

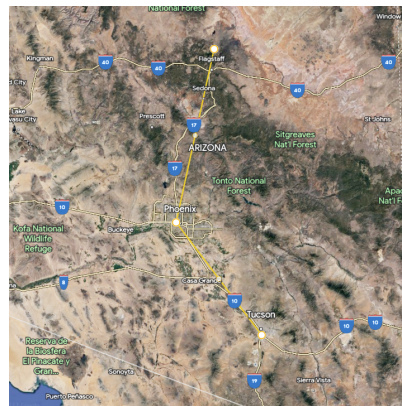
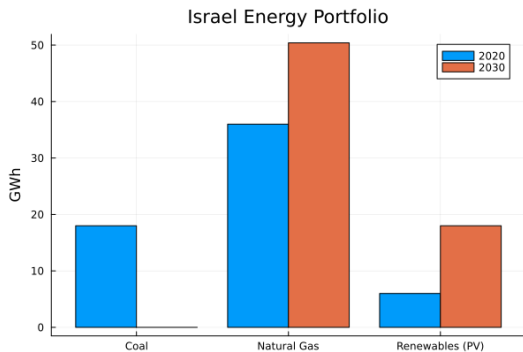
# Control of Line Pack in Natural Gas System of Israel: Balancing Limited Resources under Uncertainty

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# Context



# Project Goals

- Operations-aware modeling and simulation of a reduced model of Israel's natural gas network.
  - Flux control at inlet nodes
  - Realistic initial conditions
  - Assessing relevant challenges
    - Robustness in the case of uncertain PV generation
    - Robustness in the case of an insult to the system
- Model & open-source tool development
  - Solver suite specifically suited to the needs of natural gas networks
  - Advanced automatic controls
  - Monte-Carlo/Uncertainty Quantification

# Reduced Model of Israel's Gas Network



<sup>0</sup>[https://www.gov.il/he/departments/guides/distribution\\_area](https://www.gov.il/he/departments/guides/distribution_area)

# Effective Gas Flow Equations

Under reasonable assumptions, the system of PDEs governing gas flow is

$$\partial_t \rho + \partial_x \phi = 0 \quad (1)$$

$$\partial_t \phi + \partial_x P = -\beta \frac{\phi |\phi|}{\rho} \quad (2)$$

These, supplemented with initial

$$\rho(x, 0) = \rho_0(x) \quad (3)$$

$$\phi(x, 0) = \phi_0(x) \quad (4)$$

and boundary conditions at each node

$$\rho_i(t) \text{ or } \phi_i(t) \quad (5)$$

and an equation of state relating pressure and density

$$P(\rho) = \dots \quad \rho(P) = \dots \quad (6)$$

# Staggered Grid Method

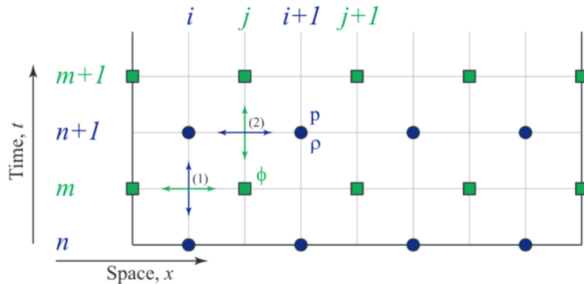


Figure taken from Gyrya, Zlotnik: "An explicit staggered-grid method for numerical simulation of large-scale natural gas pipeline networks"

