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Application of surrogate models for performance-based evaluation of multi-story concrete buildings at early design

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ABSTRACT: Data incompleteness and uncertainty impede the application of performance-based design of structures at early design, which relies on data- and time-intensive numerical simulations. Early design is the most influential stage in a buildings' life cycle performance, hence neglecting quantitative methods to evaluate the design in preliminary stages can lead to missing on opportunities to improve building resiliency. This study presents a framework to implement surrogate models for supporting performance-based early design of concrete multi-story buildings. Five different surrogate models including multiple linear regression, random forest, extreme gradient boosting, support vector regression machines, and k-nearest neighbors are developed and compared to represent the seismic-induced structural loss of 720 generic concrete office buildings using early design parameters. Additionally, variance-based sensitivity is used to determine influential parameters for the best performing model. The results show that extreme gradient boosting and support vector regression machines can be used to relate crude topology and design parameters to building seismic performance with reasonable accuracy.

KEYWORDS: Surrogate modeling; early design; performance-based engineering; machine learning; concrete frames

1 INTRODUCTION

The current paradigm of resiliency requires design and assessment methods that link buildings' physical characteristics to their life-cycle performance against natural hazards. Performance-based engineering (PBE) frameworks (Ghobarah 2001; Porter 2003) provide a systematic approach for mapping structural engineering responses such as deformation or strength demands to decision variables that are of interest to different stakeholders. Due to the uncertain nature of natural hazards and engineering systems behavior, these methods employ probabilistic measures of contributing factors (such as hazard intensity or structural response) through sequential stages (i.e. pinch-points), where each stage is only dependent on the successor.

Early design is perhaps the most important stage to shape building resiliency (Flint et al. 2016) since the majority of important decisions, such as subsystem selection and building topology, are yet to be made (Basbagill et al. 2013). Therefore, communicating the risks of design decisions will aid the designer to achieve better-performing designs that might not be initially visible to them (Shahtaheri et al. 2018). Nevertheless, introducing quantitative methods in early design is challenging due to its fast-paced, imprecise, and dynamic nature (Østergård et al. 2016a; Rezaee et al. 2019).

PBE has been successfully implemented for seismic assessment and design of different building classes such as tall buildings (Bijelić et al. 2018; Zaker Esteghamati et al. 2018), retrofitted buildings (Andrea et al. 2019; Tarfan et al. 2019) and buildings equipped with different dissipative devices (Dehghani et al. 2021; Zaker Esteghamati and Farzampour 2020; Zhai et al. 2020). In addition, an inventory of published literature on performance-based seismic assessment for mid-

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rise buildings with different structural systems has been compiled (Zaker Esteghamati et al. 2020). Recently, PBE has been extended to the design and assessment of buildings for other hazards such as wind (Micheli et al. 2019) and fire (Alasiri et al. 2020).

While PBE is frequently used in the design and assessment of different building types and hazards, it has not yet been implemented at early stages of design. The main challenges in the application of PBE at early design are time- and effort-intensiveness of the analysis, and PBE's reliance on different input data, such as the building's taxonomy, which are often not available or incomplete at preliminary stages. Furthermore, the dynamic nature of early design requires methods that are low-effort (Kovacic and Zoller 2015; McIntosh et al. 2011) and sensitive to design feedbacks (Østergård et al. 2016b), which is not the case for conventional PBE frameworks.

Surrogate modeling is an efficient technique to substitute intensive simulations with low-cost mathematical metamodels. In this approach, a statistical approach (i.e. sampling or design of experiment) is used to perform a limited number of simulations for specific values of model inputs. The results are then used to train mathematical models that can relate model input to the observed response. After validating model performance, the surrogate model is able to predict system response for the given domain of input values.

This paper introduces PBE for early design of multi-story concrete offices using surrogate modeling. The application of surrogate models allows for rapid performance assessment with a low computational cost. Therefore, first, a workflow is described to develop a performance inventory for 720 multistory office buildings. Then, the developed inventory is used to train several surrogate modeling approaches, tune their model parameters, and measure their accuracy. Lastly, the sensitivity assessment is performed both for feature reduction and to determine the most influential parameters. A distinctive aspect of this paper is to develop generalizable surrogate models for a class of buildings instead of a single design. Additionally, contrasting to the available literature, surrogate models are developed to predict building performance endpoint (e.g. loss) using crude features that are suitable at early stages of design.

