

SPE-GCS CFD Study Group Symposium

August 22nd , 2024

ACCELERATED CFD MODELING OF PLASMA ASSISTED IGNITION WITH PHYSICS ENHANCED MACHINE LEARNING

ISLAM KABIL, CHAO XU

Multi-physics Computational Section, Transportation and Power Systems Division
Argonne National Laboratory

Not for further distribution without permission

DISCLAIMER & ACKNOWLEDGMENT

The submitted manuscript has been created by UChicago Argonne, LLC, Operator of Argonne National Laboratory (“Argonne”). Argonne, a U.S. Department of Energy Office of Science laboratory, is operated under Contract No. DE-AC02-06CH11357. The U.S. Government retains for itself, and others acting on its behalf, a paid-up nonexclusive, irrevocable worldwide license in said article to reproduce, prepare derivative works, distribute copies to the public, and perform publicly and display publicly, by or on behalf of the Government. The Department of Energy will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan. <http://energy.gov/downloads/doe-public-access-plan>

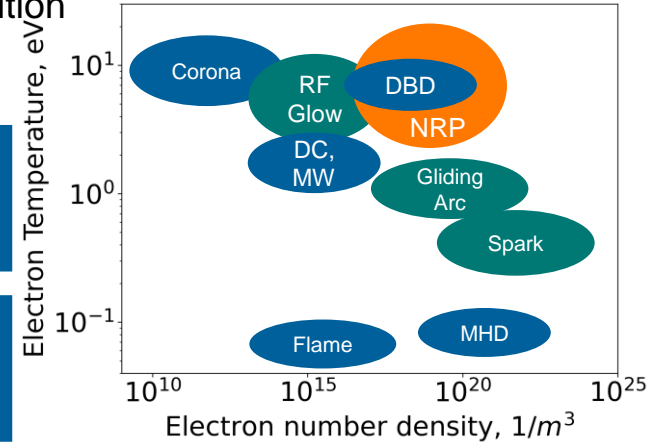
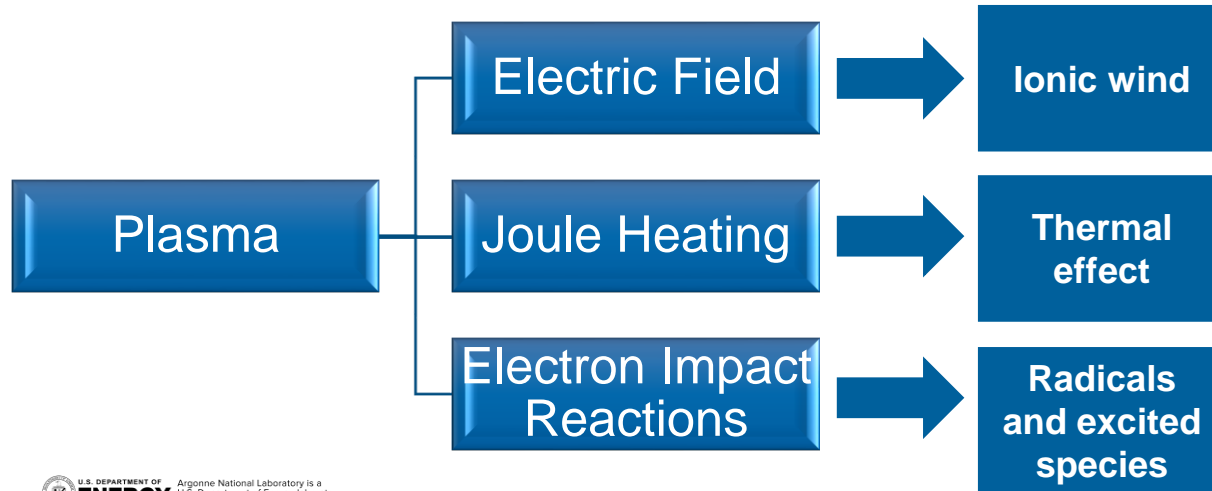
- **Gurpreet Singh and Kevin Stork, DOE VTO program managers, for funding support (DOE project DE-EE0008875)**
- **Bebop cluster at Argonne’s Laboratory Computing Resource Center (LCRC) for computational resources**



INTRODUCTION

PLASMA ASSISTED IGNITION

- ▶ The oldest plasma assisted ignition technology is the spark plug that dates back to 1858
- ▶ Why further research on plasma ignition devices is needed?
 - ▶ The thermal plasma discharge lasting milliseconds, commonly used in spark-ignition engines and gas turbines, may not be the optimal solution for igniting challenging fuel mixtures



Non-equilibrium

* Adapted from, Y. Ju, W. Sun, Plasma assisted combustion: Dynamics and chemistry, Progress in Energy and Combustion Science 48 (2015)

CHALLENGES & GAPS

PLASMA ASSISTED IGNITION

▶ Challenges

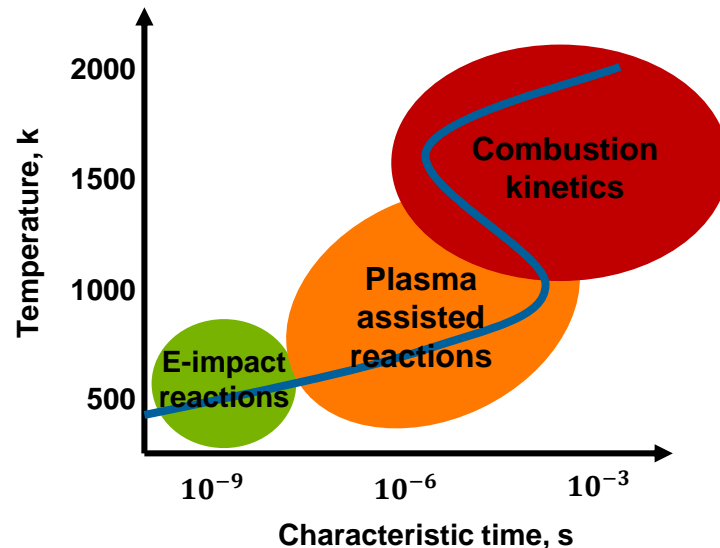
- ▶ Non-equilibrium processes
- ▶ Multi-timescales
- ▶ Complex chemical kinetics

▶ Common solution approaches

- ▶ Reduce Plasma Chemistry
- ▶ Lump excited species
- ▶ Phenomenological models
- ▶ **Data-driven model**

▶ Research gaps

- ▶ Limited capabilities for multi-dimensional simulations of PAI using detailed plasma chemistry
- ▶ Understanding the influence of plasma excited species on combustion and transport



* Adapted from, Y. Ju, W. Sun, Plasma assisted combustion: Dynamics and chemistry, Progress in Energy and Combustion Science 48 (2015)

OBJECTIVES

PLASMA ASSISTED IGNITION

Develop a data-driven modeling framework capable of replicating the effect of a plasma discharge on a reacting gas mixture

▶ **Theoretical Modeling**

- ▶ Assemble a toolbox of physics based 0D and 1D models

▶ **Data-driven Model development**

- ▶ Develop a machine learning framework to model plasma kinetics
- ▶ New feature selection method based on Directed Relation Graphs

▶ **Multi-dimensional Modeling**

- ▶ Extend the capabilities of model plasma assisted ignition in realistic configurations

