

# Towards Pulsating Heat Pipe Performance Prediction

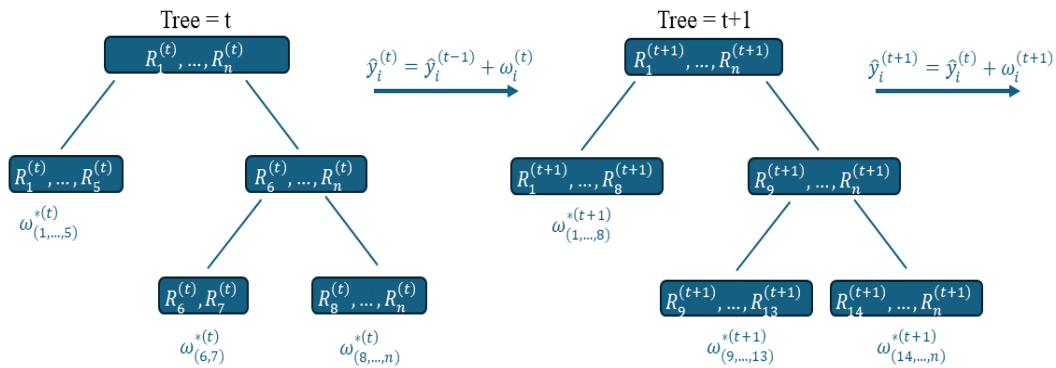


Friedrich Franke, Marvin Illbruck, Markus Kober, Lars Enghardt, Stefan Kazula | DLR | Stuttgart 2026

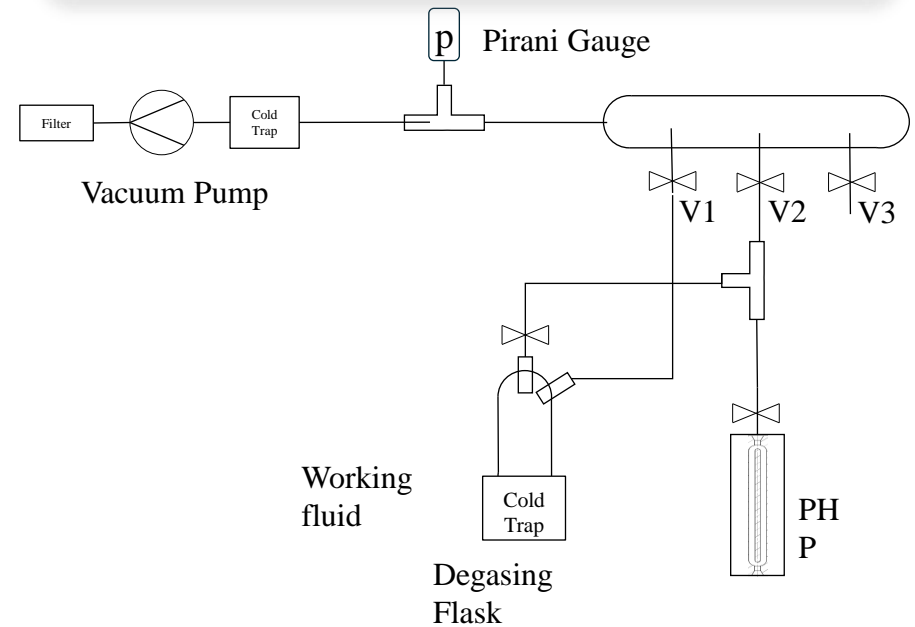
# Towards Pulsating Heat Pipe Performance Prediction

## Gradient Boosting

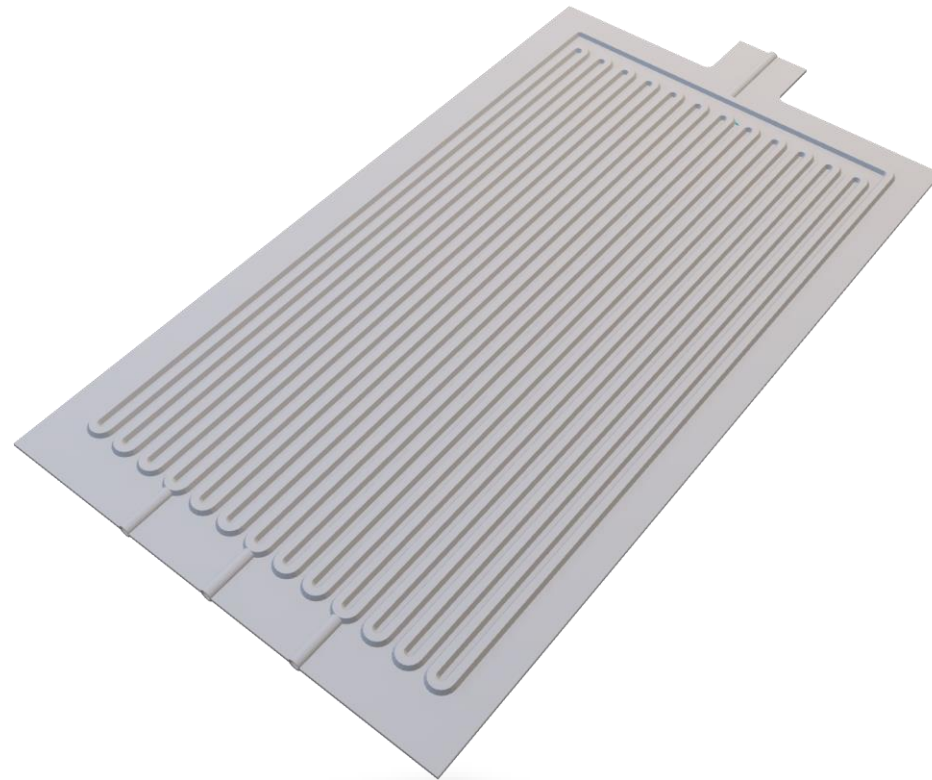
## Experimental Iteration



&

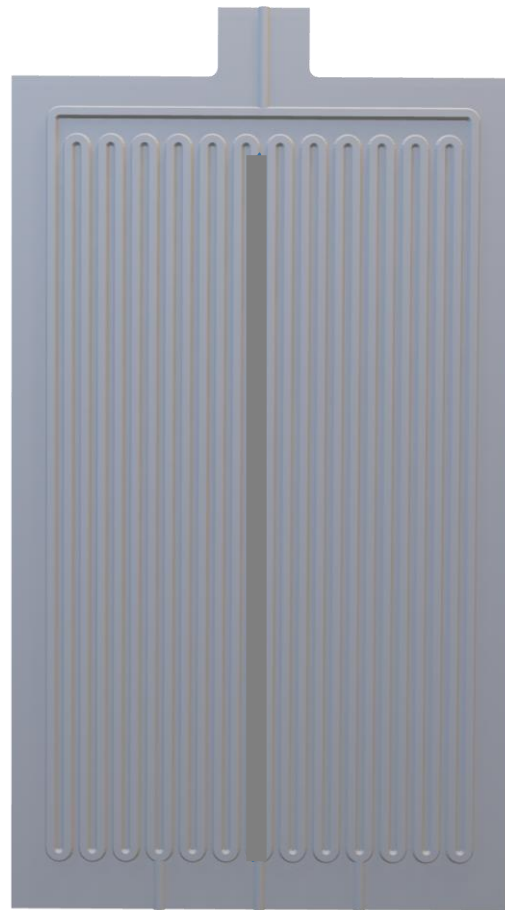


# Pulsating Heat Pipe (PHP)

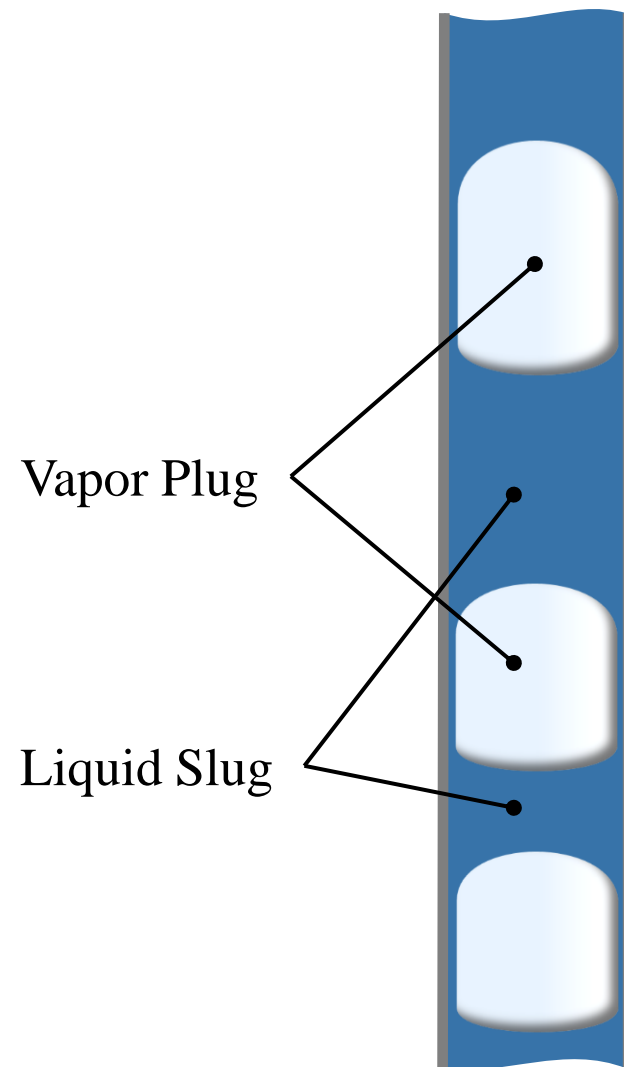


Friedrich Franke | DLR | Stuttgart 2026

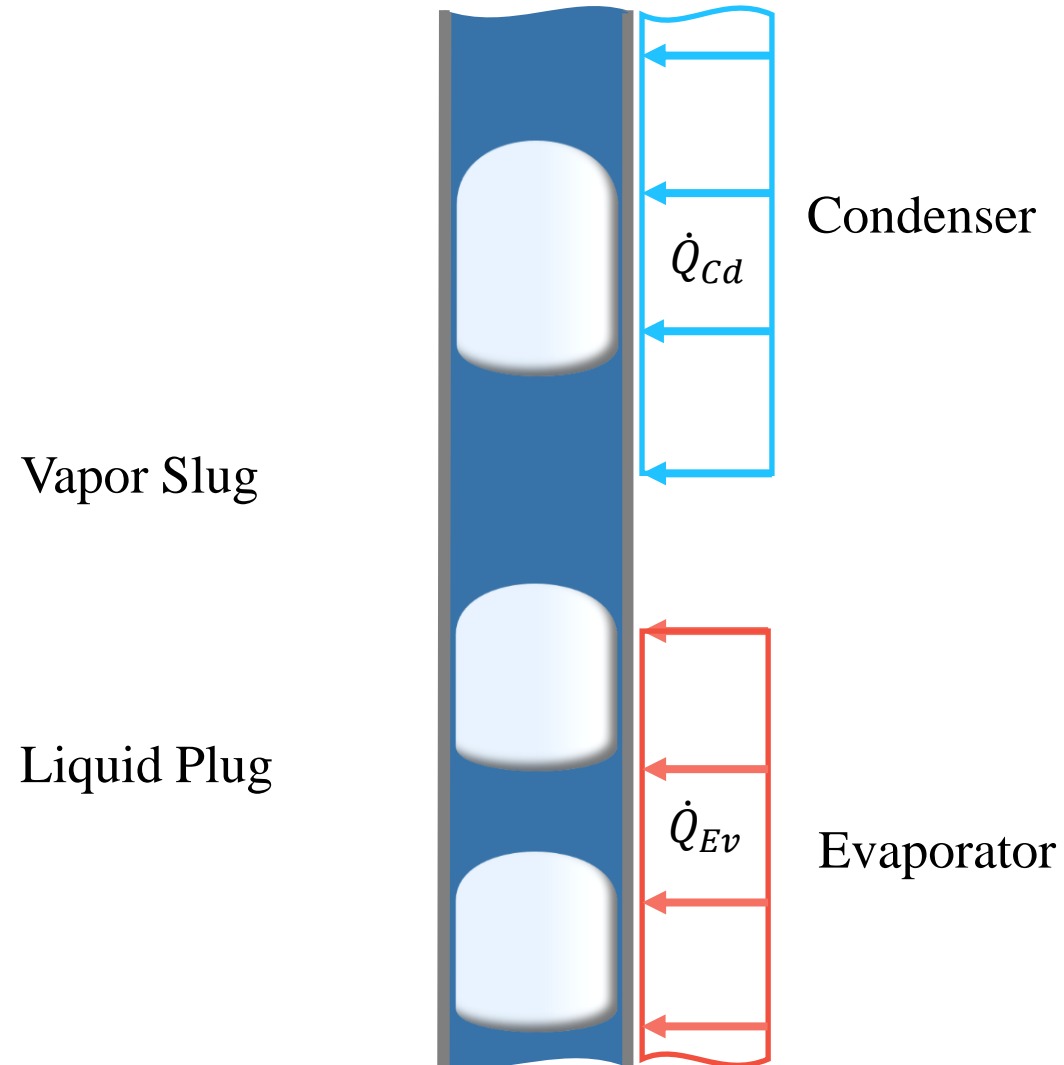
# Pulsating Heat Pipe (PHP)



