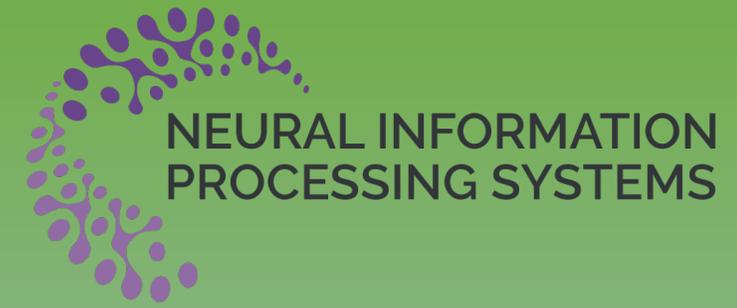
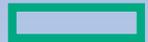
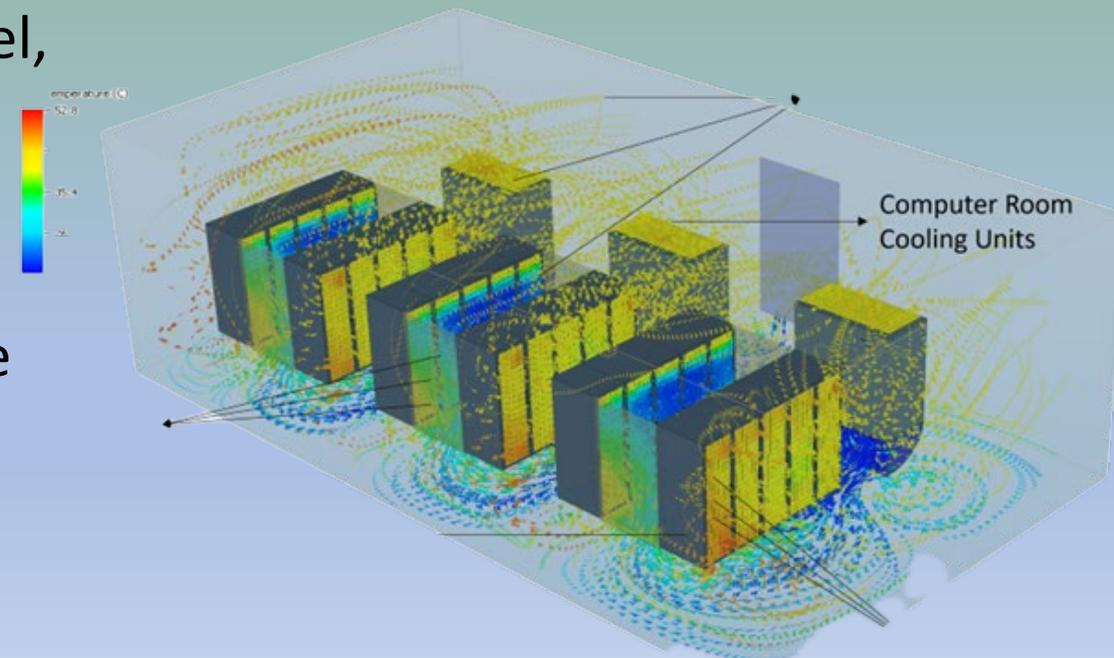


# Enhancing Data Center Sustainability with a 3D CNN-Based CFD Surrogate Model



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**Hewlett Packard**  
Enterprise