0D REACTOR MODEL FRAMEWORK

▶ The kinetic model in 2 parts:

- ▶ Plasma kinetic model
- ▶ Combustion kinetic model

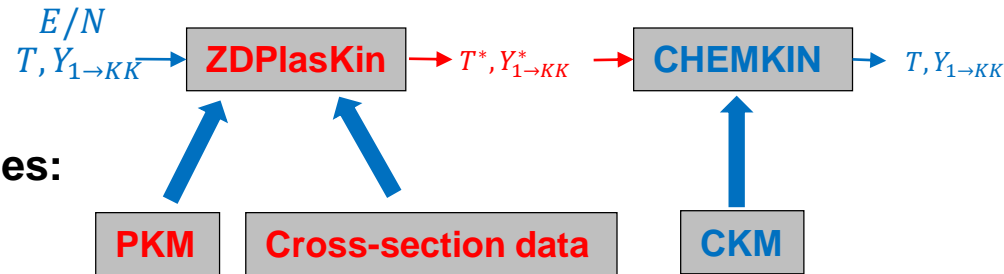
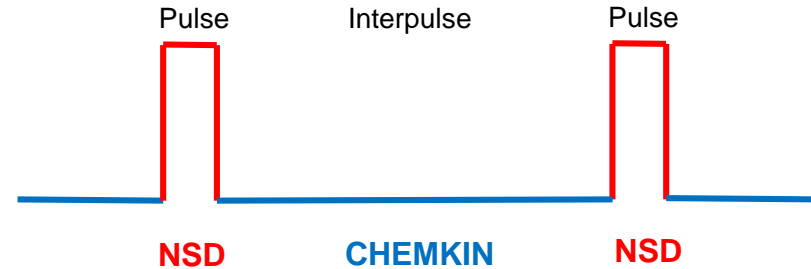
▶ Plasma kinetic model (PKM) includes:

- ▶ Excited species quenching reactions
- ▶ Electron-ion recombination reactions
- ▶ Charge exchange reactions
- ▶ Excitation and ionization electron collision reactions

▶ Combustion kinetic model (CKM) includes:

- ▶ Excited species quenching reactions
- ▶ Electron-ion recombination reactions
- ▶ Charge exchange reactions
- ▶ Neutral ground state species-reactions

NSD: NanoSecond Discharge



▶ The adopted model couples

- ▶ ZDPlasKin (needs to know E/N)
- ▶ CHEMKIN (0D SENKIN)

1D REACTOR MODEL FRAMEWORK

▶ Model Assumptions:

- ▶ A two-fluid model is adopted for electrons and heavy species with two different temperatures
- ▶ The discharge properties only vary in the direction perpendicular to the electrodes
- ▶ Drift-diffusion approximation for fluxes
- ▶ Local field approximation
- ▶ Uniform pre-ionization in the discharge volume

▶ Governing equations during the Pulse

$$\frac{\partial n_k}{\partial t} + \nabla \cdot \Gamma_k = \dot{\Omega}_k \quad \rightarrow \text{Species equations}$$

$$\Gamma_k = q_k \mu_k n_k \mathbf{E} - D_k \nabla n_k \quad \rightarrow \text{Drift diffusion assumption}$$

$$\mathbf{E} = -\nabla \phi$$

$$\nabla \cdot \varepsilon_d \nabla \phi = -\frac{e}{\varepsilon_0} (n_+ - n_- - n_e)$$

$$\rho \frac{\partial e_g}{\partial t} = -\nabla \cdot \mathbf{q} + A_{coll} + \dot{Q}_{JH}$$

$$\mathbf{q} = \lambda \nabla T_g + \sum_k \Gamma_k C_{p,k} T_g$$

$$A_{coll} = \frac{3}{2} k_b n_e \frac{2m_e}{m_g} v_{e,g} (T_e - T_g) + \sum_j \Delta E_j^g r_j$$

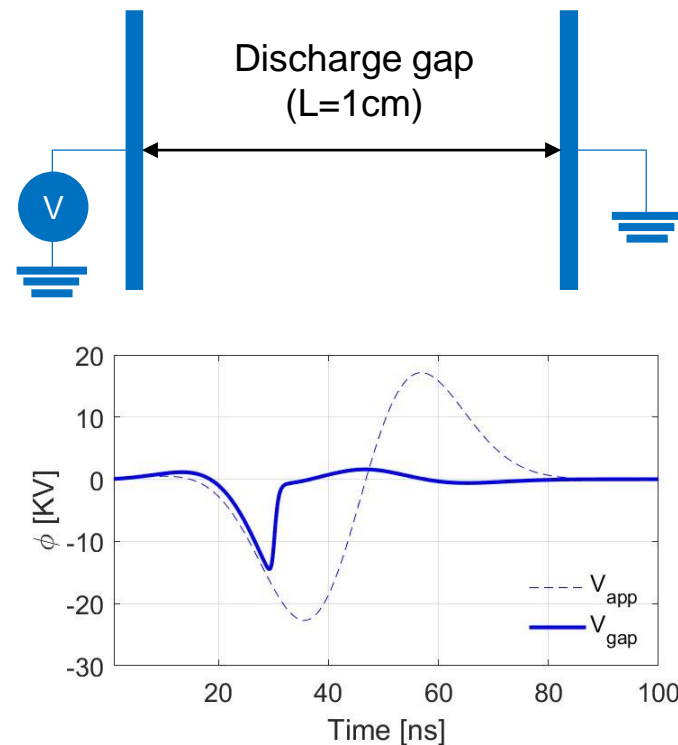
$$\dot{Q}_{JH} = e \mathbf{E} \cdot \sum_k q_k \Gamma_k$$

1D REACTOR MODEL

VALIDATION – NRP PLASMA IN AIR

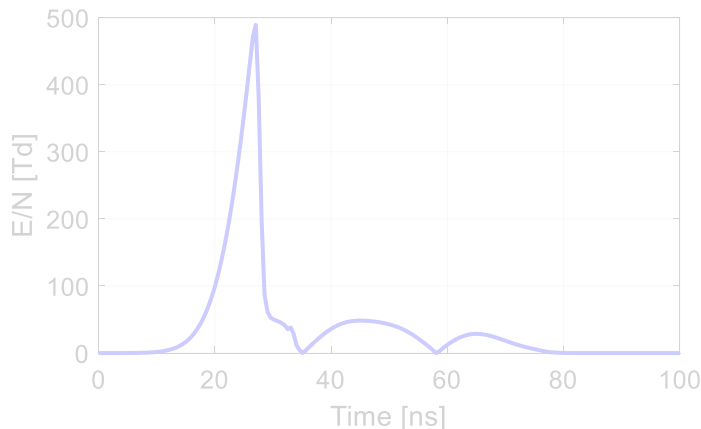
▶ Operating Conditions

- ▶ 1D plane-to-plane geometry
- ▶ Pressure = 0.07 [atm] ~ 50 [torr]
- ▶ Temperature = 300 [K]
- ▶ Applied Electric potential (V_{app})
 - ▶ $t_{pulse} = 100$ [ns]
 - ▶ V_{app} range [- 22 : 17] KV
- ▶ Plasma kinetics:
 - ▶ 18-species, 115-reaction mechanism based on (Uddi 2009, Nagaraja 2013)

