Performance-based design optimization of steel structures subjected to seismic actions

Isabela D. Rodrigues[1], Seymour M. J. Spence[2], Andre T. Beck[1]

[1]*Dep. of Structural Engineering, Sao Carlos School of Engineering, University of Sao Paulo*
Sao Carlos, 13566-590, Sao Paulo, Brazil
idrodrigues@usp.br, atbeck@sc.usp.br
[2]*Dep. of Civil and Environmental Engineering, University of Michigan*
Ann Arbor, 48109, Michigan, USA
smjs@umich.edu

Abstract. Finding an optimal design for a structural system subject to seismic actions to minimize failure probability, repair costs, and injuries to occupants, significantly contributes to the resilience of buildings in earthquake regions. This research presents a comprehensive framework for the performance-based design optimization of steel structures, incorporating the Performance-Based Earthquake Engineering (PBEE) methodology delineated in FEMA P-58 [1]. A selected set of ground motions, consistent with the seismic hazard intensity of interest, and a nonlinear finite element model, established using OpenSees, enable the assessment of the system's dynamic response. To address the computational complexity related to evaluating the probability of failure of the system during an optimization iteration when using the PBEE methodology for assessing performance, this study introduces metamodeling techniques as a substitute for the original high-fidelity nonlinear finite element model. In particular, Kriging is employed to approximate both the median and standard deviation of the Engineering Demand Parameters (EDPs) in the design domain. The parameters of the Kriging metamodels are derived from nonlinear dynamic analyses performed using the original high-fidelity model and an optimal sampling plan obtained through Latin Hypercube sampling. Under the assumption of a lognormal distribution, the metamodel is then used to generate a large number of simulated demand sets necessary for the Monte Carlo procedure adopted by FEMA P-58 to calculate the distribution of probable losses for any given value of the design variable vector. Additionally, the median and standard deviation of the fragility function modeling collapse are also approximated by a Kriging metamodel, in which the parameters are derived from an Incremental Dynamic Analysis (IDA) for any given value of the design variable vector. The scheme is illustrated on a full-scale case study consisting of the performance-based optimization of the buckling-restrained braces of a steel seismic force-resisting system in terms of expected losses and construction costs. The study demonstrates that the proposed risk-based optimization scheme effectively balances construction costs with expected financial losses from earthquakes, thus enhancing the seismic performance of the system.

Keywords: Performance-Based Earthquake Engineering, Risk Optimization, Surrogate models

1 Introduction

Seismic events are natural disasters with the potential to cause significant economic and social losses in various parts of the world. A strategy to mitigate the consequences and reduce the impact of disasters associated with earthquakes is to understand how losses may occur in a specific structure and develop structural improvements to help prevent those consequences. To enhance this understanding, Performance-Based Engineering has emerged as a way to predict and evaluate a structure's performance with sufficient confidence, enabling decisions based on the possible losses that may occur [2, 3]. Specifically for earthquakes, Performance-Based Earthquake Engineering (PBEE) involves designing, evaluating, and constructing buildings to meet needs and social goals during earthquakes, based on a probabilistic description of the hazards.

Among the numerous frameworks presented in the literature, the FEMA P-58 methodology [1] has emerged as a modern and comprehensive approach for assessing structures within the PBEE framework and has gained significant recognition in recent research studies [4–6]. The methodology evaluates structural performance based on the probability of various performance metrics, including casualties, repair and replacement costs, repair time, and environmental impacts. The approach relies on a modified Monte Carlo method for assessing building damage [7].

While ensuring satisfactory seismic performance, a basic criterion of PBEE techniques, it is also important to strive for an economically efficient design. Optimization techniques can be naturally integrated within the PBEE methodology by adopting total expected losses as the decision-making metric [8, 9]. However, the primary challenge in solving optimization problems considering the PBEE methodology lies in the fact that probabilistic constraints require the evaluation of the decision variables inside the optimization loop [10–12].

To obtain an optimum design of structures equipped with energy dissipation devices subjected to seismic loads within the PBEE setting, this work proposes a framework for solving a risk optimization problem. Referred to in this work as Performance-Based Risk Optimization (PBRO), the framework evaluates the optimum design by considering the construction costs and expected repair costs of a structure subjected to a specific hazard as an objective function. The optimized design results in a balance between the objectives of minimum construction cost and minimum expected repair cost of the structure.

