Performance optimization of uncertain and dynamic high-dimensional wind-excited systems

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ABSTRACT: This paper focuses on the development of an efficient design optimization framework for wind-excited systems that is capable of handling not only high-dimensional and complex probability spaces, but also high-dimensional spaces of design parameters. Data-driven simulation models are utilized in assessing the system-level probabilistic measures. To efficiently solve the performance-based design optimization problem, a framework is proposed that is based on approximately decoupling the stochastic simulation from the optimization process. Local approximation models, constructed from results of a single stochastic simulation, are used to define a deterministic composite function that relates the design parameters to the system-level performance metrics. The explicit nature of this relationship is then exploited to define a sequence of deterministic optimization sub-problems that yield solutions to the original stochastic optimization problem. To illustrate the applicability of the proposed approach, a large-scale building system is optimized under stochastic wind tunnel-informed excitations and subject to system-level loss constraints.

1. Introduction

The performance assessment of wind-excited systems is moving towards probabilistic system-level settings in which both the stochastic nature of the external excitation and the uncertainties in system parameters are explicitly modeled. This inevitably leads to problems characterized by high-dimensional spaces of random variables. Within the context of modern wind performance-based design (e.g. Chuang and Spence, 2017; Cui and Caracoglia, 2018), the need to estimate system-level metrics, such as expected repair cost and expected repair time, introduces additional complexity in the form of discontinuous loss functions. If optimal structural systems are to be defined in this setting, optimization methods capable of handling not only high-dimensional and complex probability spaces but also the generally high-dimensional space of design parameters are required. Indeed, most design problems of practical interest are characterized by hundreds of free design parameters. This paper focuses on the development of an efficient framework for solving this class of problems in the case of stochastic wind excitation. Data-driven simulation models are utilized in assessing the system-level probabilistic measures. To efficiently solve the performance-based design optimization (PBDO) problem, a framework is proposed that is based on approximately decoupling the simulation from the optimization process. Local approximation models are constructed from the results of a single simulation carried out exclusively in the current design point. Through the approximation scheme, a deterministic composite function is defined that relates the design parameters

to the system-level performance metrics. The explicit nature of this relationship is then exploited to define a sequence of deterministic optimization sub-problems that yield solutions to the original stochastic optimization problem.

2. Performance Optimization Problem

To determine the optimal trade-off between initial cost and anticipated loss, this work proposes a framework for obtaining designs that minimize the upfront cost of the system, while ensuring intended performances under a wind hazard of given intensity. In particular, the performance measures are defined in terms of the expected value of D system-level decision variables DV. Hence, the PBDO problem may be mathematically formulated as:

$$\begin{aligned} &\text{Find} \quad \mathbf{x} = \{x_1, ..., x_N\}^{\mathrm{T}} \\ &\text{to minimize} \quad W = f(\mathbf{x}) \\ &\text{s. t.} \quad \mu_{DV}^{(d)}(\mathbf{x}; im) \leq L_0^{(d)} \quad d = 1, ..., D \\ &x_n \in \mathbb{X}_n \quad n = 1, ..., N \end{aligned} \tag{1}$$

where $\mathbf{x}$ is a high-dimensional design variable vector containing the deterministic parameters used to define the structural system (e.g., beam and column sizes); W represents the initial cost function (e.g., structural weight); $\mu_{DV}^{(d)}(\mathbf{x}; im) = E[DV^{(d)}(\mathbf{x})|im]$ is the expected value of the dth system-level loss measure $DV^{(d)}$ (e.g., expected repair cost or expected repair time), conditional on the intensity im of the windstorm; D is the total number of expected loss constraints; $L_0^{(d)}$ is the threshold value of the decision variable $DV^{(d)}$; while $\mathbb{X}_n$ is the discrete set to which the nth component of the design variable vector must belong. In particular, the conditional expected loss can be derived based on recent wind PBD frameworks as (the superscript (d) is dropped for clarity):

