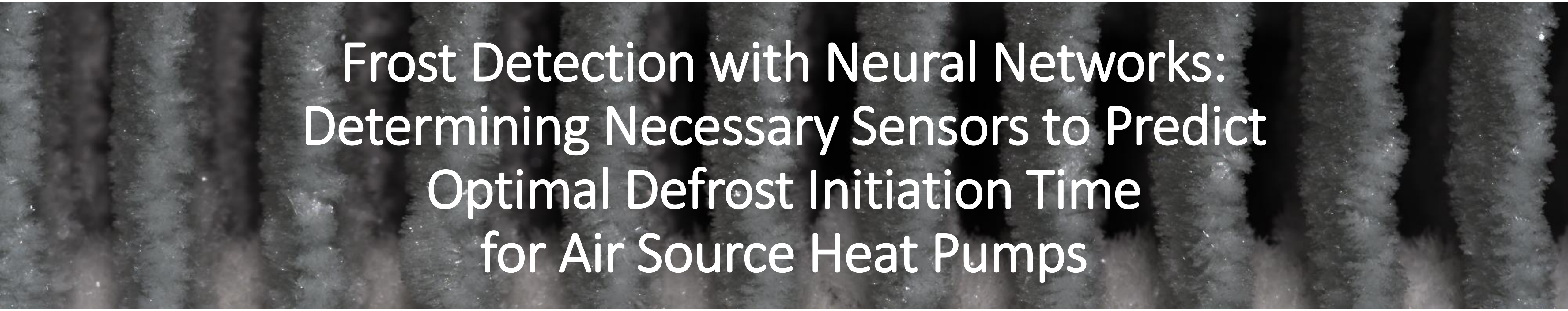
14th IEA HEAT PUMP CONFERENCE



Frost Detection with Neural Networks: Determining Necessary Sensors to Predict Optimal Defrost Initiation Time for Air Source Heat Pumps

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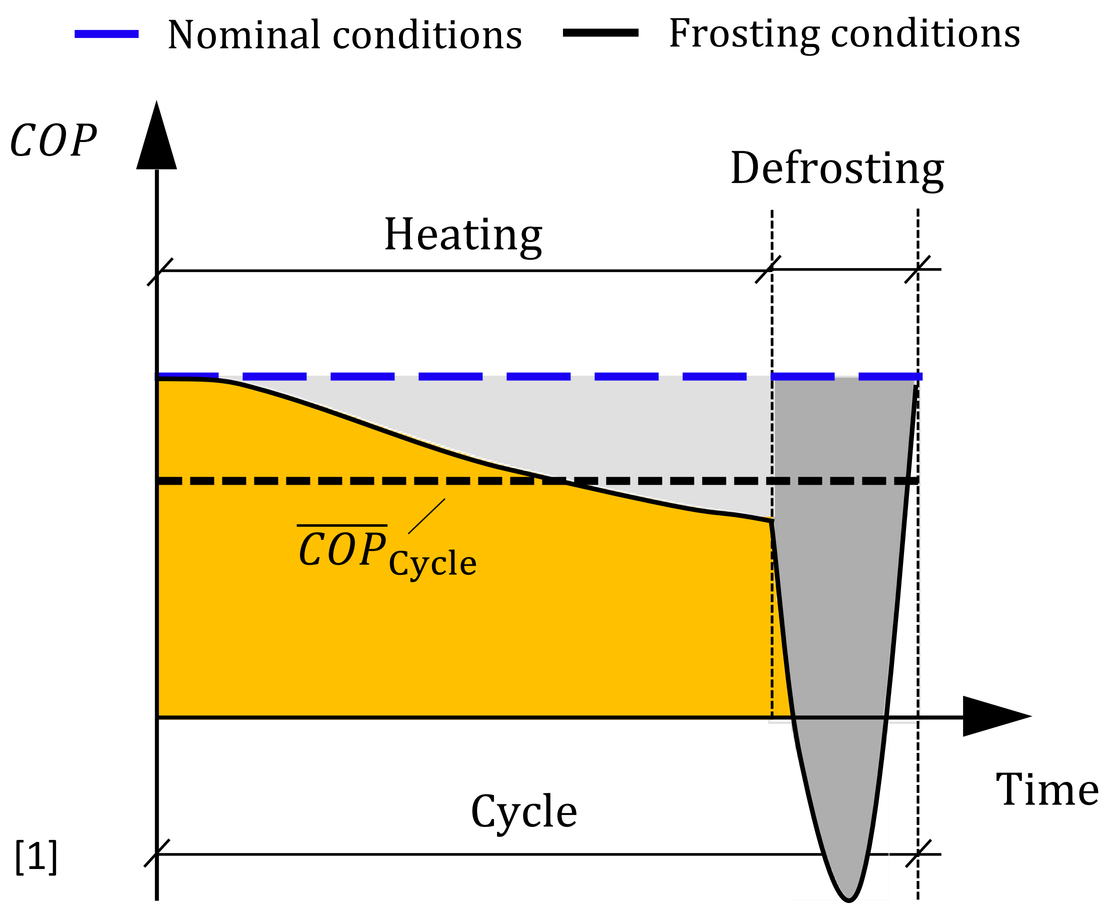
Projektträger Jülich Forschungszentrum Jülich

