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Performance-based wind assessment of nonlinear systems through LSTM-based metamodeling and transfer learning

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SUMMARY:
The merit of probabilistic performance-based wind engineering in delivering more rational and economic designs has gained tremendous interest over the past two decades. Nonetheless, the inevitable need for repeated nonlinear analysis in propagating uncertainty can be a significant computational bottleneck. To address this issue, this work is focused on integrating a non-intrusive long short-term memory (LSTM) metamodeling technique with a state-of-the-art stratified sampling scheme. To cope with the typical high-dimensionality of engineering structures, a reduced space is first defined by proper orthogonal decomposition over a set of high-fidelity response samples. The LSTM neural network is introduced to learn the sequence-to-sequence mapping from excitation to responses directly in the reduced space. Subsequently, in probabilistic performance assessment, the stratified sampling scheme is considered for efficient sampling of rare wind events. It is proposed to train an LSTM neural network first for a set of extreme wind intensities generated based on the statistics of the largest sample in the last stratum. Transfer learning is further introduced to efficiently adapt the calibrated LSTM neural network to the remaining strata. The scheme is illustrated on a 37-story steel frame subjected to stochastic wind excitation.

Keywords: Performance-based wind engineering, Metamodeling, Transfer learning, Machine learning

1. MOTIVATIONS

Performance-based wind engineering (PBWE) is gaining significant interest as a means of enabling rational and sustainable designs (Ciampoli et al., 2011; Chuang and Spence, 2017; Cui and Caracoglia, 2018; Ouyang and Spence, 2020; Ouyang and Spence, 2021). However, the significant computational demand caused by the need to repeatedly evaluate nonlinear models during the propagation of uncertainty is an important limit to the application of PBWE in practice. Recently, the long short-term memory (LSTM) metamodeling technique has been seen to be a promising remedy to this issue (Li and Spence, 2022). Nonetheless, this metamodeling technique has not been fully integrated into a PBWE scheme. To bridge this gap, this work explores this possibility through embedding stratified sampling schemes with LSTM metamodels with knowledge transfer among strata by transfer learning.

2. METHODS

In this work, the excitation and responses are first reduced through projection by proper orthogonal decomposition (POD). The LSTM neural network subsequently learns the mapping between the reduced excitation and the reduced responses. This, compared to the previously proposed scheme (Li and Spence, 2022), avoids the intrusive Galerkin scheme. For efficient uncertainty propagation, the LSTM metamodeling scheme is integrated into the stratified sampling scheme recently introduced in Arunachalam and Spence, 2023. To cope with the large range of wind speeds and directions required by the stratified sampling scheme, the LSTM neural network is first calibrated to data generated from the statistics of the largest samples in the most extreme stratum, i.e., the group of samples exhibiting the most severe response nonlinearity. The LSTM network is subsequently adapted to the remaining strata by parameter-based transfer learning.

2.1. Problem setting

Performance assessment in PBWE is, in general, based on solving the following high-dimensional nonlinear dynamic equations of motion:

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

where $\dot{\boldsymbol{x}}(t)$ and $\ddot{\boldsymbol{x}}(t)$ are the velocity and acceleration response vectors; $\boldsymbol{M}$ and $\boldsymbol{C}$ are the mass and damping matrices; $\boldsymbol{F}_{nl}(t)$ is the nonlinear restoring force; and $\boldsymbol{F}(t; v_H, \alpha)$ is the stochastic wind excitation that depends on the wind speed, v_H, and direction, α. Eq. (1) can be solved by general direct integration schemes and provides the knowledge necessary for carrying out a probabilistic performance assessment. However, the process of solving Eq. (1) in this way is in general extremely time-consuming.