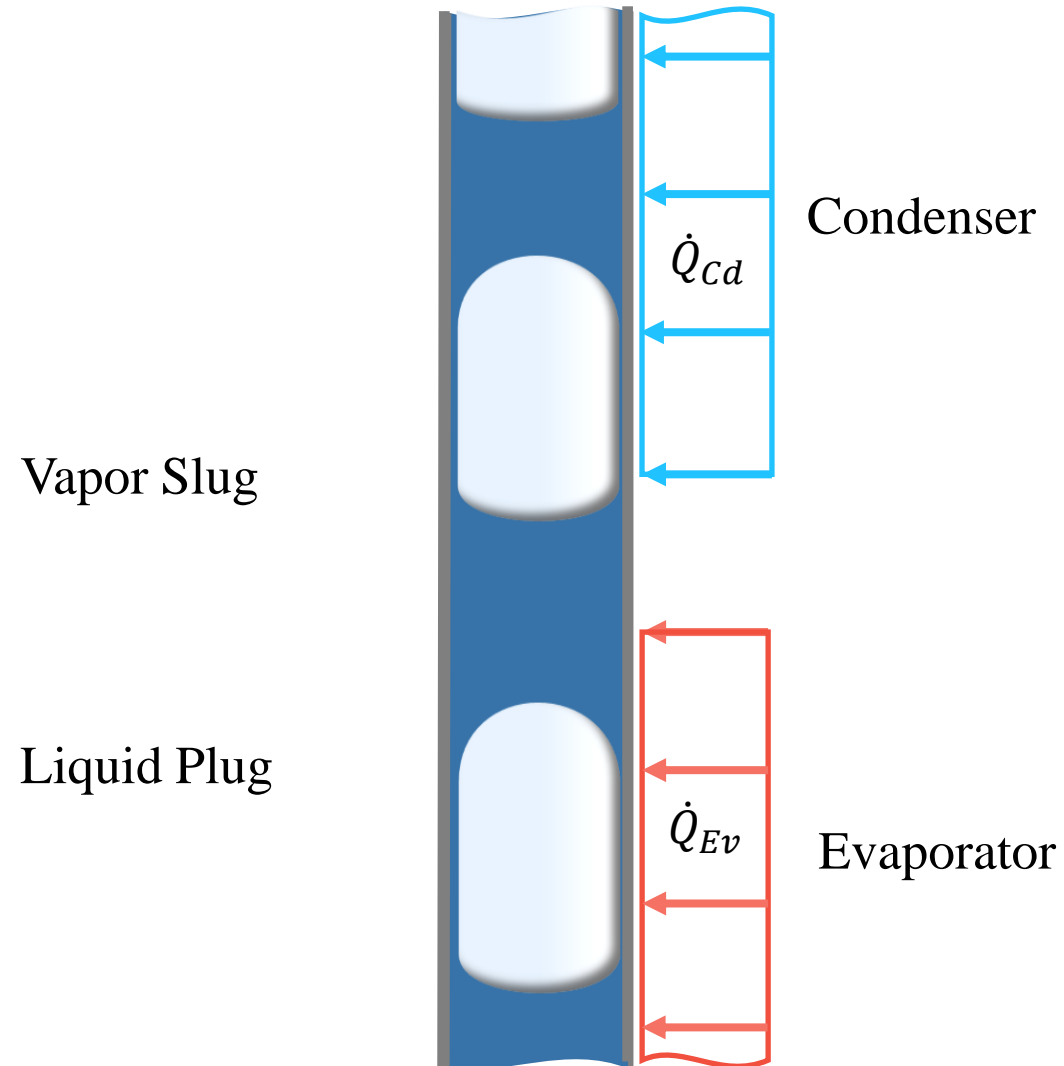
# PHP Working Principle



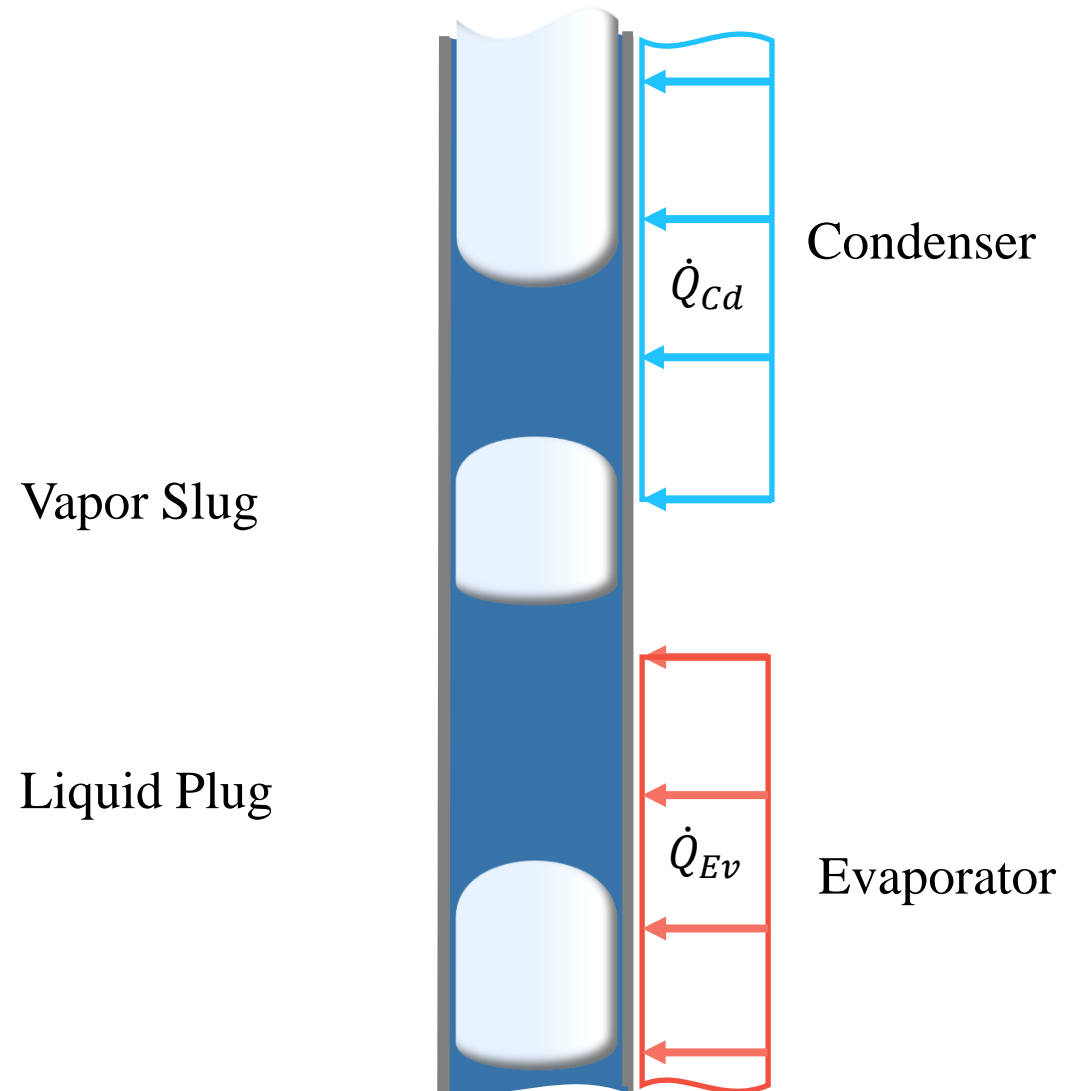
# PHP Working Principle



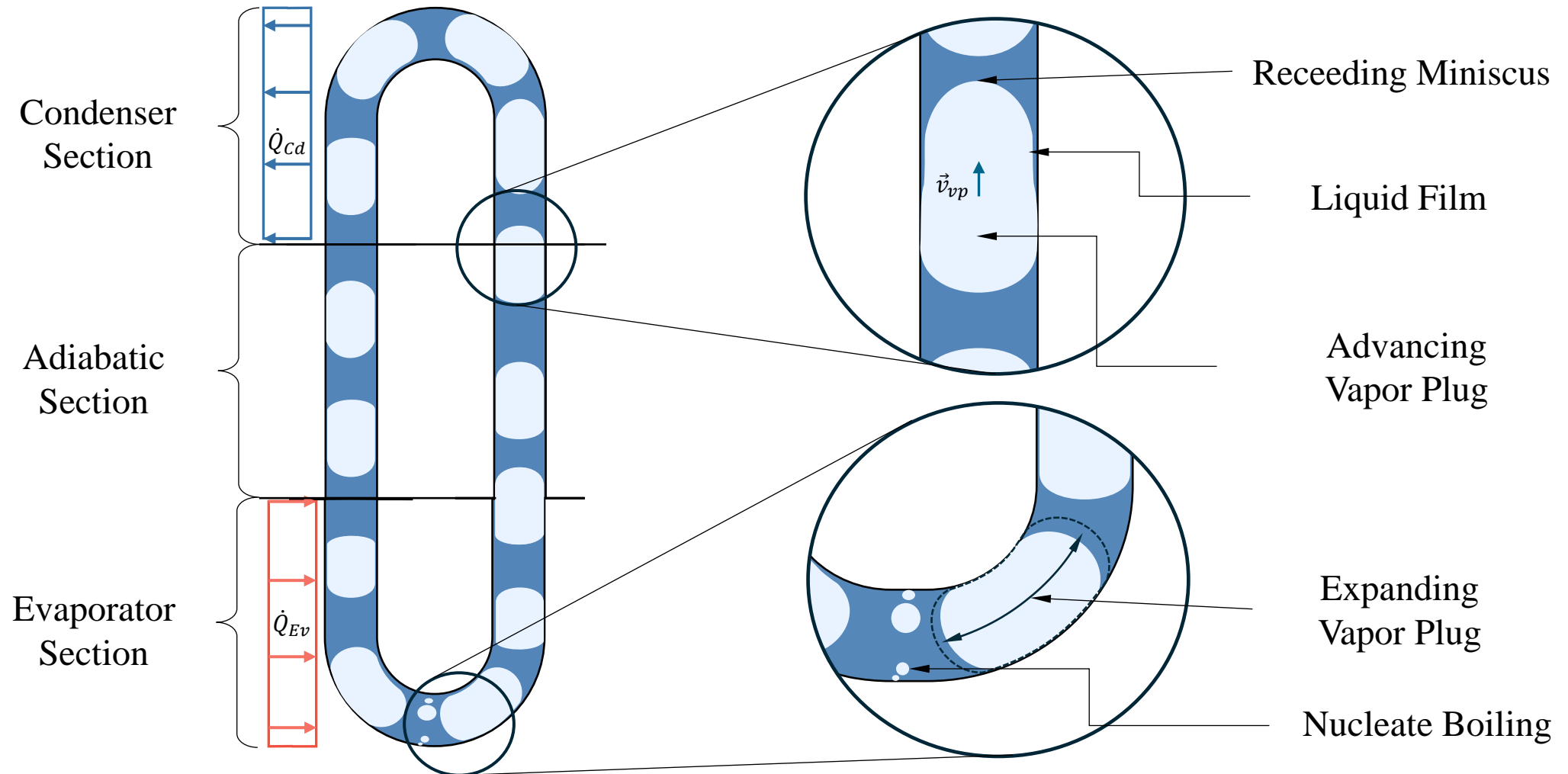
# PHP Working Principle



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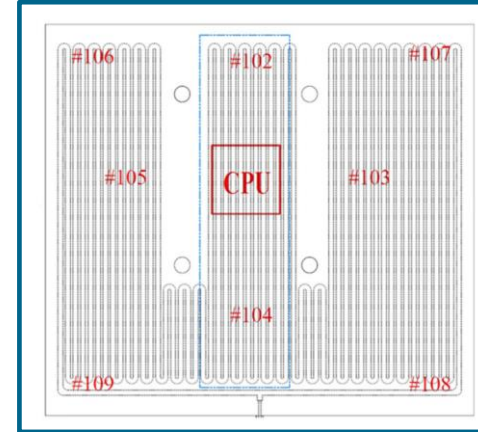


# PHP Working Principle

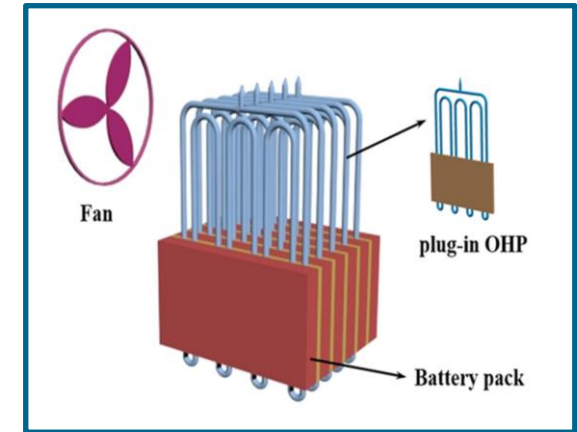


## Applications

- CPU cooling, [Li 2023]
- Battery cooling [Wei 2019]
- Electric machines [Aziza 2025]
- Fuel cell cooling



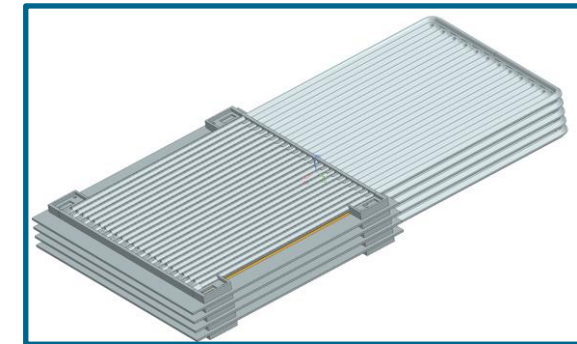
CPU Cooling [Li 2023]



Battery Pack Cooling [Wei 2019]



Electric Machine [Aziza 2025]



