



Original Article

Efficient prediction of turbulent cross flow in helical coil steam generators of SMR via deep learning-driven reduced-order models

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ABSTRACT

SMR have emerged as next-generation nuclear power system, offering enhanced safety, efficiency, and economic advantages. Among their critical components, HCSGs have been extensively studied for their effective heat exchange capabilities. However, primary-side cross flow within HCSG could induce vortices and turbulent structures between tubes, resulting in flow instabilities that negatively impact overall system stability. Large eddy simulation based CFD can accurately capture this complex behavior but requires fine meshes and short time-steps, leading to high computational costs. In this study, a deep-learning-based reduced-order modeling strategy is proposed to maintain both accuracy and computational efficiency in analyzing local flow regions between HCSG tube layers. POD, DMD, and nonlinear autoencoder are employed to reduce data dimensionality, followed by a Long Short-Term Memory network for predicting flow evolution. These ROM frameworks are compared to reduce simulation overhead while preserving CFD-level predictive accuracy. The results indicate that linear methods effectively capture dominant features such as vortex formation and dissipation, whereas the nonlinear autoencoder tends to preserve finer-scale fluctuations. Notably, the POD-LSTM model demonstrates superior performance in predicting flow field dynamics, achieving $R^2 = 0.9701$ on the test set ($AE = 0.9477$, $DMD = 0.9409$).

1. Introduction

Small Modular Reactor (SMR) represent the next generation of nuclear power systems, offering significant advantages in safety, efficiency, and economics compared to traditional large reactors. In particular, the compact design of SMR necessitates miniaturized heat exchangers, thereby requiring innovative approaches to achieve high heat transfer efficiency within limited space. In this context, helical coil steam generators (HCSG) have been recognized for their excellent spatial efficiency and enhanced performance. Their helical configuration increases the heat transfer area, which is critical to the thermal management system of SMR. However, a cross flow occurs as the tube is arranged perpendicular to the flow direction. This cross flow generates vortices and turbulent structures between the tube layers, leading to flow-induced vibrations, nonuniform heat transfer and thermal-load heterogeneity, and flow instabilities that can significantly affect internal stability [1–6]. Therefore, a precise analysis and control of the

primary-side cross flow within HCSG is essential for optimizing design and operational efficiency.

Computational Fluid Dynamics (CFD), including techniques like Large Eddy Simulation (LES), have been employed as powerful tools to capture the complex turbulent structures and vortex phenomena induced by cross flow. Previous studies have utilized LES-based CFD analyses to accurately resolve the cross flow and turbulence patterns arising from the multilayer structure within HCSG, where various tube arrangements, including inline and staggered configurations, were examined [1–4]. They have also combined LES with particle image velocimetry (PIV) experiments to analyze the flow field [5]. These studies have demonstrated that LES can capture complex turbulent structures and vortex shedding phenomena with high fidelity, providing crucial insights into heat transfer and pressure drop characteristics within HCSG. In addition, hybrid RANS/LES approaches such as detached eddy simulation have also been used to examine fluctuation in multilayer helical tube bundles for FIV-related analyses [7]. However,

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LES turbulence models require high-resolution grids and fine temporal discretization, resulting in substantial computational resource demands and extended simulation times. To alleviate this computational burden while maintaining LES-level accuracy in predicting turbulence, artificial intelligence has been proposed as a promising alternative [8].

Direct training on high-dimensional transient CFD data is impractical, necessitating data preprocessing and compression, while deep learning and machine learning increasingly augment and replace traditional thermal fluid simulation [9,10]. Dimensionality-reduction-free, deep-learning-based autoregressive models that directly predict high-dimensional flow fields have been reported to suffer from error accumulation, which limits the stability of long-term predictions [11]. Recent advancements in deep-learning-based flow prediction has given rise to reduced-order model (ROM) based methods that effectively reduce CFD computational costs. Linear reduced-order modeling methods, such as Proper Orthogonal Decomposition (POD) and Dynamic Mode Decomposition (DMD), compress complex flow data into low-dimensional modes, thereby significantly reducing computational burden [12–15]. POD has been successfully applied to decompose cross flow data around the multi-tube layers of HCSG, efficiently extracting dominant flow patterns [4]. In a different line of research, POD has also been used to reduce steam-generator thermal-hydraulic fields, where the resulting low-dimensional representations were learned by an artificial neural network for rapid estimation under various conditions [16]. The low-dimensional data are subsequently combined with time-series models based on Long Short-Term Memory (LSTM) networks to effectively predict the temporal evolution of the flow field [8,17–19]. Furthermore, unsupervised nonlinear reduced-order modeling methods using autoencoders have been actively investigated as alternatives to linear compression methods for efficiently compressing high-dimensional CFD data [8,18–21]. For nuclear system applications, DMD-based reduced-order modeling coupled with LSTM networks has been applied to efficiently predict flow and structural responses from high-dimensional unsteady data [22]. Research applying ROM and deep learning to LES-based unsteady flow-field prediction for components in SMR systems, particularly HCSG tube bundles, remains limited. Moreover, fair comparisons of diverse dimensionality-reduction methods and prediction models using the same dataset are even rarer. Therefore, this study systematically compares the performance of multiple ROM techniques and deep learning architectures under identical conditions. The results provide clear evidence for model selection and clarify the applicability and limitations of ROM-based surrogate modeling for unsteady flow-field prediction.

The objective of this study is to establish a practical benchmark for ROM-based surrogate modeling that supports real-time inference in SMR digital twin applications, focusing on HCSGs as a critical thermal-hydraulic component. Because high-dimensional LES/CFD data are too expensive to be used directly in real-time workflows, dimensionality reduction is a prerequisite for reliable and efficient unsteady flow-field prediction. Using LES-based CFD data, this study analyzes primary-side cross flow characteristics in an HCSG and develops an efficient training dataset. Dominant modes are extracted using linear reduced-order modeling methods and coupled with an LSTM network to build ROM-LSTM models. Additionally, an Autoencoder-LSTM model is investigated as a nonlinear reduced-order approach. The predictive performance and compression efficiency of POD, DMD, and autoencoder-based methods are systematically compared under identical conditions to identify an effective strategy for this HCSG case study.

2. Numerical analysis and datasets

2.1. Computational domain and geometry

This study considers a localized primary-side cross-flow region of an SMR HCSG. The tube diameter (12 mm), radial pitch (17 mm), and axial pitch (13.5 mm) were taken from the design report of the System-

integrated Modular Advanced Reactor (SMART) developed by the Korea Atomic Energy Research Institute [23]. Since simulating the entire steam generator cassette is impractical, the analysis domain was simplified to a local section by arranging the tube layers in a 3×3 array and sufficiently extending the lower wake region to capture flow development. Vortical structures generated by cross flow in tube layers are predominantly governed by localized wake interactions arising from boundary-layer separation between adjacent tubes. Consequently, a 3×3 array encompassing the eight immediate neighbors of a central tube can be regarded as the minimum representative volume element (RVE) that captures the statistical characteristics of these local vortical flows.

Replicating the actual helical configuration would increase the complexity of mesh generation and numerical analysis due to the tube rotation. Therefore, the tubes were modeled as straight pipes oriented perpendicular to the flow direction. The present study employs a simplified configuration in which the helical coil is idealized as a straight tube-bank model and the helix angle is neglected. While this controlled benchmark setup facilitates systematic comparisons, it is not strictly equivalent to the real primary-side flow in an HCSG [1]. Coil curvature and helix angle may introduce curvature effects and secondary motions, potentially altering dominant modes and fluctuation spectra. Accordingly, the conclusions of this work are limited to the benchmark tube-bank dataset used here under identical conditions. The overall domain dimensions were set to a depth of 0.02 m, a width of 0.056 m, and a height of 0.08 m, as shown in Fig. 1. Previous research reported negligible mean out-of-plane motion ($\langle w \rangle$) for a tube-bank idealization [1], and thus the depth was kept small (0.02 m) to reduce computational cost while focusing on the dominant in-plane dynamics for ROM training.

The objective of the present study is not a detailed analysis of vortical or turbulent structures, but rather the development and validation of a ROM-based framework for dimensionality reduction and time-series prediction of localized cross flow dynamics. In future work, we plan to increase the axial domain extent (incorporating a longer downstream wake) to mitigate entrance effects, thereby improving flow development and statistical convergence before extending the framework toward more realistic HCSG geometries.

