Flow reconstruction of single-phase planar jet from sparse temperature measurements

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November 13-15, 2023, KFUPM, Saudi Arabia

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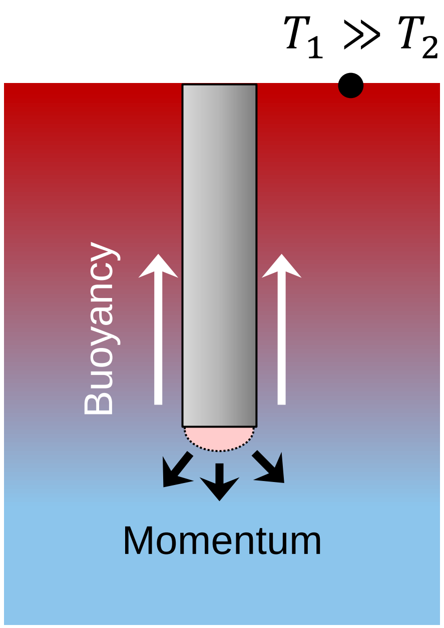
- Methodology
- Test on benchmark dataset
- Test on experimental measurements
- Conclusion

Code and data availability: SparseT2V:https://github.com/xichenggege/SparseT2V

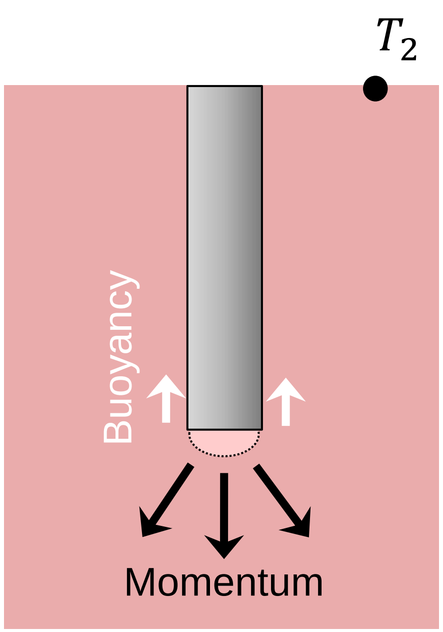
Steam injection into Pressure Suppression Pool

Safety concerns of thermal stratification

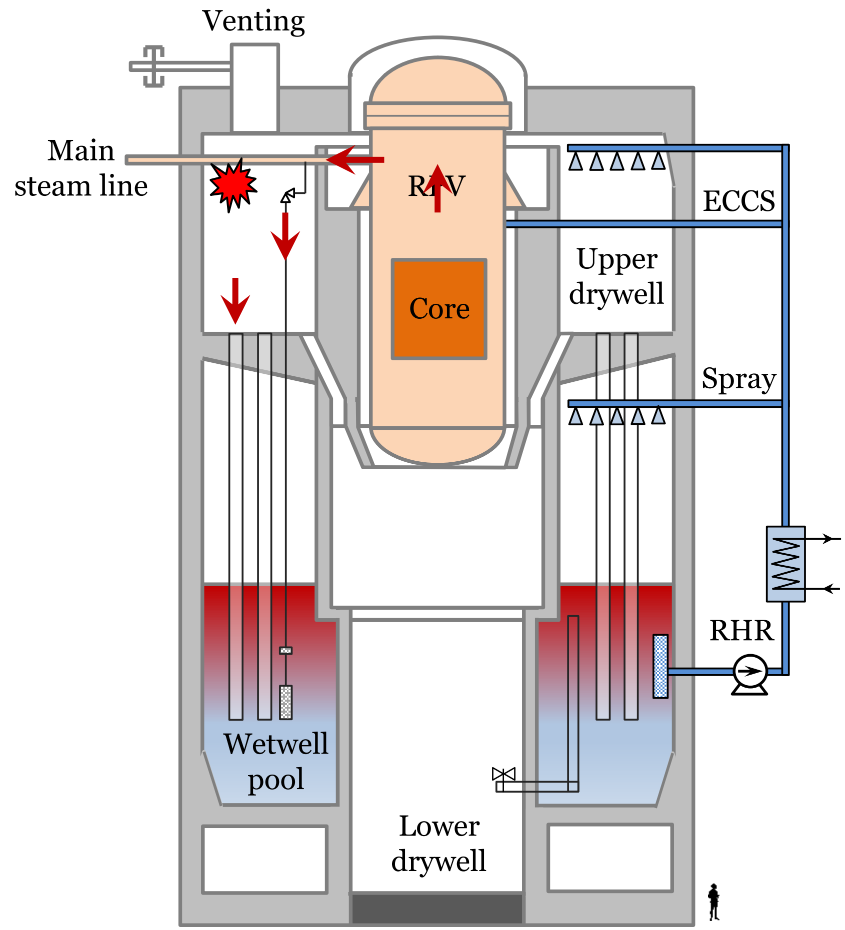
- Higher containment pressure than in mixed pool conditions.
- Lower NPSH at Emergency Core Cooling Systems (ECCS) and spray pumps
  - Risk for cavitation
  - Pumps are shut down at $T_L \approx 95^{o}$C



