

Deep learning for turbulent boundary layers: spatio-temporal reconstruction and prediction

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Abstract: Spatio-temporal prediction of turbulent flow fields remains a challenging task due to complex multi-scale dynamics and high-dimensional data. Recent advances in deep learning offer promising data-driven approaches, yet their comparative performance under physical constraints warrants further investigation. In this study, a physics-informed neural network (PINN) framework and a long short term memory (LSTM) network are implemented and systematically compared for the spatio-temporal prediction of turbulent boundary layer flows over a wide range of Reynolds numbers. Both models are trained and tested using simulated data from a shock-induced turbulent boundary layer and experimental data from particle image velocimetry (PIV) measurements of turbulent channel flow. Prediction accuracy is evaluated across multiple time horizons, with particular attention to short-term and extended temporal extrapolation. Results indicate that the PINN framework achieves higher physical fidelity and robustness in reconstructing velocity and pressure fields from sparse or incomplete data, especially in scenarios requiring alignment with fundamental flow physics. The comparative analysis highlights the complementary strengths and limitations of physics-embedded and purely data-driven deep learning approaches for turbulent flow prediction, providing guidance for method selection based on prediction horizon, data availability, and physical accuracy requirements.

Keywords: Turbulent boundary layer flow; physics-informed neural networks; long- and short-term memory network; spatial reconstruction; time prediction;

Introduction

Spatio-temporal prediction of flow fields is a fundamental challenge in fluid mechanics, with critical applications across engineering, aerospace, and environmental sciences. Traditional high-fidelity numerical simulations, while accurate, are computationally prohibitive for real-time or large-scale analyses. This limitation has driven the development of alternative methodologies, evolving from classical model reduction techniques to contemporary data-driven paradigms.

Initially, methods like Proper Orthogonal Decomposition (POD) and Dynamic Mode Decomposition (DMD) provided avenues for dimensionality reduction and extraction of coherent structures^[1]. However, their linear foundations often struggle with the inherent nonlinearity and multi-scale nature of turbulent flows. The advent of big data in fluid mechanics, fueled by advanced experiments and simulations, has enabled a shift toward machine learning. Deep learning architectures, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional capability as universal approximators for tasks such as spatial super-resolution and reconstruction of flow fields from sparse data. Zhao et al. ^[2] introduced a neural operator capable of zero-shot super-resolution, with reconstruction accuracy matching or surpassing that of conventional CNN-based methods.

For temporal prediction, Recurrent Neural Networks (RNNs) and their advanced variant, Long Short-Term Memory (LSTM) networks, have become prominent. LSTMs are uniquely designed to model sequential data, using gating mechanisms to capture long-term dependencies, a crucial feature for forecasting the evolution of dynamic flows. They have been successfully integrated into Reduced-Order Modeling (ROM) frameworks, where auto encoders compress spatial data and LSTMs learn the latent temporal dynamics, enabling efficient prediction of complex unsteady flows. Hybrid models like ConvLSTM further unify spatial and temporal learning, while combinations with Generative Adversarial Networks (GANs) enhance the generation of coherent sequences from incomplete data. More recently, LSTM-based and hybrid architectures have been extended from single-condition forecasting to parametric flow evolution across design spaces, providing improved flexibility for reduced-order prediction and surrogate modeling [3].

Despite their power, a core limitation of purely data-driven methods like LSTMs is their physics-agnostic nature. They learn statistical patterns without inherent constraints from governing physical laws, which can lead to physically inconsistent predictions, especially when extrapolating beyond the training domain. This gap in interpretability and reliability has spurred the development of physics-informed machine learning.

Physics-Informed Neural Networks (PINNs), introduced by Raissi et al., represent a paradigm shift by directly embedding physical laws into the learning process [4]. PINNs augment the standard data loss with a residual term from the governing Partial Differential Equations, ensuring the model's solutions respect underlying physics. This framework excels at solving both forward and inverse problems, such as reconstructing complete flow and pressure fields from sparse or noisy experimental measurements. Variants like Conservative PINNs (CPINNs) and Bayesian PINNs (B-PINNs) have been developed to handle complex domains and uncertainty quantification. In turbulence research, PINNs have shown promise in data assimilation and reconstructing challenging flows like turbulent boundary layers. Baramnia et al. [5] investigated flow and heat transfer in turbulent boundary layers using PINN, finding that the Prandtl number in the heat equation significantly influences the neural network structure, and that PINN predictions closely match numerical results. Hasanuzzaman et al. [6] proposed a PINN framework that integrates the RANS equation into the loss function, enabling accurate reconstruction of PIV-measured flow fields and prediction of Reynolds stresses. Wang et al. [7] employed tomographic PIV to obtain a three-dimensional (3D) sparse velocity field over a hemisphere; they reconstructed the dense velocity field with high precision and used PINN to predict the pressure field, demonstrating its potential for experimental data assimilation. Cai et al. [8] measured the temperature field above a coffee cup using tomographic background schlieren image (TBSI) measurement technology, and then predicted the velocity and pressure fields via PINN based on the measured temperature data.