2.2. Mesh and data points set-up

A polyhedral mesh was generated for the entire computational domain, consisting of 2,088,286 cells. The domain was divided into a fine and coarse cell zone. A relatively fine mesh was applied in the vicinity of the tubes and other key flow regions to capture the vortex and turbulent structures, ensuring $y^+ < 0.8$ on the tube walls with a viscous-layer growth rate of approximately 1.2. In addition, the LES resolution indicator was monitored over the fine cell zone only, confirming $k_{sgs}/(k_{sgs} + k_{resolved}) < 0.15$. In contrast, a coarser mesh was used in the downstream region, which was not the primary focus of this study, to reduce computational costs. Subsequently, to enhance training efficiency and reduce the complexity of the deep learning models (Autoencoder, POD, and DMD - LSTM), data corresponding to the XY plane were extracted from the three-dimensional simulation results. Specifically, the localized region between the second and third rows in the second column of the 3×3 tube array was selected. Fig. 2 illustrates the computational mesh on the selected two-dimensional sampling plane extracted from the three-dimensional domain (left), and the uniform stationary grid used for snapshot construction on the same plane (right). On this local 2D plane, 22,878 grid points were defined, and the velocity magnitude was recorded at each time-step and interpolated onto a stationary grid to form a snapshot. At the three points (A, B, and C) shown in Fig. 2 (right), the temporal evolution of the velocity fluctuations between the tube layers will be monitored. These locations were selected to sample representative regions of the strongest flow non-uniformity induced by the downward cross-flow around the tube sides within the inter-layer gap. The resulting data provide informative time

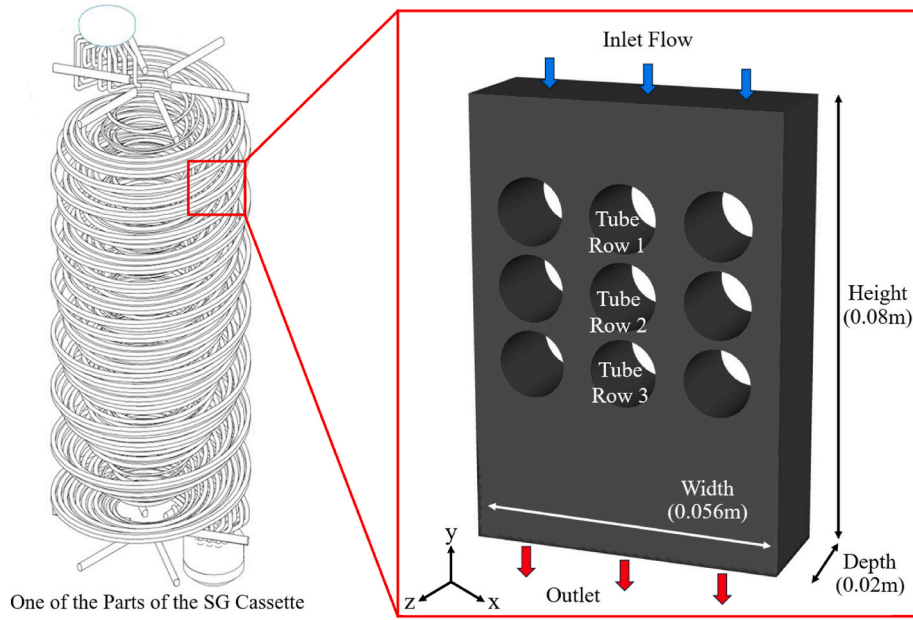


Fig. 1. One of the parts of the SG cassette [23] and fluid domain of this study.

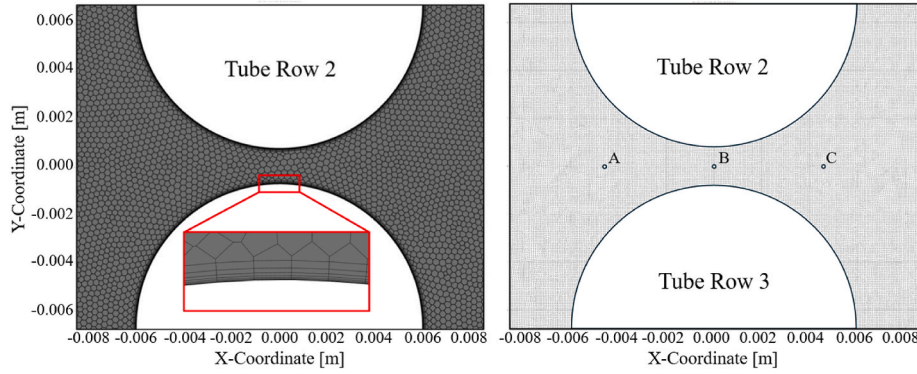


Fig. 2. Computational mesh of local 2-D region (Left) and grid points distribution (Right).

signals for subsequent ROM-based time-series prediction.

Although the benchmark LES is three-dimensional, the present study adopts a two-dimensional snapshot representation as a cost-effective first step to learn and validate the dominant local cross-flow dynamics and the ROM-LSTM workflow. Extending the same pipeline to 3D increases the degrees of freedom approximately in proportion to the number of spanwise layers, $N_{3D} \approx N_{2D}N_z$ (with $N_{2D} = 22,878$ points), which directly amplifies data storage and I/O. In the present dataset, one 2D snapshot requires ~ 1.74 MB (~ 5.22 GB for 3000 snapshots), and this scales to $\sim 5.22N_z$ GB in 3D (e.g., ~ 208 GB for $N_z = 40$). This increase raises the costs of linear decomposition and online prediction/reconstruction. The limitation of the 2D representation in capturing spanwise structures is acknowledged, and a full 3D extension is reserved as a next step.

2.3. Boundary conditions and solver settings

Numerical simulation data were generated using ANSYS FLUENT 24R2. At the inlet, a uniform flow with a velocity of $V_\infty = 0.5983$ m/s was applied, and the initial Reynolds number, calculated as $Re = (\rho V_\infty D_h)/\mu$, was approximately 1.4×10^5 . The outlet boundary was set as a pressure-outlet with a gauge pressure of 0 Pa. The tube walls were modeled as no-slip walls to account for viscous effects between the fluid

and the solid surfaces, while the remaining domain boundaries were assumed to be free-slip walls. For turbulence modeling, the LES-based Wall-Adapting Local Eddy-viscosity (WALE) model was employed. Pressure-velocity coupling was handled via the Coupled algorithm, temporal discretization used a Second-order implicit scheme, and the momentum equations were spatially discretized using the Second-order upwind method, thereby enhancing simulation accuracy.

2.4. Time stepping and data extraction

A steady-state simulation was first conducted to establish a developed flow field, which was then used as the initial condition for the transient analysis. The time-step size was set to 2×10^{-4} s, and the simulation was carried out for a total of 3000 steps, corresponding to a time interval from 0 to 0.6 s. At each time-step, velocity magnitude data on the selected two-dimensional plane (comprising 22,878 grid points) were extracted to form a snapshot, enabling the analysis of vortex formation and the temporal evolution of the turbulent structures.

2.5. Training and test dataset construction

Among the 3000 snapshots generated, the first 2000 steps (0-0.4 s) were used for training, and the remaining 1000 steps (0.4-0.6 s) were

reserved for testing. This study aims to develop a scenario-specific ROM-based surrogate for a fixed HCSG operating condition, rather than constructing a fully parametric model across varying boundary conditions or geometries. Accordingly, all snapshots correspond to a single operating condition (fixed inlet velocity and geometry), and this controlled benchmark setting is adopted to enable a fair and isolated comparison among different ROM strategies and their downstream time-series prediction performance. Extension of the framework to different Reynolds numbers, pitch ratios, or flow directions would necessitate the use of multi-condition datasets, along with data augmentation or conditional-ROM methodologies. The training and test datasets were split chronologically to evaluate roll-out (extrapolative) prediction of unsteady dynamics within the same physical regime. The training snapshots were compressed using linear ROM methods (POD, DMD) and a nonlinear ROM method (Autoencoder), and the resulting latent representations were used as inputs to the LSTM model. For the linear decompositions, POD and DMD bases were constructed using only the training snapshots (time steps 1–2000) to avoid potential information leakage. The test interval (time steps 2001–3000) was used only by projecting the test snapshots onto the fixed POD/DMD bases to obtain the corresponding coefficients and by evaluating the LSTM roll-out predictions. This setup enables a consistent comparison of predictive accuracy and computational efficiency across ROM frameworks.

3. Reduced-order modeling methods for deep learning framework

The purpose of this study is to reduce the order of transient flow datasets and train an LSTM network to predict vortex and turbulent flow phenomena occurring between tubes in the HCSG while comparing various order reduction methodologies. To achieve this, flow features are extracted from CFD simulation snapshots and then used as input to the LSTM network for forecasting future flow fields. This section details the procedures for dimension reduction using POD, DMD, and autoencoder techniques, along with the architecture of the LSTM network. In this study, three approaches—traditional linear methods (POD and DMD) and nonlinear autoencoders—are adopted to efficiently compress CFD data, which is then used as input for an LSTM-based time-series prediction framework.

