Multi Channel Corrugation Studies

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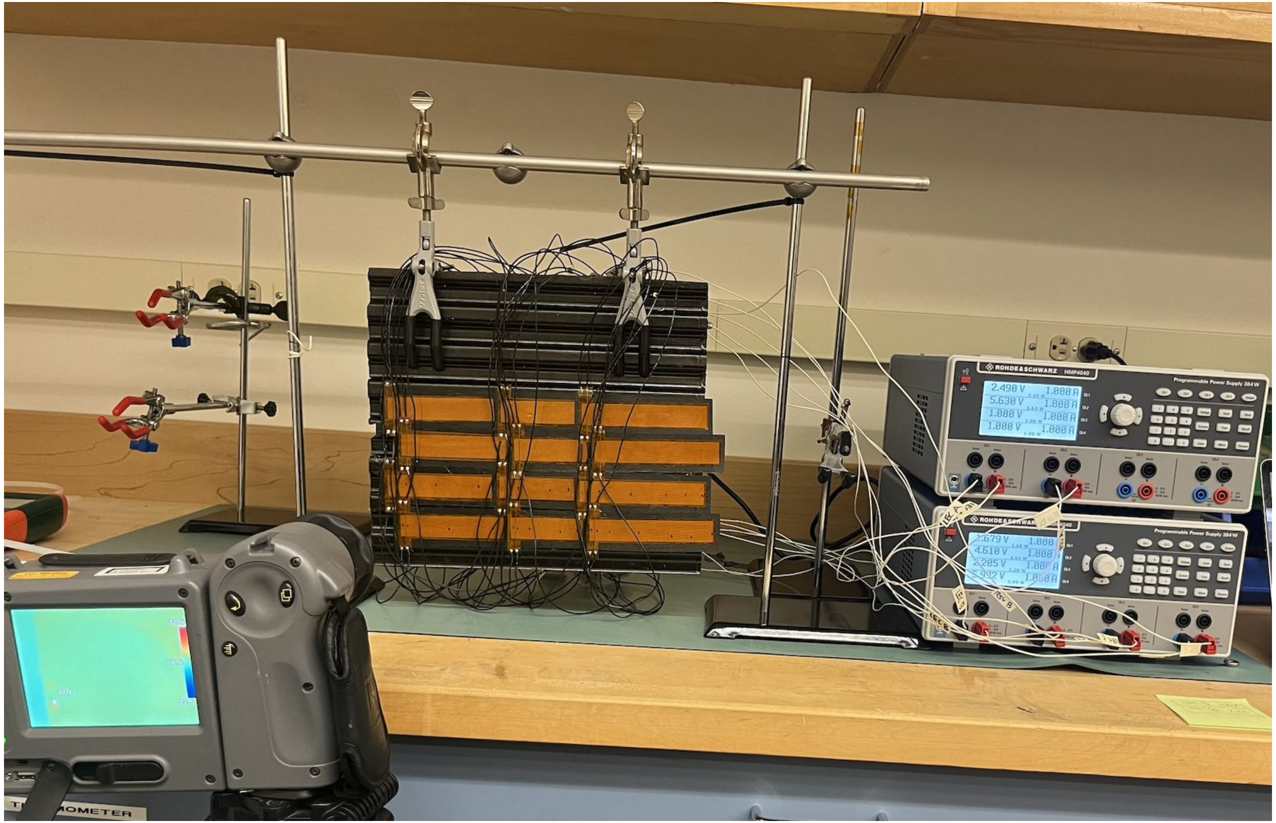
LBNL EIC Meeting
8/12/25

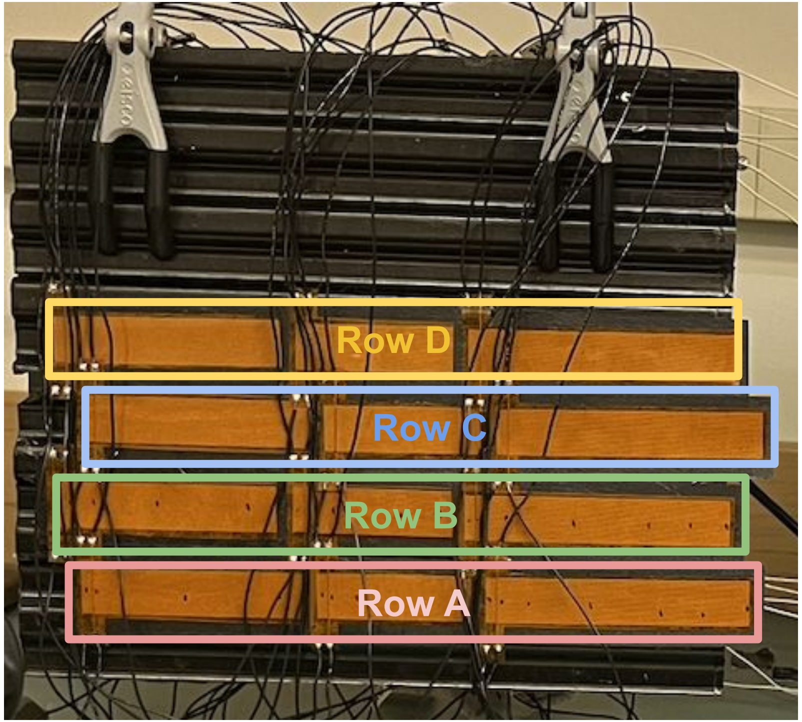
Construction: Front 4 Rows, Back 1 Row



Multi Channel Setup

Four objectives for this setup:

1. How do **varying power densities** affect temperature
2. How do **next to nearest neighbors** and further affect the temperature
3. Influence of neighbors based on **side** of carbon fiber
4. How does **air cooling** affect temperature of multiple rows

