Data-Driven Multi-mode Recognition and Reconstruction of the Rotating Detonation Chamber

Xutun Wang[1], Haocheng Wen[2], and Bing Wang[3*]
[1,2,3] School of Aerospace Engineering, Tsinghua University
Haidian, Beijing, China

1 Introduction

With the development of aerospace propulsion technology, propulsion system based on detonation is expected to improve the propulsion efficiency due to its high thermodynamic efficiency[1,2] and inherent pressure-gain property[3]. Over the past decade, various attempts have been made to design new propulsion systems based on detonation, such as Pulsed Detonation Engine (PDE)[4], Oblique Detonation Engine (ODE)[5] and Rotating Detonation Engine (RDE)[6,7]. Among them, RDE is promising for the future aerospace propulsion system, because it is suitable for a wide work range compared to ODE and can provide stable thrust compared to PDE[8]. Due to the intrinsic characteristics, RDE has different types of combustion modes attributed to the variable operating condition, which presents a challenge for building a digital surrogate model of the engine.

It is necessary for the engineering application of RDE to identify the engine operating mode. In the existing studies, the identification of the modes relies on the data measured by several sensors arranged circumferentially around the combustor[8,9]. It is a time-consuming task of relying on these data for manual modal discrimination, while an infinite variety of working conditions can be obtained theoretically by varying the combustor parameters and inlet conditions. Inspired by the development of deep semi-supervised learning methods[10], which can accomplish classification with only a small amount of labeled data, this paper presents a method that uses a small amount of data to identify the operating modes in Rotating Detonation Chamber (RDC).

Moreover, sparse scattered observation data can be used to reconstruct high-resolution flow field in RDE combustor. Inspired by the great success of machine learning in fluid mechanics[11,12], we propose a Physics-Informed Neural Network (PINN)[13] that incorporates both deep learning methods and physical knowledge. With the observed data, this network aims to reconstruct high-resolution observed physical fields as well as extrapolate unobserved physical fields based on a simplified model of rotating detonation combustor[14]. The designed PINN can reconstruct high-resolution flow field in RDE combustor using sparse scattered observation points.

This paper is arranged as follows. Section 2 introduces the detailed method of multi-mode recognition. Section 3 includes the PINN and reconstruction results. Finally, Section 4 concludes this work. Since the experiment of RDE is expensive and difficult to obtain detailed data to evaluate the results, in this work, we use numerical methods to obtain train and test datasets.

Correspondence to: wbing@tsinghua.edu.cn

2 Multi-mode Recognition

In this work, we use Convolutional Neural Network (CNN) to deal with mode recognition from scattered observation points. The mode recognition architecture is shown in Figure 1. The network structure based on Resnet-18[15] has one input convolutional layer, eight residual blocks (each residual block has two convolutional layers) and one fully connected layer. Convolution kernel size and number of channels are shown in the middle part of Figure 1. Limited by the amount of labeled data, we use semi-supervised learning method to train the model. The semi-supervised learning method used in this paper is MixMatch[16].