$$E[DV|im] = \iiint dv \cdot p(dv|dm) \cdot p(dm|edp) \cdot p(edp|im) \cdot \mathrm{d}dv \cdot \mathrm{d}dm \cdot \mathrm{d}edp \tag{2}$$

where $E[\cdot|\cdot]$ and $p(\cdot|\cdot)$ denote the conditional expectation and the conditional probability density function respectively; IM is the intensity measure of the event (e.g., wind speed associated with the return period of interest); DM is the damage measure identifying the level of damage of the components of the system (e.g., gasket failure in the cladding); while EDP is the engineering demand parameter (e.g., peak inter-story drift ratios). Throughout this paper, upper case letters will be adopted for indicating the random variables while lower case letters will be used for their realizations.

For practical uncertain systems subject to stochastic wind loads, Eq. (2) involves high-dimensional integrals which generally do not emit a closed-form solution. Hence, it is proposed here to use simulation-based methods for estimating solutions to Eq. (2).

3. Data-Driven Performance Assessment

This section outlines a simulation-based framework for assessing the expected loss of the system. In particular, this framework requires four sub-tasks to be carried, models for which will be outlined in the following sections.

3.1. System-Level Loss

To estimate the total loss to the system, it is observed that the total loss can be seen as the summation of losses over all sub-systems. In this work, each sub-system is termed a performance group (PG) and consists of components that are susceptible to the same structural demand. Hence, the total expected loss may be written in terms of the expected group-level losses as:

$$E[DV|im] = \sum_{k=1}^{N_G} \mu_{DV_k}(im) \tag{3}$$

where N_G is a total number of PGs in the system while $\mu_{DV_k}(im)$ represents the expected loss of the kth PG conditioned on the wind event intensity im.

A Monte Carlo simulation is adopted in estimating the expected loss of Eq. (2) in terms of the group-level losses as described in Eq. (3). Within this context, the expected loss may be calculated as:

$$E[DV|im] \approx \sum_{k=1}^{N_G} \left(\frac{1}{N_S} \sum_{i=1}^{N_S} dv_k^{(i)}(\mathbf{u}^{(i)}, im) \right) \tag{4}$$

where N_S is the total number of samples in the simulation; $dv_k^{(i)}$ represents the ith realization of the loss associated with the kth PG; and $\mathbf{u}^{(i)}$ is the ith realization of an uncertain vector collecting all the uncertain parameters used in all the models necessary for the performance assessment.

To determine a realization of DV_k, losses from all components in the kth PG are summed together as:

$$dv_k(\kappa) = \sum_{a=1}^{N_c} c_k^{(a)}(\kappa_k^{(a)}) = \sum_{a=1}^{N_c} \mathrm{F}_{C_{k|j}}^{-1}(\kappa_k^{(a)}|dm_k^{(a)} = j) \tag{5}$$

where $\kappa = \{\kappa_k^{(1)}, ..., \kappa_k^{(a)}, ..., \kappa_k^{(N_c)}\}^T$, subvector of $\mathbf{u}$, collects independent and uniform random variables in $[0,1]$ used in the loss model; N_c is the total number of components in the kth PG; $c_k^{(a)}$ is the loss associated with the ath component in the kth PG that can be estimated from the conditional inverse cumulative distribution function of the component-level loss given that damage state j has occurred, i.e. $\mathrm{F}_{C_{k|j}}^{-1}$.

3.2. Component-Level Damage

To estimate the damage state for each damageable component, a suite of fragility functions corresponding to each PG may be used. For a component in the kth PG having m possible damage states, the damage measure can be determined through:

$$dm_k^{(a)}(\theta) = \begin{cases} 0 & \text{if } \mathrm{Fr}_k(1|edp_k) < \theta_k^{(a)} \\ 1 & \text{if } \mathrm{Fr}_k(2|edp_k) < \theta_k^{(a)} \\ & \quad \leq \mathrm{Fr}_k(1|edp_k) \\ ... & \\ m & \text{if } \theta_k^{(a)} \leq \mathrm{Fr}_k(m|edp_k) \end{cases} \tag{6}$$

where $\theta = \{\theta_k^{(1)}, ..., \theta_k^{(a)}, ..., \theta_k^{(N_c)}\}^T$, subvector of $\mathbf{u}$, collects independent and uniform random variables in $[0,1]$ used in the damage model; $\mathrm{Fr}_k(m|edp_k) = p(dm_k = m|edp_k)$ represents a fragility function defined as the conditional probability that the damage state $DM_k = m$ occurs given the engineering demand parameter assumes the value edp_k. In this work, the damage levels are assumed to be sequential and uncorrelated.

