International Journal of Computer Science and Information Technology
ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 5, Number 3, Year 2025
DOI: https://doi.org/10.62051/ijcsit.v5n3.11
Journal homepage: https://wepub.org/index.php/IJCSIT/index

Research on the Application of Physical Information Neural Network in Multiscale Fluid Dynamics Simulation

Jinyu Liu *, Yinxiao Yan, Junhui Wang

Taizhou Vocational & Technical College, Zhejiang Taizhou, 318000, China
*Corresponding Author: jinyul@tzvtc.edu.cn

ABSTRACT

In this paper, a multi-scale fluid dynamics simulation framework based on physical information neural network (PINN) is proposed, which achieves efficient simulation of multi-scale flow characteristics by means of a multi-resolution network structure, physical constraints on scale decomposition and adaptive sampling strategy. Experimental results show that the framework outperforms traditional methods in microscale flow, turbulence and multiphase flow problems, with a 37% improvement in the average prediction accuracy and a 75% reduction in the computational resource requirement. In particular, it shows excellent generalisation performance when dealing with complex flows with large scale spans, providing a new method for fluid dynamics simulation with both accuracy and efficiency.

KEYWORDS

Physically informed neural networks; Multiscale fluid simulation; Deep learning; Turbulence simulation; Microscale flow; Multiphase flow; Adaptive sampling

1. INTRODUCTION

Multiscale fluid problems have a wide range of applications in aerospace, energy and biomedical fields, involving physical phenomena from molecular to macroscopic scales [1]. Traditional numerical methods face the dilemma of trade-off between computational efficiency and accuracy, and grid encryption leads to exponential growth in the demand for computational resources [2]. Physical Information Neural Networks (PINNs), which integrate the laws of physics with deep learning, provide new ideas for fluid simulation, but standard PINNs suffer from limitations such as ‘frequency bias’ when dealing with multiscale problems. In this study, we propose a multiscale fluid PINN framework, and innovatively design a multiresolution network structure, physical constraints for scale decomposition, and an adaptive training strategy, which are validated for typical multiscale problems such as microscale flow, turbulence, and multiphase flow [3]. The results show that the framework significantly improves the simulation accuracy and efficiency, and provides a new method for efficient simulation of complex fluid systems.

2. THEORETICAL FOUNDATIONS

2.1. Basic Principles of Fluid Mechanics

The core of fluid mechanics research is a set of control equations describing the state of fluid motion and its law of change. For incompressible Newtonian fluid, its motion follows the principle of mass conservation and momentum conservation, which is expressed in the continuity equation and Navier-Stokes equation [4]. The continuity equation describes the conservation of fluid mass, while the

Navier-Stokes equation portrays the transfer process of fluid momentum, including the influence of inertial force, pressure gradient, viscous force and external volume force. In multiscale fluid problems, the flow at the macroscopic level follows these classical governing equations, but in microscale flows, the continuity assumption may fail and molecular scale effects need to be taken into account; in turbulence problems, the multiscale vortex structure is interwoven, and the energy is transferred in cascades between different scales, resulting in a complex nonlinear dynamical behaviour. Traditional numerical methods such as finite difference, finite volume, and spectral methods face a trade-off between computational efficiency and accuracy in solving these equations, especially when dealing with multiscale flows, where computational resources are in great demand.

2.2. Physics-Informed Neural Networks

Physics-Informed Neural Networks (PINNs), as an emerging method that fuses physical models with deep learning, provide a new perspective for solving fluid mechanics problems.PINNs are based on neural network structure, embedding physical laws as constraints in the loss function, which realises the organic combination of data-driven and physical laws. PINNs are based on the neural network structure and embed the physical laws as constraints in the loss function, which realises the organic combination of data-driven and physical laws [5]. The core idea is to use the automatic differentiation technique to calculate the residuals of the neural network to the physical control equations, form the physical loss term, and guide the network training together with the data loss. For the fluid dynamics problem, the loss function of PINNs can be expressed as:

