Development of a Reduced-Order-Model from synthetic CFD data using Convolution Neural Network

Vishal Rasaniya
School of Engineering and Applied Sciences
Mechanical Engineering, Ahmedabad University
Ahmedabad, India 380009
Email: Vishal.r@ahduni.edu.in

Abstract—**Computational Fluid Dynamics (CFD) is a widely used numerical approach for solving fluid flow and heat transfer problems, but its high computational cost often limits its efficiency in large-scale simulations. Reduced-Order Models (ROMs) provide an effective solution by reducing the spatial and temporal complexity of CFD simulations while retaining essential physics. In this study, a Convolutional Neural Network (CNN)-based ROM is developed to reduce the spatial resolution of a CFD dataset for heat transfer in a rectangular enclosure heated from both sides. The computational domain, initially resolved at 10,000 spatial points, is downsampled to 1,000 spatial points while maintaining the accuracy of heat flux predictions. The training dataset is generated using Ansys Fluent 18, with a uniform heat flux of 500 W/m² applied at both sides of the enclosure. The CNN model is trained on this synthetic CFD dataset to learn spatial correlations and optimize the representation of heat transfer characteristics. This approach significantly reduces computational costs and enables faster surrogate modeling for heat transfer applications.**

1. Introduction

Computational Fluid Dynamics (CFD) plays a crucial role in predicting heat transfer and fluid flow in various engineering applications. However, high-fidelity CFD simulations require extensive computational resources, limiting their practicality in real-time decision-making scenarios. To address this challenge, Reduced-Order Models (ROMs) provide a data-driven approach to approximate complex simulations with significantly lower computational cost.

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have gained prominence in scientific computing due to their ability to capture spatial dependencies in high-dimensional datasets. CNNs are well-suited for learning patterns in CFD-generated heat transfer data, allowing for efficient spatial downsampling while preserving key physics. In this study, a CNN-based ROM is developed for a rectangular enclosure heated from both sides, reducing the spatial domain from 10,000 to 1,000 points. The dataset for model training is generated using Ansys Fluent 18, with a constant heat flux of 500 W/m² applied at the enclosure walls. The goal is to develop a robust model capable of accurately predicting temperature and velocity distributions with reduced spatial complexity.

This study contributes to the field of physics-informed machine learning by integrating CNNs with synthetic CFD data to enhance computational efficiency in heat transfer modeling. The proposed ROM can be further extended to real-time simulations, optimization, and control of thermal systems.

2. Literature Survey

1. Machine Learning-Based Predictions of Flow and Heat Transfer Characteristics in a Lid-Driven Cavity

Authors: Hussein Kokash, Khalil Khanafer, Mihai Burzo

Source: Energies 2024, 17, 5220

Summary: This study explores machine learning (ML) techniques for predicting heat transfer characteristics in a lid-driven cavity with a rotating cylinder. The research compares different ML regression models and physics-informed neural networks (PINNs) to evaluate their accuracy against computational fluid dynamics (CFD) simulations. The results show that the random forest model consistently performs well at different Reynolds numbers, while PINNs trained with CFD data exhibit lower errors compared to purely theoretical PINNs.

2. CFD and Machine Learning-Based Simulation of Flow and Heat Transfer Characteristics of Micro Lattice Structures

Authors: Disha Deb et al.

Source: IOP Conf. Ser.: Earth Environ. Sci. 850 (2021) 012034

Summary: This paper presents a CFD-based dataset used for training ML models to predict final fluid temperature and pressure drop in micro-lattice structures. The study evaluates six different lattice structures and highlights the potential of ML in predicting thermal performance. The ML model's predictions align closely with simulated results, indicating its applicability in practical industrial settings.

3. Enhancing CFD Solvers with Machine Learning Techniques

Authors: Paulo Sousa, Carlos Veiga Rodrigues, Alexandre Afonso

Source: Computer Methods in Applied Mechanics and Engineering, 2024

Summary: This study integrates ML surrogate models into CFD solvers to accelerate pressure computation in incompressible flow simulations. The ML-enhanced solvers achieve an eightfold reduction in execution time while maintaining accuracy in drag coefficient and Strouhal number predictions. The research highlights hybrid CFD solvers that combine physics-informed methods with data-driven surrogate models.

4. Data-Driven Modeling of Geometry-Adaptive Steady Heat Conduction Based on CNNs

Authors: Jiang-Zhou Peng, Xianglei Liu, Nadine Aubry, Zhihua Chen, Wei-Tao Wu

Source: Case Studies in Thermal Engineering, 2021

Summary: This study proposes a CNN-based model for predicting steady-state heat conduction in objects with arbitrary geometries. Using a signed distance function (SDF) to represent geometry, the model generalizes well to unseen geometries and is over an order of magnitude faster than traditional numerical methods.

3. Dataset Discussion

The dataset used in this study is generated using **Computational Fluid Dynamics (CFD)** simulations performed in **Ansys Fluent 18**. The computational domain represents a **rectangular enclosure** subjected to heat transfer, where both side walls are heated with a constant heat flux of **500 W/m²**. The dataset is structured to capture the thermal and flow characteristics of the enclosure, providing a high-resolution representation of temperature and velocity fields across the domain.