3.1. Linear reduced-order modeling methods

Among linear reduced-order modeling methods, Proper Orthogonal Decomposition (POD) is employed to extract dominant spatial structures in high-dimensional flow data, revealing the characteristic flow patterns. POD approximates the original system in a lower-dimensional subspace by extracting an orthogonal basis that preserves the principal energy or variance of the system [12]. In this study, the variations in velocity magnitude are organized as a space–time function, and snapshots obtained at specific time instants t_i are used to construct the following flow matrix:

$$U = \begin{bmatrix} u(x_1, t_1) - \bar{u}(x_1) & u(x_1, t_2) - \bar{u}(x_1) & \cdots & u(x_1, t_m) - \bar{u}(x_1) \\ \vdots & \vdots & \ddots & \vdots \\ u(x_n, t_1) - \bar{u}(x_n) & u(x_n, t_2) - \bar{u}(x_n) & \cdots & u(x_n, t_m) - \bar{u}(x_n) \end{bmatrix}, \quad (1)$$

where, n represents the number of grid points (in space), m represents the number of snapshots (in time), and in the case of the position vector, it is represented as $x = (x, y)$. Subsequently, a singular value decomposition (SVD) is performed on the snapshot matrix U , which can be expressed as follows:

$$U = \Phi \Sigma V^T. \quad (2)$$

In the above equation, Φ is an $n \times m$ orthogonal matrix whose columns

represent the POD modes $\phi_i(x)$. Through the SVD in Eq. (2), these modes are obtained as the left singular vectors of the snapshot matrix U . The POD modes can also be interpreted as eigenvectors of the spatial correlation matrix UU^T , with the corresponding eigenvalues given by σ_i^2 . Here, Σ is a $m \times m$ diagonal matrix containing the singular values σ_i , and V is an $m \times m$ orthogonal matrix. By retaining a prescribed number of leading singular values, most of the energy in the dataset can be captured, and the flow field is approximated as a linear combination of the dominant modes:

$$u(x, t) \approx \sum_{i=1}^r a_i(t) \phi_i(x). \quad (3)$$

Here, r denotes the number of leading modes chosen, and $a_i(t)$ represents the time-dependent coefficients. POD decomposes the flow field into spatially orthogonal modes and is known for its nice performance in extracting large-scale vortex structures from turbulent flows.

Another linear reduced-order modeling method employed in this study is Dynamic Mode Decomposition (DMD). DMD is a method that identifies spatiotemporal coherent structures associated with specific frequencies and growth/decay rates. In contrast to POD, which focuses on extracting spatial modes that preserve most of the energy, DMD assumes a linear temporal evolution and extracts modes and eigenvalues that directly capture the system's frequency content and stability characteristics [14]. To accomplish this, a snapshot matrix is first constructed from the flow data, and a second snapshot matrix is obtained by shifting the data by one time-step as shown in

$$X_1 = \begin{bmatrix} \nu(x_1, t_1) - \bar{\nu}(x_1) & \nu(x_1, t_2) - \bar{\nu}(x_1) & \cdots & \nu(x_1, t_{m-1}) - \bar{\nu}(x_1) \\ \vdots & \vdots & \ddots & \vdots \\ \nu(x_n, t_1) - \bar{\nu}(x_n) & \nu(x_n, t_2) - \bar{\nu}(x_n) & \cdots & \nu(x_n, t_{m-1}) - \bar{\nu}(x_n) \end{bmatrix}, \quad (4)$$

$$X_2 = \begin{bmatrix} \nu(x_1, t_2) - \bar{\nu}(x_1) & \nu(x_1, t_3) - \bar{\nu}(x_1) & \cdots & \nu(x_1, t_m) - \bar{\nu}(x_1) \\ \vdots & \vdots & \ddots & \vdots \\ \nu(x_n, t_2) - \bar{\nu}(x_n) & \nu(x_n, t_3) - \bar{\nu}(x_n) & \cdots & \nu(x_n, t_m) - \bar{\nu}(x_n) \end{bmatrix}. \quad (5)$$

Performing a singular value decomposition on X_1 yields a low-dimensional orthogonal basis. Only the top r modes that represent the highest energy content are retained for dimensionality reduction, as indicated in

$$X_1 = U \Sigma V^T. \quad (6)$$

The time evolution is assumed to be governed by a linear operator A , and instead of using the high-dimensional operator A , a low-dimensional operator $\tilde{A}$ obtained by projecting A onto the subspace spanned by U_r , derived from the SVD, is employed:

$$X_2 \approx A X_1, \quad (7)$$

$$\tilde{A} = U_r^T X_2 V_r \Sigma_r^{-1}. \quad (8)$$

Through the eigen-decomposition of the low-dimensional operator $\tilde{A}$, the eigenvalues and eigenvectors are obtained by solving the eigenvalue problem $\tilde{A} w_k = \lambda_k w_k$, where λ_k and w_k denote the eigen values and eigenvectors, respectively. These eigenvalues capture the growth, decay, and oscillatory frequency characteristics of the modes. Here, w_k are the eigenvectors of the reduced operator $\tilde{A}$, and the corresponding full-state DMD modes ϕ_k in the original state space are reconstructed by Eq. (9). In the high-dimensional space, the DMD modes, denoted by ϕ_k , represent the spatially distributed modal structures and can be reconstructed as follows:

$$\phi_k = X_2 V_r \Sigma_r^{-1} w_k. \quad (9)$$

By expressing the time evolution of each mode as $e^{i\lambda_k t}$ and incorporating the initial condition coefficients b_k , whose product $b_k e^{i\lambda_k t}$ is commonly referred to as the temporal coefficient in DMD, the complete state vector $v(x, t)$ can be reconstructed as

$$v(x, t) \approx \sum_{k=1}^r b_k e^{i\lambda_k t} \phi_k(x). \quad (10)$$

DMD is known for its exceptional performance in quantitatively analyzing time-varying flow fields by sorting the system's frequencies and isolating the impact of each frequency component on the flow dynamics. In DMD, the snapshot-to-snapshot evolution of the flow field is approximated by a linear mapping, and an eigen decomposition of this operator yields DMD modes and their corresponding eigenvalues. The eigenvalues encode the growth or decay rates and the oscillation frequencies of the modes, so each mode represents a coherent spatial structure associated with a single characteristic frequency. This frequency-resolved representation enables identification of dominant unsteady mechanisms and their contributions to the overall flow dynamics.

3.2. Nonlinear reduced-order modeling methods

An autoencoder is a nonlinear neural network architecture that trains to compress input data into a latent space and then reconstruct it back to the original dimension [21]. Unlike linear dimension reduction methods such as POD or DMD, an autoencoder leverages nonlinear activation functions to more flexibly capture complex data distributions. Specifically, at time t , the high-dimensional state vector $v(t)$ is mapped to a latent variable $z(t)$ via an encoder function, and subsequently, the original-dimension vector $v(t)$ is reconstructed from $z(t)$ using a decoder function, as shown below:

$$z(t) = f(v(t)), \quad (11)$$

$$\tilde{v}(t) = h(z(t)). \quad (12)$$

Here, f and h correspond to the encoder and decoder, respectively. Through this process, the autoencoder compresses the key features of the data into the latent space, effectively eliminating noise and capturing the complex structure of high-dimensional simulation data. Recent studies have demonstrated that this approach provides superior representational capability compared to POD or DMD in terms of improved reconstruction fidelity, including better preservation of small-scale (high frequency) fluctuations and strongly nonlinear dynamics [18].

3.3. Long Short-Term Memory network

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed to handle sequential data such as time-series [19]. Conventional RNNs often struggle to learn long-range dependencies due to vanishing or exploding gradients, and LSTM mitigates this limitation by introducing an explicit memory (cell) state and a gating mechanism. To address the long-term dependency problem, LSTM networks incorporate a dedicated memory cell that stores and conveys past information reliably. Within an LSTM, several gates interact to selectively update and manage the incoming information and past state, enabling the network to learn and retain important patterns over long sequences.

More specifically, the input gate regulates the incorporation of new data into the cell state, the forget gate determines which information from previous states should be discarded, and the output gate selects the relevant parts of the cell state to be passed on to subsequent layers. As illustrated in Fig. 3, the LSTM cell receives the current input x_t together with the previous hidden state h_{t-1} and the previous cell state c_{t-1} . The forget gate f_t controls how much information is retained from c_{t-1} , and the input gate i_t regulates how much of the candidate cell state $\tilde{c}_t$ is written into the updated cell state. The cell state is updated as

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \quad (13)$$

and the output gate o_t determines the hidden state h_t via

$$h_t = o_t \odot \tanh(c_t), \quad (14)$$

where $\odot$ denotes element-wise multiplication.

In this study, the LSTM is trained on low-dimensional time coefficients obtained from POD and DMD, or on latent vectors obtained from the autoencoder, and it is used in an autoregressive manner to predict the next low-dimensional state over the test interval. The predicted coefficients (or latent vectors) are then mapped back to the high-dimensional flow field through the corresponding ROM reconstruction. Leveraging its robust handling of complex temporal dynamics, this research employs LSTM to train on LES data spanning 0 to 0.4 s and to predict the flow field from 0.4 to 0.6 s, which is a core aspect of our approach for accurate turbulence prediction in flow simulations.