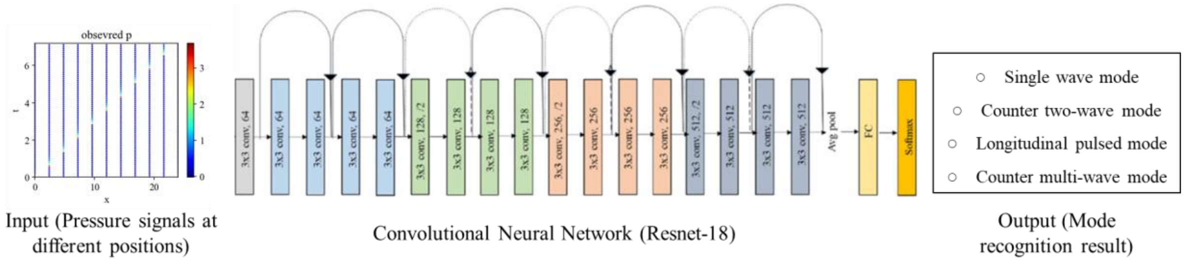


Figure 1: Architecture of mode recognition model

The implementation for the proposed model is performed using PyTorch, which is an open-source deep learning framework in Python. The loss function presented is optimized using Adam optimizer[17] and the learning rate is set to 5E-3. The batch-size is set to 36 and 50 epochs in total. Figure 2 shows the test confusion matrix, the predicted results match well with the ground truth with the accuracy 99.98%. If the training is performed through supervised learning with only a small amount of labeled data, the prediction accuracy is only 90.37%.

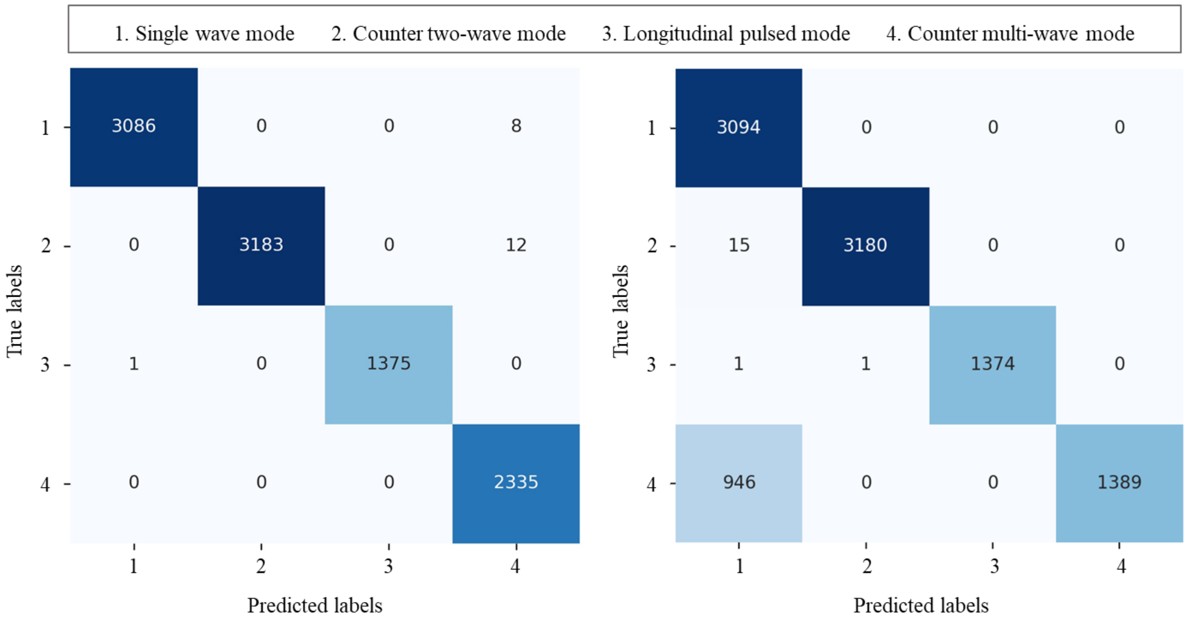


Figure 2: Confusion matrix of mode recognition model trained with (left) and without (right) semi-supervised learning method

3 Multi-mode Flow-field Recognition

In this paper, we use the lumped-volume combustor model developed by Koch and Kutz[14]. The nondimensional one-dimensional govering equation shown as below.

$$\frac{\partial}{\partial t}\begin{bmatrix}\rho \\ \rho u \\ E \\ \rho\lambda\end{bmatrix}+\frac{\partial}{\partial x}\begin{bmatrix}\rho u \\ \rho u^2+p \\ u(E+p) \\ \rho u\lambda\end{bmatrix}=\begin{bmatrix}\alpha\left(A^{+}H-A^{-}\sqrt{p\rho}\right) \\ 0 \\ \frac{\alpha}{\gamma-1}\left(A^{+}H-TA^{-}\sqrt{p\rho}\right)+\dot{\omega}q \\ \dot{\omega}-\rho\kappa H+\alpha\lambda\left(A^{+}H-A^{-}\sqrt{p\rho}\right)\end{bmatrix} \tag{1}$$

