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Time-History Wind Response Analysis of High-Rise Buildings using Latent Space Time-Step Operators

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SUMMARY

Evaluating wind-resistant design and serviceability for high-rise buildings requires analyzing responses to long-term turbulent aerodynamic loads, yet repetitive analysis using full-order models involves prohibitive computational costs. This study proposes a latent space time-integration operator framework. Structural states, time-varying aerodynamic loads, and wind-induced responses are embedded into low-dimensional latent vectors to approximate dynamic behavior via a learned time-step operator. The model is trained on a linear high-rise RC structure using wind tunnel data, utilizing full-order simulation results as a teacher. The reconstructed time series are evaluated for fidelity in reproducing fluctuating components and peak characteristics. Furthermore, the framework's capability to represent load-structure interactions and ensure extrapolation stability is analyzed from a wind engineering perspective through comparisons with modal truncation and DeepONet/FNO approaches.

Keywords: *Aerodynamic response, Temporal extrapolation, Latent reduced-order model, Time-step neural operator, High-rise buildings*

1. MOTIVATION

Accurate prediction of wind-induced behavior is essential for high-rise safety and habitability. However, repetitive finite element time-history analyses for complex aerodynamic loads create a significant computational bottleneck. While modal truncation offers efficiency, it is limited by high-order mode contributions. Similarly, neural operators like DeepONet (Lu et al., 2021) and FNO (Li et al., 2021) are constrained by fixed time-domain mappings, making them unsuitable for the long-duration simulations required in wind engineering.

This study proposes a surrogate model that learns a time-step operator within a low-dimensional latent space, rather than reducing physical degrees of freedom. By leveraging the stationarity of wind tunnel-based loads, the model ensures stable long-duration predictions. Its utility is validated through comparisons with modal techniques and direct operator models.

2. BACKGROUND INFORMATION

2.1. Wind-induced response analysis and structural dynamics

The wind-induced vibration of high-rise buildings is generally governed by the following linear equation of motion:

$$M\ddot{x}(t) + C\dot{x}(t) + Kx(t) = F(t) \quad (1)$$

where $x(t)$ denotes the nodal displacement vector; M, C, and K denote the system matrices.

The wind load vector $F(t)$ is the aerodynamic load derived by integrating wind pressure over the building surface, comprising both the mean component and the fluctuating component caused by turbulence. In a full-order model analysis, the degrees of freedom (n_x) can reach tens of thousands; consequently, the statistical characteristics of the response (e.g., RMS, peak factor), obtained via numerical integration methods such as the Newmark- β method, serve as critical design parameters. Although modal truncation techniques reduce the dimensionality of the analysis from n_x to n_r ($n_r \ll n_x$) by approximating the displacement as $x_t \approx \Phi_r q(t)$, the computational cost of processing long-duration time-history data—often exceeding several hundred seconds—remains substantial, making it impractical to use as a large-scale dataset for AI research.

2.2. POD-based data dimensionality reduction

As a data-driven approach, dominant fluctuation modes are extracted by applying Proper Orthogonal Decomposition (POD) to the time-history wind response $R = [R_1, \cdots, R_N]$. The linear mapping utilizing the top d_z basis vectors, Φ_{POD} is defined as follows:

$$z_t = \Phi_{\mathrm{POD}}^T R_t,\ \hat{R}_t = \Phi_{\mathrm{POD}} z_t \tag{2}$$

where the latent response z_t denotes a compact representation of the aerodynamic behavior of the structure; d_z denotes the latent dimension, chosen to encompass both the wind load frequencies and the structural natural frequencies.

2.3. Neural Operator

DeepONet (Lu et al., 2021) and Fourier Neural Operator (FNO) (Li et al., 2021) learn nonlinear mappings between function spaces. However, since conventional neural operators typically predict the entire output domain simultaneously for a fixed input domain, prediction accuracy may deteriorate in wind engineering analyses where the duration of input wind loads is variable or extends significantly (extrapolation). To address this limitation, this study adopts a time-stepping learning strategy that preserves dynamic causality.

3. METHODOLOGY

3.1. Full-order solver and teacher operator

The numerical integration process of Eq. (1), performed using commercial structural analysis software, is defined as H:

$$R_t = H(S, F_t, R_{t-1}) \tag{3}$$

where S denotes the building information; F_t denotes the story-level wind force vector at time t; H denotes the teacher model that performs complex numerical operations.