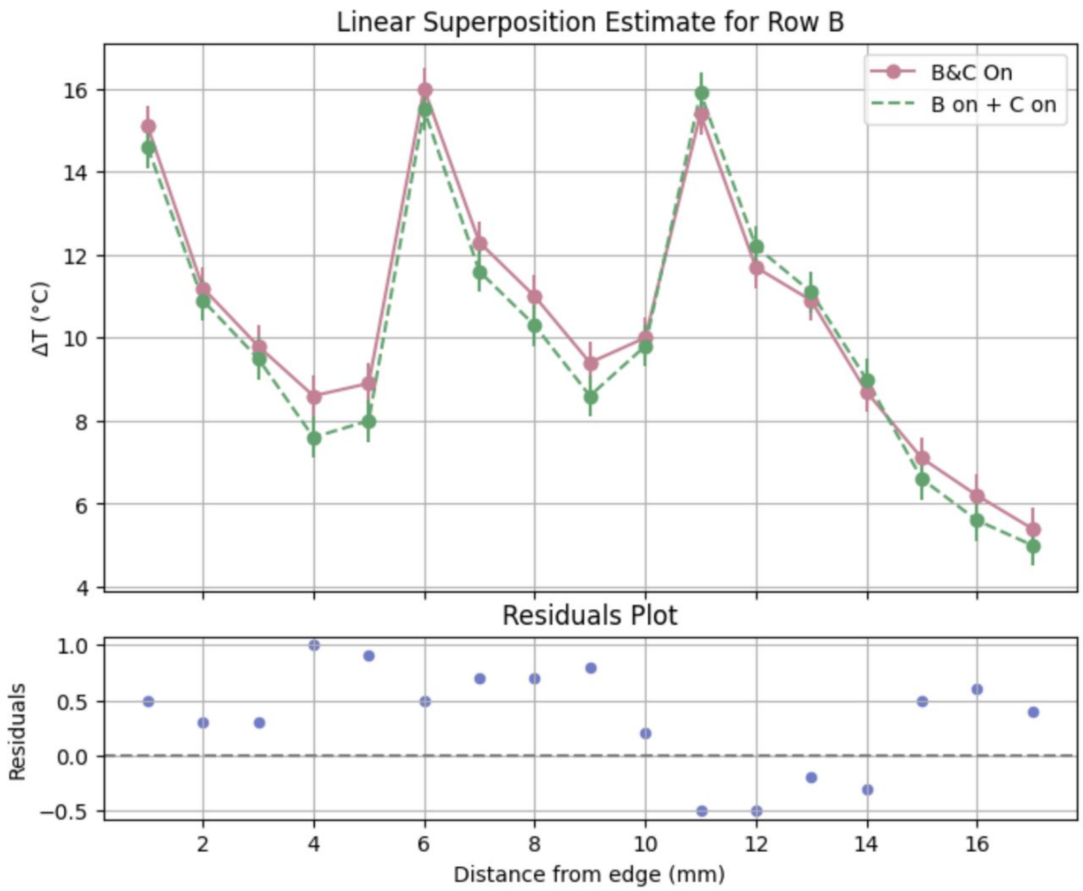


Reproducibility

Linear Superposition

- Ideally for this model, **dT of B&C On** is about equal to **B On + C On**.
- Error matches previous test setup!

Heat Data:
https://docs.google.com/spreadsheets/d/1JYRFwtVZQbA0ORGAF7ZDx16DwuzYTf7v/edit?gid=469816021#gid=469816021

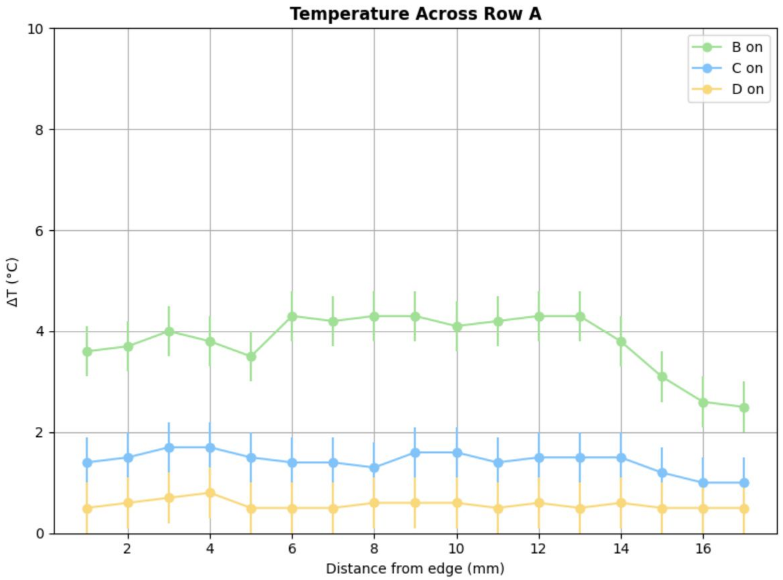


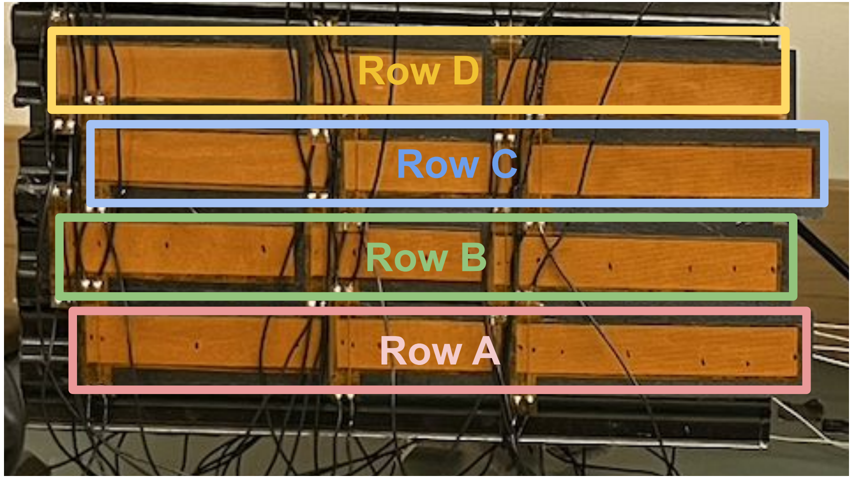
I. Neighbor Studies

Nearest + Next To Nearest Neighbor

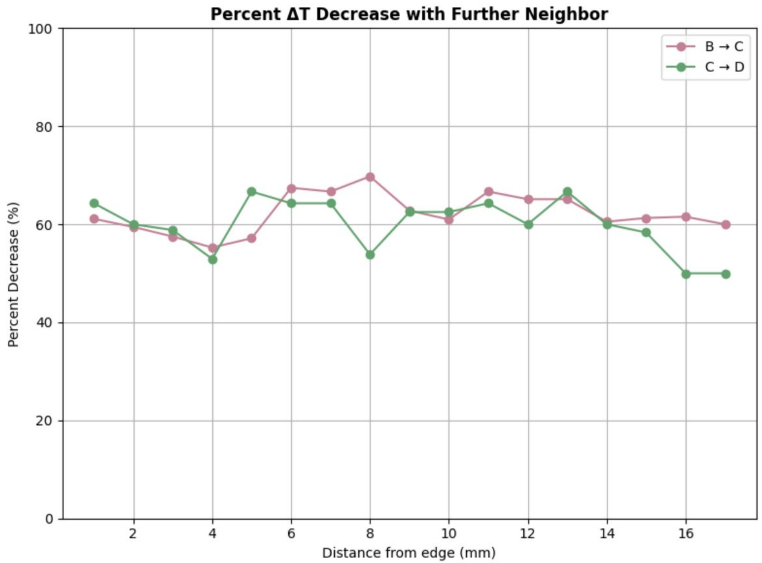
Measurements were taken across **Row A**

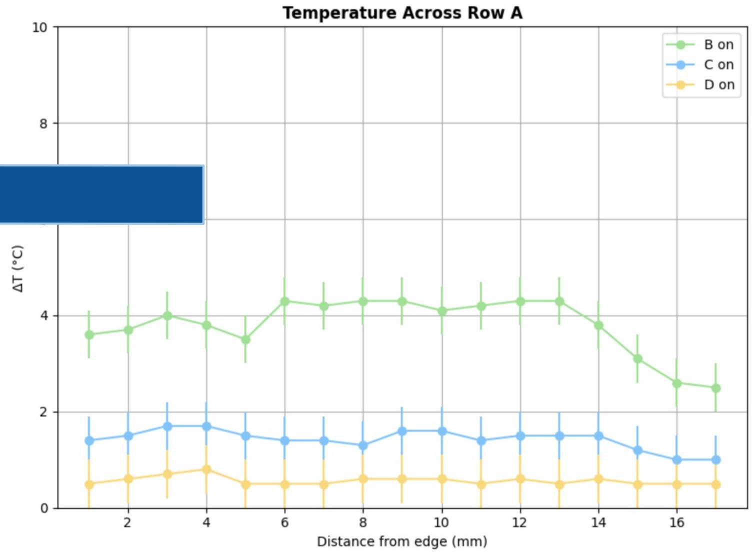
- Last component needed for a full model of **one side** of the corrugation is the impact of neighbors
- Measured with **Row A turned Off**, and at **MAX** power





