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Experimental demonstration of deep reinforcement learning adaptive control of thermoacoustic instabilities in a lean-premixed methane/hydrogen/air combustor

Bassem Akoush[1]; Guillaume Vignat[1]; Ryan Finley[1]; Wai Tong Chung[1]; Matthias Ihme[1,2,3]

[1]*Department of Mechanical Engineering, Stanford University, Stanford, CA, USA*

[2]*Department of Energy Science and Engineering, Stanford University, Stanford, CA, USA*

[3]*Department of Photon Science, SLAC National Accelerator Laboratory, Menlo Park, CA, USA*

Abstract

In high performance combustion systems, an unstable feedback loop can develop between the flame, injection system, and the acoustic field within the combustion chamber. Such thermoacoustic instabilities can reach very high amplitude and lead to the rapid destruction of the engine. These instabilities generally manifest through supercritical Hopf bifurcations and are extremely sensitive to changes in operating parameters. The current impetus to develop highly fuel flexible devices capable of operating with a wide range of fuels therefore becomes a major challenge. Active control of thermoacoustic systems using, *e.g.*, microphones, acoustic drivers, and feedback loops, has been demonstrated as an effective solution to dampen such unstable systems. In the present work, we enrich a conventional thermoacoustic control system using model free deep reinforcement learning (RL). By adaptively tuning the control system t different operating conditions, the proposed RL system addresses a major limitation of conventional active control systems: it enables damping of thermoacoustic oscillations over entire operating range of the burner. The RL control system is implemented on a laboratory-scale bluff-body-stabilized premixed methane/hydrogen/air flame, which is operated over a large range of equivalence ratios (0.5 – 1.0) and fuel composition (from 0% to 80% H_2). Thermoacoustic instabilities reached amplitudes of up to 160 dBSPL over a large range of the operating map and were damped by the RL control system after training on one operating condition. Extending training to four conditions lead to further refinement of the control policy and an additional reduction in the sound pressure level within the burner. With this training, we demonstrated a sixfold reduction in the thermoacoustic source term over the entire operating range. A reduction of at least 26 dB compared to the no-control reference case was achieved over more the 50% of the investigated operating conditions.

Keywords: Reinforcement Learning; Adaptive Control; Machine Learning; Combustion Instability; Hydrogen Combustion; Fuel-flexible Combustion; Multi-sensor control