2 Problem Setting

2.1 Performance-Based Earthquake Engineering

Performance-based seismic design involves designing new structures or retrofitting existing buildings to meet specific performance objectives. The foundation of the methodology lies in the framework developed by researchers at the Pacific Earthquake Engineering Research Center (PEER) [13]. This framework employs the total probability theorem to assess earthquake consequences by determining the probability of exceeding specific values of performance measures through the following integral [7]:

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

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; and $G\left(x|y\right)$ indicates the conditional cumulative distribution function (CDF) of a random variable X given a particular outcome $Y = y$ of a random variable Y.

Yang et al. [7] developed an application of this framework by employing a Monte Carlo approach to solve Equation 1. This involves using inferred statistical distributions of building responses derived from limited sets of analyses. This application forms the basis of the performance assessment outlined in FEMA P-58 [1], and it will be used in this work as detailed in the following sections.

2.2 Optimal design problem

In the context of Performance-Based Engineering, optimization techniques are naturally integrated in the assessment of Equation 1. The main goal is to compare design alternatives to improve the decision variable dv and identify the most cost-effective solution. Considering a Risk Optimization methodology, that aims to find an economical balance between construction costs and failure costs, the problem can be termed Performance-Based Risk Optimization (PBRO) and represented through the following optimization problem:

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

where $\mathbf{x}$ is a high-dimensional design variable vector with N random parameters that define the structural system; W indicates the cost function, given by the initial construction cost $C_{cons}\left(\mathbf{x}\right)$ and the expected annual repair cost $C_{exReCo}\left(\mathbf{x}\right)$, which is dependant on the mean annual rate of events $\lambda\left(dv < DV\right)$; $\mathcal{X}_n$ is the set of continuous values from which all the components of $\mathbf{x}$ can be chosen.

As mentioned in the introduction, the main challenge in solving the optimization problem represented in Equation 2 is that the stochastic simulation loop is nested within the optimization loop. This work proposes a method to address this problem by applying Kriging metamodels to replace the original high-fidelity finite element model within the optimization iteration.

The expected annual repair cost $C_{exReCo}(\mathbf{x*})$ is calculated in this work based on the FEMA P-58 methodology [1]. This metric is expressed in probabilistic terms using the mean value to account for the inherent uncertainties associated with the problem. The five steps for the performance evaluation are described as follows:

1 **Assemble Building Performance Model:** This involves an organized collection of data defining the building assets vulnerable to the effects of ground motion. The data includes basic building information, occupancy and population models, vulnerable structural and nonstructural components, along with fragility and performance groups.

2 **Definition of Earthquake Hazard:** This entails quantifying the intensity of earthquake effects and the probability that effects of a given intensity will be experienced at a specific site. This work focuses on intensity-based assessment to evaluate structural performance, considering the building's response to a single acceleration response spectrum. Each ground motion pair should be amplitude-scaled by the ratio of the spectral acceleration at the first mode period $S_a\left(\bar{T}\right)$ obtained from the target spectrum to the geometric mean of the recorded components.

3 **Analyze Building Response:** This involves providing median estimates of key response parameters predictive of structural and nonstructural damage. Structural analysis is used to evaluate building response, with key parameters including floor acceleration, floor velocities, story drift ratios, and residual drift ratios. A Finite Element nonlinear model is developed for predicting these structural responses.

4 **Collapse Fragility:** This involves evaluating the probability of building collapse and casualties due to an earthquake. The collapse fragility function defines the probability of structural collapse as a function of ground motion intensity and is an input to the building performance model. This work employs the Incremental Dynamic Analysis (IDA) procedure to determine the collapse fragility function.

5 **Calculate Performance:** This involves calculating the building's performance, including generating simulated demands, assessing collapse, determining damage, and computing losses in terms of repair costs. Ideally, this process would involve numerous structural analyses to account for a wide range of input ground motions and random variations in the analytical model's properties, which is impractical. Therefore, a Monte Carlo approach is used to evaluate a range of possible outcomes based on the statistical distribution of demands from a series of building responses evaluated with a limited set of inputs. Assuming a jointly lognormal distribution for the matrix of building responses, a statistically consistent demand set is generated to represent a large number of possible building response states.