Nevertheless, the application of PINN to spatiotemporal optimization and prediction of complex three-dimensional turbulent flow fields still faces several challenges. For high-Reynolds-number flows, PINN models require longer training times and exhibit lower fitting accuracy, which limits their practicality for engineering applications [9]. Furthermore, when dealing with intricate turbulent structures and multi-scale features, PINN's predictive accuracy remains insufficient, often failing to fully satisfy experimental requirements. Consequently, improving PINN's capability to predict complex 3D turbulent flows remains a key research priority.

Conversely, LSTMs offer flexible and powerful sequence learning but typically lack physical guarantees. However, regardless of the network architecture used in spatiotemporal prediction frameworks, the effectiveness of predictions depends not only on the model structure but also critically on the temporal organization of the input data [10]. Specifically, three key factors, namely, the length of the historical sequence, the temporal stride between consecutive samples, and the alignment between the input window and the target prediction horizon, determine how completely the model can capture the underlying flow dynamics [11]. Prior research indicates that an insufficient or poorly chosen history length can hinder convergence, degrade control or prediction performance, and amplify

forecast errors as the prediction horizon increases ^[12]. These issues become even more pronounced when data are limited. Therefore, a systematic assessment of the training window configuration is essential for building reliable data-driven models of unsteady flows.

This context highlights a clear trade-off: LSTMs deliver strong empirical performance in learning temporal dynamics but may violate physical principles, whereas PINNs enforce physical consistency yet face computational and optimization challenges. To address this gap, the present study implements and rigorously compares LSTM and PINN frameworks for predicting turbulent boundary layer flows across a range of Reynolds numbers. Using both simulated and experimental (PIV) data, we evaluate their performance in four key aspects: accuracy in short-term temporal extrapolation, robustness to sparse data, physical consistency of outputs, and computational efficiency. Through this comparative analysis, we clarify the strengths and operational boundaries of each approach, thereby providing guidance for method selection and paving the way for future hybrid models that synergistically combine data-driven learning with physical faithfulness.

2. Methodology

2.1 Physics-informed neural network

PINNs are a class of deep neural networks that learn input-output mappings by incorporating physical laws such as PDEs directly into the loss function. By minimizing this physics-informed loss through gradient descent and leveraging automatic differentiation, they efficiently approximate PDE solutions while avoiding the curse of dimensionality inherent in traditional methods. Thus the expression is as follows,

$$(U, p) = F_{NN}(X, t, \sigma) \quad (1)$$

Where the outputs U, p is the velocity and the pressure of the flow field, while the inputs (X, t, σ) represents spatial coordinates, time coordinates, and activation function hyperparameters. F_{NN} denotes this neural network.

During neural network backpropagation, the weight parameters of the network are updated by minimizing a total loss function via gradient descent. This total loss comprises two primary components: the data residual, measuring the difference between predicted values and observed data, and the equation residual, enforcing the constraints defined by the governing partial differential equations. For compressible flow fields, the total loss function L_{total} is defined as follows,

$$L_{\text{total}} = \alpha L_{\text{data}} + \beta L_{\text{eqns}} \quad (2)$$

$$L_{\text{data}} = \sum_{j=1}^{N_{\text{data}}} |U_{\text{data}}(X^j, t^j) - U_{\text{pred}}(X^j, t^j)|^2 \quad (3)$$

$$L_{\text{eqns}} = \sum_{i=1}^4 \sum_{j=1}^{N_{\text{data}}} e_i(X^j, t^j) \quad (4)$$

$$\begin{cases} e_1 = \rho u_t + \rho u u_x + \rho v u_y + \rho w u_z + P_x - \frac{1}{\text{Re}}(u_{xx} + v_{yy} + w_{zz}) \\ e_2 = \rho v_t + \rho u v_x + \rho v v_y + \rho w v_z + P_y - \frac{1}{\text{Re}}(u_{xx} + v_{yy} + w_{zz}) \\ e_3 = \rho w_t + \rho u w_x + \rho v w_y + \rho w w_z + P_z - \frac{1}{\text{Re}}(u_{xx} + v_{yy} + w_{zz}) \\ e_4 = \rho_x + \rho_y + \rho_z \end{cases} \quad (5)$$

Here, L_{total} denotes the total loss function, where α and β are weighting coefficients. L_{data} represents the data residual (computed via mean squared error), while L_{eqns} is the governing equations residual. The latter is derived from the Navier-Stokes equations: momentum conservation (e_1, e_2, e_3) and mass conservation (e_4). An Adam optimizer is used during network training.