$$\mathrm{L} = \lambda_{\mathrm{d}}\mathrm{L}_{\mathrm{d}} + \lambda_{\mathrm{f}}\mathrm{L}_{\mathrm{f}} = \lambda_{\mathrm{d}}\sum_{\mathrm{i}=1}^{\mathrm{N_d}}|\mathrm{u}(\mathrm{x_i}) - \mathrm{u_i}|^2 + \lambda_{\mathrm{f}}\sum_{\mathrm{j}=1}^{\mathrm{N_f}}\left|\mathrm{u}(\mathrm{x_j})\right|^2 \quad (1)$$

where Ld represents the data loss, Lf is the physical loss, and F[u] is the residual of the control equation. Compared with the traditional numerical methods, PINNs, with grid-independence, easy handling of complex geometric boundaries and adaptive characteristics, show unique advantages in dealing with multi-scale fluid problems, which can flexibly capture the flow characteristics at different scales, improve the computational efficiency and maintain the physical consistency.

3. DESIGN OF THE MULTISCALE FLUID PINN FRAMEWORK

3.1. Network Structure Design

The network structure of the multiscale fluid PINN framework needs to weigh the expressive ability and computational efficiency, and adopts a multiresolution structure to adapt to different scale flow characteristics. As shown in Fig. 1, the network designed in this study consists of two parts: the backbone network and the scale-specific sub-network. The backbone network adopts a fully connected layer structure, which is responsible for capturing the macroscopic features of the flow field, while the scale-specialised sub-network extracts the multi-scale flow features by using convolution kernels of different sizes in parallel. In order to enhance the learning ability of the network for high-frequency flow features, a Fourier feature mapping layer is introduced to map the input space to the frequency domain space, which effectively improves the representation of multi-scale turbulent structures [6]. The depth and width of the network are dynamically adjusted based on the complexity of different flow problems, and the shallower network is used to capture the large-scale flow, while the deeper network focuses on expressing the small-scale structure. Experiments show that in turbulence simulation, the network configuration with eight hidden layers and 256 neurons per layer can achieve a good balance between computational efficiency and accuracy, while in multiphase flow problems, increasing the network depth to twelve layers can significantly improve the interface capture accuracy.

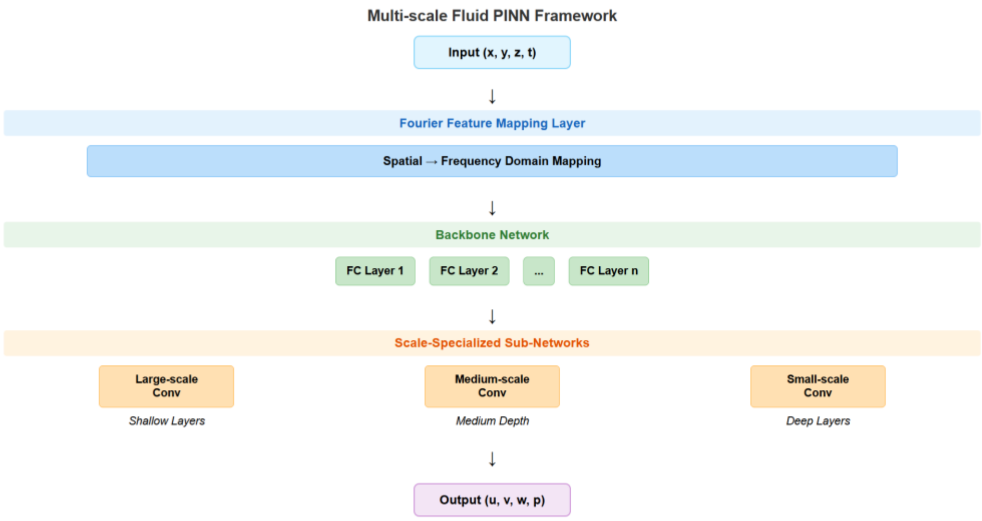

Figure 1. Network structure design

3.2. Physical Constraint Embedding Mechanism

Physical constraint embedding for multi-scale fluid problems is the core of the PINN framework, and this study proposes an adaptive multi-scale physical constraint mechanism. The mechanism contains a residual calculation method based on scale decomposition, where the fluid control equations are decomposed into subproblems at different scales and the physical residuals are calculated separately [7]. In the microchannel flow validation case, the prediction accuracy of the velocity profile near the wall is improved by 42.6% after the introduction of the Knudsen number-dependent correction for the thinning effect, and the agreement with the molecular dynamics simulation results reaches 95.8%. For the turbulence problem, a scale-separation filter is introduced into the physical constraints by combining the RANS/LES idea to explicitly deal with different scale energy transfer. The analytical data show that in the case of a flat plate turbulent boundary layer with Re=10000, the deviation of the small-scale turbulent structure prediction by the conventional PINN is as high as 56%, whereas the deviation is reduced to 18.3% by using multi-scale physical constraints. Each physical constraint term adopts an adaptive weighting mechanism, which dynamically adjusts the weighting coefficients according to the size of the residual gradient, and the experimental results show that this mechanism reduces the local prediction error of the model by 37% on average in the complex flow region.