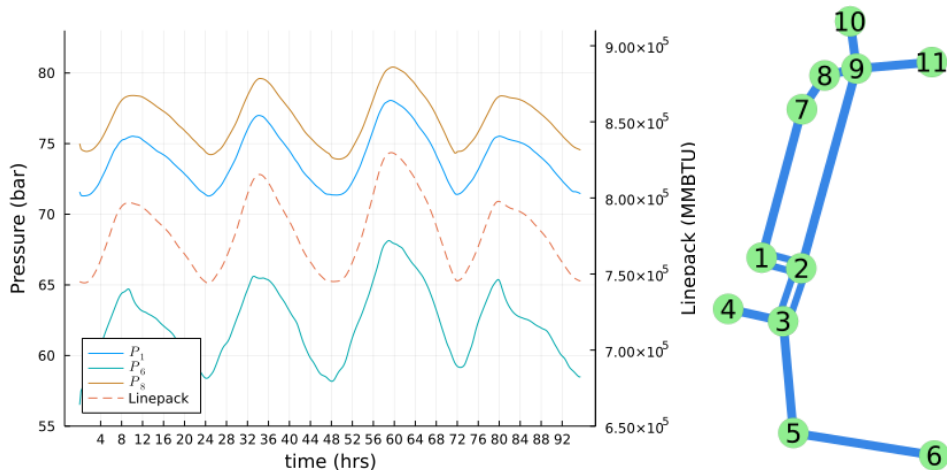
$$\partial_t \rho + \partial_x \phi = 0$$

$$\partial_t \phi + \partial_x P = -\beta \frac{\phi |\phi|}{\rho}$$

CFL stability condition:

$$\sqrt{P'(\rho)} \frac{\Delta t}{\Delta x} \leq 1$$

# Results: Scenario 1



Nominal week in August.

# Uncertainty

Moderate uncertainty at demand nodes is represented through addition of a random noise at the consumption site

$$d_i(t) \rightarrow X_i(t) \quad (7)$$

where

$$dX_i(t) = \alpha(d_i(t) - X_i(t))dt + \gamma dW \quad (8)$$

is a Ornstein–Uhlenbeck process

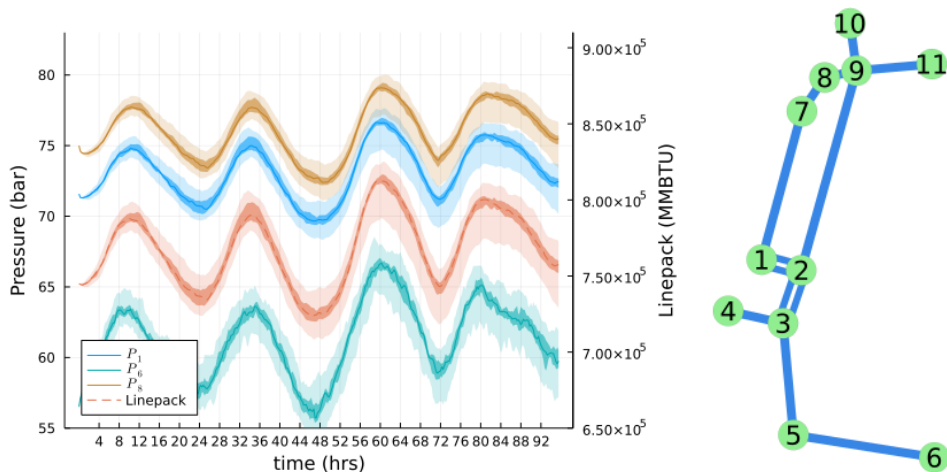
- $\mathbb{E}[X_i(t)] = d_i(t)$
- $\text{Var}(X_i(t)) = \frac{\gamma}{2\alpha} (1 - e^{-2\alpha t})$
- The parameters were tuned heuristically to ensure the mean was respected, and the variance approaches

$$\text{Var}(X_i(t)) \approx 0.01\mu_i^2 \quad (9)$$

With  $\mu_i$  being the mean withdrawal of node  $i$ .

