

DNS of Turbulent Combustion in Complex Flows

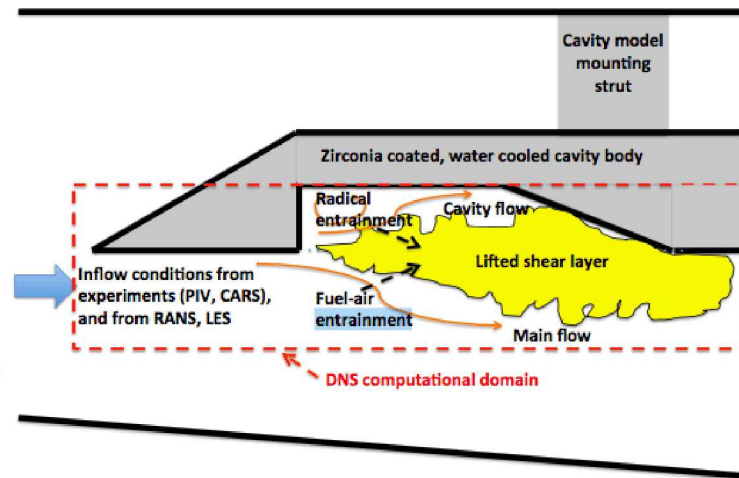
UK Consortium on Turbulent
Reacting Flows Annual Meeting



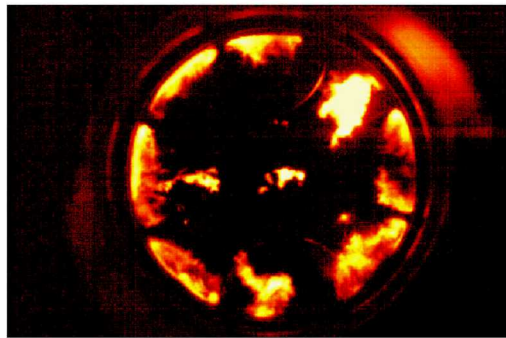
Selwyn College
Cambridge University
September 12-13, 2018



Motivation



Early injection PCCI

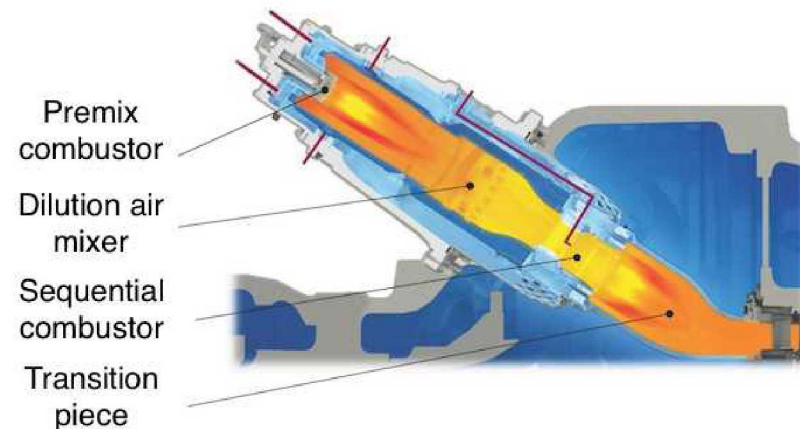


Experiments
PIV, PLIF
(UVa, GWU,
NASA)



Gain insights into:

- Flame stabilization mechanism
- Effect of heat release
- Turbulence-chemistry interactions



DNS of Flame Propagation and Structure Behind a Backwards Facing Step

A. Konduri, H. Kolla, and J. H. Chen

Sandia National Laboratories

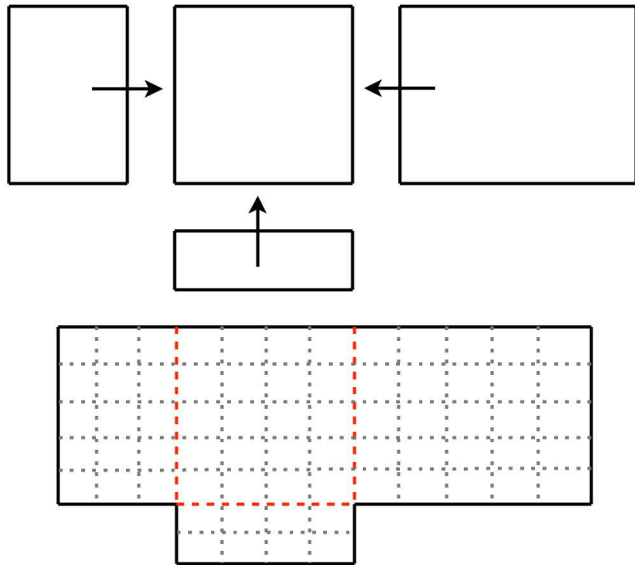


Office of Science
U.S. Department of Energy

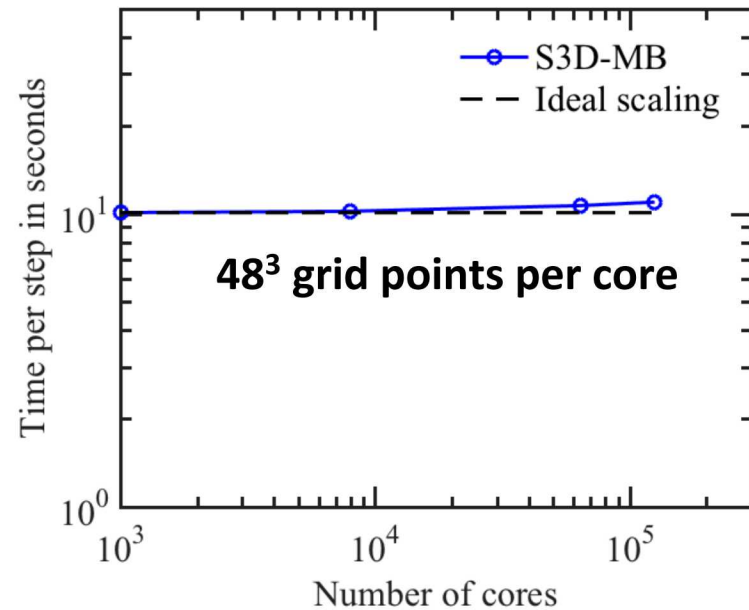


S3D - multiblock

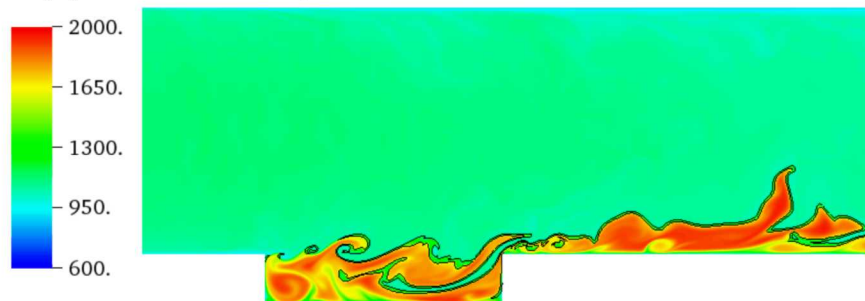
Multiblock construction



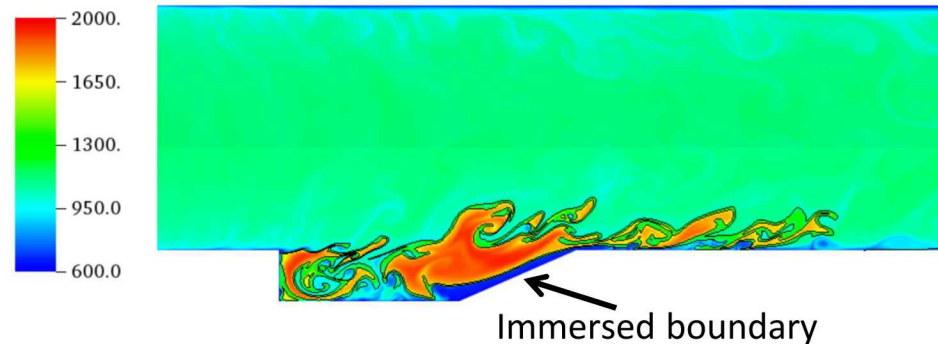
Weak scaling on Titan



T (K) Sample from 2D simulation

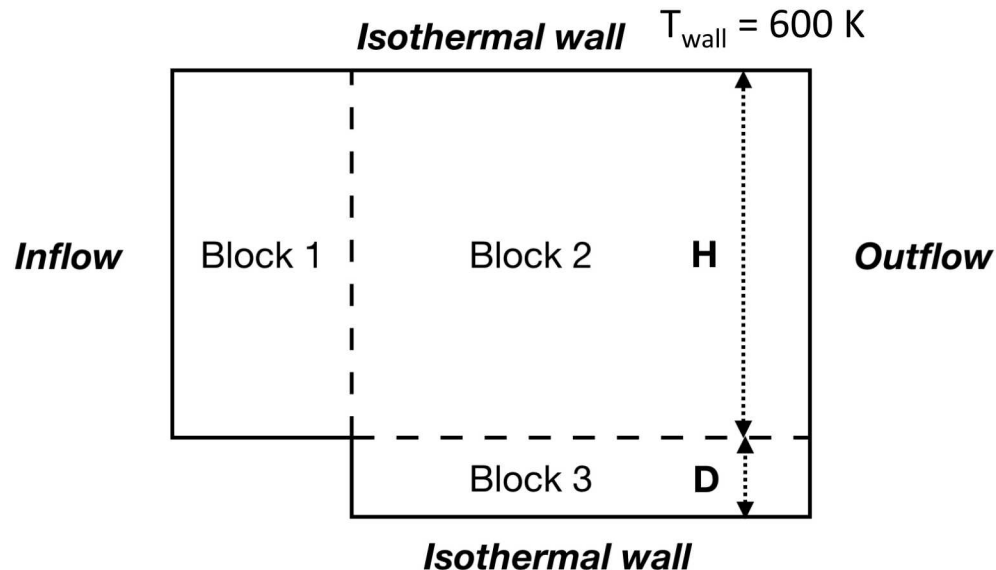


With IBM



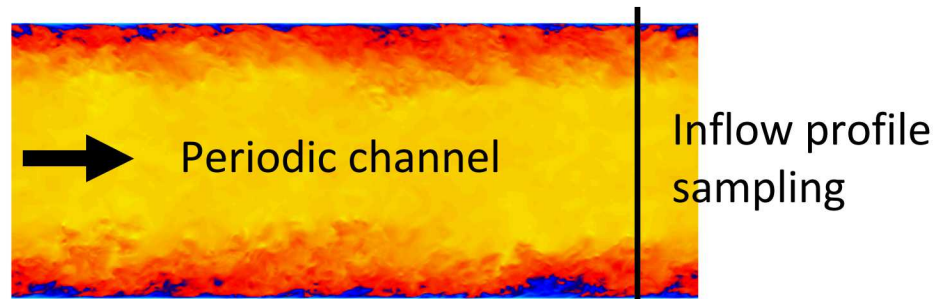
Backward-facing step

Ethylene-air
 $\Phi = 0.42$
 $U = 200$
 m/s
 $u' = 10\%$
 $T = 1125$ K



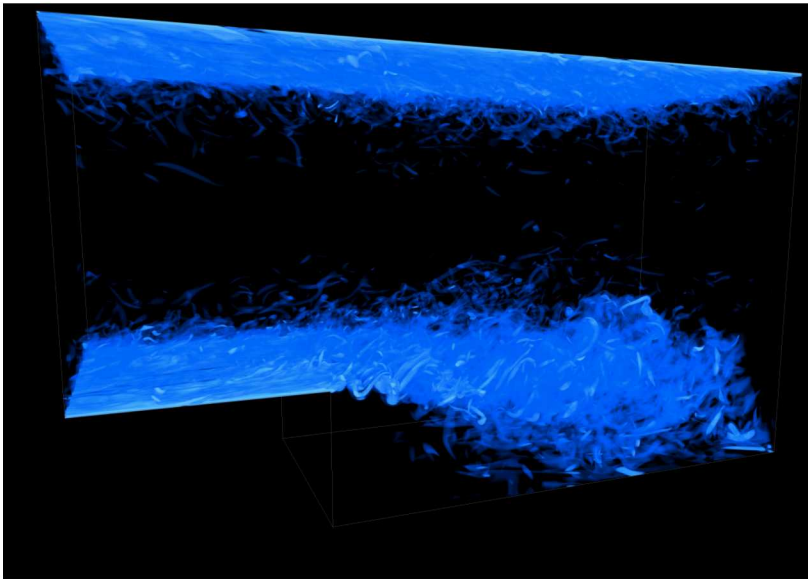
H	1.47 cm
D	0.3048 cm
Re_H	35000
Re_D	788
Grid count	2.6 billion
CPU hrs	25 million

- **Mechanism:** 22 species non-stiff reduced ethylene-air (Lu et al. 2012)
- **Transport model:** mixture averaged
- **Turbulent inflow profile:** feed data generated from a separate 3D DNS of channel

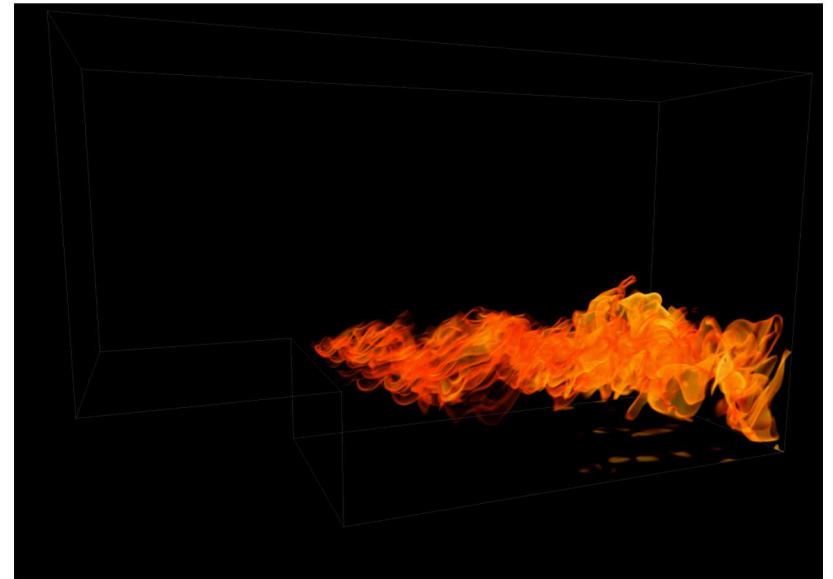


Results

Vorticity magnitude

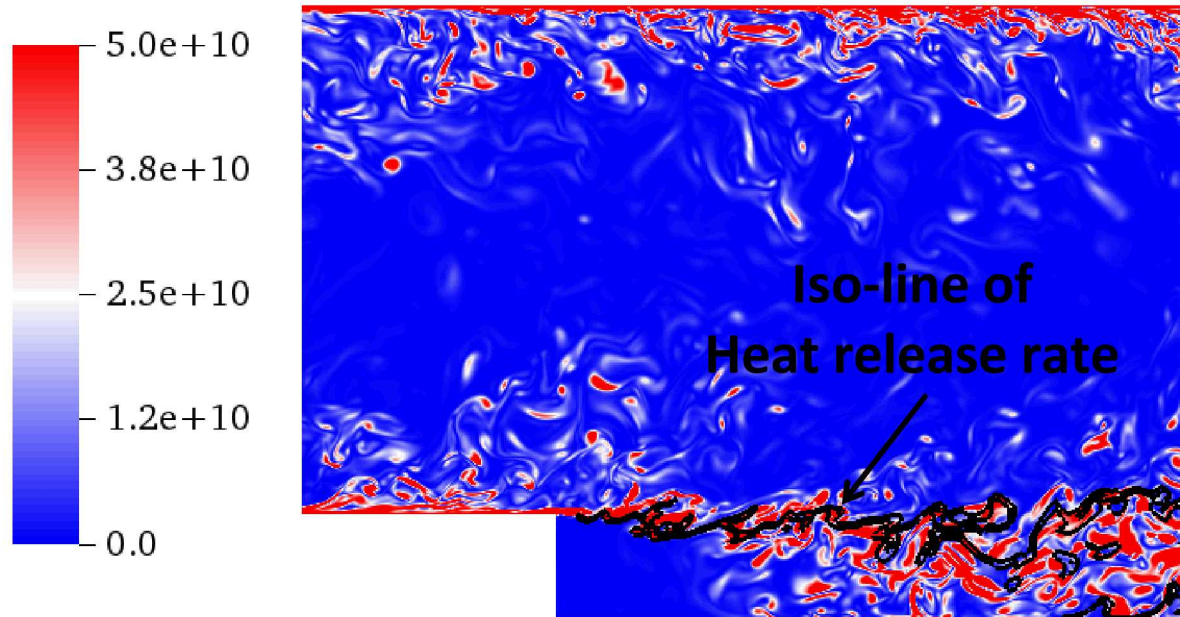


Heat release rate



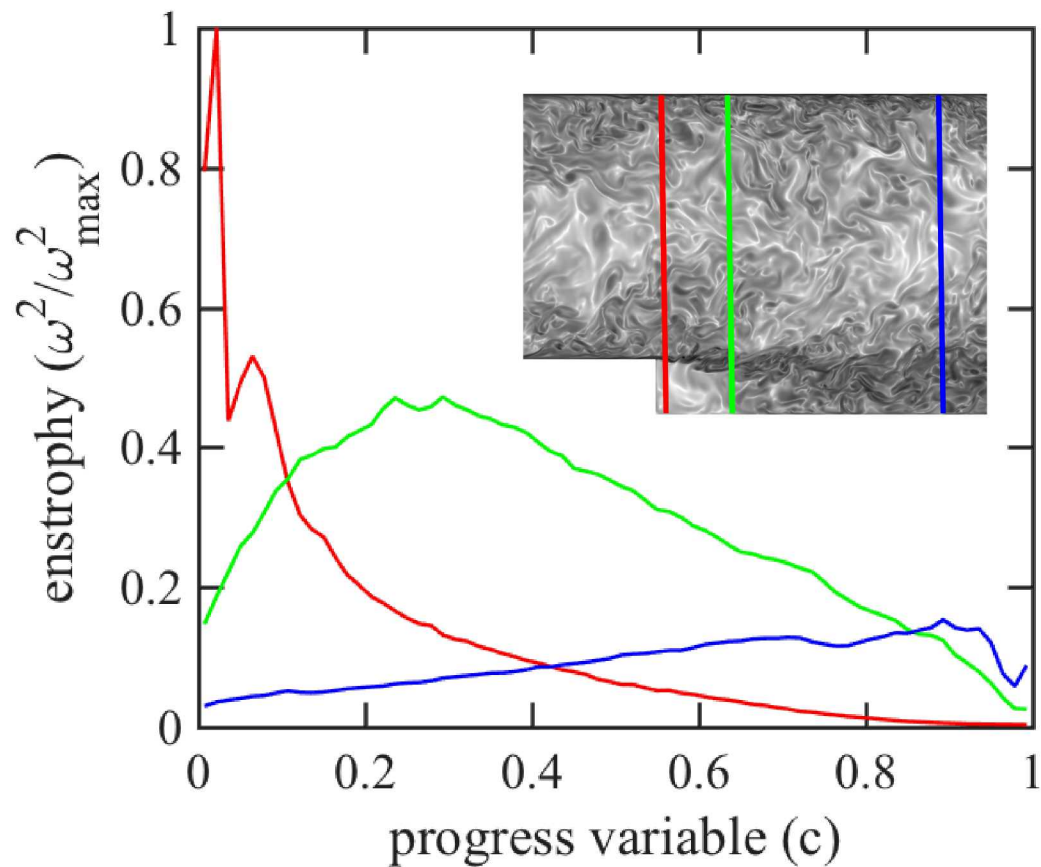
Vorticity dynamics

Enstrophy

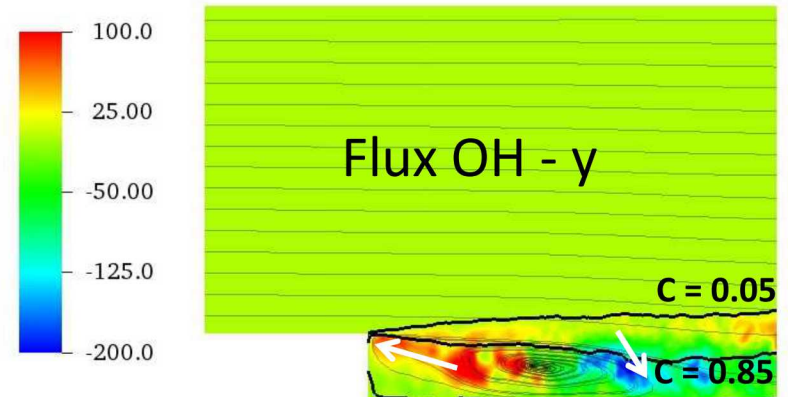
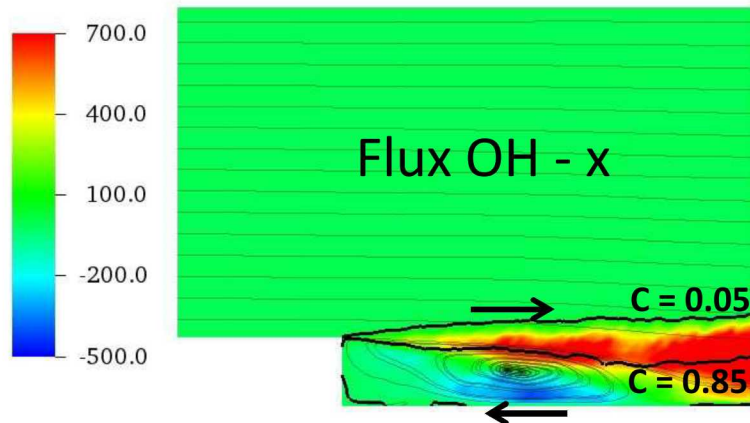
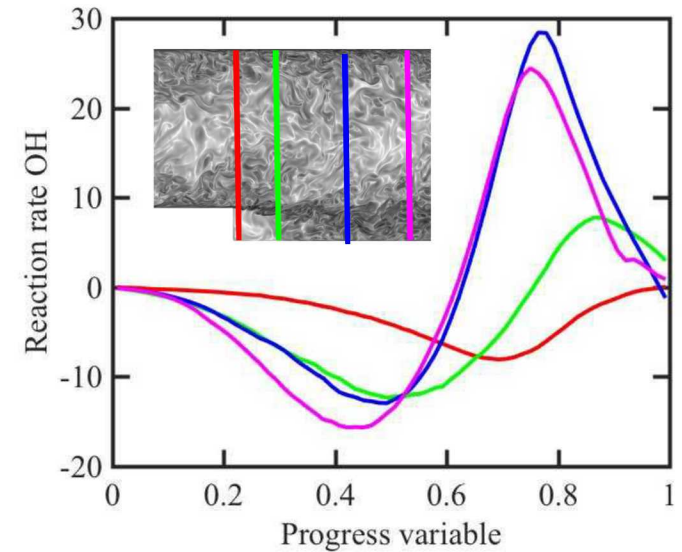
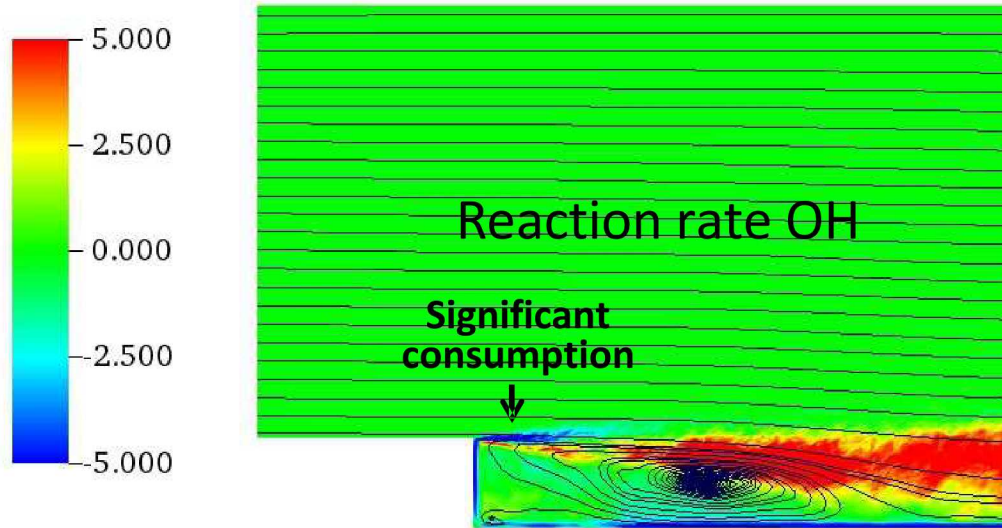