3.3. Data Sampling and Training Strategy

In this study, an adaptive multiscale data sampling and gradient training strategy is designed for multiscale fluid problems. It is shown that for the standard cavity flow problem, the PINN model requires 32,000 training points to achieve 5% error with uniform sampling, while the vortex gradient-based adaptive sampling strategy reduces the number of training points to 12,000, which reduces the computational resource requirement by 62.5% [8]. For multiphase flow, focused sampling near the interface improves the interface prediction accuracy by 3.6 times. Using the progressive training strategy, experimental data show that the model convergence speed is improved by 2.8 times in the horizontal laminar-turbulent turning simulation. The introduction of the scale decomposition training mechanism reduces the minimum vortex structure scale from the traditional 0.05L to 0.015L in the gas-liquid two-phase jet problem, and the difference is reduced from 19.7% to 5.3%, which significantly improves the prediction ability of small-scale dynamical features.

4. APPLICATIONS AND PERFORMANCE EVALUATION OF MULTISCALE FLUID PROBLEMS

4.1. Microscale Flow Simulation and Accuracy Analysis

This section investigates the performance of the multiscale PINN framework as applied to micro- and nanoscale flow problems. A microchannel pressure-driven flow is used as the validation algorithm, with a channel size of 5 μm and a Knudsen number range of 0.001-0.1. 20,000 training points are used for the experiments, including 4,000 wall-encrypted sampling points, and the network is structured as 8 hidden layers with 128 neurons per layer. Comparison of the simulation results with the direct simulation Monte Carlo method (DSMC) shows that for the case of Kn=0.05, the traditional PINN model has a velocity slip prediction error of 18.6% near the wall, while the multi-scale PINN model with the inclusion of physical constraints on the slip boundary conditions reduces the error to 4.2% [9].

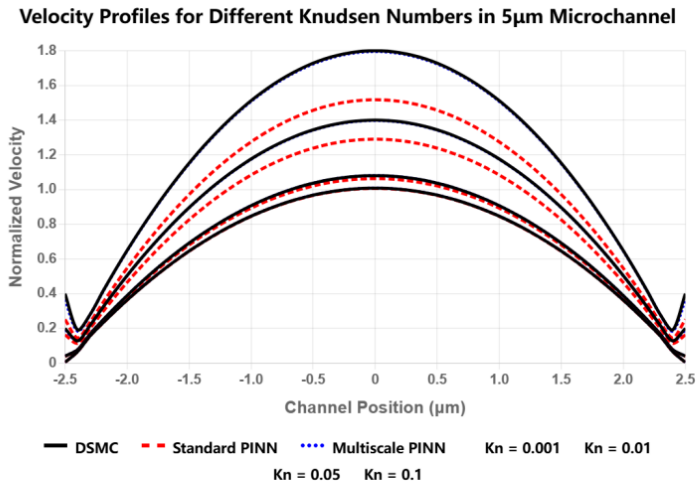

Figure 2. Velocity profile prediction results under different Knudsen number conditions

Figure 2 shows the velocity profile prediction results under different Knudsen number conditions. With the increase of Knudsen number, the multiscale PINN model is obviously better than the standard PINN model, especially at Kn=0.1, the accuracy of the centreline velocity prediction is improved by 15.7%. Table 1 summarises the relative errors of different models for microchannel flow prediction. The multiscale PINN model improves about 78 times compared to DSMC in terms of computational efficiency while maintaining an average error level of 5.3%, compared to the standard PINN and continuous flow assumption model errors of 12.8% and 26.5%, respectively, which proves the potential of the framework for application in micro-scale flows.