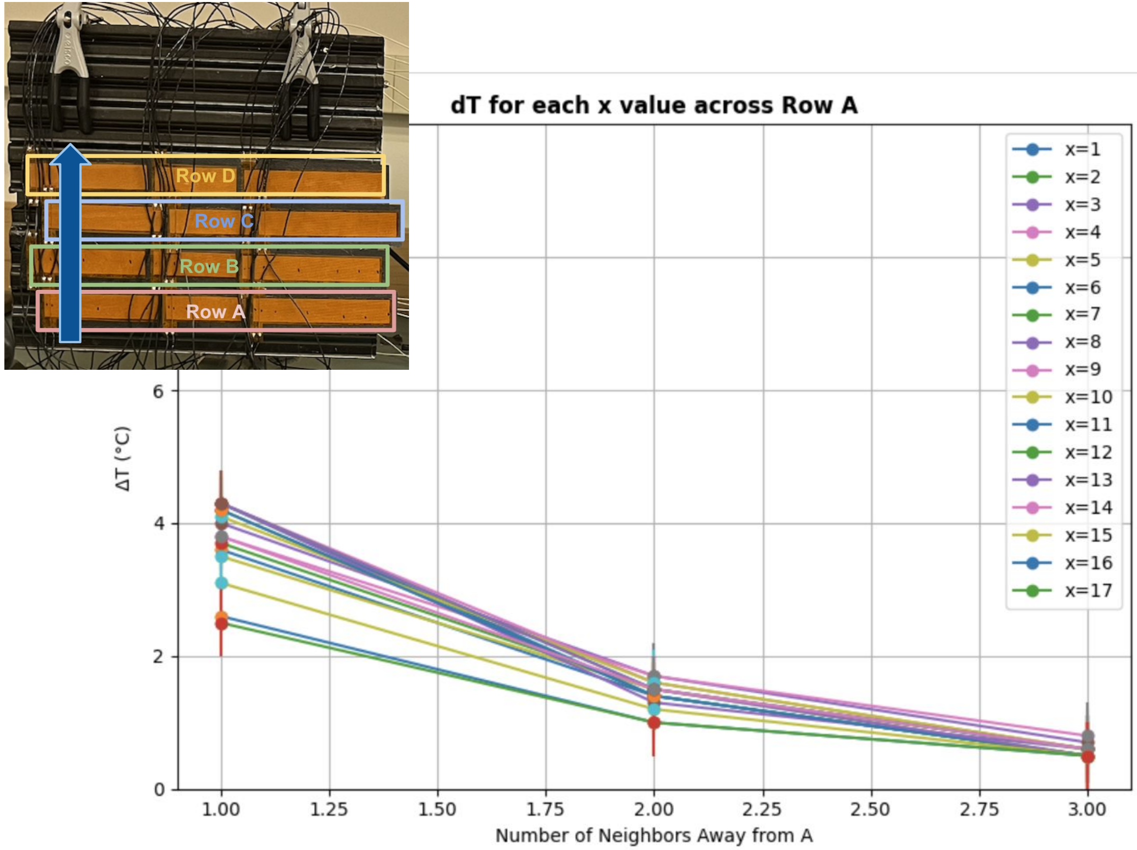
Nearest + Next To Nearest Neighbor





- Plot % decrease at each x value as we go from B -> C & C -> D
- Impact on Row A is as follows:
  - Consistent ~60% decrease with each added neighbor
  - As if now typical: edge effects and LECs cause slight variation

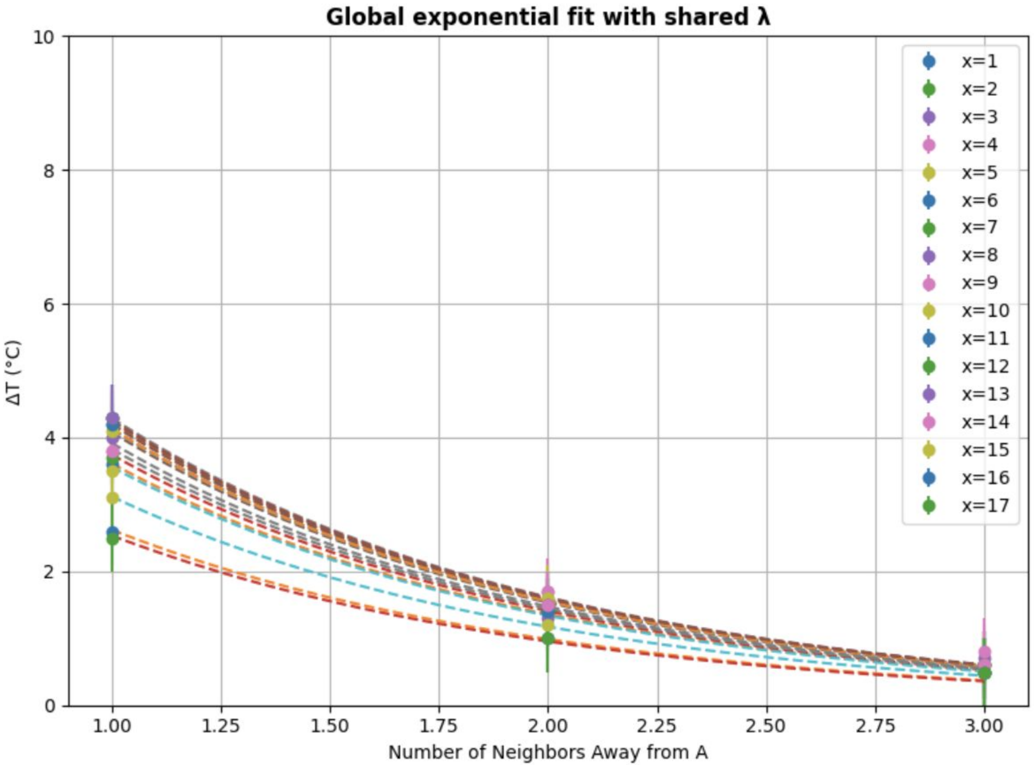
Nearest + Next To Nearest Neighbor



- Plot dT at a given x value on Row A vs how many neighbors away
- **Fit a decay function**
  - Assume that for any given x location along Row A, when heaters farther and farther away are turned on, the temperature rise ΔT at that x drops off exponentially with “number of neighbors away” n