3.3. Wind Demands

In this work, the engineering demand parameter, edp_k, is taken as the absolute maximum response to occur over N_α wind directions and windstorm of duration T:

$$edp_k(\upsilon) = \max_{\beta=0,...,N_\beta} \left[\max_{t\in[0,T]} |y_k(t;\beta,\upsilon)| \right] \tag{7}$$

where υ is a subvector of $\mathbf{u}$ collecting random variables used in the structural analysis model; β denotes the wind directions; while $y_k(t)$ represents the kth wind-induced response process in $[0,T]$. In particular, $y_k(t)$ can be efficiently calculated through the load-effect model (Spence and Kareem, 2014):

$$y_k(t;\beta,\upsilon) = \upsilon_1 \Gamma_{y_k}^T \left[\mathbf{K}\Psi_n^T \mathbf{q}_{R_n}(t;\beta,\upsilon) + \mathbf{f}(t;\beta) \right] \tag{8}$$

where υ_1 is a random variable (component of υ) accounting for the epistemic uncertainty in using the load-effect model; Γ_{y_k} is a vector of influence functions giving the response in y_k due to a unit load acting at each degree of freedom of the system; $\mathbf{K}$ is the stiffness matrix of the system; $\Psi_n = [\psi_1, ..., \psi_n]$ is the mode shape matrix of order n; $\mathbf{q}_{R_n}(t) = \{q_{R_1}(t), ..., q_{R_n}(t)\}^T$ is a vector collecting the resonant modal responses; while $\mathbf{f}(t)$ is a realization of the external aerodynamic loads.

3.4. Wind Tunnel-Informed Stochastic Wind Loads

With respect to the wind hazard, the intensity measure is taken in this work as the mean wind speed, $\bar{v}_w$, of averaging time τ and mean recurrence interval (MRI) w years. In partcicular, $\bar{v}_w$ can be estimated from an appropriate meteorological dataset. From this dataset, the site-specific wind speed, $\bar{v}_H$, averaged over a time interval T can be obtained through transformation models (e.g. Minciarelli et al., 2001).

To generate a realization of the vector-valued stochastic external aerodynamic loads $\mathbf{f}(t)$, a spectral representation model is adopted in this work that is based on proper orthogonal decomposition (POD) (Chen and Kareem, 2005). In particular, the POD modes and vectors are directly estimated from experimental wind tunnel data therefore ensuring the inclusion of complex phenomena such as acrosswind vortex-induced excitation.

Within this setting, each component of $\mathbf{f}(t)$ is given by:

$$\mathrm{f}_k(t;\bar{v}_H,\beta,\varepsilon) = \sum_{l=1}^{N_l}\sum_{n_1=1}^{N_{n_1}-1}\Bigg\{|\Phi_{jl}(\omega_{n_1};\beta)| \sqrt{2\Lambda_l(\omega_{n_1};\bar{v}_H,\beta)\Delta\omega} \cdot\cos(\omega_{n_1}t+\vartheta_{jl}(\omega_{n_1};\beta)+\varepsilon_{n_1 l})\Bigg\} \tag{9}$$