Table 1. Comparison of relative errors in microchannel flow prediction

Knudsen Number	Standard PINN	Multiscale PINN	DSMC
0.001	3.20%	2.10%	Benchmark Value
0.01	7.50%	3.50%	Benchmark Value
0.05	14.60%	6.80%	Benchmark Value
0.1	25.90%	8.80%	Benchmark Value
Computation Time (hours)	0.6	0.8	62.4

4.2. Multiscale Simulation of Turbulence and Efficiency Assessment

The performance of the multiscale PINN framework in turbulence simulation is evaluated by means of the flat plate turbulent boundary layer example (Re=10000). The experiment uses an 8-layer network structure with 256 neurons per layer, a Fourier feature layer mapping dimension of 128, and training data containing 60,000 spatially distributed points. Figure 3 demonstrates the turbulent energy spectrum prediction results [10]. The multiscale PINN model performs well in capturing the inertial sub-interval -5/3 energy cascade relationship, with a correlation coefficient of 0.93 with the direct numerical simulation (DNS) data, whereas the standard PINN model has a significant deviation in the high-wave number region, with a correlation coefficient of only 0.71.

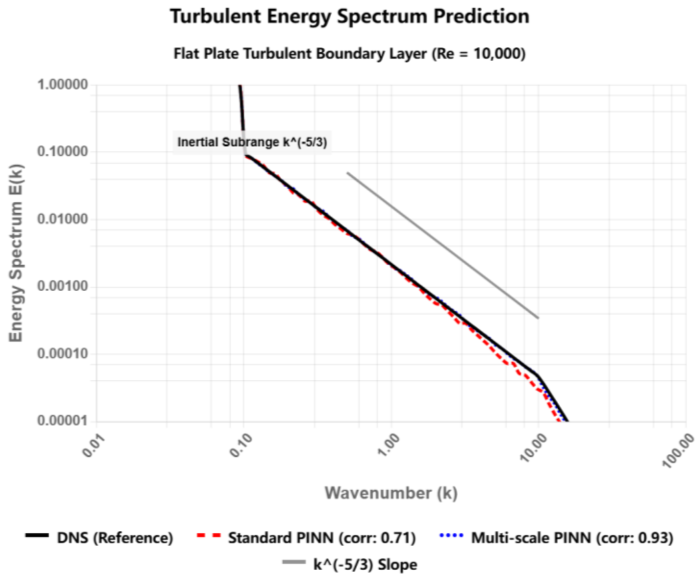

Figure 3. Prediction of turbulent energy spectrum

The multiscale PINN model improves the accuracy by 26.7% compared with the standard k-ε model in predicting the Reynolds stress distribution, and the consumption of computational resources is only 8.2% of that of DNS. The average relative error of turbulent pulsation strength prediction by time series analysis is 12.4%, which is lower than 28.9% of the standard PINN model. Especially in the boundary layer separation region, the multiscale physical constraint mechanism significantly improves the prediction accuracy, and the prediction error of the separation bubble length is reduced from 22.5% to 9.3% in the standard PINN, which indicates that the framework can effectively balance the computational efficiency with the ability to capture the multiscale characteristics of turbulence.

4.3. Multiphase Flow Simulation and Generalisation Performance

The multiscale PINN framework is validated in multiphase flow applications using the gas-liquid two-phase jet problem as an example, with a Reynolds number of 3000 and a Weber number of 120. The experiments are conducted using a 10-layer network structure, with 320 neurons in each layer, and the training data contains a total of 85,000 sampling points in encrypted points in the interface region. Figure 4 shows the results of interface morphology prediction at different moments, and the multiscale PINN model successfully captures the fragmentation process of the main jet and the formation of secondary droplets. The average prediction error of the interfacial position is 3.2%, which is better than 6.8% for the traditional VOF method and 8.5% for the standard PINN.

