Deep Transfer Learning for Efficient Performance-based Assessment of Stochastic Nonlinear Dynamic Systems through Metamodeling

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ABSTRACT: Performance-based wind engineering has gained significant interest over the past decade as a means to achieve innovative designs with increased performance at reduced costs. Nonetheless, the vast computational demand required for propagating uncertainty through general nonlinear high-dimensional systems in estimating probabilistic performance metrics represents a significant barrier to further application. To address this issue, a non-intrusive long short-term memory (LSTM)-based metamodeling scheme for nonlinear response history prediction is embedded in a state-of-the-art stratified sampling scheme, therefore, enabling the efficient and accurate performance assessment of nonlinear wind-excited systems. To treat high dimensional problems, the excitation and response time histories are reduced by projection through a basis obtained via proper orthogonal decomposition. It is proposed to learn the mapping from the projected excitation and responses directly through the LSTM neural network, which avoids the need for schemes, such as Galerkin projection, that are intrusive in nature. For training, the LSTM neural network is calibrated based on the distribution of the largest wind speeds to occur in the most extreme stratum. The trained LSTM network is then rapidly transferred to the remaining strata with computationally negligible effort. The proposed framework is illustrated through a case study consisting of a 37-story full-scale nonlinear steel moment-resisting frame. A site-specific wind hazard is considered with wind directionality captured through a sector-by-sector approach. The calibrated LSTM metamodel was seen to require four orders of magnitude less effort than state-of-the-art direct integration algorithms while maintaining remarkable accuracy. The capability to use the LSTM neural network with transfer learning for direct estimation of the exceedance probabilities was shown for multiple engineering demand parameters of interest, including residual drift.

1. INTRODUCTION

Performance-based wind engineering (PBWE) has gained significant interest over the past decade for enabling more economic and innovative designs. Numerous theoretical frameworks have been developed for its application in practice (Jain et al., 2001; Ciampoli et al., 2011; Barbato et al., 2013; Chuang and Spence, 2017; Cui and Caracoglia, 2018; Ouyang and Spence, 2020; Chuang and Spence, 2019; Cui and Caracoglia, 2020; Ouyang and Spence, 2021b,a; Chuang and Spence, 2022; Arunachalam and Spence, 2022), eventually leading to the publication of the Prestandard for Performance-Based Wind Design by the American Society of Civil Engineers (American Society of Civil Engineers, 2019). Nonetheless, the vast computational demand required in propagating general uncertainty through nonlinear structural systems for providing a probabilistic assessment of performance can represent a significant barrier to implementation. This limitation calls for the development of alternative methods that can reduce the computational effort in propagating uncertainty through high-dimensional finite element models of nonlinear systems. Metamodeling schemes provide a promising remedy to this issue by seeking to define a model of the model that is capable of accurately reproducing the response of the original problem at a fraction of the computational effort. Recently the long short-term memory (LSTM) neural network has been introduced as a metamodeling approach for reproducing the response time histories of nonlinear structural systems subject to general stochastic excitation (Li and Spence, 2022). In particular, without loss of accuracy, this metamodeling approach has been seen to be remarkably efficient in applications involving full-scale engineered buildings (Li and Spence, 2022).

Motivated by the potential shown by LSTM-based metamodeling schemes, this paper investigates the possibility of developing a rapid performance-based wind assessment framework enabled by integrating LSTM-based metamodeling with a general uncertainty propagation framework based on recent advances in stratified sampling (Arunachalam and Spence, 2023). In particular, to cope with the typically high dimensional systems associated with engineering problems, a reduced space is defined by applying proper orthogonal decomposition (POD) over a set of response snapshots of the original model output. The basis functions of the reduction are used to directly project/reduce both the excitation and responses. It is then proposed to use the LSTM neural network to directly learn the mapping from the projected excitation to the projected responses, therefore avoiding the need to solve the reduced model even during training. This LSTM metamodeling scheme is subsequently integrated into a recently introduced stratified sampling scheme for wind engineering applications. To enhance the transferability among different wind speed strata, the metamodel is calibrated based on a statistical representation of the largest wind speeds to occur in the most extreme stratum. Subsequently, the calibrated metamodel is transferred to the remaining strata with negligible computational effort. The entire scheme is illustrated on a 37-story steel moment-resisting frame subject to stochastic wind excitation. The calibrated metamodel is shown to be capable of accurately predicting the exceedance probability curves associated with various engineering demand parameters of interest, including peak and residual responses, with more than four orders of magnitude gains in efficiency as compared to state-of-the-art direct integration schemes.