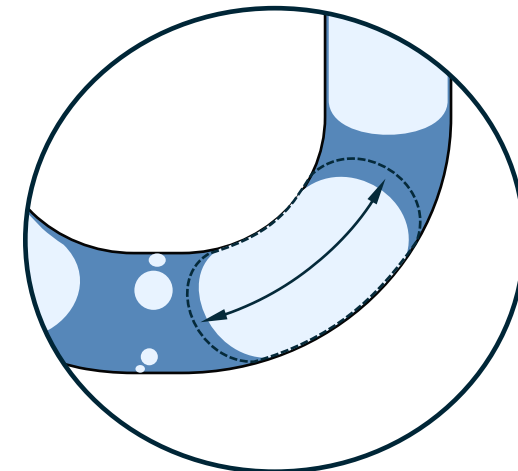
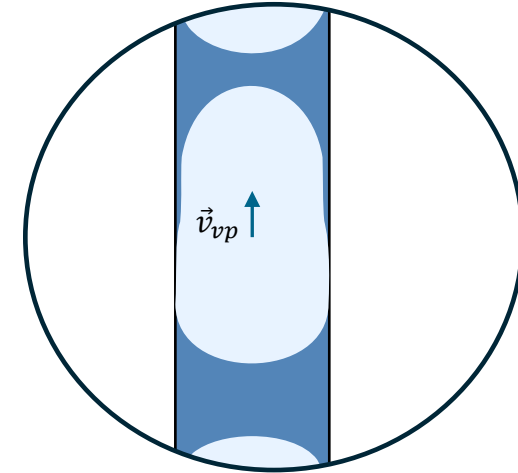
Fuel Cells [Franke 2025]

## ▪ Applications

- CPU [Li 2023], Battery [Wei 2019]
- Electric machines [Aziza 2025], Fuel Cells

## ▪ Simulation

- Complex multiphase & capillary interactions
- transient nature and long start up times [Fang 2024]
- *CFD lacks predictive capability*
- *1D-abstraction: some successes [Nikolayev 2021]*



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- CPU [Li 2023], Battery [Wei 2019]
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## ▪ Simulation

- Complex multiphase & capillary interactions
- transient nature and long start up times [Fang 2024]
- *CFD lacks predictive capability*
- *1D-abstraction: some successes [Nikolayev 2021]*

2 Phase  
problem

Small scale  
capillary  
forces

Wall friction &  
wetting

Unclear  
vapour state

Boiling,  
condensing &  
evaporation

Film  
deposition  
mechanics

Dynamic and  
long start up  
time

## Applications

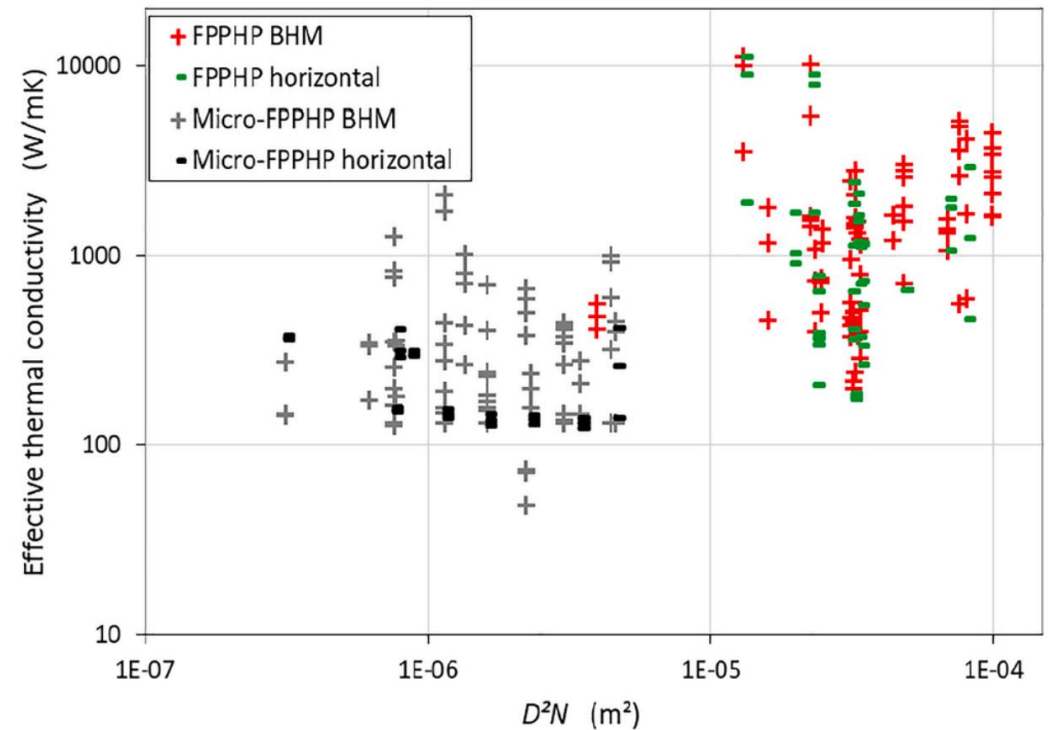
- CPU [Li 2023], Battery [Wei 2019]
- Electric machines [Aziza 2025], Fuel Cells

## Simulation

- Comple, Transient [Fang 2024]
- CFD lacks predictive capability
- 1D-abstraction: [Nikolayev 2021]

## Experimentation

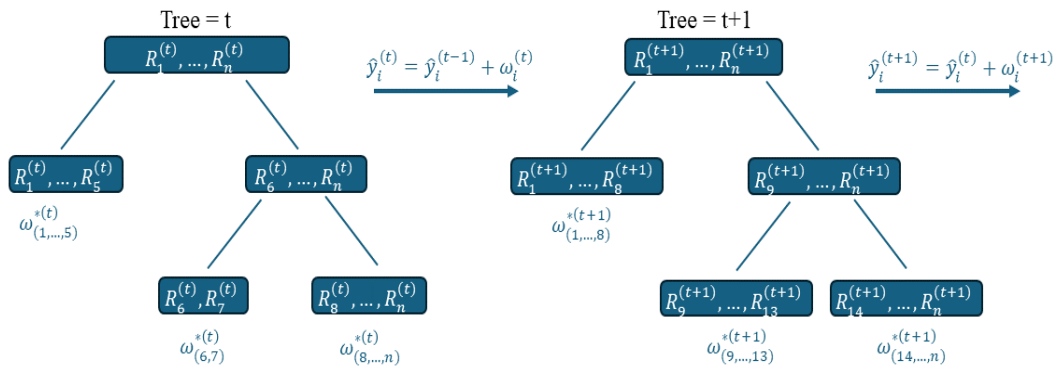
- Large variation in measured thermal performances [Ayel 2021]
- Variations in experimental setup



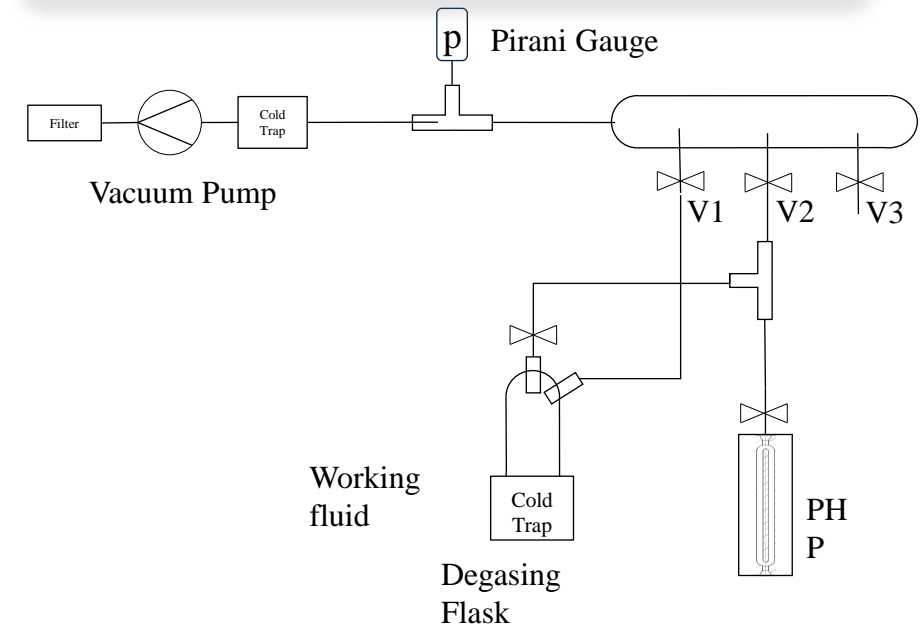
Equivalent thermal conductivities; data from [Ayel 2021]

# Dual Approach of this Work

## Thermal Resistance Prediction With Gradient Boosting

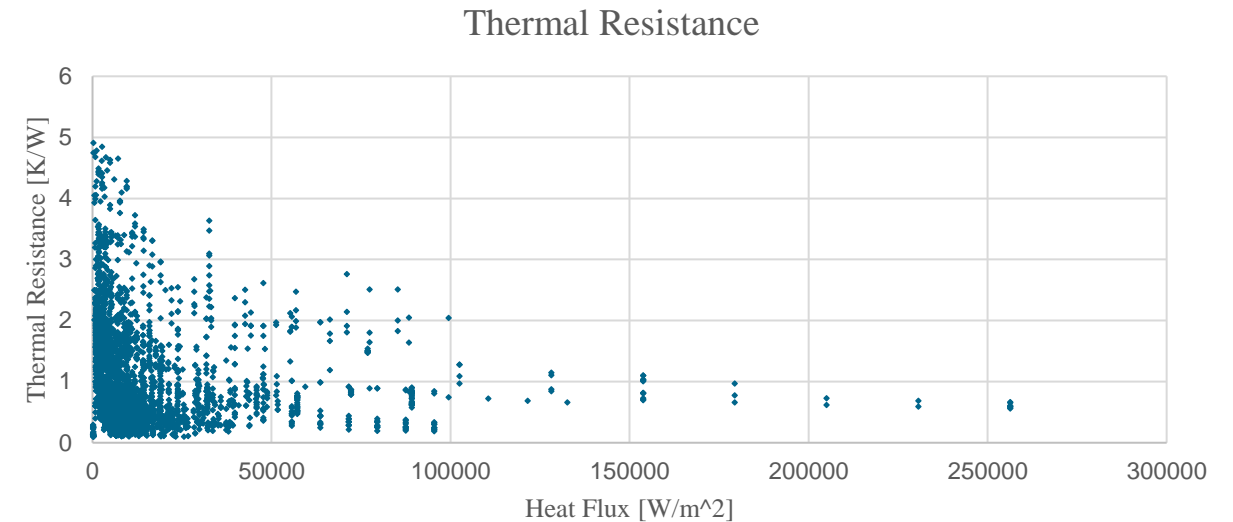


## Setup for Design of Experiments



# Thermal Resistance Prediction With Gradient Boosting

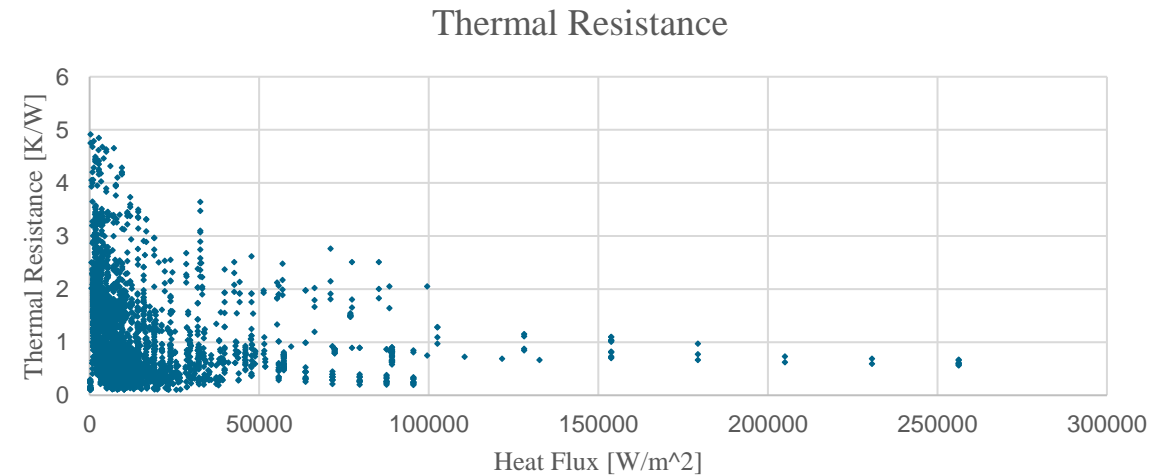
- **Collecting & curating PHP data**
  - 3441 Cases from Literature *[ref. in Appendix]*



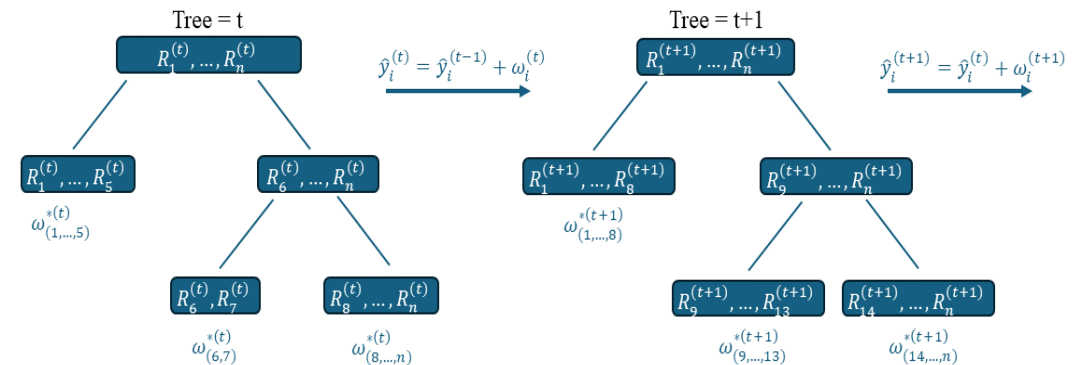
Visualization of the XG Boost Algorithm

# Thermal Resistance Prediction With Gradient Boosting

- **Collecting & curating PHP data**
  - 3441 Cases from Literature [ref. in Appendix]
- **Train a ML model [Illbruck 2026]**
- **Predict thermal performance**
  - *Key metric: Thermal resistance  $R_{th}$*