Models Data Center Thermodynamics



Reveals areas where equipment is overheating or underutilizing cooling resources



Optimize data center cabinet and server placement,



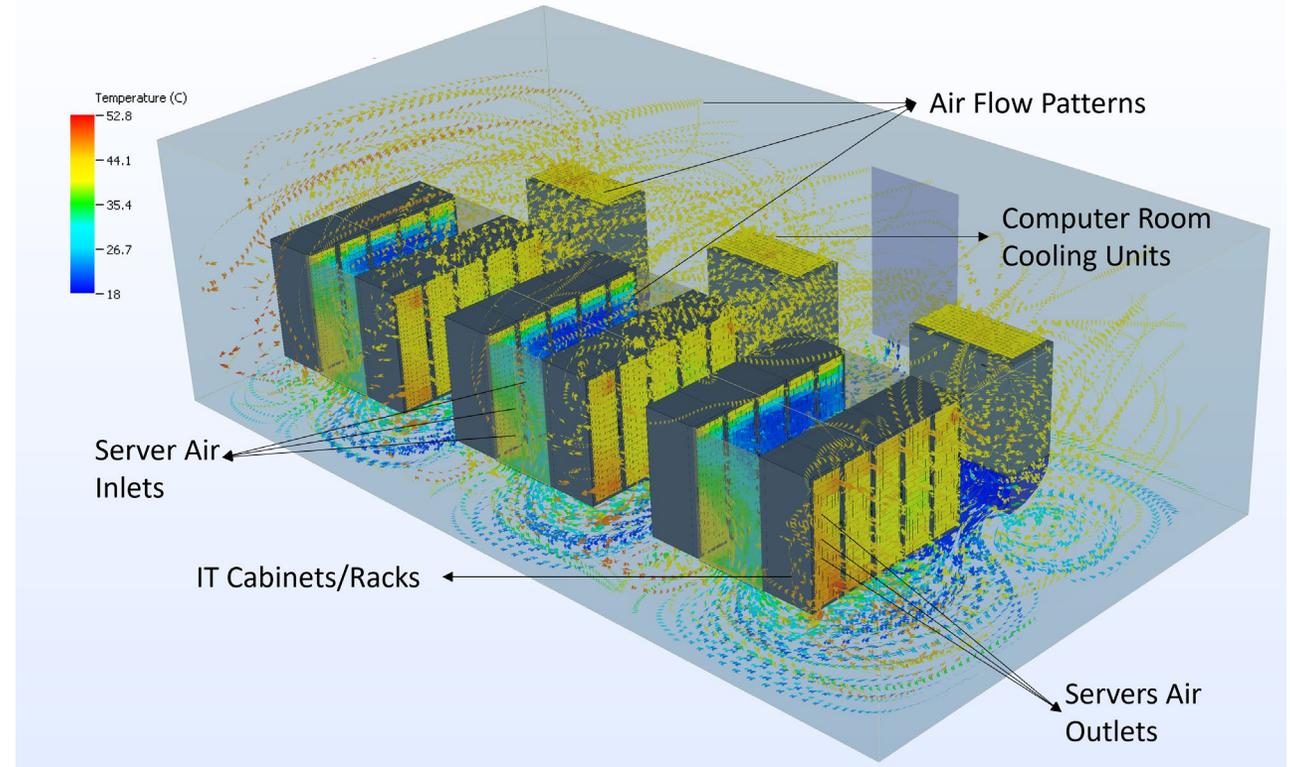
Prevent hot-spot-related server



Increase equipment longevity.



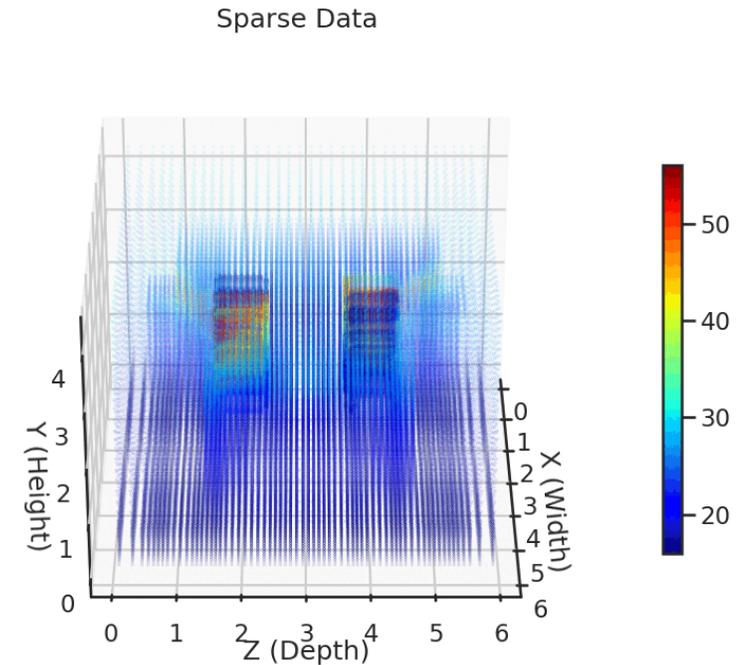
**A fast thermal analysis can enable control, which will enable real-time control to significantly lower carbon footprint.**