To ensure a consistent and robust temporal predictor across ROM variants, a sensitivity test was conducted by varying the LSTM hidden units (64-512) and the number of stacked LSTM layers (1-3). Tables 1 and 2 show that the prediction accuracy improves up to 256 hidden units but does not further increase with larger widths, while deeper LSTMs consistently degrade R^2 in the time-extrapolation regime. Accordingly, a single-layer LSTM with 256 hidden units is adopted as the common temporal predictor in the following ROM-LSTM frameworks, so

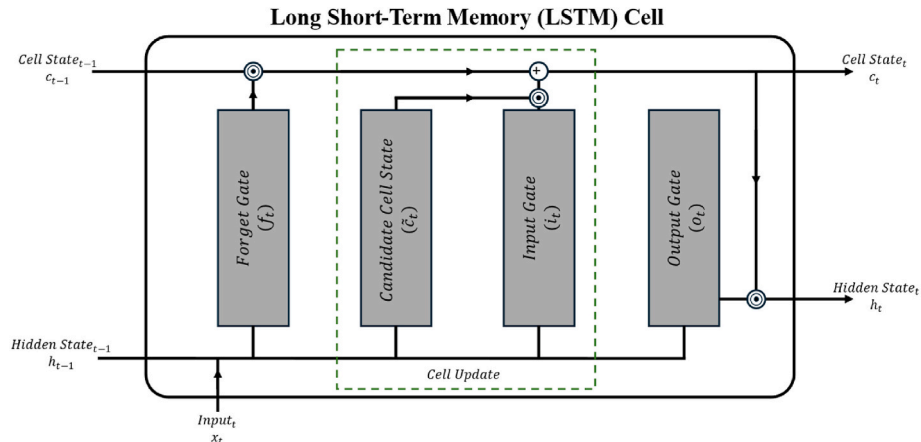


Fig. 3. Schematic of an LSTM cell.

Table 1Effect of LSTM hidden units on forecasting R^2 (1-Layer).

Linear-ROM	64	128	256	512
POD	0.9565	0.9656	0.9701	0.9684
DMD	0.9364	0.9375	0.9409	0.9385

Table 2Effect of stacked LSTM layers on forecasting R^2 (256 units).

Linear-ROM	1	2	3
POD	0.9701	0.9553	0.9503
DMD	0.9409	0.9302	0.9270

that the comparative results primarily reflect differences in the spatial reduction/representation methods rather than differences in the temporal model capacity.

3.4. Linear and nonlinear ROM-LSTM method

We propose a novel ROM framework that integrates methods such as POD, DMD, and autoencoders with an LSTM network to forecast future flow fields from CFD snapshot data. Each technique was implemented using TensorFlow/Keras, and all models were trained with the Adam optimizer with a learning rate set to 0.001, utilizing the mean squared error loss function, a batch size of 32, and for 100 epochs. To prevent overfitting during training, callback functions such as EarlyStopping and ReduceLROnPlateau were employed. These functions halt training early or progressively reduce the learning rate when the validation loss does not improve over a specified period, thereby stabilizing the optimization process. The proposed framework connects linear techniques (POD, DMD) and a nonlinear autoencoder to an LSTM-based prediction model, enabling comparative evaluation of compression efficiency and forecasting accuracy for transient flow field analysis.

In the POD-LSTM approach, POD is applied to the entire dataset comprising 2000 time-steps to extract the top 50 spatial POD modes and their corresponding temporal coefficients. These coefficients are then segmented using a sliding window of length 5 and fed into the selected LSTM architecture to predict future temporal coefficients, which are subsequently used to reconstruct the full-order data. The test interval (time steps 2001–3000) is used only by projecting the test snapshots onto the fixed POD modes to compute the coefficients and by evaluating the LSTM roll-out predictions.

The DMD-LSTM method follows a similar procedure, where DMD is used to extract 50 dynamic modes that encapsulate the system's frequency content and stability characteristics. An LSTM network with the same sequence length and architecture is then employed to forecast the DMD temporal coefficients, using the same temporal predictor configuration as POD-LSTM, which are used to reconstruct the high-dimensional state.

In the Autoencoder-LSTM approach, the high-dimensional input data $v(t) \in \mathbb{R}^N$ is nonlinearly compressed into a 50-dimensional latent space $z(t) \in \mathbb{R}^N$ via an encoder composed of fully connected layers with 512, 256, and 50 units. The decoder reverses this process through layers with 256 and 512 units followed by a reconstruction to the original dimension. The latent vectors obtained from the trained encoder are segmented using a sliding window and fed into the same LSTM temporal predictor to predict future latent states, which are then mapped back to the high-dimensional space using the decoder.

The prediction performance of the model was evaluated using three key metrics. First, the coefficient of determination R^2 quantifies how well the model explains the data by comparing the differences between the actual values y_i and the predicted values $\hat{y}_i$. It typically ranges between 0 and 1. R^2 is computed as shown in

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}, \quad (15)$$

where $\bar{y}$ denotes the mean value of the actual data.

The second metric is the mean squared error (MSE), defined as the average of the squared differences between the actual and predicted values across all data points:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2. \quad (16)$$

In order to express the prediction error in the same units as the original data, the root mean squared error (RMSE) is also employed, which is calculated as the square root of the MSE;

$$RMSE = \sqrt{MSE}. \quad (17)$$

4. Results and discussion

4.1. Characterization of cross flow dynamics

A CFD analysis was conducted to capture complex flow characteristics, such as vortex formation between tube layers induced by cross flow, confirming that the selected case is well-suited for our research. Fig. 4 presents streamlines of the velocity field from six snapshots extracted between 0.1 s and 0.6 s. Observations indicate that flows from the left and right sides alternately collide with the lower tube, forming stagnation points, while the resulting the wake vortex oscillates aperiodically from side to side. Moreover, the size of these vortices varies over time, and since the flow patterns observed in the six snapshots do not repeat, they cannot be regarded as representative of the entire flow structure.

To further quantify this non-repeating behavior, we used the POD temporal coefficients and defined a simple regime indicator from the sign of the second coefficient $a_2(t)$ with a small deadband to avoid spurious flips. Over the training record, the flow exhibits intermittent regime switching with a mean dwell time of $1.67 \times 10^{-2} \text{ s}$ ($\pm 1.38 \times 10^{-2} \text{ s}$) and a range of $6.02 \times 10^{-4} - 6.42 \times 10^{-2} \text{ s}$. The positive- and negative- a_2 states occur with comparable occupancy ($\approx 54.1\%$ vs. 45.9%) within the finite record, indicating that both regimes are sufficiently sampled for the present benchmark analysis. Finally, the short record length limits very-low-frequency characterization ($f_{min} \approx 1/T \approx 2.5 \text{ Hz}$), so slower regime persistence would require longer records.

The present LES dataset is constructed as a controlled single-condition benchmark to develop and validate the proposed ROM framework, rather than to establish fully developed long-time statistics. Therefore, the dataset design prioritizes sufficiently sampling representative unsteady dynamics, such as wake interactions and mixing, that are relevant for short-horizon reconstruction and forecasting. These findings suggest that the cross flow within the HCSG exhibits complex and diverse dynamic patterns. Unlike canonical Karman vortex shedding with clear periodicity, the aperiodic flow considered here does not hinge on resolving a specific phase. Instead, it is more important to capture a broad range of patterns within a finite time window, including intermittent regime switching. Based on this rationale, 2000 snapshots were used for training and 1000 snapshots for testing. Furthermore, given the non-periodic and highly complex nature of the flow, applying dimension reduction techniques for feature extraction is crucial to effectively capture multi-scale structures and identify key patterns.

4.2. Dimension reduction with POD, DMD and autoencoder

In reduced-order modeling methods that project high-dimensional data onto a lower-dimensional subspace, data loss during the mapping

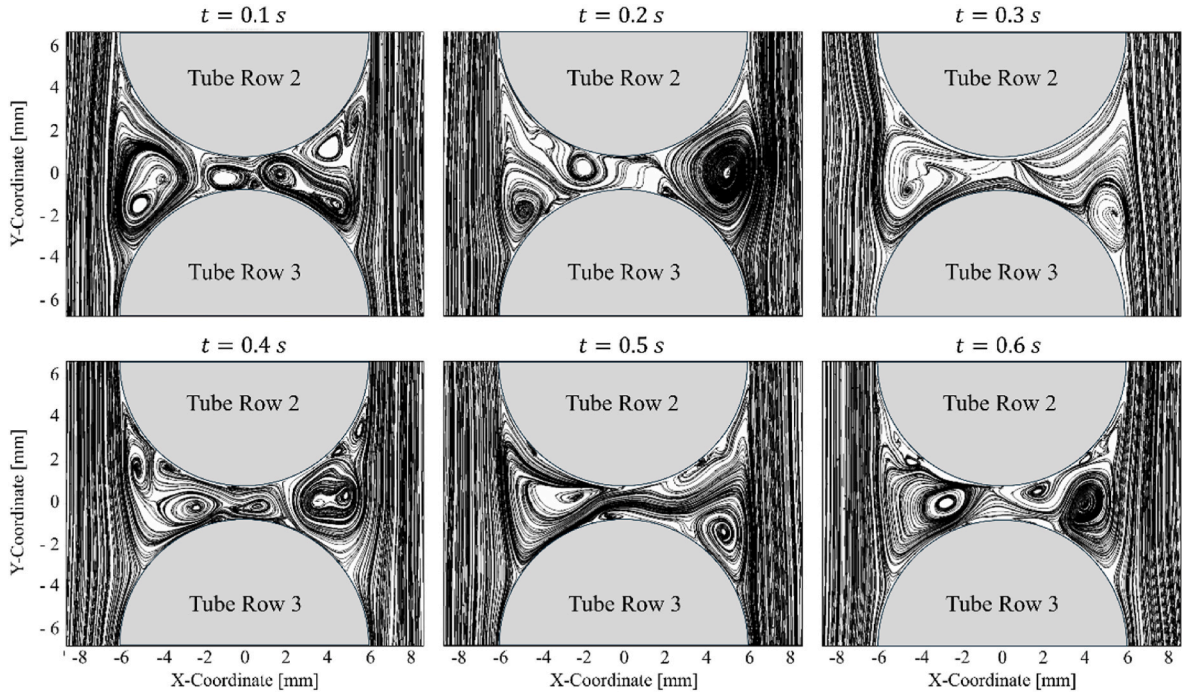


Fig. 4. Streamlines of the velocity fields occurring between tube row 2 and 3.