3 Proposed Approach

For the optimization problem proposed in this work, the calculation of the expected repair cost depends on the following parameters obtained with a high-fidelity finite element model:

- The first mode period of the structure $\bar{T}$, obtained through a modal analysis;
- Collapse fragility functions, represented by the lognormal parameters of the spectral acceleration at the first mode period $S_a\left(\bar{T}\right)$, denoted as μ_{coll} for the median and σ_{coll} for the dispersion;
- Distribution parameters of the Engineering Demand Parameters (EDPs), represented by a joint lognormal distribution with median $\mu_{i,edp}$, dispersion $\sigma_{i,edp}$, and correlation matrix $\rho_{ij,edp}$.

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

$$C_{exReCo}\left(\mathbf{x}\right) = g_{NL}\left(\bar{T}\left(\mathbf{x}\right), \mu_{coll}\left(\mathbf{x}\right), \sigma_{coll}\left(\mathbf{x}\right), \mu_{i,edp}\left(\mathbf{x}\right), \sigma_{i,edp}\left(\mathbf{x}\right), \rho_{ij,edp}\left(\mathbf{x}\right)\right) \tag{3}$$

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

This work proposes to replace the high-fidelity Finite Element model necessary to obtain the demand parameters with a Kriging metamodel [14]. An interpolation is considered for the first mode period of the structure, indicated as $\tilde{\mathcal{M}}_{\bar{T}}\left(\mathbf{x}\right)$, and Kriging regressions (noisy Kriging) for the statistics of the collapse fragility function and key response parameters of the structure, indicated as $\hat{Y}_{\mu_{coll}}\left(\mathbf{x}\right)$, $\hat{Y}_{\sigma_{coll}}\left(\mathbf{x}\right)$, $\hat{Y}_{\mu_{i,edp}}$ and $\hat{Y}_{\sigma_{i,edp}}$.

The uncertainty associated with record-to-record variability, included through the noise in the Kriging metamodels, is considered based on the FEMA P-58 methodology [1] when considering the collapse fragility functions. For the engineering demand parameters, a study of noise based on ground motion selection is performed for the case study. It is then assumed that the correlation matrix $\rho_{ij,edp}$ is weakly dependent on $\mathbf{x}$, and Equation 3 can be approximated as:

$$C_{exReCo}\left(\mathbf{x}\right) = \tilde{g}_{NL}\left(\tilde{\mathcal{M}}\bar{T}\left(\mathbf{x}\right), \hat{Y}\mu coll\left(\mathbf{x}\right), \hat{Y}\sigma coll\left(\mathbf{x}\right), \hat{Y}\mu i, edp\left(\mathbf{x}\right), \hat{Y}\sigma i, edp\left(\mathbf{x}\right), \rho_{ij,edp}\left(\mathbf{x}_0\right)\right) \tag{4}$$

where $\mathbf{x}_0$ is the point at which the correlation matrix is estimated.

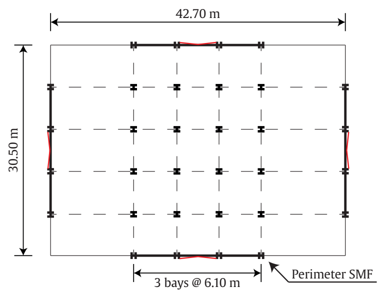
Equation 4 is exact at the point $\mathbf{x}_0$ but becomes an approximation for design options that differ from $\mathbf{x}_0$, since the statistics of the correlation matrix $\rho ij, edp$ are fixed at $\mathbf{x}_0$. Equation 4 will provide a good approximation of the expected repair cost of the structure if the assumption about $\rho ij, edp$ is acceptable.

The assumption in this work is that the point $\mathbf{x}_0$ represents the mean of all the support points considered. Thus, the correlation matrix $\rho ij, edp$ becomes the correlation among all the support points, denoted as $\bar{\rho}$.

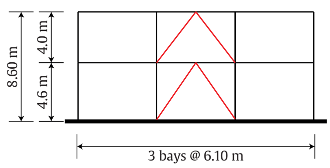
With Equation 4, the objective function of the optimization problem is now calculated without any calls to the high-fidelity Finite Element Model, which significantly reduces the computational time required for the optimization problem.