Modelling Decay

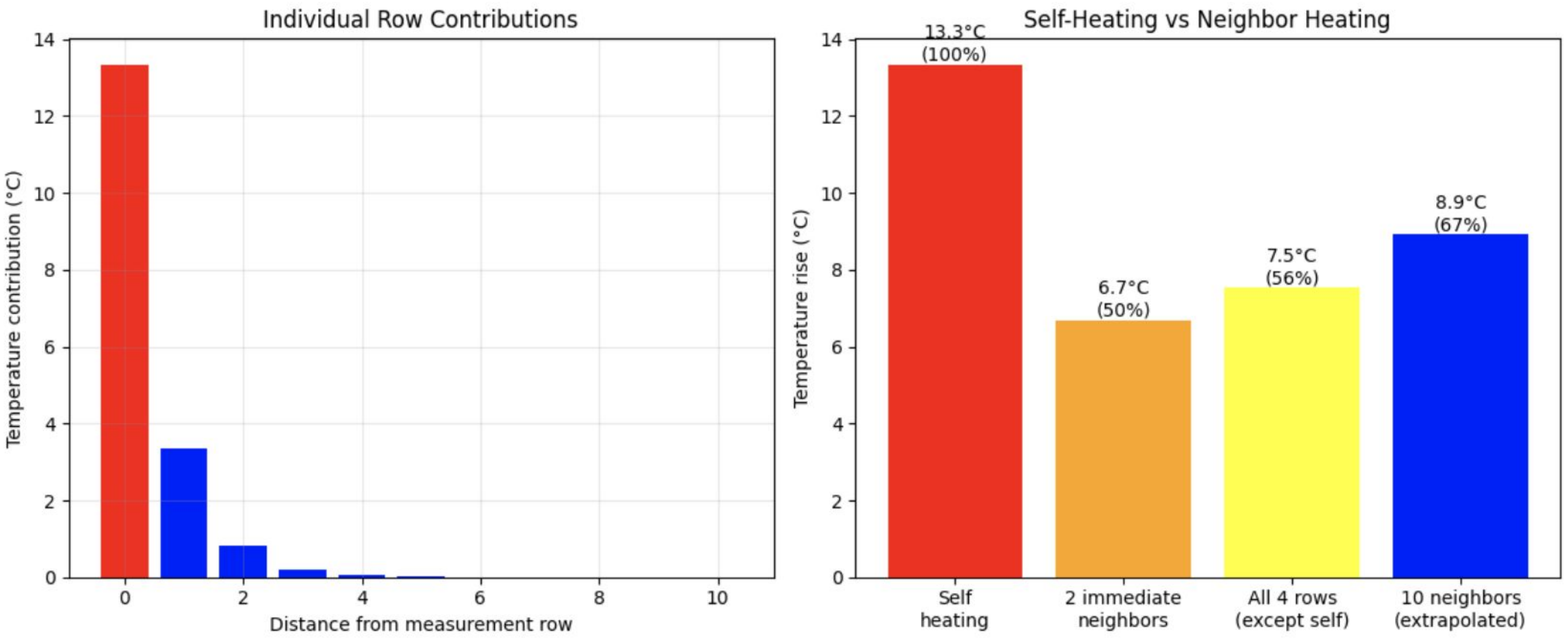
```
Amplitudes: [ 9.59670679  9.94378493 10.83413852 10.40933837  9.45417368 11.19692674
 10.96832389 11.14326254 11.40147178 10.94426608 10.96832389 11.31540203
 11.28299648 10.17238778  8.28155305  6.9663993   6.73779645]
Shared decay length λ: 1.0237208085396297
```



$$\Delta T_x(n) = T_{0,x} \cdot e^{-n/\lambda}$$

- **T0,x** → the amplitude for location x. This is the ΔT if the heater directly adjacent (n = 1) is on.
- Simplifies the model
- **λ** → the same for all curves; the decay length in “neighbor units” that describes how quickly heat dissipates away along the structure.
- Forces all curves to share the same λ but let each have its own T0,x

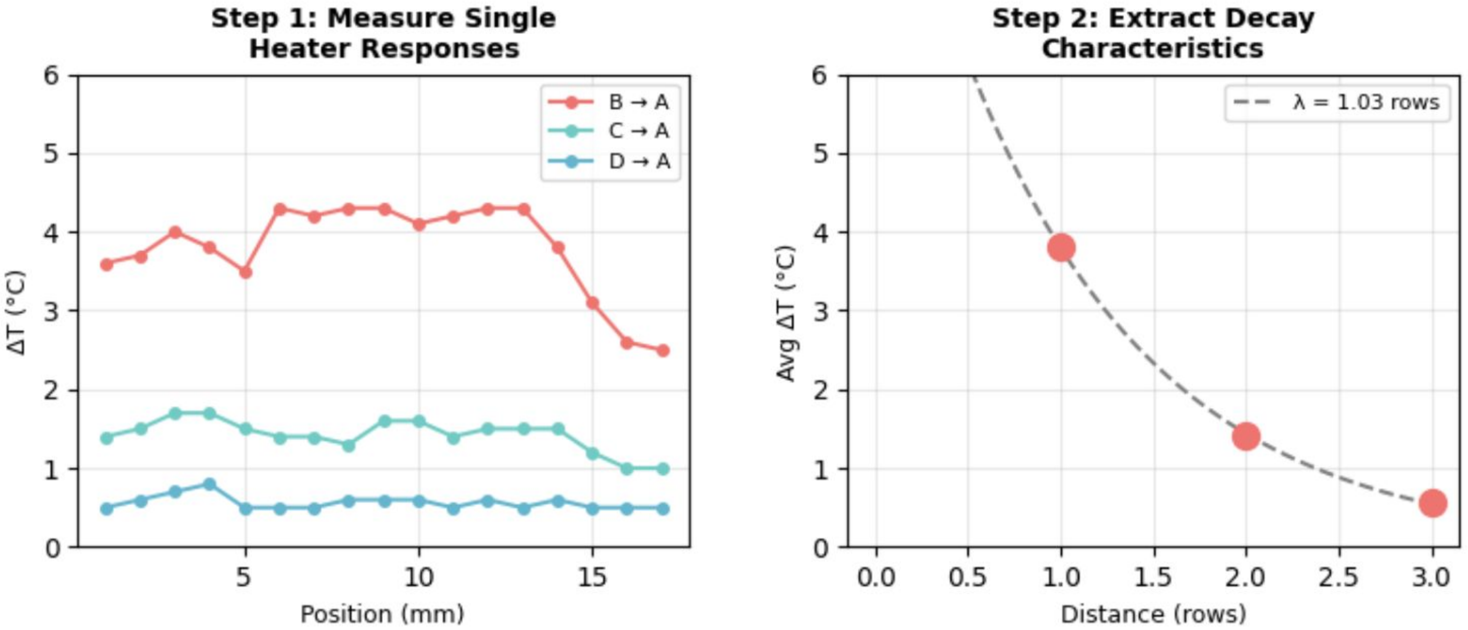
Comparison to Self Heating



- Need ~100 neighbors to match the dT from self heating
- Trying to capture the difference with A off vs on