- Enstrophy present dominantly on product side

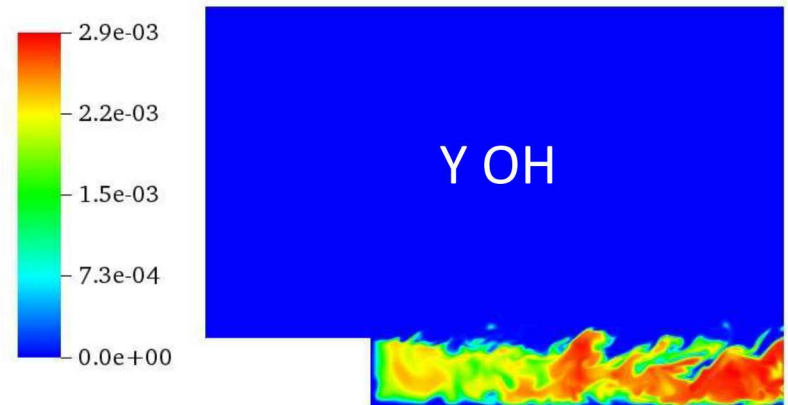
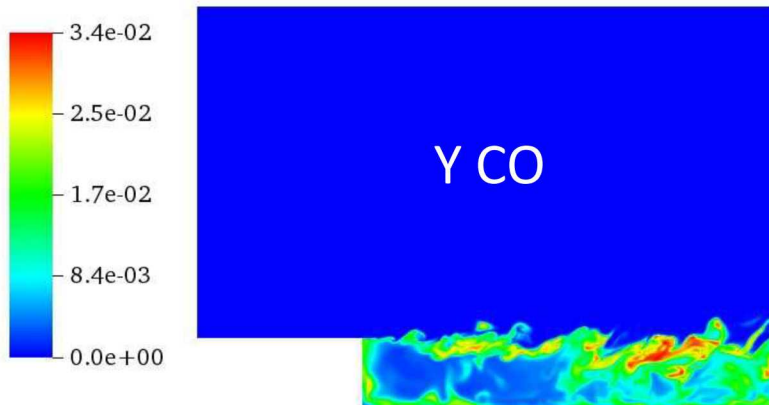
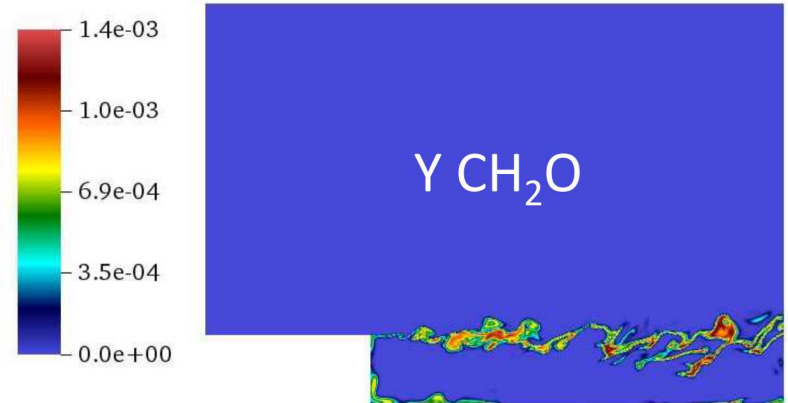
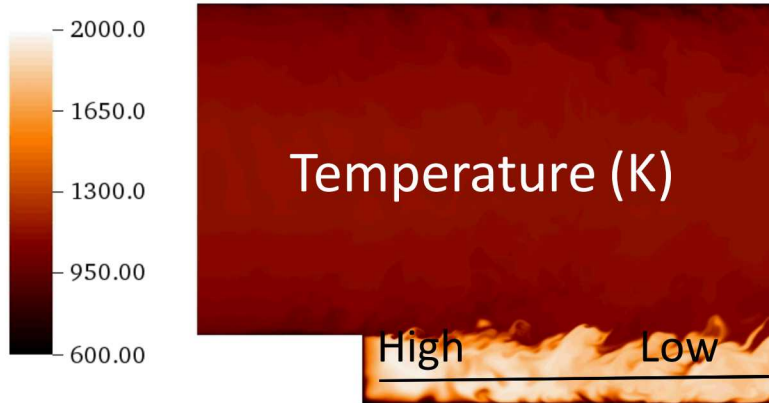
Vorticity dynamics



Flame stabilization

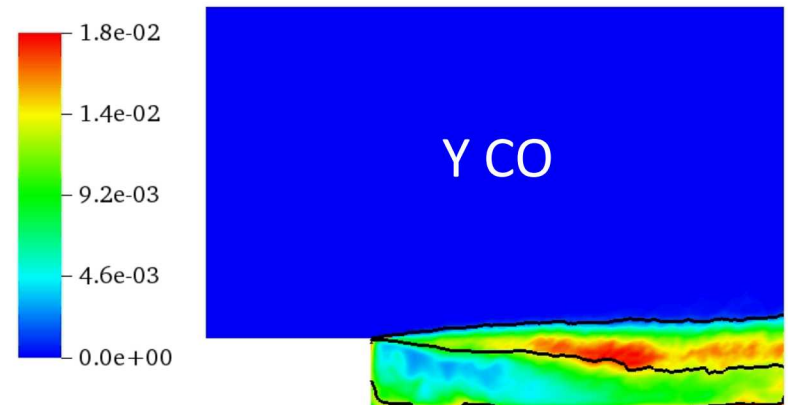
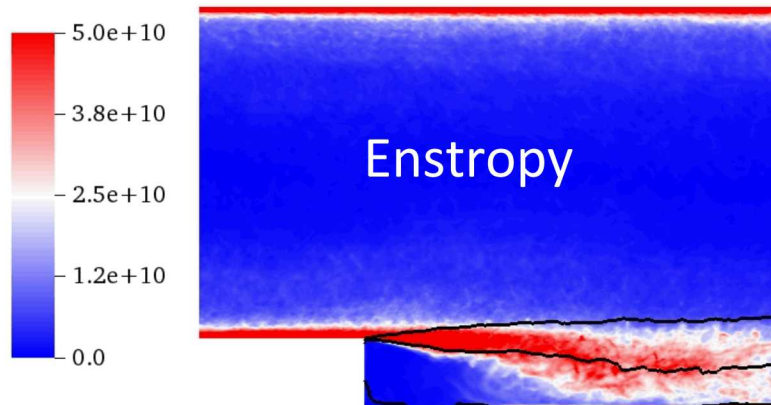
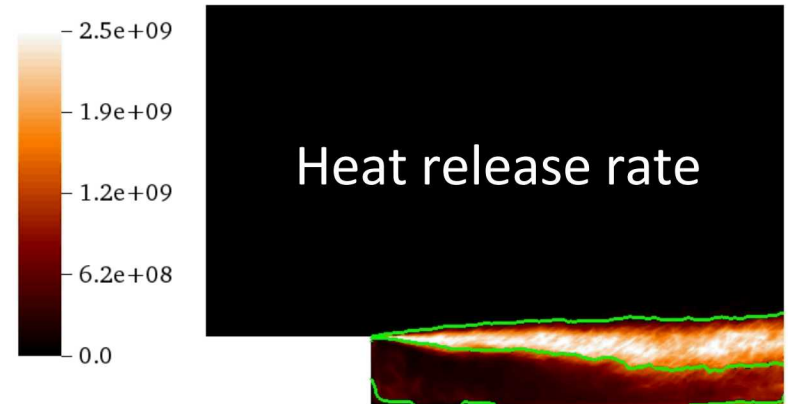
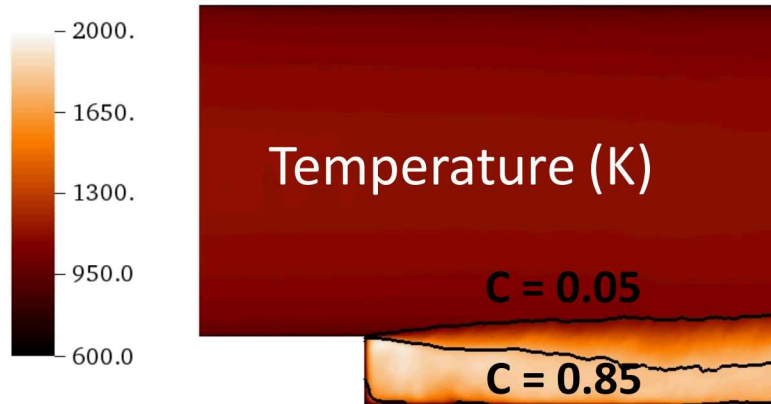


Flame structure

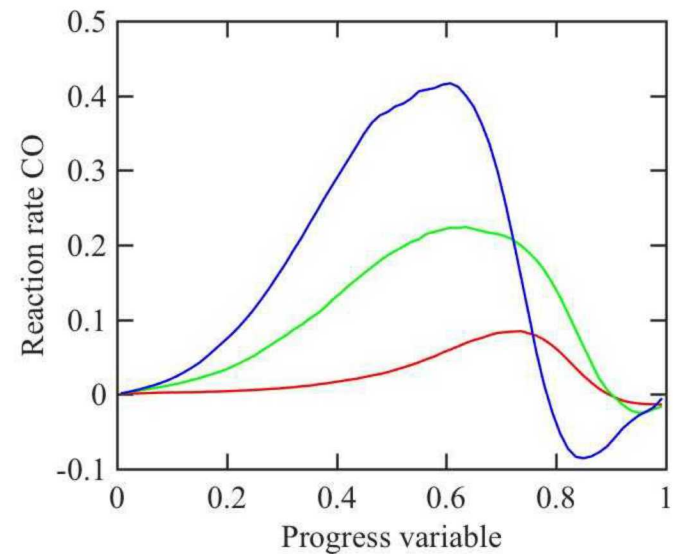
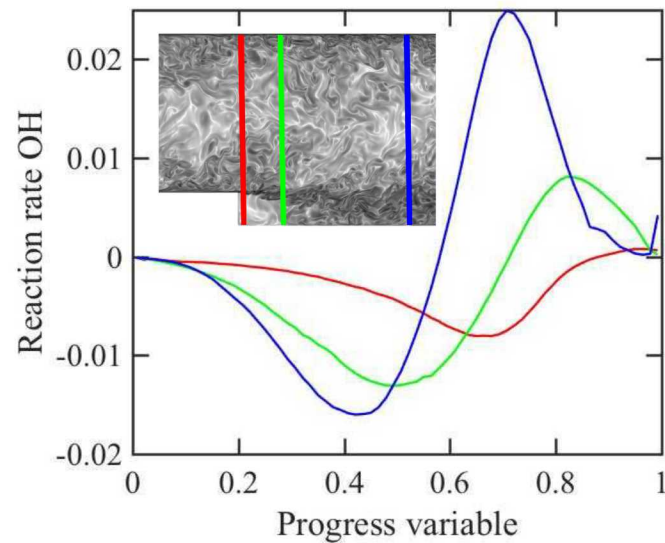
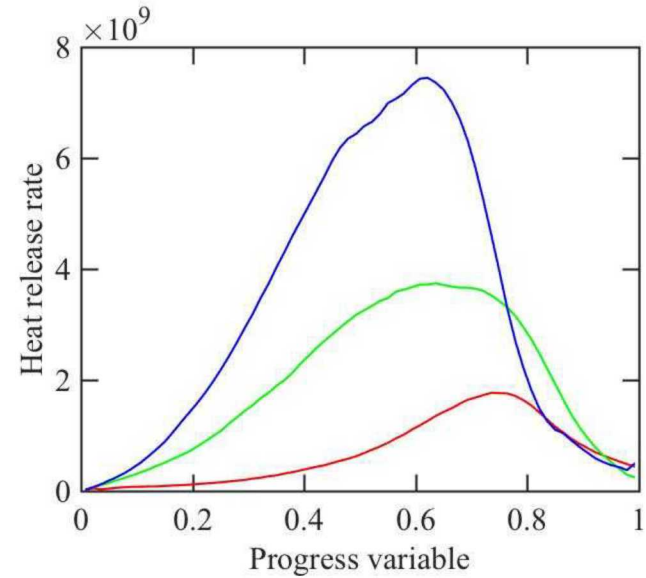
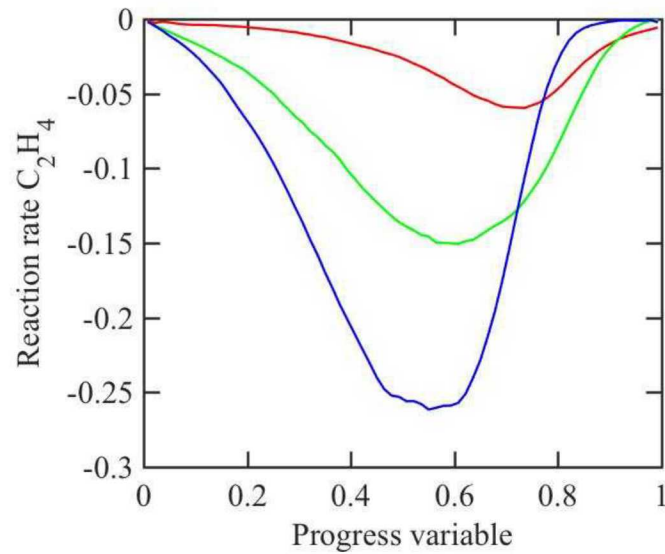


- Flame structure varies with distance from the step
- Flame-flame interaction present due to the shear
- Incomplete oxidation

Flame structure



Flame structure



Summary

- DNS of C₂H₄/air flame stabilization behind a backwards facing step
- Strong interaction between recirculation zone, shear layer, and flame brush
- Radicals from the recirculation zone assist in anchoring the flame
- Turbulence generation migrates towards products downstream of the stabilization point
- Implications for modifications to flame structure and heat losses to the wall

Direct Numerical Simulation of flame stabilization assisted by auto-ignition at *reheat* conditions

Konduri Aditya^a, Andrea Gruber^b and Jacqueline H. Chen^a

^aCombustion Research Facility, Sandia National Laboratories, Livermore, CA, USA

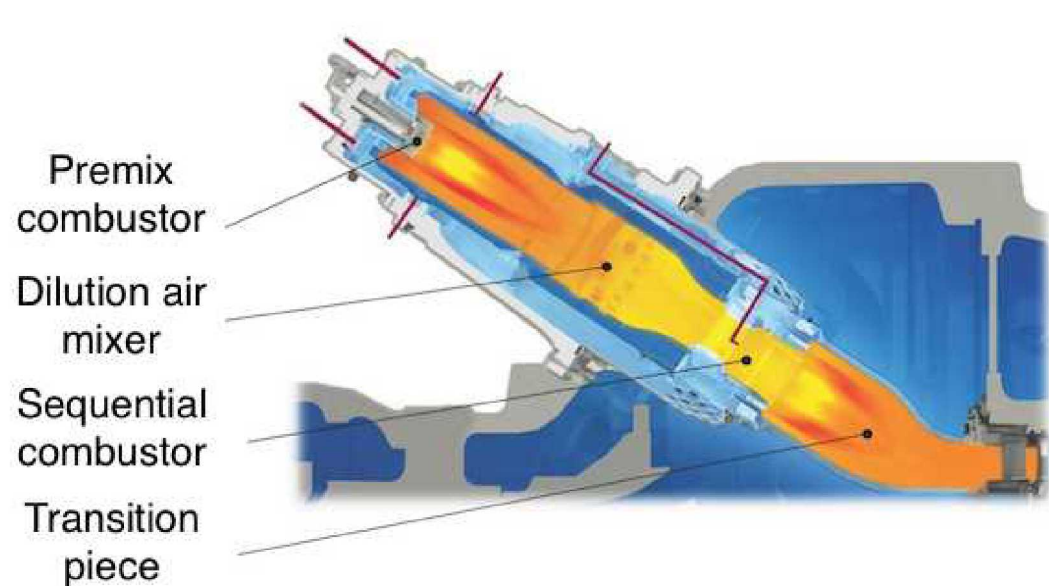
^bSINTEF Energy Research, Trondheim, Norway



Acknowledgements:

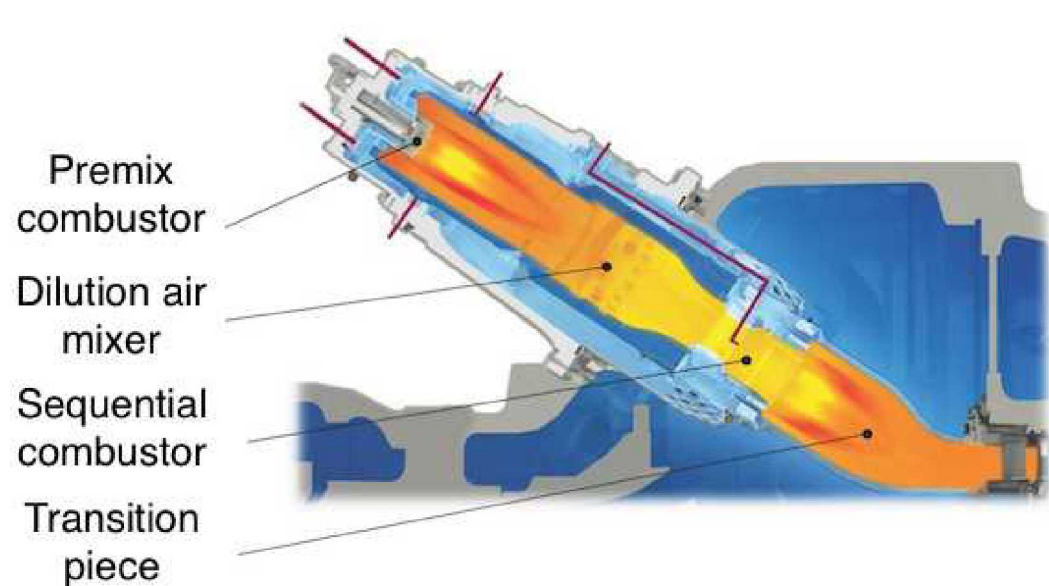
Basic Energy Sciences, Office of Science, DOE
OLCF, NERSC, Norwegian CCS Research Centre (NCCS)