- **Validate Prediction**
  - Design of Experiments Setup



Visualization of the XG Boost Algorithm

# Thermal Resistance Prediction With Gradient Boosting



- **Train a ML model** [Illbruck 2026]
  - *XG Boost Algorithm*  
[Friedman 2012, Chen 2016]

Case	Heat [W]	Pipe mat.	Fluid	$R_{th}$ [K/W]
1	20	Copper	Water	1.00
2	40	Aluminium	Ethanol	0.85
3	60	Copper	Ethanol	0.60
4	80	Copper	Methanol	0.55
5	100	Aluminium	Water	0.20

Hypothetical, simplified PHP Data set

# Thermal Resistance Prediction With Gradient Boosting

- **Train a ML model** [Illbruck 2026]
  - *XG Boost Algorithm*  
[Friedman 20012, Chen 2016]

Initial Guess:  $\hat{y}^{(0)} = 1$

$$r = \hat{y}^{(0)} - y$$

Case	Heat [W]	Pipe mat.	Fluid	$R_{th}$ [K/W]	Residual r
1	20	Copper	Water	1.00	0
2	40	Aluminium	Ethanol	0.85	0.15
3	60	Copper	Ethanol	0.60	0.4
4	80	Copper	Methanol	0.55	0.45
5	100	Aluminium	Water	0.20	0.8

Hypothetical, simplified PHP Data set

# Thermal Resistance Prediction With Gradient Boosting



Initial Guess

$$\hat{y}^{(0)} = 1$$

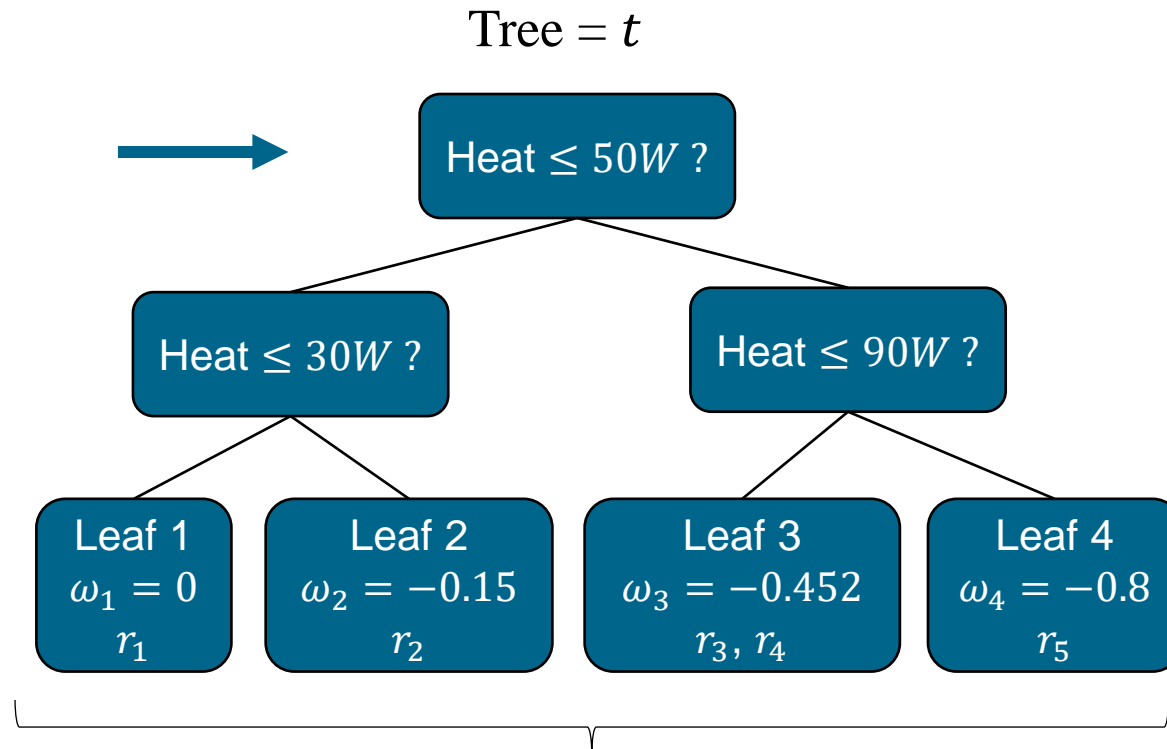
$$r = \hat{y}^{(0)} - y$$

# Thermal Resistance Prediction With Gradient Boosting

Initial Guess

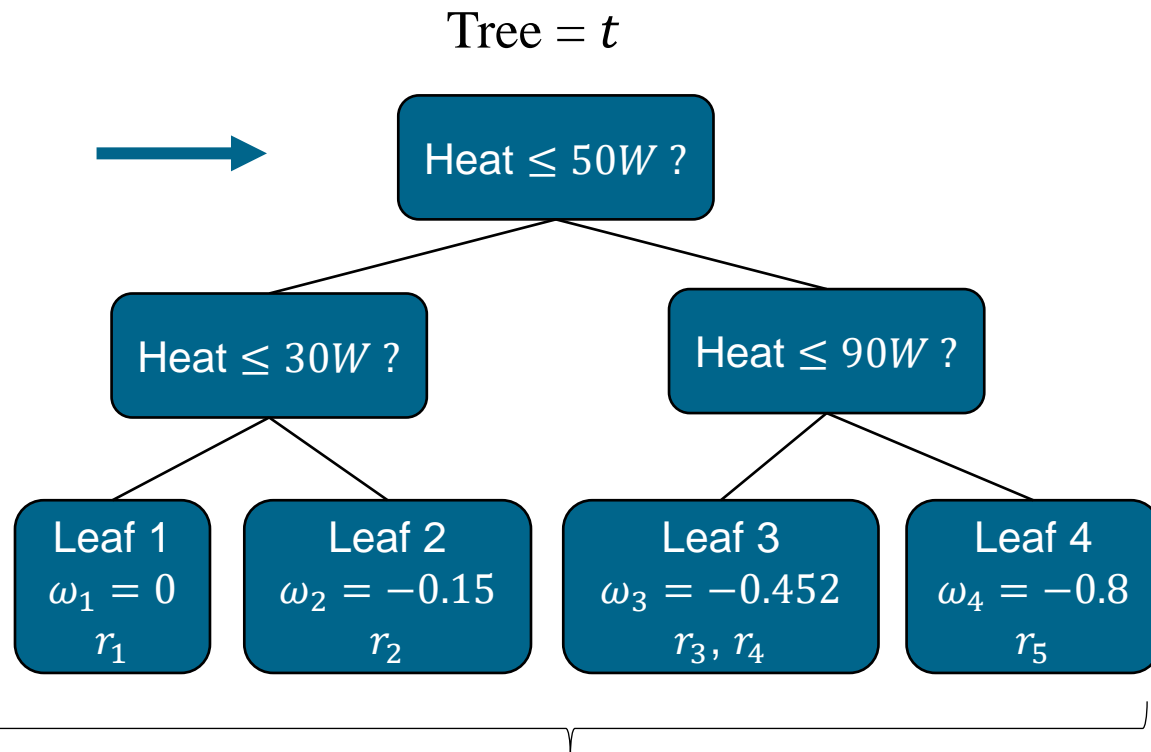
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Clustering residuals and calculating weights  $\omega_i$

# Thermal Resistance Prediction With Gradient Boosting



Clustering residuals and calculating weights  $\omega_i$

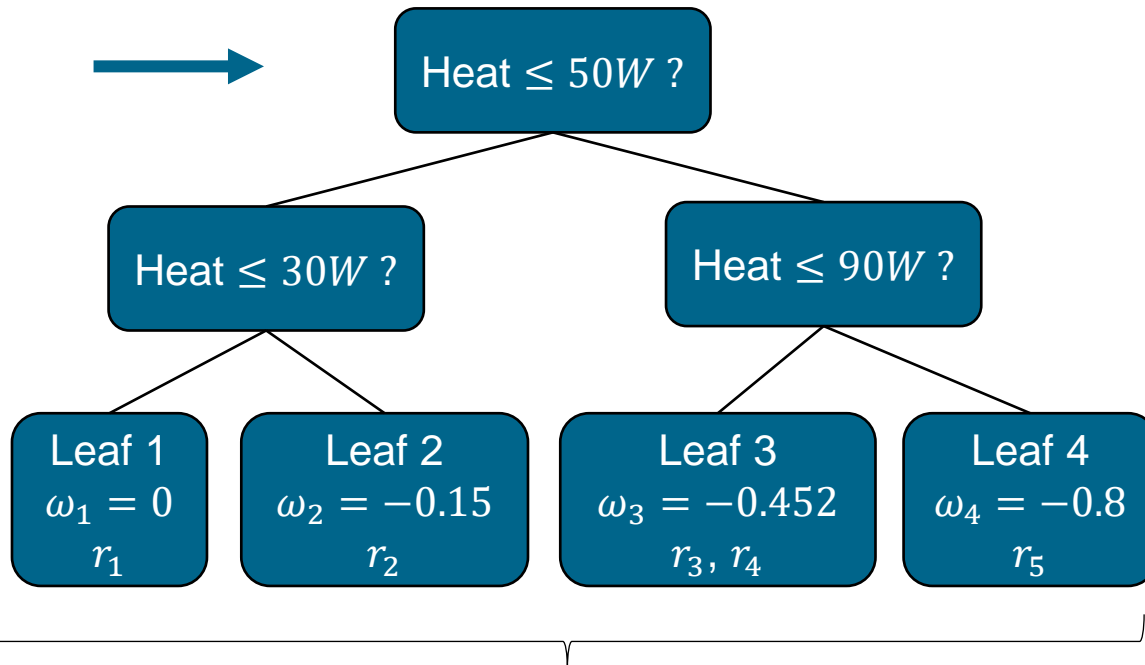
- **Evaluation function**

$$L^{(t)} = \sum_{i=1}^n l(y_i, \hat{y}_i^{t-1} + f_t(x_i)) + \Omega(f_t)$$

- **Regularization term**  $\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \|\omega^2\|$

# Thermal Resistance Prediction With Gradient Boosting

Tree =  $t$



Clustering residuals and calculating weights  $\omega_i$

- **Evaluation function**

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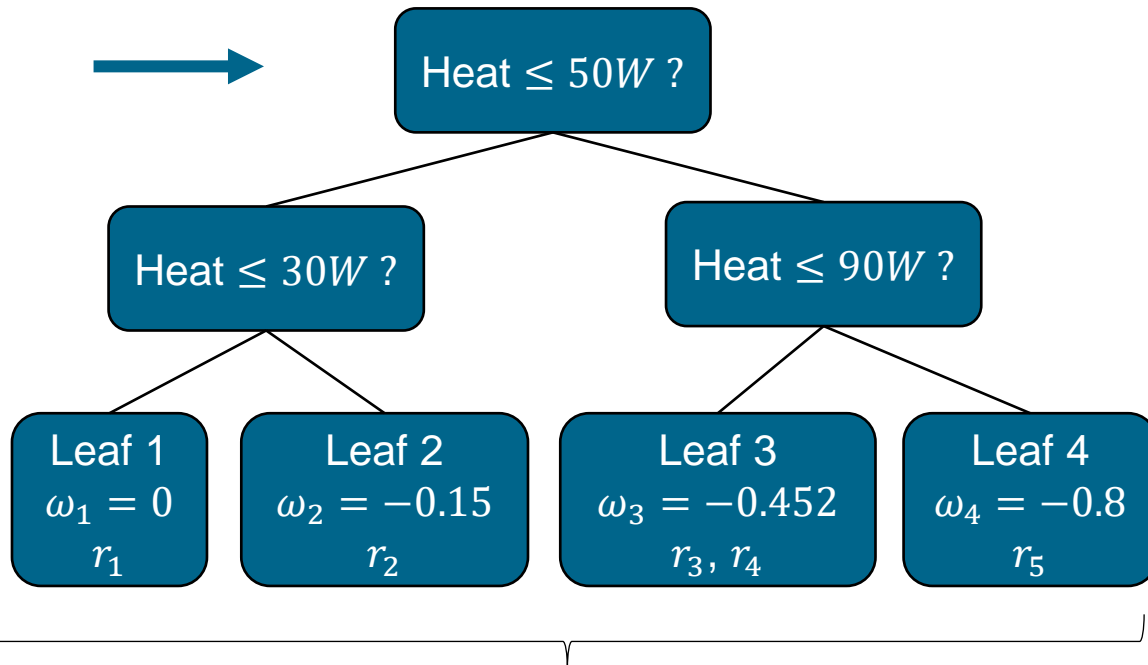
- **Regularization term**  $\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \|\omega^2\|$

- **Taylor Approximation**

$$L^{(t)} \approx \sum_{i=1}^n \left[ l(y_i, \hat{y}_i^{t-1}) + \frac{\partial l(y_i, \hat{y}_i^{t-1})}{\partial \hat{y}_i} f_t(x_i) + \frac{1}{2} \frac{\partial^2 l(y_i, \hat{y}_i^{t-1})}{\partial \hat{y}_i^2} f_t(x_i)^2 + \mathcal{O} \right] + \Omega(f_t)$$

