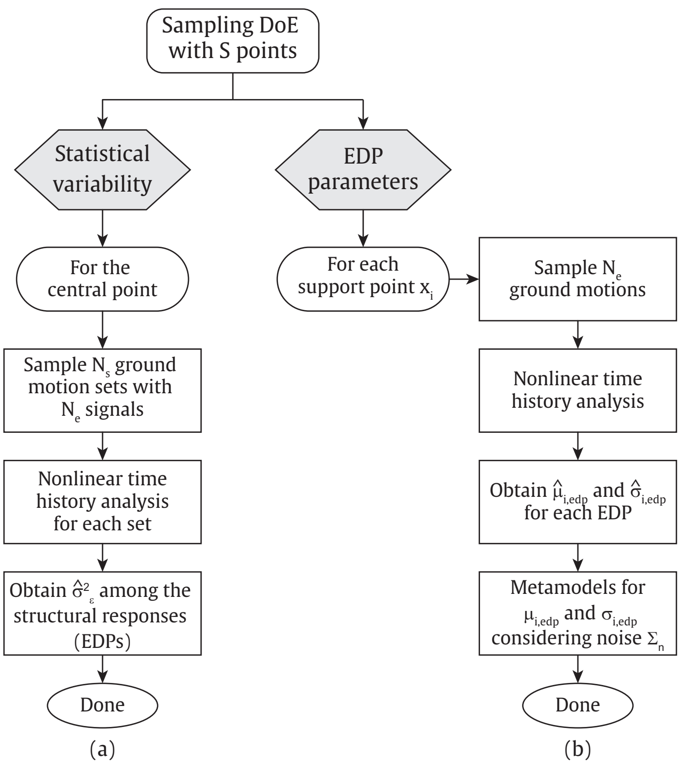
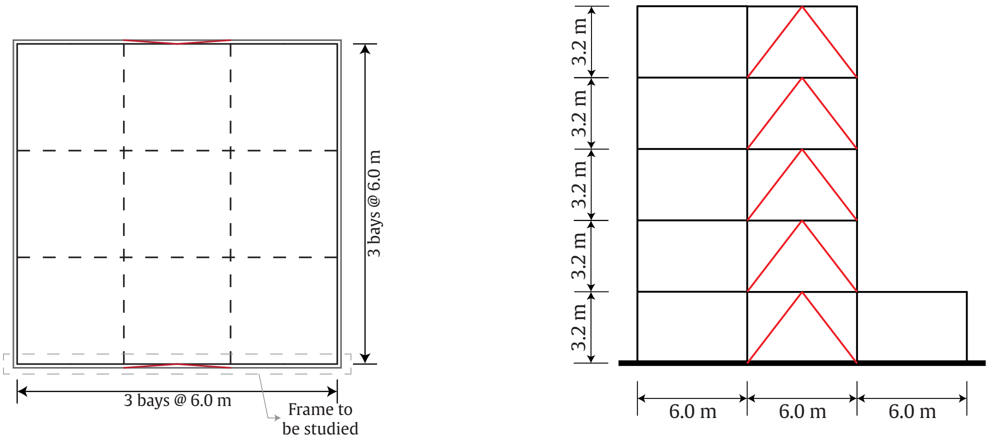


Figure 2: Flowchart of the proposed methodology to predict: (a) statistical variability from aleatoric uncertainty; (b) structural responses from the nonlinear dynamic analysis.



(a) (b)

Figure 3: Case study structure: (a) typical plan view of the building; (b) representation of the Special Steel Moment Frame.

4 CASE STUDY

The case study selected to evaluate the proposed framework involves a five-story special moment-resisting frame with an irregularity of 26.67%. The building design follows AISC 360 [19] and AISC 341 [20]. Buckling Restrained Braces (BRBs) are incorporated into the building's design. Beams and columns are constructed from Steel St 37, which has yield and ultimate stresses of 240 MPa and 370 MPa, respectively. The steel considered in the core of the BRB section corresponds to the ASTM A36 material. Figure 3 illustrates the structure considered in this case study, with the typical plan view shown in Figure 3a and the elevation of the perimeter frame depicted in Figure 3b.