Staged gas turbine combustion



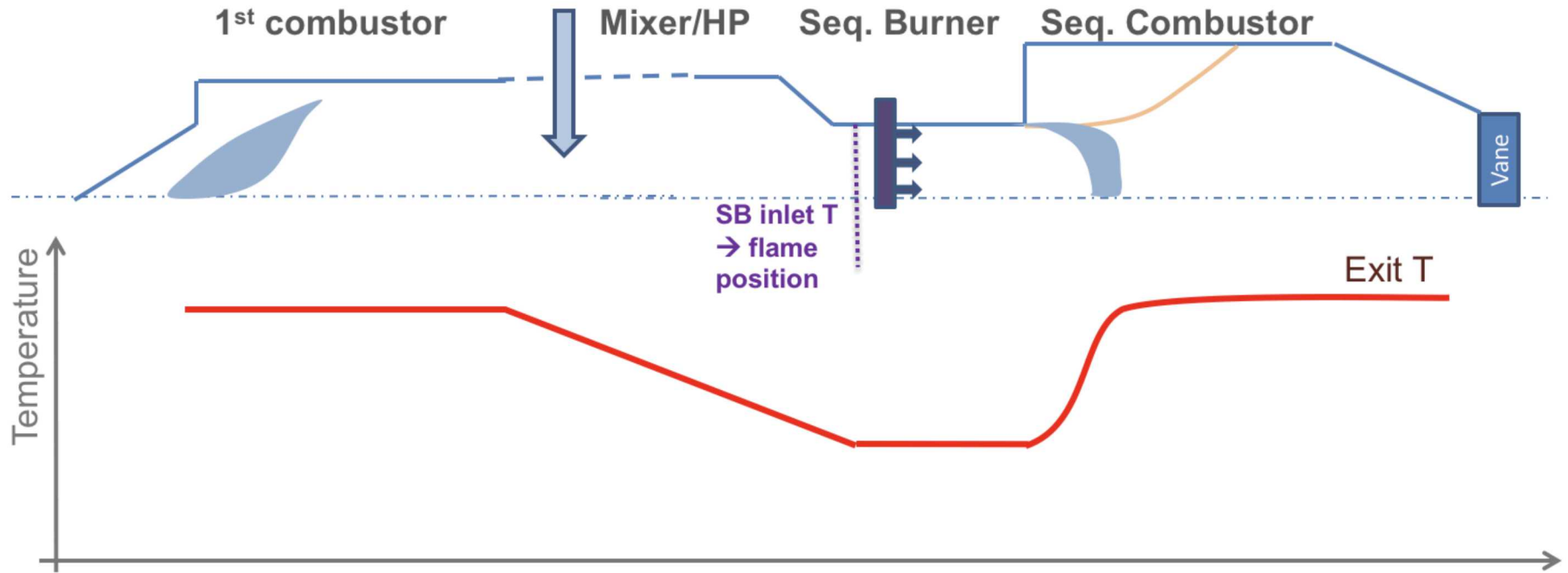
- Originally developed by ABB for high efficiency, load flexibility and low emissions
- Recently improved and simplified (reduced cost) for the H-class GT36
- First (premix) combustion stage based on flame propagation
- Second (sequential) combustion stage based on auto-ignition

Staged gas turbine combustion



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Staged gas turbine combustion

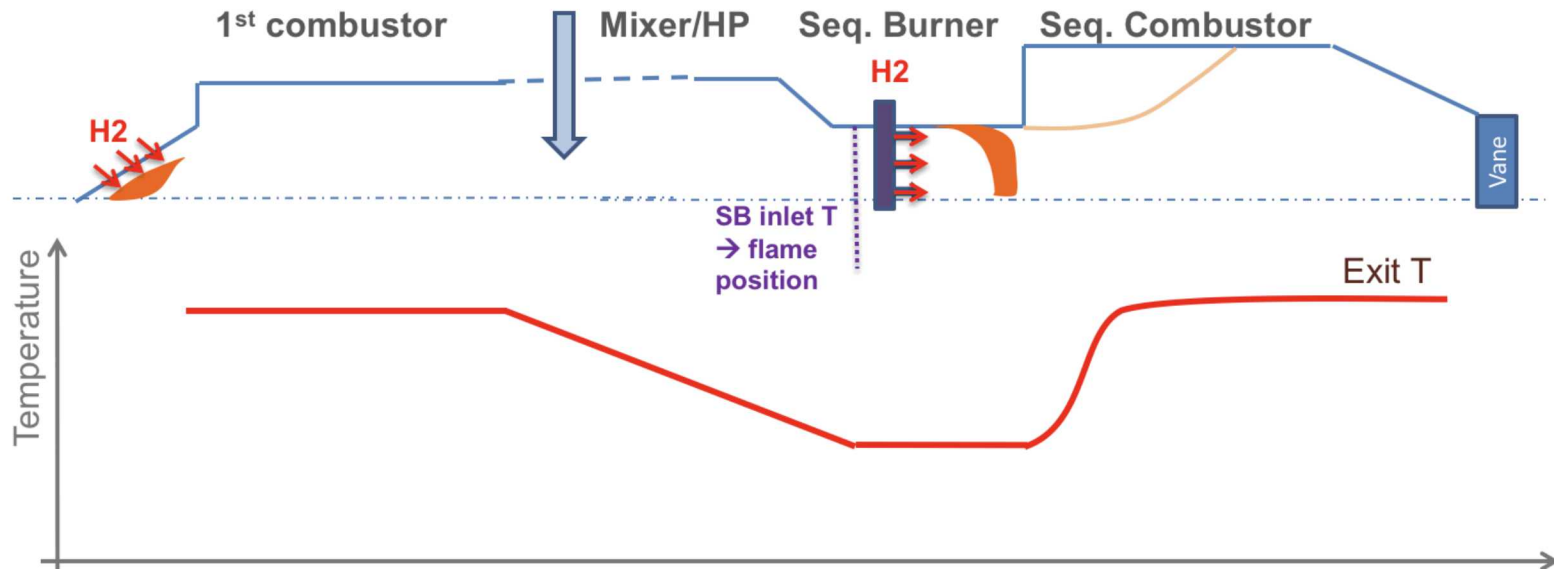


- Adjusting firing temperature of 1st stage allows control of t_{ign} in 2nd stage

Staged gas turbine combustion

Hydrogen fuel

- Flashback in 1st stage
- Early auto-ignition in 2nd stage

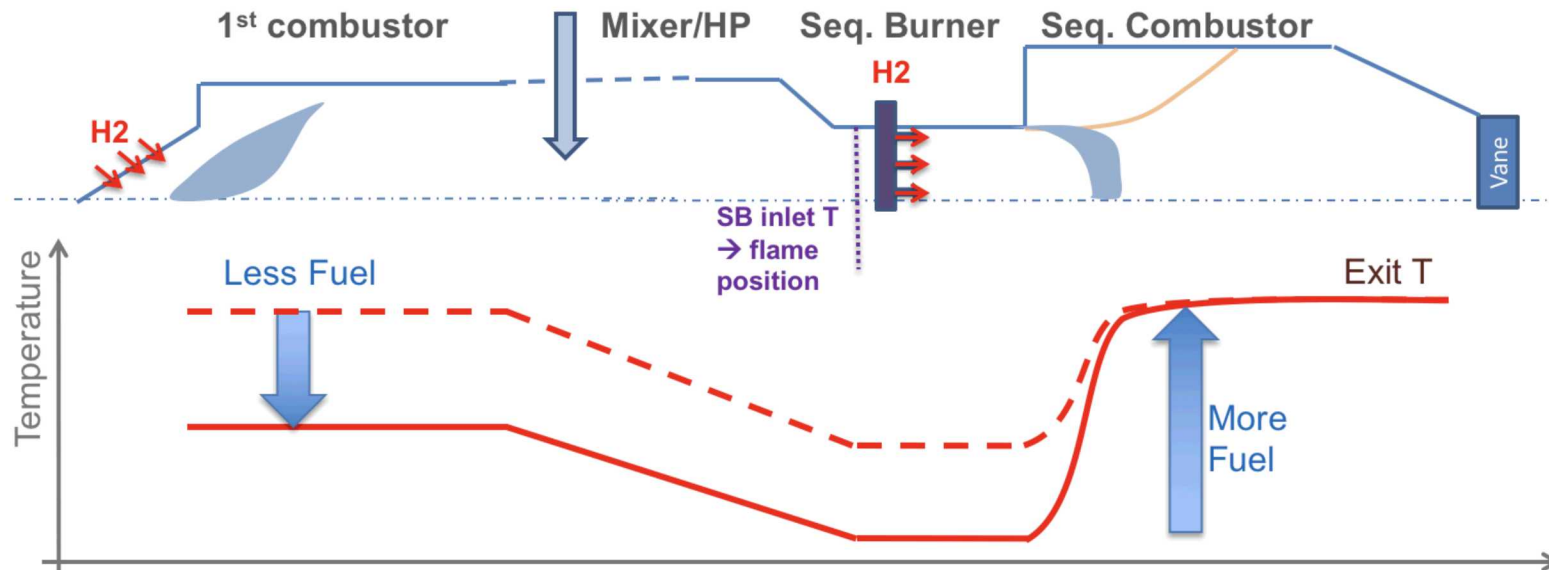


- 2nd stage is mainly auto-ignition stabilized
- 2nd stage inlet temperature needs to be decreased and not 2nd stage flame temperature

Staged gas turbine combustion

Hydrogen fuel

- Flashback in 1st stage
- Early auto-ignition in 2nd stage



- 2nd stage is mainly auto-ignition stabilized
- 2nd stage inlet temperature needs to be decreased and not 2nd stage flame temperature
- 1st stage de-rating is compensated by shifting fuel to 2nd stage

Reheat burner

DNS of idealized reheat burner configuration from Ansaldo Energia

Operating conditions:

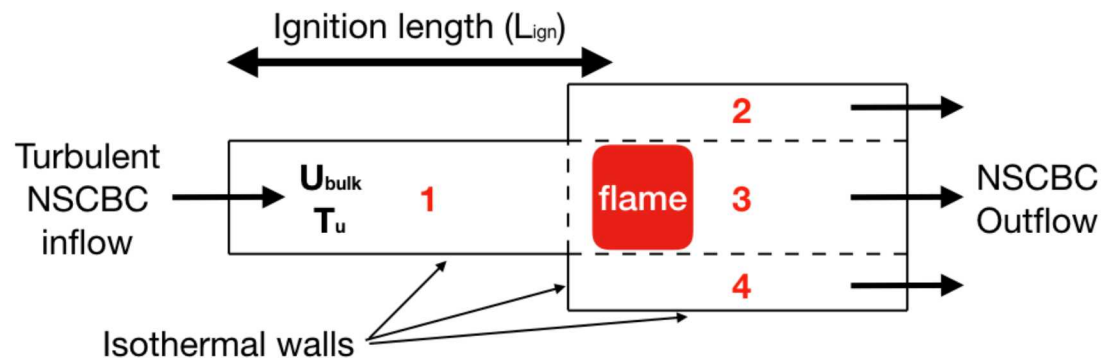
- Inlet temperature: ~ 1100 K
- Pressure: ~ 20 atm

Scaled conditions:

- Mean inlet temperature:
- Pressure: 1 atm
- Fuel: hydrogen

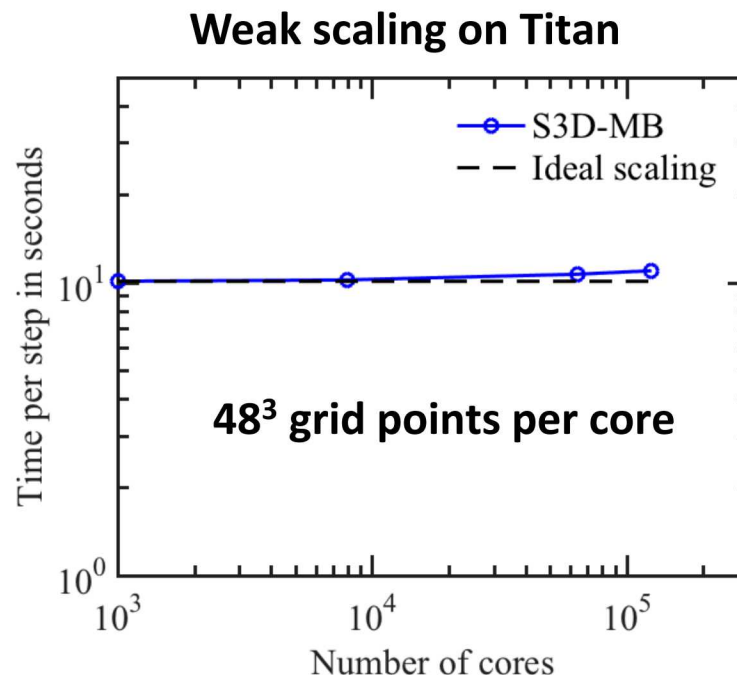
Objective:

- Understand the flame stabilization
- Identify the modes of combustion
- Quantify the role of auto ignition



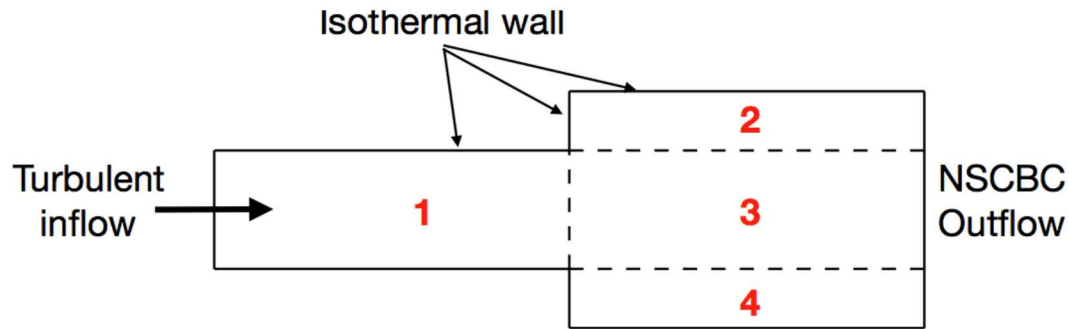
S3D - Multiblock

- Mildly complex geometry enabled by multi-block DNS capability
- Construct geometries by assembling several cuboidal blocks (like Lego)
- Compressible formulation (J. H. Chen et al., CSD 2009)
- Spatial derivatives: 8th order CD schemes & 10th order filter
- Time integration: 4th order Runge-Kutta
- Mixture averaged transport model



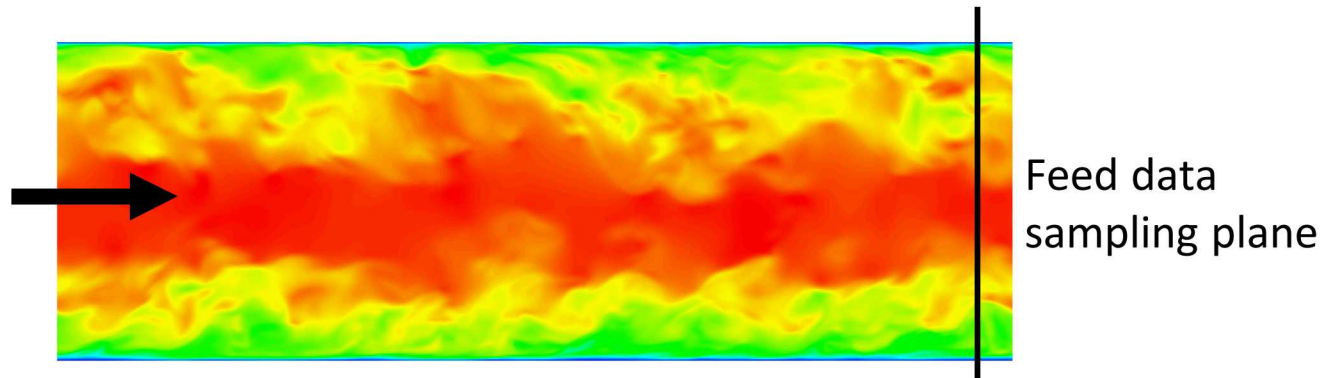
Code scales well on
hundreds of thousands of
processors

Simulation details

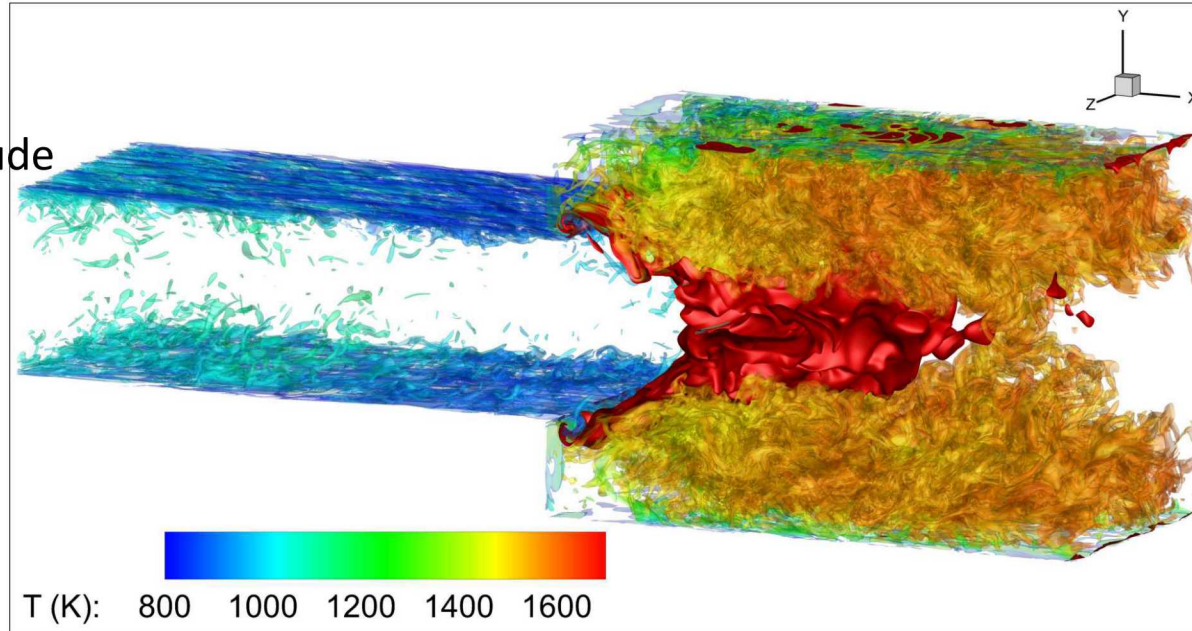


1.25 billion grid points
20 million CPU hours
 $Re_b = 13000$

- **Chemical mechanism:** 9 species hydrogen-air (Li et al., 2004)
- **Inflow composition:** premixed $H_2 + O_2 + N_2 + H_2O$ ($\phi = 0.35$)
- $U_{bulk} = 200\text{m/s}$, $u' = 20\text{m/s}$, $T_{inlet} = 1100\text{K}$, $T_{wall} = 750\text{K}$
- **Inflow profile:** feed from DNS of a fully developed channel flow



Iso-surfaces of
vorticity magnitude
colored by
temperature

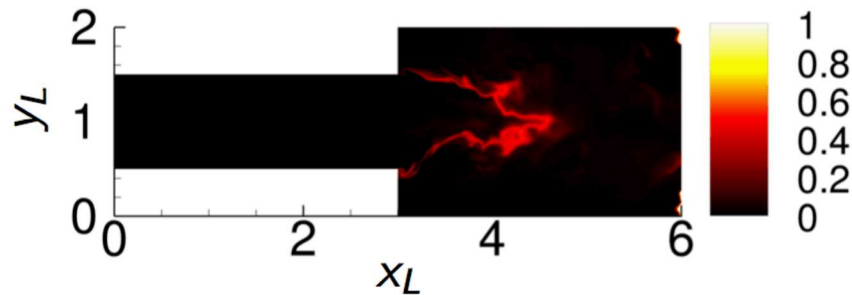


Two combustion configurations are observed:

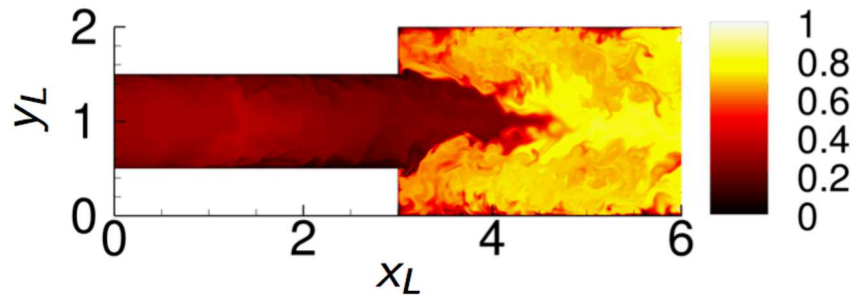
- Design state: mainly auto-ignition in the combustion chamber
- Intermittent auto-ignition state: ignition in mixing section

Design combustion state

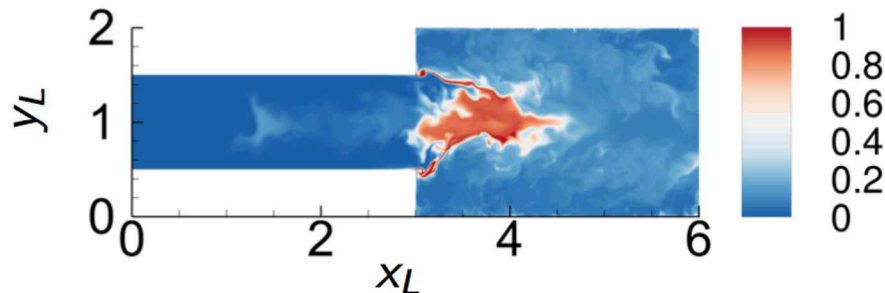
Heat release rate



Temperature



Mass fraction of HO_2



Combustion modes:

- Autoignition along center-line
- Flame propagation near corners
- HO_2 : indicative of chain branching

Transport budget analysis

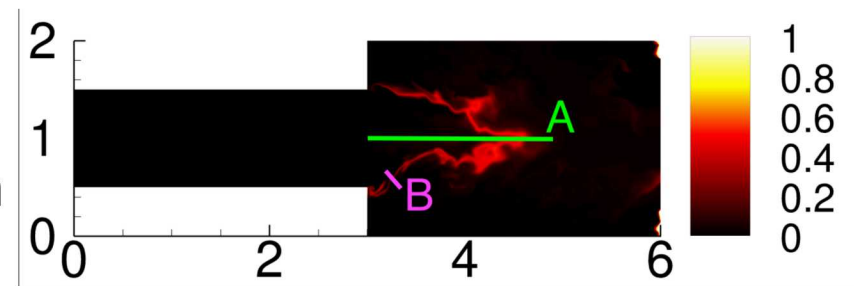
$$\frac{\partial (\rho Y_{OH})}{\partial t} = \underbrace{-\nabla_{\beta} \cdot (\rho Y_{OH} \mathbf{u}_{\beta})}_{\text{Advection}} - \underbrace{\nabla_{\beta} \cdot (\rho Y_{OH} \mathbf{V}_{\beta, OH})}_{\text{Diffusion}} + \underbrace{W_{OH} \dot{w}_{OH}}_{\text{Reaction}}$$