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Tree =  $t$



Clustering residuals and calculating weights  $\omega_i$

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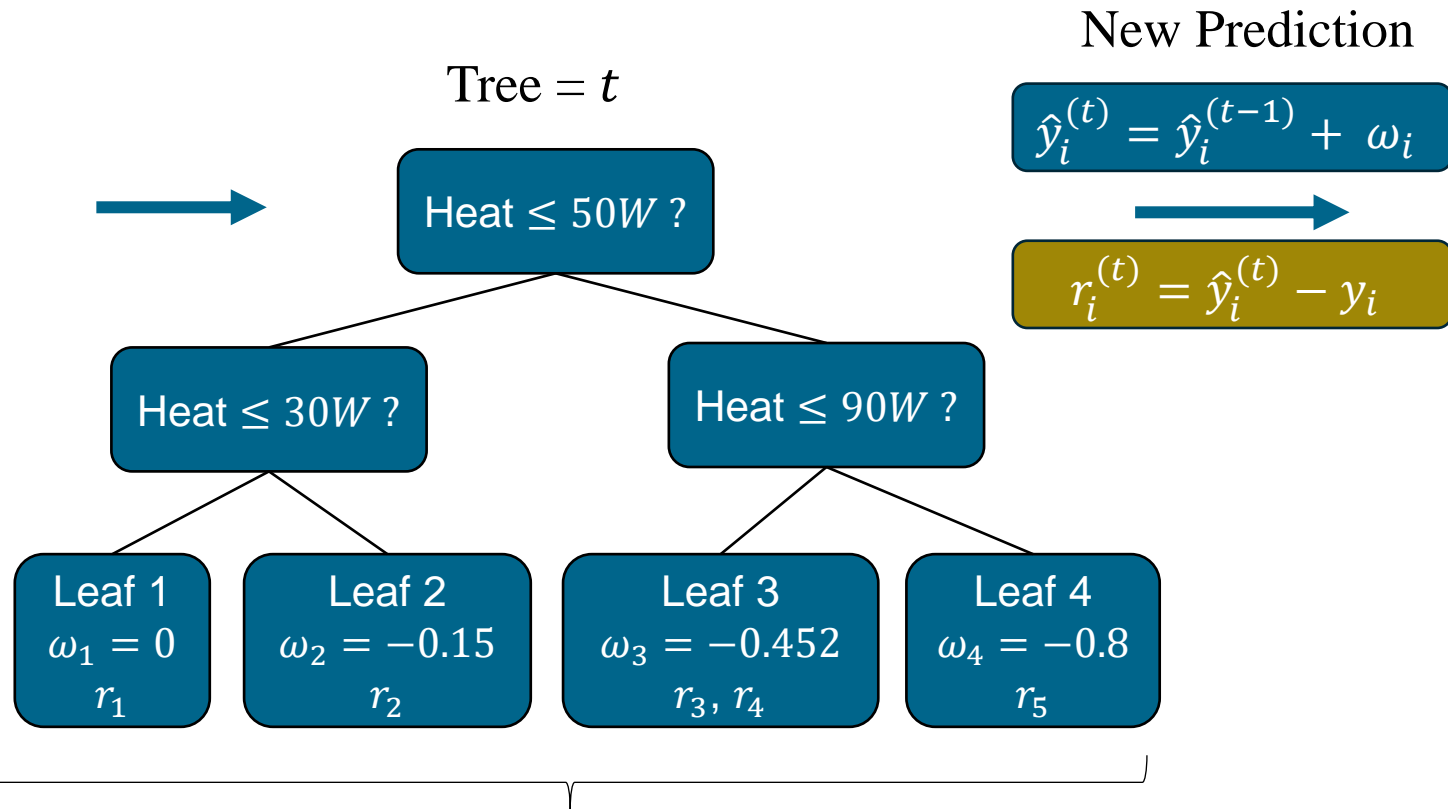
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- **Gradient**  $\frac{\partial L^{(t)}}{\partial f_t} = 0$

$$f_t(x_i) = \omega_j^* = - \frac{\sum_{i \in I_j} \frac{\partial l(y_i, \hat{y}_i^{t-1})}{\partial \hat{y}_i}}{\sum_{i \in I_j} \frac{\partial^2 l(y_i, \hat{y}_i^{t-1})}{\partial \hat{y}_i^2} + \lambda}$$

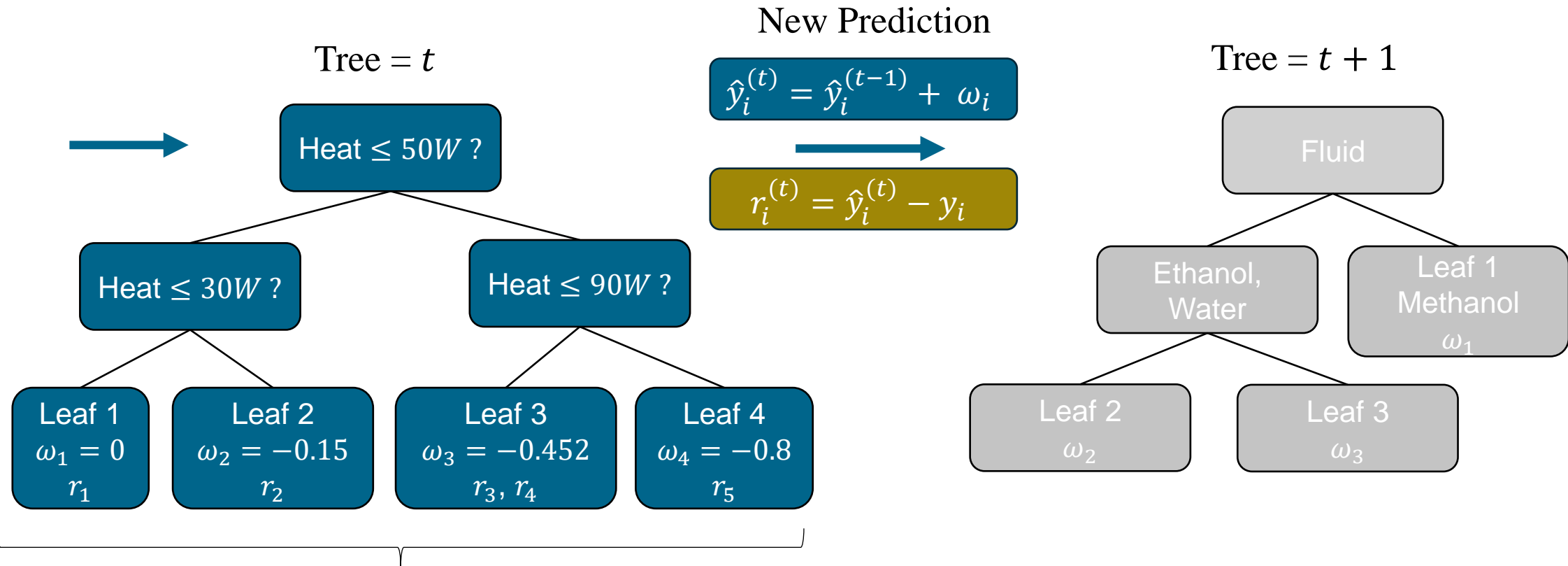
# Thermal Resistance Prediction With Gradient Boosting



Case	New $R_{th}$ Prediction
1	1
2	0.85
3	0.548
4	0.548
5	0.2

Clustering residuals and calculating weights  $\omega_i$

# Thermal Resistance Prediction With Gradient Boosting



Clustering residuals and calculating weights  $\omega_i$

# Thermal Resistance Prediction With Gradient Boosting

New Prediction

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + \omega_i$$



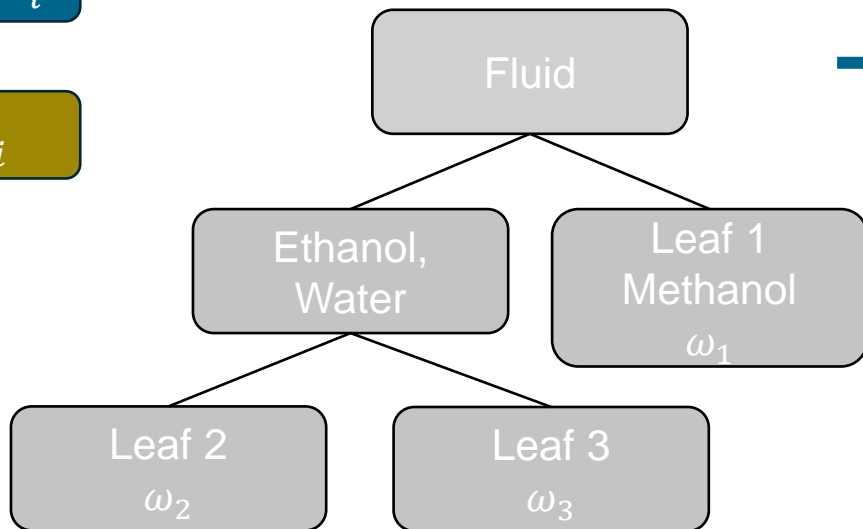
$$r_i^{(t)} = \hat{y}_i^{(t)} - y_i$$

?