Thermal stratification
Buoyancy ≫ Momentum

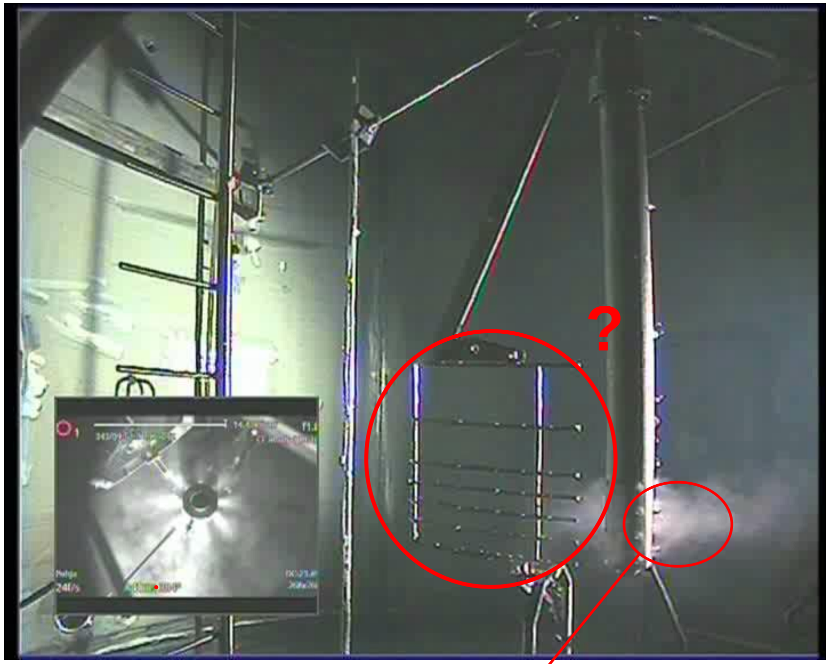


Mixing
Momentum ≫ Buoyancy



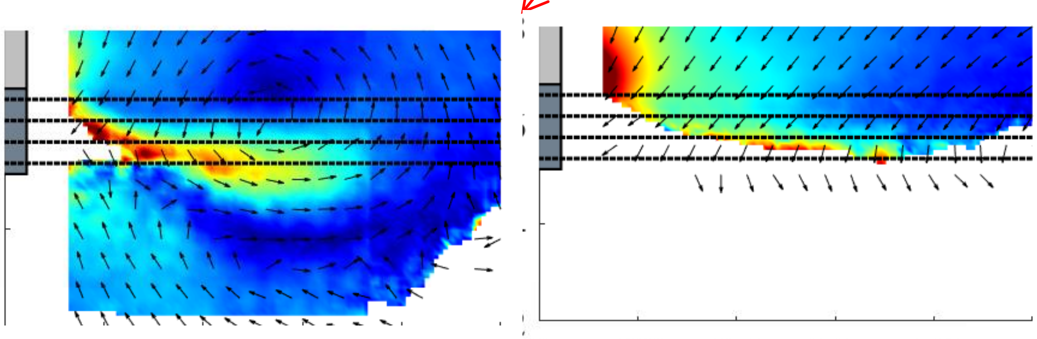
Nordic BWR containment (ASEA-ATOM)

Challenge for measurement of condensed steam jet



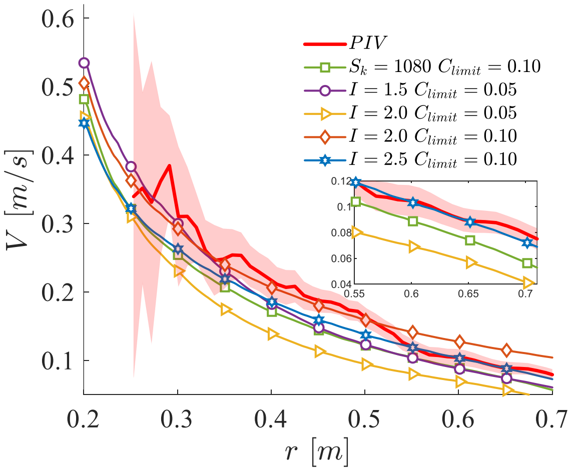
Sparger experiment in the PPOOLEX facility.
SPA-T6, low steam injection phase

- **Model development requires data from**
  - Large scale pool tests
  - Small scale separate effect tests
- **Velocity measurement**
  - Provide database for code development and validation.
  - Reproduction of velocity is essential for simulating energy transportation
    - To capture the key phenomena of the pool
      - i.e. thermal stratification or mixing
- **PIV is challenging**
  - rapid collapse of bubbles
  - significant temperature gradient
- **PIV is infeasible**
  - Non-transparent fluid, e.g. liquid metal



$\dot{G}_s = 70\ kg/m^2 s$ $\quad$ $\dot{G}_s = 162\ kg/m^2 s$

PIV measurement of turbulent velocity induced by steam condensation in PANDA experiments



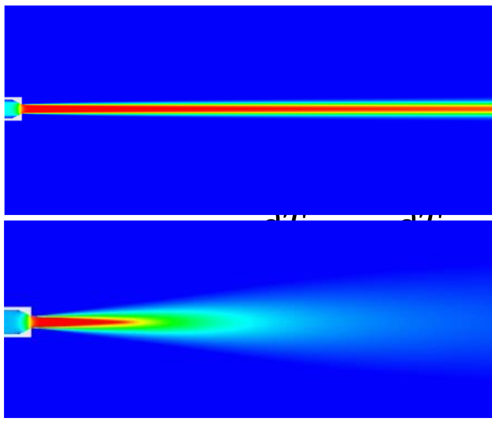
Comparison of centreline velocity profiles between PIV and CFD scoping analysis

Velocity reconstruction by sparse temperature measurement

Sparse temperature field

?

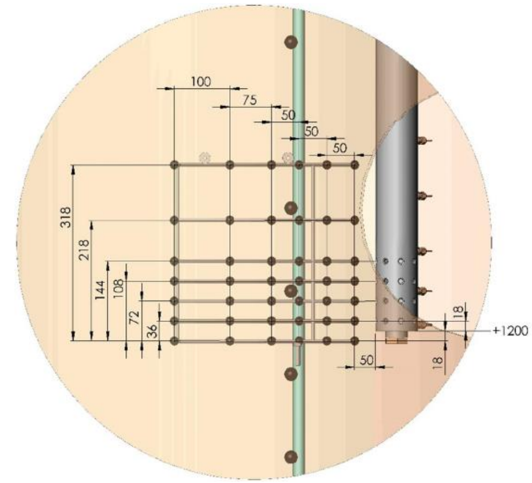
Full velocity field



$$\left(\frac{1}{Re}+\frac{1}{Re_t}\right)\left(\frac{\partial^2 U}{\partial x^2}+\frac{\partial^2 U}{\partial y^2}\right)$$

$$\left(\frac{1}{Pe}+\frac{1}{Pe_t}\right)\left(\frac{\partial^2 T}{\partial x^2}+\frac{\partial^2 T}{\partial y^2}\right)$$

$$Pe_t = Re_t Pr_t \ (Pr_t = 0.85)$$



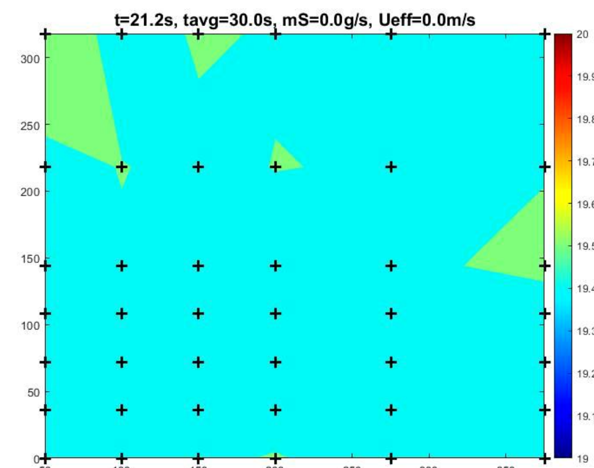
TC grid near the sparger in PPOOLEX test

Goal and motivation

- Investigate the capability of flow velocity reconstruction from sparse temperature measurement. Specifically, propose a farmwork that can map:
  - Input: sparsely measured temperature, other info if necessary
  - Output: full space velocity, temperature

Database (generated by CFD)

- Benchmark case
- Engineering application



Temperature measured by TC grid in PPOOLEX. Contours were interpolated via sparse data