Data Center Heat Flow

## What is the Challenge?

- ❑ High computational complexity
- ❑ Not scalable for real-time applications
- ❑ Fast ML surrogates make real-time control possible
- ❑ ML surrogate can scale to very large data centers



Generated by ML Surrogate for CFD

## 3D Input Data:

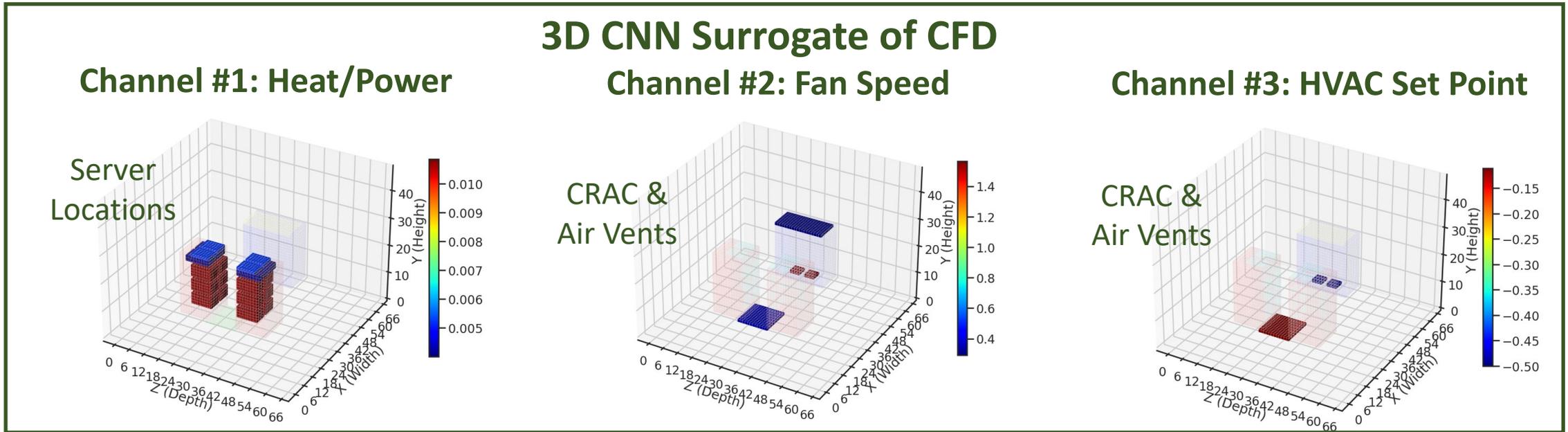
**Power:** volume-normalized power

**ACU Set Point:** Encodes the normalized ACU temperature

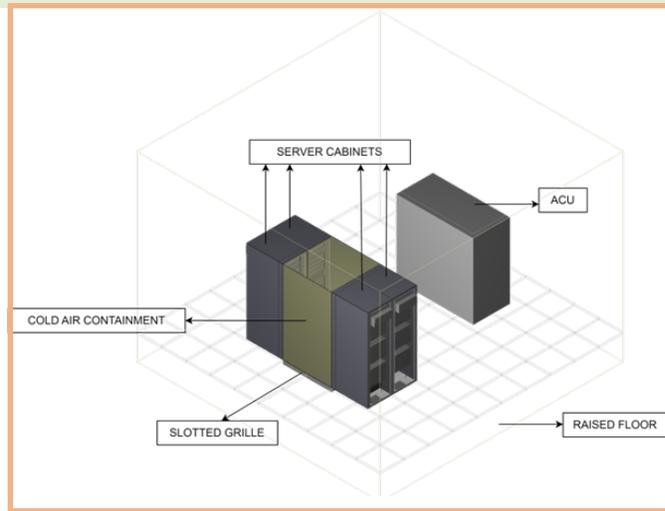
**ACU Fan Speed:** Volume-normalized fan