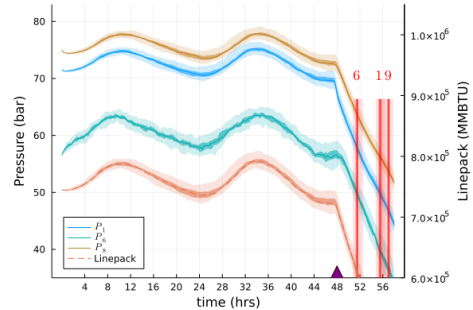
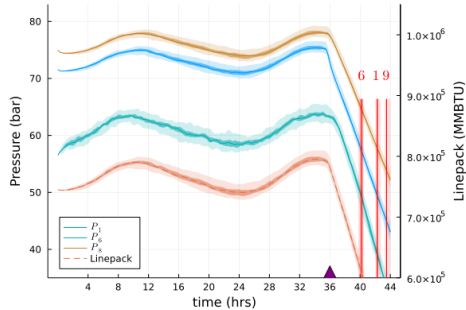


# Results: Scenario 2



Linepack and pressures for random perturbation on top of nominal August days.

# Results: Scenario 3 & 4

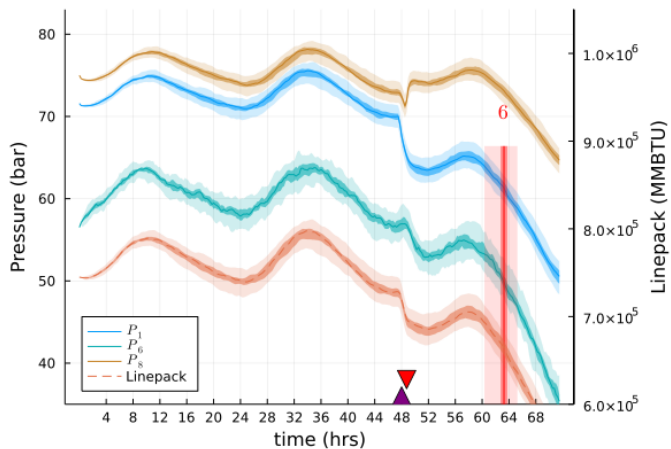


Linepack and pressures responding to loss of supply at node 1. (Left) shows the insult at a peak of intraday linepack, and (right) shows the same insult at the trough.

$$\tau = 4.13 \pm 0.38 \text{ hrs}$$

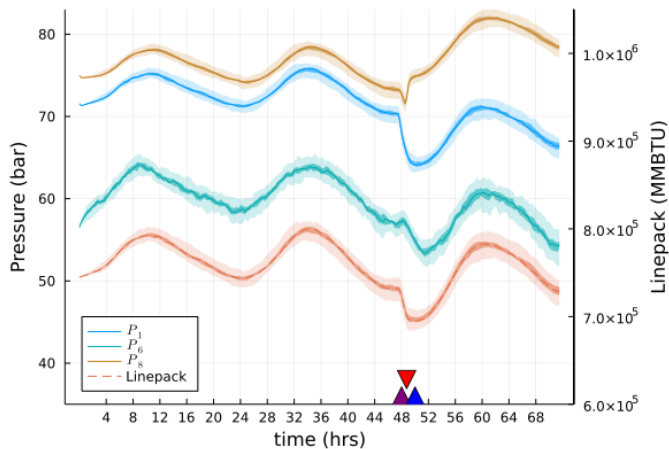
$$\tau = 3.58 \pm 0.89 \text{ hrs}$$

# Results: Scenario 5



Linepack and pressures for insult at hour 48, implementing a max-flow control on the remaining supply at node 8.  $\tau = 14.17 \pm 4.07$  hrs

# Results: Scenario 6



Linepack and pressures for insult at hour 48, implementing a max-flow control on the remaining supply at node 8, and curtailing demand 2 hours after the insult.

# Next Steps

- Better UQ: Stochastic Finite Volumes(?)
- Higher order method and efficient implementation to allow for parallelization and acceleration.
- Advanced automatic controls
  - This would mimick some actual protocol, and allow you to make statements such as, "with 95% confidence, using protocol A, the natural gas system is robust to an insult of type B"
- Simulation and optimization of the joint power and gas grids, under uncertainty.