back to the original high-dimensional space is an inherent consequence. Therefore, the level of dimensionality reduction in the low-dimensional subspace must yield reconstruction errors that are within acceptable limits. In these methods, the dimensionality of the reduced subspace is determined by the number of leading spatial modes for POD and DMD, and by the number of neurons in the network's bottleneck layer in the case of an autoencoder. To determine a reliable compression level, POD and DMD analyses were conducted on the training dataset. Fig. 5 illustrates the energy distribution for each mode extracted by the two linear reduction techniques, showing that the top 5 modes capture approximately 58% of the energy, the top 25 modes capture roughly 90%, and the top 50 modes capture about 96%. In POD, the energy represents the total variance contained in the data, corresponding to the direction with the highest energy, while in DMD the energy metric is defined such that it best reconstructs the time evolution operator over the temporal segmentation. Consequently, the bottleneck layer in the autoencoder was parameterized to have 5, 25, and 50 neurons, and the models were trained and tested on both the training and test datasets. The R^2 values for the test dataset are presented in Table 3. For POD and the autoencoder, increasing the dimension of the reduced space enhances reconstruction accuracy and reduces approximation error, whereas the accuracy for DMD decreases slightly, albeit without a significant

Table 3

Approximation errors (R^2) of the dimension reduction.

Dimension	POD-LSTM	DMD-LSTM	AE-LSTM
5	0.9526	0.9453	0.9440
25	0.9658	0.9480	0.9446
50	0.9701	0.9409	0.9477

difference. To ensure a fair comparison across POD, DMD, and autoencoder compression, we fixed the reduced dimension to 50 when evaluating ROM-LSTM prediction performance, thereby controlling the state dimension provided to the LSTM. This choice is supported by the reconstruction sensitivity results (5/25/50) and is consistent with prior studies that compare POD rank truncation and autoencoder bottleneck dimensions at matched latent sizes [18].

Fig. 6 displays the first three features (modes) extracted using POD (Above) and DMD (Below), respectively. Although both POD and DMD are decomposition-based linear reduced-order modeling methods, the modes they produce differ. The main reason is that POD modes capture the spatial patterns that maximize the variance of the data, thereby identifying the most significant structures, while DMD modes focus on the temporal evolution, representing dynamic characteristics such as

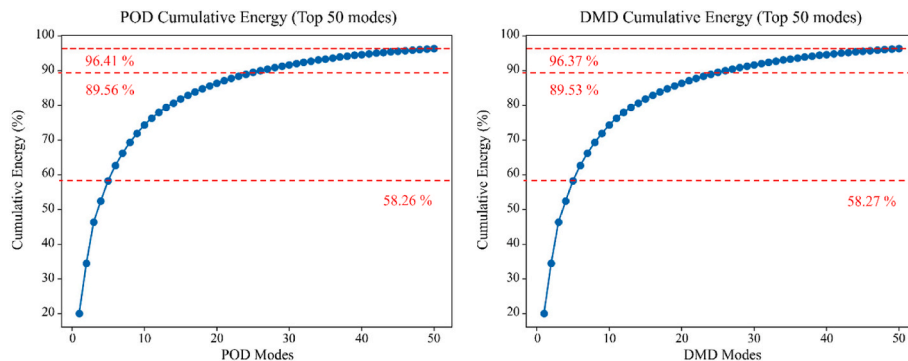


Fig. 5. Cumulative energy and percentage; POD (Left) and DMD (Right).

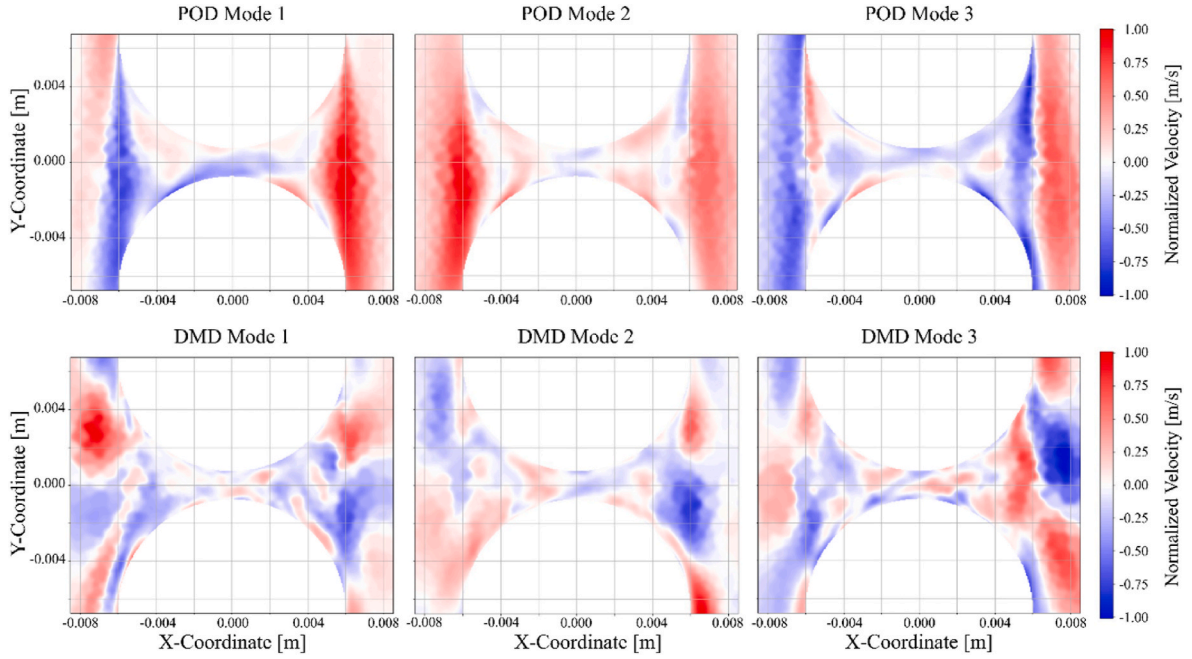


Fig. 6. Top 3 modes of POD (Top) and DMD (Bottom).

oscillation and growth or decay rates. Moreover, the eigenvalues and eigenvectors obtained from DMD contain imaginary components that encode oscillatory frequencies and spatial phase information; for clarity, the imaginary parts of the DMD modes are omitted in the contour plots. Consequently, the DMD modes presented in Fig. 6 (Below) correspond to modes one, three, and five rather than one, two, and three.

Furthermore, spectral analysis of the POD temporal coefficients within the training dataset reveals a distinct physical hierarchy, where the mean dominant frequency increases from 14.6 Hz for the first 10 modes to 67.4 Hz for modes 41–50 (*Spearman* $\rho = 0.64$). This systematic scale separation indicates that the training data encapsulates multiscale flow dynamics, ranging from large-scale wake motions to higher-frequency fluctuations, and provides a physically interpretable basis for reduced-order feature learning and subsequent time-series prediction.

4.3. Comparison between ROM-LSTM models

This section compares the future state prediction performance of the three proposed ROM frameworks (POD-LSTM, DMD-LSTM, and Autoencoder-LSTM) validated on both training (for reconstruction) and test (for prediction) datasets, with a uniform compression dimension of 50. Table 4 reports the R^2 , MSE, and RMSE values, showing that POD-LSTM achieved the highest test accuracy ($R^2 = 0.9701$), followed by Autoencoder-LSTM ($R^2 = 0.9477$) and DMD-LSTM ($R^2 = 0.9409$), although RMSE analysis indicates that none fully replaces CFD. Fig. 7 displays the temporal variation of velocity at points A, B, and C (Fig. 2, right), where the gray regions denote reconstructed training data and the white regions represent predicted test data. All models show a decrease in prediction accuracy over time, especially at point A, although they still capture general trends in this LES-based turbulent

flow characterized by non-periodicity and irregular vortex formation and decay. Fig. 8 shows velocity-magnitude contours at three test times, where POD-LSTM and DMD-LSTM attenuate small-scale fluctuations through dimensionality reduction, thereby emphasizing the dominant large scale vortical structures. Meanwhile, Autoencoder-LSTM tends to preserve finer-scale content, which can be beneficial for representing small scale turbulence but may also introduce sensitivity to spurious fluctuations during multi-step prediction. Because the narrow flow passage between tube layers produces strongly constrained and intermittent vortical motions, POD-LSTM provides the most consistent reconstruction of the dominant vortical patterns in this dataset. Further validation is still required for larger-scale configurations with more grid points and multiple tube layers.