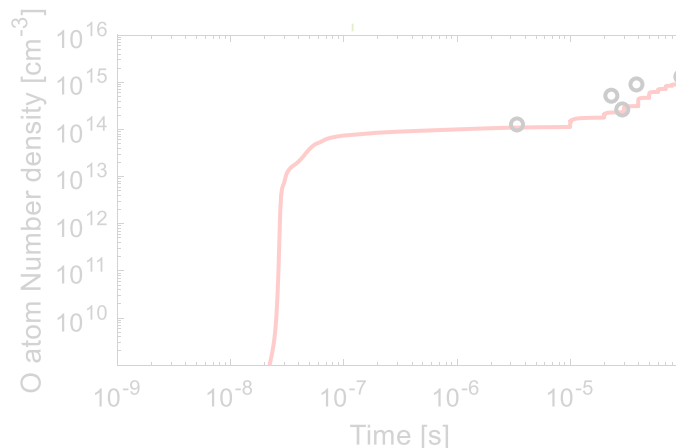


1D REACTOR MODEL

VALIDATION – NRP PLASMA IN AIR



- ▶ **Reduced electric field (E/N)**
 - ▶ 3 peaks (~500, ~50, ~40 Td)
 - ▶ The highest peak is responsible for electronic excitation and ionization



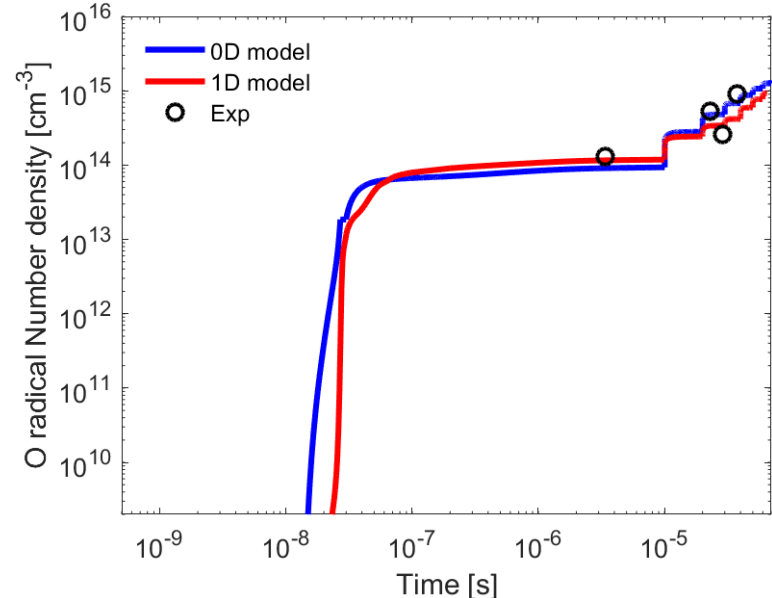
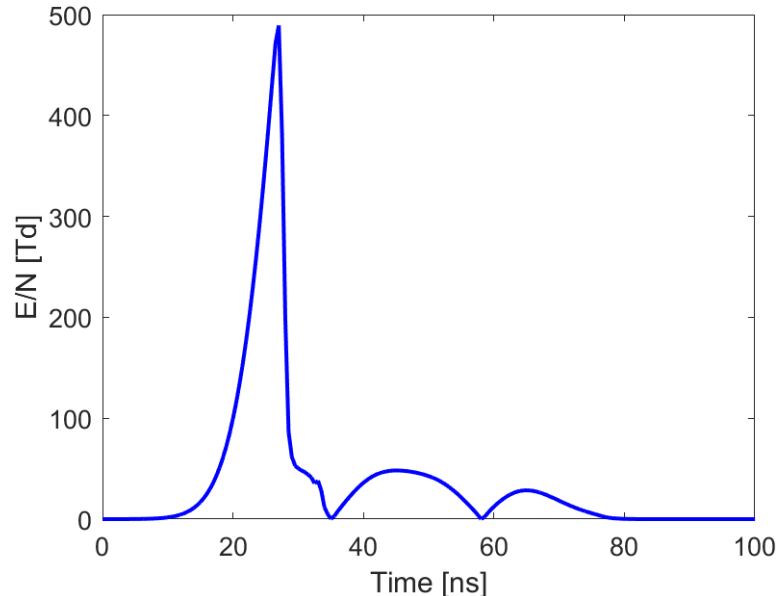
- ▶ **O atom concentration history**
 - ▶ Agreeable matching for the multipulse measurements
 - ▶ Concentration keeps building up

4~5 Days to complete the simulation of 10 pulses

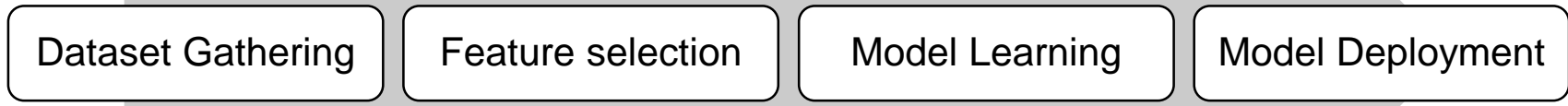
0D REACTOR MODEL

VALIDATION – NRP PLASMA IN AIR

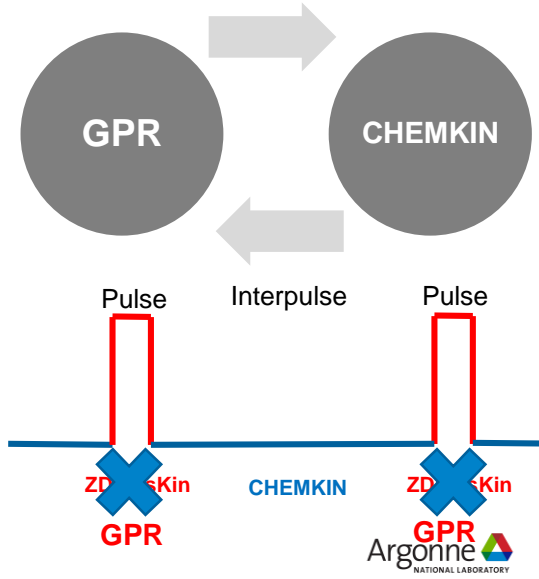
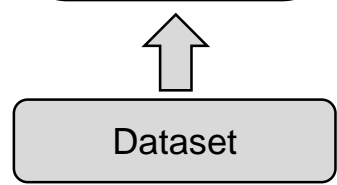
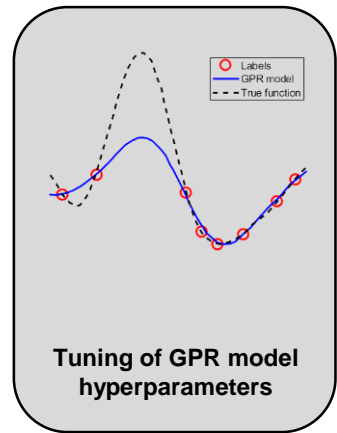
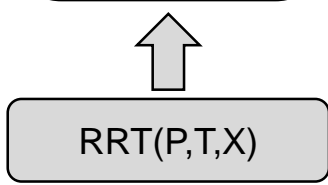
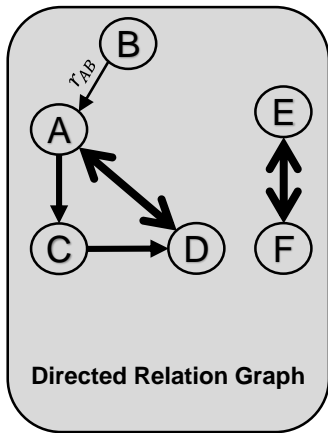
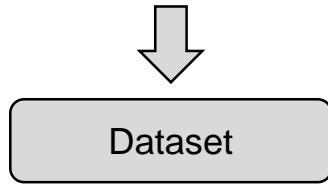
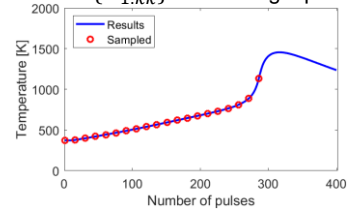
- ▶ The main issue with 0D reactor model is how to tune the model
- ▶ Proposed solution: Use 1D results of E/N for a given pressure to calibrate the 0D model for multi pulse simulations