# Questions/Comments/Suggestions?

- `cmhyett@math.arizona.edu`
- `https://arxiv.org/abs/2304.01955`
- `https://github.com/cmhyett/FluxControlLinepack`

# Velocity gradient prediction using parameterized Lagrangian deformation models

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# Motivation

- The **velocity gradient tensor** (VGT) describes many important aspects of turbulence. It displays characteristic **non-Gaussian statistics** including **intermittency**, describes the **deformation of a fluid volume**, and encapsulates **alignment between strain and vorticity**.
- Similar to velocity in the Eulerian frame, the VGT is the natural object of study in the **Lagrangian frame**.
- We combine **phenomenological models** of the VGT with **physics-informed machine learning** to create efficient (and interpretable?) **reduced-order models of the VGT**.



# Governing Equations for the Velocity Gradient Tensor

- The **velocity gradient tensor** (VGT) is defined by  $A_{ij} = \frac{\partial u_i}{\partial x_j}$ , so from Navier Stokes

$$\frac{\partial u_i}{\partial t} + u_k \frac{\partial u_i}{\partial x_k} = -\frac{\partial P}{\partial x_i} + \nu \frac{\partial^2 u_i}{\partial x_k \partial x_k} \quad (10)$$

- We apply spatial derivatives, and use incompressibility to find the governing equations for the VGT:

$$\frac{dA_{ij}}{dt} = - \left( A_{ik} A_{kj} + \frac{1}{3} A_{mn} A_{nm} \delta_{ij} \right) - \left( \frac{\partial^2 P}{\partial x_i \partial x_j} - \frac{1}{3} \frac{\partial^2 P}{\partial x_k \partial x_k} \delta_{ij} \right) + \nu \frac{\partial^2 A_{ij}}{\partial x_k \partial x_k} \quad (11)$$

- The main challenge is to predict the nonlocal **deviatoric** part of the pressure hessian, defined as

$$H_{ij} = - \left( \frac{\partial^2 P}{\partial x_i \partial x_j} - \frac{1}{3} \frac{\partial^2 P}{\partial x_k \partial x_k} \delta_{ij} \right) \quad (12)$$

# Previous Work

- (a) Restricted Euler
- (b) Deviatoric Pressure Hessian
- (c) Viscous Term
- (d) Combined

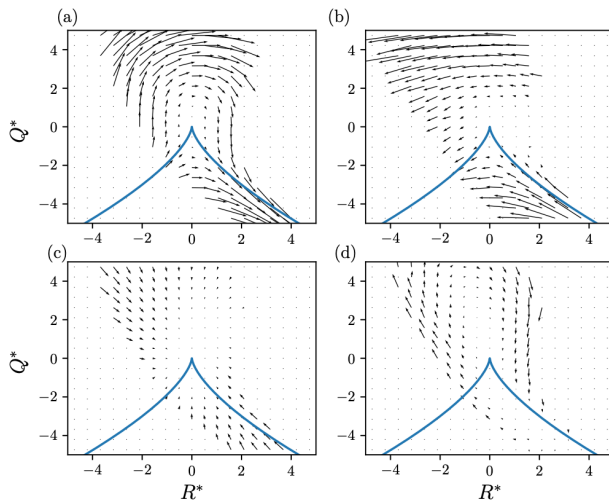


Figure taken from Tian et.al 2021

# Tensor Basis Neural Network

- We can write the formal solution for the deviatoric pressure hessian as<sup>1</sup>

$$H_{ij}(\mathbf{x}) = \iiint \frac{\delta_{ij} - \hat{r}_i \hat{r}_j}{2\pi r^3} Q(\mathbf{x} + \mathbf{r}) d\mathbf{r} \quad (13)$$

- Using a Taylor expansion, Cayley-Hamilton Theorem, and Tensor Basis expansion<sup>2</sup>, we can write

$$\hat{H} = \sum_{i=1}^{10} g^{(i)}(\lambda_1, \dots, \lambda_5) \cdot \hat{T}^{(i)}(\hat{A}) \quad (14)$$

$$\lambda_1 = \text{tr}(\hat{S}^2) \quad \lambda_2 = \text{tr}(\hat{W}^2) \quad \lambda_3 = \text{tr}(\hat{S}^3) \quad \lambda_4 = \text{tr}(\hat{W}^2 \hat{S}) \quad \lambda_5 = \text{tr}(\hat{W}^2 \hat{S}^2)$$

- We use the natural timescale  $\tau = \langle \|S^2\|_2 \rangle^{-1}$  to normalize our VGT, and thus all of the  $\lambda_i, T^{(j)}$ .

