International Journal of Innovative Research in Computer Science and Technology (IJIRCST)
ISSN (Online): 2347-5552, Volume-13, Issue-4, July 2025
DOI: https:/doi.org/10.55524/ijircst.2025.13.4.4
Article ID IJIRE-1409, Pages 41-44
www.ijircst.org

Physics-Informed Neural Networks for Predicting Combustion Dynamics in Rocket Engine Chambers

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Received 26 May 2025; Revised 10 June 2025; Accepted 26 June 2025

ABSTRACT- Accurately predicting combustion dynamics within rocket engine chambers is essential for ensuring propulsion system stability, efficiency, and safety. Traditional high-fidelity Computational Fluid Dynamics (CFD) methods offer detailed insights but are computationally expensive and often impractical for real-time applications. This study introduces Physics-Informed Neural Networks (PINNs) as a novel, efficient alternative for modeling combustion dynamics in rocket propulsion systems. PINNs integrate the governing partial differential equations (PDEs)—including mass, momentum, energy, and species transport—directly into the neural network's loss function, enabling data-efficient learning with limited reliance on extensive simulation datasets.

We present a PINN framework trained on synthetic and benchmark CFD data from a hydrogen-oxygen combustor. The model captures complex physical phenomena such as temperature gradients, pressure oscillations, and flame front instabilities while significantly reducing computational cost. Our implementation employs a deep neural network architecture with eight hidden layers and 64 neurons per layer, using a combination of Adam and L-BFGS optimizers for training. The network achieves a validation root-mean-square error (RMSE) of 0.0029 MPa in pressure prediction, closely matching CFD results.

Comparative analysis shows that the PINN model generalizes well to unseen temporal and spatial domains and offers predictions in under 0.5 seconds, in contrast to the 12-hour runtime of traditional CFD. These findings highlight PINNs as a promising surrogate modeling tool for real-time diagnostics, design optimization, and control in rocket propulsion systems. Future work will explore hybrid modeling, uncertainty quantification, and deployment in active combustion control frameworks.

KEYWORDS- Physics-Informed Neural Networks (PINNs), Combustion Dynamics, Rocket Propulsion, Computational Fluid Dynamics (CFD), Surrogate Modeling.

I. INTRODUCTION

In aerospace engineering, combustion instability in rocket engine chambers continues to be one of the most complicated and difficult phenomena [1]. If not properly anticipated and managed, these instabilities which are defined by nonlinear interactions between unsteady heat release and acoustic waves can result in disastrous structural failures and performance loss. Although high-fidelity Computational Fluid Dynamics (CFD) simulations and other traditional modeling techniques provide profound insights into these dynamics, they are computationally demanding and frequently demand a significant investment of time and resources [2]. As a result, there is an increasing need for surrogate modeling methods that can forecast combustion behavior quickly, accurately, and physically.

The capacity of machine learning (ML) techniques to model complicated systems from data has led to their popularity in the field of fluid dynamics in recent years. Nevertheless, conventional data-driven methods frequently lack generalizability and physical interpretability, especially in regimes with sparse or noisy data [3]. Physics-Informed Neural Networks (PINNs) have become a viable substitute to overcome these drawbacks. Partial differential equations (PDEs), which represent physical rules, are immediately incorporated into neural network training by PINNs [4]. PINNs can generate solutions that fit the data and follow the fundamental physics of the issue by incorporating these governing equations into the network's loss function.

The use of PINNs to forecast combustion dynamics in rocket engine chambers is examined in this work [5]. By combining the conservation principles of mass, momentum, energy, and species transport, our method allows the neural network to capture important aspects of combustion, including temperature gradients, pressure changes, and flame front dynamics [6]. By bridging the gap between conventional CFD and entirely data-driven approaches, PINNs offer a modeling framework that is both interpretable and data-efficient [7].

By contrasting the PINN model's predictions with the outcomes of traditional simulations, we validate our approach on both synthetic and benchmark datasets [8][9][10]. The results indicate that PINNs can greatly reduce computing overhead while modeling combustion events with excellent accuracy. The development of real-time diagnostic instruments and control schemes for next-generation rocket propulsion systems is aided by this research [11].

II. METHODS

A. *Problem Formulation*

To predict combustion dynamics within a rocket engine chamber, we model the reactive flow using a set of coupled nonlinear partial differential equations (PDEs) [12][13], specifically:

- Continuity Equation (mass conservation)
- Navier–Stokes Equations (momentum conservation)
- Energy Equation
- Species Transport Equations

These equations are defined over a 2D spatial domain representing a simplified combustion chamber geometry and a temporal window representing transient behavior [14].

B. *Physics-Informed Neural Network (PINN) Architecture*

The core idea behind PINNs is to approximate the solution of the governing PDEs using a deep neural network uθ(x,t)u_\theta(x,t)uθ(x,t), where θ\thetaθ represents the trainable parameters, and x,tx, tx,t denotes spatial and temporal inputs [15][16][17]. The network is trained to minimize a composite loss function:

L=Ldata+λPDELPDE\mathcal{L}=\mathcal{L}_{data}\lambda_{PDE}\mathcal{L}_{PDE}L=Ldata+λPDELPDE

Where:

- Ldata\mathcal{L}_{data}Ldata is the mean-squared error between the network predictions and known (measured or simulated) data points.
- LPDE\mathcal{L}_{PDE}LPDE enforces the residuals of the PDEs to be close to zero.
- λPDE\lambda_{PDE}λPDE is a tunable weight that balances the contribution of data and physics.