The main goal of this case study is to optimize the areas of the BRBs in all stories of the building. In the proposed optimization problem, the design variables are the BRB areas for the first story ($A_{BRB,1}$), second story ($A_{BRB,2}$), third story ($A_{BRB,3}$), fourth story ($A_{BRB,4}$) and fifth story ($A_{BRB,5}$). The corresponding optimization problem is represented as:

$$\begin{gathered}\text{Find } \mathbf{x}^* = \{A_{BRB,1}, A_{BRB,2}, A_{BRB,3}, A_{BRB,4}, A_{BRB,5}\}^T \\ \text{to minimize } W(\mathbf{x}) = \left[C_{cons}(\mathbf{x}), \tilde{C}_{exReCo}(\mathbf{x})\right]^T \\ 9.7 \leq \{A_{BRB,i}\}_{i=1}^{5} \leq 64.5\, cm\end{gathered} \tag{6}$$

where $C_{cons}(\mathbf{x})$ represents the initial construction cost of the structural steel frame (including beams, columns, and BRBs), and $\tilde{C}_{exReCo}(\mathbf{x})$ is the expected annual repair cost, calculated based on the FEMA P-58 methodology [4].

The construction cost of the steel frame, indicated in Equation 6 as $C_{cons}(\mathbf{x})$, is estimated as follows:

$$C_{cons}(\mathbf{X}) = C_{steel}(W_{beams} + W_{columns}) + C_{BRB} W_{BRB} \tag{7}$$

where C_{steel} corresponds to the cost per unit weight of steel, C_{BRB} represents the cost of the BRBs, and W_{beams}, $W_{columns}$, and W_{BRB} indicate the weight of the beams, columns, and BRBs, respectively.

Costs for steel and BRBs adopted in this work are: $C_{steel} = \$4.72/kg$ [6] and $C_{BRB} = \$8.99/kg$ [21]. For beams and columns, the nominal weight is obtained from the AISC database - v16.0 [19].

Table 1: Performance information for the case study building.

Number of stories	5
Floor area - First floor	$324\,m^2$
Floor area - other floors	$216\,m^2$
Replacement Cost, RC	$\$\,2,485,900.00$
Total loss threshold (% RC)	100

For the BRBs, weight is calculated as: $W_{BRB} = A_{BRB} \times L_{BRB} \times \rho$, where L_{BRB} is the length of the element, and ρ is the density of the material, which for ASTM A36 steel is $\rho = 7850\,kg/m^3$.

Based on the FEMA P-58 methodology, calculating the expected annual repair and reconstruction cost, $\tilde{C}_{exReCo}(\mathbf{x})$, requires defining the building performance model. In this case study, the irregular building is assumed to function as an office space, with key performance details provided in Table 1. An estimation of the building's Replacement Cost is made, assuming its location is in an urban area of California. For a commercial office in this region, the construction cost is estimated at $\$\,2093.75/m^2$. To account for costs independent of their proximity to the total Replacement Cost, the total Loss Threshold is set at 100%. Environmental impacts are not considered in this study but could be incorporated in future assessments.

A two-dimensional representation of the archetype steel building was developed in OpenSees [22]. This model exclusively accounts for the bare steel structural elements of the perimeter special moment frame, disregarding the composite slab and the elements associated with gravity framing. Beams and columns were modeled using displacement-based elements considering the *Steel02* material [23]. BRBs are represented using the corotational truss element and the elastoplastic material model *SteelBRB* [24, 25]. A Rayleigh damping model (2% for the first and third modes) and P-Delta effects are considered.

The stochastic ground motion model considered in this work corresponds to a point-source model that takes into account both the physics of fault rupture and wave propagation. As implemented in [26, 27], these models are based on a parametric description of the ground motion's radiation spectrum, which is dependent on the earthquake magnitude and the epicentral distance, and is expressed as a function of frequency.

To address the problem described in Equation 6, 50 sample points are selected as the Design of Experiments (DoE) considering optimal Latin Hypercube Sampling (LHS). The Engineering Demand Parameters considered in this problem are: Interstory Drifts of stories 1 ($Drift_1$), 2 ($Drift_2$), 3 ($Drift_3$), 4 ($Drift_4$) and 5 ($Drift_5$); Peak Floor Acceleration of floors 1 (PFA_1), 2 (PFA_2), 3 (PFA_3), 4 (PFA_4), 5 (PFA_5) and 6 (PFA_6); and Residual Drift (RDR).