where $\bar{v}_H$ is the wind speed at the top of the building; N_l denotes the number of loading modes considered; $\Delta\omega$ is the frequency increment (accordingly, the Nyquist frequency is $N_{n_1}\Delta\omega/2$, with N_{n_1} the total number of discrete frequencies considered); $\omega_{n_1} = n_1\Delta\omega$; $\varepsilon_{n_1 l}$ is an independent uniformly distributed in $[0,2\pi]$ random variable characterizing the stochastic nature of the wind; ε is a subvector of $\mathbf{u}$ collecting all the random variables $\varepsilon_{n_1 l}$; $\vartheta_{jl} = \tan^{-1}(\mathbf{Im}(\Phi_{jl})/\mathbf{Re}(\Phi_{jl}))$; while $\Phi_{jl}(\omega)$ and $\Lambda_l(\omega)$ are components of $\Phi(\omega)$ and $\Lambda(\omega)$ obtained from solving the following eigenvalue problem:

$$[\mathbf{S}_f(\omega;\bar{v}_H,\beta)-\Lambda(\omega;\bar{v}_H,\beta)\mathbf{I}]\Phi(\omega;\beta)=0 \tag{10}$$

where $\mathbf{S}_f$ is the smoothed cross power spectral density matrix of the wind tunnel estimated full-scale loading processes.

4. Proposed Optimization Strategy

This section outlines a strategy based on approximately decoupling the simulation-based performance assessment from the optimization process. This allows the definition of a high quality deterministic optimization sub-problem that can be used to identify solutions to the original stochastic optimization problem.

4.1. Loss Approximation

As the design $\mathbf{x}$ moves away from the point $\mathbf{x}_{MC}$ in which the simulation is carried out, μ_{DV_j} may be estimated through an appropriate local approximation model, $\tilde{\mu}_{DV_j}$. Within this setting, the expected system loss of Eq. (3) can be approximated as:

$$E[DV(\mathbf{x})|\bar{v}_w] \approx \sum_{k=1}^{N_G}\tilde{\mu}_{DV_k}(\mathbf{x};\bar{v}_w) \tag{11}$$

It can be observe that any change in the expected group-level loss μ_{DV_k} is directly related to the change in the associated demand parameter, EDP_k. Based on this observation, it is here proposed to use as a measure of this change, the second order statistics of the group-level demands. In particular, the following Taylor series expansion, centered in $\mathbf{x}_{MC}$, is used to explicitly model this dependency (where the explicit dependency on $\bar{v}_w$ is dropped in the following for clarity):

$$\begin{aligned}\tilde{\mu}_{DV_k}(\mathbf{x}) = \quad & \mu_{DV_k}(\mathbf{x}_{MC}) \\ & + \Bigg\{ [\mu_{EDP_k}(\mathbf{x})-\mu_{EDP_k}(\mathbf{x}_{MC})]\cdot\frac{\partial\mu_{DV_k}}{\partial\mu_{EDP_k}}\bigg|_{\mathbf{x}_{MC}} \\ & + [\sigma_{EDP_k}(\mathbf{x})-\sigma_{EDP_k}(\mathbf{x}_{MC})]\cdot\frac{\partial\mu_{DV_k}}{\partial\sigma_{EDP_k}}\bigg|_{\mathbf{x}_{MC}}\Bigg\}\end{aligned} \tag{12}$$

where μ_{EDP_k} and σ_{EDP_k} are the mean and standard deviation of EDP_k respectively; while $\frac{\partial\mu_{DV_k}}{\partial\mu_{EDP_k}}\Big|_{\mathbf{x}_{MC}}$ and $\frac{\partial\mu_{DV_k}}{\partial\sigma_{EDP_k}}\Big|_{\mathbf{x}_{MC}}$ are the partial derivatives of the group-level losses with respect to μ_{EDP_k} and σ_{EDP_k} and evaluated in $\mathbf{x}_{MC}$.