Advection

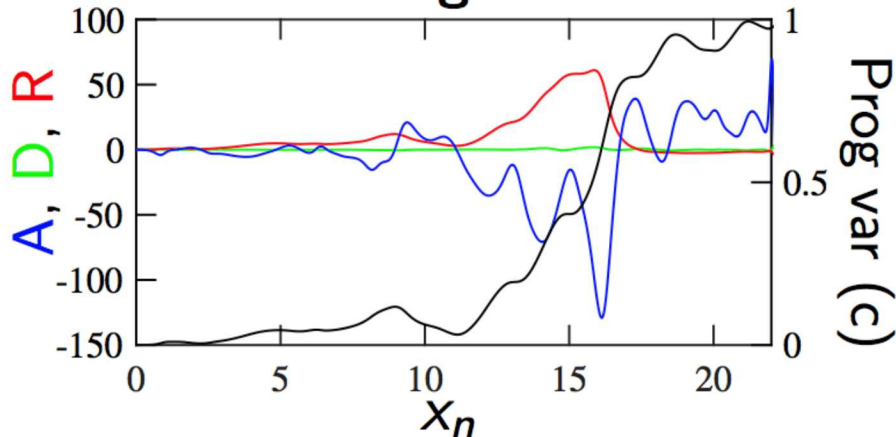
Diffusion

Reaction

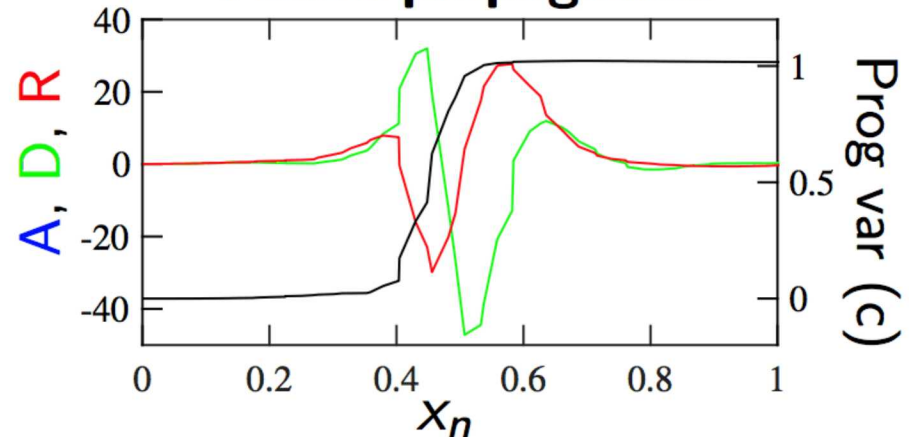
- Auto-ignition: balance between **advection** and **reaction**
- Flame propagation: balance between **diffusion** and **reaction**



Auto-ignition



Flame propagation

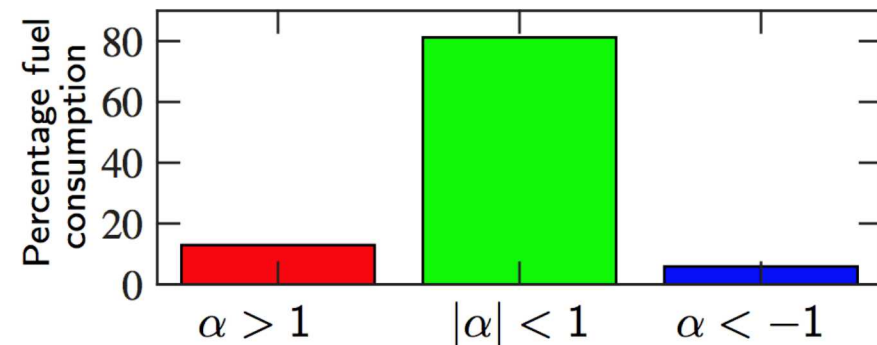
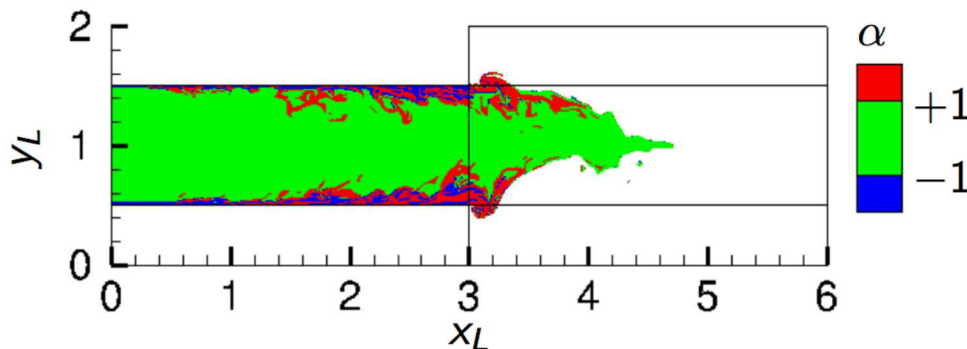


Chemical Explosive Mode Analysis

- $\alpha = \phi_s / \phi_\omega$: ratio of the projected non-chemical source term and the projected chemical source term (C. Xu et al., PROCI 2018)

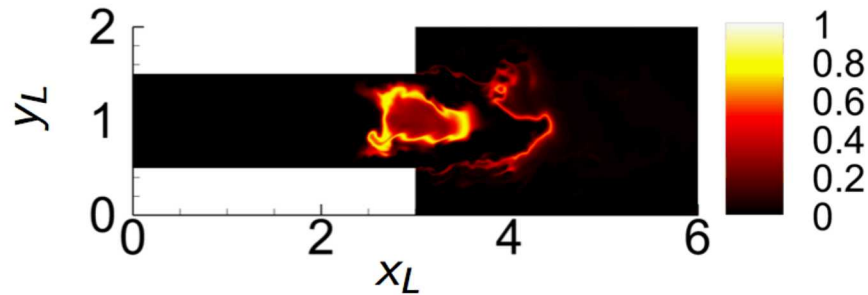
Three mode are identified:

- **Assisted-ignition** ($\alpha > 1$): diffusion significantly promotes reaction
- **Auto-ignition** ($-1 < \alpha < 1$): chemistry plays a dominant role
- **Extinction zone** ($\alpha < -1$): diffusion dominates chemistry and suppresses ignition

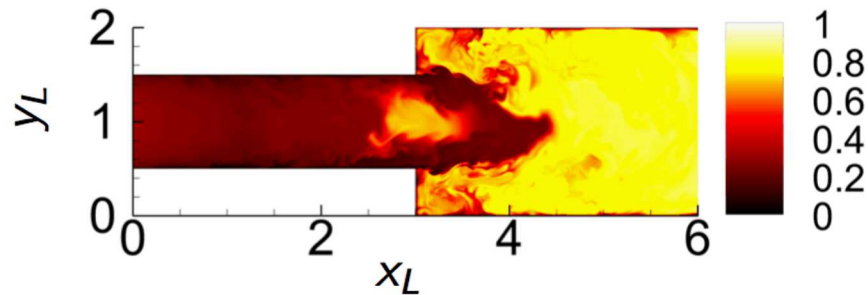


Intermittent auto-ignition state

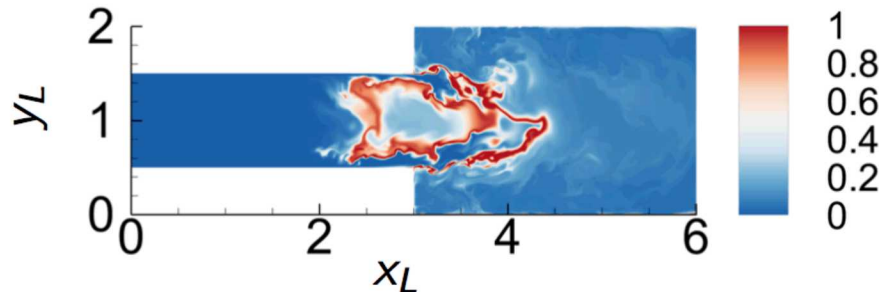
Heat release rate



Temperature

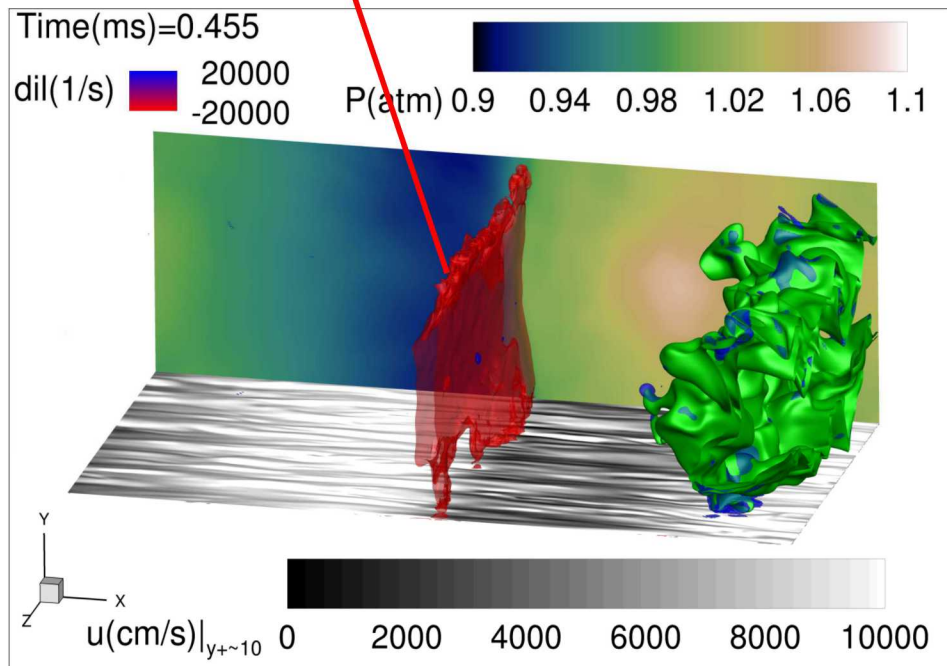
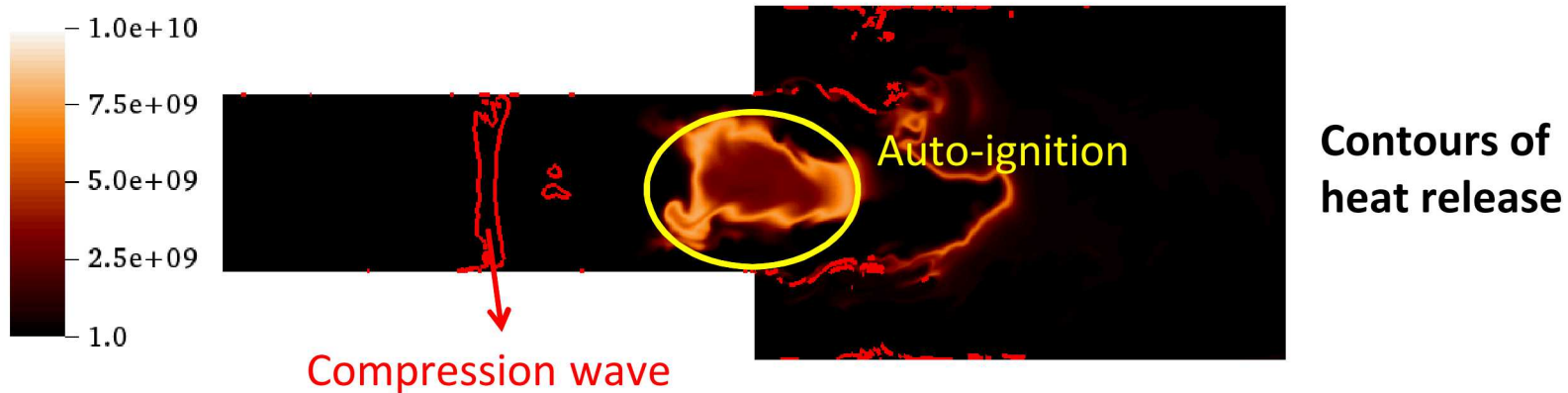


Mass fraction of HO_2



- Early auto-ignition in the mixing section
- Ignition kernel advects downstream
- Occurs intermittently

Intermittent auto-ignition state

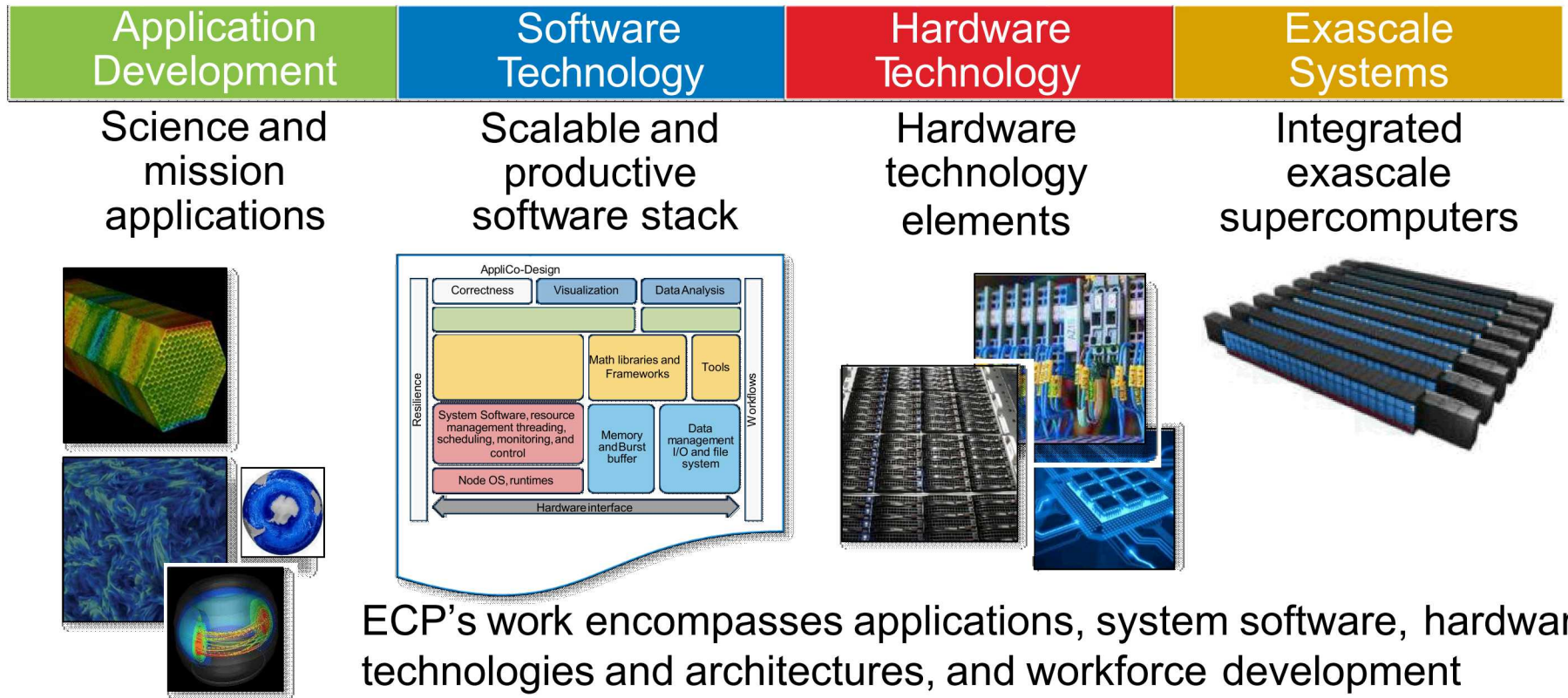


- Local rise in pressure
- Increases local temperature by 20-30 K
- High reactivity of hydrogen
- Decrease in ignition delay time (30%)

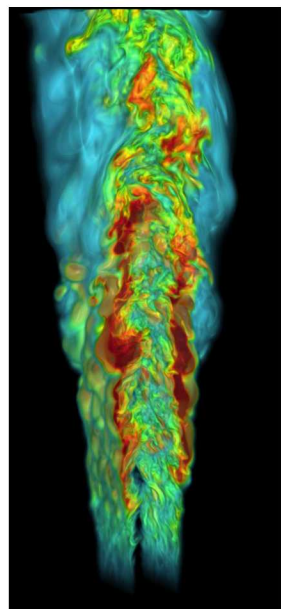
Conclusions

- Performed DNS of a reheat burner at scaled conditions
- Two states of hydrogen/air combustion have been observed:
 - design state: flame propagation and auto-ignition in the combustor
 - intermittent auto-ignition in mixing section
- Premature auto-ignition arises due to pressure (and following temperature) rise in mixing section
- Quantified the contribution of different modes towards heat release using chemically explosive mode analysis (CEMA)
- Future work:
 - characterize the unstable flame behavior and the conditions leading to it
 - find the inlet conditions for statistically stationary reheat flame
 - perform 2D and 3D simulations with varying fuel composition and its stratification

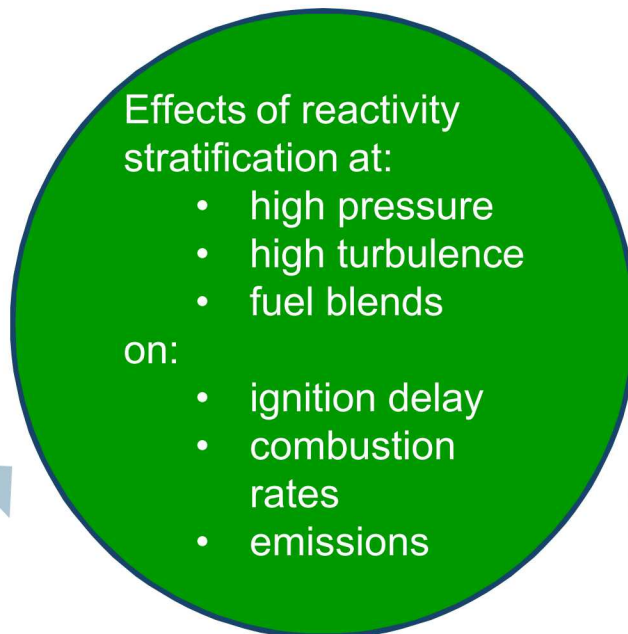
ECP has formulated a holistic approach that uses co-design and integration to achieve capable exascale



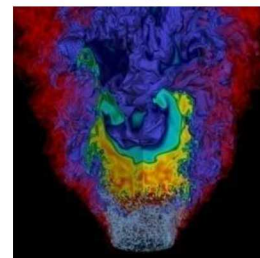
ECP application: Transforming Combustion Science and Technology Through Exascale Simulation (Pele)



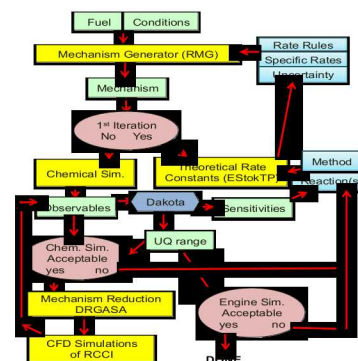
**S3D: multi-block compressible reacting
DNS multi-physics validation: spray,
soot, radiation**



Pele: Block-structured adaptive mesh refinement, multi-physics: spray, soot, and radiation, real gas, complex geometry



Automated Mechanism Generation



Challenge Problem & Roadmap

Challenge Problem & Roadmap

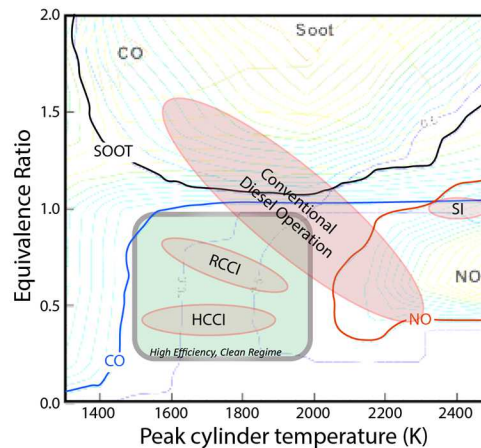


- # Challenge Problem & Roadmap

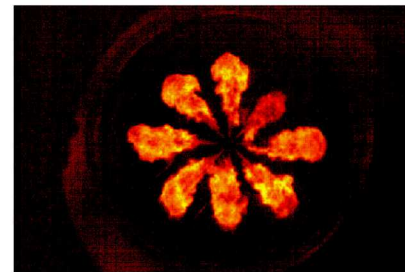


Challenge Problem - Motivation

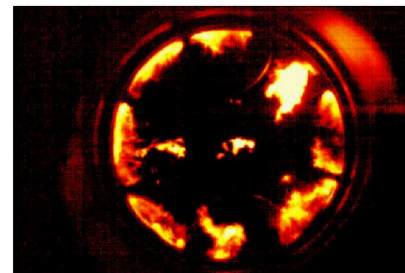
Advanced combustion regimes (LTC)



Conventional diesel *



Early injection PCCI



PCCI/HCCI – load limitations
Requires precise charge preparation and
combustion control mechanisms
(for auto-ignition and combustion
timing)

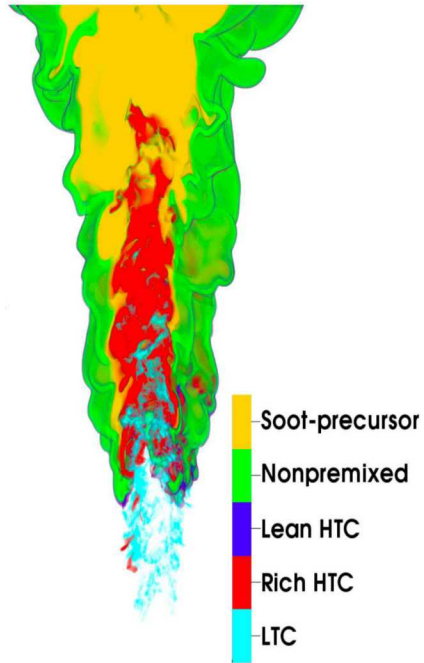


UNIVERSITY OF WISCONSIN - ENGINE RESEARCH CENTER



*Adapted from
content provided
by University of
Wisconsin
Engine Research
Center*

High Fidelity DNS and Hybrid DNS/LES of RCCI Diesel Combustion



*DNS of a ndodecane
spatially evolving
turbulent diesel jet flame
at 60 bar, combustion
modes, Dalakoti et al.
2018*