Where H denotes the injection model function describing the variation of flow rate with combustion chamber pressure, **H** is the Heaviside step function, whose expression is:

$$H(p)=\mathbf{H}(1-p)\left(1-\mathbf{H}(p-X)\frac{p-X}{1-X}\right), X=\left(1+\left(\frac{\gamma-1}{2}\right)\right)^{-\frac{\gamma}{\gamma-1}} \tag{2}$$

$\dot{\omega}$ denotes the dimensionless reaction rate, which satisfies Arrhenius' law with the expression:

$$\dot{\omega}=Da\exp\left(-E_a\left(\frac{1}{T}-\frac{1}{T_{VN}}\right)\right)\rho(1-\lambda) \tag{3}$$

There are 4 physical variables in equation set (1): density(ρ), velocity(u), pressure(p) and chemical reaction progress(λ). However, λ cannot be measured directly and only p, u, T are able to be observed by sensors fixed in the specified points with limited sampling frequency. Thus, the flow field reconstruction in RDE combustor is a typical inverse problem, which indicates the problem to reconstruct continuously, fully-dimensional data with dispersed, partial-dimensional observations and cannot be solved by traditional CFD methods. To improve the identification performance of PINN in different modes, we use meta-learning algorithm that allows the model to integrate knowledge from different working modes to improve the generalization performance of the PINN model. As shown in Figure 3, the outer optimization of meta-learning improves the performance of the model for multiple modes. Finally, the present PINN model is obtained that can be quickly adapted to new working modes.