3.1. Dataset Generation

The high-fidelity dataset is obtained through CFD simulations with the following setup:

- **Computational Domain:** Rectangular enclosure.
- **Boundary Conditions:**
  - Left and right walls: **500 W/m² constant heat flux**.
  - Top and bottom walls: **Adiabatic (no heat transfer)**.
  - Fluid inside the enclosure: **Natural convection-driven flow**.
- **Mesh Resolution:**
  - **10,000 spatial points (high-fidelity data)**.
  - Structured or unstructured grid depending on numerical accuracy.
- **Simulation Parameters:**
  - Governing Equations: **Navier-Stokes and Energy equations**.
  - Solver: **Finite Volume Method (FVM)**.
  - Turbulence Model: **Laminar or turbulence model depending on Rayleigh number**.

3.2. Data Representation and Features

The dataset consists of numerical solutions for the following field variables:

- **Temperature (T):** Capturing heat distribution across the domain.
- **Velocity Components (u, v):** Representing convective flow patterns.
- **Pressure (P):** Recording pressure variations due to convection.

Each variable is stored as a **spatial field**, discretized over 10,000 points. The CNN-based Reduced-Order Model (ROM) aims to downsample this dataset to **1,000 spatial points**, preserving essential features while reducing computational complexity.

3.3. Training Data Selection

Since the model is trained using a **single dataset**, the selection of an appropriate time step and spatial resolution is critical. The dataset needs to sufficiently represent the steady-state or transient flow physics, ensuring that key thermal and flow features are preserved after dimensionality reduction.

3.4. Challenges and Considerations

- **Data Sparsity:** Reducing from 10,000 to 1,000 points requires an effective mapping strategy to maintain accuracy.
- **Feature Preservation:** CNN must capture essential heat transfer and flow patterns while reducing redundant spatial points.
- **Generalization:** The trained model should maintain predictive capability for different heating conditions or boundary variations.

3.5. Expected Outcome

By leveraging CNNs for spatial reduction, the dataset will be transformed into a **lower-dimensional representation** while preserving high accuracy in temperature and velocity predictions. The reduced dataset will enable faster simulations and real-time predictions, making it suitable for practical applications in thermal system modeling.

4. Approach

To develop the Reduced-Order Model (ROM) using a Convolutional Neural Network (CNN), the following approach is adopted:

CFD Data Generation:

- A high-fidelity dataset is generated using **Ansys Fluent 18**, simulating heat transfer in a rectangular enclosure.

- The enclosure is subjected to a constant heat flux of **500 W/m²** on both side walls.
- The CFD output consists of temperature, velocity components, and pressure distributions across **10,000 spatial points**.

Preprocessing and Feature Extraction:

- The dataset is structured and normalized for optimal CNN performance.
- Feature selection ensures key thermal and flow properties are preserved.

CNN Model Development:

- A deep CNN architecture is designed to learn spatial correlations in temperature and velocity fields.
- The model is trained using the CFD dataset to downsample the spatial domain from **10,000 points to 1,000 points**.
- Loss functions are optimized to minimize errors in heat transfer predictions.

Model Validation and Performance Evaluation:

- The CNN-based ROM is tested against the high-fidelity CFD data.
- Performance metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are computed.
- The efficiency of the reduced model is evaluated in terms of computational time and accuracy.

Deployment and Application:

- The trained CNN-based ROM is integrated into a workflow for real-time heat transfer predictions.
- The model is tested for its generalization capability under varying heat flux conditions.

5. Future Work

While the proposed CNN-based ROM achieves significant computational efficiency, several areas for further research and improvement remain:

- **Multi-Scenario Generalization:** Extending the model to handle different heat flux distributions and varying boundary conditions.
- **Time-Dependent Analysis:** Integrating recurrent neural networks (RNNs) or Long Short-Term Memory (LSTM) networks to predict transient heat transfer behavior.
- **Hybrid ML-CFD Models:** Combining traditional physics-based CFD solvers with machine learning techniques to enhance predictive accuracy.
- **Adaptive Mesh Refinement (AMR):** Implementing an adaptive CNN framework that can dynamically refine spatial resolution in critical regions of the enclosure.
- **Experimental Validation:** Comparing the CNN-based ROM predictions with experimental heat transfer data to further validate its real-world applicability.
- **Parallelization and GPU Acceleration:** Optimizing the training and inference process using GPU computing for faster execution.
- **Integration with Digital Twins:** Deploying the model in digital twin applications for real-time monitoring and control of heat transfer systems.

The integration of machine learning techniques with CFD-based heat transfer simulations presents a promising pathway toward faster and more efficient predictive models. Further research will aim at expanding the model's capabilities to complex geometries and industrial-scale applications.

References

[1] Matthias Eichinger, Alexander Heinlein, and Axel Klawonn. Surrogate Convolutional Neural Network Models for Steady Computational Fluid Dynamics Simulations. *Electronic Transactions on Numerical Analysis*, 56:235-255, 2022.

[2] A. Trullo, M. Pasini, F. Bonaccorso, S. Bianco, R. Caramazza, P. Napoletano, D. De Falco, F. Piccialli A graph-based machine learning approach for predicting the compressive strength of concrete *Scientific Reports*, 14, 9732 (2024).

[3] B. Bogosel, S. Bordeu, C. Fiterau, L. Grigori, and S. Li. Data-driven reduced-order modelling for parameter identification in groundwater remediation. *Proceedings of the Royal Society A*, 479(2278):20230058, 2023.

[4] Jian-Ping Lyu, Xiao-Wei Yu, and Hong-Nan Li. Multifidelity Bayesian optimization for structural reliability analysis with limited data. *CMES-Computer Modeling in Engineering & Sciences*, 134(2):1489-1510, 2023.