DEVELOPMENT OF DATA-DRIVEN MODELS FRAMEWORK



Features : $\{P, T, X_{1:kk}\}$ at the start of the pulse
 Labels : $\{\omega_{1:kk}\}$ over a single pulse



DEVELOPMENT OF DATA-DRIVEN MODELS

DATASET

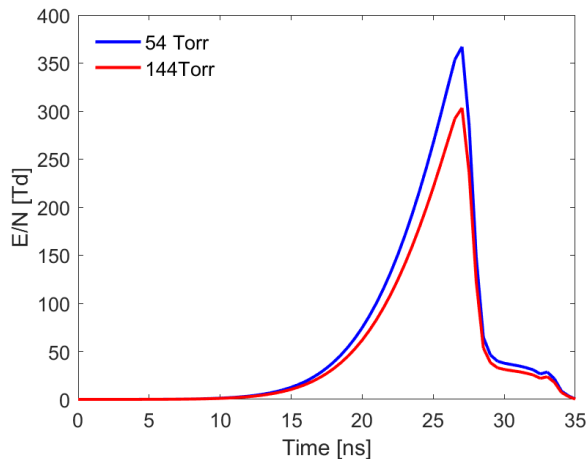
▶ The kinetic model is separated into 2 parts:

(26 species)

- ▶ Plasma kinetic model (ZDPlasKin)
 - ▶ Electron impact reactions
 - ▶ Excited species Relaxation
- ▶ Combustion kinetic model (CHEMKIN)
 - ▶ Excited species Relaxation
 - ▶ Combustion kinetics

▶ Targeted Experimental conditions*

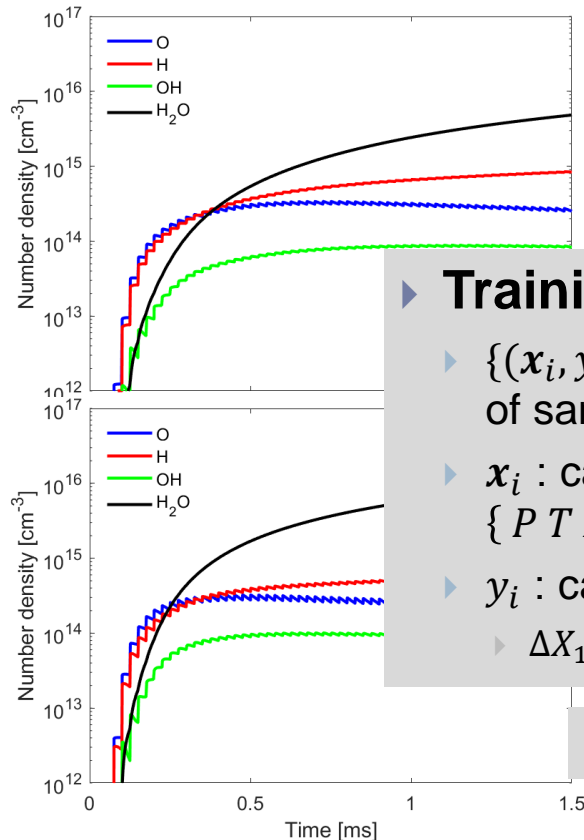
- ▶ Stoichiometric H_2/Air
- ▶ Pressure = 54 ~ 144 Torr
- ▶ Temperature = 373 ~ 473 K
- ▶ Frequency = 20 ~ 40 kHz
- ▶ V_{app} = - 22 ~ 17 KV
- ▶ t_{pulse} = 100 ns



* Yin, Zhiyao, Keisuke Takashima, and Igor V. Adamovich. "Ignition time measurements in repetitive nanosecond pulse hydrogen–air plasmas at elevated initial temperatures." *IEEE Transactions on Plasma Science* 39.12 (2011): 3269-3282.

DEVELOPMENT OF DATA-DRIVEN MODELS

DATASET



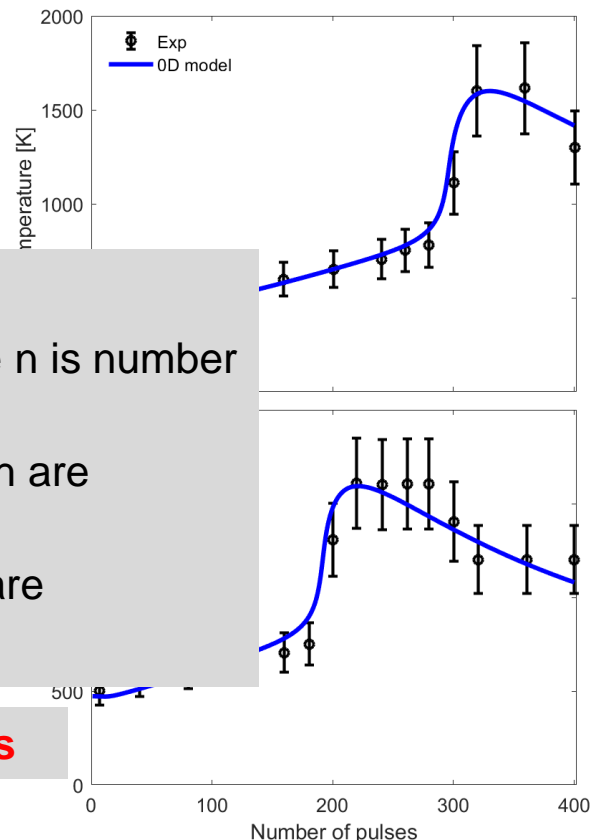
64Torr
473K

84Torr
373K

▶ Training dataset

- ▶ $\{(x_i, y_i) ; i = 1, 2, \dots, n\}$ where n is number of sample points
- ▶ x_i : carries the features which are $\{P T X_{1:kk}\}$
- ▶ y_i : carries the labels which are
 - ▶ $\Delta X_{1:kk} / pulse$

Sampled ~ 7000 tuples



DEVELOPMENT OF DATA-DRIVEN MODELS

TRAIN GPR MODEL

► Method

- Gaussian process regression GPR with an exponential kernel

$$\text{Cov}(x_i, x_j) = \sigma^2 \exp\left(-\frac{\sqrt{(x_i - x_j)^T(x_i - x_j)}}{l}\right)$$