The network maps spatio-temporal inputs (x, y, t) to the outputs (u, v, p) through 8 hidden layers with 20 neurons each, using Tanh activation functions and a linear output layer.

2.2 Long- and short-term memory network

For reproducibility, the main hyper-parameters of the LSTM architecture are summarized as follows. A single LSTM layer with hidden dimension $H = 50$ is used. At each time step, the input is a three-component velocity vector $\mathbf{x}_t = [U_t, V_t, W_t]^T \in \mathbb{R}^3$. The network takes an input window of length L_{in} (chosen according to the characteristic time scale of the flow, e.g. several vortex-shedding periods) and predicts the subsequent $L_{out} = 10$ time steps. The internal activation $\phi(\cdot)$ is implemented as ReLU, while all gates use the sigmoid nonlinearity. No dropout is applied in this study. Network structure diagram of LSTM is shown in Figure 1.

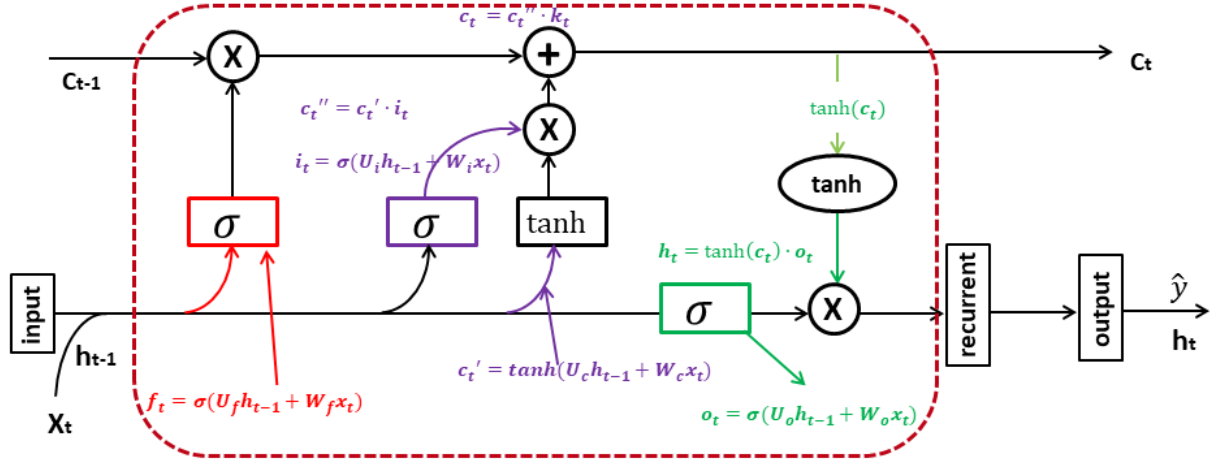


Figure 1 Network structure diagram of LSTM

3. Results and Discussion

In this section, PINN and LSTM Networks are employed to investigate high-precision flow field reconstruction and time prediction of turbulent boundary layer flows across a wide range of Reynolds numbers ($Re_\delta = 3700 \sim 1.26 \times 10^5$, where δ is the thickness of the turbulent boundary layer), using both numerical simulations and experimental data. The performance of PINN and LSTM is thoroughly evaluated in terms of convergence rate and learning accuracy for turbulent flow problems.

3.1 Spatial reconstruction of turbulent flow fields

Reconstructing flow field data from incomplete measurements is a computationally demanding inverse problem. Traditional solutions rely on interpolation or variational methods, but in recent years, several optimization frameworks that incorporate sparse measurements along with physical constraints have been proposed to address this challenge. For turbulent flow reconstruction, which requires both high spatial resolution and rigorous physical consistency, PINNs offer a promising solution because they naturally combine sparse observational data with the governing equations.

In this study, we first consider a supersonic flow at $Ma = 1.85$ featuring shock-wave/turbulent-boundary-layer interaction, simulated using the LES method. This flow serves as the training dataset for investigating spatial reconstruction via PINN. The turbulent flow field is visualized in Figure 2 using an iso-surface at $\Omega_R = 0.52$. From the fully developed turbulent stage, a subdomain (indicated by a blue box in the figure) is extracted as the original simulation dataset, with a spatiotemporal size of $N_{data} = N_x \times N_y \times t = 100 \times 100 \times 100$. We then assume that a region of missing data exists within this original dataset (as illustrated in the subdomain flow field of Figure 2). PINN is applied to reconstruct the full flow field from this incomplete dataset, thereby further validating its data-assimilation capability.