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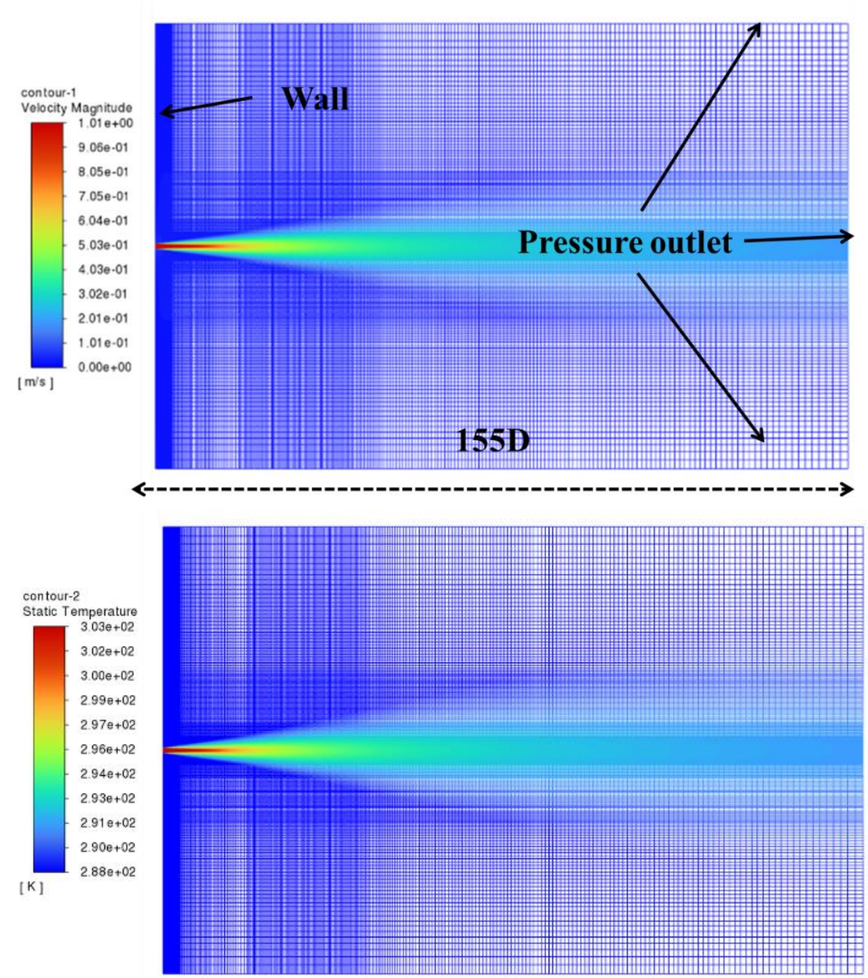
Training data (benchmark case)

Training data

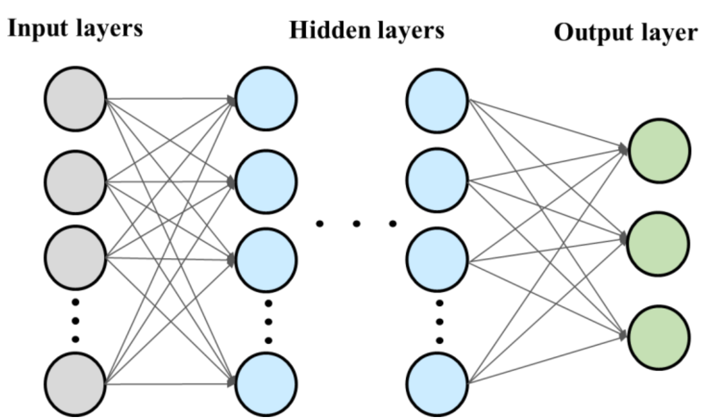
- Generated by ANSYS Fluent
  - *steady-state case*
  - 2D planar jet
  - K-omega RANS
- 3740 cases, varying on
  - U_0: $0.1{\sim}10\ m/s$, T_0: $20{\sim}80$ ℃
  - I_0: $5\%{\sim}70\%$, μ_l/μ_t: $10{\sim}5000$
  - I_{eff}: $10\%{\sim}300\%$, U_0: $1{\sim}6\ m/s$
    - Additional turbulence source
- With special focus on capturing
  - diffusion of the momentum and energy under diverse boundary conditions.



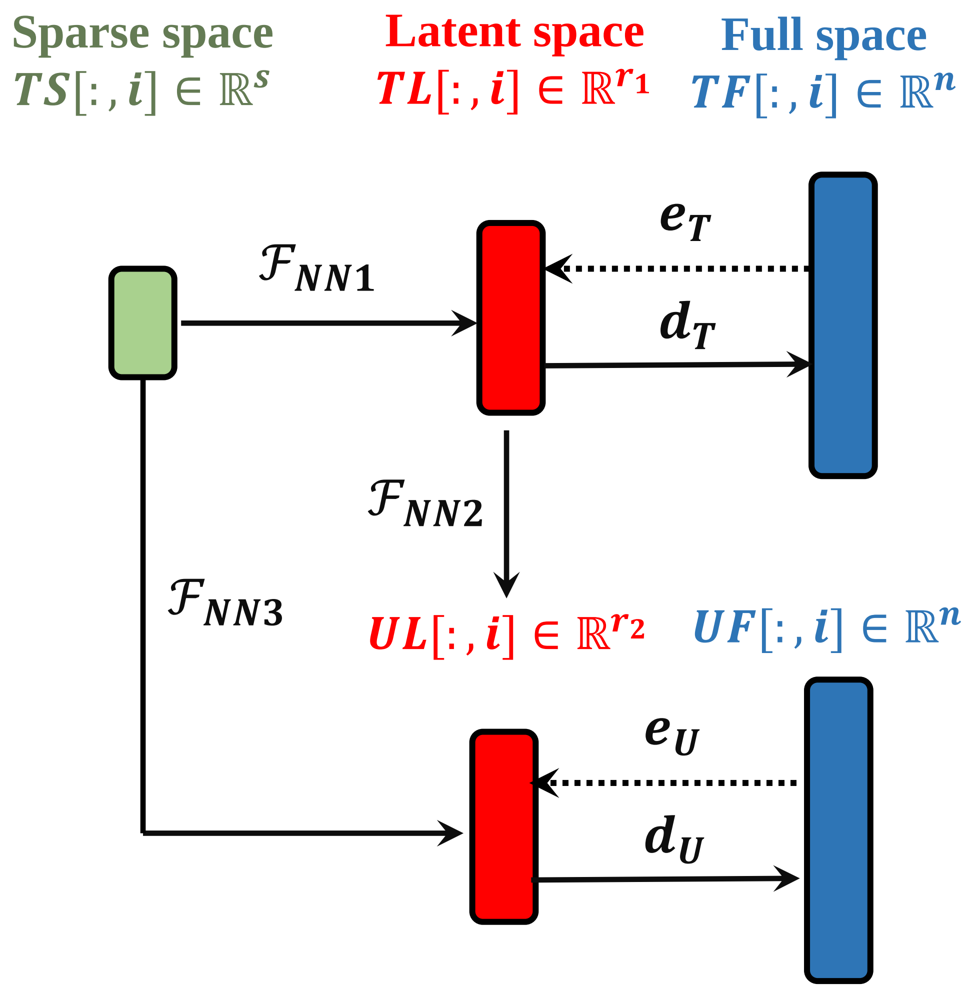
Contours of velocity (top) and temperature (bottom) obtained by CFD simulations