2.2. Dimensionality reduction

To deal with the high dimensionality of typical engineering structures, a reduced space can be defined by POD-based dimensionality reduction (Li and Spence, 2021). In particular, Eq. (1) can be seen as a high-dimensional mapping of the form $\boldsymbol{F}(t) \rightarrow \boldsymbol{x}(t)$. Through dimensionality reduction, both the excitation and responses are transformed into the following reduced space:

$$\boldsymbol{p}(t) = \boldsymbol{\Phi}^{\mathrm{T}}\boldsymbol{F}(t),\ \boldsymbol{q}(t) = \boldsymbol{\Phi}^{\mathrm{T}}\boldsymbol{x}(t) \tag{2}$$

where $\boldsymbol{p}(t)$ and $\boldsymbol{q}(t)$ are reduced inputs and outputs and $\boldsymbol{\Phi}$ is the coordinate transformation matrix. To obtain $\boldsymbol{\Phi}$, POD is carried out on snapshots of the response collected from a set of response samples. Eq. (2) converts the high-dimensional problem into a low-dimensional mapping of the form $\boldsymbol{p}(t) \rightarrow \boldsymbol{q}(t)$. This can now be learned by LSTM neural networks.

2.3. LSTM metamodeling

A LSTM network is a type of recurrent neural network developed to be capable of learning both short- and long-term relationships. To facilitate training, both the time series $\boldsymbol{p}(t)$ and $\boldsymbol{q}(t)$ should be normalized and further converted to reduced series of wavelet coefficients. The LSTM network is then trained to predict the wavelet coefficient series by minimizing the regression error with appropriate gradient descent algorithms.

2.4. Training and simulation strategy

The wind hazard in PBWE is generally described as a joint complementary cumulative distribution (CCDF) between wind speed and direction, $G(v_H, \alpha)$. In implementation, this can be reduced to the non-directional wind speed CCDF, $G(v_H)$, and directionality factors. In applying stratified sampling, which aims to allocate samples between both frequent and rare wind speed events, the range of v_H is divided into N_w exhaustive and mutually exclusive strata, $E_k = [v_{H,k}^{\mathrm{lb}}, v_{H,k}^{\mathrm{ub}})$, with samples optimally generated in E_k. These samples are subsequently used to estimate a wide range of probabilistic performance metrics, including distributions, through the application of the law of total probability. The idea explored in this work is to train the LSTM in the last stratum E_{N_w}, i.e., the one with the most severe nonlinearity, and then adapt the network to the remaining strata through knowledge transfer. To ensure the capability of the network to cope with extreme samples during simulation (i.e., prediction), the training data for the LSTM is generated from, $\hat{P}(v_H)$, the distribution of largest values over N_{N_w} samples:

$$\hat{P}(v_H) = \left[P_{E_{N_w}}(v_H)\right]^{N_{N_w}} \tag{3}$$

where N_{N_w} is the number of samples to be generated in E_{N_w} during simulation mode; $P_{E_{N_w}}(v_H)$ is the cumulative distribution of $v_H \in E_{N_w}$. Once the LSTM neural network is calibrated, its parameters are transferred to all remaining strata and fine-tuned if necessary. It should be observed that, since the fine-tuning is performed for a neural network trained for scenarios with high nonlinearity, far less computational effort and data are required in the fine-tuning phase.

3. CASE STUDY AND RESULTS

The case study consists of a 37-story moment-resisting steel frame located in New York City (Fig. 1a). The height of the frame is 150 m, with a first story height of 6 m and the rest of 4 m. The width of the building is 30 m, with 6 bays of equal 5 m width. The structural system is composed of AISC wide flange beams and squared box-section columns.