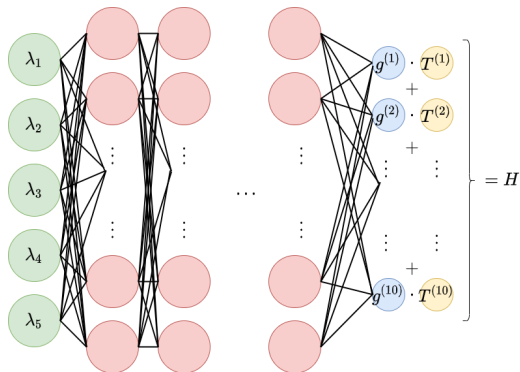
<sup>1</sup>Ohkitani, K. & Kishiba, S. *Physics of Fluids* 1995.

<sup>2</sup>Pope, S. B. *Journal of Fluid Mechanics* 1975.

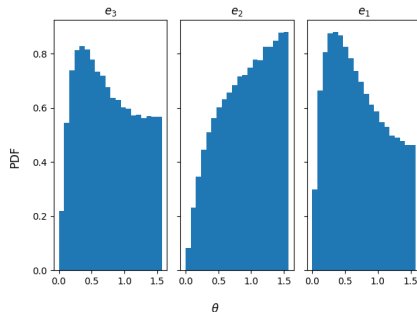
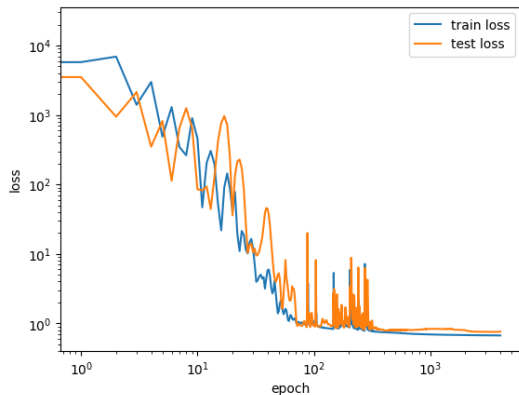
# Tensor Basis Neural Network

$$\hat{H} = \sum_{i=1}^{10} g_{\theta}^{(i)}(\lambda_1, \dots, \lambda_5) \cdot \hat{T}^{(i)}(\hat{A}) \quad (15)$$

$$\lambda_1 = \text{tr}(\hat{S}^2) \quad \lambda_2 = \text{tr}(\hat{W}^2) \quad \lambda_3 = \text{tr}(\hat{S}^3) \quad \lambda_4 = \text{tr}(\hat{W}^2 \hat{S}) \quad \lambda_5 = \text{tr}(\hat{W}^2 \hat{S}^2)$$