2 DEVELOPING SEISMIC PERFORMANCE INVENTORY

To address early design of multi-story concrete buildings, symmetric mid-rise concrete frame buildings are adopted here. The buildings are assumed to be located in Charleston, South Carolina. Figure 1 shows the archetype concrete frame building, which can be described through four topological parameters: number of bays in the X and Y directions, bay's length, and building height. Following the design practice of concrete moment-resisting frames (Moehle et al. 2008), it is assumed that in each direction the building will have between 2 to 6 bays, where the bay's span ranges from 21 ft (6.4 m) to 30 ft (9.14 m). The buildings have 3 to 6 stories, ranging from 38 ft (11.58 m) to 74 ft (22.56 m).

The workflow shown in Figure 1 is used to generate nonlinear finite element models for the range of defined early design parameters. First, a Latin hypercube sampling scheme is used to define 60 combinations of the four parameters. For each topological sampling point, twelve different design alternatives are generated in terms of different combinations of beams' and columns' sections. The design alternatives are produced by applying some rule-based heuristic to pre-defined lists of beams' and columns' sections. The pre-defined lists define beams and columns section that conforms to building codes (ACI Committee 318 2008) requirements on concrete section sizing and reinforcement.

The section sampling module initiates by choosing a column section from the list for the first floor, and subsequently selects a smaller or equal beam section for the beams of the same floor. It should be noted that any pre-defined beam section with the same size as the column section has relatively smaller reinforcement, hence is "weaker". These heuristic are incorporated to ensure that selected beams are weaker than the column, implicitly considering the strong-column weak-beam requirement. In the next iteration, the selected sections are removed from the list and the

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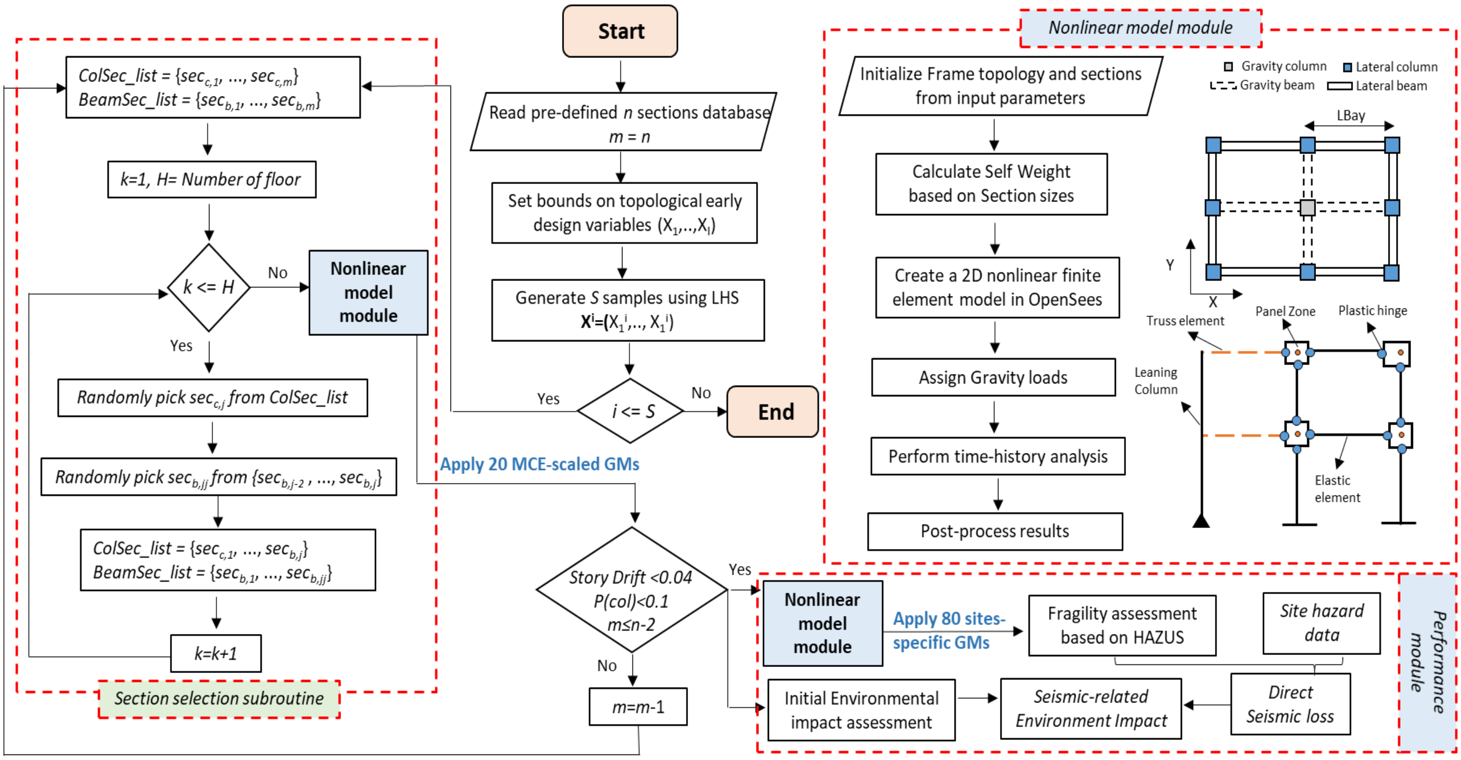