Proposed data-driven framework

- (FDD1) $\boldsymbol{UF = d_U \circ \mathcal{F}_{NN2} \circ \mathcal{F}_{NN1} \circ TS}$
  - $d_{U(T)}$ & $e_{U(T)}$
    - decoder and encoder to reduce dimensions
    - by Proper Orthogonal Decomposition (POD)
  - $\mathcal{F}_{NN}$
    - Fully-connected Neural Network (FCNN)
- $\boldsymbol{TF = T_U \circ \mathcal{F}_{NN1} \circ TS}$
- (FDD2) $\boldsymbol{UF = d_U \circ \mathcal{F}_{NN3} \circ TS}$



Schematic of FNN

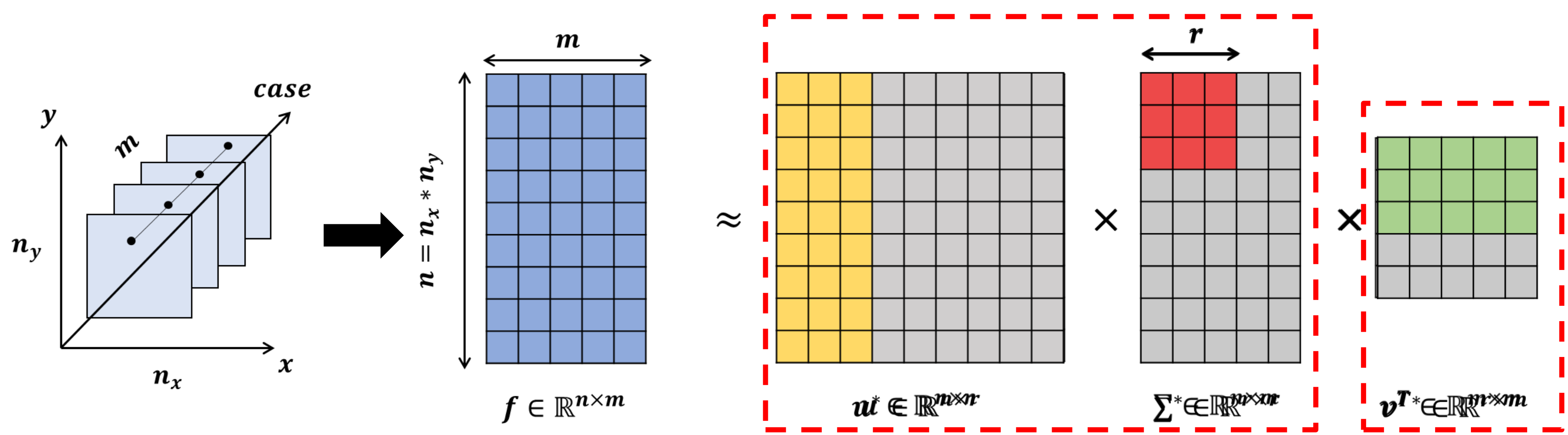


Data-driven framework

Dimension reduction by POD

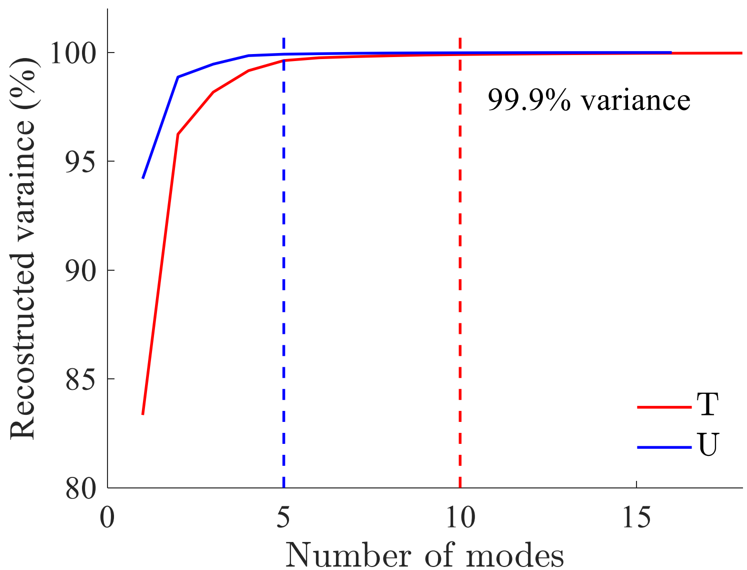
- The matrix for a variable in full field space is $f_{n\times m}$
  - n: *dimensions of a single snapshot*
  - m: number of cases
- By conducting SVD
  - $f_{n\times m} = u_{n\times n}\Sigma_{n\times m}v^T_{m\times m}$

- f can be approximated by the matrices with lower dimensions $(r \ll n)$
  - $f_{n\times m} \approx u^*_{n\times r}\Sigma^*_{r\times r}v^{T*}_{r\times m}$
  - $u^*_{n\times r}\Sigma^*_{r\times r}$ spatial components (modes)
  - $v^{T*}_{r\times m}$ are coefficients in latent space to be predicted by FNN with sparse temperature