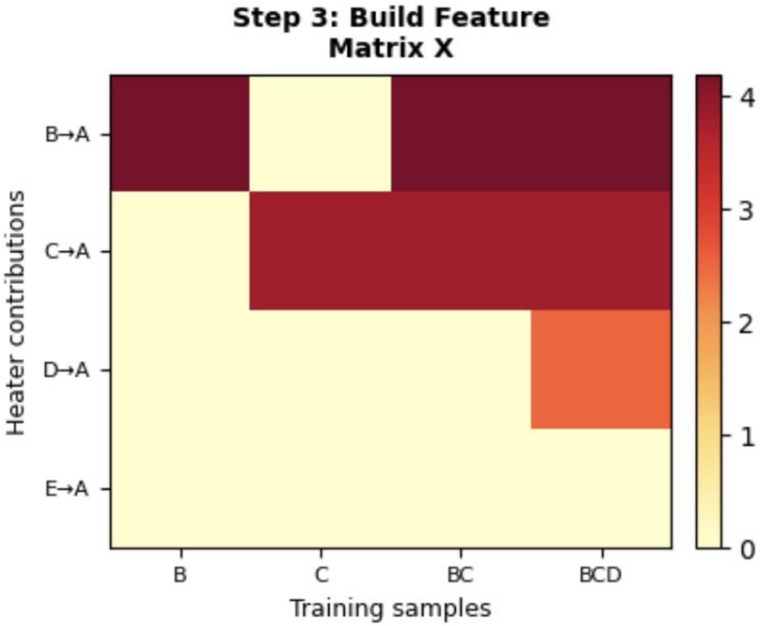
Model Construction

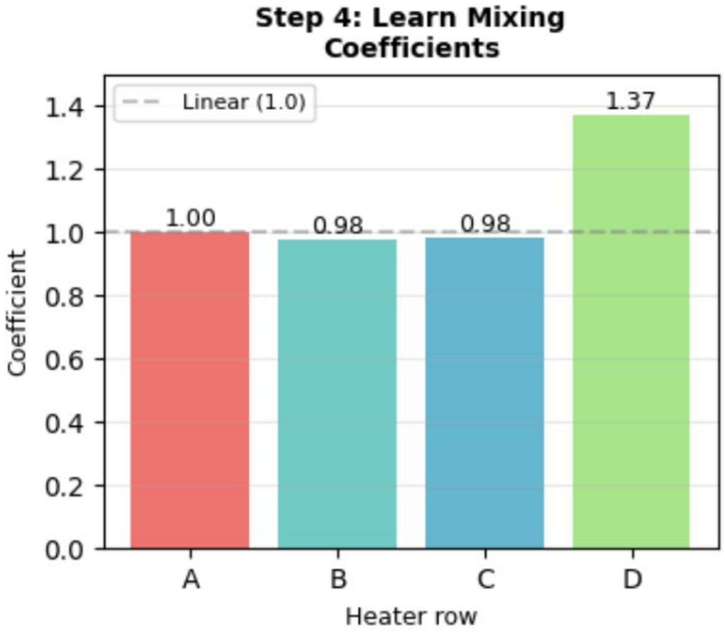
- **Step 1:** Start by measuring individual heater responses. When only heater B is on, we record the temperature rise at measurement row A across all positions. We repeat this for each heater in isolation.
- **Step 2:** Analyze how heat decays with distance. The exponential decay parameter λ tells us how quickly heat dissipates between rows



Model Construction

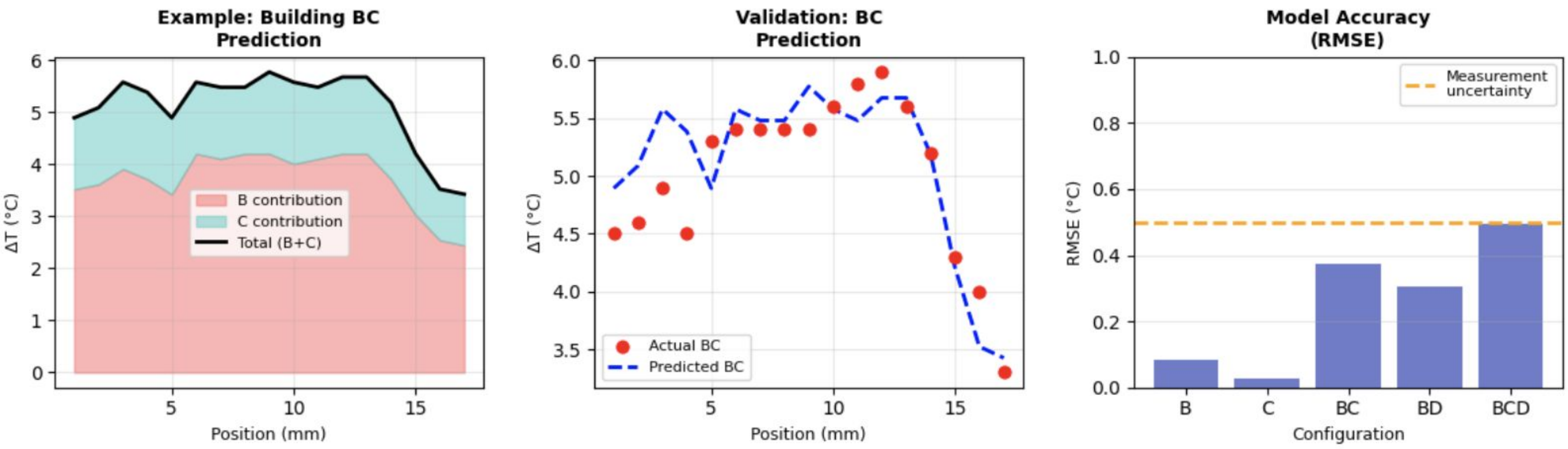
- **Step 3:** Construct a feature matrix where each column represents a heater's contribution to the temperature. For multi-heater configurations, we stack the individual responses.
- **Step 4:** Learn mixing coefficients as we did in the previous model I showed.