4 Case Study

In this study, an archetype two-story Special Steel Moment Frame (SMF) building is evaluated. It is designed according to guidelines provided in [15, 16]. Located in urban California, the structure features a first-story height of 4.6 m, with subsequent stories maintaining a standard height of 4 m. Steel ASTM A992 Gr. 50 is used for the beams and columns. Comprehensive information on the design and geometry is available in [17, 18]. The typical plan view of the building is shown in Figure 1a, and an elevation of the perimeter frame is represented in Figure 1b. The Buckling Restrained Braces (BRBs) included in the design of the SMF building, considering ASTM A36 steel, are represented in red in Figure 1.



(a) Plan view of the building.



(b) Representation of the SMF.

Figure 1. Case Study Structure.

For the proposed optimization problem, the design variables are the areas of the BRBs in stories 1 ($A_{BRB,1}$) and 2 ($A_{BRB,2}$). The design domain for each BRB area is specified in the following equation, which represents the optimization problem to be solved:

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

where $C_{cons}(\mathbf{x})$ represents the initial construction cost of the structural steel frame (including beams, columns, and BRBs), and $C_{exReCo}(\mathbf{x})$ is the expected annual repair cost, calculated based on the FEMA P-58 methodology [1].

The construction cost of the steel frame is estimated as follows:

$$
C_{cons}(\mathbf{X}) = C_{steel}(W_{beams} + W_{columns}) + C_{BRB} W_{BRB} \tag{6}
$$

where C_{steel} corresponds to the cost of the 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.

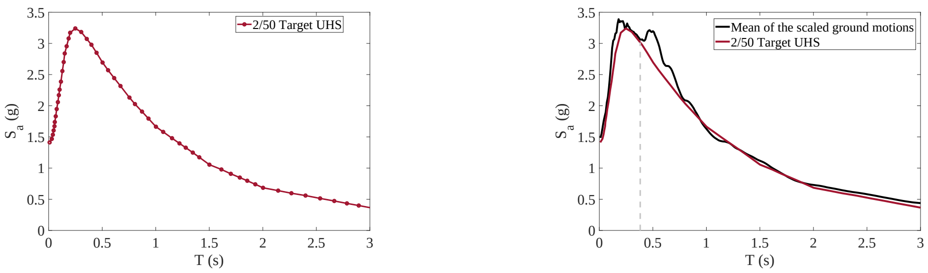
Costs for steel and BRBs adopted in this work are: $C_{steel} = \$471.79/kg$ [4] and $C_{BRB} = \$899.48/kg$ [19]. For beams and columns, the nominal weight is obtained from the AISC database - v16.0 [20]. For the BRBs, weight is calculated as: $W_{BRB} = A_{BRB} \times L_{BRB} \times \rho$, where L_{BRB} is the length of the element, and ρ is the density of the material, which for ASTM A36 steel is $\rho = 4861.09 kg/m^3$.

To calculate the expected annual repair cost $C_{exReCo}(\mathbf{x})$ based on the FEMA P-58 methodology, the building performance model must be defined. The structure evaluated is used as an office building. The building Replacement Cost is estimated for a commercial office with 2-4 stories, considered in this work to be $\$2093.75/m^2$.

The total Loss Threshold is considered to be 100% to obtain costs regardless of how close they are to the total Replacement Cost. Environmental impacts are not incorporated in the assessment developed in this work.

To perform the activities related to building repair, the number of workers is set as 1 worker per 1000 square feet of floor area, as recommended by FEMA P-58 [1]. The population model defined for the building is the "Commercial Office" occupancy, with an expected peak population of approximately 4 persons per $100, m^2$. Data for the fragility functions for each of the building contents are considered based on the database prepared for the PACT tool [21]. The associated demand parameter for the fragility functions is the Story Drift Ratio (SDR). The quantities for each component are calculated based on the Normative Quantity Estimation Tool provided in the support materials of FEMA P-58 [1].

The 5% damped, 2% in 50 years (2/50) Uniform Target Hazard Spectrum represented in Figure 2a is considered for defining the hazard. The FEMA P-695 [22] far-field record set is used as the selected pair of earthquake ground motions. This set corresponds to 22 ground motion record pairs, and each horizontal motion record is applied to the 2D frame evaluated in this work. The ground motion pairs are also scaled for consistency with the target response spectrum at the fundamental period of the structure, as represented in Figure 2b.



(a))

(b)

Figure 2. Target Uniform Hazard Spectrum.