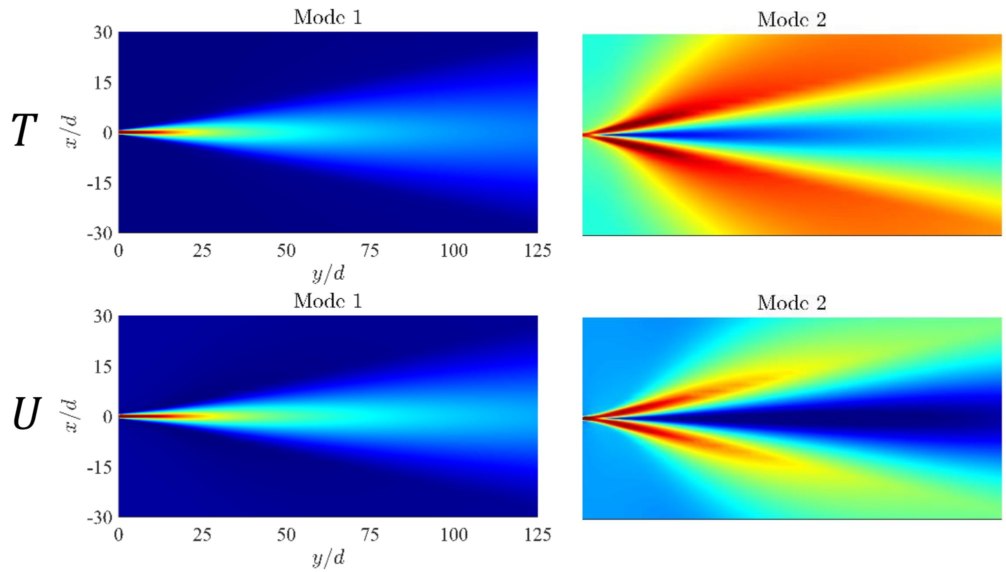


Dimension reduction by POD

- 99.9% variability of T and U fields can be described by 10 and 5 modes, respectively
- Modes from both fields behave similar
  - Mode 1: convection-dominant
  - Mode 2: diffusion-dominant.



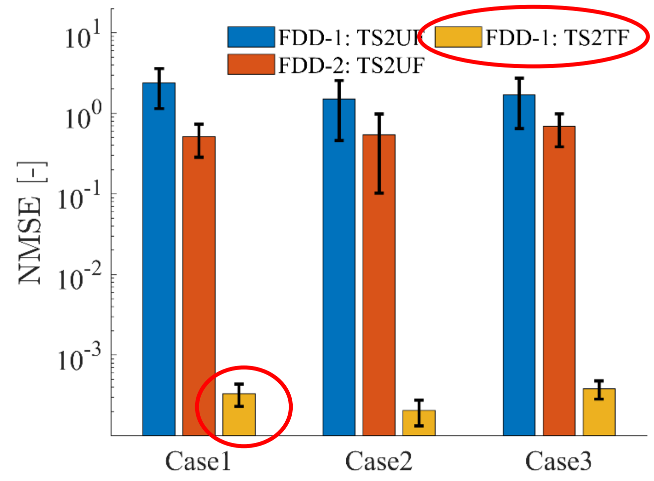
Reconstructed variance as a function of the number of modes



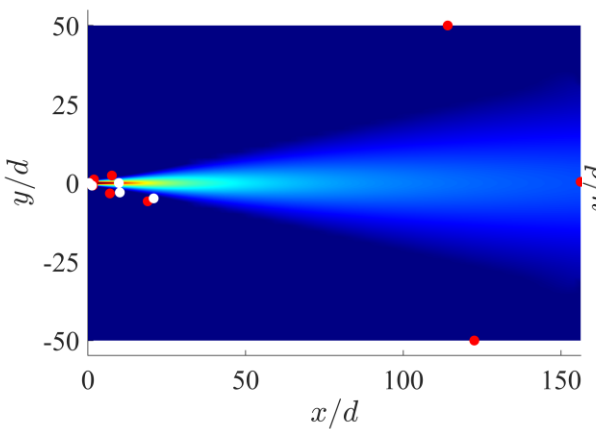
First and second POD modes of temperature (top) and streamwise velocity (bottom) the turbulent planar jet.

Effect of sensor placement and frameworks

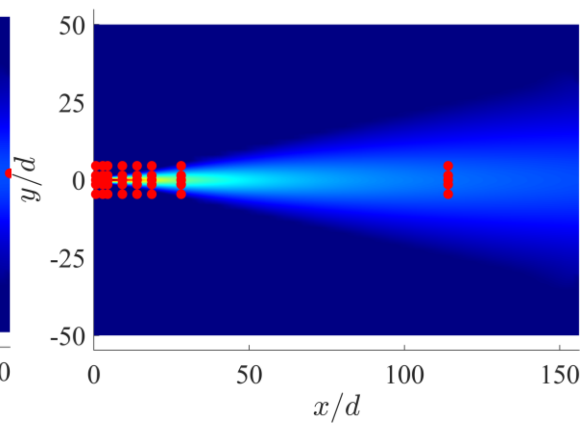
- Optimized sensor placements (7~8 sensors) yields similar performance as a TC grid with 40 sensors.
- Reconstruction of full T (TS2TF) is much better than U (TS2UF) and the two frameworks doesn't show significant difference.
- Major error arises from low velocity cases



NMSE compared within different frameworks and sensor arrangements

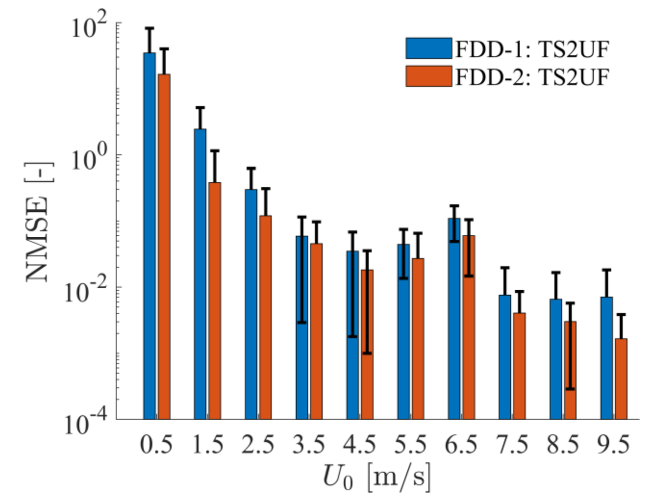


(a)



(b)

Temperature sensors determined by (a) optimal sensor placement on T field (***case1*** in red) and U field (***case2*** in white), and (b) similar arrangement as PPOOLEX experiments (***case3***). Visualized are the temperature profiles.