Characteristic / Need	Approach
Impulsively started jets with disparate scales between fronts and turbulence. (Outer scales: 10cm, ms Inner timescales: microns, ns)	Dynamic adaptive mesh refinement
High speed injection followed by subsonic conditions downstream	Compressible and low-Mach capabilities
Long time horizons to set up turbulence for studying fundamental TCI	Hybrid DNS/LES [Non-reacting LES, DNS for flame]
Lean, rich, and low temperature chemistry critical in multi-stage ignition and formation of soot precursors.	Accurate and detailed thermochemistry.
Liquid fuel injection	Lagrangian spray model
Coupling between mixture preparation and emissions	Detailed kinetics including emissions, sectional model for soot with radiation
Mixture preparation dependent on re-entrainment of combustion products	Realistic piston dish and cylinder wall geometry
Performant on exascale architecture	

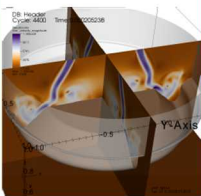
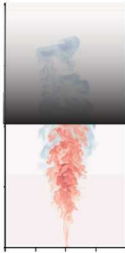
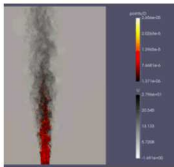
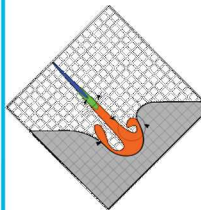
Design Philosophy, Strategy

- The Pele suite:
 - Compressible (**PeleC**) and low Mach number (**PeleLM**) integrators, compatible design, data, I/O, etc
 - Shared physics (ideal/real gas kinetics, thermodynamics, transport, sprays, etc) - **PelePhysics**
 - Block-structured adaptive mesh refinement, built on **AMReX** framework
 - Robust, accurate, extensible finite-volume (conservative) discretizations
 - Embedded boundary treatment of arbitrary geometries
 - Enables CAD-to-compute, avoids expensive, time-consuming difficult mesh generation step
 - AMReX-supported X+Y parallelism (inter-node X and intra-node Y)
 - Parallel mesh and particle data, specialized to needs of AMR (temporal subcycling, etc), plus Fork-Join type temporary redistribution strategies, high-performance I/O and in-situ/in-transit analysis support
 - Combustion-specific agile code generation: Fuego+SINGE for GPU-optimized CUDA kinetics evaluation, Kokkos-based kernels for particle/fluid coupling terms
- Agile development framework, open source modular design, continuous integration/testing
- Close interaction with AMReX for new capabilities in development
 - App-relevant GPU/A21 implementation of AMReX structures/algorithms
 - Leverage AMReX multi-app development

Pele Code Design Overview

- Baseline algorithm design for multicomponent flow with stiff reactions, AMR
 - **PeleC**: Comparable advection, diffusion time scales, motivates IMEX-type scheme based on Spectral Deferred Corrections (**SDC**) with *time-implicit* chemistry
 - Robust highly efficient time-explicit Godunov-type upwind advection, simple centered diffusion
 - BDF-style implicit chemistry ODE integration, with sources that approximate the other processes
 - **PeleLM**: acoustics filtered away analytically, but still want robust, time-explicit advection
 - Chemistry *and* diffusion are now *time-implicit* – **iterative timestep** simultaneously incorporates flow constraint (constant pressure), mutually coupled species/energy diffusion and chemistry. Entire system evolved stably on slower advection time scales across AMR grid hierarchy
- SDC-based iterative timestep – treats each process essentially independently, with accelerated iteration to couple everything nicely together
- Robust baseline allows stable, well-behaved *extensible* time step
 - Switch 2nd order advection scheme with more accurate 4th order algorithm
 - Option for “destiffened” chemistry model that allows highly efficient time-explicit advance
 - Robust to other, potentially stiff, tightly coupled processes, such as sprays, radiation, soot, etc

Project Roadmap

	2017	2018	2019	2020	2021	2022
Model Development	Hybrid LES/DNS ✓	Deep learning SGS model training methodology	Rare event detection		In situ training	
Compressible Capabilities	Non-ideal, single level sprays, static EB geometry ✓✓	Non-reacting LES, AMR sprays ✓✓	Hybrid LES/DNS	Soot	Radiation	Moving EB geometry
Capability Towards Challenge Problem	 60 Bar open, gas phase dodecane low mach jet	 Atmospheric pressure, compressible static geometry flows	 60 Bar open, ideal gas dodecane low mach jet wall impingement	 60 Bar open, dodecane jet with hybrid multi-physics	 60 Bar compressible + low Mach, re-entrainment	
Low Mach Capabilities			Static EB geometry	Sprays, Hybrid LES/DNS	Hybrid compressible / LM Non-ideal EOS	
Automated Thermochem	Initial demonstration ✓	Pressure independent kinetics	Mechanism generation	Reduced dual-fuel mechanism		
Performance and software	PeleC Exists ✓ Understand potential of task parallel ✓	PeleLM tiling	GPU performance Multi-physics load balancing	Performance portability		A21 / Frontier Performance Enhancements

DNS of Multi-Injection Diesel Combustion with PeleLM

M. Rieth¹, M.S. Day² and J. H. Chen¹

¹Sandia National Laboratories

²Lawrence Berkeley Laboratories



Office of Science
U.S. Department of Energy



EXASCALE
COMPUTING
PROJECT

DNS of N-dodecane Multi-injection Jet at Diesel Conditions - Parameters

- N-dodecane/air injection with $Y_{\text{NC}_{12}\text{H}_{26}}=0.45$, 446K
- Jet: $D=0.17\text{mm}$, $U=30\text{m/s}$, $\text{Re}=15,000$
- Environment: 60 bar, 900K, 15/85% O_2/N_2 ('spray A')
- 10 micron resolution
- 53 species mechanism
- Age variable tracks the fluid age/residence time

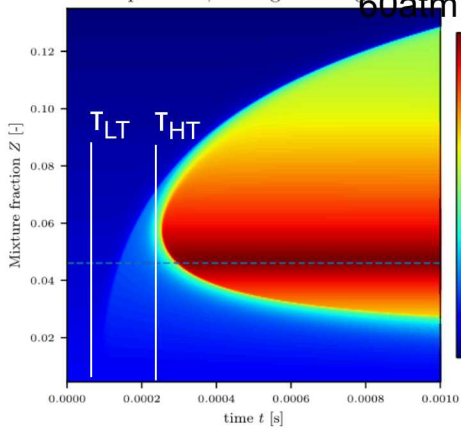
Diffusion
coefficient
based on
 $\text{Le}=1$ for all
add. scalars

$$\frac{\partial \rho a}{\partial t} + \frac{\partial \rho u_j a}{\partial x_j} = \frac{\partial}{\partial x_j} \left(\rho D \frac{\partial a}{\partial x_j} \right) + \rho$$

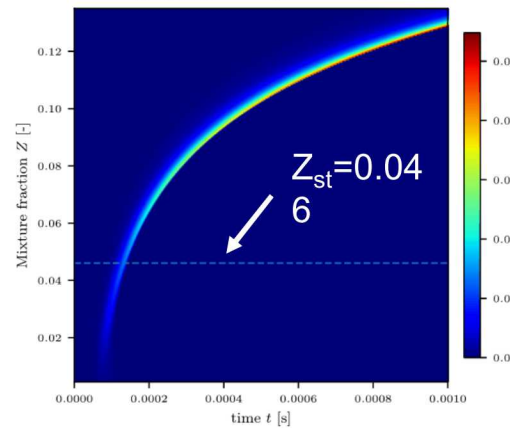
Reactor studies – standard conditions ('spray A')

Fuel side: NC12H26/air @Z=0.45 & 446K, oxidizer: 15%O2 900K,

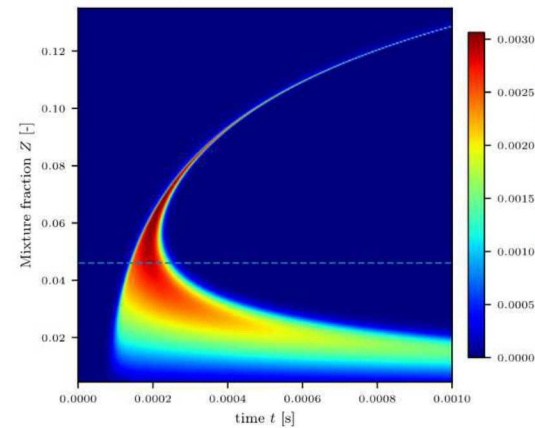
Temperature, homogeneous ignition, 60atm



$Y_{OC_{12}H_{23}OOH}$, homogeneous ignition



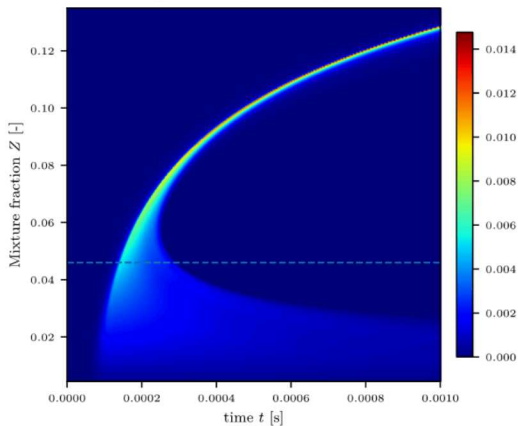
$Y_{H_2O_2}$, homogeneous ignition



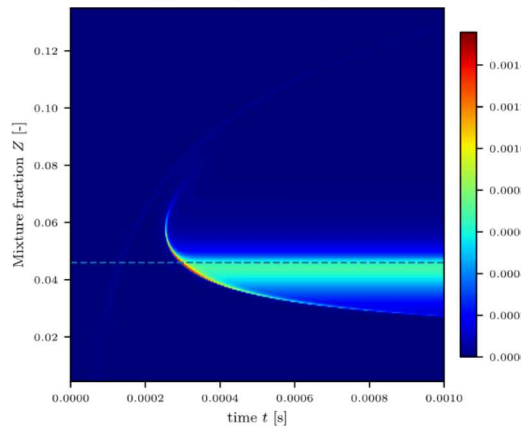
Low T ign.:
0.05ms,
 $Z < 0.02$

High T ign.:
0.25ms,
 $Z = 0.057$
($\sim 1.24 Z_{st}$)

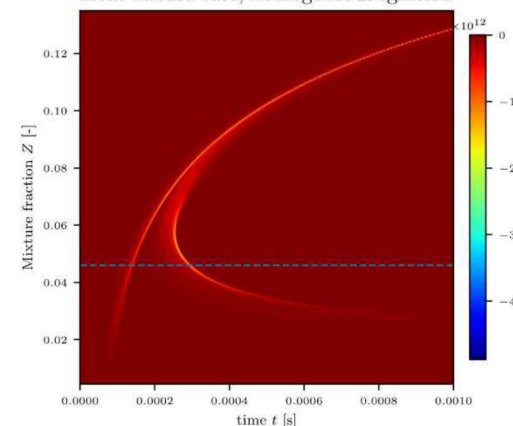
Y_{CH_2O} , homogeneous ignition



Y_{OH} , homogeneous ignition



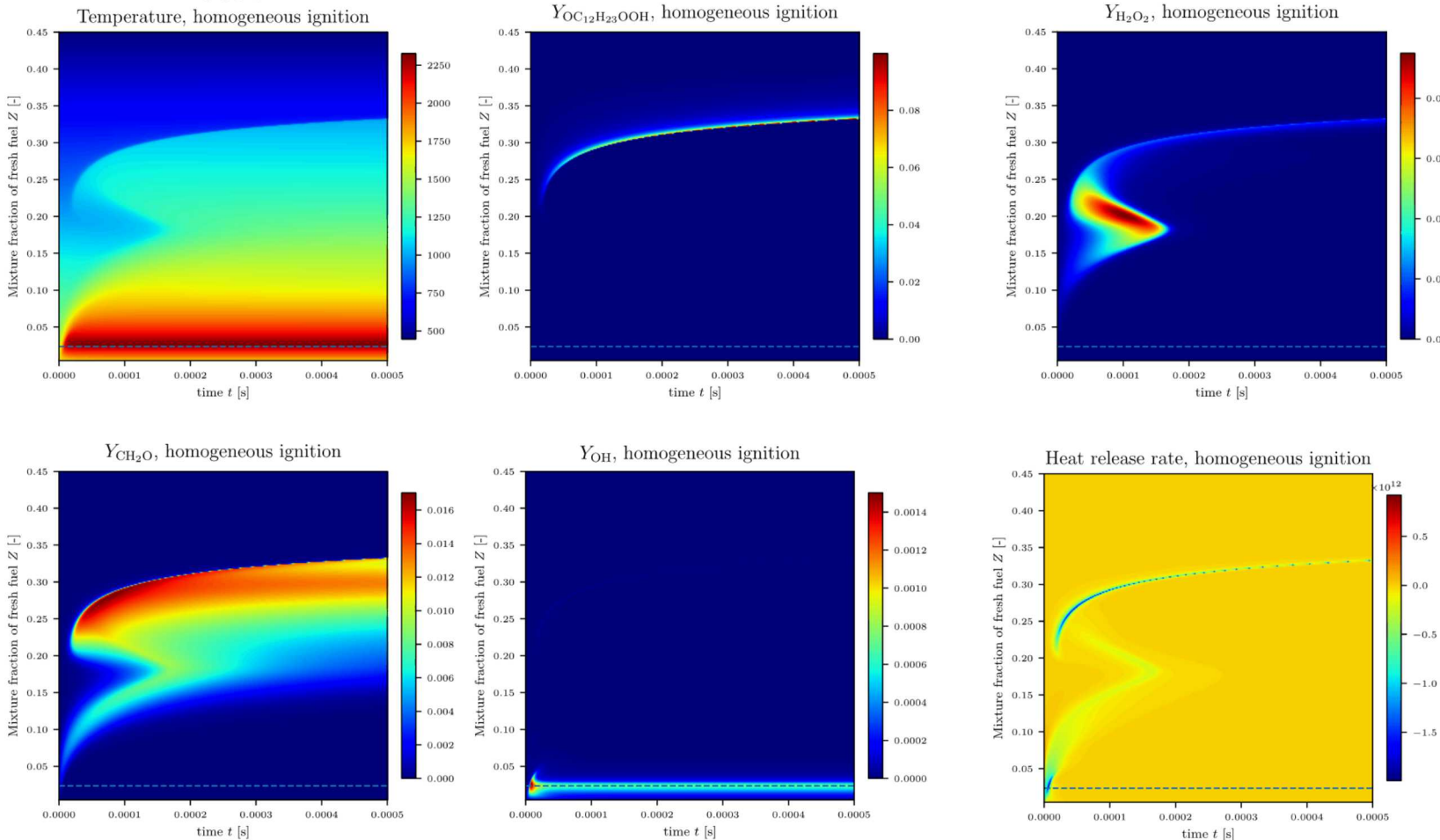
Heat release rate, homogeneous ignition



$\Delta T_{HT,LT} = 0.2ms$

Reactor studies – oxidizer consists of lean products ($Z=0.025$)

Fuel side: NC12H26/air @ $Z=0.45$, oxidizer: equilibrated NC12H26/air @ $Z=0.025$, 60atm



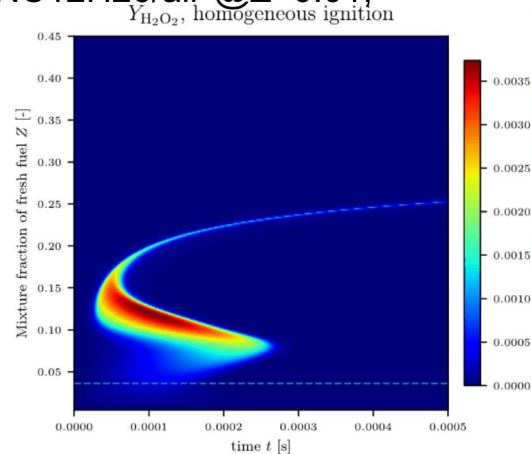
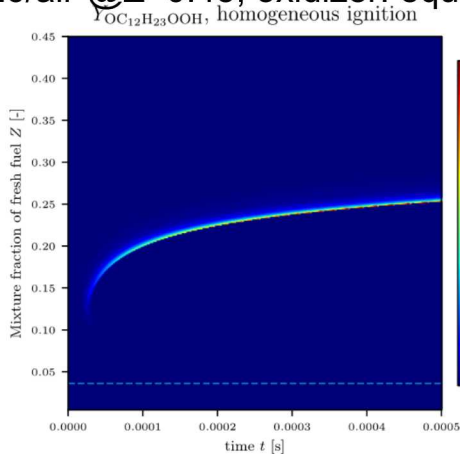
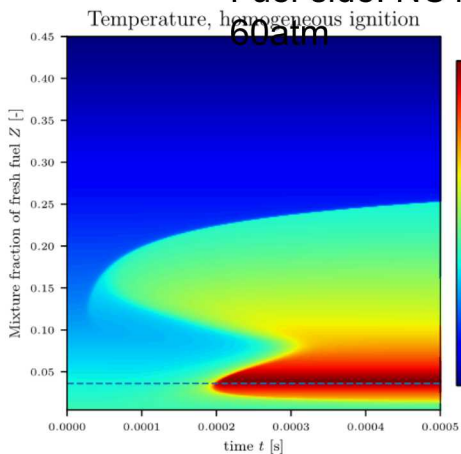
Low T ign.:
0.03ms, $Z=0.2$

High T ign.:
<0.01ms,
 $Z<0.02$
($<\sim 0.44 Z_{st}$)

$\Delta T_{HT,LT} < 0$ ms

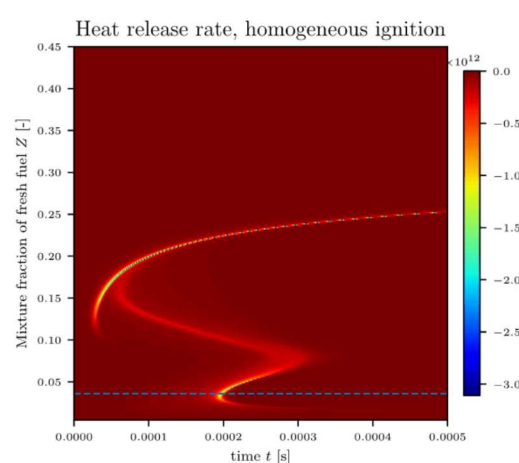
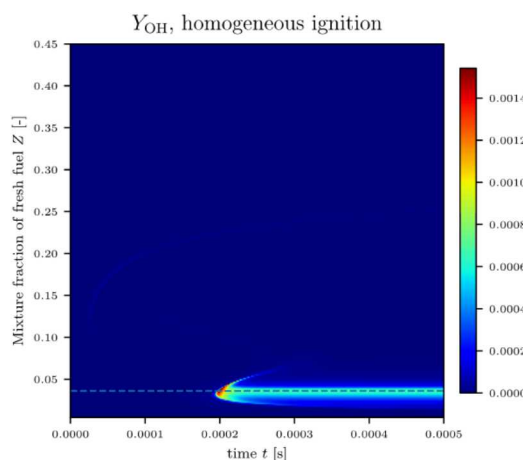
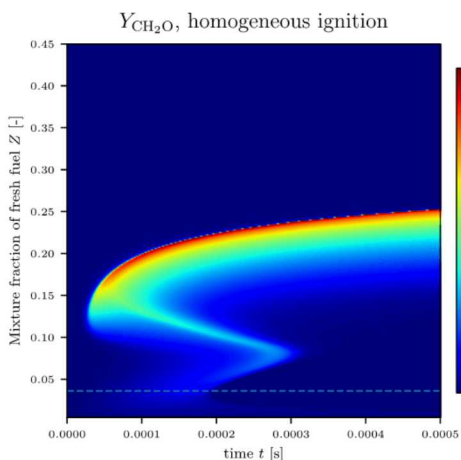
Reactor studies – oxidizer consists of lean products ($Z=0.01$)

Fuel side: NC12H26/air @ $Z=0.45$, oxidizer: equilibrated NC12H26/air @ $Z=0.01$,
60atm



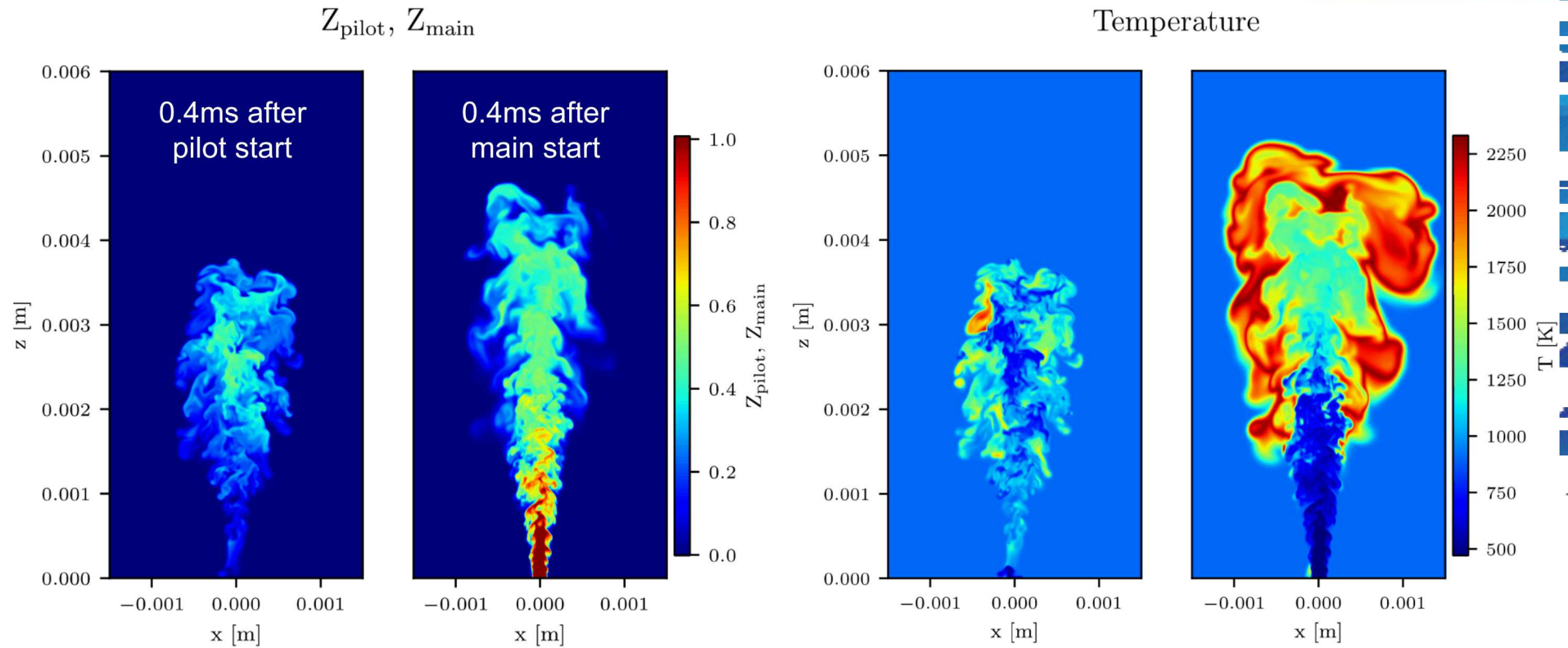
Low T ign.:
0.05ms,
 $Z=0.12$

High T ign.:
0.2ms,
 $Z=0.042$
($\sim 0.91 Z_{st}$)