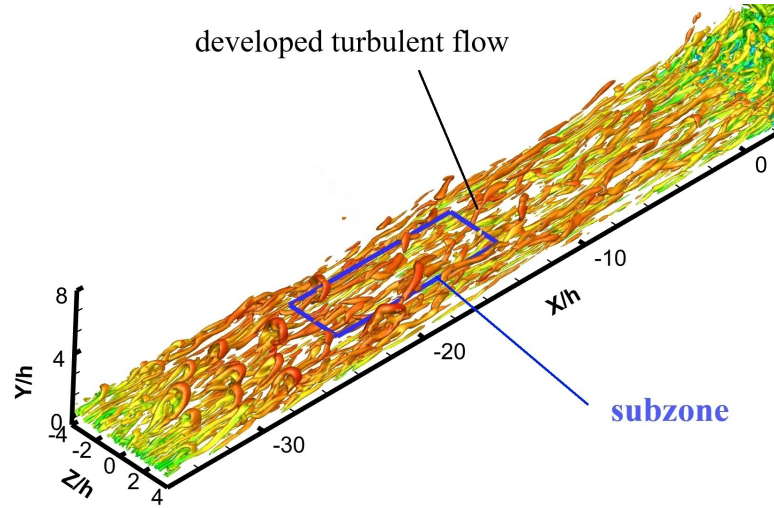
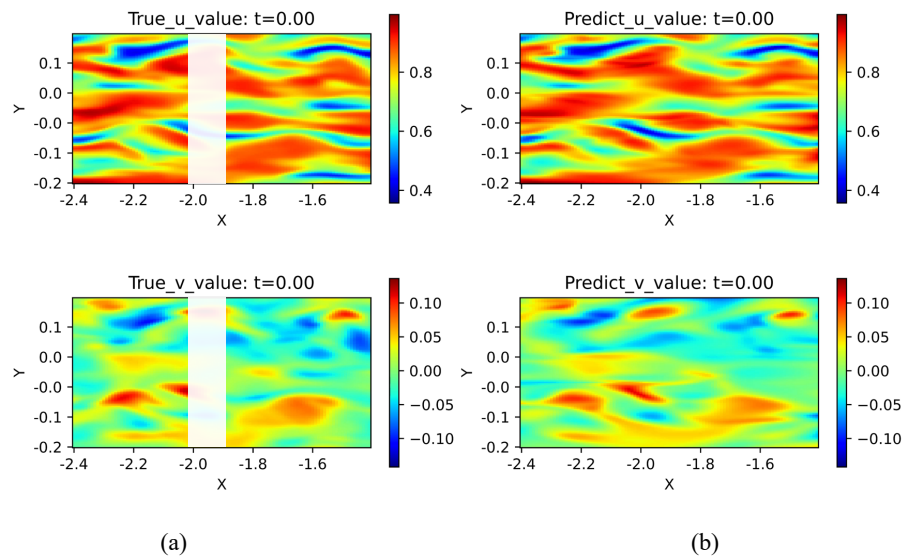


Figure 2 Flow field visualization of shock wave/ turbulent boundary layer interaction at $Ma = 1.85$ by iso-surface $\Omega_R = 0.52$

A configuration was considered in which the original simulation dataset contained 20% missing data, and this dataset was used as the training set. The spatial reconstruction of the near-wall turbulent flow field for this configuration is shown in Figure 3. In this figure, the original numerical simulation flow field and the PINN-based reconstruction are contrasted in subfigures (a) and (b). When the training dataset with 20% missing data was used, the missing regions were effectively reconstructed by PINN while physical consistency with the surrounding areas was maintained. As is shown in the streamwise velocity distribution (Figure 3b), the characteristic near-wall structures, particularly high-speed and low-speed streak pairs, were accurately captured and predicted. However, relatively lower prediction accuracy was observed in the spanwise velocity field, which is attributed to the high temporal resolution required for resolving spanwise fluctuations. Furthermore, a quantitative comparison of the velocity profile extracted at $x/h = -1.7$ is provided in Figure 3(c). The streamwise velocity is shown in the left panel, while the spanwise velocity is shown in the right panel. As can be seen in the left figure, regions of alternating high and low magnitudes correspond to high- and low-speed streaks. These features were accurately captured by the predictions, and good agreement with the simulation data was observed. However, similar to what was seen in Figure 3(b), relatively lower prediction accuracy was exhibited by the spanwise velocity profile due to the high temporal resolution requirements, with amplified errors being particularly evident in low-velocity regions.