2. PROBLEM SETTING

Performance-based wind assessment is generally based on probabilistic response metrics estimated from propagating uncertainty in the form of stochastic wind excitation through finite element models of the structural system. This generally involves the repeated evaluation of the following high-dimensional nonlinear equation of motion:

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{C}\dot{\mathbf{x}} + \mathbf{f}(\dot{\mathbf{x}}, \mathbf{x}) = \mathbf{F}(t; v_H, \alpha) \tag{1}$$

where $\mathbf{x}$, $\dot{\mathbf{x}}$, and $\ddot{\mathbf{x}}$ are respectively the vectors of displacement, velocity, and acceleration; $\mathbf{M}$ and $\mathbf{C}$ are the mass and damping matrices; $\mathbf{f}(\dot{\mathbf{x}}, \mathbf{x})$ is the potentially nonlinear restoring force; $\mathbf{F}(t; v_H, \alpha)$ is the vector of external stochastic wind excitation calibrated to a maximum mean hourly wind speed, v_H, of direction α. Typically, it is extremely computationally cumbersome to solve Eq. (1) directly, making it difficult to implement probabilistic performance-based wind assessments based on direct propagation of uncertainty.

3. PROPOSED FRAMEWORK

The proposed framework integrates a LSTM-based metamodeling framework with knowledge transfer into the general uncertainty propagation scheme outlined in (Arunachalam and Spence, 2023). In particular, the high-dimensional problem of Eq. (1) is first converted to a low-dimensional mapping from the space of the projected excitation to the space of the projected responses through dimensionality reduction based on POD. Subsequently, this mapping is directly captured by the LSTM neural network. Moreover, given the implementation of stratified sampling for uncertainty propagation, the LSTM neural network is first trained based on data extracted from the largest value distributions of the wind speeds belonging to the most extreme stratum with transfer to all remaining strata. This framework provides a highly efficient tool for wind performance assessment incorporating both load stochasticity as well as uncertainty in wind speed and direction.

3.1. POD-based dimensionality reduction

The high dimensionality typically associated with engineering problems can lead to significant difficulties in metamodeling. The dimensionality reduction based on projection through a set of basis vectors, collected in the matrix Φ, is hence implemented. In particular, to minimize the dimensionality after reduction while maintaining accuracy in the nonlinear responses, Φ is constructed by collecting the first few left-singular vectors from the POD over a set of displacement snapshots obtained by solving Eq. (1). Through Φ, the excitation and responses are projected into the reduced space as:

$$\mathbf{p} = \Phi^{\mathrm{T}}\mathbf{F} \tag{2}$$

$$\mathbf{q} = \Phi^{\mathrm{T}}\mathbf{x} \tag{3}$$

where $\mathbf{p}$ and $\mathbf{q}$ are projected excitation and responses with significantly reduced dimensionality. Through Eq. (2-3), the originally high dimensional problem is reduced to a low dimensional mapping of the form: $\mathbf{p} \to \mathbf{q}$. It should be observed that this dimensionality reduction scheme does not require any knowledge of the structural system, i.e., it is non-intrusive. In the next section, the LSTM neural network will be introduced to learn the obtained low-dimensional mapping.

3.2. LSTM-based metamodeling

The LSTM is a refined version of the typical recurrent neural network capable of capturing short- and long-term dependency within response time histories. In addition, the gradient vanishing or exploding issues seen in training typical recurrent neural networks are alleviated. In particular, as the core component of an LSTM neural network, the LSTM layer is mathematically described as:

$$\mathbf{g}_{\mathrm{f}}(t) = \sigma_{\mathrm{g}}(\mathbf{w}_{\mathrm{f,H}}^{\mathrm{T}}\mathbf{z}(t-1) + \mathbf{w}_{\mathrm{f,I}}^{\mathrm{T}}\mathbf{y}(t) + \mathbf{b}_{\mathrm{f}}) \tag{4}$$