4.1.1. Partial Derivatives

The partial derivatives of μ_{DV_k} with respect to μ_{EDP_k} and σ_{EDP_k} can be efficiently estimated as byproducts of the simulation in $\mathbf{x}_{MC}$. Indeed, from the N_S samples, $edp_k^{(i)}$ for $i=1,\ldots,N_S$, generated in $\mathbf{x}_{MC}$, two sets of manipulated samples can be generated through the transformations:

$$\hat{edp}_k^{(i)} = (1+\hat{\delta})edp_k^{(i)} \tag{13}$$

$$\check{edp}_k^{(i)} = (1+\check{\delta})(edp_k^{(i)}-\mu_{EDP_k})+\mu_{EDP_k} \tag{14}$$

Due to the above transformations, the mean and standard deviation of the manipulated sets are $\hat{\mu}_{EDP_k} = \mu_{EDP_k}(\mathbf{x}_{MC})(1+\hat{\delta})$ and $\check{\sigma}_{EDP_k} = \sigma_{EDP_k}(\mathbf{x}_{MC})(1+\check{\delta})$. By carrying out the damage and loss analysis of Sec. 3.1-3.2 using these manipulated sets of demand samples, the corresponding group-level expected losses, $\hat{\mu}_{DV_k}$, can be estimated, therefore enabling the direct estimation of

the change in μ_{DV_k} given a change in μ_{EDP_k} and σ_{EDP_k}. A classic central difference scheme can then be implemented for estimating the partial derivatives.

4.1.2. Demand Statistics

To estimate the terms μ_{EDP_k} and σ_{EDP_k} in $\mathbf{x}$ necessary for solving Eq. (12) without invoking the simulation, the concept of Auxiliary Variable Vector (AVV) is adopted in this work (Spence et al., 2016; Bobby et al., 2016). Through this approach, the demand statistics can be approximated as:

$$\mu_{EDP_k}(\mathbf{x}) \approx \Gamma_{y_k}^T(\mathbf{x})\hat{\Upsilon}_k(\mathbf{x}_{MC}) \tag{15}$$

$$\sigma_{EDP_k}(\mathbf{x}) \approx \Gamma_{y_k}^T(\mathbf{x})\check{\Upsilon}_k(\mathbf{x}_{MC}) \tag{16}$$

where $\hat{\Upsilon}$ and $\check{\Upsilon}$ are the AVVs corresponding to μ_{EDP_k} and σ_{EDP_k} respectively and are obtained from the results of a single simulation carried out in $\mathbf{x}_{MC}$. Hence, Eqs. (15)-(16) represent the exact relationships in $\mathbf{x}_{MC}$. As $\mathbf{x}$ moves away from $\mathbf{x}_{MC}$, the AVVs can be kept constant as they has been demonstrated to be insensitive to changes in the design variables (Spence and Kareem, 2014; Bobby et al., 2017).

4.2. The Decoupling Approach

By observing that the approximations of Sec. 4.1 can be estimated from the results of a single simulation carried out exclusively in $\mathbf{x}_{MC}$, the following simulation-free (i.e. deterministic) optimization sub-problem can be defined in $\mathbf{x}_{MC}$:

$$\begin{aligned}
&\text{Find} \quad \mathbf{x} = \{x_1, ..., x_N\}^{\mathrm{T}} \\
&\text{to minimize} \quad W = f(\mathbf{x}) \\
&\text{s. t.} \quad \tilde{\mu}_{DV}^{(d)}(\mathbf{x}; \bar{v}_w) \leq L_0^{(d)} \quad d = 1, ..., D \\
&x_n \in \mathbb{X}_n \quad n = 1, ..., N
\end{aligned} \tag{17}$$

where $\tilde{\mu}_{DV}^{(d)}$ is the approximate expected value of the dth system-level loss measure defined based on the approximation schemes of Sec. 4.1 as:

$$\begin{aligned}
\tilde{\mu}_{DV}^{(d)}(\mathbf{x}) &= \sum_{k=1}^{N_G} \mu_{DV_k}^{(d)}(\mathbf{x}_{MC}) \\
&+ \left\{ \left(\Gamma_{y_k}^{\mathrm{T}}(\mathbf{x})\hat{\Upsilon}_k(\mathbf{x}_{MC}) - \mu_{EDP_k}(\mathbf{x}_{MC})\right) \cdot \left.\frac{\partial \mu_{DV_k}^{(d)}}{\partial \mu_{EDP_k}}\right|_{\mathbf{x}_{MC}} \right. \\
&\left. + \left(\Gamma_{y_k}^{\mathrm{T}}(\mathbf{x})\check{\Upsilon}_k(\mathbf{x}_{MC}) - \sigma_{EDP_k}(\mathbf{x}_{MC})\right) \cdot \left.\frac{\partial \mu_{DV_k}^{(d)}}{\partial \sigma_{EDP_k}}\right|_{\mathbf{x}_{MC}} \right\}
\end{aligned} \tag{18}$$