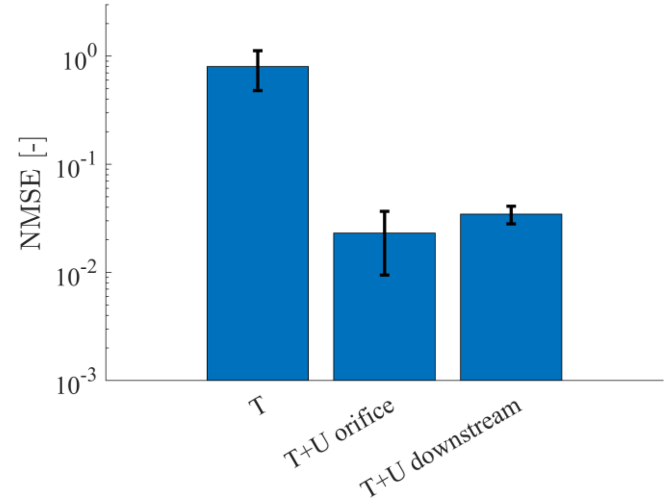


NMSE distribution over inlet velocity

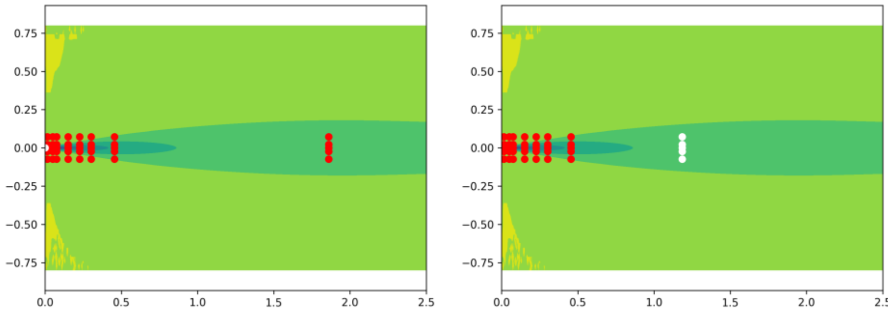
Introduction of velocity sensor

- Accuracy of velocity reconstruction (TS2UF) was significantly improved by
  - Introduce velocity sensors either at the inlet / downstream

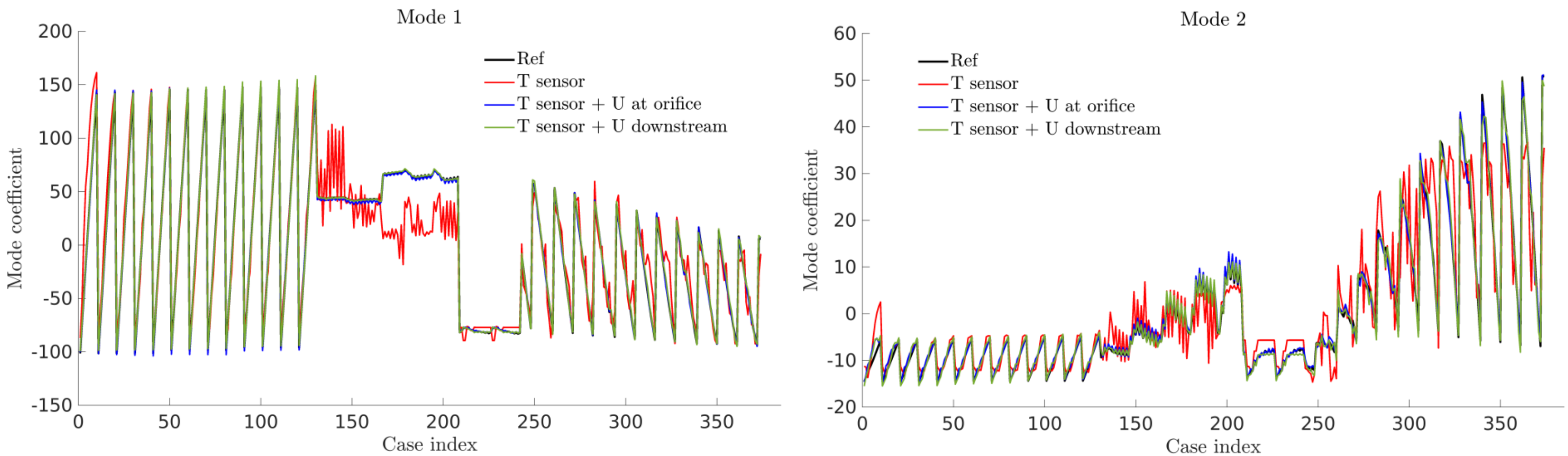
- Latent space coefficients are well represented



NMSE when introducing velocity sensor



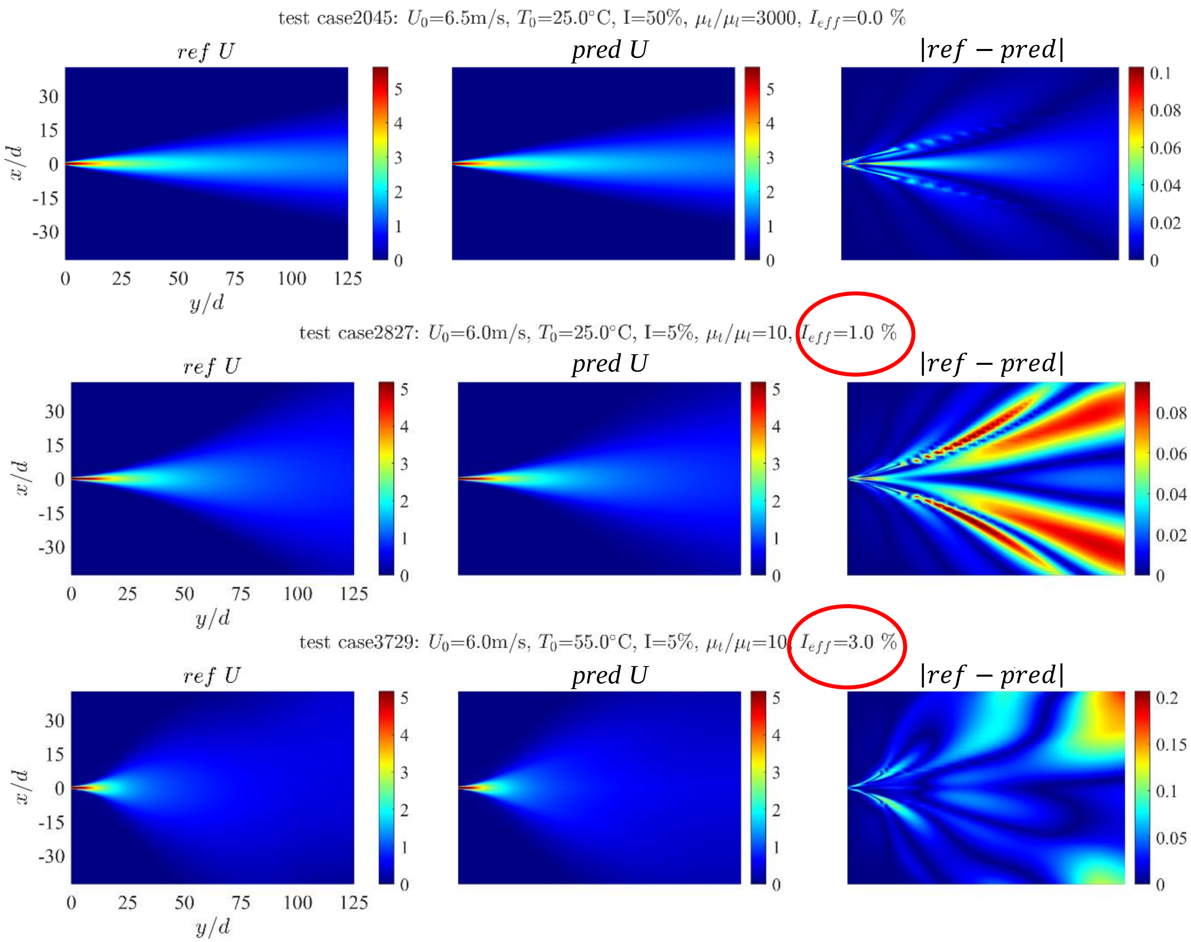
Sensor arrangement. T sensors in red and U sensors in white



Comparison of latent space coefficient for 1st (left) and 2nd (right) modes between reference and FNN predication

Sparse temperature to full velocity (TS2UF)

- Velocity profiles under diverse turbulence boundary conditions were well captured by sparse temperature (40 T sensors + 1 U sensor)



Examples of contours of streamwise velocity predicted in testing dataset.