Figure 1. Framework to develop performance inventory for mid-rise multistory concrete office buildings

algorithm picks a smaller column section for the upper floor and continues to select equal or smaller beams section for the upper story. The second heuristic ensures that stronger sections are assigned to lower floors that are expected to sustain a larger lateral load from the building code's equivalent lateral design approach (American Society of Civil Engineers 2010). When all sections are assigned, the design input is passed with topological parameters to the seismic analysis module.

The seismic analysis module generates nonlinear finite element models in OpenSees (McKenna 2011). The generic nonlinear configuration is shown in Figure 1. A concentrated plasticity model is used since the strength and stiffness degradation of frame members is a key factor to determine the frame's global performance. Therefore, beams and columns are modeled with elastic members with two nonlinear plastic hinges at both ends. The monotonic backbone curve of nonlinear hinges is defined based on regression equations by Haselton et al. (Haselton et al. 2008). Furthermore, the cyclic deterioration due to strength and stiffness is included in analytical models. In addition to components' geometric nonlinearities, a fictitious leaning column is adopted to include P-Δ effects in analytical models. The leaning column is connected to the main frame by truss elements where rotational hinges with a very small stiffness are used at each end, to remove the leaning column lateral stiffness from the model (Zaker Esteghamati et al. 2018).

The seismic analysis module then checks the generated analytical model by applying 20 site-specific ground motions (GM) that are scaled to the maximum considered earthquake (MCE) level. These GMs are a subset of a larger synthetic GM suite previously developed by authors and the details can be found elsewhere (Flint et al. in prep). The structure's response in terms of maximum inter-story drift is recorded and if (i) all story drifts do not exceed 4% (American Society of Civil Engineers 2010), (ii) maximum number of collapse cases is limited to 2 (10% collapse probability under MCE), the design is deemed admissible and a second analysis using the whole unscaled GM suite is performed. Otherwise, the workflow returns to the section sampling module to assign new sections to the frame members.

Seismic global performance is quantified based on direct repair cost after an earthquake event. An assembly-based approach is implemented, where structural peak drift and acceleration responses are mapped to structural, drift-sensitive nonstructural, and acceleration-sensitive nonstructural damage based on HAZUS guideline (Hazus 2012). This approach simplifies loss calculation as it lumps all building components into assembly categories, reducing the required information that is needed in a rigorous component-based approach.

Following Ramirez et al. (Ramirez et al. 2012), the expected total seismic loss (L_T) is decomposed to collapse-related (L_C) and non-collapse (L_{NC}) losses as follows:

$$\mathrm{E}(L_T)=\mathrm{E}(L_{NC})\left(1\text{-}\mathrm{P}(C|IM)\right)+\mathrm{E}(L_C)\mathrm{P}(C|IM) \tag{1}$$

where E(X|Y) is the expected value of random variable X conditioned on Y, and P(X) shows the probability of random variable X. The non-collapse loss is then disaggregated to structural (L_S), drift-sensitive non-structural ($L_{NS,DS}$), and acceleration-sensitive non-structural assemblies ($L_{NS,AS}$) as follows:

$$\mathrm{E}(L_{\mathrm{NC}}|NC,IM)=\mathrm{E}(L_S|NC,IM)+\mathrm{E}\left(L_{NS,DS}\middle|NC,IM\right) \\ +\mathrm{E}\left(L_{NS,AS}\middle|NC,IM\right) \tag{2}$$