It should be observed that the derivative of $\tilde{\mu}_{DV}^{(d)}$ with respect to $\mathbf{x}$ can be derived using the chain rule. Hence, the sub-problem of Eq. (17) can be solved efficiently through any gradient-based deterministic optimization algorithm. In this work, the pseudo-discrete Optimality Criteria algorithm (Chan et al., 1995) is adopted. By solving a sequence of optimization sub-problems, each formulated in the solution of the previous, a solution to the original stochastic optimization problem of Eq. (1) can be found in a limited number of design cycles.

5. Application

5.1. Case Study Description

The objective of this case study is to obtain the optimal design for a lateral load-resisting frame envisioned as part of a 3D tube system as shown in Figure 1(a)-(b). The building has a total of 37 stories. The first story is 6 m high while the other stories are 4 m high, resulting in a total height of 150 m. The total width in the X-direction is 30 m while the total width in the Y-direction is 60 m. Two load-resisting frames are responsible for carrying the loads in the X-direction. Each frame consists of six 5-m bays. All floors consist of steel beams that belong to the set of AISC W24 profiles. All columns consist of steel box sections having mid-line diameter, D_i, belonging to the discrete set $\{0.2\text{ m}, 0.25\text{ m}, 0.3\text{ m}, ..., 4\text{ m}\}$ with corresponding thickness $D_i/20$. Symmetry is imposed with respect to the center vertical line. This results in a truly large-scale PBDO problem with 259 independent design variables. The total mass of the system is the sum of the mass of all elements and the added mass of 100kg/m^3. The resonant response of the building is estimated using three vibration

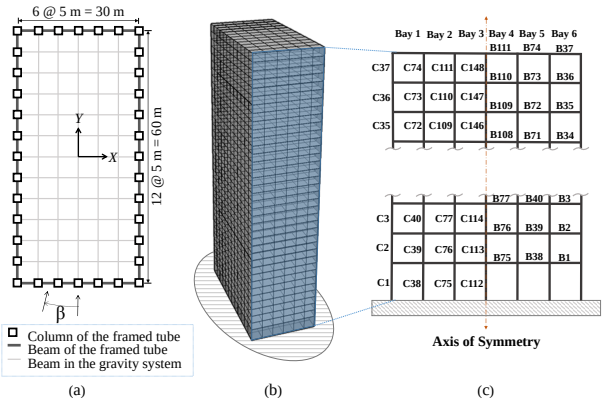

Figure 1: (a) 37-story building plan; (b) Isometric view; (c) Frame layout showing beam and column assignments.

modes. Two different initial designs are considered defining Trial 1 and Trial 2 as described in Table 1. All mean modal damping ratios are assumed to be 1.5%. The uncertain parameters associated with the structural system are calibrated according to Table 2 of Suksuwan and Spence (2018).

5.1.1. Wind Excitation

The reference wind speed corresponding to a 1700-year MRI, $\bar{v}_w$, was obtained from a Type II extreme value distribution of mean and standard deviation 32 m/s and 4.7 m/s respectively. The reference wind speed $\bar{v}_w$ was transformed into samples of uncertain site-specific wind speeds, $\bar{V}_H$, through the transformation proposed in Minciarelli et al. (2001). In particular, The averaging time, the roughness length, and the height at the meteorological station were taken as $\tau = 60$ s, $z_{01} = 0.01$ m, and $H_{met} = 10$ m, respectively. The averaging time and the roughness length at the site of interest were assumed to be $T = 3600$ s and $z_0 = 1$ m, respectively. Marginal distributions for the uncertain parameters associated with the wind hazard are reported in Table 3 of Suksuwan and Spence (2018).