## 3D Output Data:

**3D Heat Map**

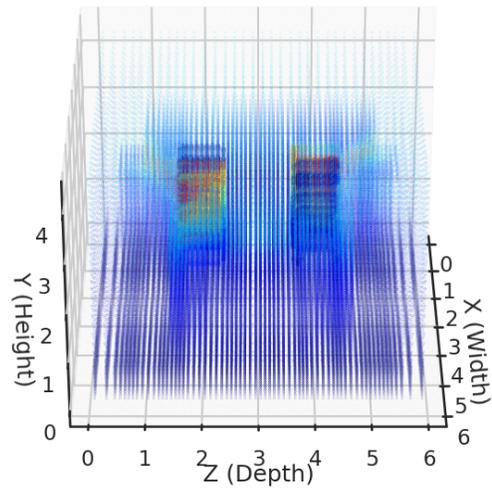


# 3D CNN Surrogate: Output Generation

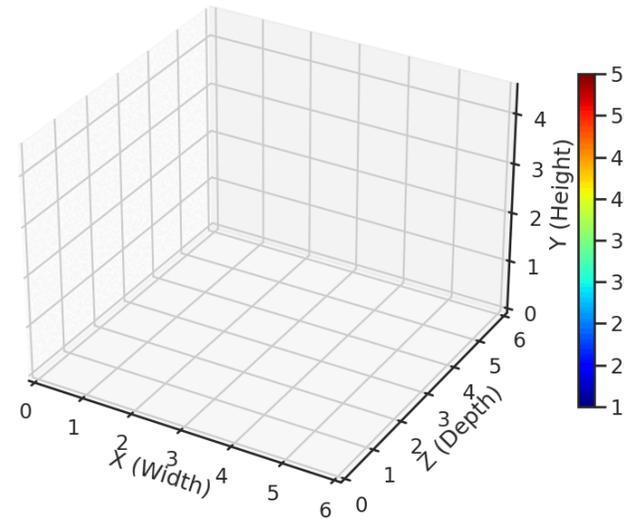


## Data Center Configuration

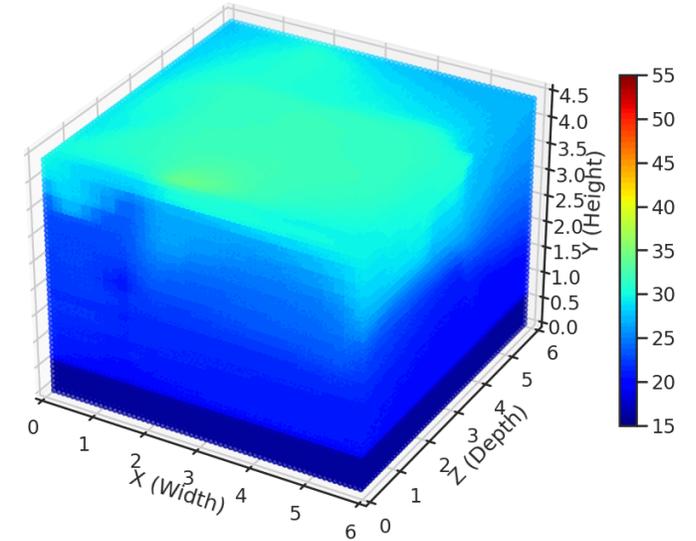
Sparse Data

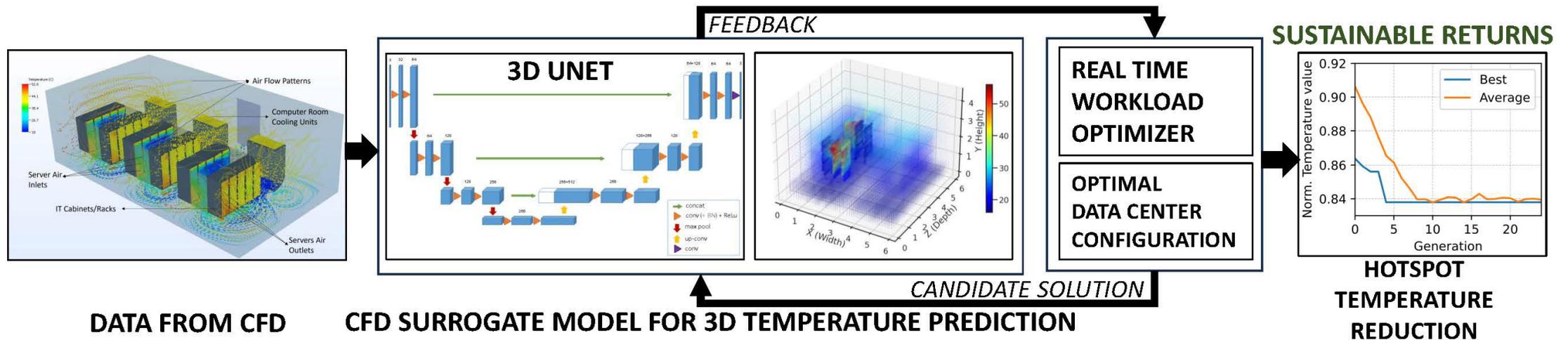


Smoothed Interpolated Data



Smoothed Interpolated Data





**Model accuracy evaluation metrics :** To evaluate the effectiveness of our approach, we consider several metrics: inference time, mean-squared-error (MSE), mean maximum absolute error (AE), mean AE, top- $t$  AE, and 3D structural similarity (SSIM). Top- $t$  AE is especially useful for evaluating how well our approach models hot spots in data centers. It is defined below:

$$\text{Top-}t \text{ AE}(\mathbf{Y}, \hat{\mathbf{Y}}) = \sum_{n=1}^N \sum_{i,j,k \in \text{top-}t(\mathbf{y}_n)} \frac{|y_{n1ijk} - \hat{y}_{n1ijk}|}{Nt} \quad (1)$$

The function  $\text{top-}t(\cdot)$  returns the 3D indices of the largest  $t$  elements of its tensor argument, i.e., the hottest  $t$  temperature locations of a ground truth heatmap. In our evaluation, we set  $t$  to 10% of the number of heatmap elements. The inference time is the time to predict a single sample after the model and data are loaded into GPU memory.

- Goal: Optimal workload distribution → Reduce Temperature Hotspots
- Genetic Algorithm Optimizer
- Objective Function : Trained surrogate model
- Reducing hotspots by approximately 7.70% within 25 iterations .
- 99% reduction in optimization time