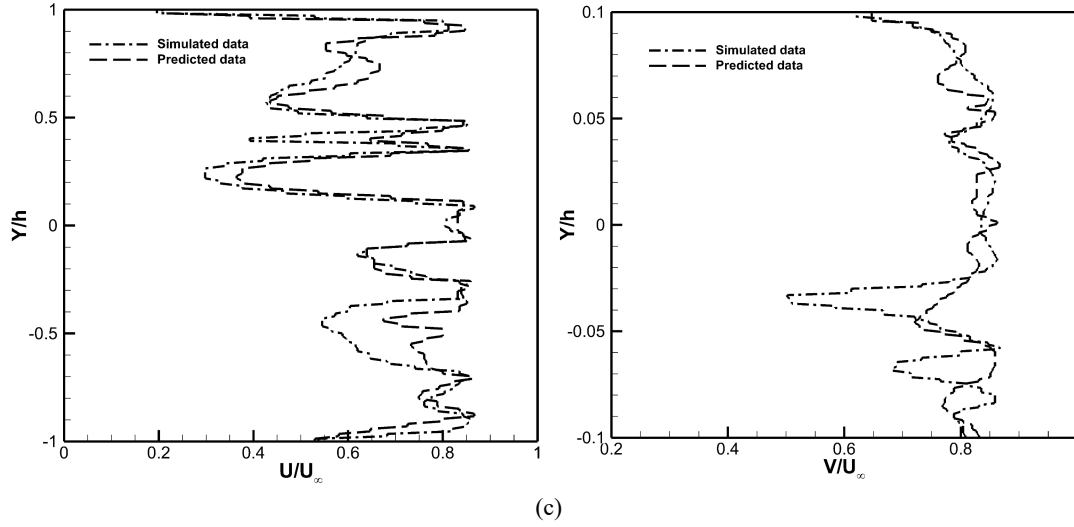


Figure 3 Velocity contour of the subzone flow field (a) Flow field from the original numerical simulation (b) PINN prediction by using the training dataset with 20% missing data (c) Velocity profile extracted at $x/h = -1.7$ (left: streamwise velocity; right: spanwise velocity)

To further validate the PINN framework on experimental data, it is applied to reconstruct a turbulent channel flow field ($Re = 3700$) measured by PIV, from which a rectangular region is intentionally removed to simulate realistic data loss. The model integrates the sparse velocity measurements with the incompressible Navier-Stokes equations to reconstruct the missing flow region. As shown in Figure 4, the PINN-reconstructed field closely matches the original PIV data, accurately capturing key features such as streamline patterns and regions of concentrated vorticity. The results demonstrate that PINN can reliably reconstruct flow structures, including primary vortex locations and boundary layers, even in areas with significant data voids.

Quantitative velocity profiles at $X=0.036$ shown in Figure 5 demonstrate close agreement between PINN-reconstructed and PIV-measured data in both streamwise and spanwise directions. This confirms the PINN framework's effectiveness in inferring complete flow field information from incomplete measurements.