The expected loss of jth assembly (L_j) is obtained by summation of building loss due to exceeding different damages states as follows:

$$\mathrm{E}\left(L_j\middle|NC,IM\right)= \\ \sum_{\mathrm{i=1}}^{\mathrm{m}}\int \mathrm{E}(DV|DS_i)\mathrm{P}(DS_i|EDP)\mathrm{P}(EDP|IM)\mathrm{d}EDP \tag{3}$$

where DV is the decision variable (here taken as direct repair cost), DS is the damage state and EDP is structure response (e.g. drift). Lastly, the expected loss is integrated over the site's hazard in term of hazard intensity measure (IM) to derive expected annual loss as follows:

$$\lambda(L_i)=\int_{IM}\mathrm{E}(L_i|IM)\,.\left|\frac{\mathrm{d}\lambda(\mathrm{IM})}{\mathrm{d}IM}\right|\mathrm{d}IM \tag{4}$$

While all relevant losses are included in the framework, this paper discusses surrogate models developed to predict structural-related annual loss, i.e. L_S.

3 SURROGATE MODELING

3.1 *Feature selection*

Figure 2 shows the framework used to develop surrogate models. First, eighteen design and topological parameters are selected as possible features for developing surrogate models. The design parameters were selected so that they can be assumed without additional effort at the preliminary design stages. The topological parameters include building height (*Height*), building dimension in X (*Xdim*) and Y (*Ydim*) dimension, bay's length (*LBay*), floor area (*FlrArea*), gross area (*GrArea*), Aspect ratio (*AspectRat*), number of columns (*ColNum*) and beams (*BeamNum*). The design parameters consist of lateral-resisting frame weight (*LatWeight*), total building weight (TotalWeight), average column (*ColAvg*) and beam areas (*BeamAvg*), first's story column (*ColSec1*) and beam (*BeamSec1*) area, average column (*RhoColAvg*) and beam (*RhoBeamAvg*) longitudinal reinforcement ratio, and first's story column (*RhoCol1*) and beam (*RhoBeamSec1*). It should be noted that while more precise parameters (such as structural period) could strongly improve model accuracy, they are resulted from careful design and are not available at early design.

3.2 *Surrogate models*

There are numerous surrogate modeling techniques and the following algorithms were selected in this study.

3.2.1 *Multiple linear regression (MLR)*

Multiple regression is perhaps the oldest surrogate modeling technique, at which the response (y) is assumed to be linearly related to multiple features (X). The coefficients of models, βs, are then obtained by minimizing the sum of squared residuals as follows (Hastie et al. 2009):

$$y=\beta_0+\beta_1\mathrm{x}_1+\ldots+\beta_\mathrm{n}\mathrm{x}_\mathrm{n}+\epsilon \\ \min\sum_{i=1}^{m}(y_i\text{-}\beta_0\text{-}\beta_1x_{1,i}\text{-}\ldots\text{-}\beta_nx_{n,i})^2 \tag{5}$$

3.2.2 *Random forest (RF)*

Random forest uses the bagging concept, where the average of a large number of noisy models (here decision trees) from resampling training data is expected to result in an unbiased model. An RF with N trees is represented as (Hastie et al. 2009):

$$y(x)= \frac{1}{n}\sum_{n=1}^{N}\sum_{j=1}^{J}\gamma_j\, \mathrm{I}(x\in R_j) \tag{6}$$

where R and γ are decision trees model parameters that are obtained by minimizing the empirical risk as follows:

$$\min \sum_{j=1}^{J}\sum_{x_i\in R_j}^{J} L(y_i,\gamma_j) \tag{7}$$

3.2.3 *Extreme gradient boosting (XGB)*

Gradient boosting methods relies on the boosting approach, at which weak models (regression trees in XGB) with low bias and high variance are used in a stage-wise fashion to retrain the trained model at each iteration. XGB uses a more regularized loss function to limit overfitting comparing to other implementations of the gradient boosting method. The objective function at iteration m is as follows(Chen and Guestrin 2016):

$$\min \sum_{j=1}^{n} l\left(y_i,\hat{y}_i^{(m-1)}+f_t(x_i)\right)+\Omega(f_t) \tag{8}$$

where l is the loss function measuring the difference of predicted (y_i) and observed response ($\hat{y}_i$), and Ω is the penalty term for model complexity.