A two-dimensional model for the two-story archetype steel building is formulated using OpenSees [23]. This model exclusively accounts for the bare steel structural elements of the perimeter special moment frame. Beams and columns are modeled using displacement-based beam-column elements with distributed plasticity. The cyclic behavior of the steel for beams and columns is simulated using the *Steel02* material in the OpenSees library, as proposed by Guiffré-Menegetto-Pinto [24]. A modulus of elasticity of 200 GPa and a yield strength of 345 MPa are adopted, with an isotropic strain hardening ratio of 1%. The Rayleigh damping model is employed to simulate inherent damping, with a ratio of 2% applied to the first and third modes of the structure. P-Delta effects are considered in the columns.

The model incorporates Buckling Restrained Braces (BRBs) using a corotational truss element available in OpenSees. The *SteelBRB* elastoplastic material model, introduced by Zona and Dall'Asta [25] and integrated into OpenSees according to Gu et al. [26], is applied for modeling the BRBs.

To build the necessary Kriging models, this study employs Latin Hypercube Sampling (LHS) to generate the initial Design of Experiments (DoE) [27]. To ensure an optimal space-filling characteristic of the DoE, an optimal Latin hypercube sampling approach is employed [28], as basic Latin hypercube sampling may not ensure this. Twenty support points are chosen to represent the initial DoE. The Kriging parameters assumed are: ordinary trend, separable correlation type, anisotropic correlation, Gaussian correlation family, and Maximum Likelihood estimation method.

Figure 3 shows the Kriging interpolation corresponding to the fundamental period of the structure ($\tilde{\mathcal{M}}\bar{T}$). In Figure 4, Kriging regressions for the mean ($\hat{Y}\mu_{coll}\,(\mathbf{x})$ - Figure 4a) and standard deviation ($\hat{Y}\sigma coll\,(\mathbf{x})$ - Figure 4b) of the collapse fragility curves are indicated. A known homoscedastic noise corresponding to $\beta = 0.45$, as proposed in FEMA P-58 to account for record-to-record variability, is considered for the Kriging surfaces of the fragility function parameters.

To obtain the Kriging surfaces for the statistics of the jointly lognormal distribution of the demand parameters, a noise evaluation is performed. The main goal is to understand the uncertainty related to record-to-record variability in the nonlinear time history analysis. For this evaluation, 100 pairs of hazard-consistent earthquakes were selected from the PEER database [29], representing 200 records in both directions. The signals are randomly allocated into 10 groups with 20 signals in each group, and a nonlinear dynamic analysis is carried out for each support point considering each earthquake group. For each support point, a mean and standard deviation are obtained from the results of the 10 earthquake groups, considering each statistic of the demand parameters evaluated. The mean of the standard deviations among all the support points is used in the Kriging surfaces as the homoscedastic noise for each demand parameter. The Kriging surfaces for the mean and standard deviation of the jointly log-

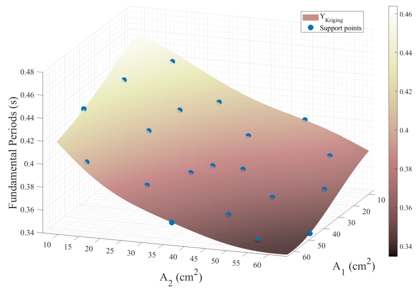
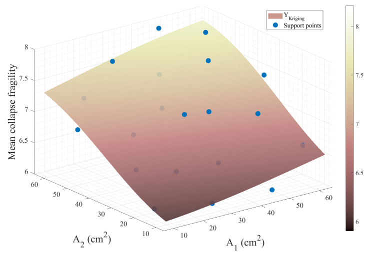
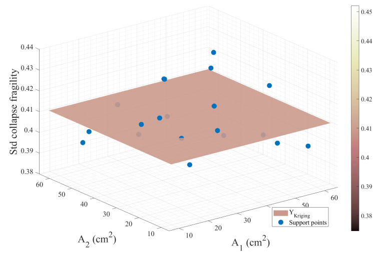


Figure 3. Kriging surface for the Fundamental Period ($\tilde{\mathcal{M}}_{\bar{T}}$).



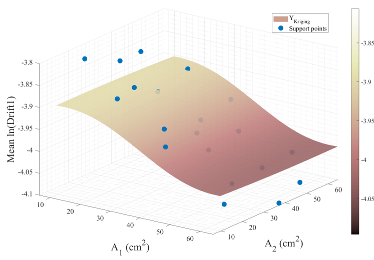
(a) Median ($\hat{Y}_{\mu_{coll}}$ $(\mathbf{x})$).