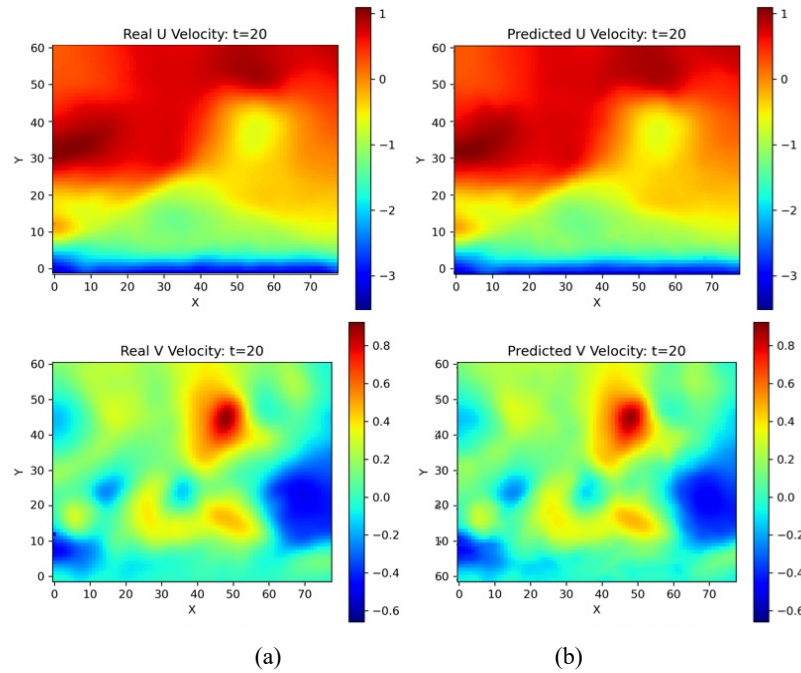
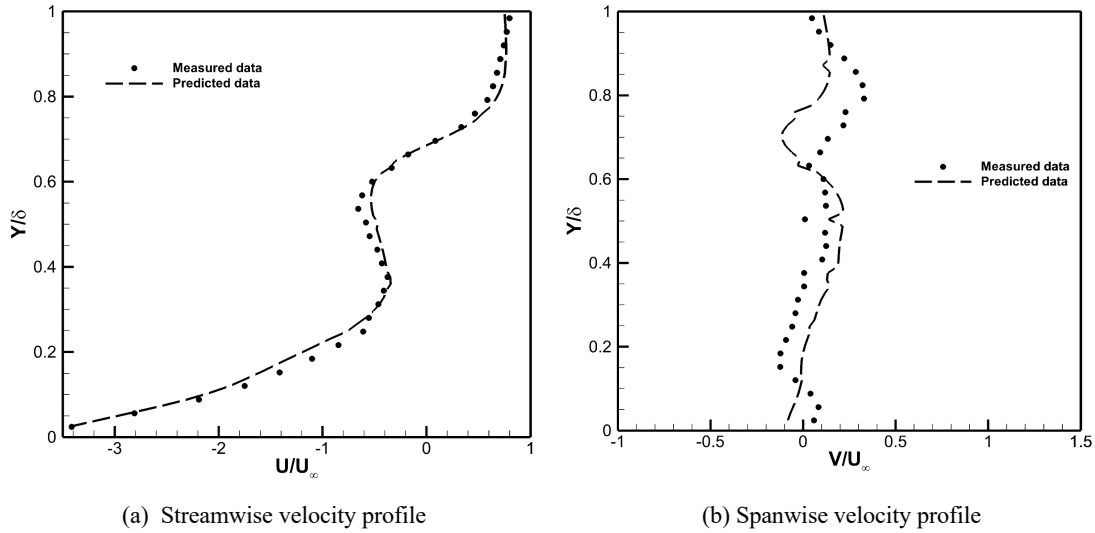


Figure 4 Velocity and vorticity magnitude distribution of the turbulent channel flow field (a) Original data measured by PIV with a rectangular region intentionally removed (b) Flow field reconstruction by PINN

Figure 5 Velocity profile of the line extracted from $X = 0.036$

3.2 Time prediction of turbulent flow field by LSTM

Temporal prediction of turbulent flow fields from limited snapshots is regarded as a high-dimensional sequential learning problem. Classical approaches typically rely on reduced-order models or linear stochastic formulations, whose accuracy is compromised in flows characterized by strong nonlinearity and multi-scale dynamics. In recent years, recurrent neural networks, especially LSTM networks, have been established as powerful data-driven surrogates. With these models, nonlinear temporal evolution operators are learned directly from time-resolved data, without the need for explicit closure assumptions. In the present study, an LSTM network is employed for short-term turbulent flow forecasting, and the effect of training-sequence time-window selection on prediction accuracy and stability is systematically assessed.

The predictive capability of the LSTM model is evaluated using a three-dimensional turbulent backward-step flow. A large-eddy simulation (LES) of this flow was conducted, and the resulting dataset was used as the reference database for temporal prediction. As shown in Figure 6, a wall-parallel plane at $Y/h = 0.02$ was extracted from the full three-dimensional flow field. Within this plane, a rectangular subregion (indicated by the red box) was selected as the computational domain, with a spatial resolution of $N_x \times N_y = 100 \times 100$. Furthermore, the dataset is composed of 500 consecutive snapshots, yielding a total spatiotemporal dimension of $N_{data} = 100 \times 100 \times 500$. Each input sequence is formed by 90 consecutive time steps $\{x_{ta}, x_{ta+1}, \dots, x_{ta+89}\}$, and the subsequent 10 steps $\{x_{ta+90}, x_{ta+91}, \dots, x_{ta+99}\}$ are used as the target output. Consequently, a nonlinear temporal mapping from a 90-step flow history to the following 10 snapshots is learned by the network. This mapping is then applied recursively to generate multi-step predictions.