Leaf 4  
 $\omega_4 = -0.8$   
 $r_5$

hts  $\omega_i$

Tree =  $t + 1$



Tree =  $t^K$

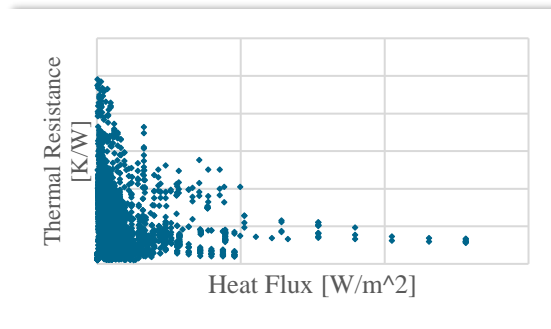


Final Prediction

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i)$$

# Thermal Resistance Prediction With Gradient Boosting

## 1 Data curation

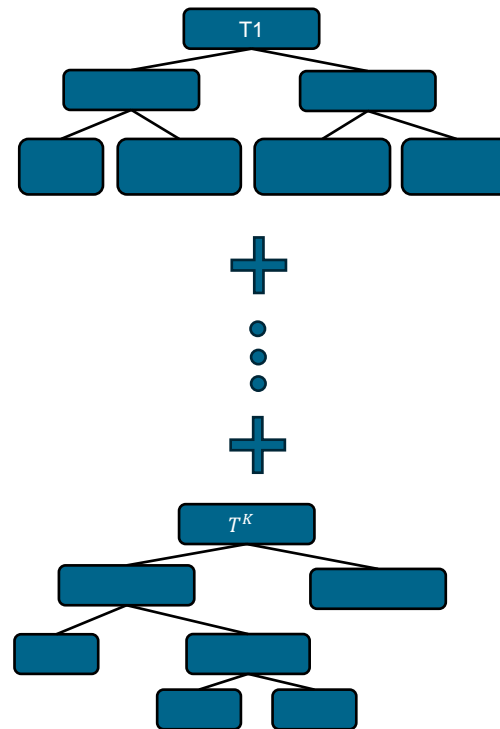


Data Split

Training  
70%

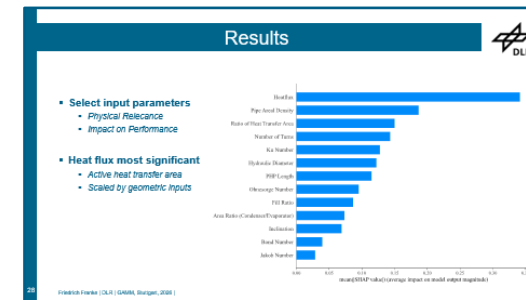
Test  
30%

## 2 Model training



## 3 Testing & application

Result of  
Prediction



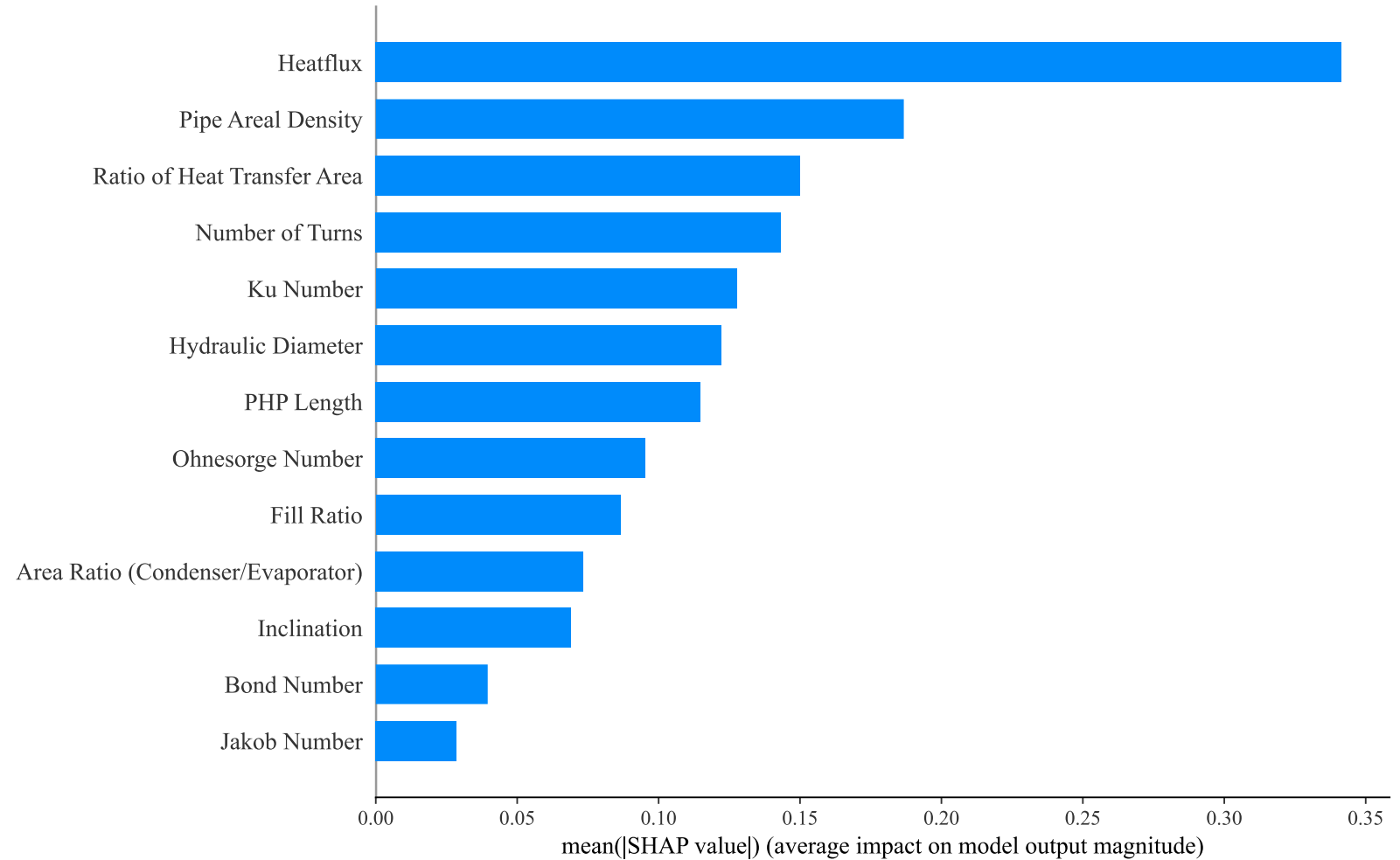
## 4 Validation & Expansion

- **Select input parameters**

- *Physical Relevance*
- *Impact on Performance*

- **Heat flux most significant**

- *Active heat transfer area*
- *Scaled by geometric inputs*



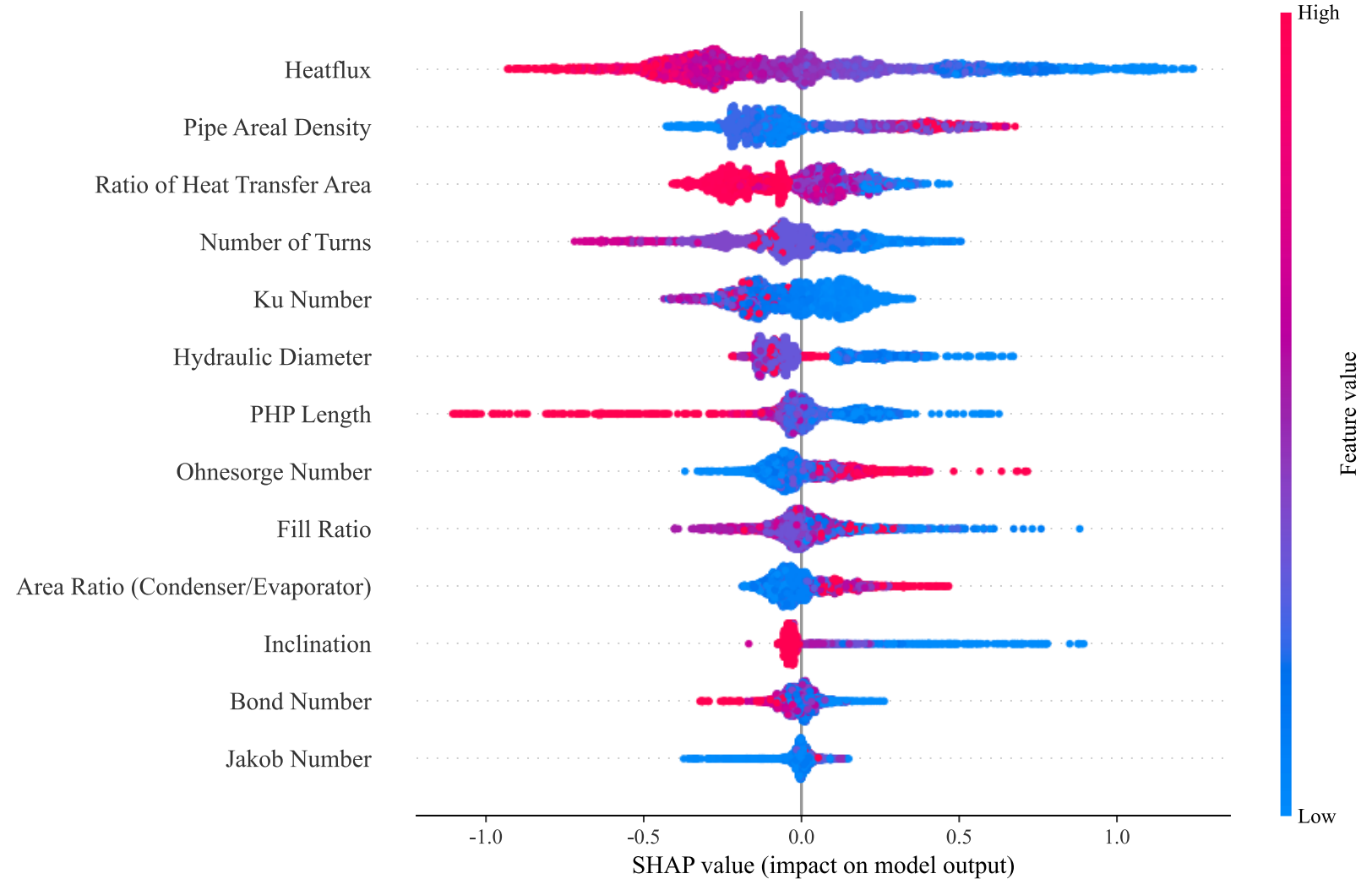
# Results

- **Select input parameters**

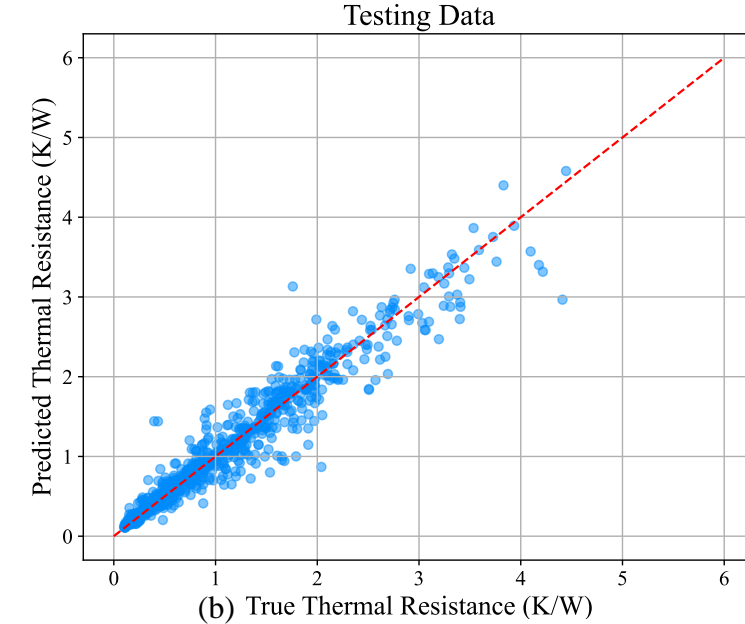
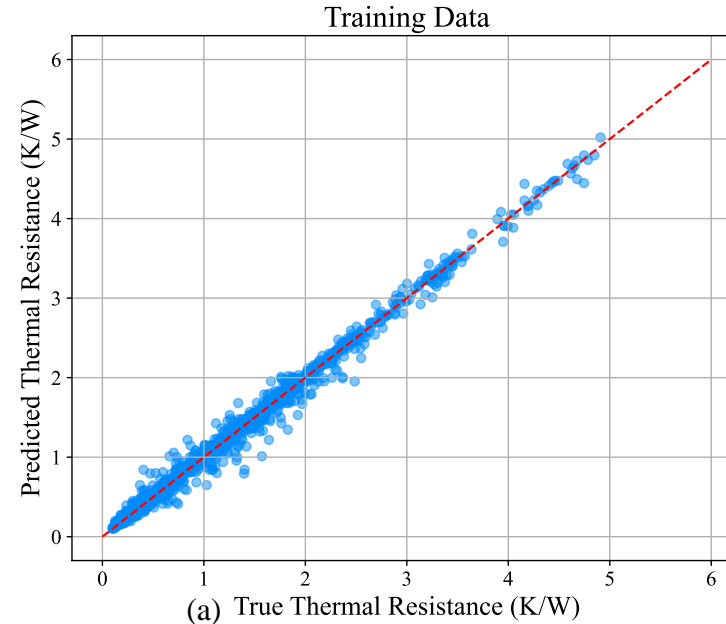
- *Physical Relevance*
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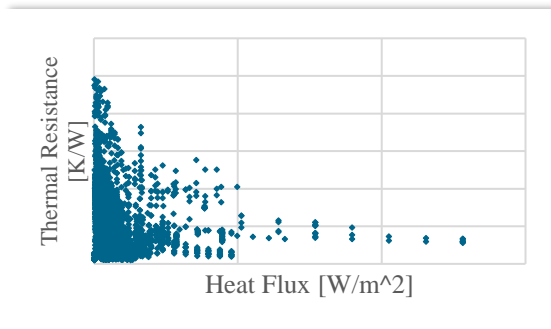
- **Select input parameters**
  - *Physical Relevance*
  - *Impact on Performance*
- **Heat flux most significant**
  - *Active heat transfer area*
  - *Scaled by geometric inputs*
- **Very high model accuracy**
  - *Mean Average Error = 0.11 K/W*
  - *Corresponds to approx 20% relative error*



Parity plots for model training (a) and testing (b)

# Thermal Resistance Prediction With Gradient Boosting

## 1 Data selection

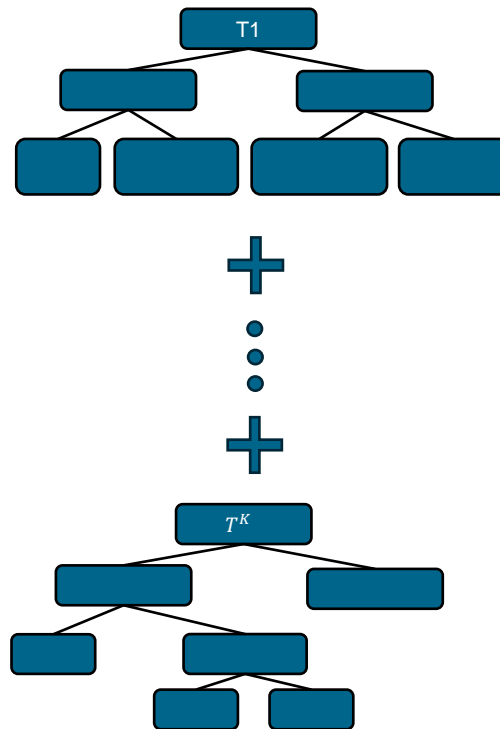


Data Split

Training  
70%

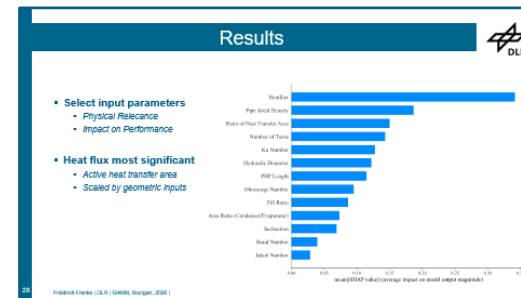
Test  
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## 2 Model training



## 3 Testing & application

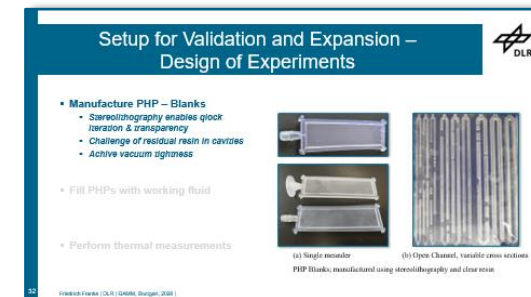
Result of  
Prediction



## 4 Validation & Expansion

Validation

Expansion to  
new Geometries



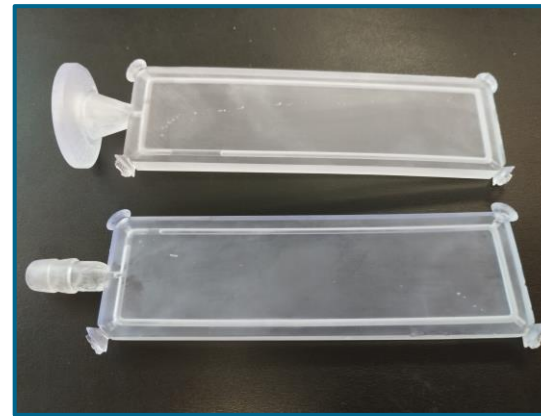
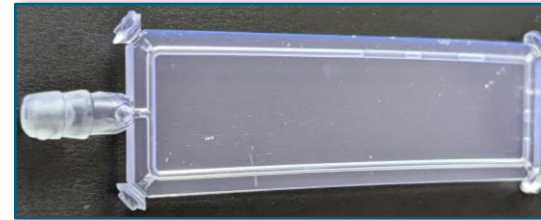
Setup for Validation and Expansion – Design of Experiments

- Manufacture PHP – Blanks
  - Stereolithography enables glass transition & transparency
  - Challenge of residual resin in cavities
  - Active vacuum signness
- Fill PHPs with working fluid
- Perform thermal measurements

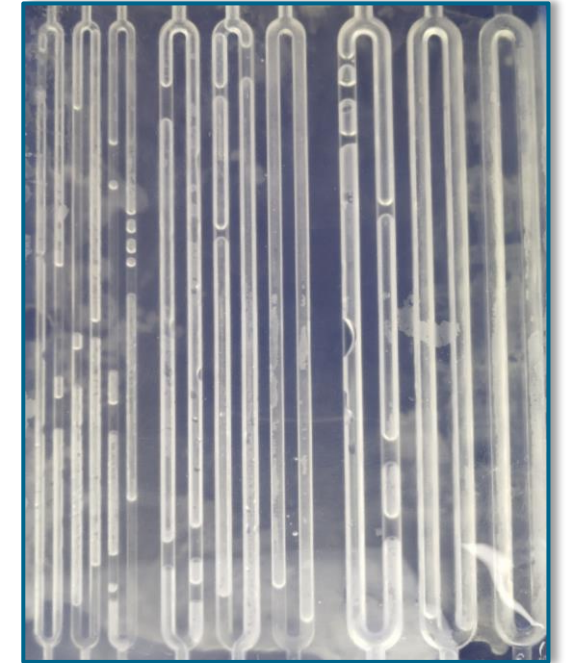
(a) Single moulder (b) Open Channel, variable cross sections  
PHP Blanks, manufactured using stereolithography and clear resin