$$\mathbf{g}_{\mathrm{i}}(t) = \sigma_{\mathrm{g}}(\mathbf{w}_{\mathrm{i,H}}^{\mathrm{T}}\mathbf{z}(t-1) + \mathbf{w}_{\mathrm{i,I}}^{\mathrm{T}}\mathbf{y}(t) + \mathbf{b}_{\mathrm{i}}) \tag{5}$$

$$\mathbf{g}_{\mathrm{o}}(t) = \sigma_{\mathrm{g}}(\mathbf{w}_{\mathrm{o,H}}^{\mathrm{T}}\mathbf{z}(t-1) + \mathbf{w}_{\mathrm{o,I}}^{\mathrm{T}}\mathbf{y}(t) + \mathbf{b}_{\mathrm{o}}) \tag{6}$$

$$\Delta\mathbf{C}(t) = \sigma_{\mathrm{s}}(\mathbf{w}_{\mathrm{c,H}}^{\mathrm{T}}\mathbf{z}(t-1) + \mathbf{w}_{\mathrm{c,I}}^{\mathrm{T}}\mathbf{y}(t) + \mathbf{b}_{\mathrm{c}}) \tag{7}$$

$$\mathbf{C}(t) = \mathbf{g}_{\mathrm{f}}(t) \circ \mathbf{C}(t-1) + \mathbf{g}_{\mathrm{i}}(t) \circ \Delta\mathbf{C}(t) \tag{8}$$

$$\mathbf{z}(t) = \mathbf{g}_{\mathrm{o}}(t) \circ \sigma_{\mathrm{s}}(\mathbf{C}(t)) \tag{9}$$

where $\mathbf{y}$ and $\mathbf{z}$ are respectively the layer input and output vector; $\mathbf{C}(t)$ is the LSTM cell state with $\Delta\mathbf{C}(t)$ its increment; $\mathbf{w}_{\mathrm{f,H}}, \mathbf{w}_{\mathrm{i,H}}, \mathbf{w}_{\mathrm{o,H}}, \mathbf{w}_{\mathrm{c,H}}$, $\mathbf{w}_{\mathrm{f,I}}, \mathbf{w}_{\mathrm{i,I}}, \mathbf{w}_{\mathrm{o,I}}, \mathbf{w}_{\mathrm{c,I}}$, and $\mathbf{b}_{\mathrm{f}}, \mathbf{b}_{\mathrm{i}}, \mathbf{b}_{\mathrm{o}}, \mathbf{b}_{\mathrm{c}}$ are respectively the weights of $\mathbf{z}(t-1)$, weights of $\mathbf{y}(t)$, and biases in $\mathbf{g}_{\mathrm{f}}(t)$, $\mathbf{g}_{\mathrm{i}}(t)$, $\mathbf{g}_{\mathrm{o}}(t)$, and $\Delta\mathbf{C}(t)$; $\sigma_{\mathrm{g}}(\cdot)$ and $\sigma_{\mathrm{s}}(\cdot)$ are respectively the gate activation function and the state activation function; and $\circ$ is the element-wise product operator. The LSTM network usually consists of one or more LSTM layers, augmented with, for example, fully connected layers, for better flexibility. For calibration, the LSTM network is trained by adjusting the parameters of all the layers so as to minimize output error. Noting that the computational effort and memory demand in the training process is highly dependent on the length of the input and output series, it is generally convenient to perform a wavelet transformation of $\mathbf{p}$ and $\mathbf{q}$. The resulting wavelet coefficient series associated with $\mathbf{p}$ and $\mathbf{q}$ are generally considerably shorter and be considered as the inputs and target outputs of the LSTM neural network.

3.3. Training and simulation strategy

To propagate uncertainty in wind hazard intensity, measured through v_H and α, and load stochasticity, the aforementioned LSTM-based metamodeling scheme is integrated with the stratified sampling scheme outlined in (Arunachalam and Spence, 2023). In particular, a sector-by-sector approach is adopted for modeling wind direction in which the sectorial wind speed distributions are linearly related to the non-directional distribution function of v_H. Stratification can therefore be carried out directly in terms of the non-directional distribution function of v_H (Chuang and Spence, 2022). Within each sector, uncertainty in wind direction, α, is modeled through a uniform distribution. In implementing the stratified sampling scheme, the support of the wind speeds, v_H, is partitioned into a set of mutually exclusive and collectively exhaustive strata: E_i, $i = 1, 2, ..., N_w$. Any quantity of interest to be evaluated is first conditioned on each E_i through an optimal allocation of samples, as outlined in (Arunachalam and Spence, 2023), and subsequently unconditioned based on the law of total probability.