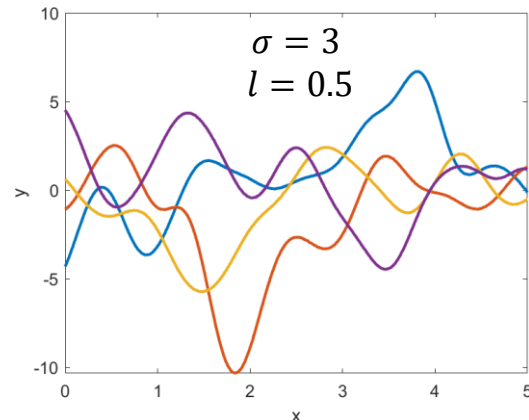
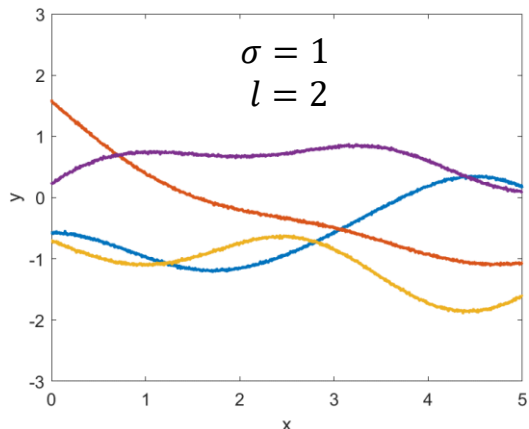
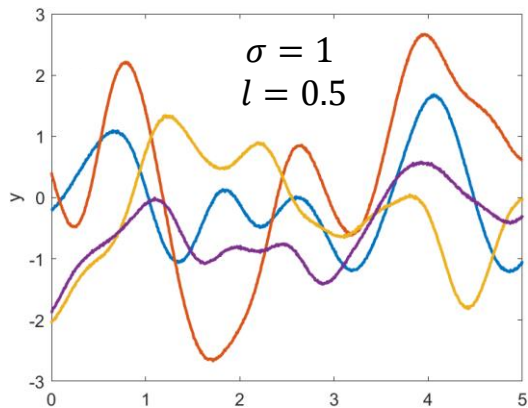
- Model hyper-parameters are varied to maximize the likelihood of reproducing the target output

► Inference

$$y^* = k_*^T (K + \sigma_n^2 I)^{-1} y$$

Involves inverting the covariance matrix which might be expensive in the case of large datasets

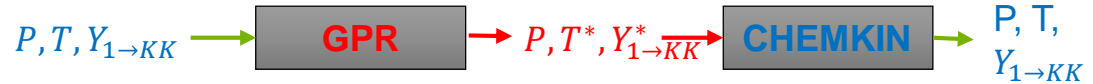
Trained models hold normalized RMSE below 3%



DEVELOPMENT OF DATA-DRIVEN MODELS

A GPR-CHEMKIN MODEL

- ▶ GPR model coupled to CHEMKIN



- ▶ All species source terms were modeled, except for $E, O_2, N_2,$ and H_2

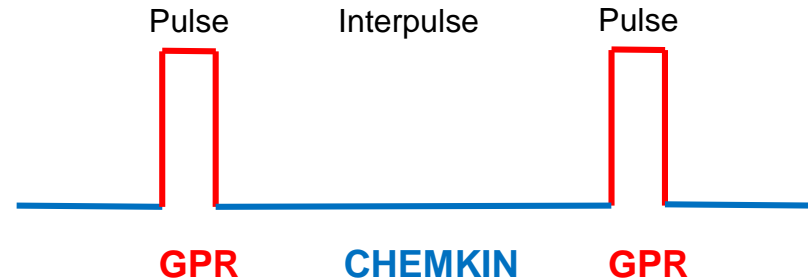
Element Conservation

- ▶ $E, O_2, N_2,$ and H_2 are excluded from the model correction

$$\theta_{1 \rightarrow 4} = \nu_{ij} \cdot \Delta X_j$$

where:

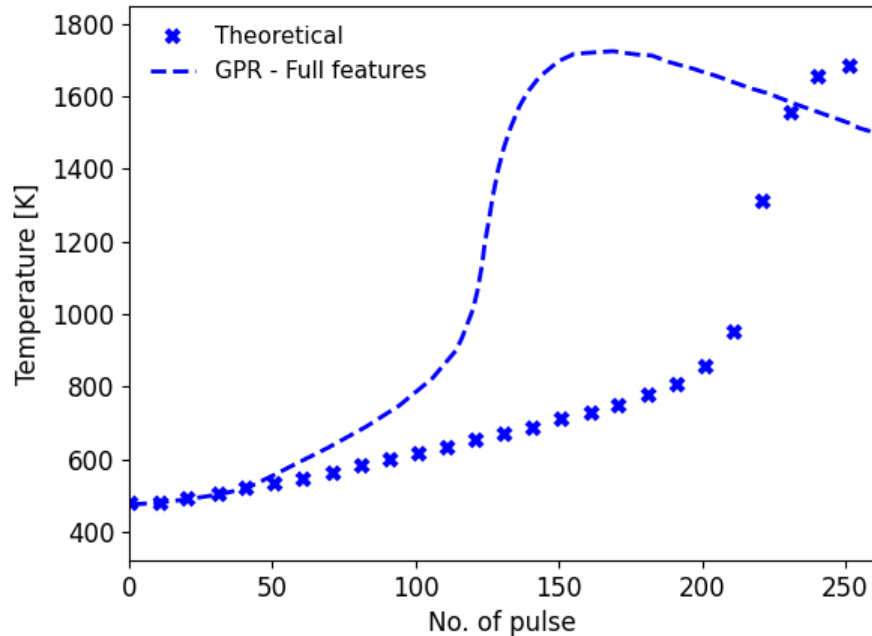
- ▶ $\theta = [\Delta X_E, 2\Delta X_{O_2}, 2\Delta X_{N_2}, 2\Delta X_{H_2}]^T$
- ▶ ν_{ij} is the i^{th} element in the j^{th} species ($j = 5: KK$)



GPR model accelerated plasma source term evaluation by 30-fold

DEVELOPMENT OF DATA-DRIVEN MODELS

FIRST RESULT FROM THE GPR MODEL



Test case:

- ▶ P = 84Torr
- ▶ 40 kHz
- ▶ Stoichiometric H_2/Air mixture

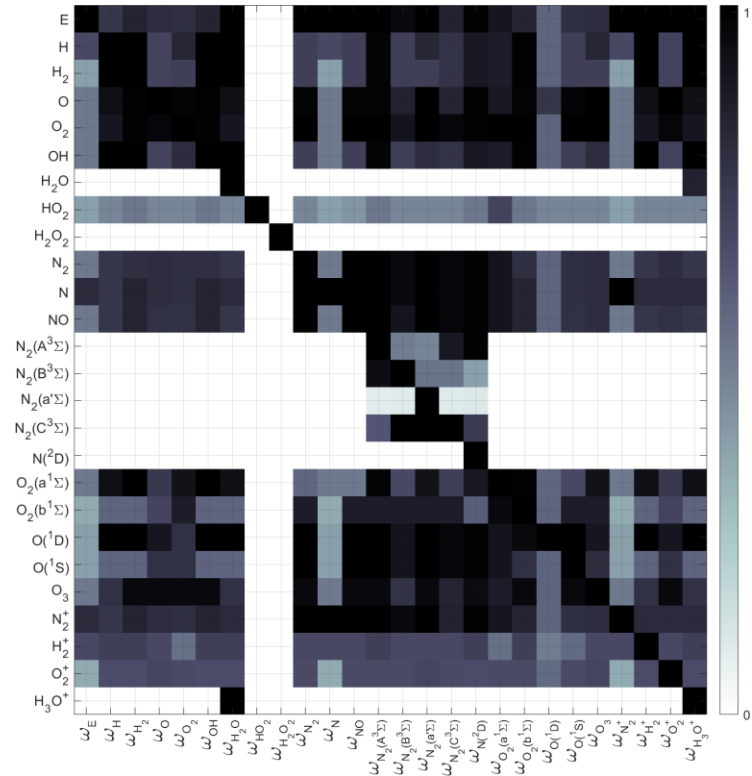
DEVELOPMENT OF DATA-DRIVEN MODELS

FEATURE SELECTION – DIRECTED RELATION GRAPHS (DRG)