# Setup for Validation and Expansion – Design of Experiments

- **Manufacture PHP – Blanks**
  - *Stereolithography enables quick iteration & transparency*
  - *Challenge of residual resin in cavities*
  - *Achieve vacuum tightness*
- Fill PHPs with working fluid
- Perform thermal measurements



(a) Single meander

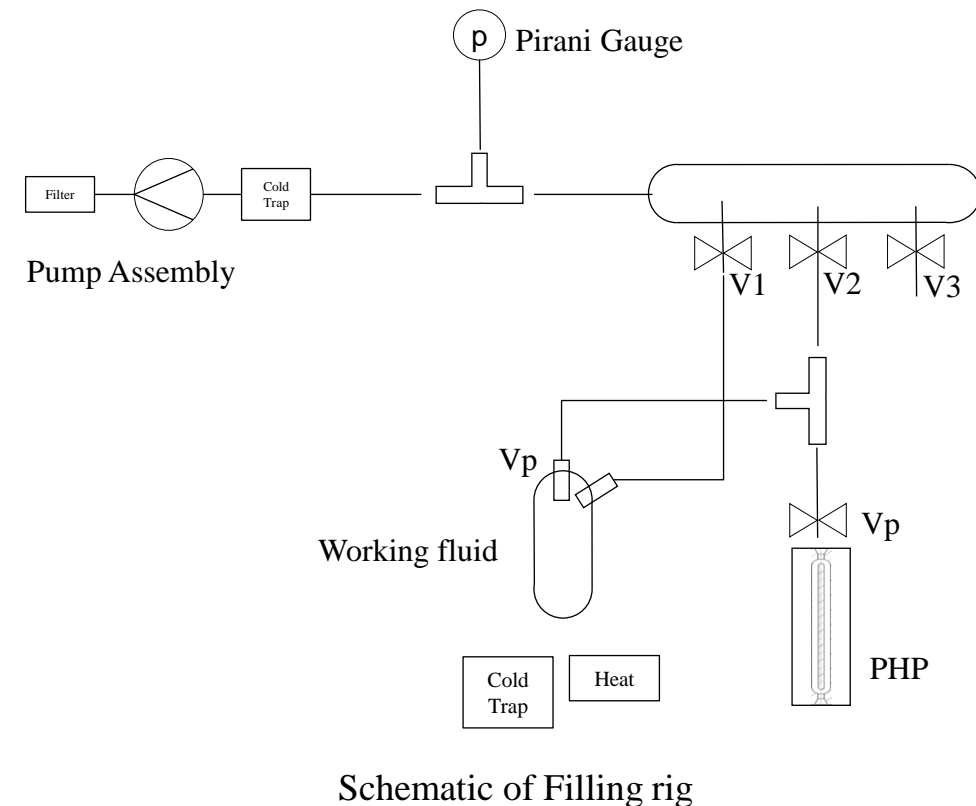


(b) Open Channel, variable cross sections

PHP Blanks; manufactured using stereolithography and clear resin

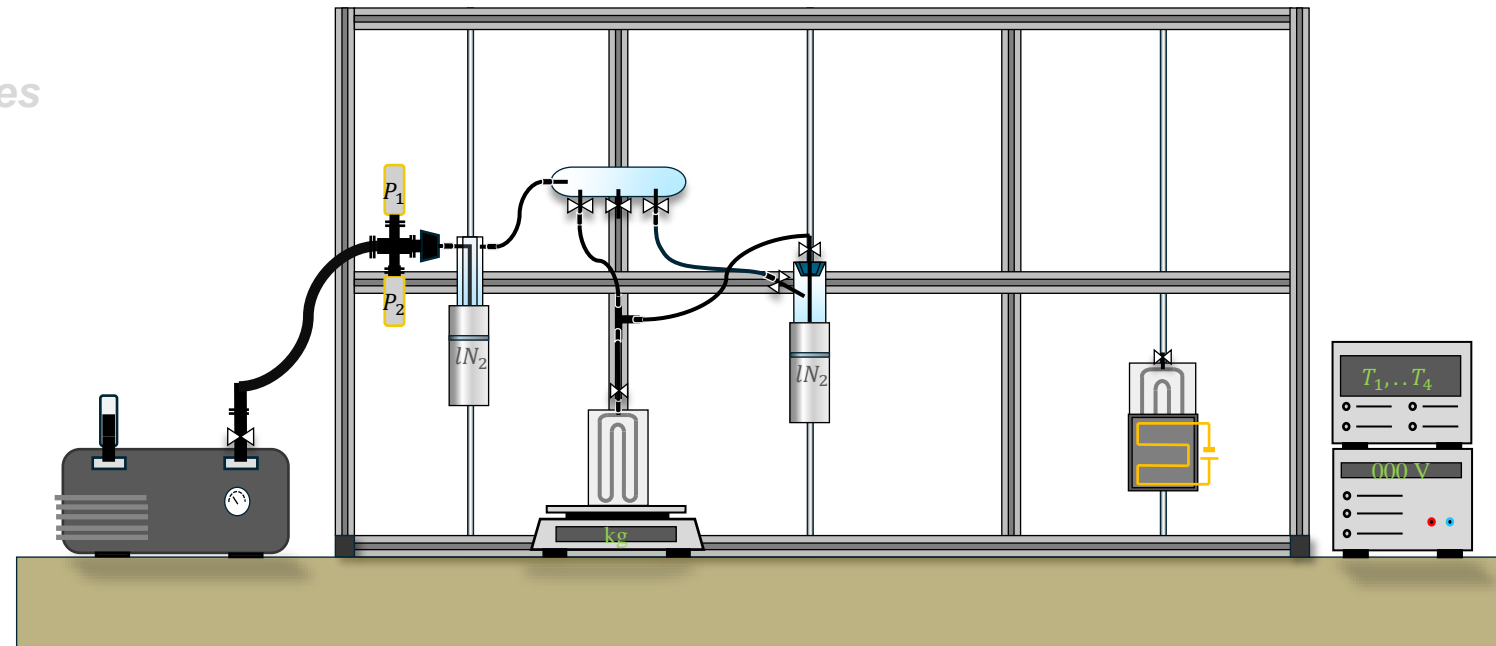
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- **Fill PHPs with working fluid**
  - **Evacuate PHP to  $p \leq 10^{-5} \text{ bar}$**
  - **Degas working fluid & filling rig**
  - **Transfer working fluid**
  - **Seal PHP**
- **Perform thermal measurements**



# Setup for Validation and Expansion – Design of Experiments

- **Manufacture PHP – Blanks**
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Schematic of filling rig

- **Perform thermal measurements**

# Setup for Validation and Expansion – Design of Experiments

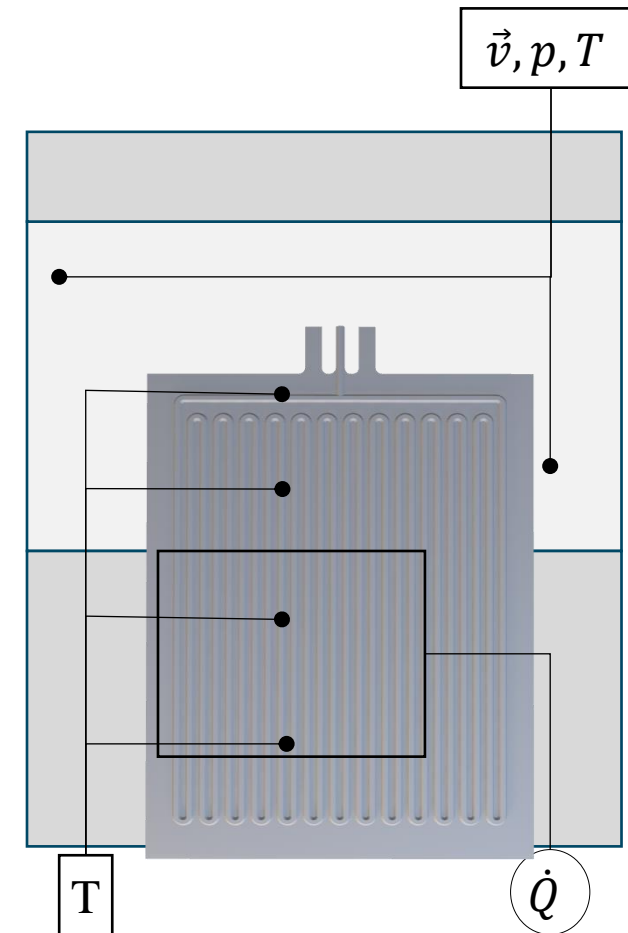
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Schematic of filling rig

# Setup for Validation and Expansion – Design of Experiments

- **Manufacture PHP – Blanks**
  - *Stereolithography enables quick iteration & transparency*
  - *Challenge of residual resin in cavities*
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  - Evacuate PHP to  $p \leq 10^{-5} \text{ bar}$
  - Degas working fluid & filling rig
  - Transfer working fluid
  - Seal PHP
- **Perform thermal measurements**
  - Apply calibrated heat source and sink
  - Measure Temperature Distribution



Schematic of thermal testing environment

# Conclusions

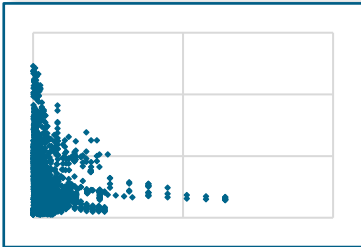


## Gradient Boosting

Conventional simulation challenging

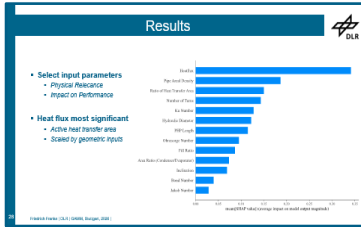


Large data set with 3441 cases  
Collected from literature



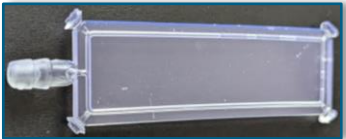
XG-Boost Model trained and tested

Tests show decent prediction  
capability rel. error  $\approx 20\%$

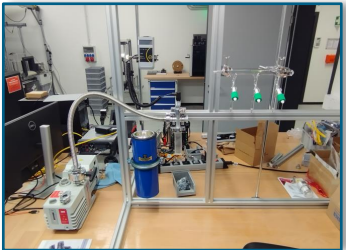


## Experimental Iteration

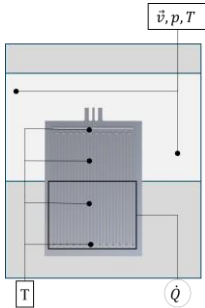
3D printing Manufacturing approach  
for experimental PHPs developed



Experimental setup for intermediate-  
vacuum filling built



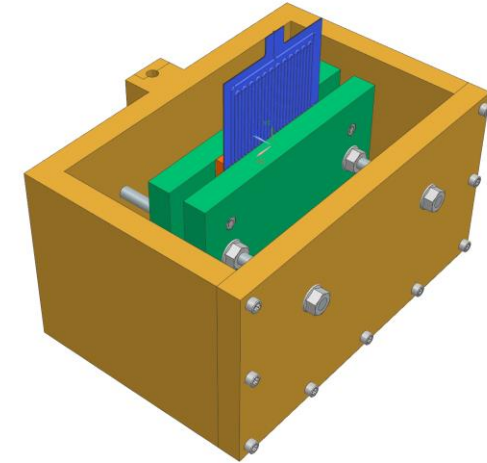
Test Bench for thermal  
measurements designed



# Future Research

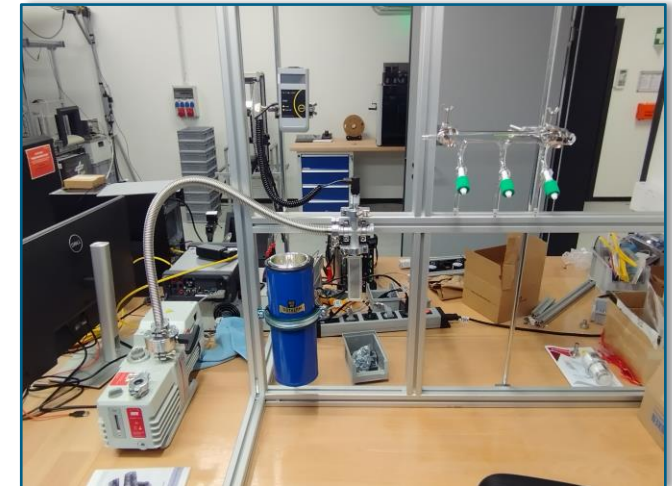
## XG Boost Model

- Validate Predictions made by the Trained Model
- Expand the training data set using alternating cross sections



## Trials

- Examine tightness and outgassing in transparent PHPs
- Perform Filling of Resin PHP
- Evaluate fluid behavior under heat load



A 3D perspective rendering of a ribbed aircraft wing section, showing the internal structure and the outer skin. The ribs are arranged in a regular pattern, and the leading and trailing edges are clearly defined. The rendering is in a light gray color with some blue highlights.