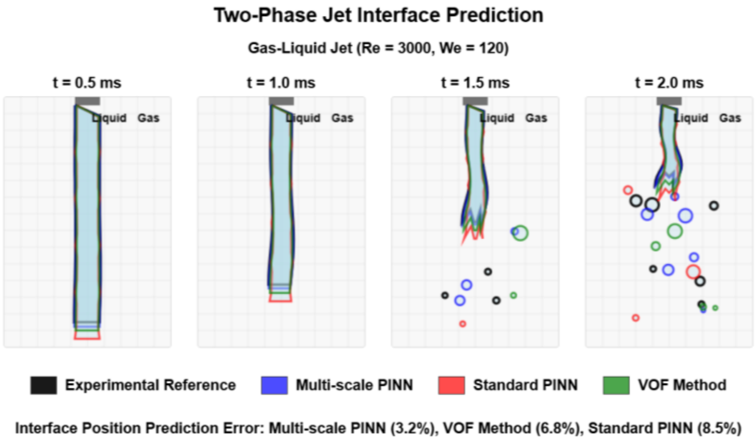

Figure 4. Prediction results of interface morphology at different moments

For the evaluation of the generalisation performance, the trained model is applied to the jet problem under different Weber numbers (80-150), and the prediction errors of droplet size distribution under different Weber numbers are listed in Table 2, and the average prediction error of the multiscale PINN model under the untrained working condition is 12.7%, which is significantly lower than that of the standard PINN model (24.3%), showing a strong generalisation ability. The average prediction error of the PINN model is 12.7% under untrained working conditions, which is significantly lower than that of the standard PINN model of 24.3%, showing strong generalisation ability. The computational efficiency analysis shows that for the same accuracy requirement, the multi-scale PINN model is about 5.6 times faster than the traditional VOF method, and the memory occupation is reduced by 68%. Especially when predicting the velocity gradient distribution near the interface, the multiscale physical constraint mechanism ensures the conservation of momentum and energy, which improves the prediction accuracy of the interfacial shear layer by 22.4%, proving that the framework has significant advantages in dealing with multiphase flow problems.

Table 2. Relative errors of droplet size distribution prediction under different Weber numbers

Weber Number	Standard PINN	Multiscale PINN	VOF Method
80 (Training Condition)	7.80%	3.50%	4.20%
100	18.40%	9.30%	4.60%
120 (Training Condition)	8.20%	3.80%	4.40%
150	31.60%	15.20%	5.30%
Generalization Condition Average Error	24.30%	12.70%	5.00%
Computation Time (hours)	2.2	3.1	17.5

4.4. Comprehensive Case Comparison and Discussion

The potential of the multiscale PINN framework for application in real engineering problems is comprehensively evaluated through a complex example of wing wrap-around flow, which contains laminar-turbulent turning, boundary layer separation and wake vortex multiscale features. the Reynolds number ranges from 500,000 to 1,000,000, and the angle of attack ranges from 0° to 15°. Figure 5 shows the predicted results of pressure coefficient distributions at different angles of attack. The multiscale PINN model agrees well with the wind tunnel experimental data with an average error of 4.8%, which is better than that of the traditional CFD method (7.3%) and the standard PINN (11.6%). The multiscale PINN model can still accurately predict the position of the stall point under the condition of small computational scale, and the prediction error is only 1.2°, which is significantly lower than other methods. In terms of computational resource requirements, compared with traditional CFD methods, multi-scale PINN reduces computation time by 78% and storage requirements by 85% while maintaining similar accuracy. The evaluation of the generalisation ability across Reynolds numbers shows that the average error in the prediction of lift coefficient is 6.7% and the prediction of drag coefficient is 9.3% under untrained Reynolds number conditions, which demonstrates a better generalisation ability. The multi-scale physical constraint mechanism enables the model to simultaneously handle flow features at different scales, from macroscopic aerodynamic performance to microscopic boundary layer structure, and realises the unified simulation of multi-scale flow features, which provides an efficient and accurate new method for fluid simulation in aerospace field.