Fig. 9 compares the power-spectral density (PSD) of velocity-fluctuation signals at monitoring points A, B, and C. The top row represents the reconstruction (training) interval (time-steps 1–2000) and the bottom row represents the prediction (test) interval (time-steps 2001–3000). In this study, PSD was computed for the scalar velocity-fluctuation time series at each point. Here, the scalar velocity fluctuation was defined as the mean-removed fluctuation of the three-dimensional velocity magnitude, $u'_{mag}(t) = |u(t)| - |\bar{u}|$, where $|u(t)| = \sqrt{u(t)^2 + v(t)^2 + w(t)^2}$. Therefore, directional information from individual vector components (u, v, w) is not included. The low-to-mid-frequency band (5–150 Hz) primarily reflects the dominant large-scale unsteady structures and the main portion of the energy-containing dynamics at the selected monitoring points. In the reconstruction window, all three models show modest integrated errors: even at point A, where fluctuations are the largest, the error is about 12%, and at points B and C the POD and DMD models differ by roughly 2%, with the AE model at about 4%. For frequencies above 150 Hz, the error exceeds 50% for

Table 4

R^2 and MSE of the examined models for the prediction and reconstruction.

Data	POD-LSTM			DMD-LSTM			AE-LSTM		
	R^2	MSE	RMSE	R^2	MSE	RMSE	R^2	MSE	RMSE
Train	0.9965	1.45e-03	0.038	0.9965	1.46e-03	0.038	0.9886	4.71e-03	0.069
Test	0.9701	1.26e-02	0.112	0.9409	2.48e-02	0.157	0.9477	2.19e-02	0.148

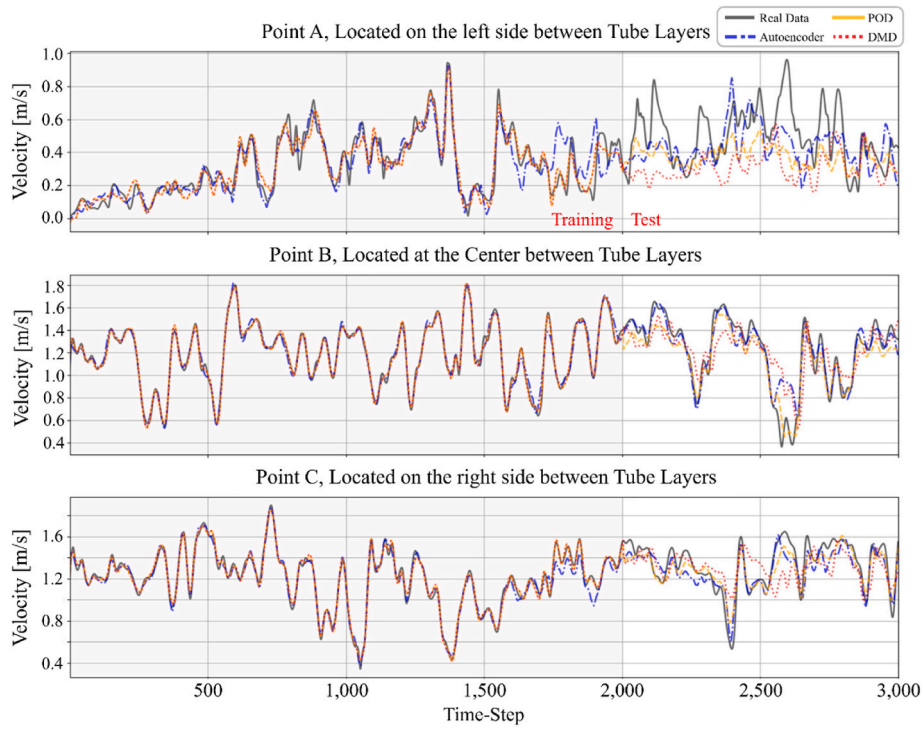


Fig. 7. Time evolution of the velocity magnitude at A, B, C; predictions against the real data.

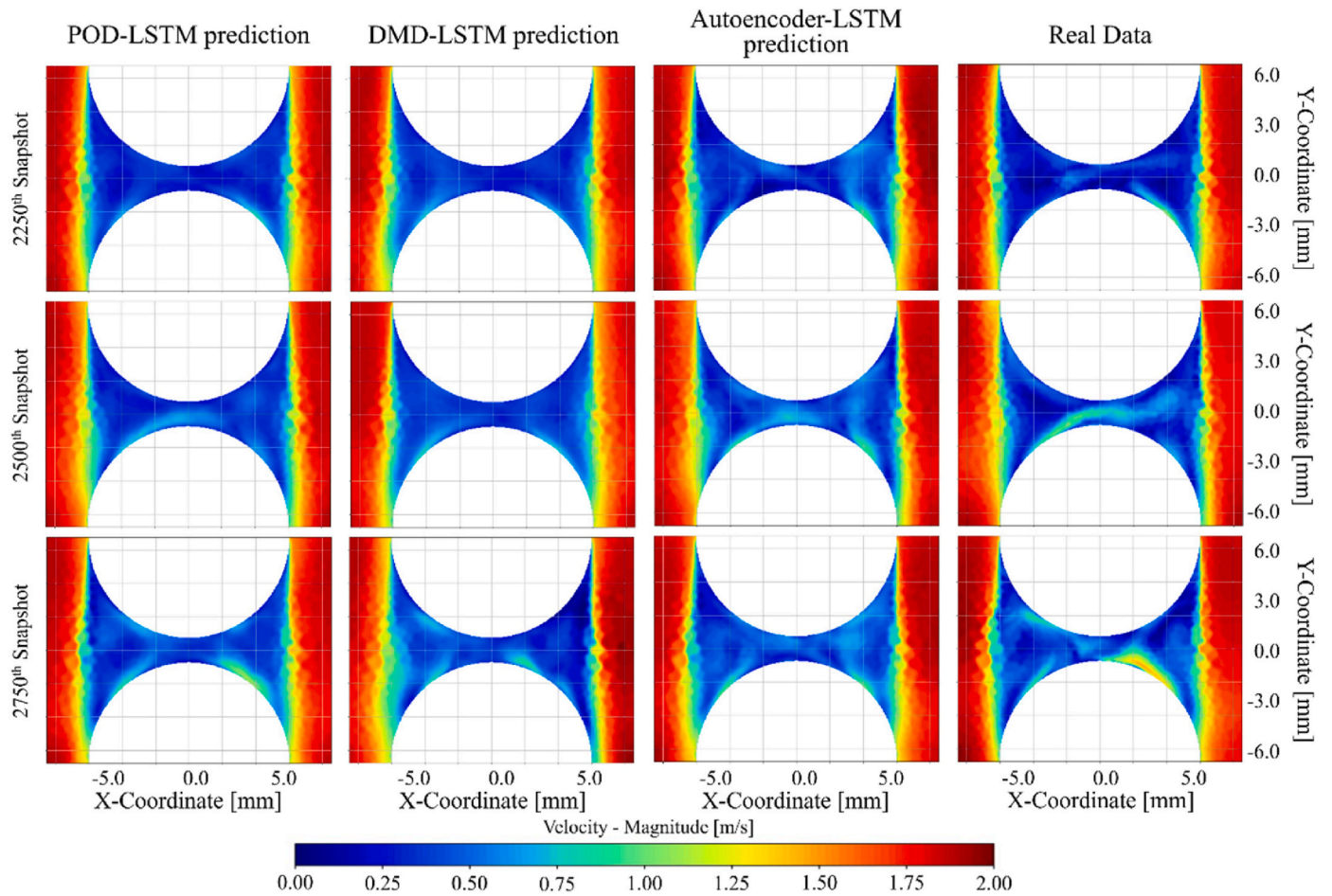


Fig. 8. Velocity magnitude contours at the 2,250th, 2,500th, and 2,750th (Prediction and Real data).