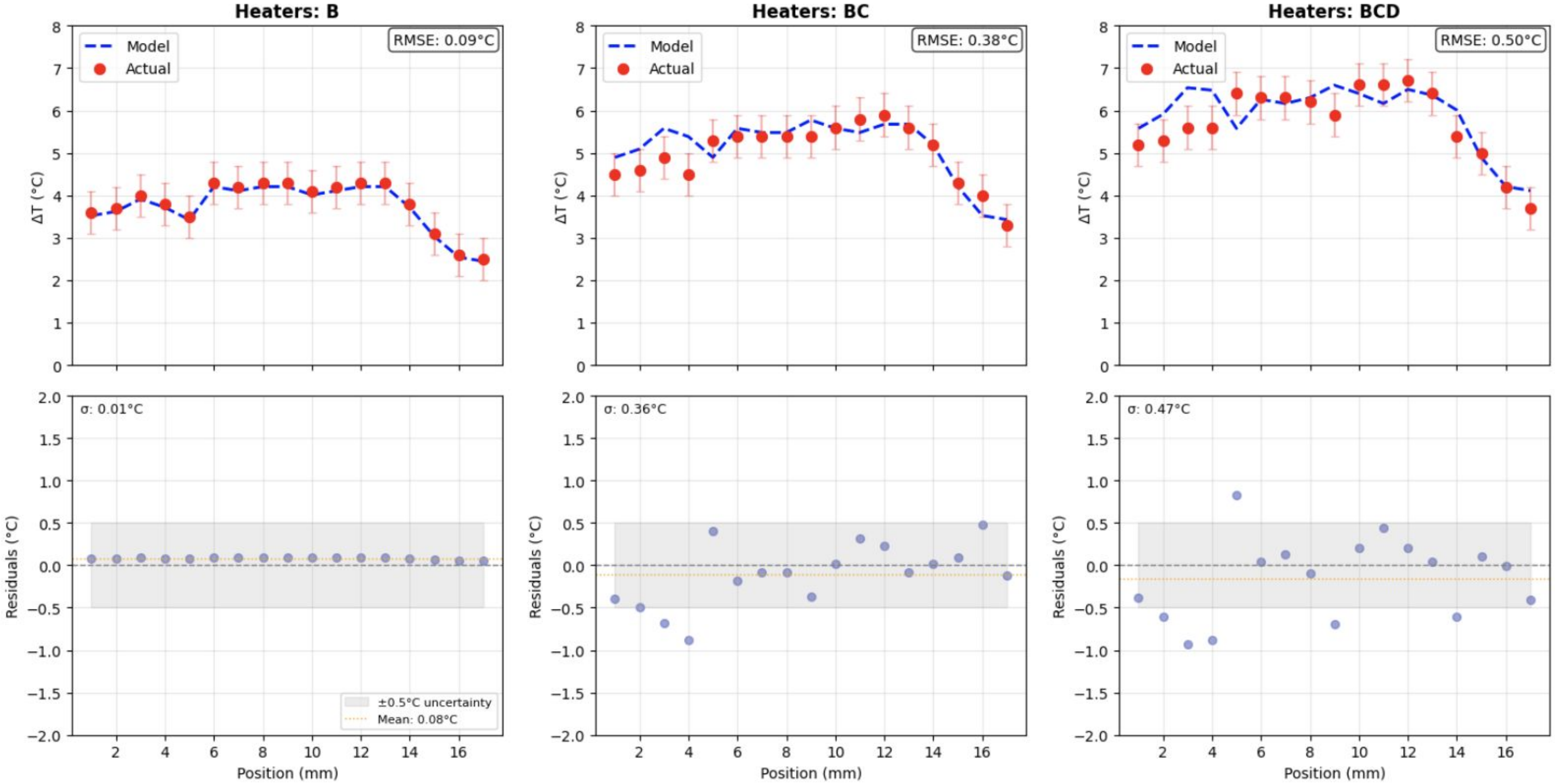


Model Construction

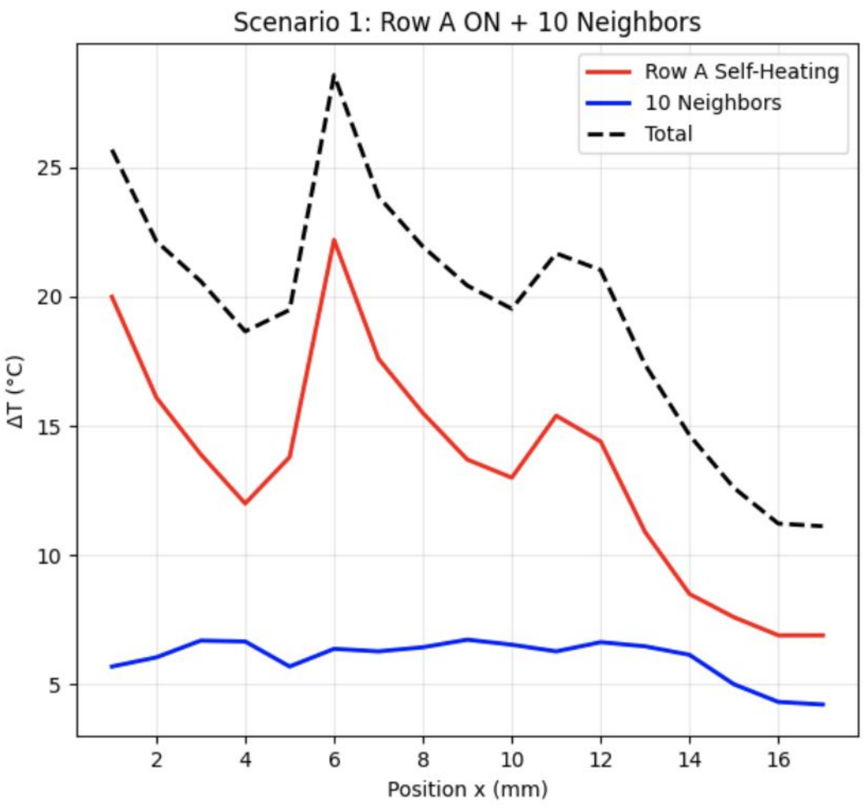
- **Example:** When predicting BC configuration, we take B's single response, multiply by its coefficient (0.84), add C via its coefficient (0.38), giving us the total prediction that closely matches experimental data
- **Validation:** The model maintains sub-0.5°C accuracy across all tested configurations, showing that learned superposition effectively captures the behavior of this multi-heater thermal system

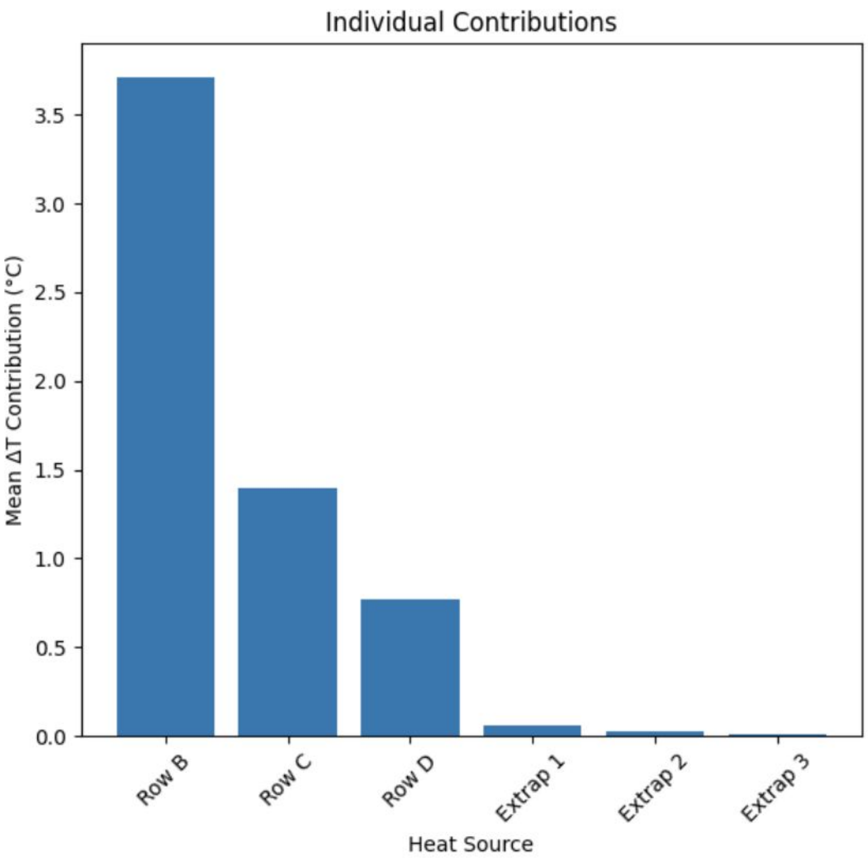


An Effective Neighbor Model (One Side!)

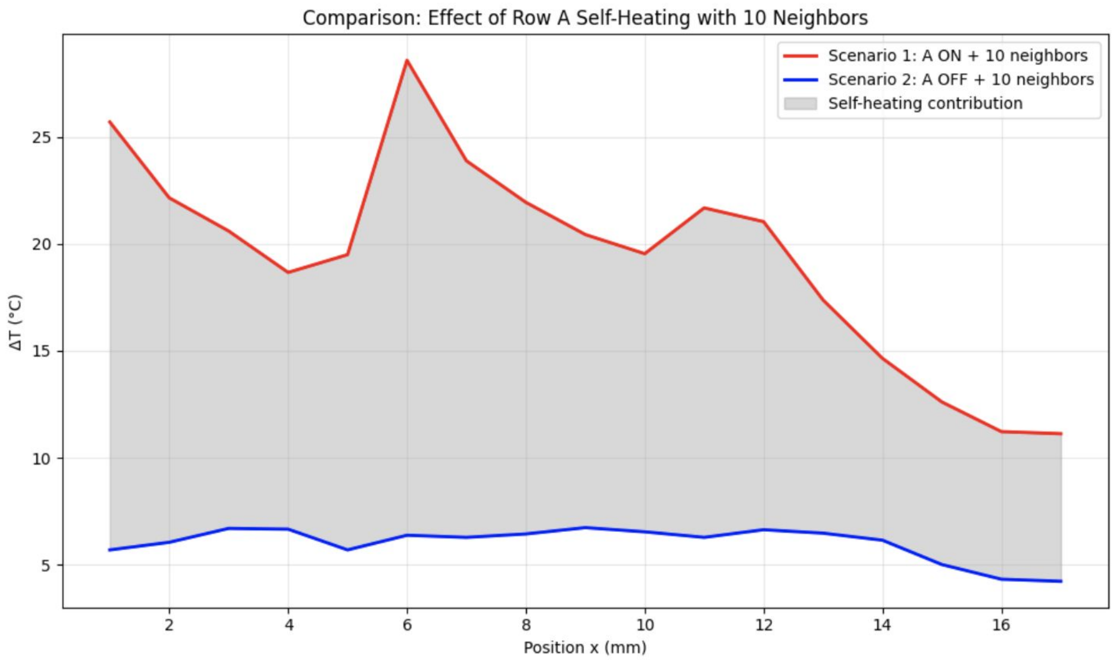


More Neighbors?