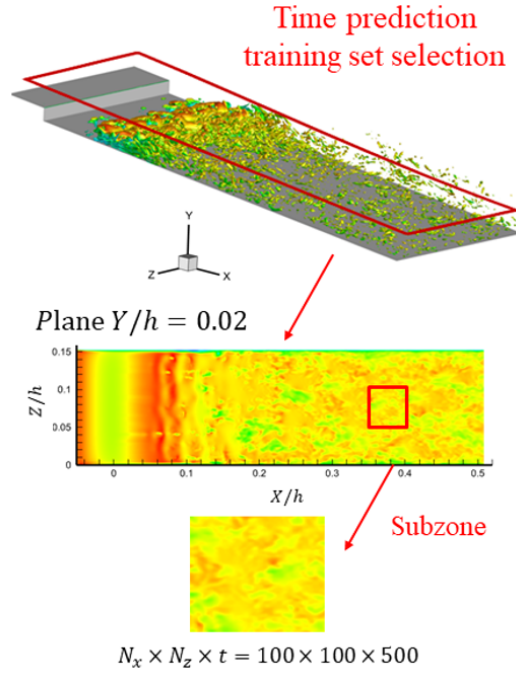
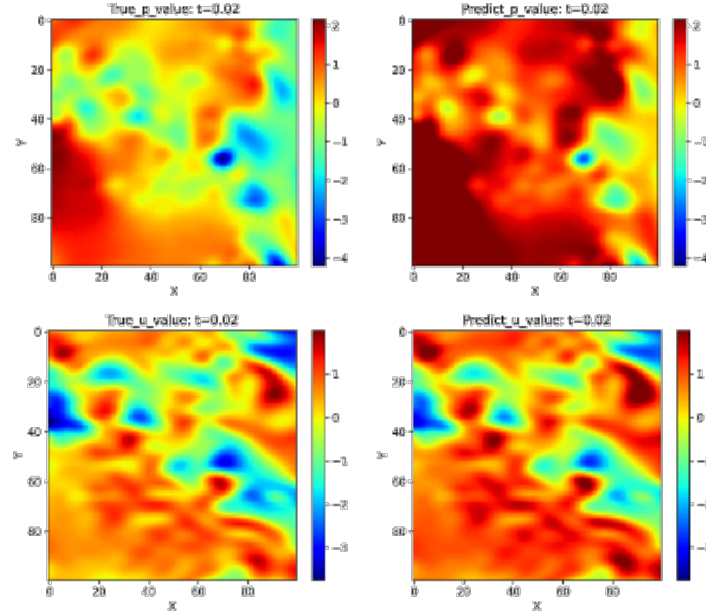


Figure 6 Schematic illustrating the selection of the computational subregion

In Figure 7, the LSTM-predicted instantaneous velocity field captures coherent high- and low-speed streaks, with absolute error peaking at the narrow shear interfaces between them. This error concentration is attributed to phase misalignment amplified in regions of strong velocity gradients, while amplitude agreement remains high in areas of weaker gradients. The error pattern, structured along shear-intensified bands rather than being random noise, indicates a gradient-dependent error mechanism. Overall, the LSTM reliably predicts the amplitude and large-scale morphology of the velocity field, with primary discrepancies localized to phase mismatches at high-gradient interfaces.



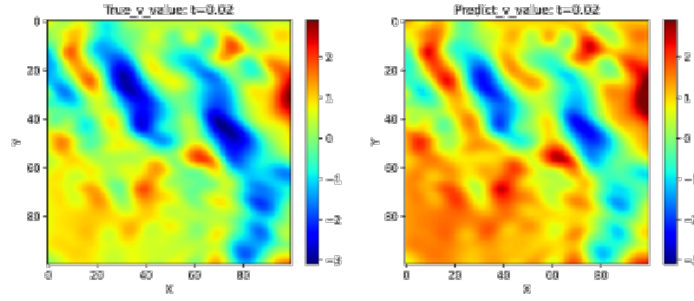


Figure 7 Time prediction of the turbulent channel flow by LSTM (the model is trained on a sequence of flow field data from t_1 to t_{80} , and is then applied to predict the flow evolution at future time steps t_{81} to t_{85})

For quantifying the pointwise discrepancy between the LSTM predictions and the large-eddy simulation (LES) reference over the final ten forecast steps, two complementary global metrics are employed: the root-mean-square error (RMSE) and the mean absolute error (MAE). Larger deviations are given greater emphasis by RMSE through its squaring operation, whereas the average error magnitude expressed in the original units is provided by MAE, which is less influenced by rare outliers. Statistical fidelity is further assessed by the use of mean and RMS profiles, supplemented with spectral diagnostics. Through a comparison of the predicted fields q^{pred} with the reference fields q^{real} across the final ten time steps of the dataset, all metrics are calculated, where $q \in \{u, v, p\}$ is taken as a generic flow quantity of interest.

The global error metrics, namely RMSE and MAE, are then examined so that the overall prediction accuracy can be evaluated. Only moderate global errors are reported for all quantities in the backward-step flow, as is summarized in Table 1. The smallest error is observed for the streamwise velocity u , while somewhat larger discrepancies are exhibited by the pressure p and the wall-normal velocity v . From this trend, it is suggested that the dominant convective component is recovered more faithfully than pressure-related and wall-normal fluctuations.