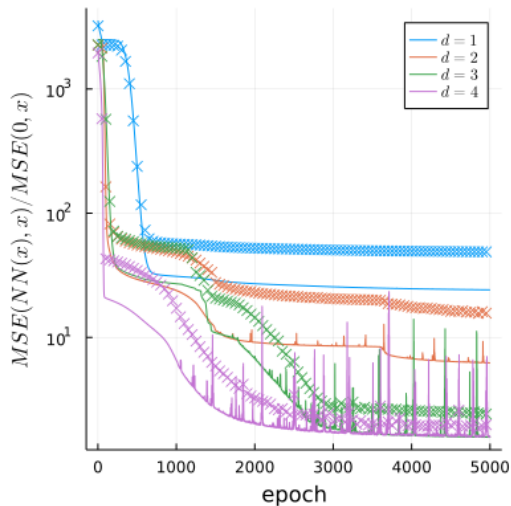
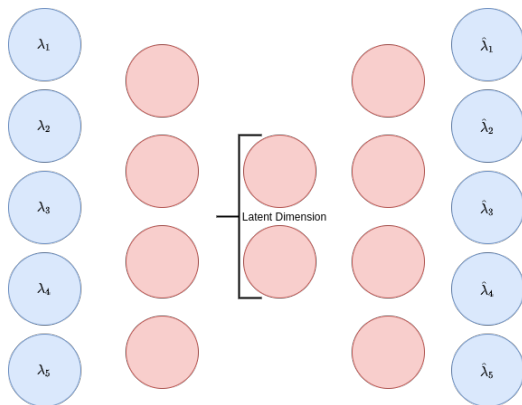


# Reproducing Results

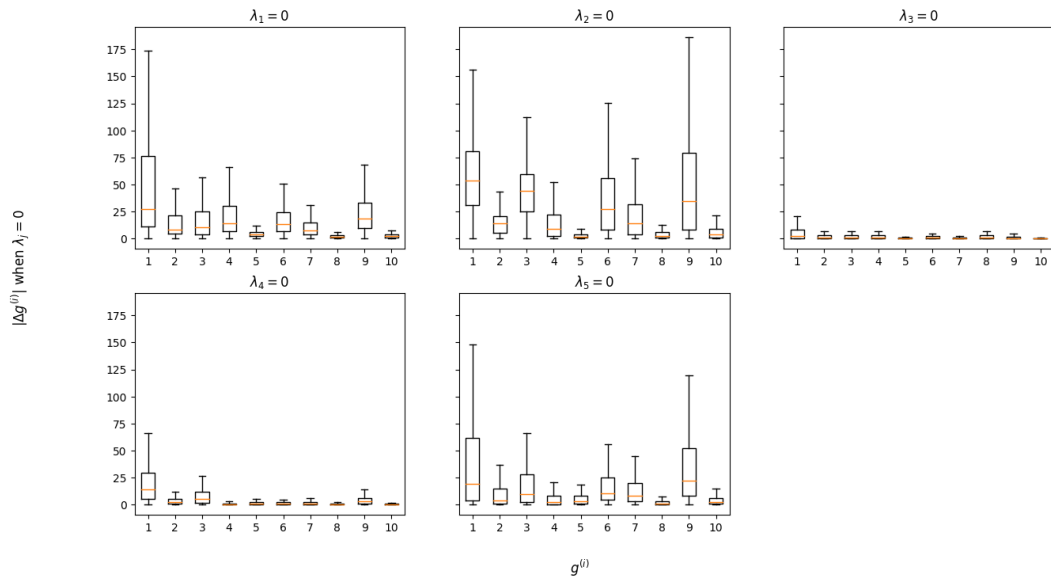


Implementing the architecture described, I show ability to train and reproduce loss plots (left) and eigenvector alignment PDFs (right)

# Poking at Interpretability?



# Poking at Interpretability?







# Future Work

- Work currently being done to enrich TBNN using history of the VGT
  - Temporal convolutions? LSTM?
- This work was originally inspired by the Tetrad model, and the coarse-grained velocity gradient tensor
  - Particle-based coarse-graining and the opportunities/nuances/challenges is another challenge entirely
- Can we learn physics?
  - Interpretability
  - Data-driven hypothesis testing



# References I

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-  Tian, Y., Livescu, D. & Chertkov, M. Physics-informed machine learning of the Lagrangian dynamics of velocity gradient tensor. *Physical Review Fluids* **6**, 094607 (2021).
-  Chertkov, M., Pumir, A. & Shraiman, B. I. Lagrangian tetrad dynamics and the phenomenology of turbulence. *Physics of Fluids* **11**, 2394–2410 (1999).