The evaluation of the statistical variability was performed with $N_e = 24$ earthquake signals in each one of the $N_s = 10$ ground motion sets. A parent group of 500 hazard-consistent earthquakes was generated using the Stochastic Ground Motion model. The selection of signals to compose the ground motion sets was completely random. The noise term $\sum_n$ in the Kriging surfaces is set as the estimated variance $\hat{\sigma}^2_\epsilon$, corresponding to the variability observed in the estimates of the probabilistic parameters of the EDPs, derived from the ground motion sets at the central support point.

All metamodels developed in this study adopt the following configurations: ellipsoidal correlation type, anisotropic correlation, and the Maximum Likelihood Estimation (MLE) method. The primary differences between the metamodels lie in the Kriging trend and the correlation families used. Initially, all metamodels were created using a linear trend and an Exponential correlation family, as

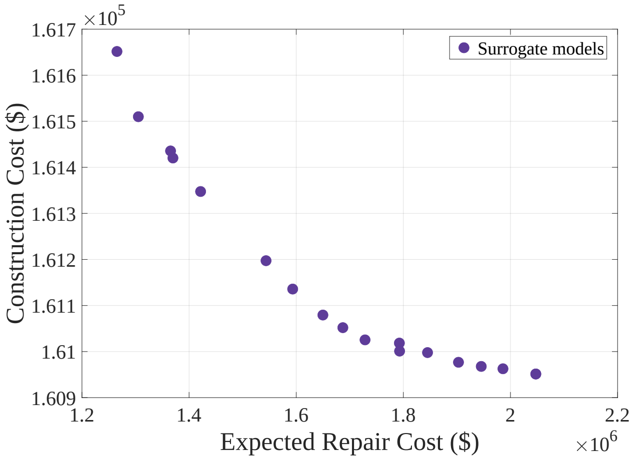


Figure 4: Pareto front for the multi-objective optimization problem.

recommended in the literature for metamodels representing EDPs. However, the linear trend failed to adequately capture the variability of Residual Drift across the design space. To reduce the leave-one-out cross-validation error in the metamodel, a quadratic trend was adopted for the *RDR* surfaces [28]. Similarly, the interpolation of the expected annual repair cost, $\tilde{C}_{exReCo}$, exhibited lower errors when employing a quadratic trend combined with a Gaussian correlation family.

Since the problem involves multi-objective optimization, accounting for both construction costs and failure costs, the Genetic Algorithm (GA) was employed in this work [29]. A population size of 50 points is considered for the solution. For each point in the population, the Kriging surface for the expected repair cost is evaluated. The results are presented in Figure 4, which illustrates the Pareto front of the Construction Cost and Expected Repair Cost.

The Pareto front illustrates an effective trade-off between construction costs and expected repair costs, facilitating the comparison of design alternatives for the diameter of the BRBs. It aids in choosing among different design options to enhance the building's resilience to seismic actions while evaluating the increase in initial construction costs.

5 CONCLUSIONS

This work proposed a PBRO framework for structures subjected to earthquake hazard, employing noisy Kriging metamodels to capture the statistical variability associated with the use of limited ground motion records in estimating seismic demands. The metamodels replace the high-fidelity Finite Element (HFFE) models within the optimization loop, enabling the estimation of the fundamental period and the jointly lognormal distribution parameters of the EDP vector, with the inherent statistical uncertainty modeled as regression noise. The results demonstrate that the use of Kriging metamodels offers an efficient and sufficiently accurate alternative to the HFFE model for expediting the optimization process. Solving the proposed multi-objective optimization problem with a Genetic Algorithm and a population size of 50 points would be computationally impractical if full reliance on the HFFE model were required to generate the simulated demand sets within the FEMA P-58 framework. By replacing HFFE models with Kriging metamodels, the proposed framework significantly improves computational efficiency within the PBEE methodology. Its application at the design stage enables the incorporation of statistical variability arising from limited seismic data, supporting more robust and informed structural design decisions.

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