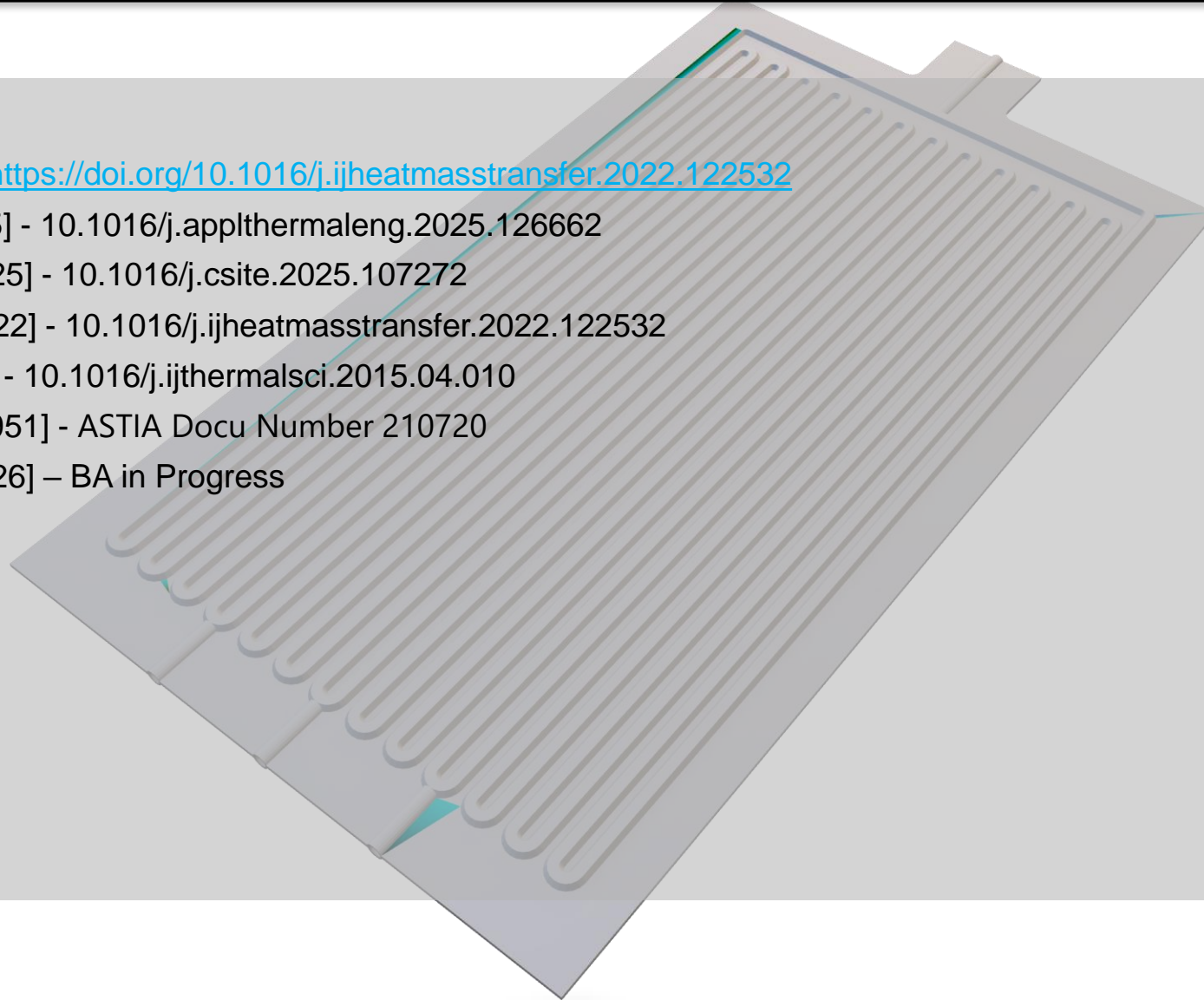
**Thank you for your attention!**

# Thank you for your attention!

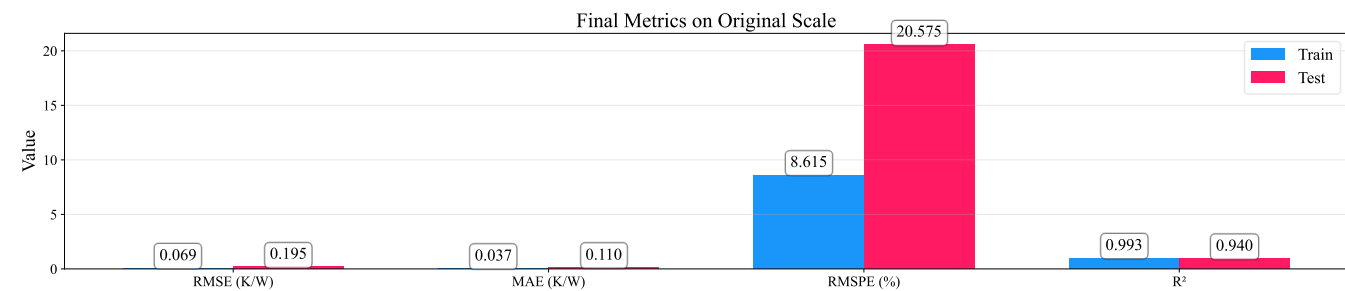
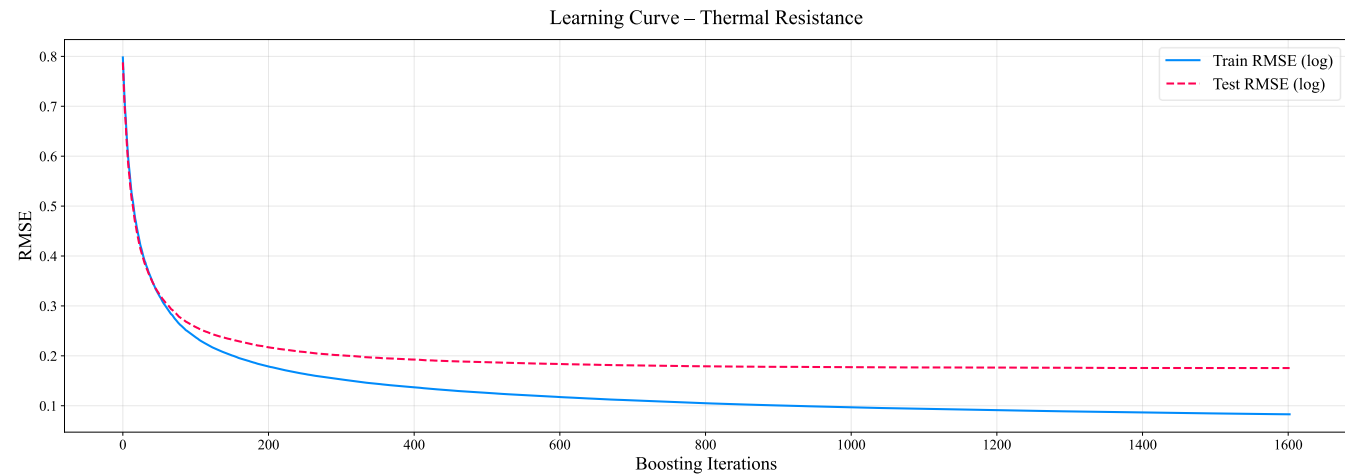


## ▪ Sources

- [Li 2023] - <https://doi.org/10.1016/j.ijheatmasstransfer.2022.122532>
- [Aziza 2025] - 10.1016/j.applthermaleng.2025.126662
- [Franke 2025] - 10.1016/j.csite.2025.107272
- [Mameli 2022] - 10.1016/j.ijheatmasstransfer.2022.122532
- [Ayel 2021] - 10.1016/j.ijthermalsci.2015.04.010
- [Shapley 1951] - ASTIA Docu Number 210720
- [Illbruck 2026] – BA in Progress



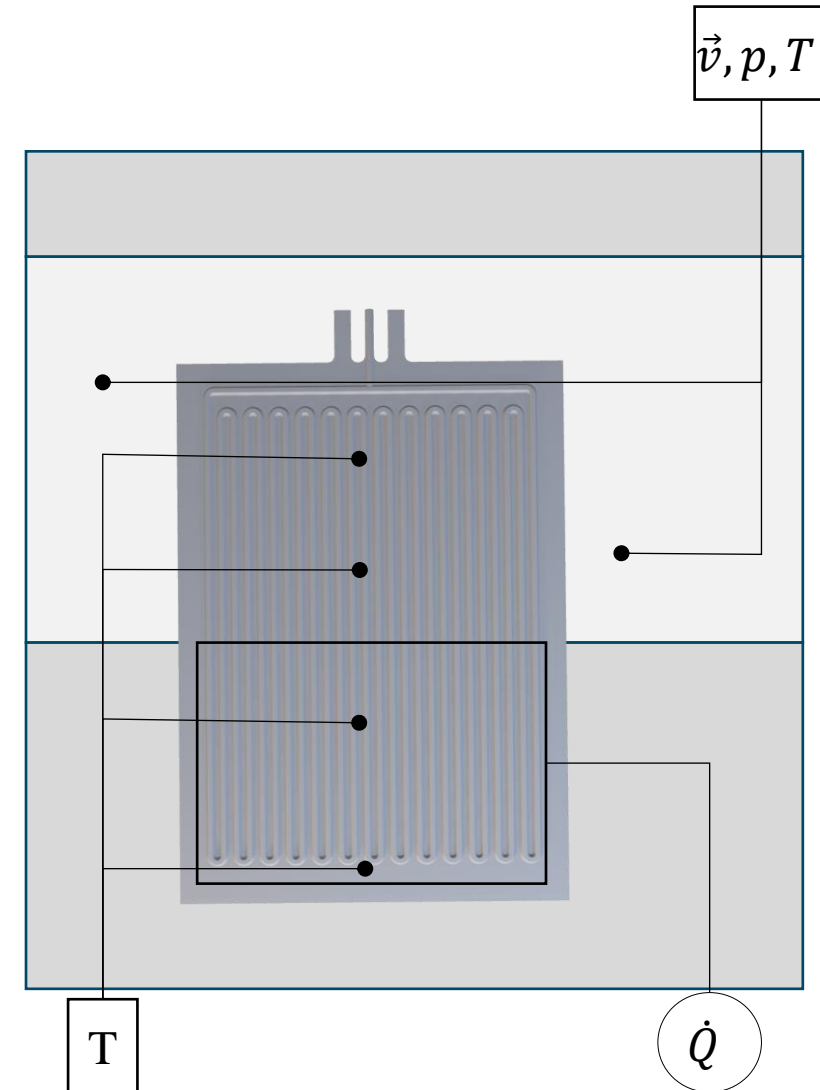
- **Select input parameters**
  - *Physical relevance*
  - *Impact on performance*
- **Heat flux most significant**
  - *Active heat transfer area*
  - *Scaled by geometric inputs*
- **Very high model accuracy**
  - *Mean Average Error = 0.11 K/W*
  - *Corresponds to approx 20% relative error*



# Measuring Performance

## (1) IPM & (2) – TMT MAD

1. Temperature Sensors on outer wall
2. IR-camera (frontal view)
3. Testing Procedure: Stepwise increase of heating power at constant airspeed
4. Alter fan power
5. Install channel obstruction / Dummy stack



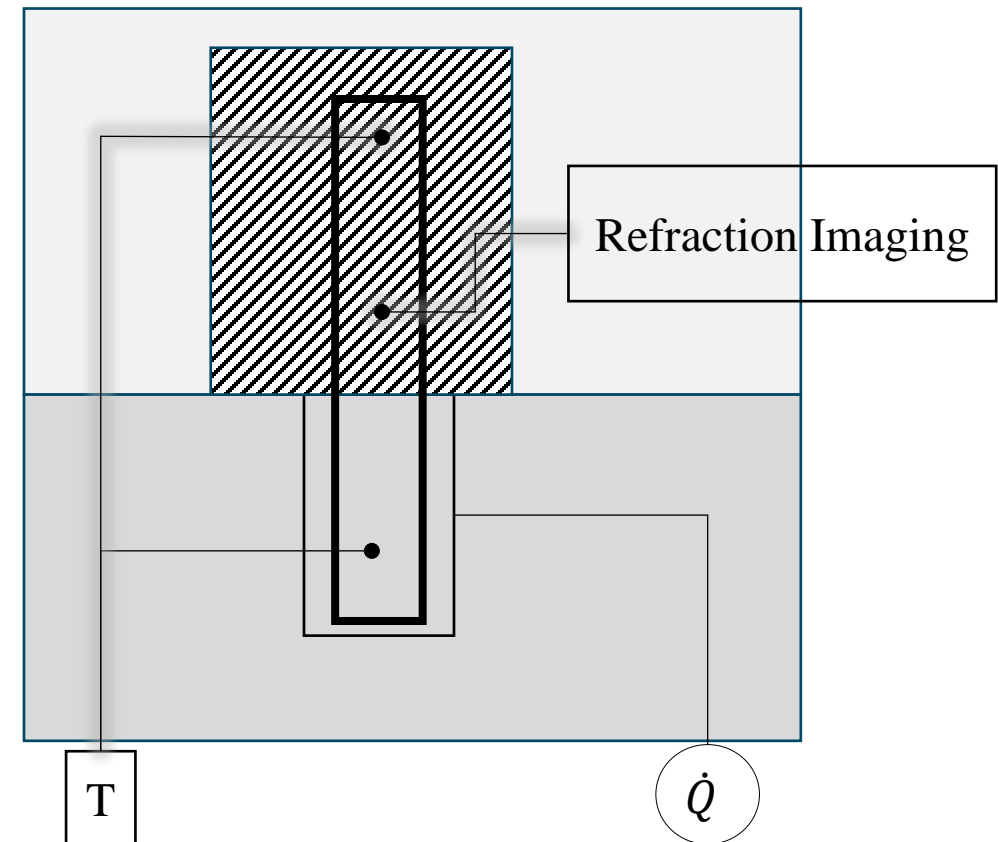
Temperature measure

Heat source

# Simultaneous tests

## Second test

1. Single Meander Tests
2. High speed, High Zoom Camera
3. Evt. High viscous, low evaporation temperature
4. Investigate varying channel cross section
5. Bubble behaviour
6. Oscillation and wall wetting phenomena



Temperature measure

Heat source