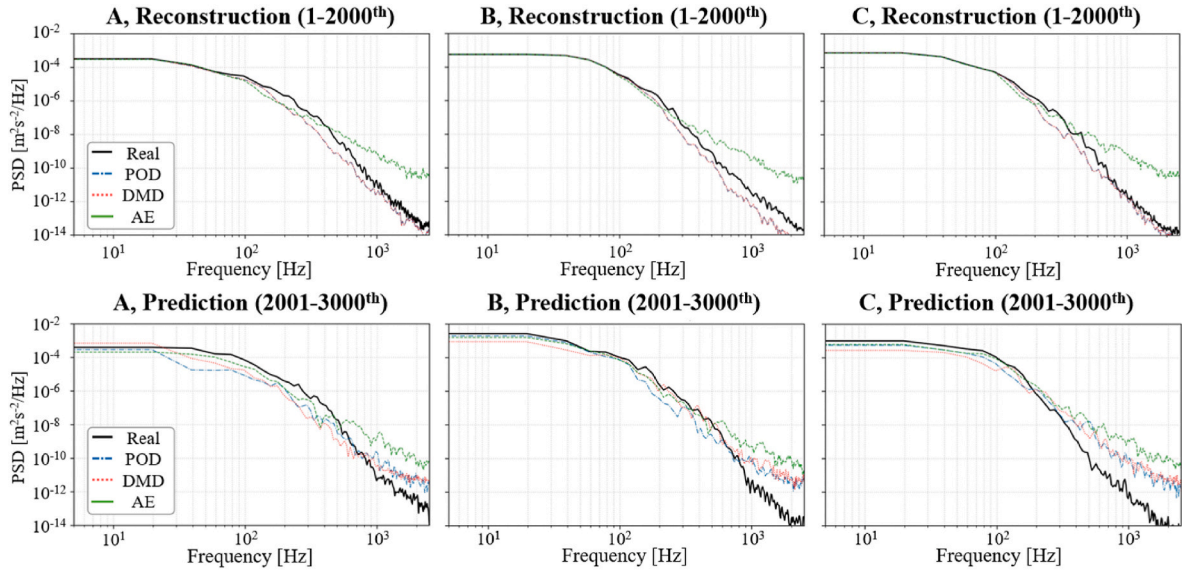


Fig. 9. PSD comparison of velocity fluctuation signals at A, B, and C.

every model, indicating that fine-scale fluctuations are strongly attenuated or distorted by dimensional compression. As a result, apparent agreement in the high-frequency tail should be interpreted cautiously because the spectral energy level is low and the content may be suppressed rather than faithfully reproduced. In the prediction window, the low-to-mid-frequency errors increase significantly. At point A, the POD and DMD models exceed 70% error, whereas the AE model remains lower at about 52%. This trend is consistent with Fig. 8, where the autoencoder-based representation tends to preserve finer-scale content, which can reduce the loss of higher-frequency fluctuations at this location. At points B and C, the POD and AE models keep the error below 40%, but the DMD model still exceeds 60%.

Overall, linear ROM-LSTM frameworks reproduce dominant flow structures with acceptable accuracy within the training window. However, roll-out (time-extrapolative) prediction deteriorates, particularly in capturing fine-scale vortices, due to mode truncation and limitations of the linear basis. In addition, the current models predict only velocity magnitude and thus do not represent directional components. To overcome these limitations, we will develop a multi-variable ROM-LSTM that predicts both velocity magnitude and components (u , v , w) and extend PSD analyses to each component to better characterize directional turbulence. We will also explore basis enrichment/adaptation, hybrid linear-nonlinear frameworks, and spectral-loss terms to retain more modal energy and preserve fine-scale structures. In addition, since

the present models are trained under a single operating condition, changes in operating or geometric parameters can shift the underlying dynamics and amplify roll-out errors; therefore, future work will construct multi-condition datasets and develop parametric/conditional ROM frameworks with conditioning inputs (e.g., Reynolds number and pitch ratios), supported by transfer learning and data augmentation to reduce additional CFD/LES requirements.

4.4. Detailed comparison of coefficient prediction in linear reduction methods

To provide a more detailed comparison between the two linear dimension-reduction techniques, Fig. 10 presents the actual and predicted coefficients for each method on the test dataset. In both POD-LSTM (left) and DMD-LSTM (right), the decomposition extracts the mean velocity, modes, and coefficients from the data. The mean velocity and modes remain fixed, while each model predicts coefficients to reconstruct the flow field via inverse decomposition. Fig. 10 (left) demonstrates that the time coefficient predictions for POD are sufficiently accurate even for this non-periodic turbulent flow case. In contrast, Fig. 10 (right) shows that DMD's temporal coefficient predictions trends notably degraded over certain intervals.

DMD-LSTM performs worse than POD due to inherent DMD limitations. It applies to a single linear evolution operator over the entire data

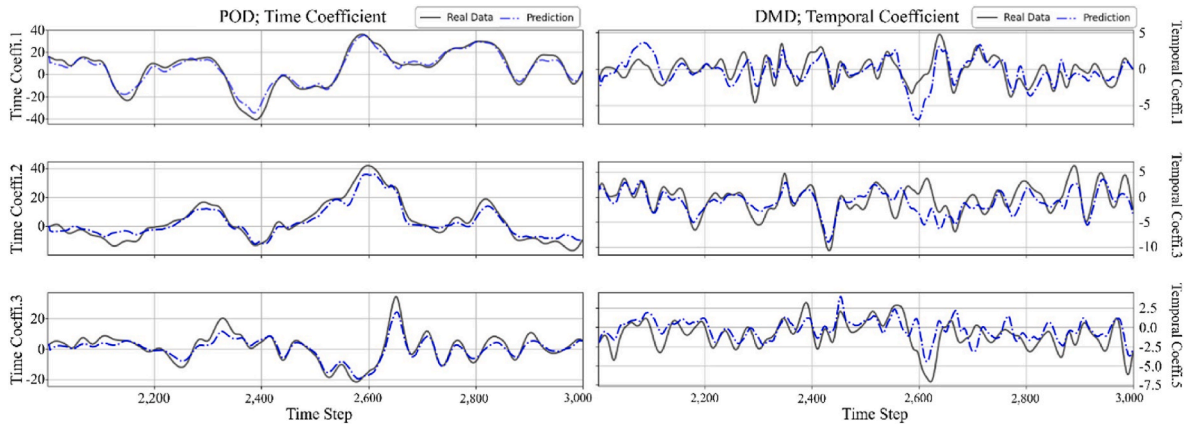


Fig. 10. Time evolution of the velocity magnitude at A, B, C; predictions against the real data.

window, which fails in non-periodic turbulent flows where dynamics change continuously. As a result, coefficient errors accumulate over time. And DMD modes are non-orthogonal, and their eigenvalues are sensitive to numerical noise, so even small prediction inaccuracies get amplified during reconstruction. In contrast, POD uses an energy-optimal, orthogonal basis that is more robust to noise, and its coefficients are learned independently for each mode, preventing error propagation.

4.5. Computational efficiency and cost analysis

This section compares the computational efficiency of the proposed ROM frameworks with the baseline LES. The total cost is divided into an offline stage for model construction (dimensionality reduction and LSTM training) and an online stage for prediction (inference and reconstruction).

As shown in Table 5, the LES wall-clock time for 1000 steps (0.4–0.6 s) was 33 h 24 min. In contrast, the online inference time of all ROM frameworks was measured to be approximately 35.5–39.2 s, which corresponds to a speed-up of about $3100\text{--}3400 \times$ relative to LES ($t_{\text{ROM}}/t_{\text{LES}} \approx 3.1 \times 10^{-4}$). Among the models, POD-LSTM achieved the fastest online inference (35.485 s, $3388 \times$), while AE-LSTM required the longest offline time (93.5 s) due to training of neural-network-based encoder/decoder components. Overall, once constructed, the ROM enables accurate and rapid assessment of unsteady flow dynamics at a negligible computational cost compared to high-fidelity LES.

A 3D extension would increase the input dimension approximately by a factor of N_z , thereby increasing storage/I/O and the ROM decomposition and online reconstruction costs accordingly. Moreover, maintaining comparable accuracy in 3D may require a larger latent dimension than the present $r = 50$, which would further increase online projection/reconstruction costs ($O(Nr)$) and the training burden of the temporal predictor.

5. Conclusion

This study demonstrates the potential of deep neural network-based reduced order models for predicting complex unsteady flows in helical coil steam generators while showcasing a creative integration of advanced deep learning techniques with physics-based CFD analysis. By combining traditional linear methods (POD and DMD) with LSTM-based time-series prediction and nonlinear compression via autoencoders, we developed three ROM frameworks (POD-LSTM, DMD-LSTM, and Autoencoder-LSTM) to reconstruct and forecast flow dynamics from LES-based CFD data. Furthermore, by systematically comparing the performance of POD, DMD and AE based ROMs coupled with LSTM under identical LES datasets and training conditions, this study is significant as it establishes the efficacy of specific methods through a controlled comparison rather than isolated case studies. These findings serve as a foundational reference for model selection in the development of thermal-hydraulic surrogate models for nuclear applications.

Our results indicate that although all methods capture dominant flow structures, they exhibited distinct characteristics. In the testing interval based on an identical compression dimension of 50, POD-LSTM demonstrated the highest prediction accuracy ($R^2 \approx 0.97$), while Autoencoder-LSTM and DMD-LSTM recorded slightly lower levels ($R^2 \approx 0.95$ and 0.94 , respectively). Specifically, POD-LSTM excels in reconstructing primary vortical patterns, whereas Autoencoder-LSTM possesses a strength in effectively capturing finer turbulent features.

In the low-to-mid-frequency band (4–150 Hz) the reconstructed coefficients remain within an acceptable error range, whereas the extrapolated predictions exhibit much larger errors, revealing the mathematical limits of the current ROM formulations. Such error growth during time extrapolation suggests that, from a digital twin perspective, stable long-term prediction requires reinforcement strategies, such as (i)

Table 5

Computational costs for training (Offline) and test (Online).