To generate realizations of $\mathbf{f}(t)$, the wind tunnel data set used in the POD procedure was obtained from the Tokyo Polytechnic University Wind Pressure Database. Three loading modes were considered. The wind tunnel tests were performed on a rigid 1:300 scale model of the aforementioned building system. Data was recorded at 510 pressure taps for a total signal length of 32 s. The sampling frequency was 1000 Hz while the mean wind speed at the top of the building model was $v_{tun} = 11$ m/s. To account for both alongwind and acrosswind actions, wind was considered from two directions, $\beta = 0°$ and $\beta = 90°$, as shown in Figure 1 .

5.1.2. Loss Model

This case study is concerned with limiting damage and loss to the cladding system. A total of 37 PGs are identified with each group consisting of 60 cladding components. All cladding components were taken as midrise stick-built curtain wall, which is susceptible to story drift in the X-direction. In particular, the engineering demand parameter for each PG is taken as the maximum story drift ratio due to wind blowing down the X or Y directions. Each component has three possible damage states with corresponding fragility curves and consequence functions taken from the fragility database found in Federal Emergency Management Agency (FEMA) (2012).

5.1.3. Optimization Objective

The goal of the PBDO problem of interest is to minimize the material weight of the lateral load-resisting system, while ensuring the system-level performance concerning the expected repair cost and repair time of the cladding system given a windstorm of MRI = 1700 years. Performance targets for both trials can be found in Table 1. A total number of 1000 samples are used for each trial.

Table 1: Descriptions of Trials 1 and 2.

Trial #	Trial 1	Trial 2
Initial Columns	$D_i = 1.0$	$D_i = 1.5$ m
Initial Beams	W24×176	W24×279
f_1	0.19 Hz	0.24 Hz
f_2	0.59 Hz	0.78 Hz
f_3	1.07 Hz	1.45 Hz
$L_0^{(1)}$ (Repair Cost)	\$500000	\$500000
$L_0^{(2)}$ (Repair Time)	30 days	30 days

5.2. Results and Discussion

With respect to the optimization objective, Figure 2 reports, for Trial 1 and Trial 2, the convergence history of the structural weight in terms of the design cycles. Both trials progressed steadily and smoothly to convergence in less than 20 cycles. This limited number of simulation cycles clearly demonstrates the efficiency of the proposed approach. It is also interesting to observe that despite the fact that Trial 1 was under-designed and Trial 2 was over-designed, both trials reached the same optimal solution. This indicates the insensitivity of the method to the initial design point.

With respect to the system-level performance constraints, Figure 3 and Figure 4 report the design cycle history curves of the expected repair cost and expected repair time. The optimal solutions from both trials satisfied both constraints. In particular, the expected repair cost was significantly lower than the threshold cost while the expected repair time converged to its limit value. This implies how, for this example, the repair time dominated the system-level performance. It is interesting to observe how systems that meet the performance targets were efficiently identified within only five design cycles with the remaining cycles serving to minimize the structural weight. This illustrates how the proposed approach is capable of identifying useful designs after only a handful of redesigns.

With respect to the approximation scheme, Figure 5 illustrates the Taylor series approximation of

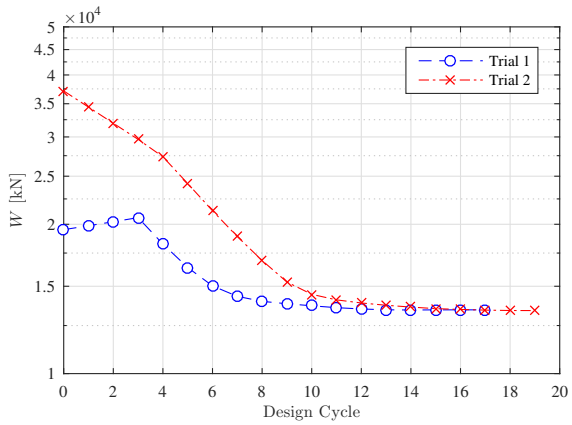

Figure 2: Design cycle history of the objective function.