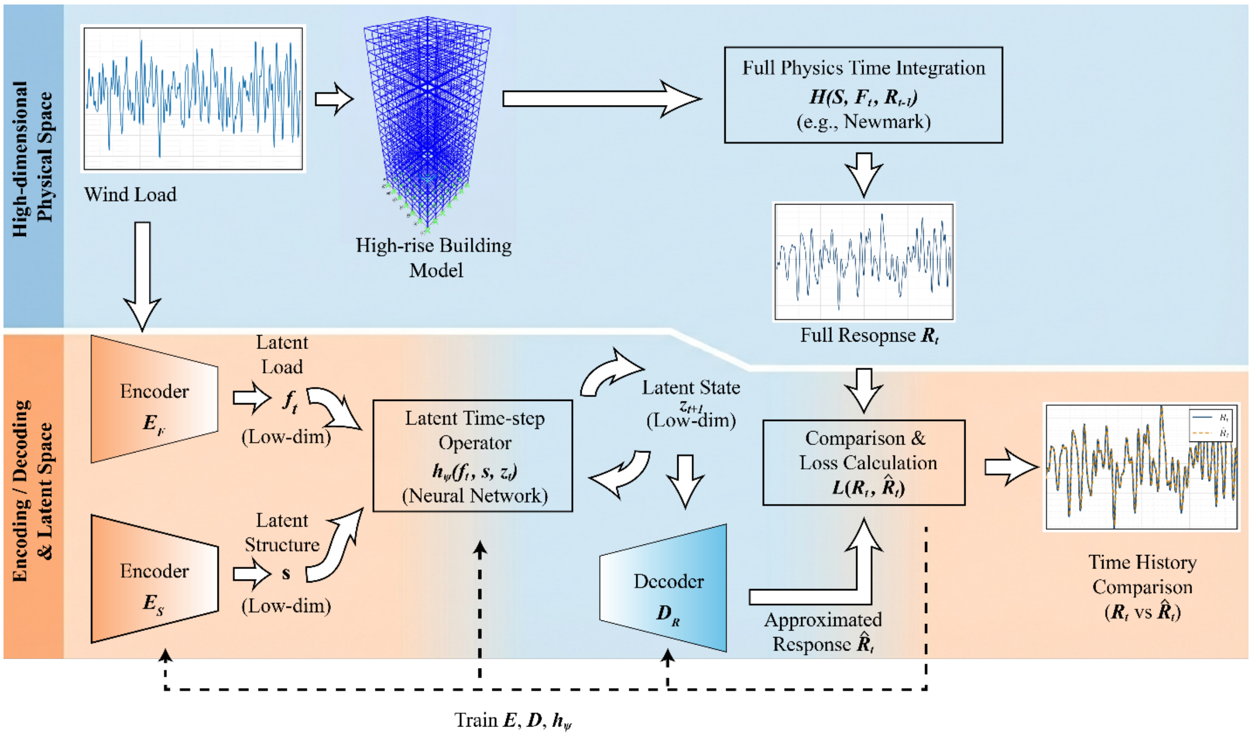

Figure 1 : Schematic of the proposed latent space time-step operator framework: full-order time integration (top) versus latent space operator learning (bottom)

3.2. Modeling time evolution in latent space

The structural state S, aerodynamic load F_t, and response R_t, are projected into a latent space via encoders E_S, E_F, and E_R respectively. The dynamic behavior within this latent space is defined by the following time-step operator T_z:

$$z_t = h_\psi(f_t, z_{t-1}) \tag{4}$$

where f_t denotes the reduced wind load feature vector; h_ψ denotes the time-step operator, implemented as a Residual MLP: $z_t = z_{t-1} + g_\psi([z_{t-1}; f_t])$, ensuring temporal continuity and numerical stability.

The training loss is a weighted sum of the single-step prediction error ($L_{1\text{step}}$) and the multi-step rollout error (L_{roll}), balancing short-term accuracy and long-term stability.

3.3. Wind engineering dataset construction

The subject of analysis is a high-rise RC grid frame structure exhibiting linear elastic behavior. To generate input wind loads, the Aerodynamic Database of Tokyo Polytechnic University (TPU) (Tamura, 2012) was utilized. Time-series data of wind pressure coefficients, obtained from wind tunnel experiments on high-rise buildings, were converted into story-level wind loads for application.

The training dataset consists of scenarios based on various wind speed and wind direction conditions. The model is trained under specific wind direction conditions and subsequently tasked with predicting responses to unseen turbulence patterns or extended time domains.

4. RESULT AND DISCUSSION

To ensure the performance of the proposed model from a wind engineering perspective, a comparative analysis was conducted against modal truncation models and direct operators. The proposed model faithfully reproduced fluctuating components and resonant frequencies in along-wind and across-wind directions. It also demonstrated superior accuracy over modal truncation with limited latent dimensions and maintained stability during long-term extrapolation, unlike direct operators.

This study provides a basis for nonlinear reduced-order time-history analysis. Furthermore, by drastically reducing the time required for time-history analysis, it suggests a pathway to facilitate the application of AI technologies in computationally intensive fields.

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