Workload Settings	Model	Inf. Time (ms)	MSE	Mean AE (C)	Max AE (C)	Top- <i>t</i> AE (C)	3D SSIM
Uniform Utilization	Res. U-Net	41.6	<b>0.00086</b>	<b>0.87</b>	<b>9.99</b>	<b>1.29</b>	<b>0.9522</b>
	U-Net	40.6	0.00094	0.93	11.0	1.34	0.9437
	V-Net	35.6	0.00112	1.44	12.8	2.32	0.9112
	SegNet	<b>15.2</b>	0.00432	2.06	14.7	6.27	0.8434
Extreme Utilization	Res. U-Net	41.6	<b>0.00010</b>	<b>0.34</b>	<b>4.65</b>	<b>0.37</b>	<b>0.9772</b>
	U-Net	40.6	0.00031	0.57	9.90	0.62	0.9565
	V-Net	35.6	0.00048	0.72	6.66	0.79	0.9343
	SegNet	<b>15.2</b>	0.00137	1.25	8.83	2.74	0.9028
Grid CPU Utilization	Res. U-Net	41.6	0.00118	0.84	8.90	1.68	0.9459
	U-Net	40.6	<b>0.00018</b>	<b>0.40</b>	<b>7.32</b>	<b>0.53</b>	<b>0.9798</b>
	V-Net	35.6	0.00312	1.93	14.5	2.35	0.8576
	SegNet	<b>15.2</b>	0.00559	2.27	19.7	5.26	0.8197
Grid CPU Utilization and Cold Aisle Containment	Res. U-Net	41.6	0.00011	<b>0.21</b>	<b>4.47</b>	<b>0.43</b>	<b>0.9939</b>
	U-Net	40.6	<b>0.00009</b>	0.23	6.39	0.44	0.9911
	V-Net	35.6	0.00176	1.30	9.40	1.84	0.8962
	SegNet	<b>15.2</b>	0.00315	1.11	20.7	4.73	0.9220

Table 1: Evaluation (Speed and Accuracy) metrics on test set. The inference time is computed on a V100 GPU.

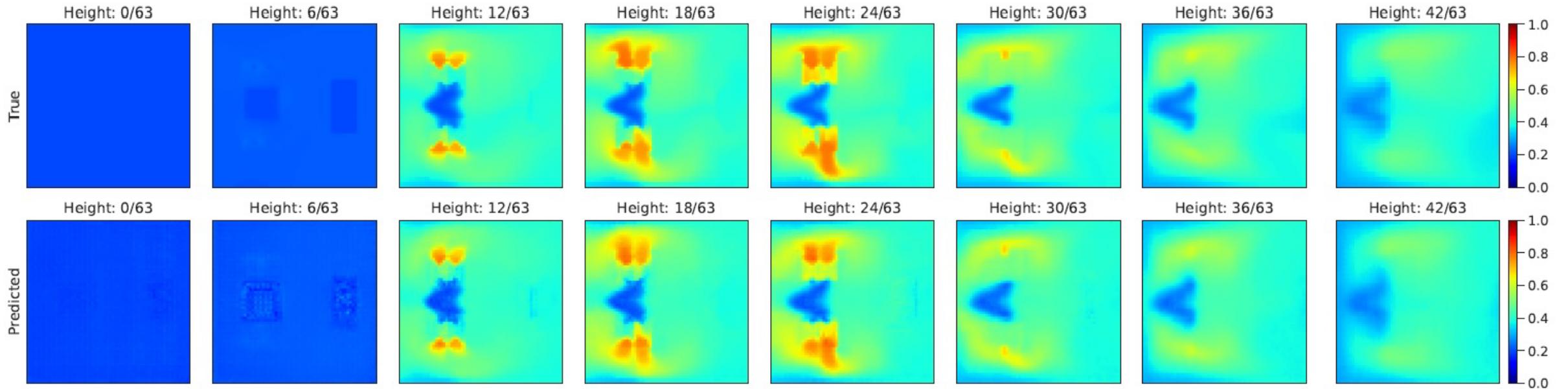


Figure 3: Matrix representation across different slices of the data center room. True outputs are in the top row, and model predictions the bottom row. Each column represents a slice at varying heights.

Applying our optimized workload configurations derived from 3D CNN and the genetic algorithm, we got:

- significant improvement in sustainability and energy efficiency
- with an optimal workload distribution, the HVAC cooling **energy consumption rates drops**, translating to cost savings and a notable carbon footprint reduction.
- the enhanced temperature regulation may lead to prolonged equipment lifespans and reduced e-waste and manufacturing carbon footprint, emphasizing the holistic benefits of our approach.
- the dual benefits of **financial savings** and **environmental impact** through optimized configurations
- as a future work, an expanded CFD surrogate will enable thermal analysis of large data centers

# Thank You

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