Method	Offline [s]	Online [s]	Speed-up [$\times$]
POD-LSTM	29.119	35.485	3388
DMD-LSTM	30.685	39.153	3071
AE-LSTM	93.515	38.715	3106
CFD	-	120,240	1

longer training time-series, (ii) physics-preserving constraints or spectral-preserving loss terms, and (iii) adaptive or hybrid ROMs.

The integration of both linear and nonlinear reduced-order modeling with deep learning techniques highlights the strategy employed in this research to address the challenges associated with high-dimensional and high-capacity LES data for SMR heat exchanger applications. The ROM-based surrogate framework proposed in this study can serve as a pivotal enabler for achieving 'near-real-time inference' and digital twin implementation in nuclear thermal-hydraulic analysis, where repetitive execution of computationally expensive LES is impractical. Quantitatively, the proposed ROMs achieved end-to-end online inference times of 35.5–39.2 s for the 0.4–0.6 s window (1000 snapshots), compared to 33 h 24 min for LES, corresponding to a speed-up of approximately $3.1 \times 10^3 - 3.4 \times 10^3$. Particularly for components requiring iterative assessment from design and safety perspectives, such as HCSGs in SMRs, these findings are significant as they quantitatively delineate the basis for ROM selection and their application limits.

Future research will extend the analysis to larger domains to assess scalability and further refine the ROM techniques to enhance prediction accuracy. To better capture spatial-temporal correlations as the framework is extended to 3D flows with more complex spatial patterns, CRNN-based models will also be considered. In addition, the model will be upgraded to predict multiple flow variables rather than a single variable, velocity magnitude. Specifically, the study plans to enlarge the modal basis beyond 50 modes or employ adaptive mode selection, and to explore hybrid ROMs that blend linear and nonlinear approaches together with spectral-loss terms to conserve small-scale vortices. These enhancements aim not only to reproduce low-frequency dominant structures but also to predict high-frequency turbulent details with higher fidelity. In addition, advanced error validation based on continuous wavelet transforms (CWT) will be adopted to exploit the non-stationary frequency components that are crucial for capturing the highly intermittent vortex dynamics present in these flows.

CRediT authorship contribution statement

Bumjin Cho: Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Chaehyeon Song:** Methodology, Data curation, Conceptualization. **Minseo Lee:** Methodology, Formal analysis, Data curation, Conceptualization. **Joongoo Jeon:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Minseop Song:** Writing – review & editing, Writing – original draft, Supervision, Investigation, Funding acquisition, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

- [1] S.J. Lee, Y.A. Hassan, Numerical investigation of helical coil tube bundle in turbulent cross flow using large eddy simulation, *Int. J. Heat Fluid Flow* 82 (2020) 108529, <https://doi.org/10.1016/j.ijheatfluidflow.2019.108529>.
- [2] H.R. Barsamian, Y.A. Hassan, Large eddy simulation of turbulent crossflow in tube bundles, *Nucl. Eng. Des.* 172 (1997) 103–122, [https://doi.org/10.1016/S0029-5493\(97\)00034-4](https://doi.org/10.1016/S0029-5493(97)00034-4).
- [3] S.J. Lee, S. Lee, Y.A. Hassan, Numerical investigation of turbulent flow in an annular sector channel with staggered semi-circular ribs using large eddy simulation, *Int. J. Heat Mass Tran.* 123 (2018) 705–717, <https://doi.org/10.1016/j.ijheatmasstransfer.2018.03.026>.
- [4] S. Lee, Y.A. Hassan, Flow structures of the cross-flow over a five-layer helically coiled steam generator geometry, *Int. J. Heat Fluid Flow* 95 (2022) 108950, <https://doi.org/10.1016/j.ijheatfluidflow.2022.108950>.
- [5] J.K. Lai, E. Merzari, Y.A. Hassan, Large eddy simulation of the flow behavior in a simplified helical coil steam generator, *J. Fluid Eng.* 141 (2) (2019) 021401, <https://doi.org/10.1115/1.4040464>.
- [6] K. Liu, M. Wang, J. Zhang, K. Guo, W. Tian, S. Qiu, G.H. Su, Numerical investigation on the thermal load heterogeneity of multi-assembly helical coil steam generator in high temperature gas-cooled reactor, *Energy* 281 (2023) 128355, <https://doi.org/10.1016/j.energy.2023.128355>.
- [7] K. Liu, H. Qiu, M. Wang, J. Zhang, K. Guo, W. Tian, G. Su, Helium turbulent fluctuation characteristics in the multilayer helical tube bundle using improved delayed detached eddy simulation, *Phys. Fluids* 37 (3) (2025) 035131, <https://doi.org/10.1063/5.0256950>.
- [8] B. Zhang, Airfoil-based convolutional autoencoder and long short-term memory neural network for predicting coherent structures evolution around an airfoil, *Comput. Fluids* 258 (2023) 105883, <https://doi.org/10.1016/j.compfluid.2023.105883>.
- [9] A. Ayodeji, M.A. Amidu, S.A. Olatubosun, Y. Addad, H. Ahmed, Deep learning for safety assessment of nuclear power reactors: reliability, explainability, and research opportunities, *Prog. Nucl. Energy* 151 (2022) 104339, <https://doi.org/10.1016/j.pnucene.2022.104339>.
- [10] C.-W. Chang, N.T. Dinh, Classification of machine learning frameworks for data-driven thermal fluid models, *Int. J. Therm. Sci.* 135 (2019) 559–579, <https://doi.org/10.1016/j.ijthermalsci.2018.09.002>.
- [11] S. Khanal, S. Baral, J. Jeon, Comparison of CNN-based deep learning architectures for unsteady CFD acceleration on small datasets, *Nucl. Eng. Technol.* 57 (10) (2025) 103703, <https://doi.org/10.1016/j.net.2025.103703>.
- [12] J. Weiss, A tutorial on the proper orthogonal decomposition, in: *AIAA Aviation 2019 Forum*, 2019, <https://doi.org/10.2514/6.2019-3333>, Dallas, TX, June 17–21.
- [13] J. Wang, G. Huang, W. Lu, P.E. Sullivan, Dynamic mode decomposition analysis of flow separation in a diffuser to inform flow control strategies, *J. Fluid Eng.* 142 (2) (2020) 021502, <https://doi.org/10.1115/1.4044981>.
- [14] J.H. Tu, C.W. Rowley, D.M. Luchtenburg, S.L. Brunton, J.N. Kutz, On dynamic mode decomposition: theory and applications, *J. Comput. Dynam.* 1 (2) (2014) 391–421, <https://doi.org/10.3934/jcd.2014.1.391>.
- [15] T. Meng, Y. Wang, S. Qin, P. Liu, Y. Wang, C. Tao, Z. Liu, Complex flow field analysis in multi-shaft stirred reactors: dynamics of wave-vortex coupling revealed by POD and DMD methods, *Chem. Eng. Sci.* 301 (2025) 120753, <https://doi.org/10.1016/j.ces.2024.120753>.
- [16] S. He, M. Wang, J. Zhang, W. Tian, S. Qiu, G.H. Su, A deep-learning reduced-order model for thermal hydraulic characteristics rapid estimation of steam generators, *Int. J. Heat Mass Tran.* 198 (2022) 123424, <https://doi.org/10.1016/j.ijheatmasstransfer.2022.123424>.
- [17] Z. Xing-Wei, C. Jian-Qiao, Z. Ke, Z. Shi-Xiong, Y. Guang-Ping, Predictions for unsteady flow fields with deep learning models of LSTM and GRU, *IEEE Access* 12 (2024) 144788–144811, <https://doi.org/10.1109/ACCESS.2024.3473012>.
- [18] H. Eivazi, H. Veisi, M.H. Naderi, V. Esfahanian, Deep neural networks for nonlinear model order reduction of unsteady flows, *Phys. Fluids* 32 (10) (2020) 105104, <https://doi.org/10.1063/5.0020526>.
- [19] S. Hochreiter, J. Schmidhuber, Long short-term memory, *Neural Comput.* 9 (8) (1997) 1735–1780, <https://doi.org/10.1162/neco.1997.9.8.1735>.
- [20] K. Fukami, Y. Nabae, K. Kawai, K. Fukagata, Synthetic turbulent inflow generator using machine learning, *Phys. Rev. Fluids* 4 (6) (2019) 064603, <https://doi.org/10.1103/PhysRevFluids.4.064603>.
- [21] K. Berahmand, F. Daneshfar, E.S. Salehi, F. Yousefi, Y. Farjami, Autoencoders and their applications in machine learning: a survey, *Artif. Intell. Rev.* 57 (2024) 28, <https://doi.org/10.1007/s10462-023-10662-6>.
- [22] Y. Zhang, P. Li, H. Qiao, Fast prediction of the flow induced vibration of wire-wrapped fuel rod in a lead-bismuth reactor based on improved DMD and LSTM network, *Nucl. Eng. Technol.* 57 (11) (2025) 103780, <https://doi.org/10.1016/j.net.2025.103780>.
- [23] KAERI, Basic Design Report of SMART, KAERI, Daejeon, Korea, 2002. KAERI/TR-2142/2002.