Defense Nuclear Nonproliferation Research & Development

Domain-Informed Assessment of Nuclear Reactor Operations

Presented at the Virtual Workshop on Next-Gen AI for Proliferation Detection: Domain Aware Methods

Tom Reichardt, Sam Eaton, Tom Kulp, and Stephanie DeJong

Sandia National Laboratories

Will Ray, Tom Karnowski, and Randall Wetherington, Michael Willis, Omar Marcillo, Monica Maceira, and Chengping Chai

Oak Ridge National Laboratory

Edna Cárdenas, Scott Watson, and David Chichester

Idaho National Laboratory

Christine Gammans

Los Alamos National Laboratory

John Krebs

Argonne National Laboratory

Brian d’Entremont

Savannah River National Laboratory

Work performed as part of the MINOS Venture, funded by the NA-22 Proliferation Detection Office’s Data Science Portfolio (PM: Angie Sheffield, TA: Tammie Borders)

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC., a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy’s National Nuclear Security Administration under contract DE-NA0003525.

SAND2021-????

Introduction

- The execution of a specific technical activity of interest can be distinguished from other activities because it often follows *a recipe that is constrained by the laws of physics or chemistry*.

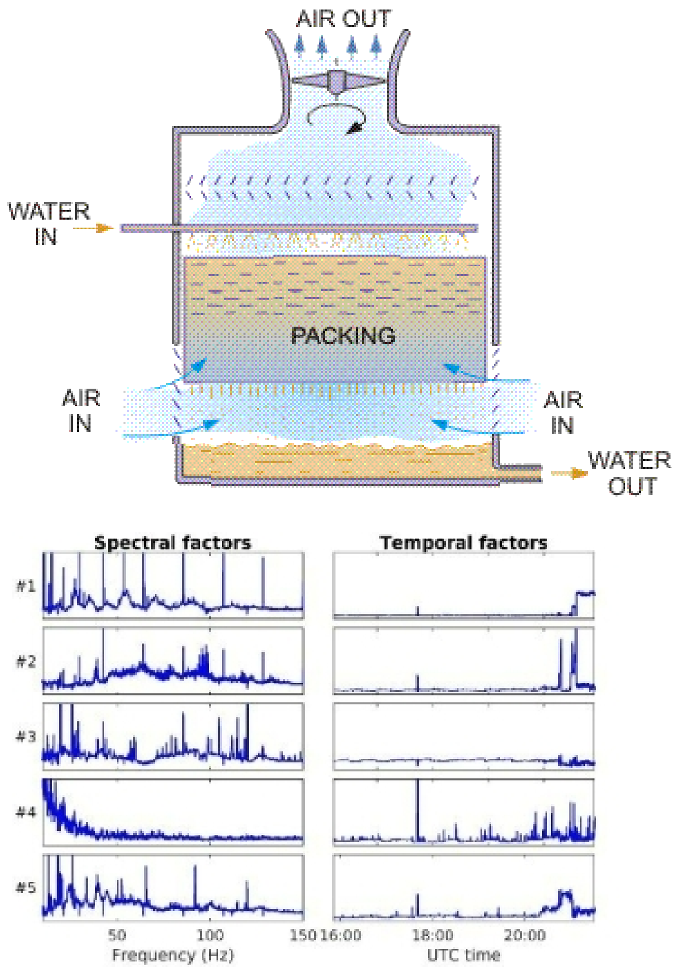
- This recipe then often defines *the nature, magnitude, and timing* of certain parameters that can be deduced from measurement of that activity.

The Challenge Problem: Assessing Reactor Power under Variable Weather Conditions

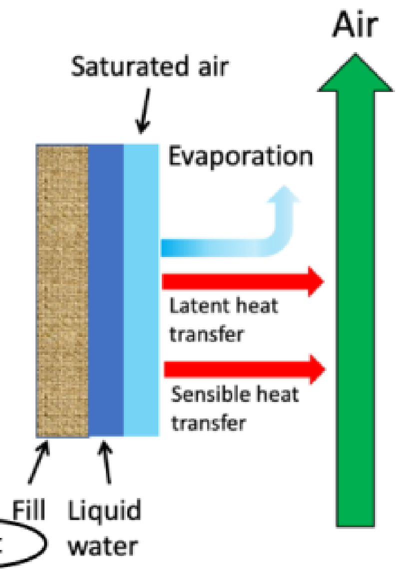
- **The High Flux Isotope Reactor (HFIR) releases heat to the environment via a secondary cooling tower.**
- **Under the MINOS Venture, sensors are continuously monitoring signals (electromagnetic, seismic, infrasound/acoustic, vibrometry) in the vicinity of this tower.**
- **We seek to account for how weather variability impacts the way these signals relate to reactor power.**