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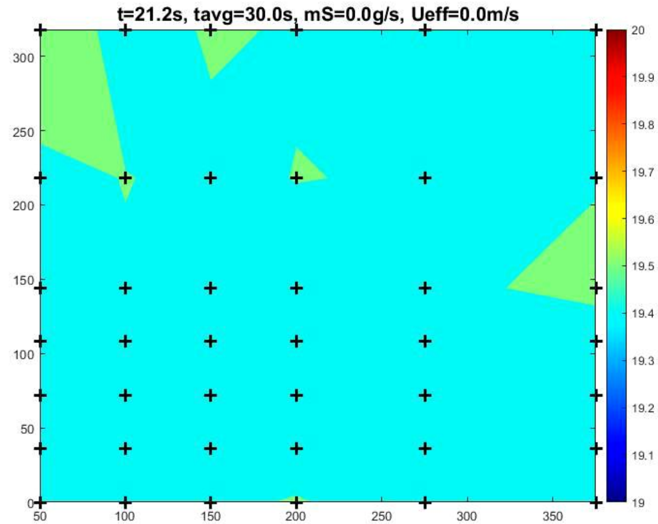
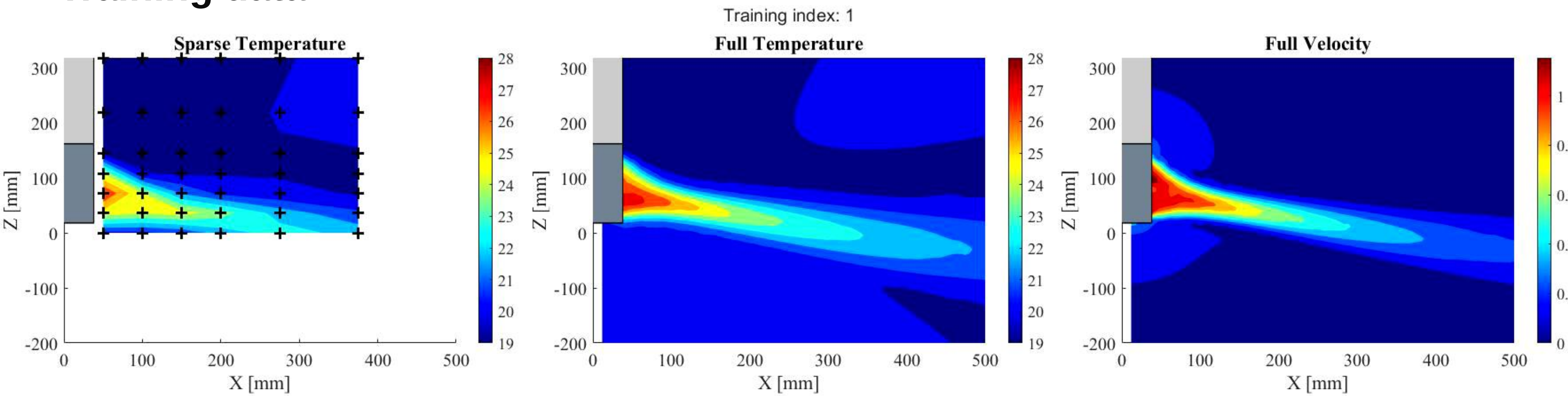
Steam injection through a multi-hole sparger