Within this setting, it is proposed to calibrate the metamodel first within the stratum with the highest wind speeds (i.e., the stratum that will produce the largest demands and therefore the most extreme nonlinearity), and then efficiently transfer to lower strata using transfer learning. To ensure the metamodel is trained to a limited set of extreme wind speeds, the training data is generated from the distribution of the largest wind speeds to occur in the most extreme stratum (i.e., the last wind speed stratum) by sampling from:

$$P(\hat{v}_H | E_{N_w}) = [P(v_H | E_{N_w})]^{n_{N_w}} \qquad (10)$$

where $P(v_H|E_{N_w})$ is the cumulative distribution function of v_H conditioned on the wind speed stratum N_w; $\hat{v}_H$ is the largest value over n_{N_w} samples where n_{N_w} is the sample size to be considered in the simulation with the trained LSTM neural network. Once the LSTM neural network is calibrated to this dataset, its structure is transferred to all the remaining strata with trivial computational effort. Once trained, this framework defines a metamodel capable of explicitly propagating a full range of uncertainty in excitation to the response of the system.

4. CASE STUDY

4.1. *Building and hazard information*

To illustrate the proposed framework, a case study consisting in a 37-story steel moment-resisting frame subject to stochastic wind excitation is considered. The moment-resisting frame is illustrated in Figure 1. The total height of the structure is 150 m, with a story height of 6 m for the first floor and 4 m for all remaining floors. The width of the six bays of the structure is 6 m, leading to a total width of 30 m. The structural system is composed of box section columns and AISC (American

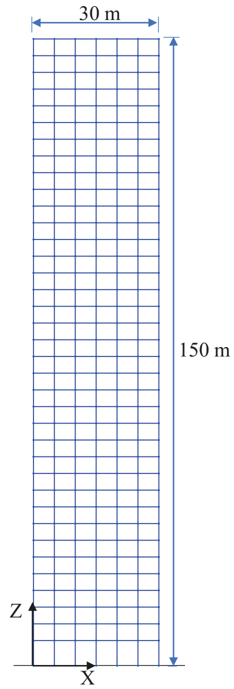

Figure 1: The structural system of the case study steel building.

Institute of Steel Construction) wide flange beam sections. The site-specific non-directional distribution for v_H is defined through a Weibull distribution calibrated based on the site-specific point value wind speeds transformed from the annual 3 s gust wind speeds of the hazard maps of the ASEC 7-22 (American Society of Civil Engineers, 2022). In total 6 strata were considered for the implementation of the stratified sampling scheme. In addition, 8 equal-sized wind sectors were considered to capture directionality effects. The high-dimensional finite element model of the system was developed in OpenSees using fiber-based modeling and an elastic-perfectly plastic material model. The stochastic wind loads had a total duration of 10 minutes and included an initial ramp-up and a final ramp-down. They were generated using a data-driven spectral POD model calibrated to wind tunnel data (Chuang and Spence, 2019). A total of 12,000 samples will be used for evaluating the system response (250 samples per stratum and sector).

4.2. *Results*

As outlined in Section 3.3, the LSTM-based metamodel is first calibrated with data generated by direct integration, carried here in OpenSees, and wind speed samples belonging to the extreme distribution of Eq. (10) where for this case, $n_{N_w} = 250$ and $P(v_H|E_{N_w})$ is the distribution function of v_H conditioned on $N_w = 6$. In total, 800 samples were used to train the LSTM-based metamodel with transfer to the remaining five wind strata. The calibrated LSTM-based metamodel was subsequently used to simulate the responses for all 12,000 samples. For validation, the OpenSees model was also run for all 12,000 samples. Comparisons between the sample responses and exceedance probability curves of the peak interstory drift, residual interstory drift, and peak drift are shown in Figure 2. It is seen that for all responses the LSTM-based metamodel shows excellent accuracy. This holds true even for the residual drift. Moreover, it is seen from Figures 2(b), (d), and (f) that a constantly high level of accuracy is maintained over the entire dataset. This highlights how the training scheme, based on data from the distribution of the largest wind speeds in stratum 6, equipped the LSTM neural network well for transfer to the remaining strata. Moreover, compared with the direct integration in OpenSees, once trained, the metamodel was more than four orders of magnitude faster. The proposed scheme allows the explicit propagation of a full range of uncertainty in the wind hazard, i.e., both the wind intensity measures (wind speed and direction) as well as wind load stochasticity. The efficiency of the scheme illustrates the potential to adopt the scheme in PBWE applications involving inelastic structural systems.