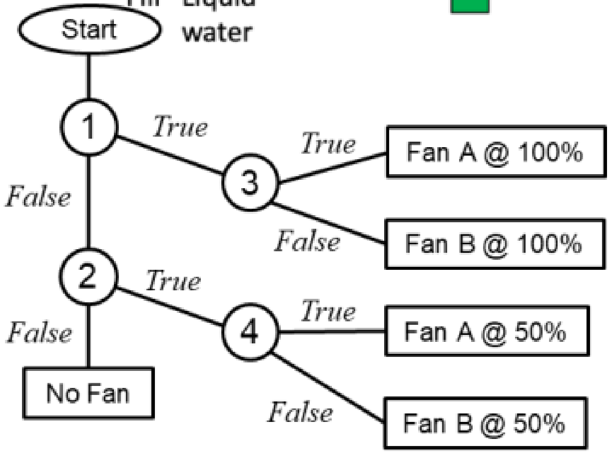
Discussion Topics

Anticipated and Extracted Infrasound/Acoustic Features

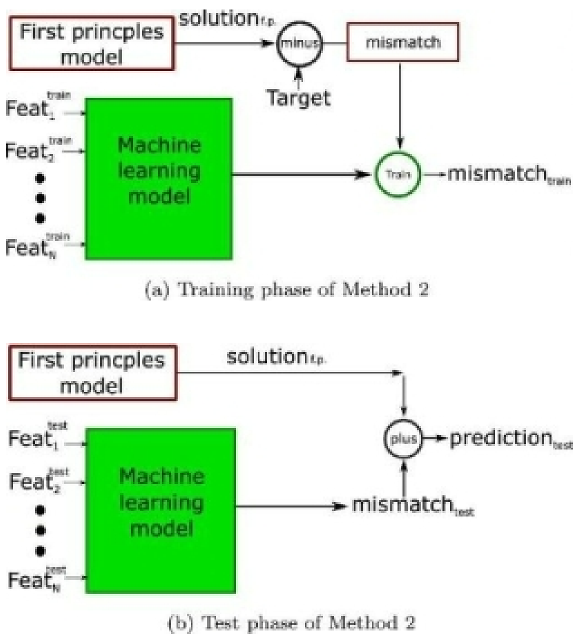


Developing Physics-Based & Interpretable Models

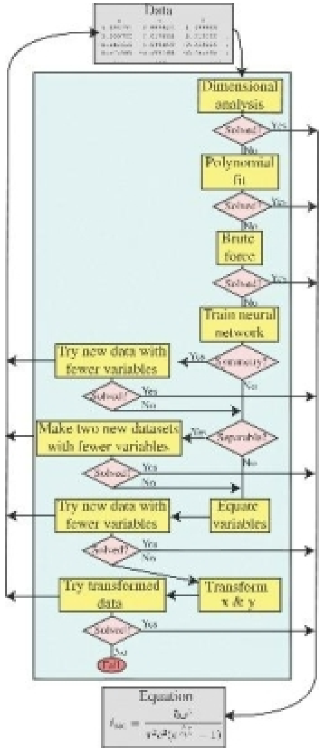




Future Directions Leveraging Recent Advancements

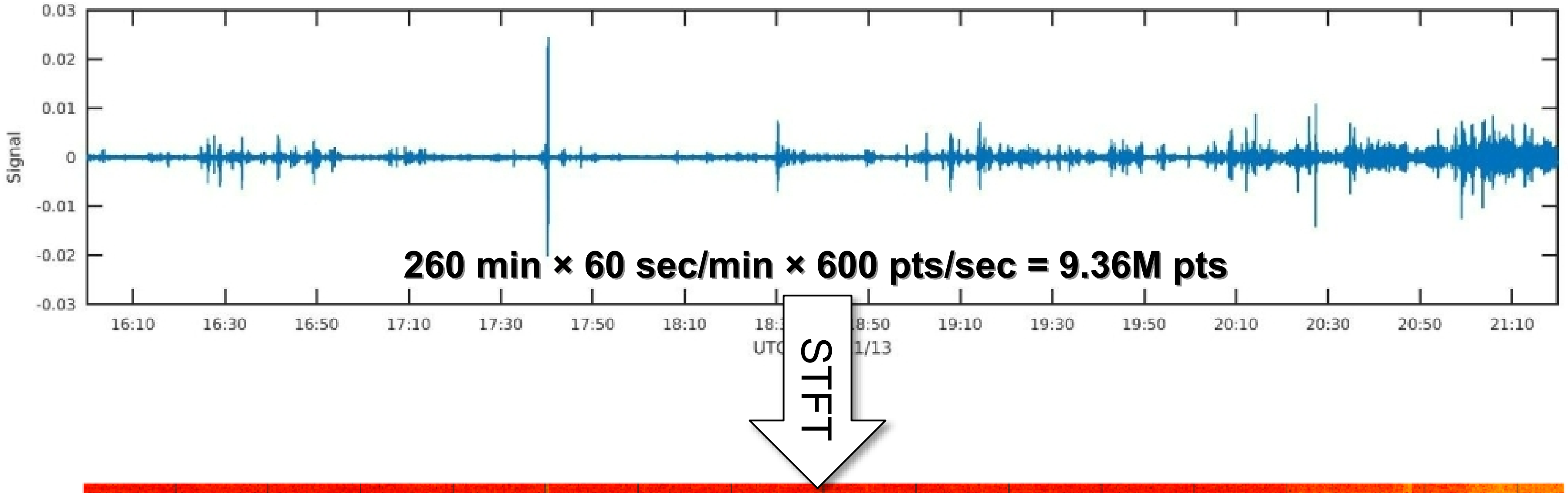


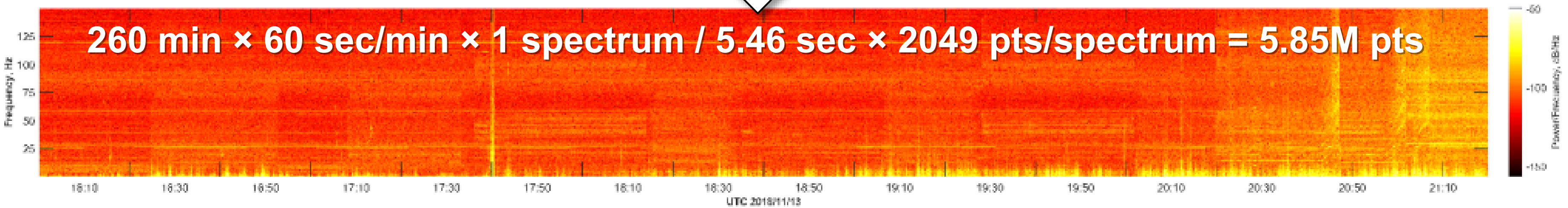
From T. Bikmukkametov and J. Jäschke, "Combining machine learning and process engineering towards enhanced accuracy and explainability of data-driven models," Comp. Chem. Eng. **138**, 106834 (2020).



From S.-M. Udrescu and M. Tegmark, "AI Feynman: A physics-inspired method for symbolic regression," Sci. Adv. **6**, eaay2631 (2020).