More Neighbors?

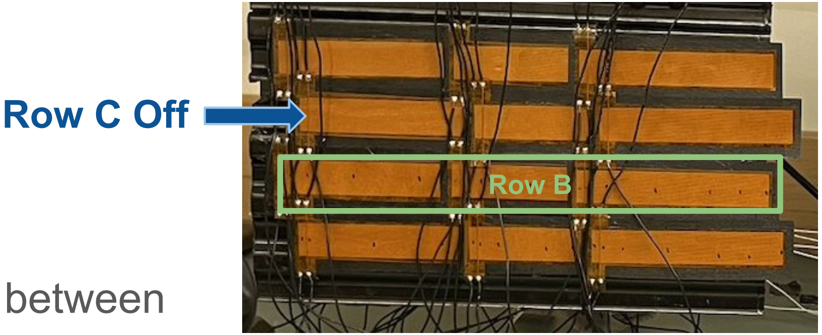


Key Insight

- Now we have created a model which can predict x vs dT for any arbitrary row. Specifically, any combination or rows turned on or off
- Profile is what we would expect AND is physically reasonable, unlike the last version

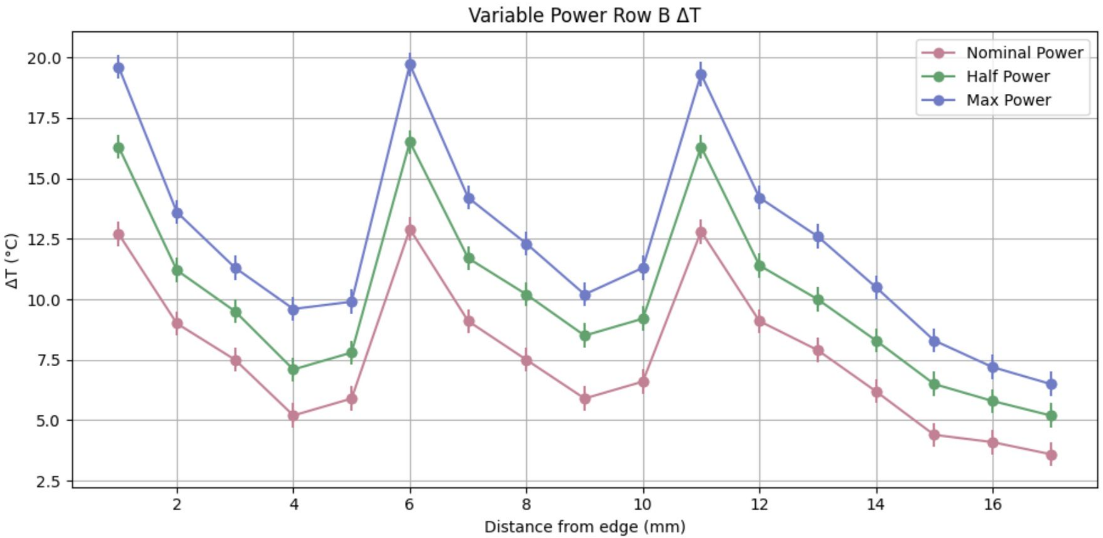
II. Power Density Studies

Single Row Power Densities



Measurements were taken across **Row B**

- Measured at nominal, maximum, and halfway between
- Difference in temperature **seems linear** with increasing power

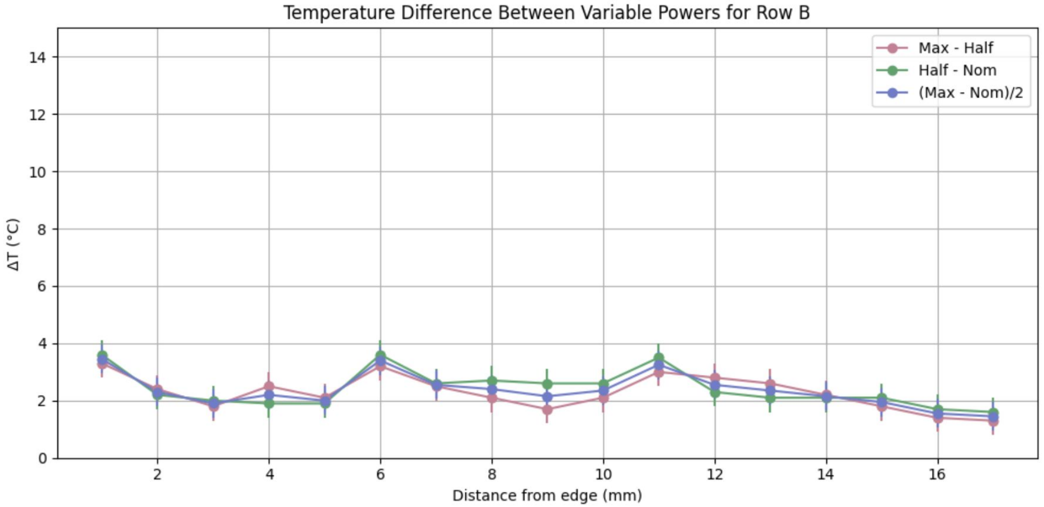


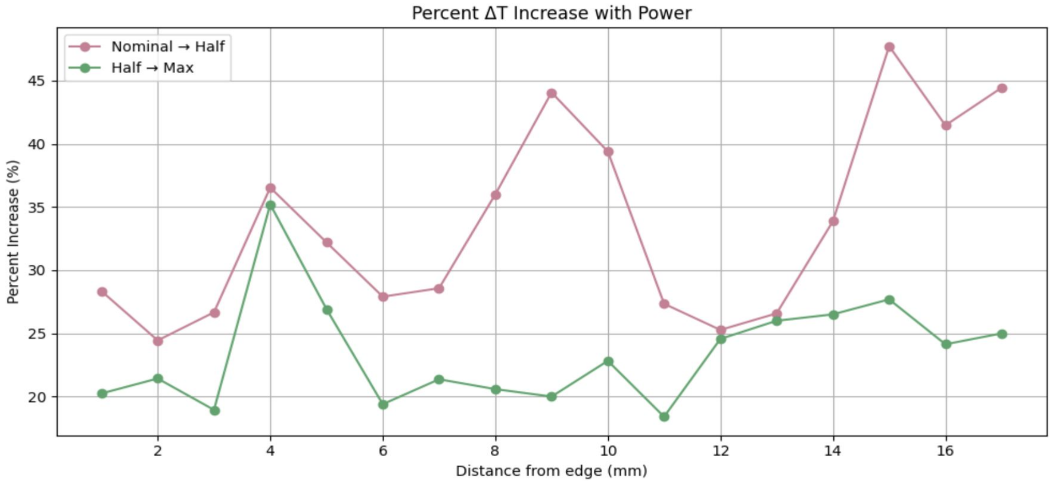
Power Data:
https://docs.google.com/spreadsheets/d/1JYRFwtVZQbA0ORGAF7ZDx16DwuzYTf7v/edit?gid=1878874453#gid=1878874453