- ▶ Weigh the coupling of species (B) to the production rate of a specific species (A)

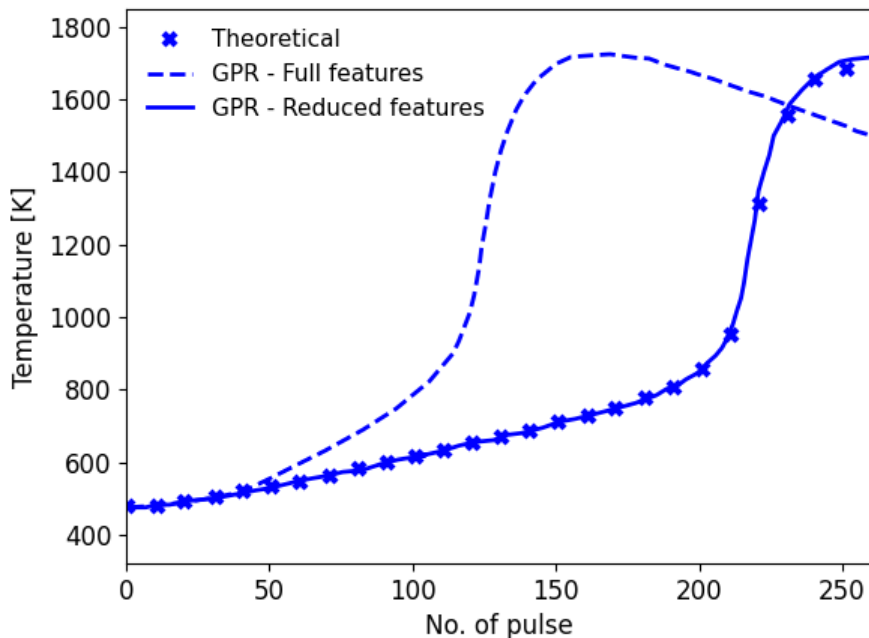
$$r_{AB} = \frac{\sum_{i=1,I} |v_{A,i} \omega_i \delta_{Bi}|}{\sum_{i=1,I} |v_{A,i} \omega_i|}$$

- ▶ Species having couplings stronger than a specified threshold ε are kept as part of feature subset of that source term
- ▶ This process is done for each species of interest to select the most important features for its production



DEVELOPMENT OF DATA-DRIVEN MODELS

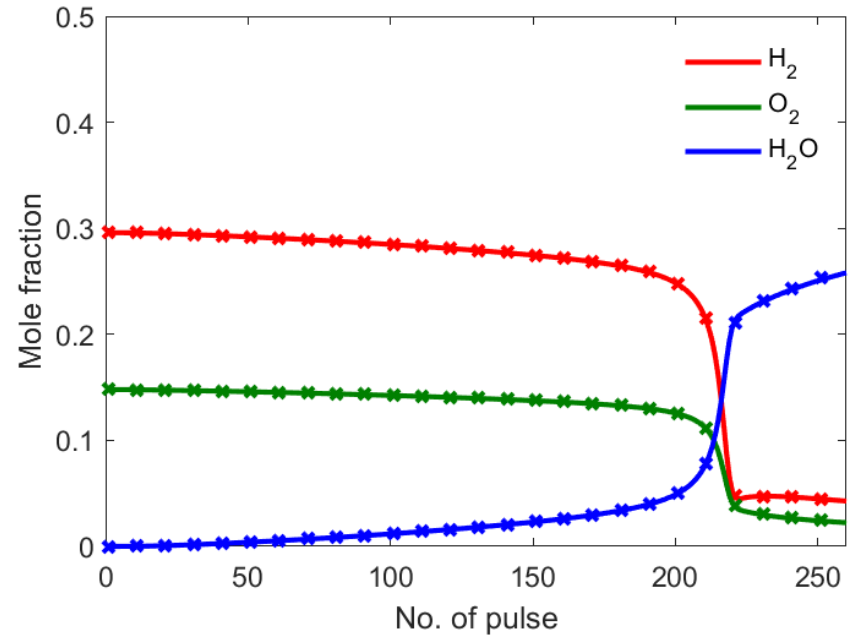
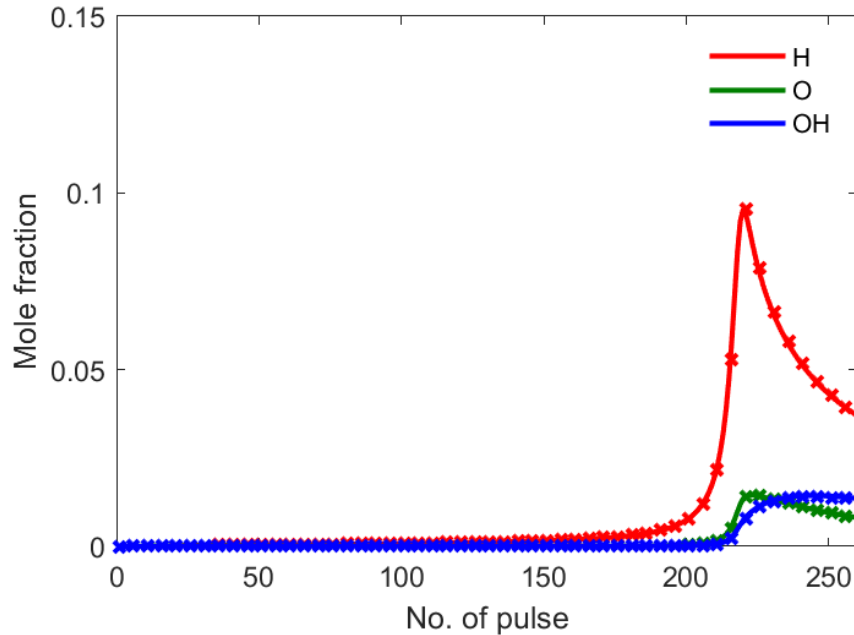
DRG MERIT IN ML TRAINING



- ▶ **Same dataset**
- ▶ **GPR – Full features:**
 - ▶ Trained on the whole feature matrix
- ▶ **GPR – Reduced features:**
 - ▶ Trained on feature matrix subsets selected via DRG per species source term.
- ▶ **Test case:**
 - ▶ P = 84Torr
 - ▶ 40 kHz
 - ▶ Stoichiometric H_2/Air mixture