Initial Assessment on Targeted Collect



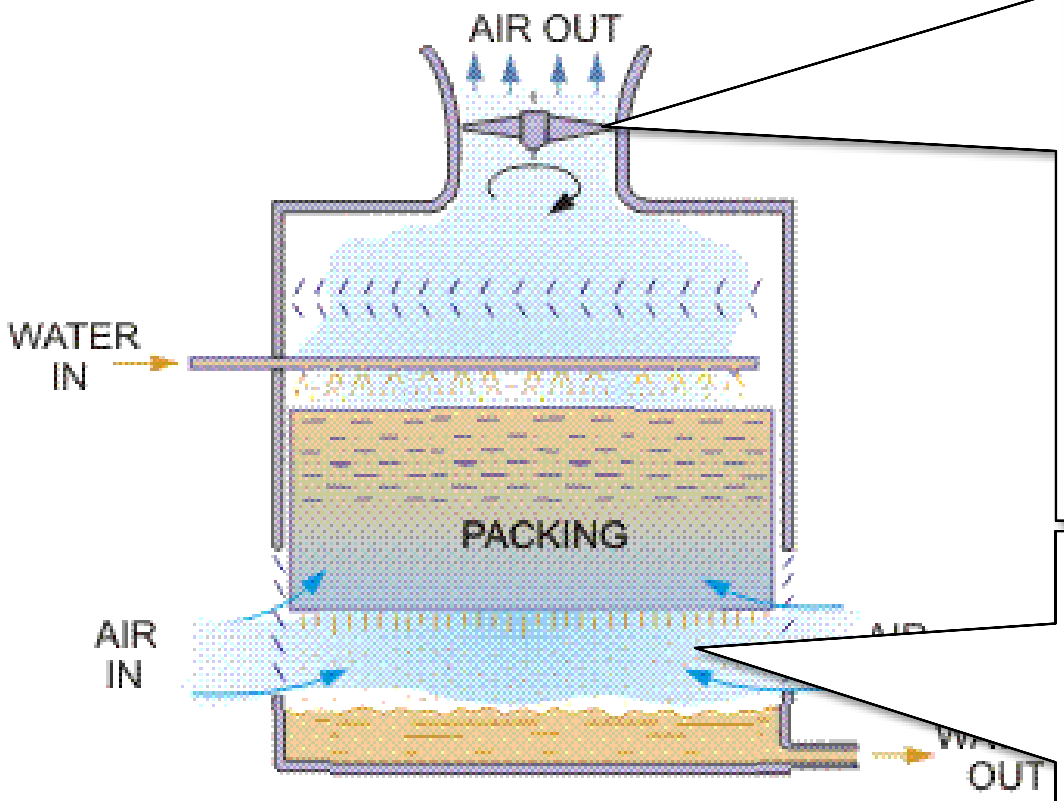


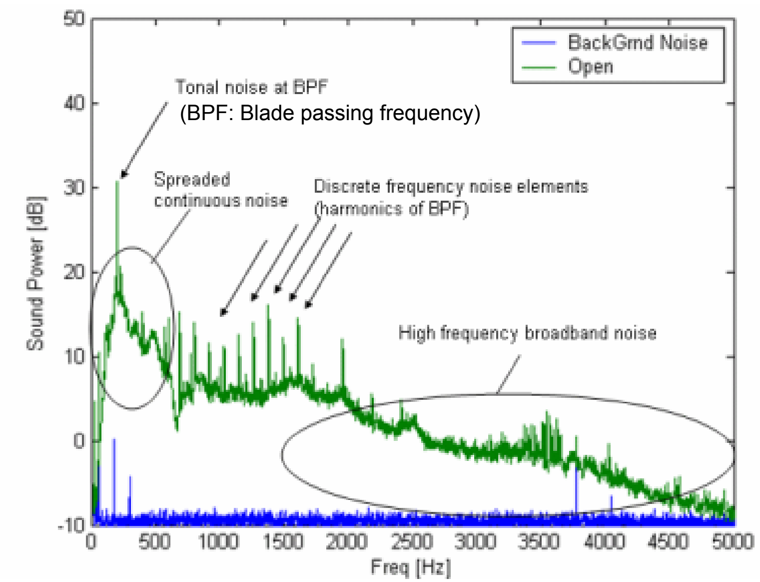
In the next viewgraphs, this will be reduced to a low-dimensional representation of 5 rank-one (spectral × temporal) matrices:

(260 min × 60 sec/min × 1 spectrum / 5.46 sec + 2049 pts/spectrum) × 5 = 24.5K elements

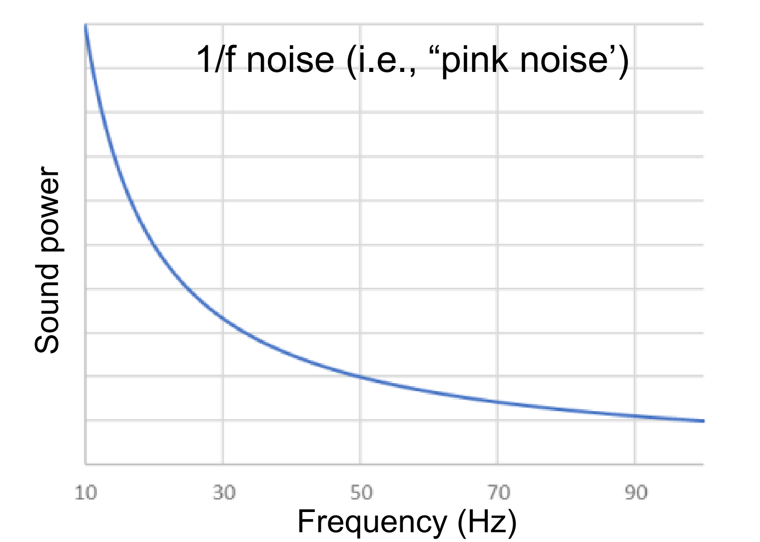
Moreover, 4/5 of those rank-one matrices will be physically interpretable.