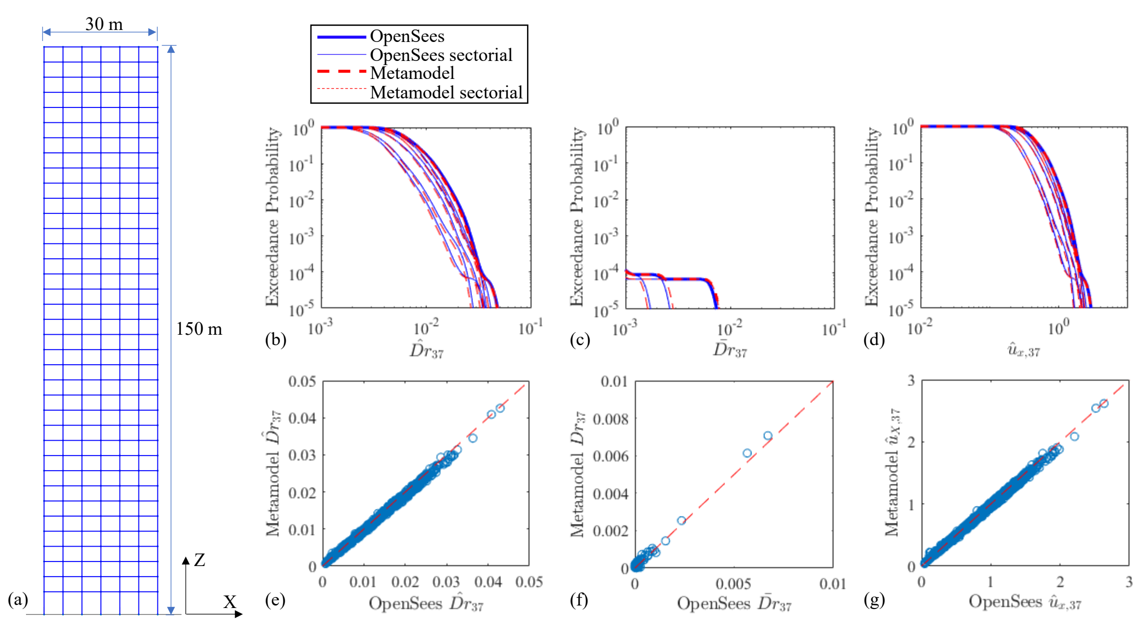

Figure 1. (a) Elevation of the steel frame; Comparison between OpenSees and metamodel for the top floor reponse: (b)-(d) exceedance probability curves of the interstory drift ratio, $\widehat{Dr}_{37}$, residual interstory drift ratio, $\overline{Dr}_{37}$, and peak drift, $\hat{u}_{x,37}$; (e)-(g) simulated samples of the interstory drift ratio, residual interstory drift ratio, and peak drift.

The site-specific wind hazard is defined based on the annual 3 s gust wind defined by the ASCE 7-22. The stratified sampling scheme is defined with 6 strata (wind speed intervals). Wind directionality is captured by the sector-by-sector approach with 8 sectors. Given wind speed and direction, a wind tunnel data-informed spectral POD simulator is used to generate samples of stochastic dynamic wind loading. Direct integration in OpenSees is adopted to simulate high-fidelity data to calibrate and test the LSTM metamodel. The comparison of peak and residual top interstory drift ratio, as well as peak top drift simulated by OpenSees and the metamodel are shown in Fig. 1 (b-g). It is seen that the metamodel is capable of simulating all the engineering demand parameters of interest with remarkable accuracy, including residual responses, which are difficult to reproduce accurately. Moreover, the metamodel is over four orders magnitude faster than the corresponding direct integration in OpenSees. This accuracy and efficiency illustrates the potential of the metamodeling scheme in PBWE.

7. CONCLUSIONS

This research explored rapid PBWE assessment by integrating LSTM metamodels with transfer learning and uncertainty quantification by stratified sampling. In particular, the excitation and responses were projected into a reduced space through proper orthogonal decomposition. Within the implementation of the stratified sampling, an LSTM metamodel is firstly calibrated in the reduced space for the stratum with most extreme responses with transfer to the remaining strata. The efficiency and accuracy of the scheme were illustrated on a case study consisting in a 37-story building subjected to stochastic wind excitation. It is seen the metamodel accurately reproduced all engineering demand parameters, including peak and residual responses, with computational speedups of around four orders of magnitude therefore illustrating its potential in performance-based wind engineering assessments.

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