Test grid as input

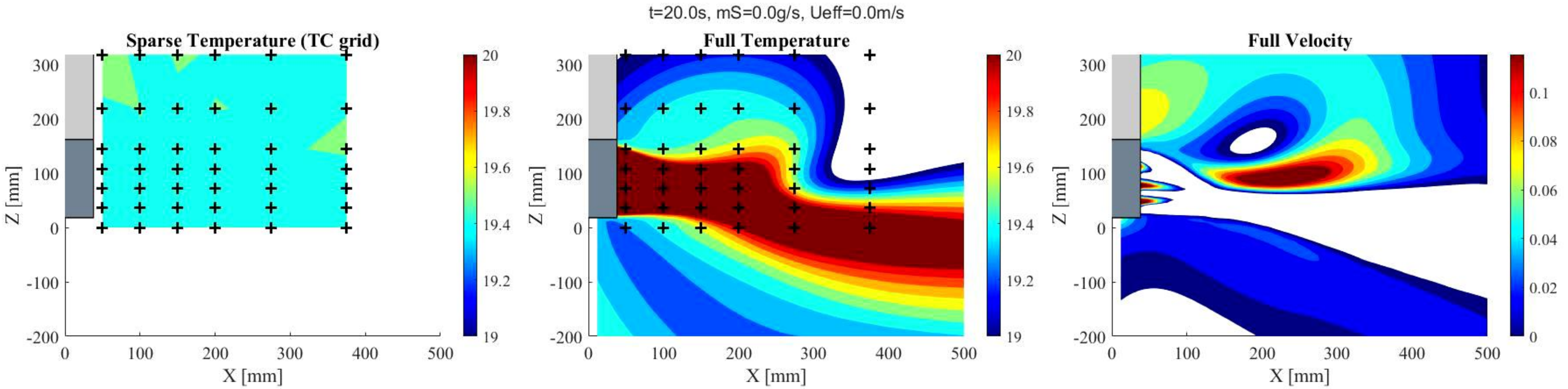


Training data



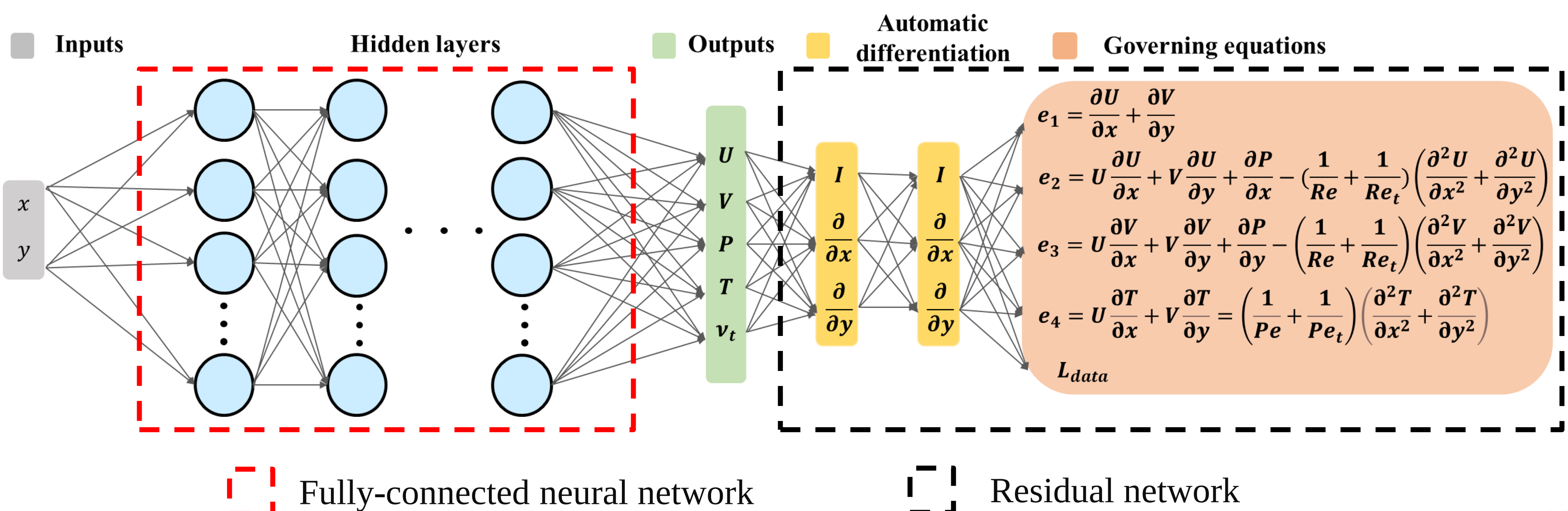
Steam injection through a multi-hole sparger

Testing on TC grid

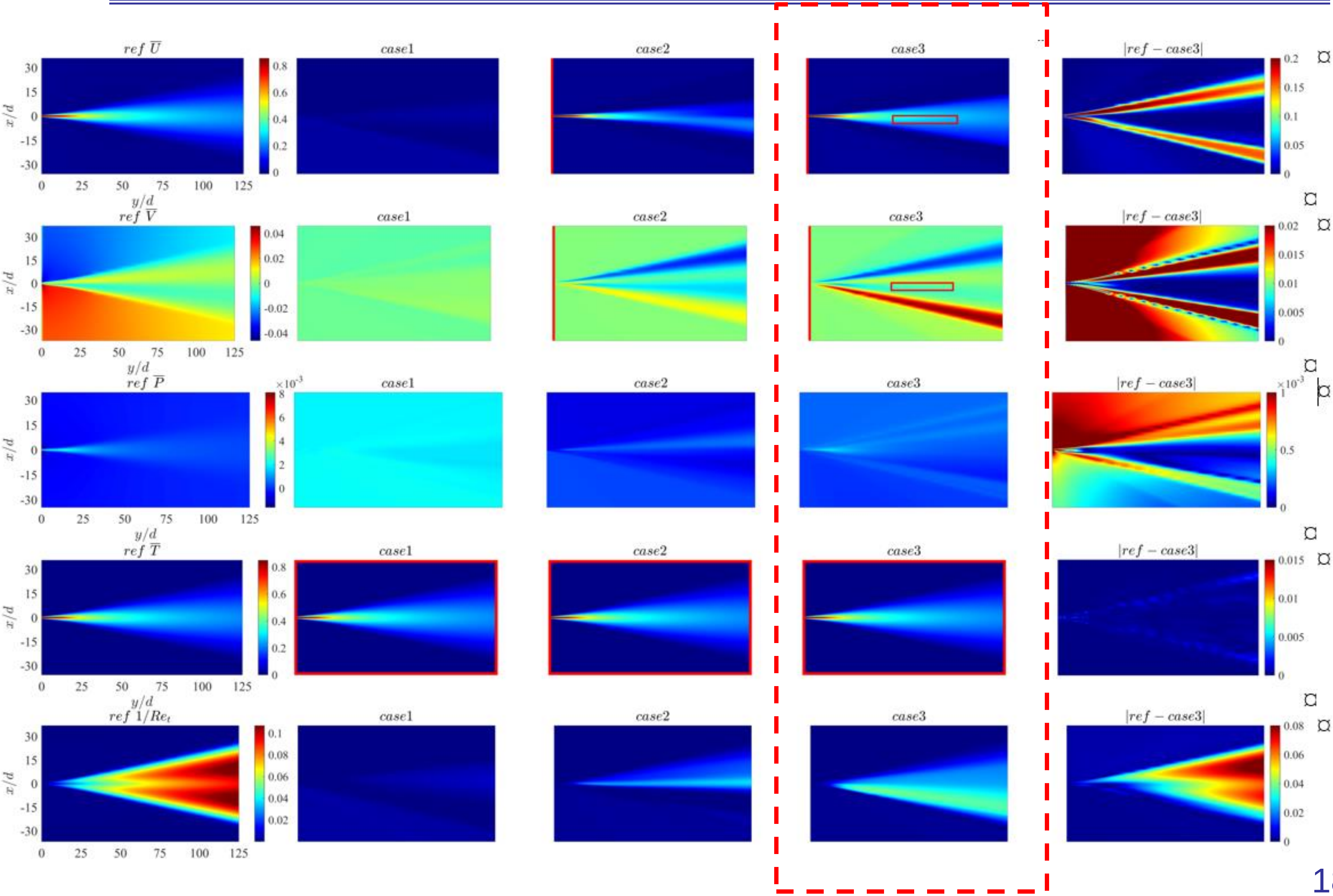


Physics-informed neural network (PINN)

- FPINN
  - Data-driven + PINN
  - $\boldsymbol{UF = \mathcal{F}_{PINN} \circ d_T \circ \mathcal{F}_{NN1} \circ TS}$
    - $\mathcal{F}_{PINN}$ encodes physics equations into the residual network.
      - Optimize a network (solution)
      - Satisfy both PDEs and available data (e.g. full temperature)



PINN prediction



Conclusion

- Feasibility and capability to reconstruct flow velocity from sparse temperature measurements were investigated.
  - Two types of frameworks are proposed and tested
    - Pure data-driven
    - Data-driven + PINN
  - Temperature measurements as the only inputs are insufficient and velocity information is necessary
  - Implementation of pure data-driven method in measured data yields promising results.

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THANK YOU