Anticipated Infrasound/Acoustic Signals from Secondary CoolingTower

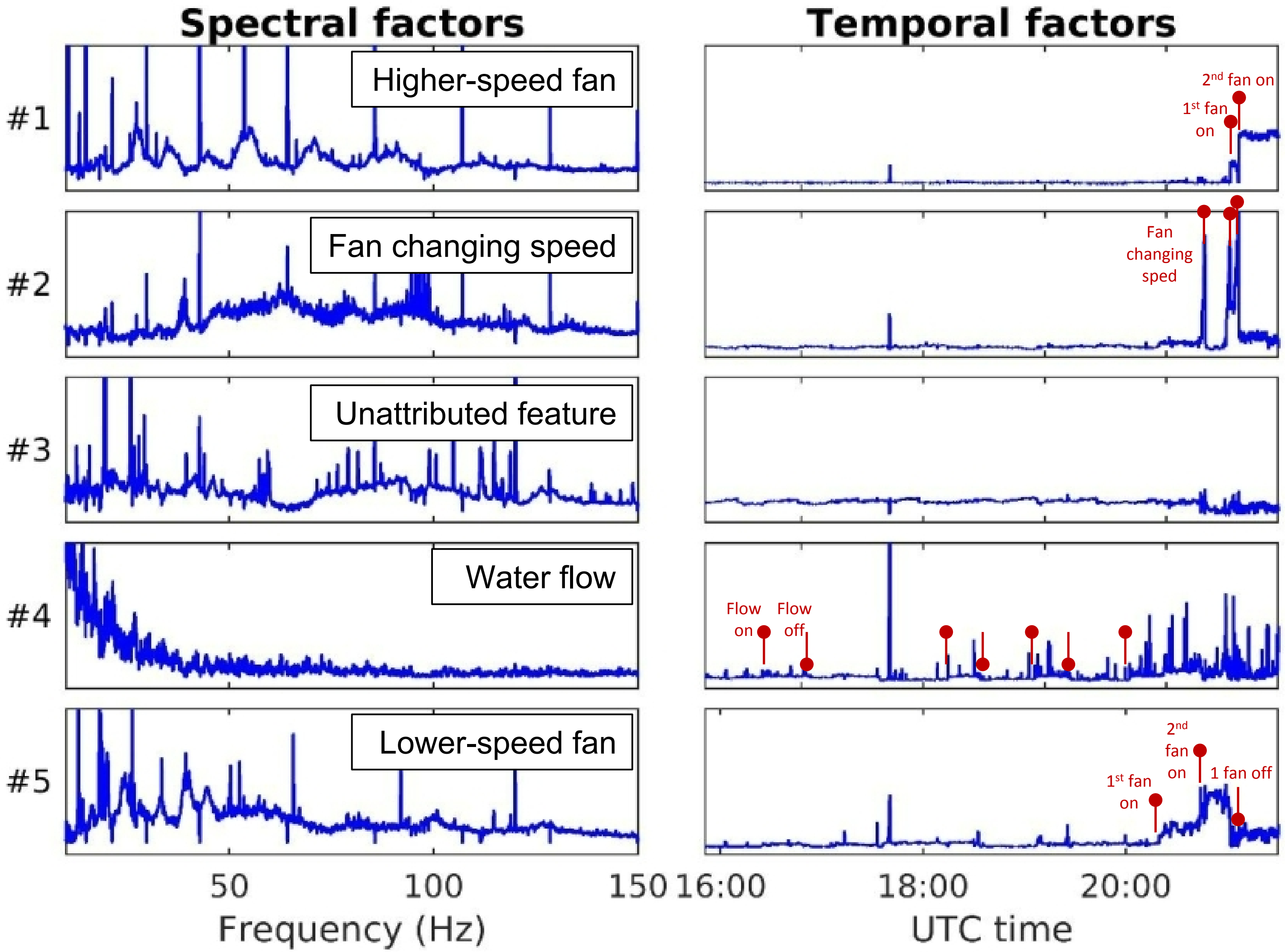




https://en.wikibooks.org/wiki/Engineering_Acoustics/Noise_from_cooling_fans



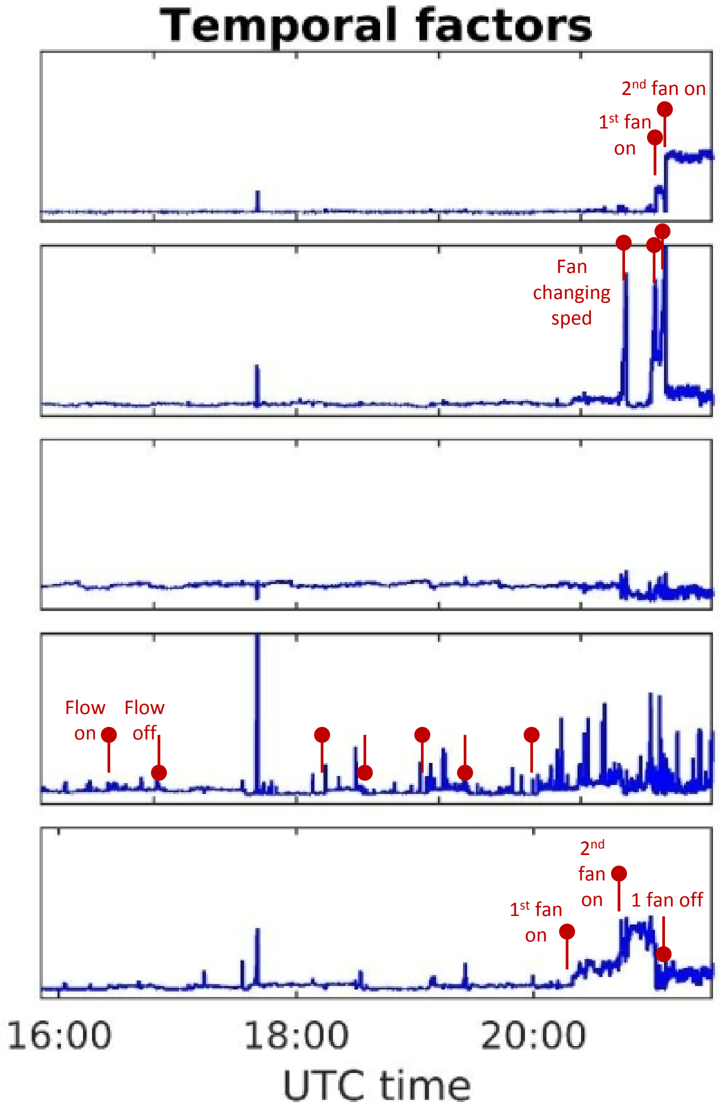
NMF of Infrasound Spectrograms



NMF Interpretation

NMF Interpretation

16:25 – Begin water flow
16:55 – End water flow
18:15 – Begin water flow
18:34 – End water flow
19:08 – Begin water flow
19:26 – End water flow
20:02 – Begin water flow
20:20 – Initial slower fan on
20:47 – Fan changing speed, 2nd slower fan on
21:02 – Fan changing speed, initial faster fan on, one slower fan off
21:07 – Fan changing speed, second faster fan on



NMF Interpretation vs. Ground Truth

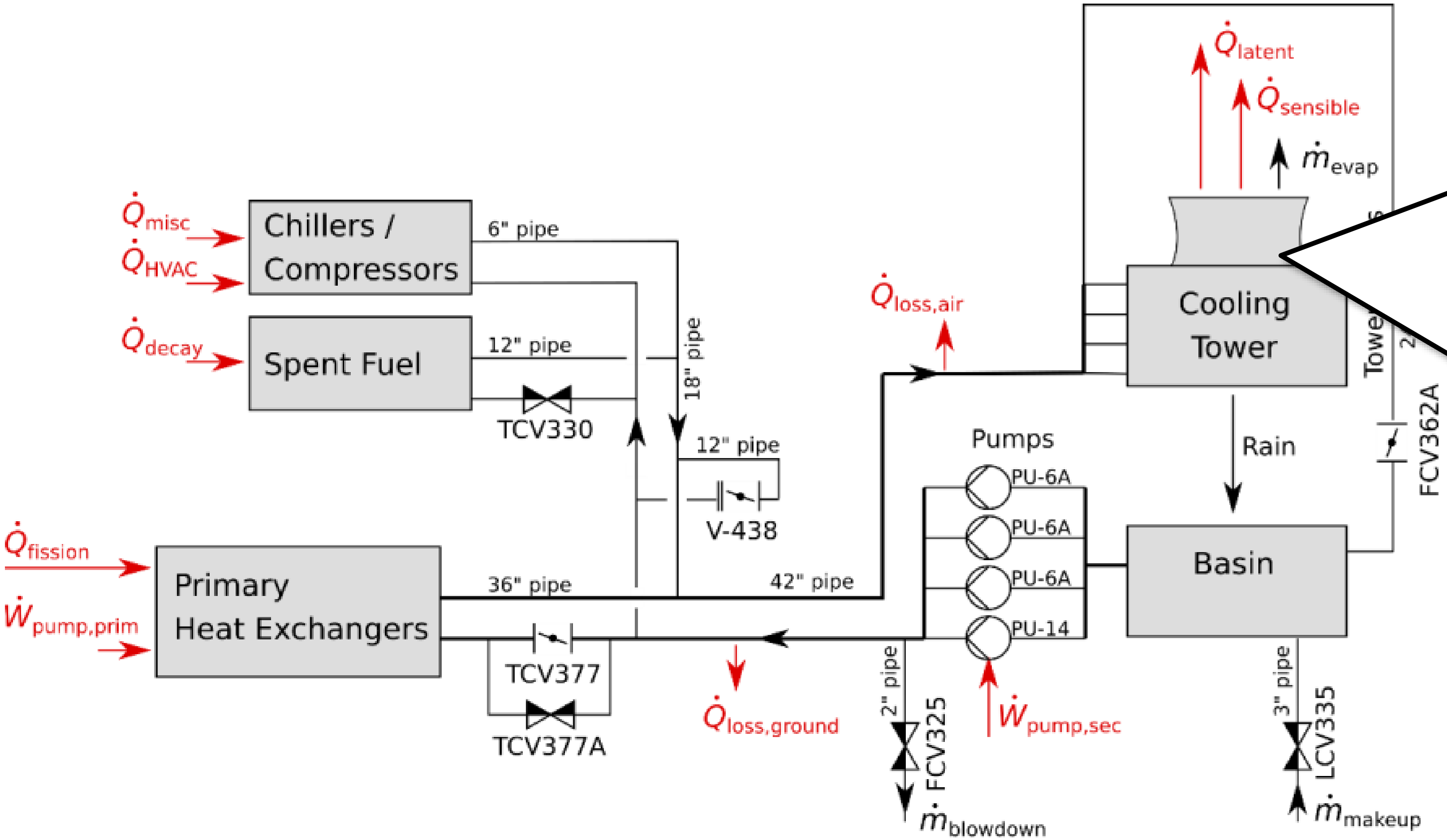
NMF Interpretation

16:25 – Begin water flow
16:55 – End water flow
18:15 – Begin water flow
18:34 – End water flow
19:08 – Begin water flow
19:26 – End water flow
20:02 – Begin water flow
20:20 – Initial slower fan on
20:47 – Fan changing speed, 2nd slower fan on
21:02 – Fan changing speed, initial faster fan on, one slower fan off
21:07 – Fan changing speed, second faster fan on