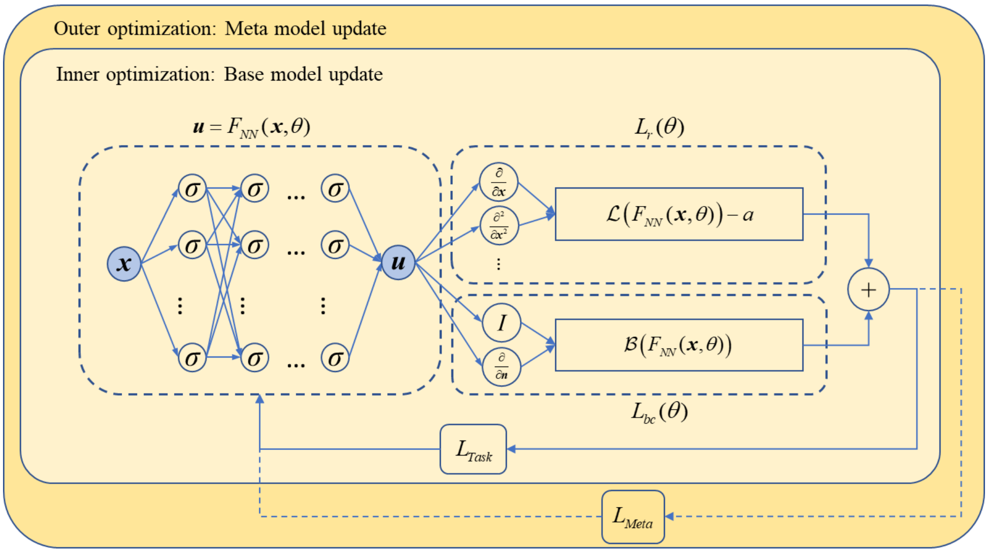
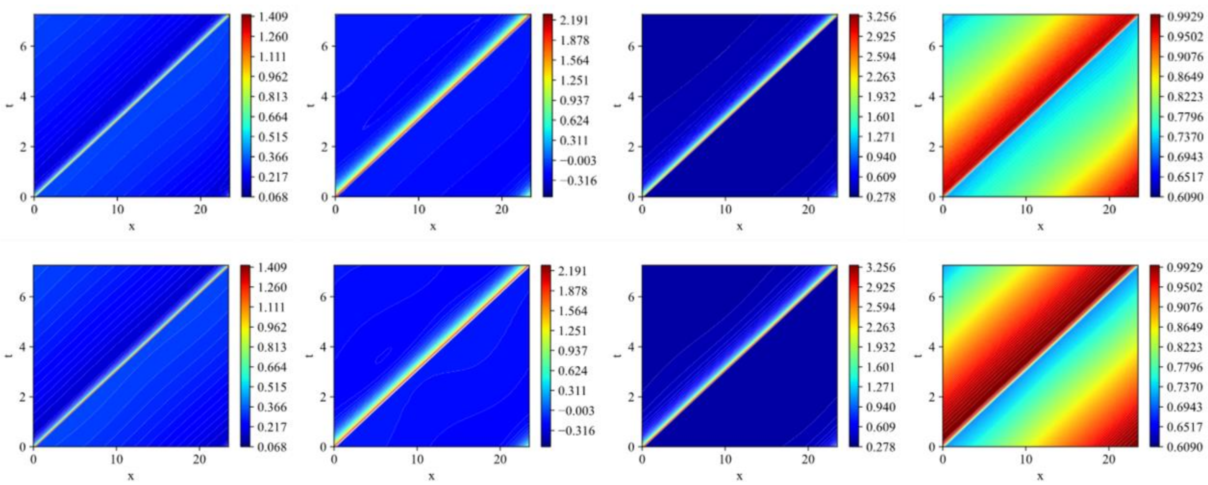
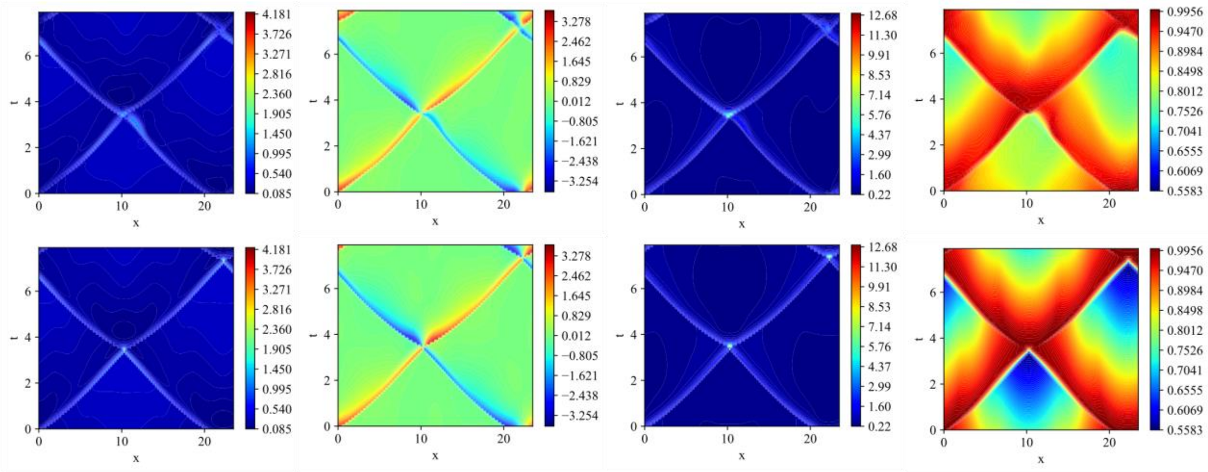


Figure 3: The structure of meta-PINN model

The reconstruction results of single wave mode and counter two-wave mode are presented in Figure 4. The PINN prediction well fits the abrupt changes in flow variables caused by the propagation of the detonation wave in the flow field. It also captures the different distribution patterns of flow characteristics before and after the wave, such as the density jump before the detonation wave compare to sharp drop and slow rebound after the detonation wave. Furthermore, the meta-learning model converges about 10 times faster than the model with random initialization, which significantly saves computational resources.