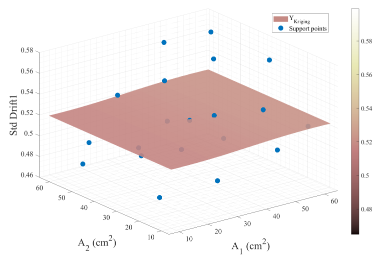
(b) Standard deviation ($\hat{Y}_{\sigma_{coll}}$ $(\mathbf{x})$).

Figure 4. Kriging surfaces for the lognormal parameters of the collapse fragility functions.

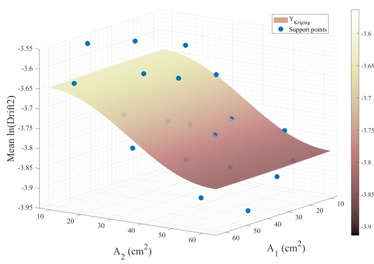
normal distribution of each demand parameter are shown in Figure 5. The demand parameters considered are the interstory drifts of story 1 ($Drift_1$) and story 2 ($Drift_2$).



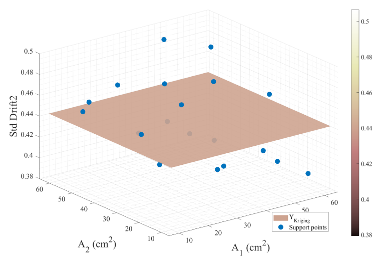
(a) Median ($\hat{Y}_{\mu_{Drift_1}}$ $(\mathbf{x})$).



(b) Standard deviation ($\hat{Y}_{\sigma_{Drift_1}}$ $(\mathbf{x})$).



(c) Median ($\hat{Y}_{\mu_{Drift_2}}$ $(\mathbf{x})$).



(d) Standard deviation values ($\hat{Y}_{\sigma_{Drift_2}}$ $(\mathbf{x})$)

Figure 5. Kriging surfaces for the parameters of the jointly lognormal Demand Parameters.

As mentioned in previous sections, the correlation matrix $\rho_{ij,edp}$ of the demand parameters is considered as the mean correlation ($\bar{\rho}$) over the 20 evaluated support points. With the parameters of the joint lognormal distribution, any number of simulated demand vectors can be generated within the optimization loop.

To solve the optimization problem, a Genetic Algorithm is adopted in this work, considering a population size of 50 points. For each population point, the Kriging surfaces are used to obtain the necessary parameters for calculating the expected repair cost. The results are shown in Figure 6, with the Pareto front of the Construction Cost and Expected Repair Cost.

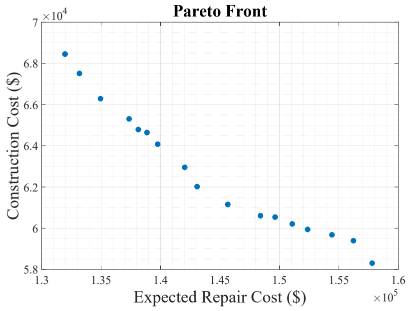


Figure 6. Pareto front for the multi-objective optimization problem.

The Pareto front shows an effective compromise between construction costs and expected repair costs. It allows one to compare the design alternatives for the BRB areas, thereby improving the decision-making process and identifying the most cost-effective solution.

5 Conclusions

This work proposes a framework for Performance-Based Risk Optimization (PBRO) of a structure subjected to seismic loads, considering both its construction costs and expected repair costs.

The results indicate that using Kriging metamodels to replace the high-fidelity Finite Element model is both efficient and sufficiently accurate for expediting the optimization process. Solving the proposed optimization problem with a multi-objective Genetic Algorithm for a population size of 50 points would be impractical if relying solely on the high-fidelity Finite Element model to generate simulated demands and collapse fragility functions. With the Kriging surfaces, each point of the population can efficiently estimate the lognormal parameters of the analysis, accounting for record-to-record variability.

Additionally, the proposed risk-based optimization scheme provides an effective balance between construction costs and expected repair costs due to earthquake loading. The Pareto front shown in the results allows one to evaluate the trade-offs between proposed solutions, compare design alternatives, enhance decision-making, and identify the most cost-effective solution.

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