DEVELOPMENT OF DATA-DRIVEN MODELS

DRG MERIT IN ML TRAINING



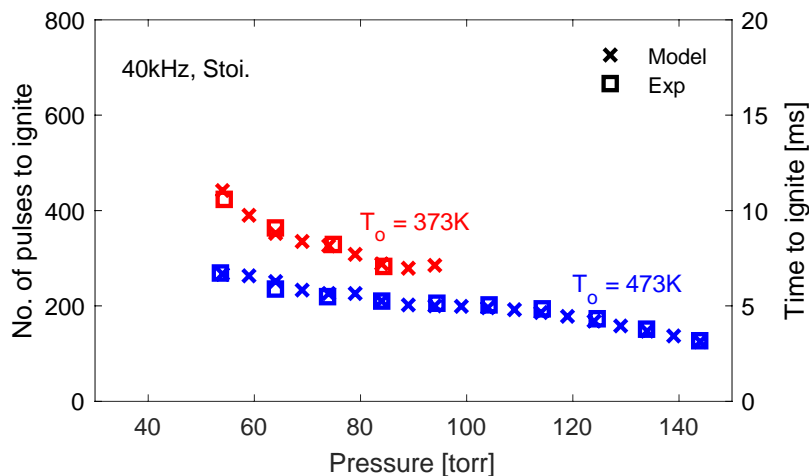
Cross: Theoretical
Line: GPR – Reduced features

DEVELOPMENT OF DATA-DRIVEN MODELS

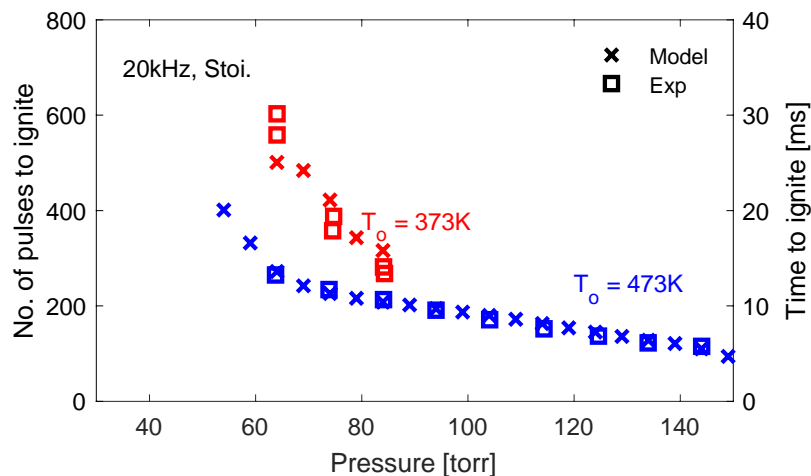
EXTENDED VALIDATION

- ▶ Model applied to a wider range of operating conditions: two pulsing frequencies (40 and 20 kHz) and two temperatures (373K and 473K)
- ▶ Excellent agreement between the predicted ignition delay using the GPR model with experiments

40 kHz



20 kHz



MULTI-DIMENSIONAL MODELING OF PLASMA ASSISTED IGNITION

2D DNS setup following Castela 2016

▶ Plasma discharge

- ▶ $E/N \rightarrow 150 \text{ Td}$
- ▶ Frequency $\rightarrow 10 \text{ kHz}$
- ▶ $\sigma_{pulse} = 1.1 \times 10^6 \text{ J/m}^3$ with $\sim 45\%$ going into vibrational excitation
- ▶ $r_d = 225 \mu\text{m}$
- ▶ $L_d = 4 \text{ mm}$

▶ Initial conditions

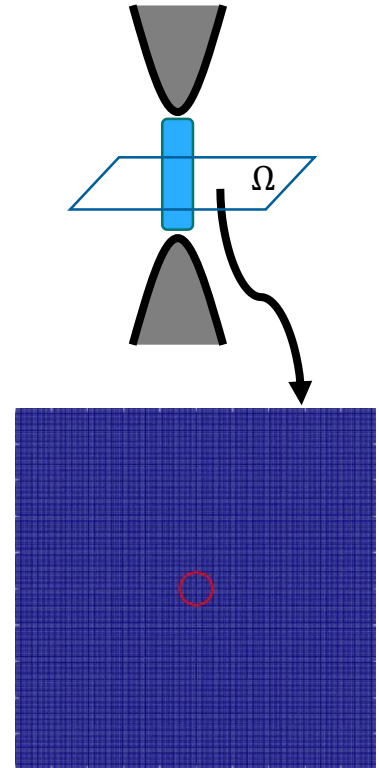
- ▶ $\text{CH}_4 - \text{Air}$ @ $\phi = 0.8$
- ▶ $300 \text{ K}, 1 \text{ atm}$

▶ Chemistry models

- ▶ Combustion kinetic model: Based on FFCM2 (25 species)
- ▶ Plasma kinetics: GPR model trained via FFCM2 + Plasma in air core mech (37 species in total)
- ▶ Sampling range: $\phi = 0.5 - 1.5, T_0 = 300 - 1500 \text{ K}$

▶ Solver and numerical setup

- ▶ Spectral element solver Nek5000
- ▶ Low-Mach number formulation
- ▶ 64×64 elements with 7th order polynomial



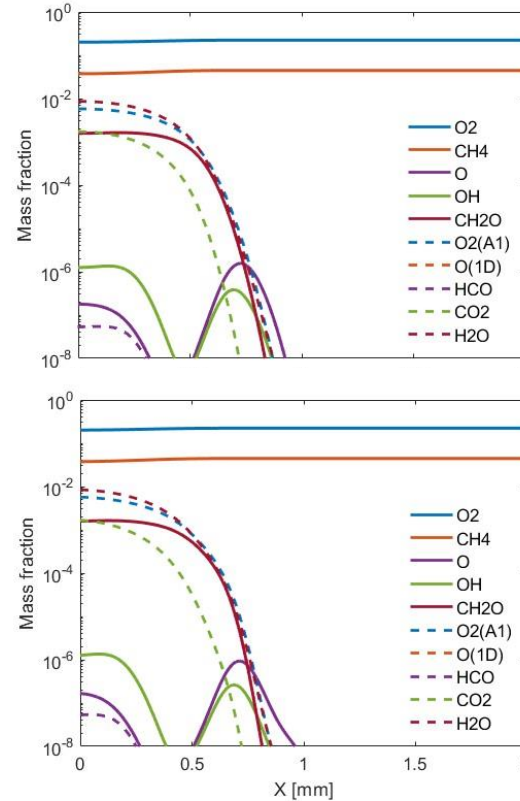
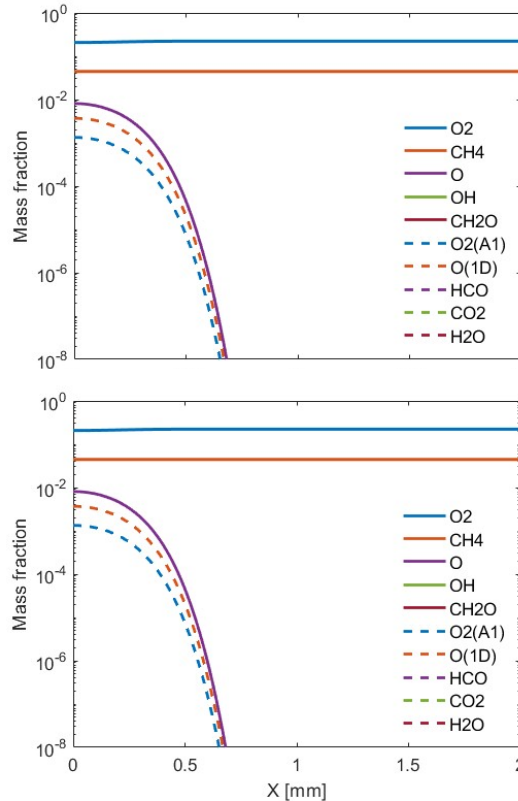
*Castela, Maria, et al. "Modelling the impact of non-equilibrium discharges on reactive mixtures for simulations of plasma-assisted ignition in turbulent flows." *Combustion and flame* 166 (2016): 133-147.