3.2.4 *Support vector regression (SVR)*

Support vector regression machines find the optimal hyperplane in the input space that deviates at maximum ε (error margin) from the decision boundary lines. This results in an added flexibility comparing to minimizing squared residuals in a conventional regression problem as follows:

$$\begin{aligned} &\min\ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}|\xi_i| \\ &\text{s.t. } |y_i - w_i x_i| \le \epsilon + |\xi_i| \end{aligned} \tag{9}$$

where ξ is the deviation from ε, w is the coefficient vector and C is the penalty term (Hastie et al. 2009).

3.2.5 *k-nearest neighbor regression (KNN)*

KNN algorithms predict response for X_i (i.e. y_i) by locating the N nearest points in input space to X_i and averaging all corresponding responses. Assuming k neighborhoods are defined, y_i is obtained as follows (Fan et al. 2019):

$$y_i=\frac{1}{k}\sum_{X\in N} y(X) \tag{10}$$

3.3 *Model selection* & validation

A comprehensive model selection requires buildings all possible models including different combinations of the selected features. However, as shown in Figure 2, instead first statistical feature selection methods (e.g. F-values and mutual information gain) are used to determine the most influential features. Then several candidate feature sets (including full features and ones selected from statistical feature selection) are used to develop each surrogate model. First, dataset is partitioned into 70% training and 30% testing data groups. Using the training dataset, for each feature set, parameters of selected models are tuned by a randomized search to find the bounds on best hyperparameter (i.e. parameters that define the learning process) and subsequently a grid search algorithm to yield optimal values. To avoid overfitting, cross-validation with 3 folds on training data is carried out for each Hypertuning algorithm.