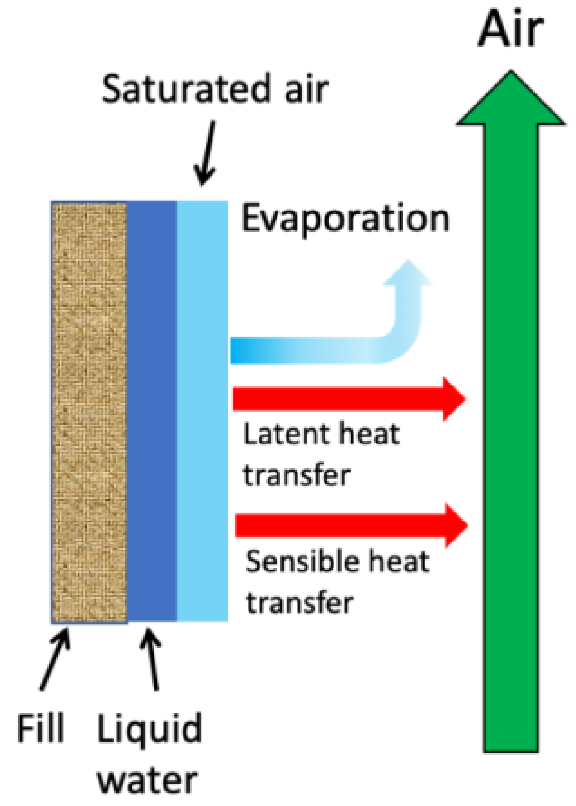
Ground Truth

16:26 – Plume present
16:54 – Plume absent
18:18 – Plume present
18:35 – Plume absent
19:09 – Plume present
19:28 – Plume absent
20:05 – Plume present
20:21 – Fan C on at half-speed
20:46 – Fan D on at half-speed
21:02 – Fan D increased to full speed
21:07 – Fan A on at half speed

Consider Various Impacts of Weather



Simplified HFIR Secondard Flow Schematic from 1546-01-M-5502 E



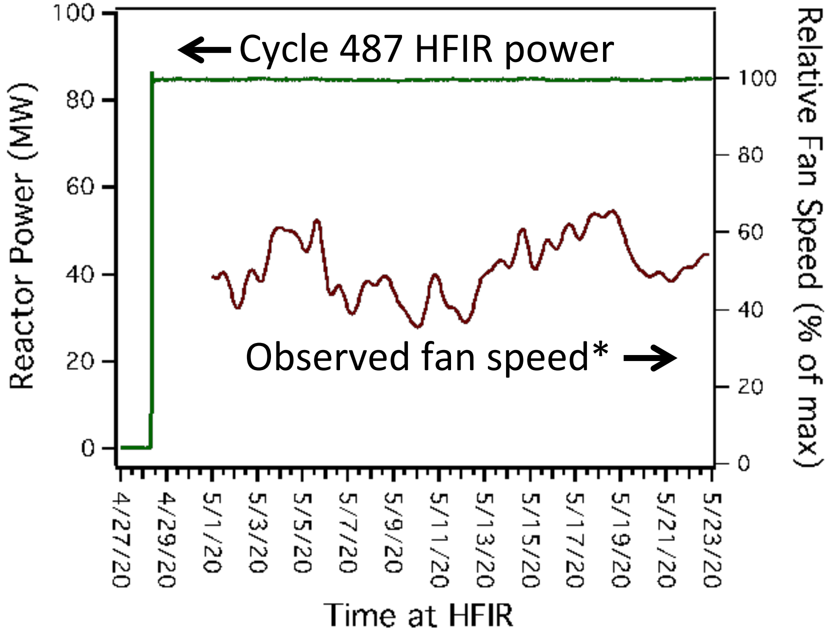
The reactor's heat release mechanism is fundamentally dependent upon the weather.

The Merkel Model

Issue: Fan speed does not correlate well with Reactor power, e.g. graph below

- Reactor held at full power, but fan speed is not at maximum
- Substantial variations in speed while reactor is constant

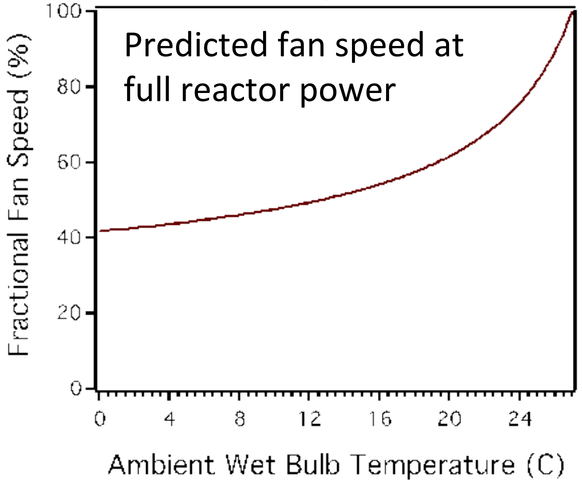
∴ An effect is missing



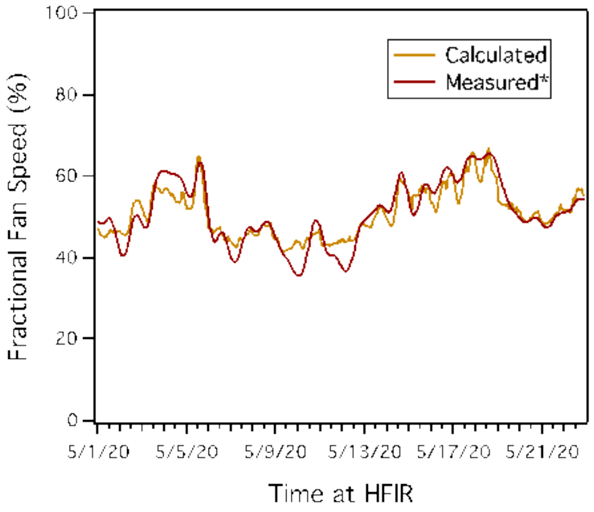
*Derived from observations by Will Ray

Approach: Fan speed changes to maintain constant cold water return when wet-bulb T changes. This causes the discrepancies. A physics model can predict these changes and be used to correct sensor-modality signals for use in data fusion.