IGNITION KERNEL EVOLUTION AFTER FIRST PULSE

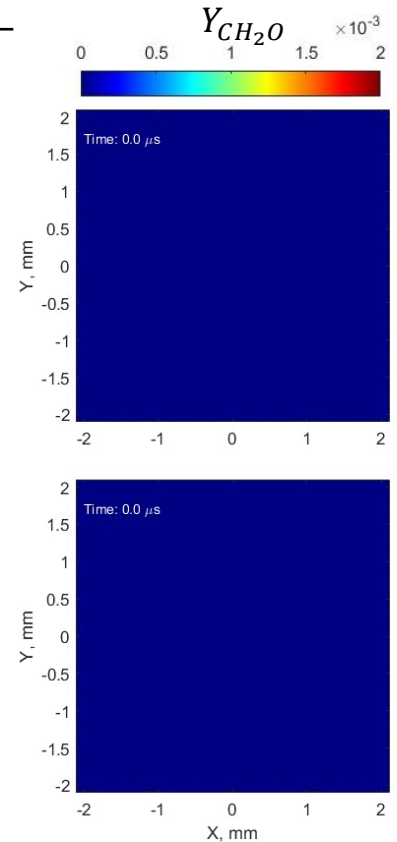
50 ns

80 μ s

Quisc.



$Re_t = 44$

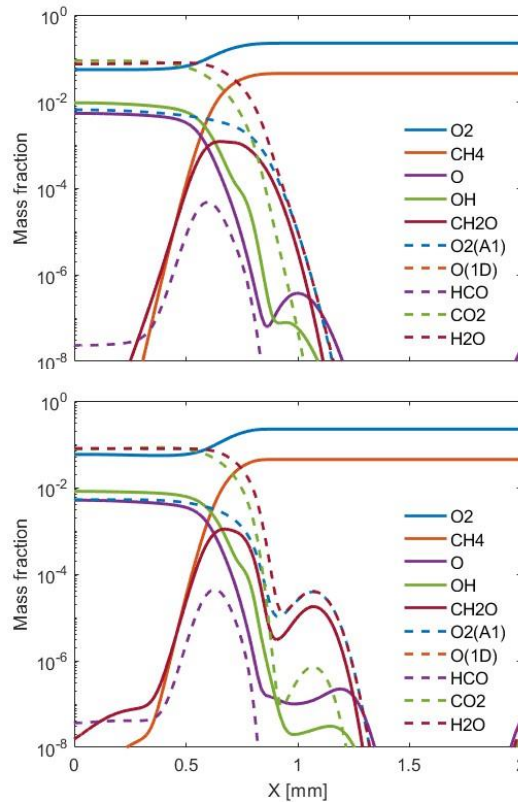
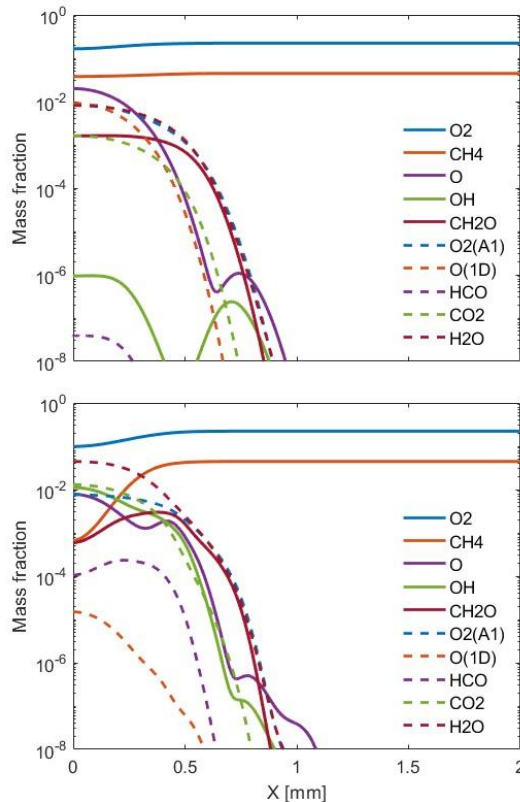


IGNITION KERNEL EVOLUTION AFTER SECOND PULSE

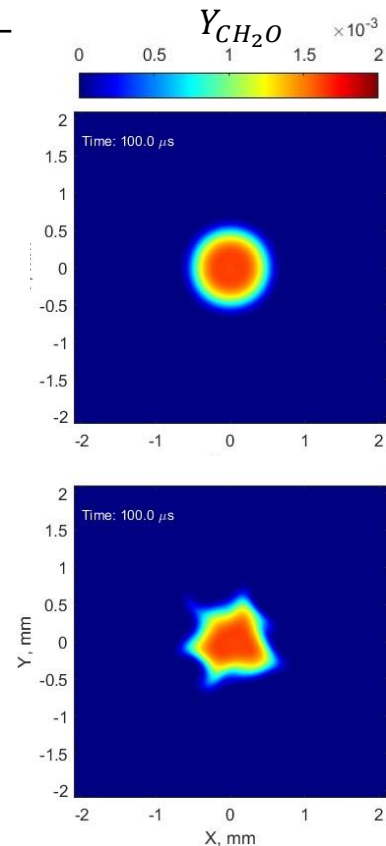
100.05 μ s

180 μ s

Quisc.



$Re_t = 44$



SUMMARY AND CONCLUSIONS

- ▶ **A data driven modeling framework has been developed for NRP plasma kinetic influence on a reacting mixture**
 - ▶ Assembled a toolbox of 0D and 1D models for dataset generation
 - ▶ Developed a GPR model to predict plasma species source terms
 - ▶ Embedded physical insights (DRG based feature down selection and elemental conservation) to improve GPR model accuracy
 - ▶ The GPR model provides a 30-fold speedup in evaluating the plasma source terms compared to ZDPlasKin using detailed chemistry

- ▶ **Extended GPR-CHEMKIN model to multi-dimensional simulations**
 - ▶ Demonstrated the effectiveness of the GPR model in enabling affordable 3D simulations of plasma assisted ignition with spectral element code Nek5000
 - ▶ The role of non-equilibrium species in the ignition process has been shown to accelerate the ignition process



THANK YOU!

Chao Xu (chaoxu@anl.gov)
Islam Kabil (ikabil@anl.gov)



Argonne National Laboratory is a
U.S. Department of Energy laboratory
managed by UChicago Argonne, LLC.