Single Row Power

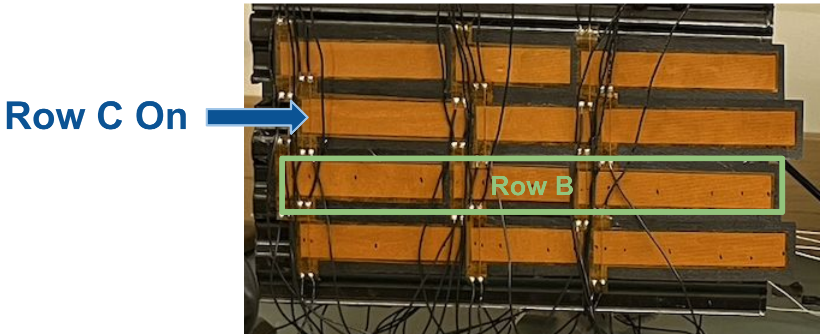
Percent difference plotted

- Going from nominal power to half power produces a larger fractional increase in ΔT than going from half Power to max Power
- That suggests diminishing returns
- **At the far right, the baseline ΔT is low since it is at the edge of the third RSU**
- The percentage jump looks huge even though the absolute temperature increase isn’t enormous



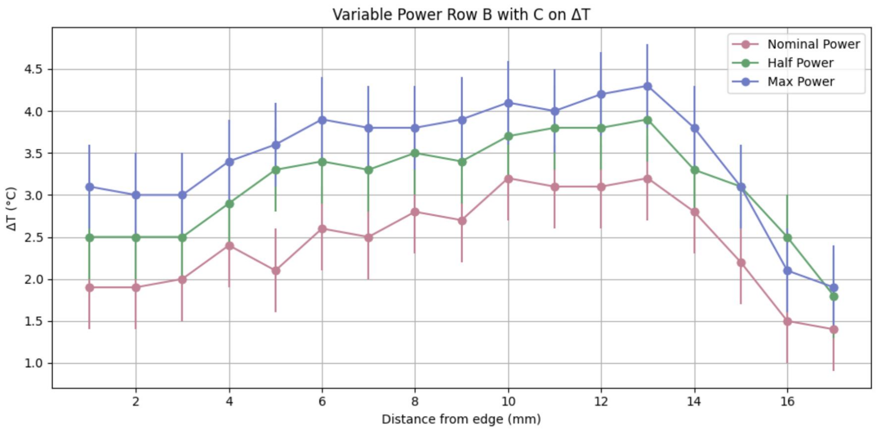


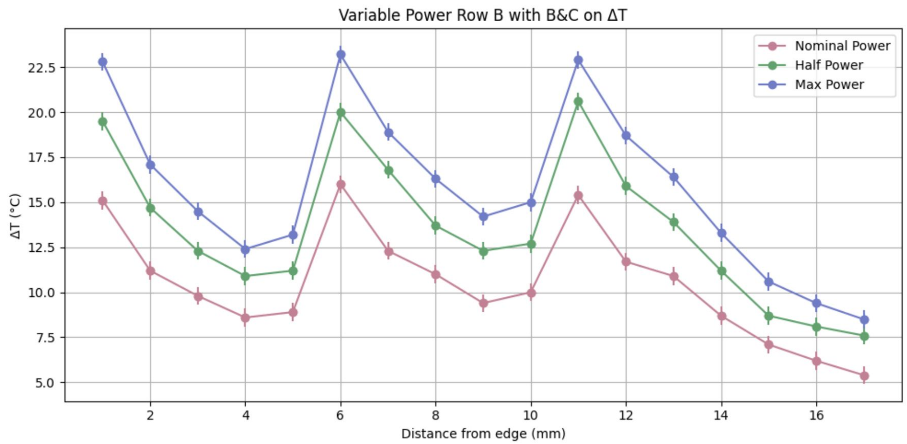
Power Densities: Multi Row



Measurements were taken across **Row B**

- This time Row C is also turned on
- Two measurements taken: with Row B&C on, and with B off and C on



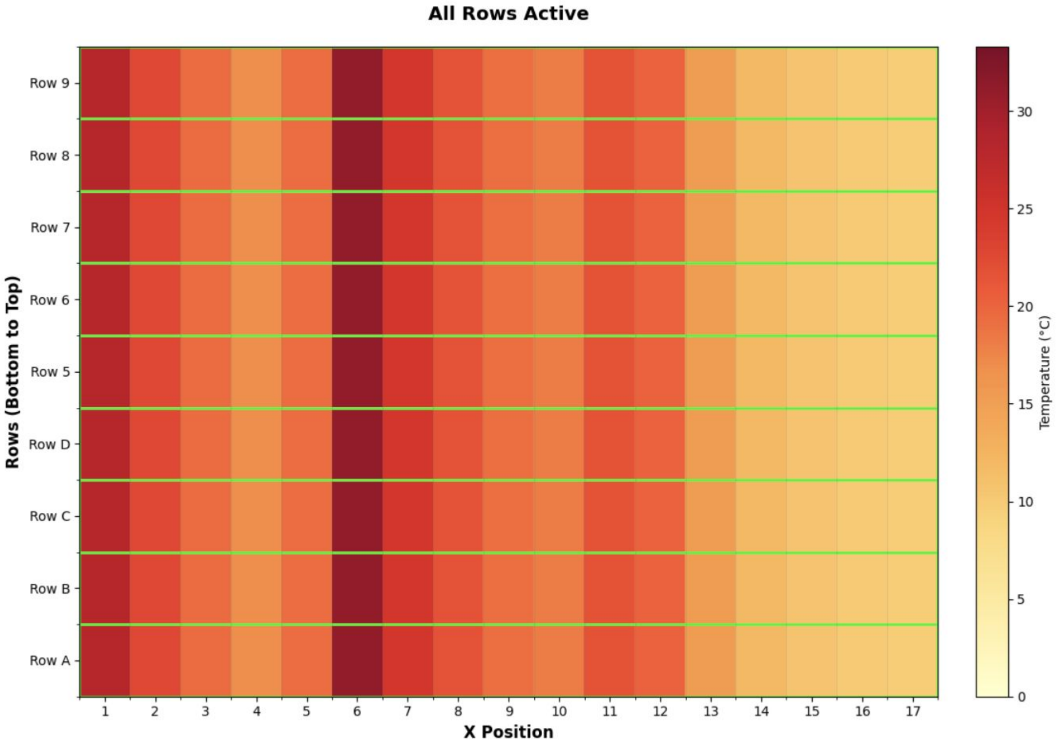


What’s Next?

To Do List

- I’ve taken data with **one row on the back of the panel**, to get how dT decays with opposite side neighbor distance
- I’ve also taken data for **symmetry considerations**, namely how turning on a row in the middle of a panel that has top and bottom neighbors acts.
- Feeding this data into the model is what will allow a full panel mock up, though there are some small problems that still need to be addressed
- Incorporating how dT scales with temperature into the model is fairly simple
- Have not yet taken air cooling data

Preview



Model

For each row:

1. Check if row is ON → Apply base temperature profile
2. Count active neighbors above and below
3. Calculate temperature multiplier based on neighbor count
4. Apply multiplier to base profile
5. Update grid with calculated temperatures