Table 1 Global error of LSTM prediction results of backward step flow

	p	u	v
RMSE	0.3361	0.2650	0.3280
MAE	0.1747	0.1705	0.1918

Overall, a clear lead-time dependence is shown by the results obtained for the backward step flow: the highest accuracy is observed at short prediction horizons, and a progressive degradation in performance is seen as the forecast lead time is increased. In spite of this gradual decline, the dominant large-scale unsteady dynamics and low-order statistics are reliably maintained by the LSTM-based model across the entire horizon that was considered; however, the residual errors, which are found to grow with lead time, are largely associated with small-scale, high-frequency fluctuations, and these errors are most pronounced when the end of the forecast horizon is approached.

5. Conclusions

In this paper, both physics-informed neural network framework and long short-term memory (LSTM) network are presented for the spatio-temporal prediction of turbulent boundary layer flow fields. The PINN model, which embeds the Navier-Stokes equations as a soft constraint, demonstrated superior performance in maintaining physical consistency, accurately reconstructing velocity and pressure fields from sparse or gappy data, and providing reliable short-term temporal predictions. In contrast, the purely data-driven LSTM model excelled at capturing temporal dynamics within the training domain but exhibited faster error accumulation and less physical coherence during extrapolation, with errors primarily concentrating in high-shear regions due to phase misalignment.

The comparative analysis reveals a clear trade-off: PINNs offer robustness and interpretability by enforcing governing physics, making them suitable for inverse problems and scenarios demanding physical guarantees, while LSTMs provide flexible and efficient sequence learning for interpolation and short-horizon forecasting. The error growth in both models is tied to the prediction horizon and is magnified in regions of strong velocity gradients.

For future complex turbulent flow applications, a hybrid paradigm that synergistically combines the temporal learning capacity of LSTMs with the physical fidelity of PINNs is recommended. Such an integrated approach holds significant potential to advance high-fidelity, efficient predictive tools for both computational and experimental fluid dynamics.

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References

- [1] Cao S, Li Y, Zhang J, et al. Lagrangian analysis of mass transport and its influence on the lift enhancement in a flow over the airfoil with a synthetic jet. *Aerospace Science and Technology*, 2019, 86, 11-20.
- [2] Zhao X, Chen X, Gong Z, et al. A resolution-invariant flow and heat field reconstruction method from sparse observations via Fourier neural operator. *International Journal of Thermal Sciences*, 2024, 195, 108619.
- [3] Portal-Porras K, Fernandez-Gamiz U, Garcia-Fernandez R, Zulueta E, Irigaray O. Hybrid LSTM+CNN architecture for unsteady flow prediction. *Materials Today Communications*. 2023, 35, 106281.
- [4] Feero, Mark A , Sullivan, et al. Influence of synthetic jet location on active control of an airfoil at low Reynolds number. *Experiments in Fluids*, 2017, 58(8), 99.
- [5] Dong X, Chen Y, Dong G, et al. Study on wake structure characteristics of a slotted micro-ramp with large-eddy simulation. *Fluid Dynamics Research*, 2017, 49(3), 035507.
- [6] Degrez G, Boccadoro C H, Wendt, et al. The interaction of an oblique shock wave with a laminar boundary layer revisited. An experimental and numerical study. *Journal of Fluid Mechanics*. 1987, 177 247-263.
- [7] Jankee G K, Ganapathisubramani B. Interaction and vectoring of parallel rectangular twin jets in a turbulent boundary layer. *Physical Review Fluids*, 2021, 6(4), 044701.
- [8] Yoshizawa, Akira. Statistical theory for compressible turbulent shear flows, with the application to subgrid modeling. *Physics of Fluid*, 1986, 29(7), 2152-2164.
- [9] Gao Y and Liu C. Rortex and comparison with eigenvalue based vortex identification criteria. *Physics of Fluids*, 2018, 30(8), 085107.
- [10] Karbasia HR, van Rees WM. A parametric LSTM neural network for predicting flow field dynamics across a design space. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*. 2025, 481(2307), 20240055.
- [11] Xia C, Zhang J, Kerrigan EC, Rigas G. Active flow control for bluff body drag reduction using reinforcement learning with partial measurements. *Journal of Fluid Mechanics*. 2024, 981.
- [12] González-Planet IC, Juez C. Hydrological insights from a comparative evaluation of LSTM and MC-LSTM networks in the Ebro River basin (Spain). *Journal of Hydrology: Regional Studies*. 2025, 61, 102719.