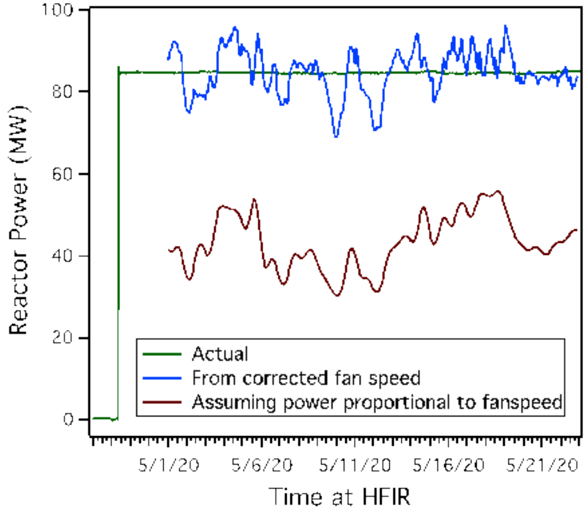
$$\frac{G'}{G} = \left(\left(\frac{\int_{T_{L,out}}^{T_{L,in}} \frac{dT}{H_G^* - H_G}}{\int_{T_{L,out}}^{T_{L,in}} \frac{dT}{H_G^* - H_G'}}\right)\right)^{\frac{1}{-1.09}}$$



Result 1: The model-calculated fan speed shows reasonable fit to observation



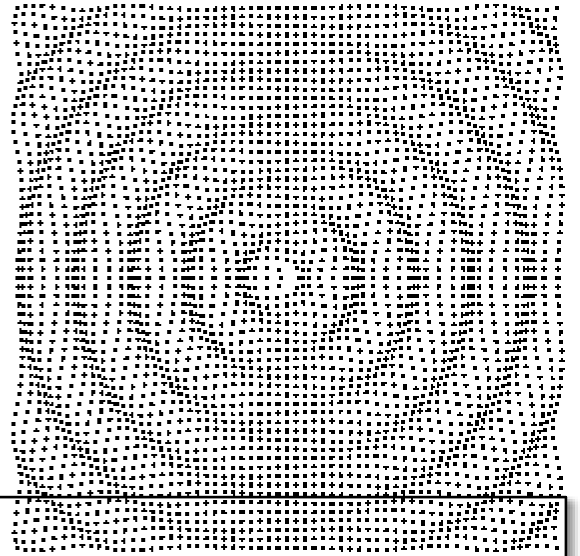
Result 2: Model-calibrated power from fan speed



- Scaled observed speed to predicted speed at wet bulb T
- Assumed full power = 85 MW

The Scaling of the BPF Acoustic Signal

- **Acoustic emanations at the BPF harmonics are highly nonlinear with fan speed.**
  - **"Fan sound law" predicts exponent = 5**
  - **Buckingham-Π predicts exponent = 5.67**
  - **Acoustic dipole model predicts exponent = 6**
- **Guided us toward implementing an interpretable decision-tree model**



PERSPECTIVE
https://doi.org/10.1038/s42256-019-0048-x
nature machine intelligence

Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead

Cynthia Rudin

Journal of Sound and Vibration (1975) **43**(1), 61–75

APPLICATION OF SIMILARITY LAWS TO THE BLADE PASSAGE SOUND OF CENTRIFUGAL FANS

W. NEISE
Deutsche Forschungs- und Versuchsanstalt für Luft- und Raumfahrt e.V., Institut für Turbulenzforschung, Berlin, Germany

(*Received* 3 *March* 1975, *and in revised form* 17 *April* 1975)

This paper is concerned with similarity laws governing the harmonic components of the sound radiated from centrifugal fans. Measurements are made with two precisely similar fans having impellers of 140 mm and 280 mm diameter. The experimental apparatus used is in accordance with the in-duct method suggested in a recent ISO-proposal [1]. The present experimental results verify Weidemann's [2] formulation of similarity laws, which describes the radiated sound pressure as a product of non-dimensional terms. The experiments also prove that it is possible to extrapolate data from a model fan to other geometrically similar fans of different size.

Extracting the BPF from the Acoustic Signal

U.S. DEPARTMENT OF ENERGY

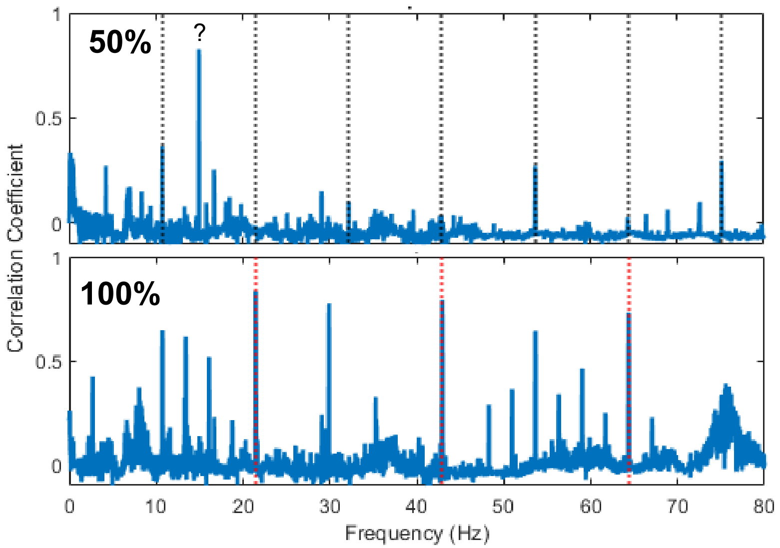
National Nuclear Security Administration
Defense Nuclear Nonproliferation

Blade Passing Frequency (BPF):

$$BPF(Hz) = \frac{Fan\ Speed\ (RPM) \times \#\ Blades}{60}$$

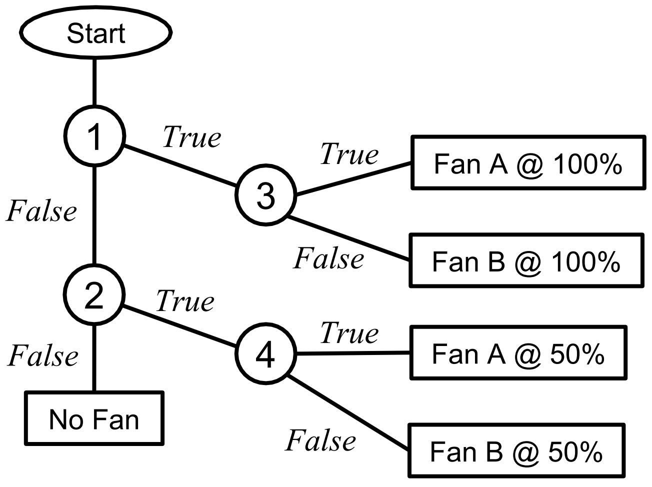
Fan Motor Speed	Fan Blade Speed*	BPF
1800 RPM (100%)	162 RPM	**21.5 Hz**
900 RPM (50%)	81 RPM	**10.8 Hz**

*11.14:1 gear reducer after motor



BPFs and higher harmonics are correlated with fan rotation.

