Transient dynamics of temperature variations using Long-Short Term Memory (LSTM) models

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***Abstract*—An LSTM code for the enclosure is heated from the sides using a constant heat source of 500 W/m^2 heat flux for 15000 seconds needs to be developed. The data is generated using Computational Fluid Dynamics (CFD) code and will be provided for training the model.**

1. Introduction

The study of transient thermal dynamics is crucial in various engineering and scientific applications, ranging from thermal management systems to climate modeling. Traditional approaches to solving heat transfer problems rely on Computational Fluid Dynamics (CFD) simulations, which, while accurate, can be computationally expensive and time-consuming. In recent years, data-driven models, particularly deep learning techniques such as Long Short-Term Memory (LSTM) networks, have emerged as powerful alternatives for modeling time-dependent physical processes.

This project focuses on developing an LSTM-based predictive model for transient temperature variations in a two-dimensional enclosure heated symmetrically from both sides using a constant heat flux of 500 W/m². The training data for this model is generated using high-fidelity CFD simulations, capturing the evolution of temperature, velocity, and pressure fields over 15,000 seconds. The objective is to train an LSTM network to learn the temporal dynamics of the thermal system and predict future states based on past observations. The model's performance will be validated by comparing its predictions with full-order CFD simulations for a test heat input scenario.

The methodology adopted in this study is inspired by recent advancements in reduced-order modeling, which leverage deep learning to approximate complex fluid flow and heat transfer phenomena with high accuracy and significantly reduced computational cost. The project also aims to demonstrate the feasibility of LSTM-based temporal prediction in heat transfer problems, bridging the gap between conventional CFD simulations and machine learning-driven surrogate models.

This report details the development and implementation of the LSTM-based model, including data preprocessing, network architecture, training strategy, and validation against CFD results. The findings of this study contribute to the growing body of research on deep learning applications in thermal and fluid systems, offering insights into the potential of neural networks for real-time predictive modeling.

2. Literature Survey

1. Hybrid Deep-Learning POD-Based Parametric Reduced Order Model for Flow Around Wind-Turbine Blade (Tabib et al., 2022)

Summary:

This study presents a non-intrusive reduced-order modeling (NIROM) framework for wind turbine blade aerodynamics. The framework employs Proper Orthogonal Decomposition (POD) and Grassmann manifold interpolation to generate basis functions for different Reynolds numbers. A Long Short-Term Memory (LSTM) network is used to predict time-dependent coefficients of the reduced model. The study demonstrates that NIROM effectively approximates high-fidelity CFD simulations, reducing computational costs while maintaining accuracy.

Key Contributions:

- Development of a hybrid deep-learning NIROM for wind turbine aerodynamics.
- LSTM-based prediction of temporal dynamics.
- Validation using CFD simulations at different Reynolds numbers.

2. A Non-Intrusive Parametric Reduced Order Model for Urban Wind Flow Using Deep Learning and Grassmann Manifold (Tabib et al., 2021)

Summary:

This study focuses on modeling urban wind flow using a non-intrusive ROM (NIROM) framework. The framework combines Proper Orthogonal Decomposition (POD) for spatial decomposition and LSTM for time-series predictions. Grassmann manifold interpolation is used to obtain basis functions for new parameter values. The methodology is applied to wind flow around buildings, demonstrating stable and accurate predictions of velocity fields and turbulent kinetic energy.

Key Contributions:

- Application of NIROM for urban wind flow modeling.

- Integration of LSTM for temporal prediction.
- Comparison with full-order CFD simulations for validation.
- Demonstration of digital twin applications in smart cities.

3. Transient Heat Transfer Modeling Techniques (Das et al., 2002)

Summary:

This paper reviews transient heat transfer modeling techniques, emphasizing computational methods for predicting heat transfer behavior in various applications. It discusses numerical methods such as Finite Volume and Finite Element Methods and highlights their advantages and limitations. The study provides insights into transient thermal analysis for engineering applications, forming the basis for developing reduced-order models for heat transfer.

Key Contributions:

- Comprehensive review of transient heat transfer modeling.
- Analysis of numerical methods for solving heat transfer problems.
- Discussion of computational challenges in transient thermal analysis.
- Application relevance in engineering and CFD simulations.

3. Data Discussion

The dataset utilized in this study originates from Computational Fluid Dynamics (CFD) simulations conducted for a heated enclosure subjected to a constant heat flux of 500 W/m^2 over 15,000 seconds. The data comprises transient temperature, velocity, and pressure distributions sampled at regular intervals, encapsulating the system's evolution over time. The primary objective is to leverage this dataset to train a Long Short-Term Memory (LSTM) network capable of accurately predicting the future temporal dynamics of temperature variations.

3.1. Data Structure and Preprocessing

The dataset consists of time-series records with statistical attributes such as mean, standard deviation, and quartile distributions. The temporal resolution of the data is critical for capturing transient effects; hence, an appropriate time-step selection is ensured to balance computational efficiency and predictive accuracy. The preprocessing steps include:

- Normalization of temperature, velocity, and pressure fields to ensure stable training of the LSTM model.
- Handling missing or noisy data through interpolation and smoothing techniques.
- Structuring the dataset into overlapping time windows to facilitate sequential learning by the LSTM network.

3.2. Training and Validation Data Splitting

To ensure robust model generalization, the dataset is partitioned into training (70%), validation (15%), and test (15%) sets. The training set enables the model to learn temporal patterns, while the validation set is used for hyperparameter tuning. The test set, which consists of unseen data, serves to evaluate the model's predictive accuracy against full-order CFD results.

3.3. Comparative Analysis with CFD Simulations

The trained LSTM model's predictions are benchmarked against the original CFD simulations for a given test heat input. Metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are computed to quantify the deviation between the predicted and simulated temperature fields. Additionally, visualization techniques like contour plots and temporal response curves are employed to assess the fidelity of the learned dynamics.

The results from this analysis establish the efficacy of the LSTM model in capturing transient thermal behaviors, thereby providing a computationally efficient alternative to full-order CFD simulations for real-time applications.

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5. Approach and Future Work

5.1. Approach

The LSTM-based model is developed by designing a sequential neural network architecture optimized for time-series forecasting. The methodology follows these key steps:

1) Data preprocessing to normalize and structure the time-series data.
2) Selection of an appropriate LSTM architecture, including the number of layers and hidden units.
3) Training the model using backpropagation through time (BPTT) and optimizing using Adam or RMSprop optimizers.
4) Hyperparameter tuning through cross-validation to improve prediction accuracy.
5) Evaluating model performance by comparing predicted temperature fields with full-order CFD results.

5.2. Future Work

Future enhancements to this study include:

- Incorporating additional physical parameters such as heat conduction and convection effects for improved accuracy.
- Exploring hybrid deep learning models that combine Convolutional Neural Networks (CNNs) with LSTMs for enhanced spatial-temporal learning.
- Extending the approach to three-dimensional enclosures to capture more complex thermal dynamics.
- Investigating transfer learning techniques to adapt the model for varying boundary conditions and heat flux inputs.
- Implementing real-time inference for practical applications in thermal management and process control.

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