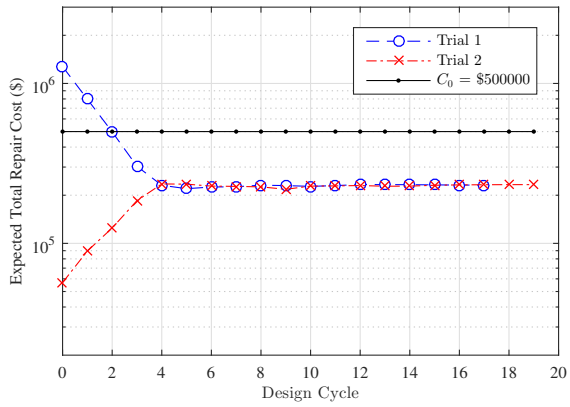

Figure 3: Design cycle history of the expected repair cost.

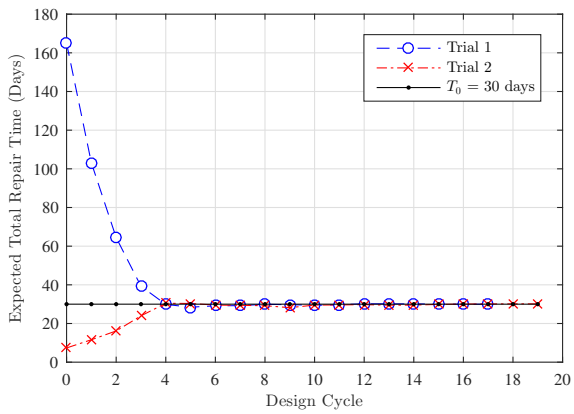

Figure 4: Design cycle history of the expected repair time.

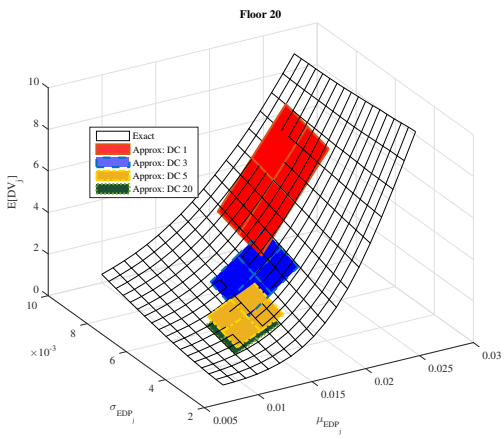

Figure 5: Example of exact and approximate surfaces of the expected repair time for Trial 1.

the expected loss of the PG associated with demands occurring at floor 20. In particular, the approximation is shown for select design cycles of the sequential optimization process. As can be seen, notwithstanding the nonlinearity of the loss surface with respect to the mean and the standard deviation of the corresponding demand, for moderate changes in the design demands, the expected loss was well approximated by the expansion.

6. CONCLUSIONS

This paper presented an efficient performance-based design optimization framework for identifying optimal wind-excited systems subject to multiple constraints on expected system-level loss. A simulation-based performance assessment was presented that utilized databases of fragility and consequent functions in estimating damage and loss of systems subject to wind tunnel-informed stochastic wind loads. The proposed framework is based on approximately decoupling the simulation from the optimization process. Local approximation models are constructed from results of a single augmented simulation. A deterministic composite function is then defined that relates the design variables to the performance metrics. The explicit nature of this relationship is then exploited to define a sequence of deterministic optimization sub-problems that yield solutions to the original stochastic optimization problem. The applicability of the proposed framework was demonstrated through the optimal design of a large-scale lateral load-resisting system subject to system-level constraints defined in terms of expected repair cost and time.

7. ACKNOWLEDGMENTS

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