



Modeling the filtered progress variable source term in lean hydrogen flames using conditional generative adversarial networks

L. Nista^{1,*}, C. D. K. Schumann², M. Vivenzo¹, T. Grenga³, J. F. MacArt⁴, A. Attili⁵, H. Pitsch¹

*Lead presenter: l.nista@itv.rwth-aachen.de

¹ Institute for Combustion Technology, RWTH Aachen University, Aachen, 52056, DE

² Department of Engineering, University of Cambridge, Cambridge, CB2 1PZ, UK

³ Faculty of Engineering, University of Southampton, Southampton, SO17 1BJ, UK

⁴ Aerospace and Mechanical Engineering, University of Notre Dame, Notre Dame, IN 46556, USA

⁵ Institute for Multiscale Thermofluids, University of Edinburgh, Edinburgh, EH9 3FD, UK

Direct numerical simulations (DNSs) and experiments have shown that turbulent lean hydrogen/air flames can exhibit thermodiffusive (TD) instabilities, leading to nonuniform reaction rate distributions along the flame and significantly increased flame speed [1]. However, DNS is computationally prohibitive for practical engineering applications, making lower-cost modeling strategies, such as large-eddy simulations (LESs), essential. Popular LES approaches often involve tabulated thermochemistry based on multiple control variables, such as the Favre-filtered progress variable, $\tilde{C}$, and Favre-filtered mixture fraction, $\tilde{Z}$, to compute the filtered progress variable source term and the filtered thermodynamic properties. Subfilter-scale effects are typically modeled using presumed probability density function (PDF) methods [1], even when multiple control variables are employed. This introduces an additional challenge due to the complexity of defining multidimensional PDFs. Common simplifications to mitigate this complexity include assuming statistical independence between control variables or applying state transformations to obtain quasi-independent variables as well as imposing a predefined PDF shape. However, these assumptions can weaken statistical correlations and introduce modeling errors that affect the filtered source term and, ultimately, the flame dynamics.

To address this challenge, we employ a conditional generative adversarial network (cGAN) that estimates the filtered progress variable source term conditioned on the input variable, $\tilde{C}$ [2]. This approach learns the statistical mapping between input and output without relying on a predefined closure structure. Adversarial training, guided by a discriminator, encourages the generator to produce output that resembles filtered DNS data, allowing the cGAN framework to better capture localized variability and nonlinearity compared to fully supervised networks. *A priori* in-sample analyses, based on the DNS performed by Berger *et al.* [1], demonstrate that cGAN predictions more closely follow filtered DNS data, particularly when the flame front is only partially resolved, compared to the chemistry tabulated chemistry model. *A posteriori* LES results confirm these trends and highlight the cGAN's potential to improve LES modeling of TD instability-driven hydrogen flames.

References

- [1] Berger, L., Attili, A., Gauding, M., and Pitsch, H., "LES combustion model for premixed turbulent hydrogen flames with thermodiffusive instabilities: a priori and a posteriori analysis," *Journal of Fluid Mechanics*, Vol. 1003, 2025, pp. A33.
- [2] Nista, L., Pitsch, H., Schumann, C. D. K., Bode, M., Grenga, T., MacArt, J. F., and Attili, A., "Influence of adversarial training on super-resolution turbulence reconstruction," *Physical Review Fluids*, Vol. 9, Jun 2024, pp. 064601.