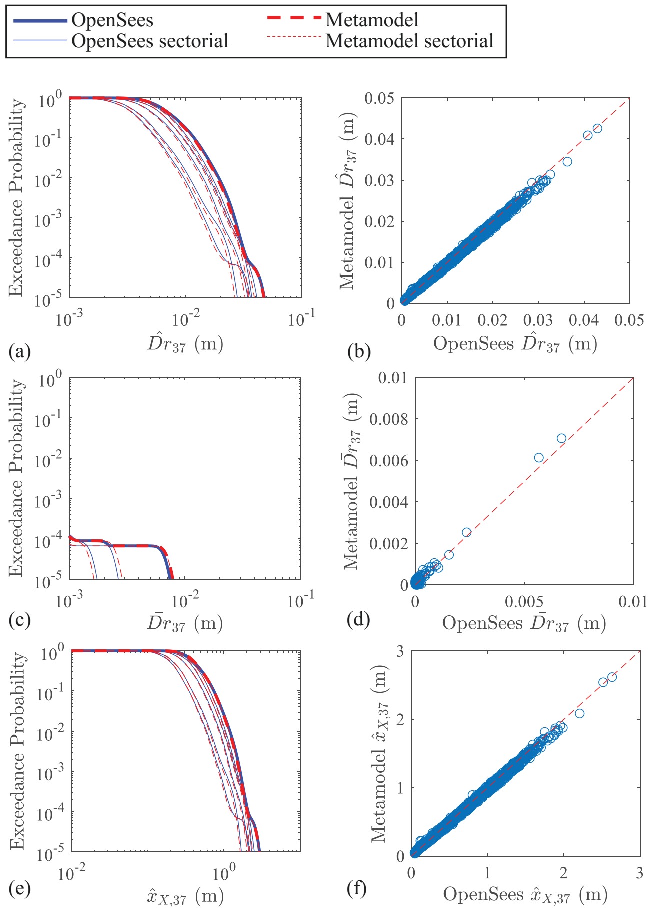

Figure 2: Comparison between the results obtained by direct integration in OpenSees and the proposed metamodel: (a) exceedance probability curves of the peak interstory drift at the top floor and (b) comparison between the peaks of all samples; (c) exceedance probability curves of the top floor residual interstory drift and (d) comparison between the peaks of all samples; (e) exceedance probability curves of the top floor displacement response and (f) comparison between the peaks of all samples.

5. CONCLUSIONS

This paper outlined the development of a rapid wind performance assessment scheme for engineered structural systems through the integration of LSTM-based metamodeling schemes and advanced stratified sampling frameworks. A POD-based projection is firstly considered to reduce both the high-dimensional excitation and responses. The low dimensional mapping from the reduced excitation to reduced responses is subsequently learned by the LSTM metamodel in a non-intrusive manner. The LSTM metamodel is applied as a response estimator in a state-of-the-art stratified sampling scheme. To ensure the transferability to different wind speed strata, the LSTM-based metamodel is calibrated with the data generated by considering the distribution of the largest wind speeds of the most extreme stratum. The proposed framework is validated on a 37-story inelastic steel moment-resisting frame. The calibrated LSTM-based metamodel is shown to have excellent transferability and accuracy in reproducing the exceedance probability curves of multiple responses of interest, including residual interstory drift. The trained LSTM-based metamodel is seen to require four orders of magnitude less computational effort than the corresponding high-fidelity model. The remarkable accuracy, efficiency, as well as transferability over a wide range of wind speeds and directions attest to the significant potential of the proposed framework for applications in PWBE.

6. ACKNOWLEDGEMENTS

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