$\Delta T_{HT,LT}=0.15m$
s

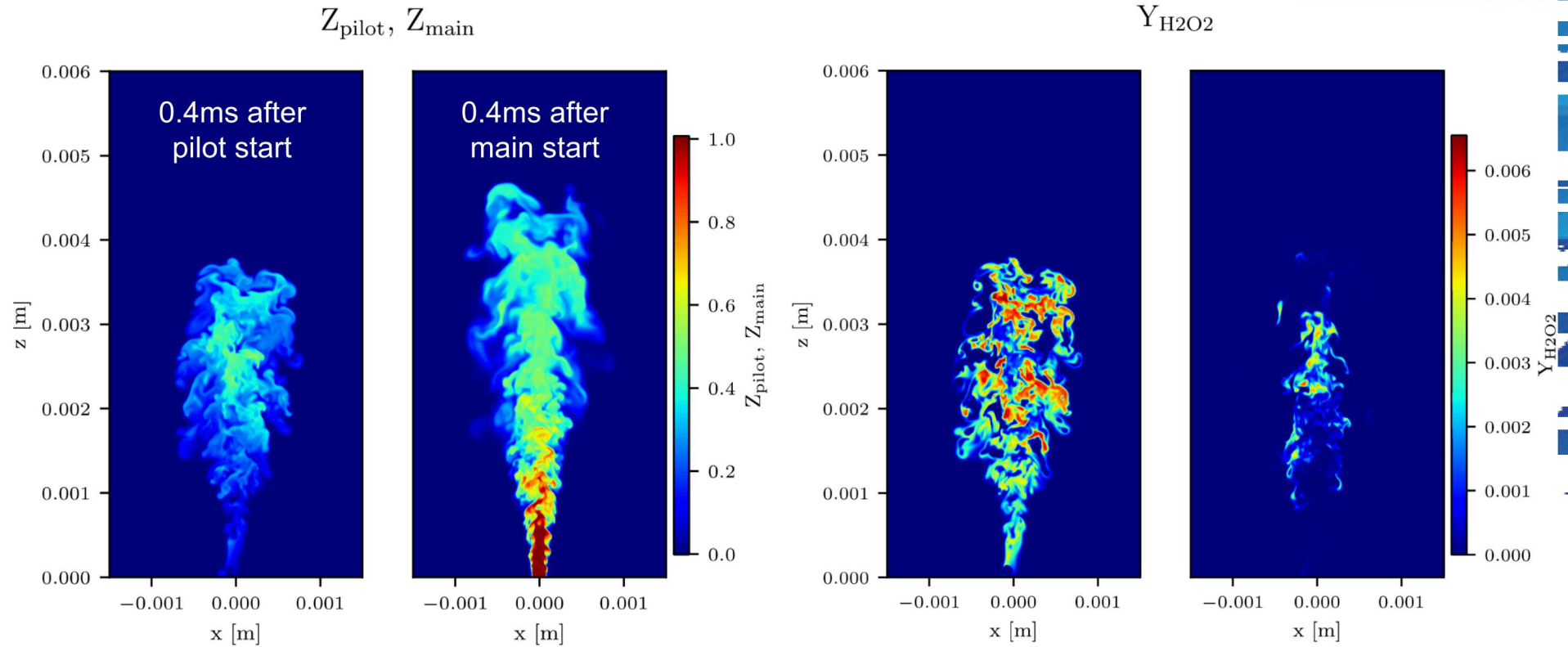
Comparison at 0.4ms after pilot/main injection start



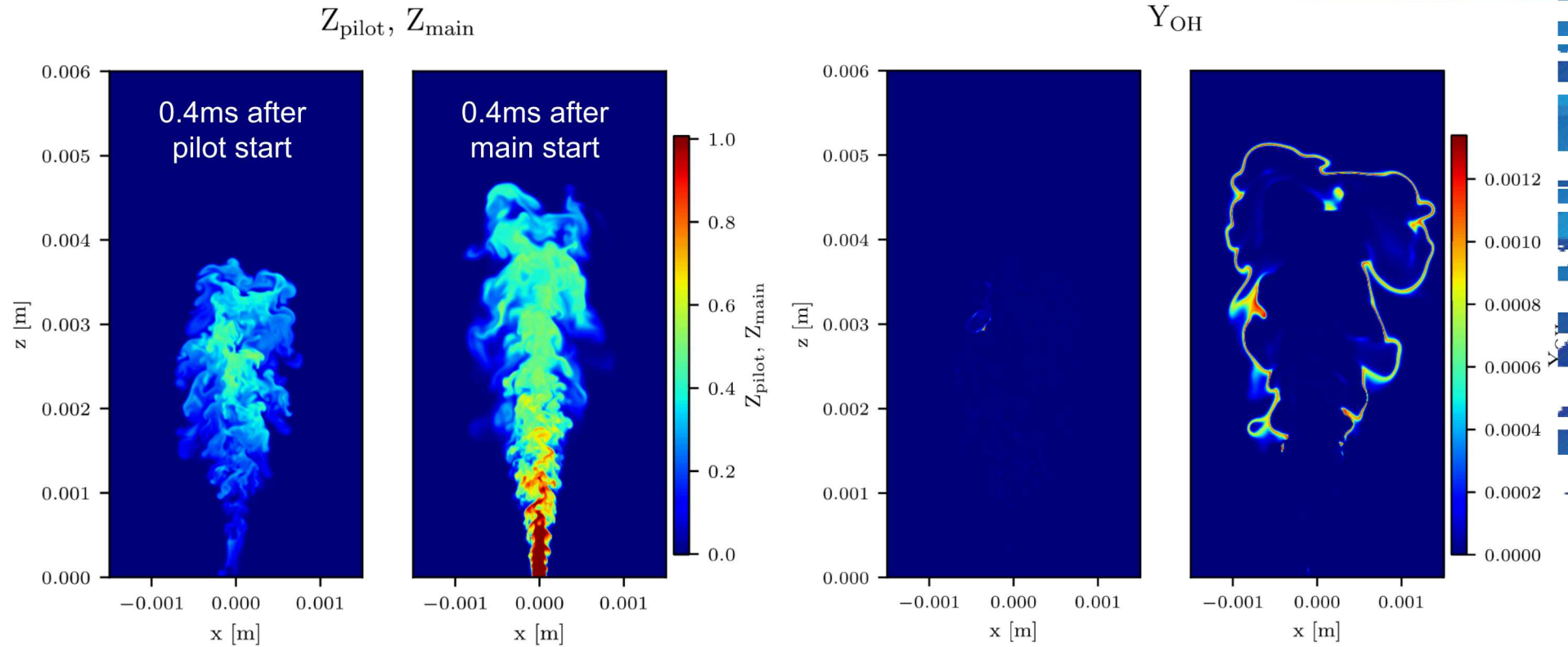
Pilot: 0.26ms, dwell: 0.17ms, main: 0.74ms

left: times w.r.t pilot start (0.4ms total time), right: times w.r.t. main start (0.83ms total time)

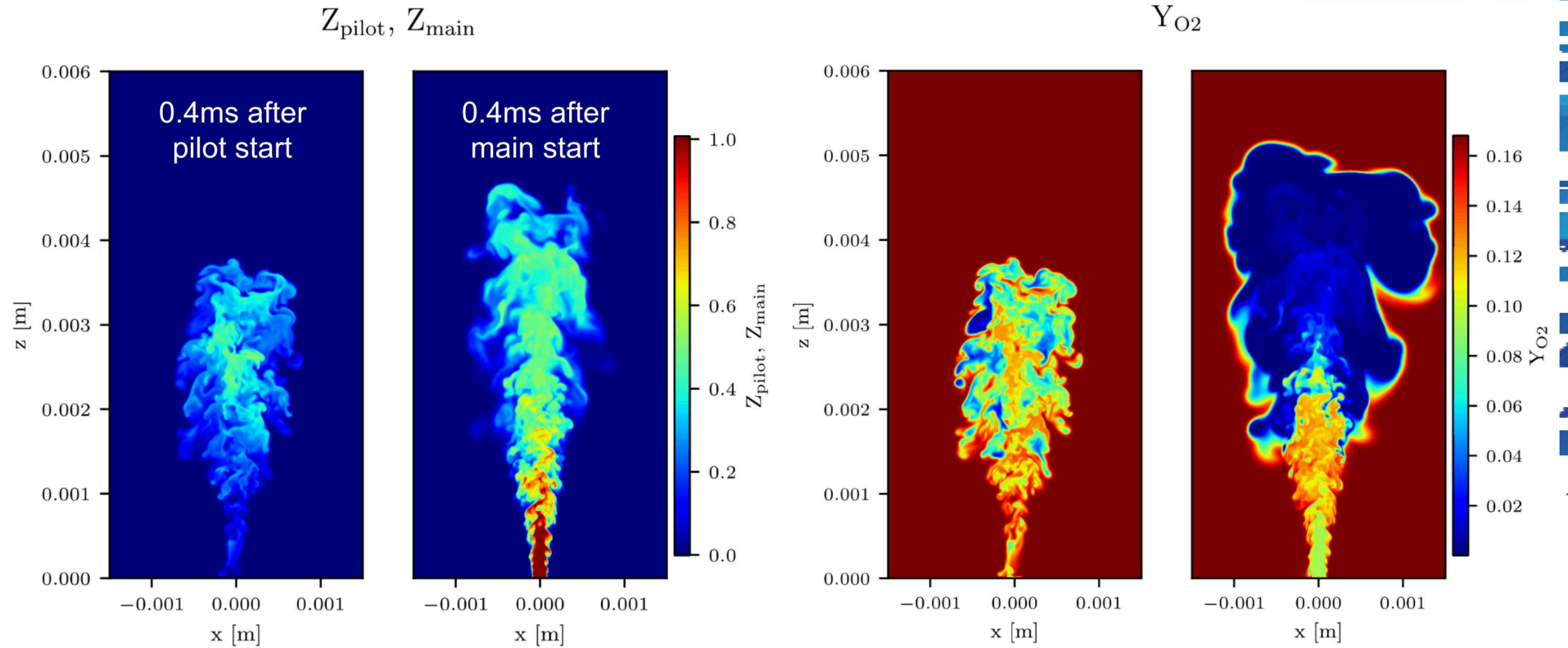
Comparison at 0.4ms after pilot/main injection start



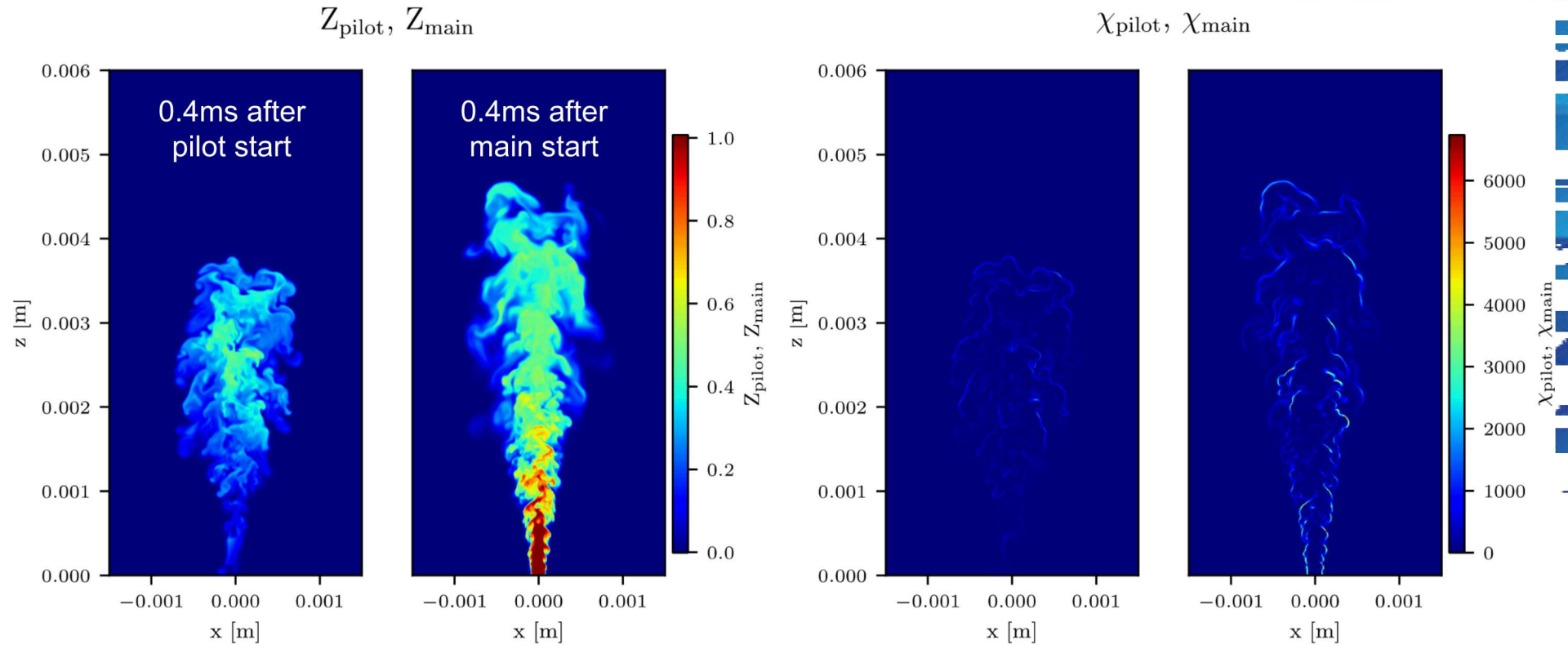
Comparison at 0.4ms after pilot/main injection start



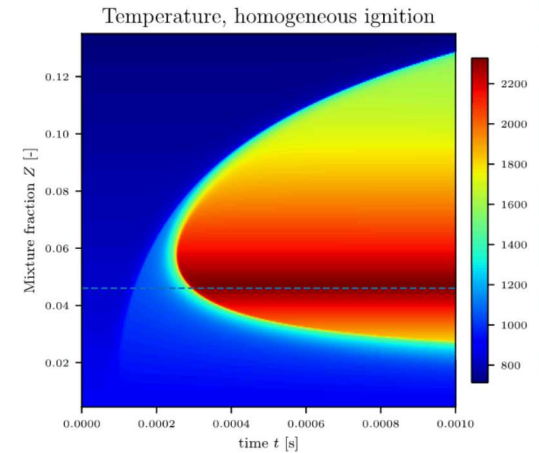
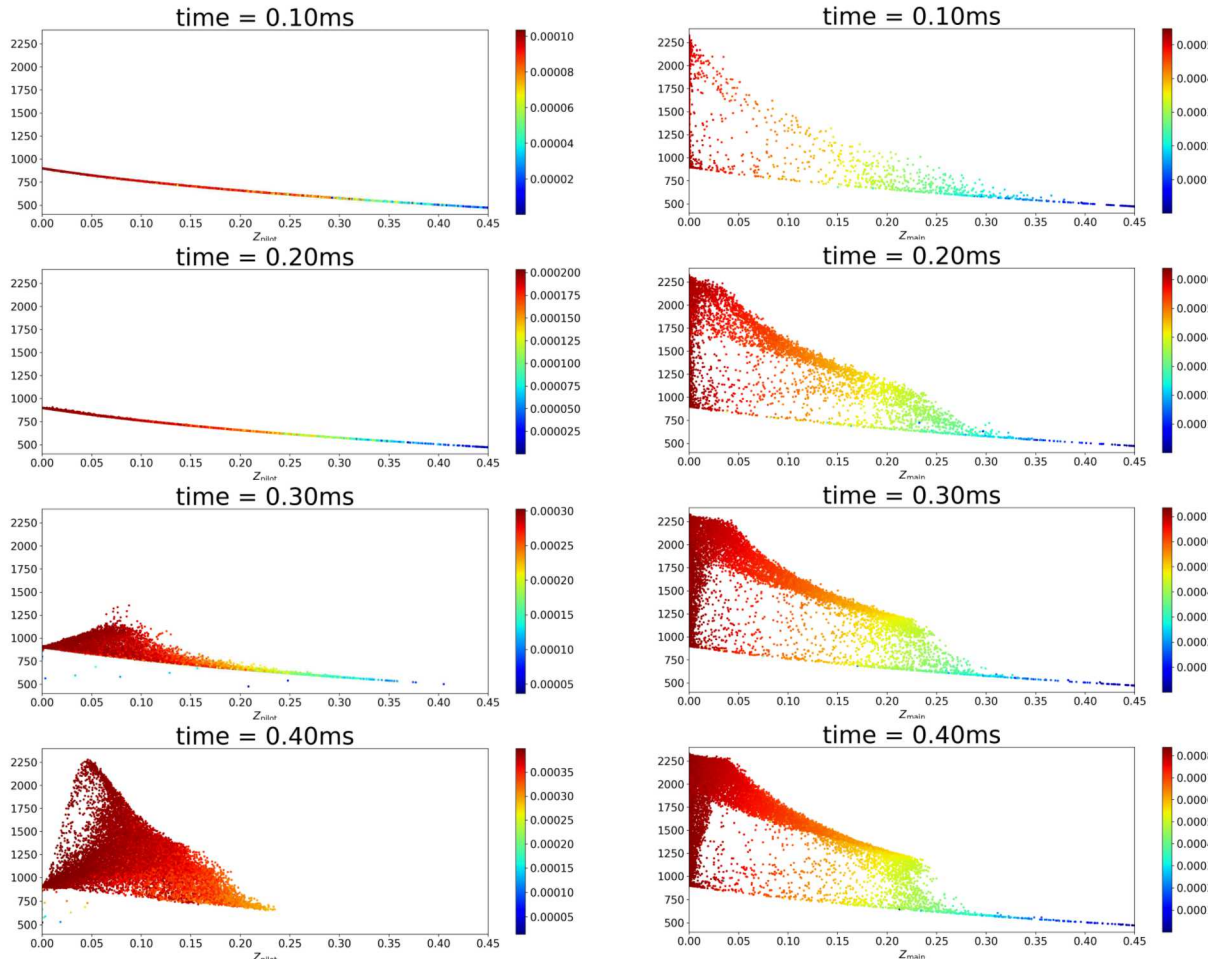
Comparison at 0.4ms after pilot/main injection start



Comparison at 0.4ms after pilot/main injection start



Difference in pilot and main ignition - temperature



Pilot:

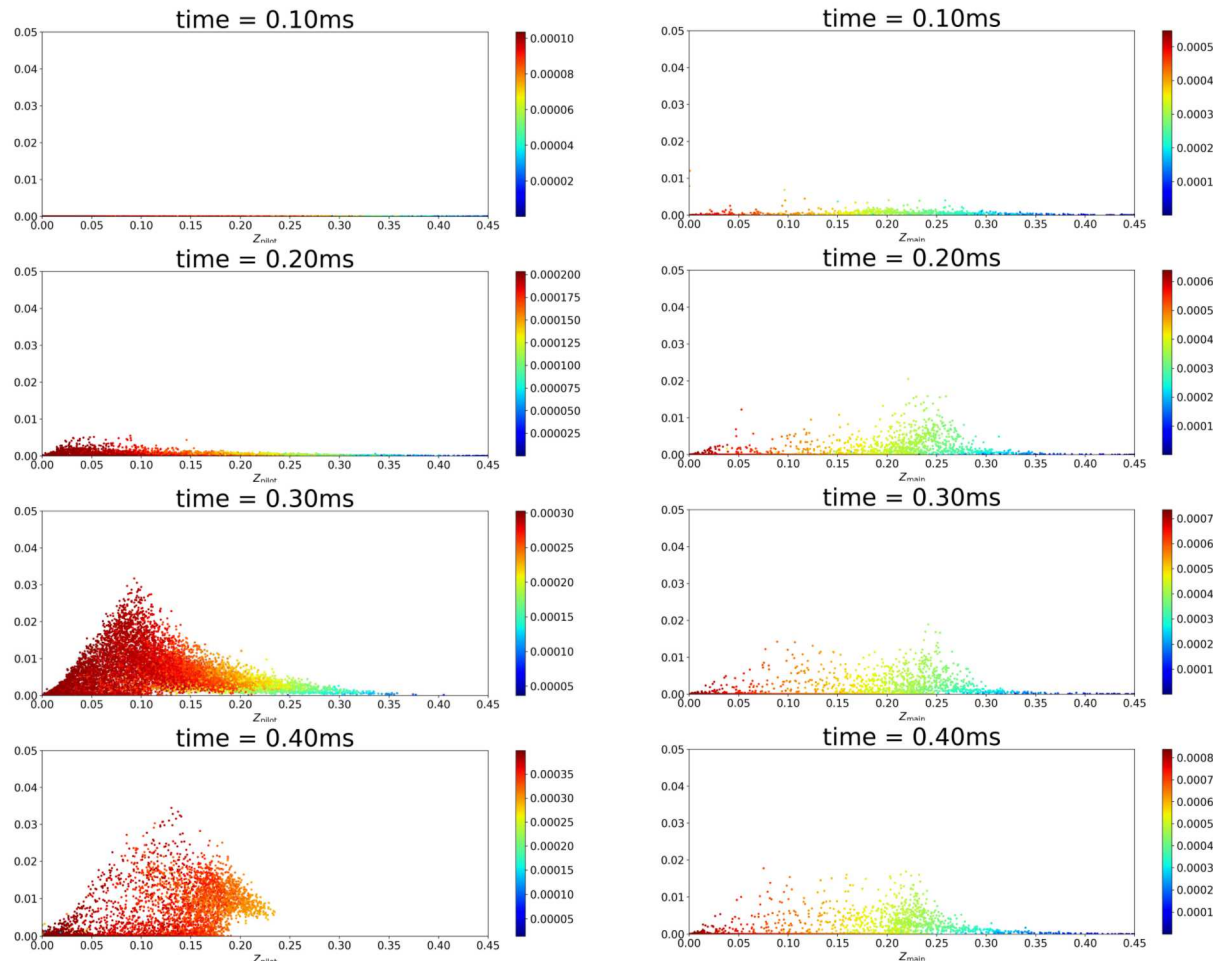
- Stoich. conditions close to homogeneous ign.
- Difference for rich cond.