(a): Single wave mode PINN prediction (top) and ground truth (bottom)



(b): Counter two-wave mode PINN prediction (top) and ground truth (bottom)

Figure 4: Reconstruction results of two typical modes (from left to right is ρ, u, p, λ)

4 Conclusion and Future Work

This paper presents a data-driven method for solving multi-mode recognition and flow-field reconstruction of RDC. The main research conclusion is summarized as follows.

- The present mode recognition network can achieve the mode classification based on scattered pressure signals. Meanwhile, the model is trained with semi-supervised learning method to achieve better prediction accuracy with small amounts of labeled data.
- The PINN is developed to reconstruct the high-resolution flow field in the RDE combustor using sparse scattered observation points. Due to the use of meta-learning methods, one PINN model can be adapted to different working modes.

In future work, we would like to apply attention mechanism to capture the critical structure of detonation wave and improve the interpretability of the mode recognition network. Besides, we can combine PINN with real experimental data to realize the real surrogate model.

References

[1] Wolański P. (2013). Detonative propulsion. Proceedings of the Combustion Institute. 34: 125.

[2] Alhussan K, Assad M, and Penazkov O. (2016). Analysis of the actual thermodynamic cycle of the detonation engine. Applied Thermal Engineering. 107: 339.

[3] Zhou J, Song F, Wu Y, Xu S, Yang X, Cheng P, et al. (2023). Investigation of pressure gain characteristics for kerosene-hot air RDE. Combustion and Flame. 247: 112503.

[4] Kailasanath K. (2003). Recent Developments in the Research on Pulse Detonation Engines. AIAA Journal. 41: 145.

[5] Choi J-Y, Kim D-W, Jeung I-S, Ma F, and Yang V. (2007). Cell-like structure of unstable oblique detonation wave from high-resolution numerical simulation. Proceedings of the Combustion Institute. 31: 2473.

[6] Rankin BA, Fotia ML, Naples AG, Stevens CA, Hoke JL, Kaemming TA, et al. (2017). Overview of Performance, Application, and Analysis of Rotating Detonation Engine Technologies. Journal of Propulsion and Power. 33: 131.

[7] Yi T-H, Lou J, Turangan C, Choi J-Y, and Wolanski P. (2011). Propulsive Performance of a Continuously Rotating Detonation Engine. Journal of Propulsion and Power. 27: 171.

[8] Wen H. (2022). Research on Stability and Pressure-gain Performance of Rotating Detonation Combustion Fueled by Kerosene, Tsinghua University.

[9] Frolov SM, Aksenov VS, Ivanov VS, and Shamshin IO. (2015). Large-scale hydrogen–air continuous detonation combustor. International Journal of Hydrogen Energy. 40: 1616.

[10] Yang X, Song Z, King I, and Xu Z. (2022). A Survey on Deep Semi-Supervised Learning. IEEE Transactions on Knowledge and Data Engineering. 1.

[11] Brunton SL, Noack BR, and Koumoutsakos P. (2020). Machine Learning for Fluid Mechanics. Annual Review of Fluid Mechanics. 52: 477.

[12] Vinuesa R and Brunton SL. (2022). Enhancing computational fluid dynamics with machine learning. Nature Computational Science. 2: 358.

[13] Raissi M, Perdikaris P, and Karniadakis GE. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics. 378: 686.

[14] Koch J and Kutz JN. (2020). Modeling thermodynamic trends of rotating detonation engines. Physics of Fluids. 32: 126102.

[15] He K, Zhang X, Ren S, and Sun J. (2016). Deep Residual Learning for Image Recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770–778.

[16] Berthelot D, Carlini N, Goodfellow I, Papernot N, Oliver A, and Raffel CA. (2019). MixMatch: A Holistic Approach to Semi-Supervised Learning. Advances in Neural Information Processing Systems.

[17] Kingma DP and Ba J. (2014). Adam: A Method for Stochastic Optimization. Proceedings of the 3rd International Conference on Learning Representations.