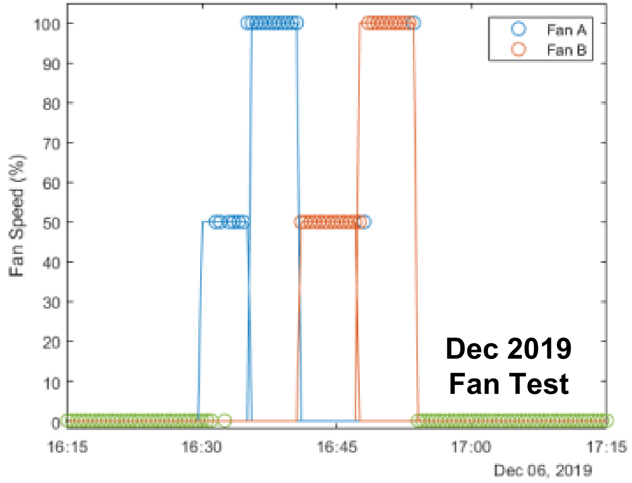
Decision Tree Classifier:

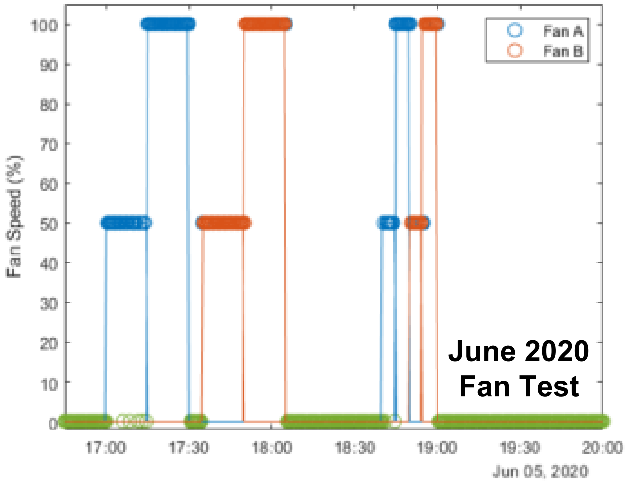


N	Condition
1	Product of 21.5 Hz harmonics (2-8) features > 2 x 10^{53}
2	Product of 10.75 Hz and 15.0 Hz features > 1 x 10^{7}
3	21.5 Hz feature < 7 x 10^{8}
4	15.0 Hz feature < 4.5 x 10^{7}

Model built primarily on BPF amplitudes.

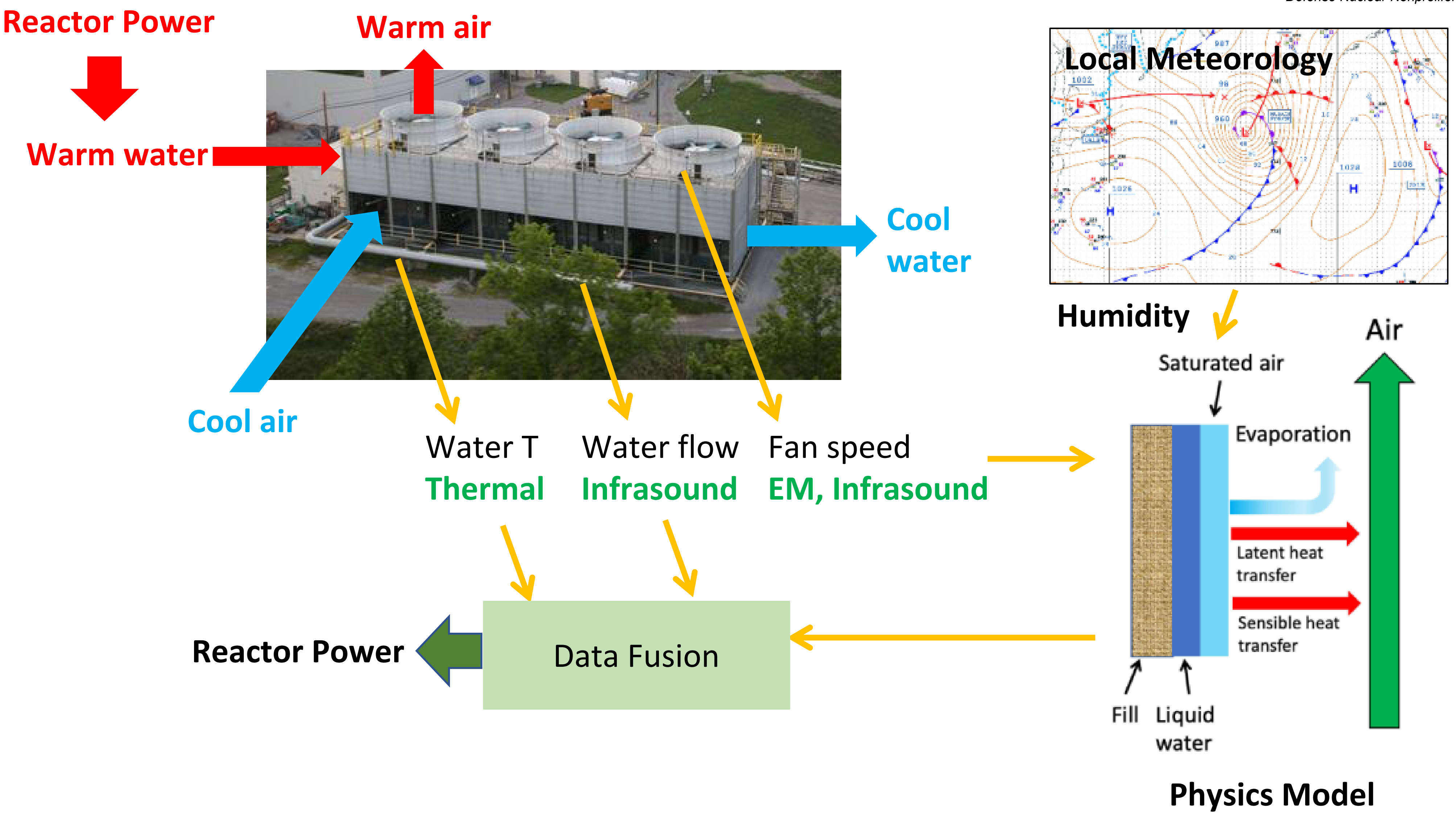
Prediction Results:





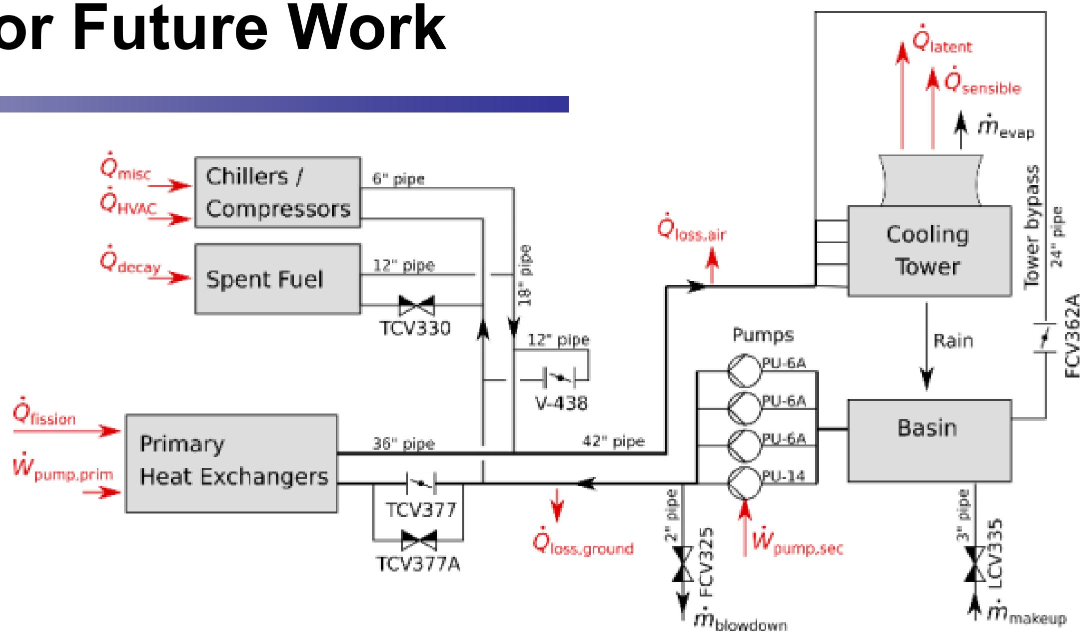
Model predicts fan identity and speed with > 96% accuracy.