Main:

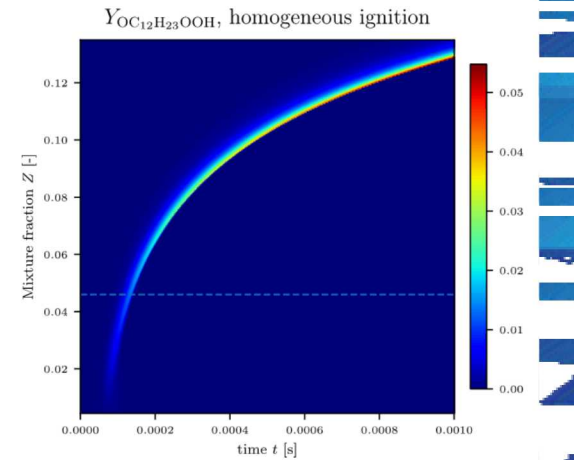
- Significant differences on rich side

Pilot: 0.26ms, dwell: 0.17ms, main: 0.74ms; left: times w.r.t pilot start, right: times w.r.t. main start

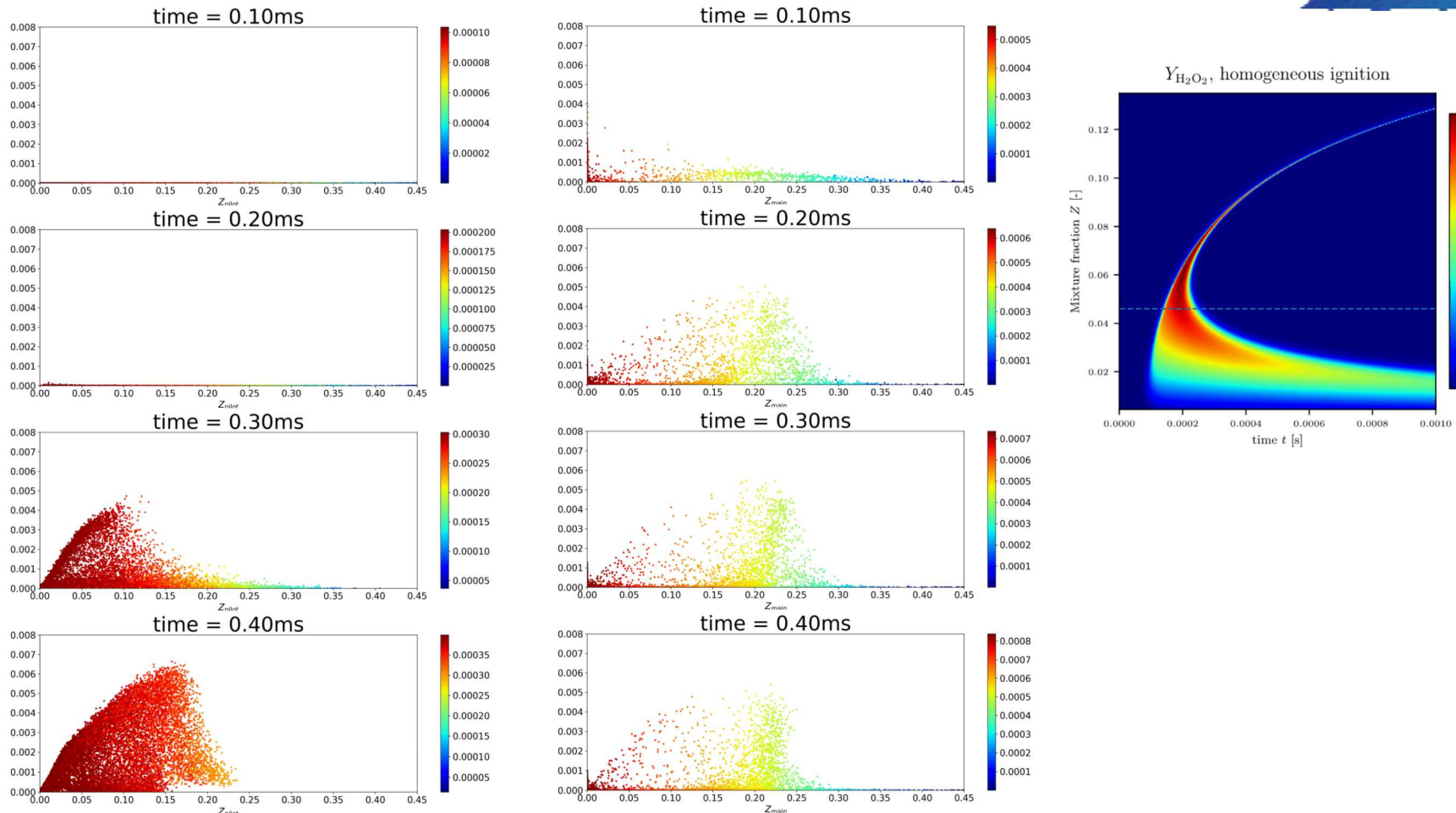
Difference in pilot and main ignition – OC12H23OOH



Pilot: 0.26ms, dwell: 0.17ms, main: 0.74ms; left: times w.r.t pilot start, right: times w.r.t. main start



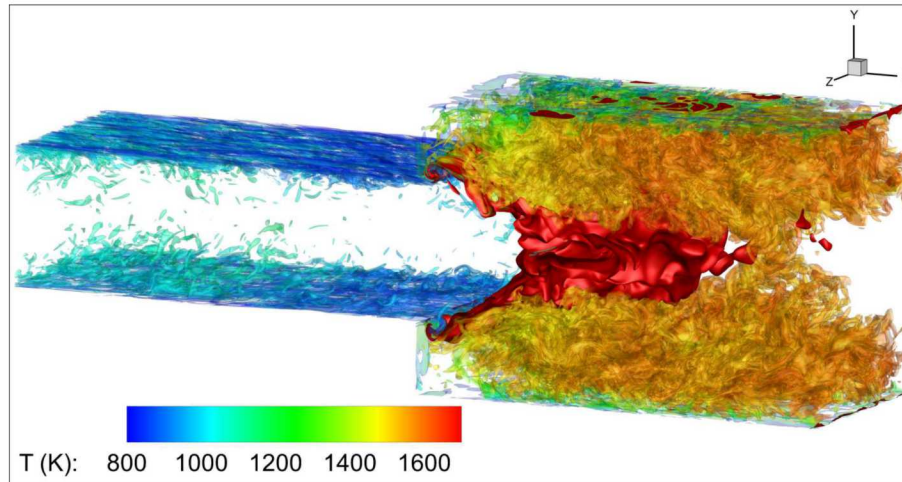
Difference in pilot and main ignition – H₂O₂



Pilot: 0.26ms, dwell: 0.17ms, main: 0.74ms; left: times w.r.t pilot start, right: times w.r.t. main start

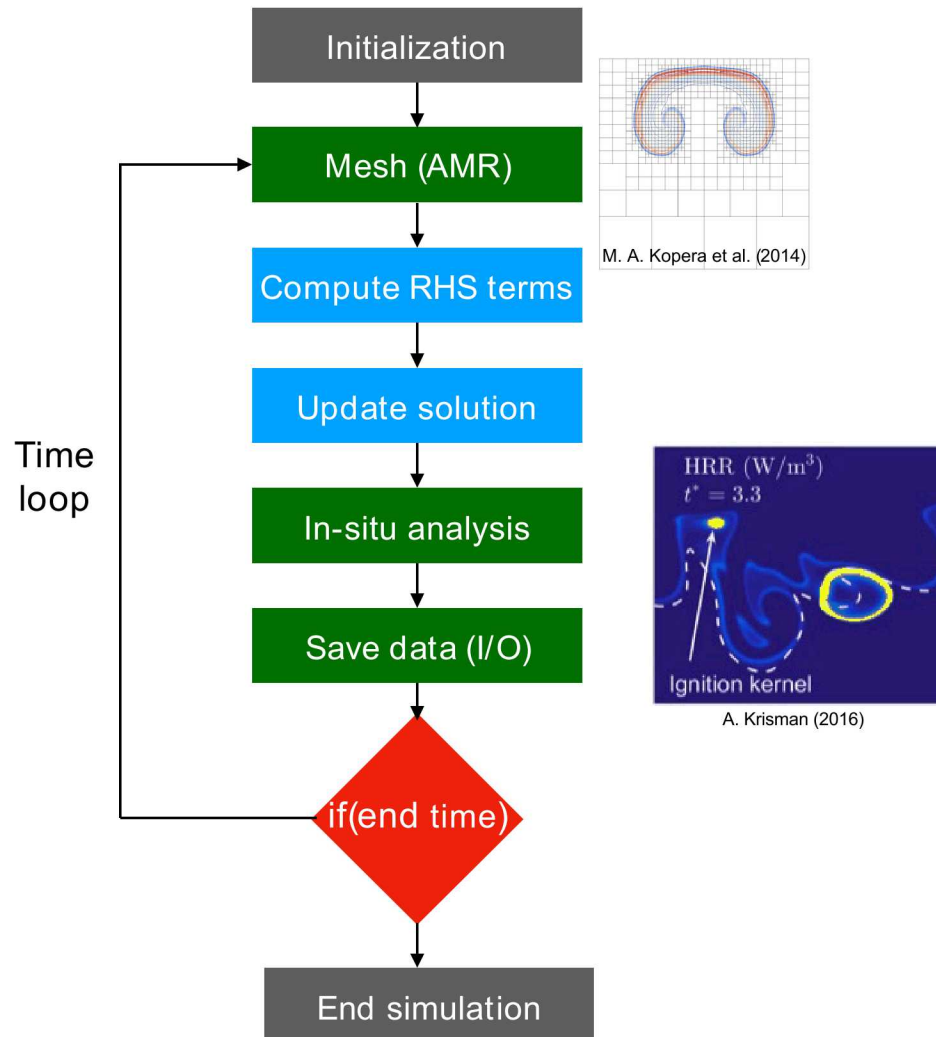
Combustion simulations

Iso-surfaces of
vorticity magnitude
colored by
temperature



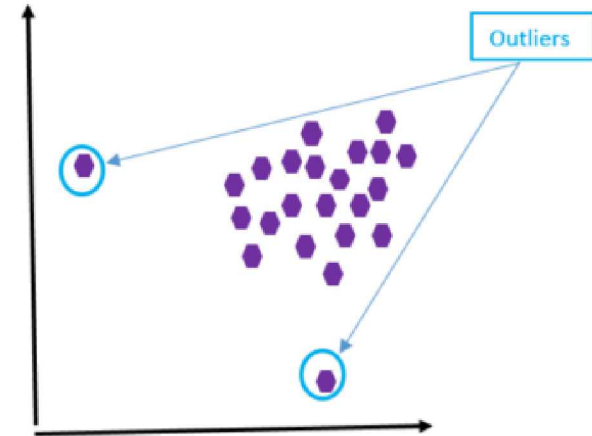
- Multi-variate data: $\sim 10 - 100$ variables
- Direct numerical simulations: resolve all the scales in space and time
- Massively parallel solvers (e.g. S3D Chen et al. (CSD 2009))
 - computationally expensive (tens millions of CPU hours)
 - large amount of data (~ 100 TB)
- Exascale (millions processing elements): need efficient workflows

Simulation workflow



Results

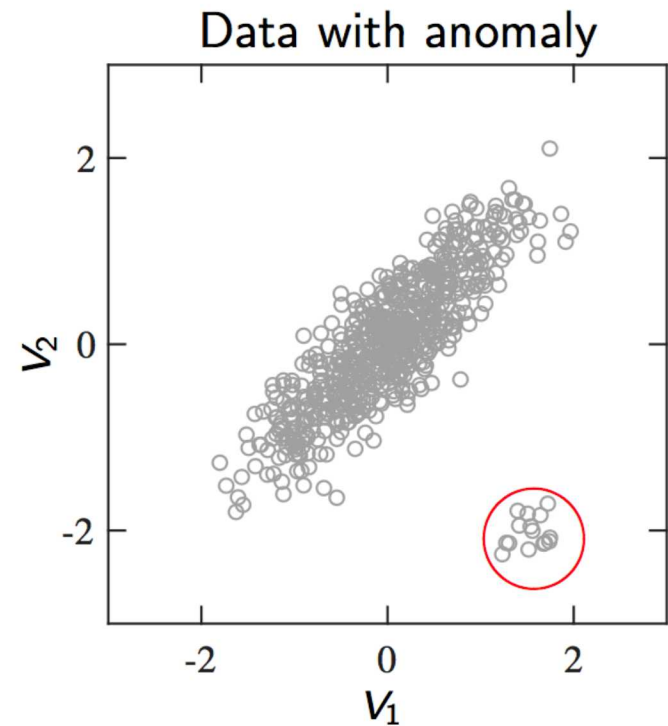
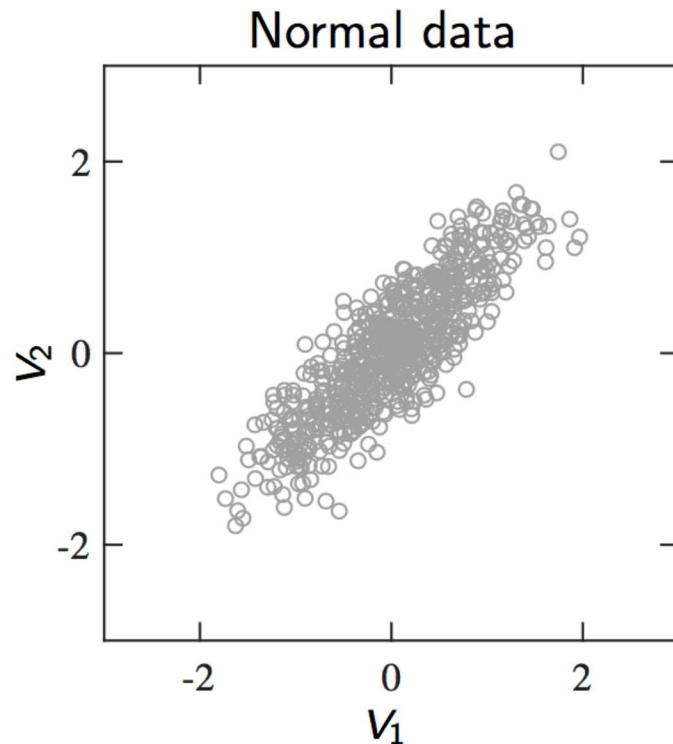
- k-nearest neighbors
 - compute “mean” distance from k nearest neighbors
- Local outlier factor
 - compute outlier score based on local density
- Supervised learning methods (e.g. neural networks)
 - regression and classification



Not efficient and expensive to compute

Idea

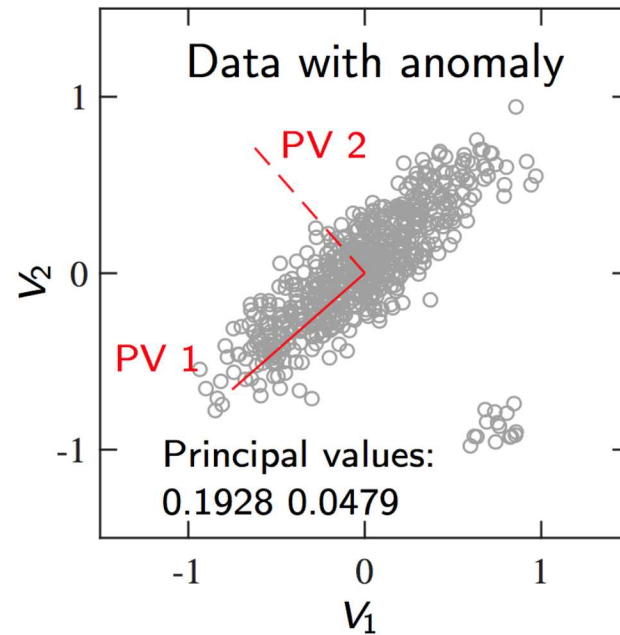
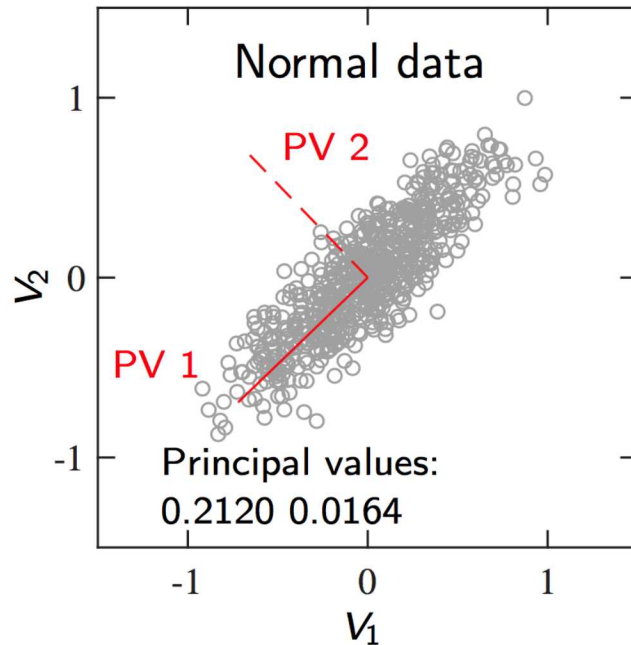
- Bivariate dataset



- Characterize the data distribution: **principal component analysis**
- Change in distribution: effects the magnitude of principal value and orientation of principal vectors

Principal component analysis

- Scale the data: with mean and maximum
- Compute the co-variance matrix (second order joint moment)
- Perform Eigen decomposition to obtain the principal values and vectors



- Mainly captures variance
- **Need to look at higher order moments to capture extreme events**

Fourth order joint moment

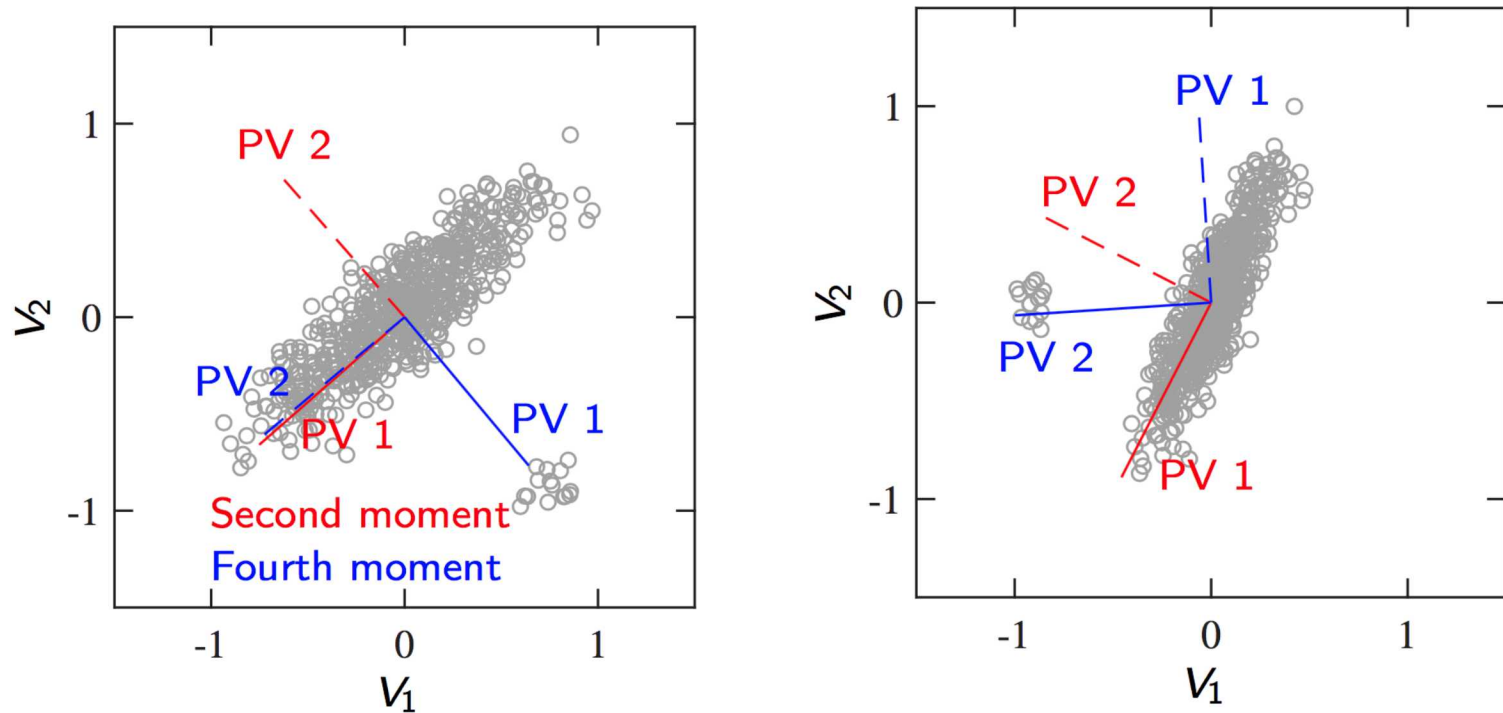
Kurtosis: measure of “either existing outliers (for the sample kurtosis) or propensity to produce outliers (for the kurtosis of a probability distribution)” (P. H. Westfall, 2014)