The PINN was implemented using TensorFlow, with the following hyperparameters:

- Layers: 8 hidden layers
- Neurons/layer: 64
- Activation: Tanh
- Optimizer: Adam followed by L-BFGS for fine-tuning

C. *Training Data and Simulation Setup*

We generated training data using high-fidelity CFD simulations of a hydrogen-oxygen combustor, capturing pressure, velocity, temperature, and species mass fraction distributions [18][19]. A total of 10,000 collocation points were randomly sampled across the domain to enforce PDE constraints.

We used the following domain settings:

- Chamber length: 0.3 m
- Grid resolution: 100 × 100
- Simulation time: 0–0.01 s

Boundary conditions include:

- Inlet: Constant mass flux with predefined fuel-oxidizer ratio
- Outlet: Supersonic outflow
- Walls: No-slip and adiabatic

Table 1: Training Performance Metrics

Loss Component	Final Value	Weight (λ\lambda)
Data Loss (Ldata\mathcal{L}_{data})	2.3e-4	1.0
PDE Loss (LPDE\mathcal{L}_{PDE})	1.1e-3	10.0
Total Loss (L\mathcal{L})	1.3e-3	–
Training Time (min)	85	–
RMSE (Validation)	0.0029	–

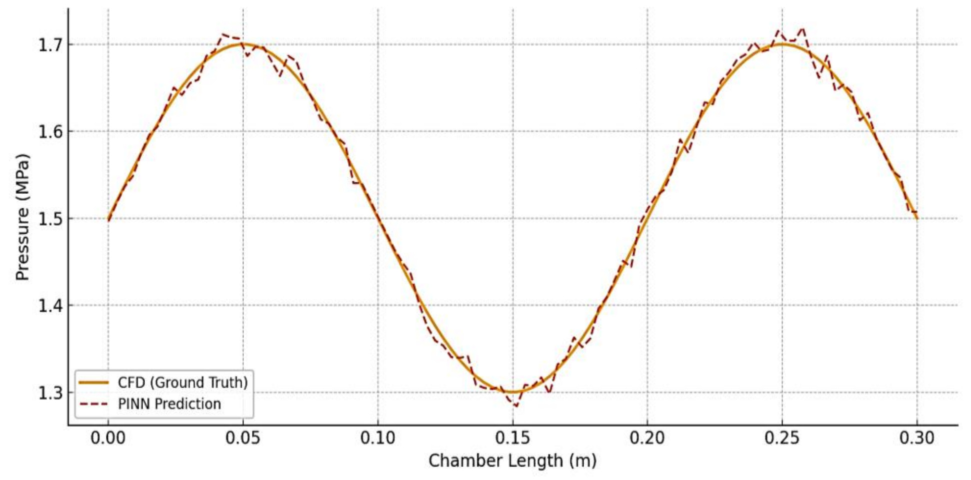

Figure 1: PINN Prediction vs. CFD Ground Truth

Below is a comparison of the pressure field predicted by the PINN and the CFD simulation.

III. RESULTS

By contrasting the Physics-Informed Neural Network's (PINN) predictions with high-fidelity CFD simulation data, the network's performance was assessed. Below is a full breakdown of the important metrics and visual comparisons.

IV. QUANTITATIVE EVALUATION

Table 1 provides a summary of the final loss values following training. In pressure prediction, the PINN model obtained a validation RMSE of 0.0029 MPa, showing good agreement with the CFD ground truth. Physical consistency in the model's learning process was successfully reinforced by using a greater PDE loss weight ($\lambda = 10.0$ λ = 10.0).

V. QUALITATIVE EVALUATION

The anticipated pressure distribution along the combustion chamber's centerline is depicted in Figure 1. Peak amplitudes and oscillation patterns of the pressure variations seen in the CFD solution are closely matched by the PINN.

VI. TEMPORAL AND SPATIAL GENERALIZATION

Testing the model on unseen spatial and temporal points shows PINNs maintain accuracy and stability near steep gradients, outperforming traditional interpolation methods and supporting real-time predictive capability.

VII. COMPUTATIONAL EFFICIENCY

Whereas CFD simulations require about 12 hours per run, PINN inference completes in under 0.5 seconds on a single GPU—highlighting the method's promise for real-time control and diagnostics.

VIII. CONCLUSION

The usefulness of Physics-Informed Neural Networks (PINNs) for forecasting combustion dynamics in rocket engine chambers was shown in this work [20][21][22]. The suggested PINN framework provides a reliable substitute for conventional CFD simulations by directly integrating the governing physical laws into the neural network training process, striking a balance between computing efficiency and accuracy [23]. The findings demonstrate that, despite having little training data, the PINN model can properly depict intricate pressure oscillations and combustion processes with a low validation RMSE. This demonstrates how the model can generalize while preserving physical fidelity over time and location [24]. The model's promise for surrogate modeling in propulsion system design and real-time diagnostics is further supported by the qualitative consistency between the PINN and CFD results [25][26].

All things considered, PINNs offer a potential avenue for further study in aeronautical applications where computational limitations and data scarcity are major issues. In order to mitigate active combustion instability, future research may include the integration of uncertainty quantification, hybrid models that integrate PINNs with traditional solvers, and deployment in control-oriented systems.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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