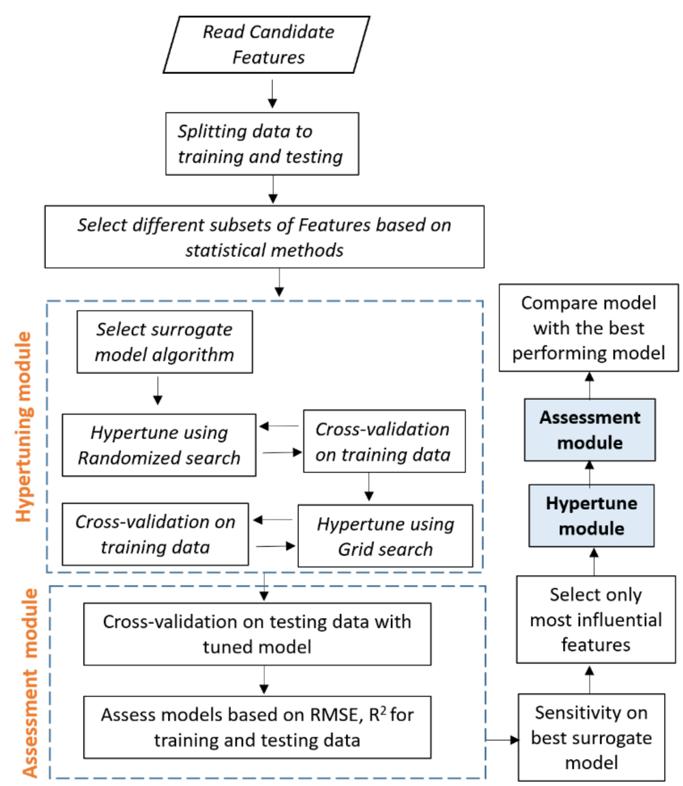

Figure 2. Surrogate Model tuning and validation workflow

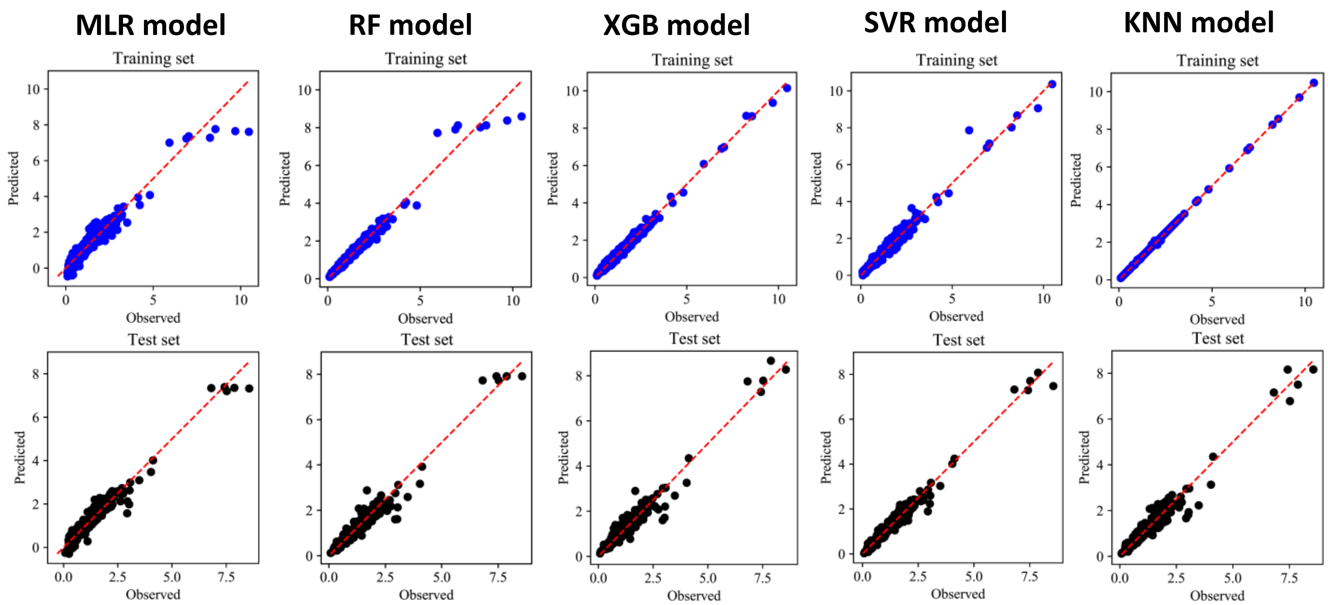

Figure 3. Comparison of best models performance on training (top) and testing (bottom) set for each algorithm

Table 1. Comparison of accuracy measures for best performing surrogate models

Model	Features	Adjusted R^2		Adjusted R^2 (10-fold CV)				RMSE	
		Train	Test	Train		Test		Train	Test
				Mean	std	Mean	std		
MLR	Height, LBay, AspectRat, LatWeight, TotalWeight, ColAvg, ColSec1	0.92	0.94	0.89	0.04	0.91	0.06	0.311	0.285
RF	Height, Ydim, FlrArea, TotalWeight, BeamAvg, ColAvg, BeamSec1	0.97	0.95	0.90	0.07	0.89	0.07	0.174	0.275
XGB	Height, Ydim, FlrArea, TotalWeight, BeamAvg, ColAvg, RhoCol1	0.99	0.96	0.92	0.03	0.90	0.08	0.109	0.247
SVR	Height, Ydim, FlrArea, TotalWeight, BeamSec1, RhoCol1	0.97	0.97	0.94	0.03	0.95	0.03	0.173	0.200
KNN	Height, LBay, Xdim, Ydim, LatWeight, TotalWeight, BeamAvg, ColAvg	1.00	0.94	0.89	0.05	0.82	0.15	0.018	0.286

The tuned model for each feature set is then used to predict testing dataset and compared based on accuracy measures such as adjusted R-squared of testing and training set. Lastly, for each surrogate algorithm, a sensitivity analysis is performed on the best tuned model to determine the most influential features. Subsequently, new surrogate models are constructed using only influential features from sensitivity analysis, and compared to the best performing model from other sets to determine whether a simpler and accurate model can be achieved.

The workflow shown in Figure 2 is repeated for all five surrogate modeling algorithms to yield the best possible model for each algorithm. Figure 3 compares the best surrogate modeling for different surrogate algorithms, and Table 1 provides the accuracy measures and selected features for each algorithm.

The results shows that SVR has the best performance, followed by XGB. SVR has an average adjusted R^2 of 0.95 with and standard deviation of 0.03 for the testing sets from 10-fold cross-validation, whereas the best XGB model has an average adjusted R^2 of 0.90 with standard deviation of 0.08 for the same sets. On the other hand, MLR and KNN have the worst performance. The MLR model has poor performance at low and high structural loss, and while its average adjusted R^2 on testing set is similar to XGB, it has the lowest RMSE on testing set. In addition, while the KNN algorithm shows maximum adjusted R^2 of 1 for the training set, it demonstrates a significantly poorer performance on the testing set with an average R^2 of

0.82 and standard deviation of 0.15, indicating overfitting.