- Compute the fourth joint moment (cumulant tensor, $\mathcal{T}$)

$$\begin{aligned}\mathcal{T} = & \mathbb{E}[v \otimes v \otimes v \otimes v] - \mathbb{E}[v_{i_1} v_{i_2}] \mathbb{E}[v_{i_3} v_{i_4}] \\ & - \mathbb{E}[v_{i_1} v_{i_3}] \mathbb{E}[v_{i_2} v_{i_4}] - \mathbb{E}[v_{i_1} v_{i_4}] \mathbb{E}[v_{i_2} v_{i_3}], \quad 1 \leq i_1 \dots i_4 \leq k\end{aligned}$$

- Decompose the fourth order symmetric tensor
 - Tensor size (N_f^4), N_f : number of features
 - Matricize the tensor and perform SVD (A. Anandkumar et al., JMLR 2014)
- Obtain principal kurtosis values and vectors

Anomaly detection

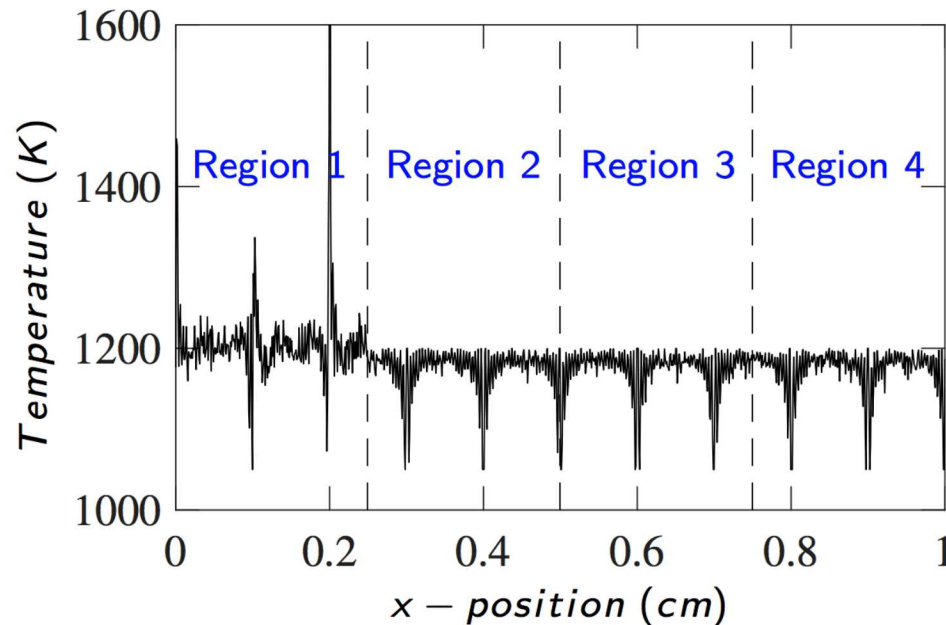


- First principal kurtosis vector aligns in the direction of anomalies
- Can be used to characterize extreme events

Results

Consider a simple problem with a 1D domain

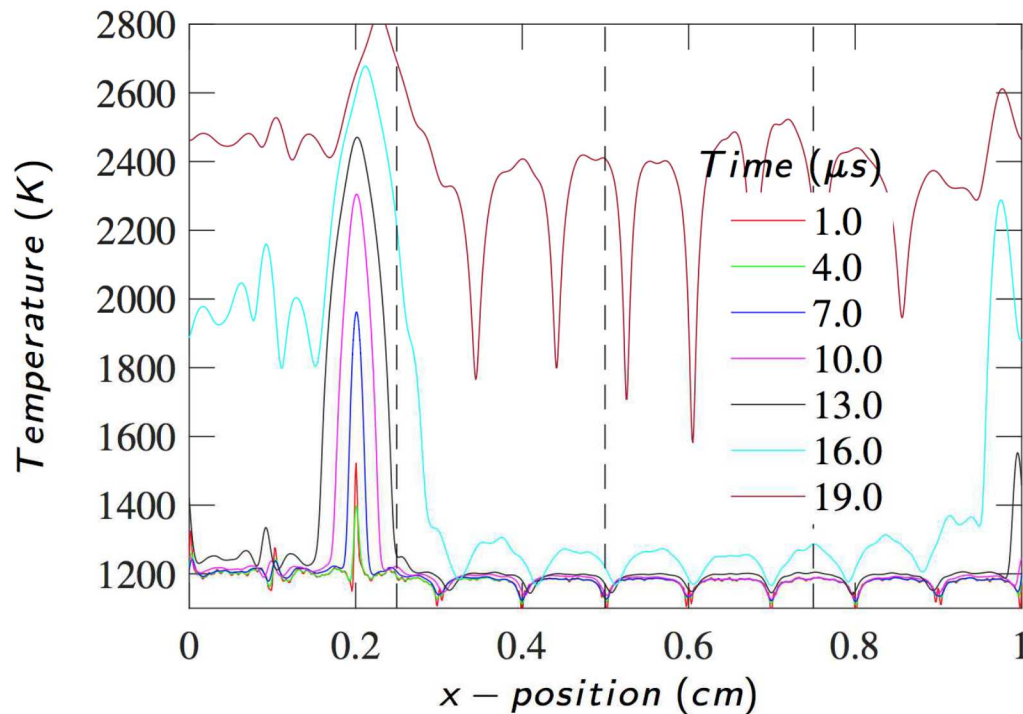
- Initial condition



- Fuel-air composition: **premixed** – $0.6CO + 0.4H_2 + 0.5(O_2 + 3.76N_2)$
- Solver: scalable reacting flow code S3D (J. H. Chen et al., CSD 2009)
- Number of subdomains: $N_d = 4$
- Time-steps: $\Delta t = 0.001 \mu s$
- Number of checkpoints: $N_t = 20$, interval: $1 \mu s$

Auto-ignition test case

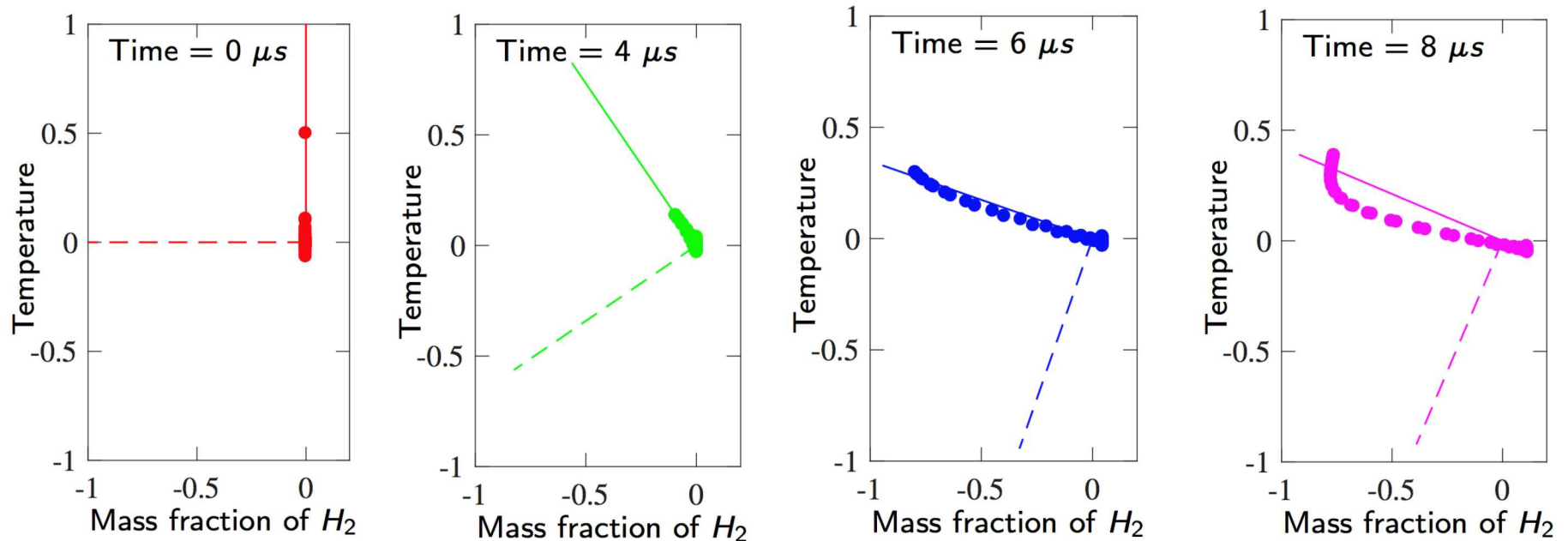
- Time evolution of temperature



- Early ignition occurs in Region 1: **spatial anomaly**
- Eventually ignites in **Regions 4, 2, and 3**

Results

Time evolution of principal vectors in [Region 1](#) (axes: scaled)



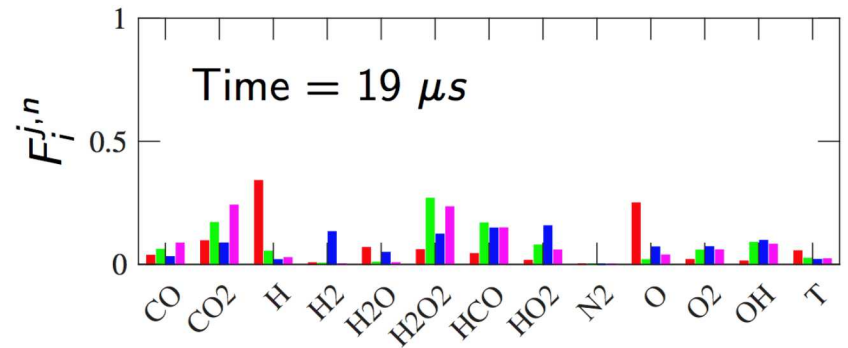
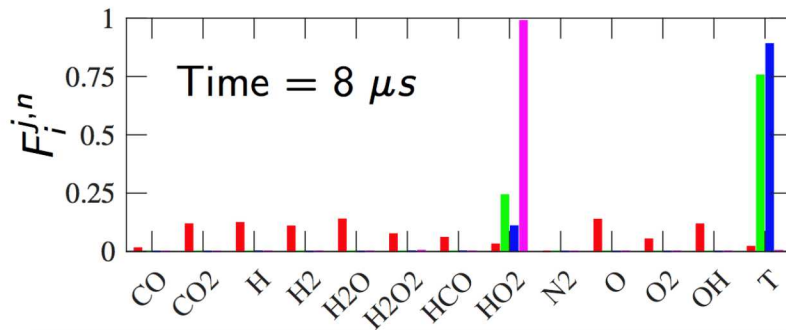
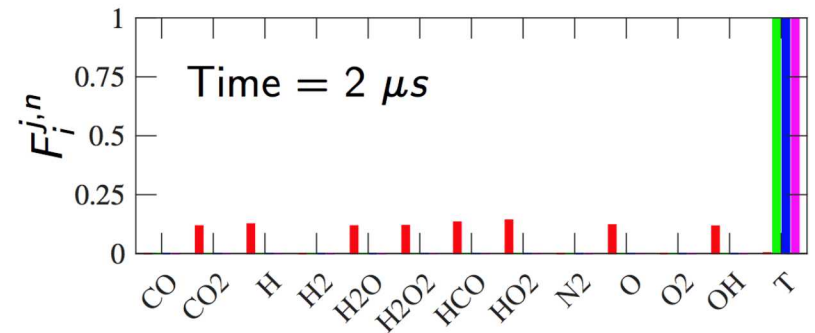
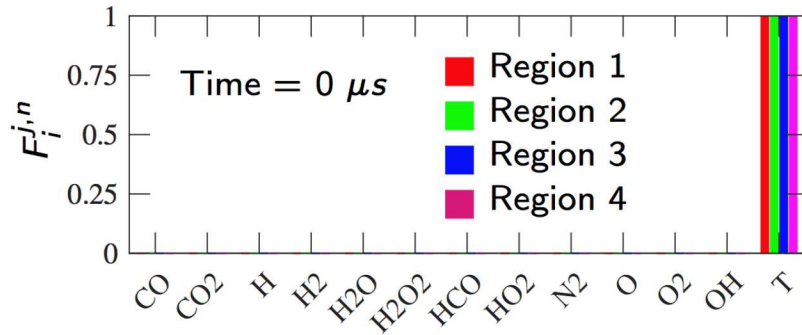
Feature moment metrics

- Number of features: $N_f = 13$ (12 species + temperature), index i
- Number of subdomains: $N_d = 4$, index j
- Number of time steps: $N_t = 20$, index n
- Project the principal vectors weighted by the principal values onto the features to obtain the feature moment metrics ($F_i^{j,n}$)

$$F_i^{j,n} = \frac{\sum_{k=1}^{N_f} \lambda_k (\hat{e}_i \cdot \hat{v}_k)^2}{\sum_{k=1}^{N_f} \lambda_k}$$

- $\hat{e} \cdot \hat{v}$ is effectively the i -th entry in the k -th vector $\hat{v}_k$
- Property: $\sum_{i=1}^{N_f} F_i^{j,n} = 1, \forall j, n$

Results



- FMMs distribute across different features when ignition (anomaly) occurs

Anomaly metrics

Identify spatial and temporal anomalies

- Statistical signature: distribution of feature moment metrics changes
- **Hellinger distance:** a symmetric measure of difference between two discrete distributions P and Q

$$D_{PQ} = \frac{1}{\sqrt{2}} \sqrt{\sum_i (\sqrt{p_i} - \sqrt{q_i})^2}$$

- **Spatial metric:** compare each FMM distribution with the **average**

$$M_1^n(j) = \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^{N_f} \left(\sqrt{F_i^{j,n}} - \sqrt{\overline{F}_i^n} \right)^2}$$

- **Temporal metric:** compare FMM distribution between **successive time steps**

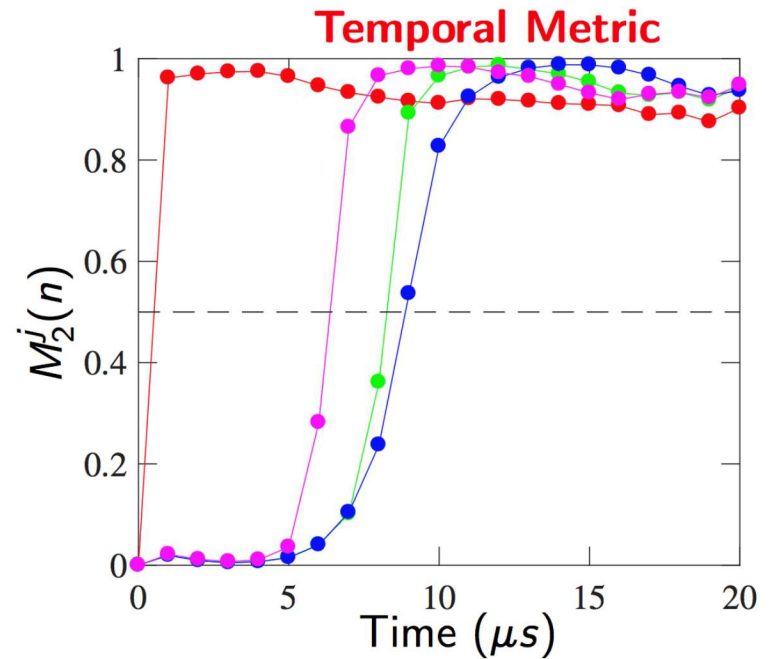
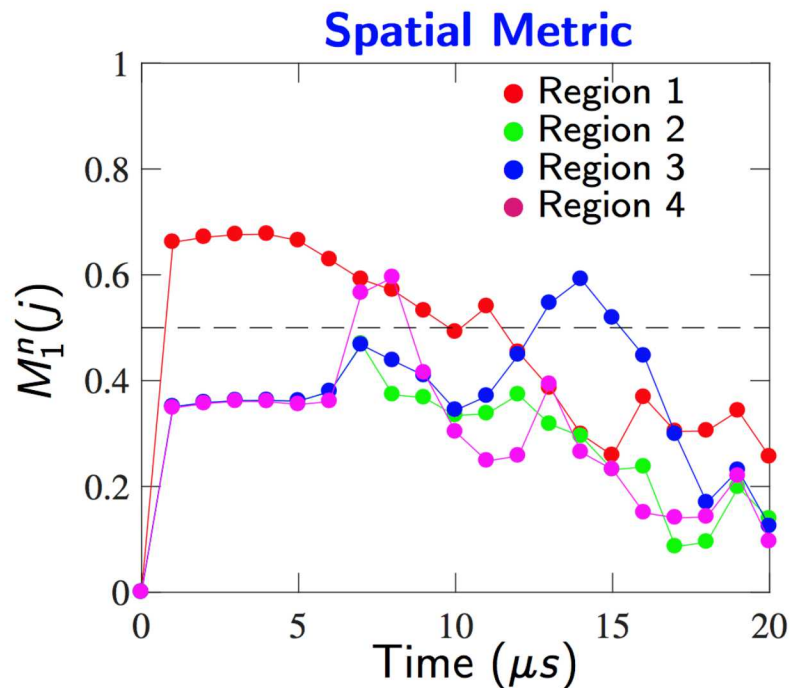
$$M_2^j(n) = \frac{1}{\sqrt{2}} \sqrt{\sum_{i=1}^{N_f} \left(\sqrt{F_i^{j,n}} - \sqrt{F_i^{j,n-1}} \right)^2}$$

Algorithm

Algorithm 1: Anomaly detection algorithm

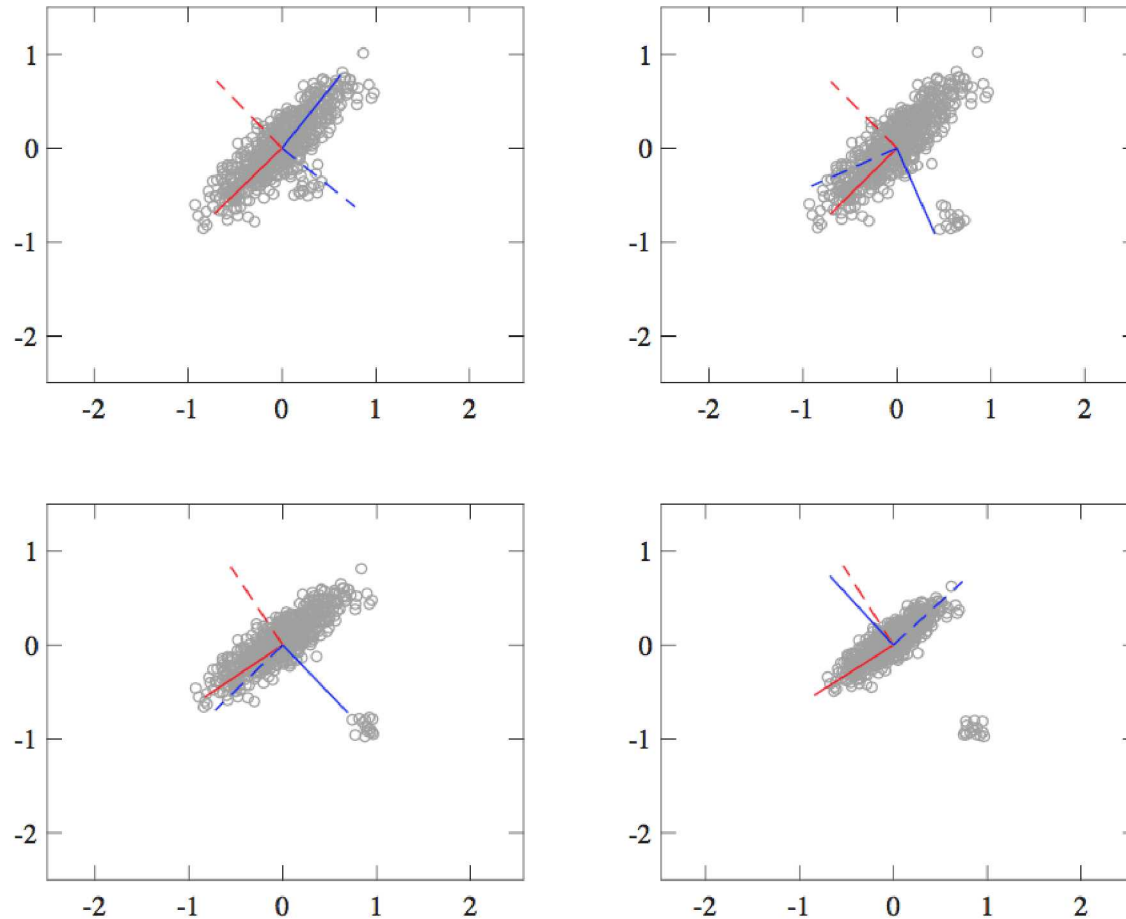
```
// initialization
1  $N_t, N_d \leftarrow$  decompose data;
2  $N_f \leftarrow$  select features;
  // time step loop
3 for  $n \leftarrow 1$  to  $N_t$  do
  | // sub-domain loop
4  | for  $j \leftarrow 1$  to  $N_d$  do
5  | | scale data;
6  | |  $\mathcal{T}^{j,n} \leftarrow$  compute joint moment tensor;
7  | | matricize tensor  $\mathcal{T}^{j,n}$  ;
8  | |  $\lambda_j, v_j \leftarrow$  perform SVD;
9  | |  $F_i^{j,n} \leftarrow$  compute feature importance;
10 | |  $M_1^n(j), M_2^j(n) \leftarrow$  compute anomaly metrics;
11 | end
12 | flag anomalous sub-domains;
13 end
```

Results



- Dash line: threshold for anomaly (=0.5)
- Anomalies detected in space and time

Forecasting



- Track the rate of change of vector orientation

Results

- Proposed an unsupervised anomaly detection algorithm
- Verified the idea using synthetic and auto-ignition data
- Future work:
 - in-situ implementation of the algorithm into the massively parallel direct numerical simulation solver (S3D)
 - evaluate scalability
 - apply the algorithm to detect anomalies in other scientific phenomena