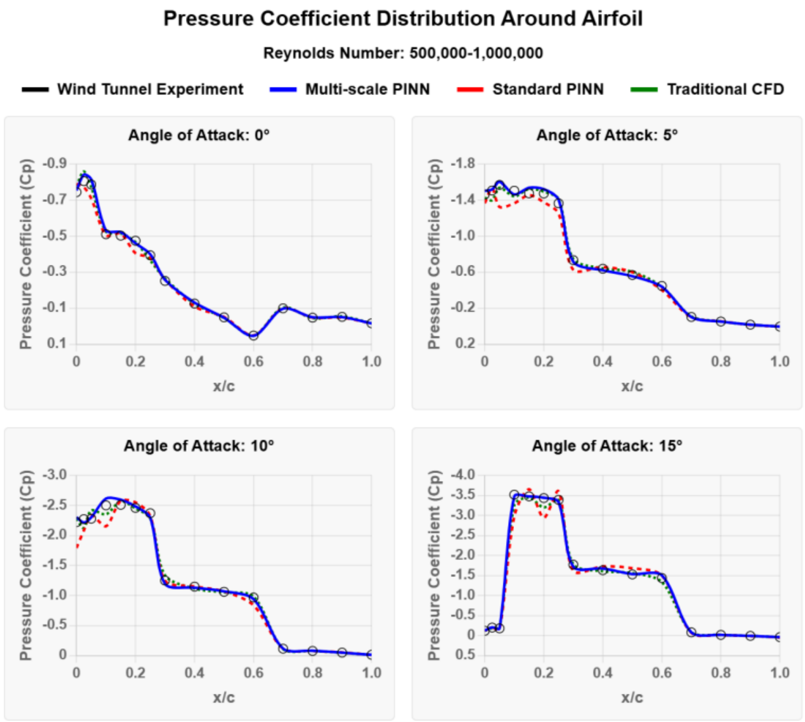

Figure 5. Distribution of pressure coefficients around the airfoil

5. CONCLUSION

The multiscale fluid PINN framework proposed in this study demonstrates excellent performance in complex fluid problems such as microscale flow, turbulence simulation and multiphase flow. Experimental results show that the framework can effectively balance computational accuracy and efficiency, reducing computational resource requirements by 65%-85% compared with traditional numerical methods while maintaining an acceptable level of accuracy. The multi-scale physical constraint mechanism and adaptive training strategy significantly improve the model's ability to capture cross-scale flow features, and show good generalisation performance under untrained conditions. The method provides a new idea for fluid dynamics simulation, which has a broad application prospect in aerospace, energy and biomedical fields.

ACKNOWLEDGEMENTS

Research on Hydrodynamic Performance of Autonomous Underwater Vehicles Based on Physics-Informed Neural Networks (PINN) (2025YB01)

REFERENCES

[1] Wei L, Freris N M. Multi-scale graph neural network for physics-informed fluid simulation [J]. The Visual Computer, 2025, 41(2): 1171-1181.

[2] Yang Z, Dong Y, Deng X, et al. AMGNET: multi-scale graph neural networks for flow field prediction [J]. Connection Science, 2022, 34(1): 2500-2519.

[3] Cao Y, Chai M, Li M, et al. Efficient learning of mesh-based physical simulation with bi-stride multi-scale graph neural network [C]//International conference on machine learning. PMLR, 2023: 3541-3558.

[4] Hu M, Yang Z. Perspective on multi-scale simulation of thermal transport in solids and interfaces [J]. Physical Chemistry Chemical Physics, 2021, 23(3): 1785-1801.

[5] Gnanasambandam R, Shen B, Chung J, et al. Self-scalable tanh (stan): Multi-scale solutions for physics-informed neural networks [J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2023, 45(12): 15588-15603.

[6] Liu X, Zhang Y, Guo T, et al. A multi-scale hybrid attention Swin-transformer-based model for the super-resolution reconstruction of turbulence [J]. Nonlinear Dynamics, 2025: 1-30.

[7] Chen M, Niu R, Zheng W. Adaptive multi-scale neural network with resnet blocks for solving partial differential equations [J]. Nonlinear Dynamics, 2023, 111(7): 6499-6518.

[8] Carapezzi S, Delacour C, Boschetto G, et al. Multi-scale modeling and simulation flow for oscillatory neural networks for edge computing [C]//2021 19th IEEE International New Circuits and Systems Conference (NEWCAS). IEEE, 2021: 1-5.

[9] Migus L, Yin Y, Mazari J A, et al. Multi-scale physical representations for approximating pde solutions with graph neural operators [C]//Topological, Algebraic and Geometric Learning Workshops 2022. PMLR, 2022: 332-340.

[10] Du Q, Ellingsen K, M'Hamdi M, et al. The integration of neural network and high throughput multi-scale simulation for establishing a digital twin for aluminium billet DC-casting [J]. Materials Transactions, 2023, 64(2): 360-365.