3.4 *Sensitivity assessment*

The best performing XGB and SVR models are used to perform a variance-based sensitivity assessment. Based on the parameters' range, Sobol's sequences were generated and first-order, and total sensitivity indices were calculated from a quasi-Monte Carlo simulation. In this method, the response variance, V(y) is decomposed into partial variances as follows (Oakley and O'Hagan 2004):

$$V(y)=\sum_{i}^{n} V_i+\sum_{i}^{n}\sum_{j>i}^{n} V_{ij}+\ldots+V_{1\ldots n} \tag{11}$$

where V_i denotes the expected reduction in the variance of the response given feature i, and V_{ij} is the expected reduction in response variance due to both features i and j, and so on. Using this formula, the first-order effect (S_i) and total effect (S_T) indices are defined as follows :

$$S_i=\frac{V_i}{V(y)}$$
$$S_T= S_T+\sum_{i\neq j} S_{ij} \tag{12}$$

Figure 4 shows the sensitivity indices for both the XGB and SVR models. Commonly, a value of 0.05 is considered as the cutoff value to distinguish influential from less important parameters in variance-based

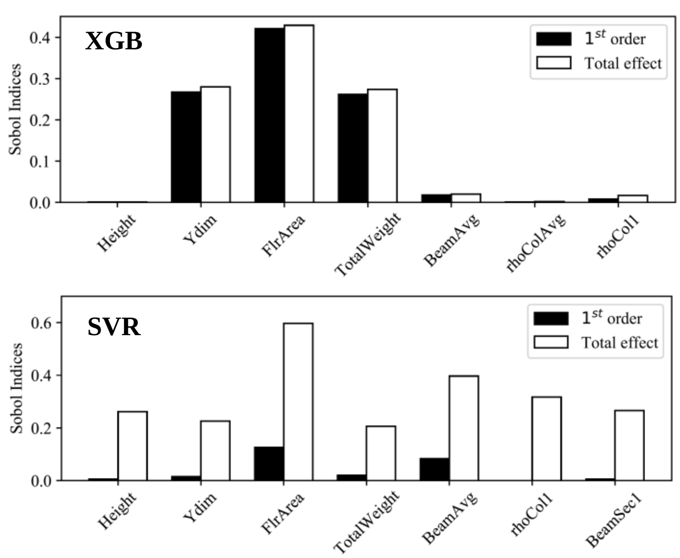

Figure 4. Variance-based sensitivity assessment on the best performing XGB (top) and SVR (bottom) models.

sensitivity assessment.

For the SVR model, the uncerainty in floor area and average beam section size dominate the 1st order and the total effect on structural loss varaince. While the 1st order impact of other features (such as reiforcement ratio of the first story's columns and height) is not significant, their total impact is considerable and on a similar magnitude, indicating that model's prediction variance is impacted by these parameters interactions. On the other hand, for XGB, floor area, total building wieght and building dimension in the direction perpendicular to the analyzed frame doimnate both the main and total effect, whereas the impact of design parameters (e.g. beam sections, column reinforcement ratio) on prediction's variance is negligible.

4 CONCLUSION

This paper presents a framework to develop surrogate models to aid with early design. The underlying notion of this framework lies in developing a performance inventory for a class of buildings to facilitate the learning process of generalizable surrogate models. The surrogate models are then used to relate crude topological and design parameters to performance endpoints (e.g. structural seismic loss). The application of crude features increases surrogate models' suitability for early design, whereas defining response in terms of performance endpoint delivers insights that are accessible to a broader decision-maker group.

The preliminary results indicate that support vector machines and extreme gradient boosting are able to perform this mapping with reasonable accuracy (an average adjusted R-squared of 95% and 90% for new data, respectively), whereas multiple regression and k-nearest neighbor algorithms show poor performance. It should be noted that through a careful tuning and feature selection workflow, similar efficiency was achieved for the gradient boosting and support vector machines algorithms. Furthermore, the variation in loss prediction from extreme gradient boosting and support vector machines are sensitive to different predictors, where the former is mostly dominated by topological parameters, and the latter is more governed by design ones.

While this paper serves as a pilot study to demonstrate that efficient surrogate models can extract the relationship between early design parameters and structural performance, further investigation is needed to assess this relationship for different classes of building and other performance measures to facilitate performance-based early design. In addition, a probabilistic approach is still needed to incorporate such modeling directly into performance-based frameworks.

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