Enabling Generalizability to Another Site (i.e., Transferability)



Two Potential Directions for Future Work

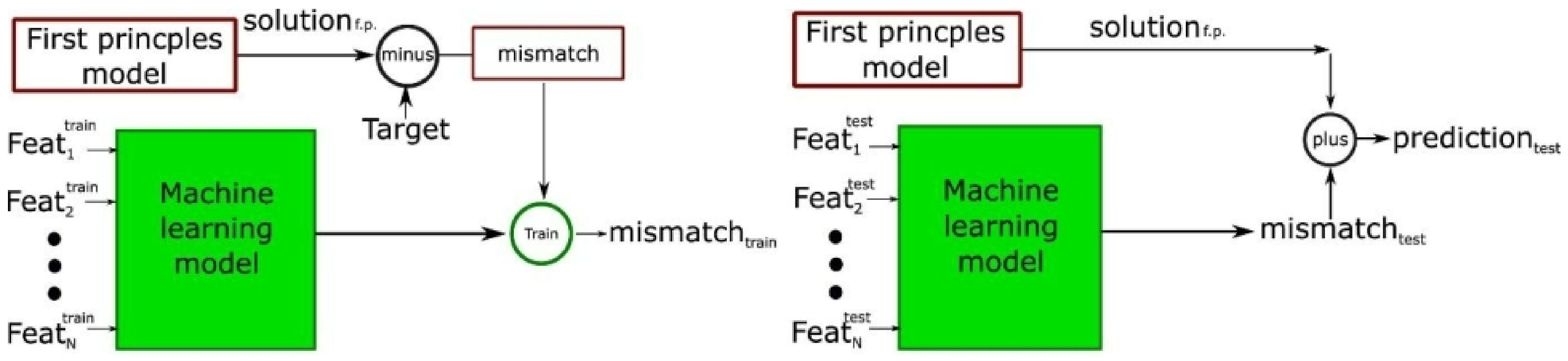
1. **Combine/augment physical model with machine learning**
   - **Merkel model accounts for fan-driven heat transfer in cooling tower**
   - **Other processes impact heat transfer…**
   - **… so *machine learn resulting mismatch*.**



Blowdown (discarded water)

Makeup (new water)

Simplified HFIR Secondard Flow Schematic from 1546-01-M-5502 E



(a) Training phase of Method 2

(b) Test phase of Method 2

From T. Bikmukkametov and J. Jäschke, "Combining machine learning and process engineering towards enhanced accuracy and explainability of data-driven models," Comp. Chem. Eng. **138**, 106834 (2020).

Two Potential Directions for Future Work

1. **Combine/augment physical model with machine learning**
   - **Merkel model accounts for fan-driven heat transfer in cooling tower**
   - **Other processes impact heat transfer…**
   - **… so *machine learn resulting mismatch*.**
2. **Demonstrate machine-learning of physical model(s) via symbolic regression**

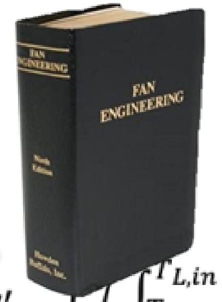
SCIENCE ADVANCES | RESEARCH ARTICLE

COMPUTER SCIENCE

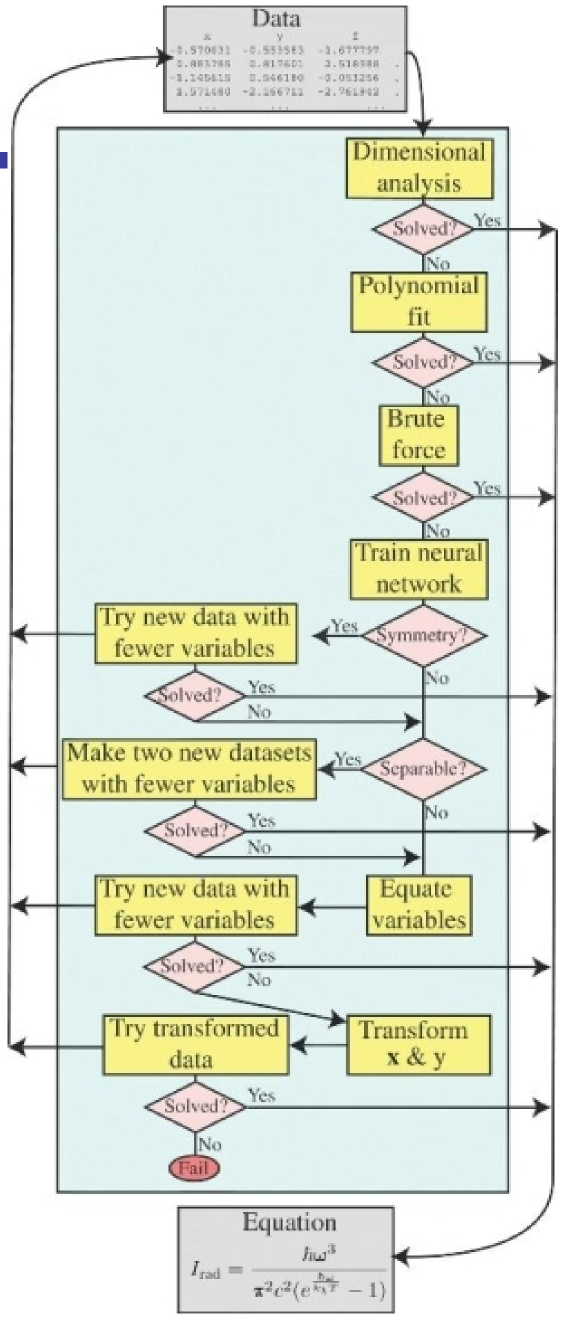
AI Feynman: A physics-inspired method for symbolic regression

Silviu-Marian Udrescu[1] and Max Tegmark[1,2]*

A core challenge for both physics and artificial intelligence (AI) is symbolic regression: finding a symbolic expression that matches data from an unknown function. Although this problem is likely to be NP-hard in principle, functions of practical interest often exhibit symmetries, separability, compositionality, and other simplifying properties. In this spirit, we develop a recursive multidimensional symbolic regression algorithm that combines neural network fitting with a suite of physics-inspired techniques. We apply it to 100 equations from the *Feynman Lectures on Physics*, and it discovers all of them, while previous publicly available software cracks only 71; for a more difficult physics-based test set, we improve the state-of-the-art success rate from 15 to 90%.



$$\frac{G'}{G} = \left(\frac{\int_{T_{L,out}}^{T_{L,in}} \frac{dT}{H_G^* - H_G}}{\int_{T_{L,out}}^{T_{L,in}} \frac{dT}{H_G^* - H_G'}} \right)^{\frac{1}{-1.09}}$$



Thanks!... Questions?