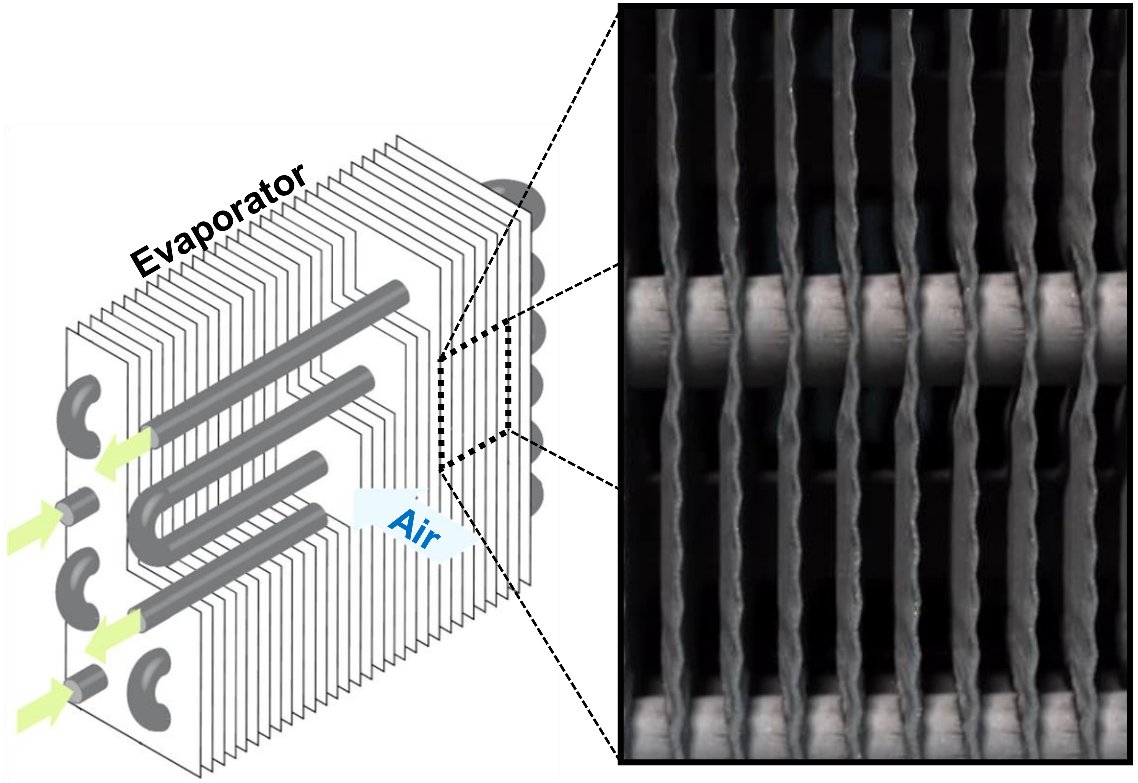
Supported by:

Federal Ministry for Economic Affairs and Climate Action

on the basis of a decision by the German Bundestag

Frost formation decreases system efficiency





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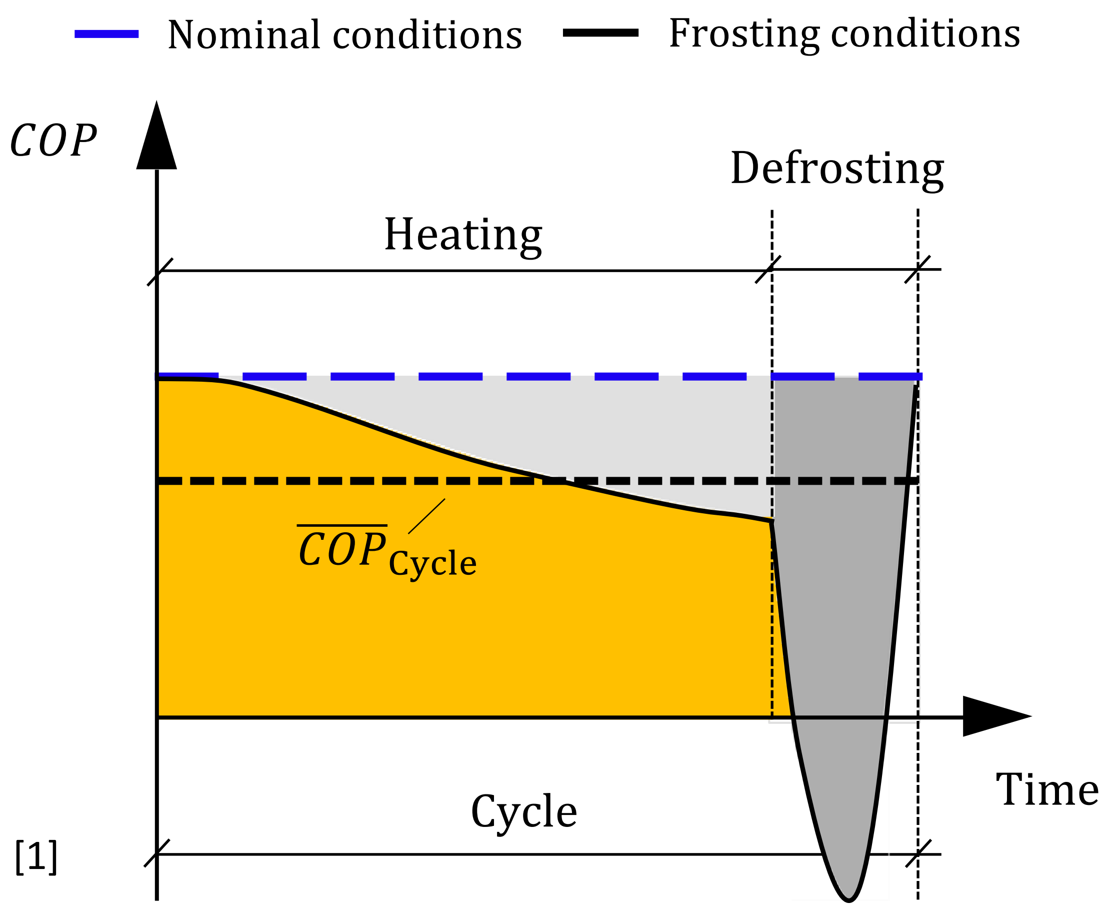
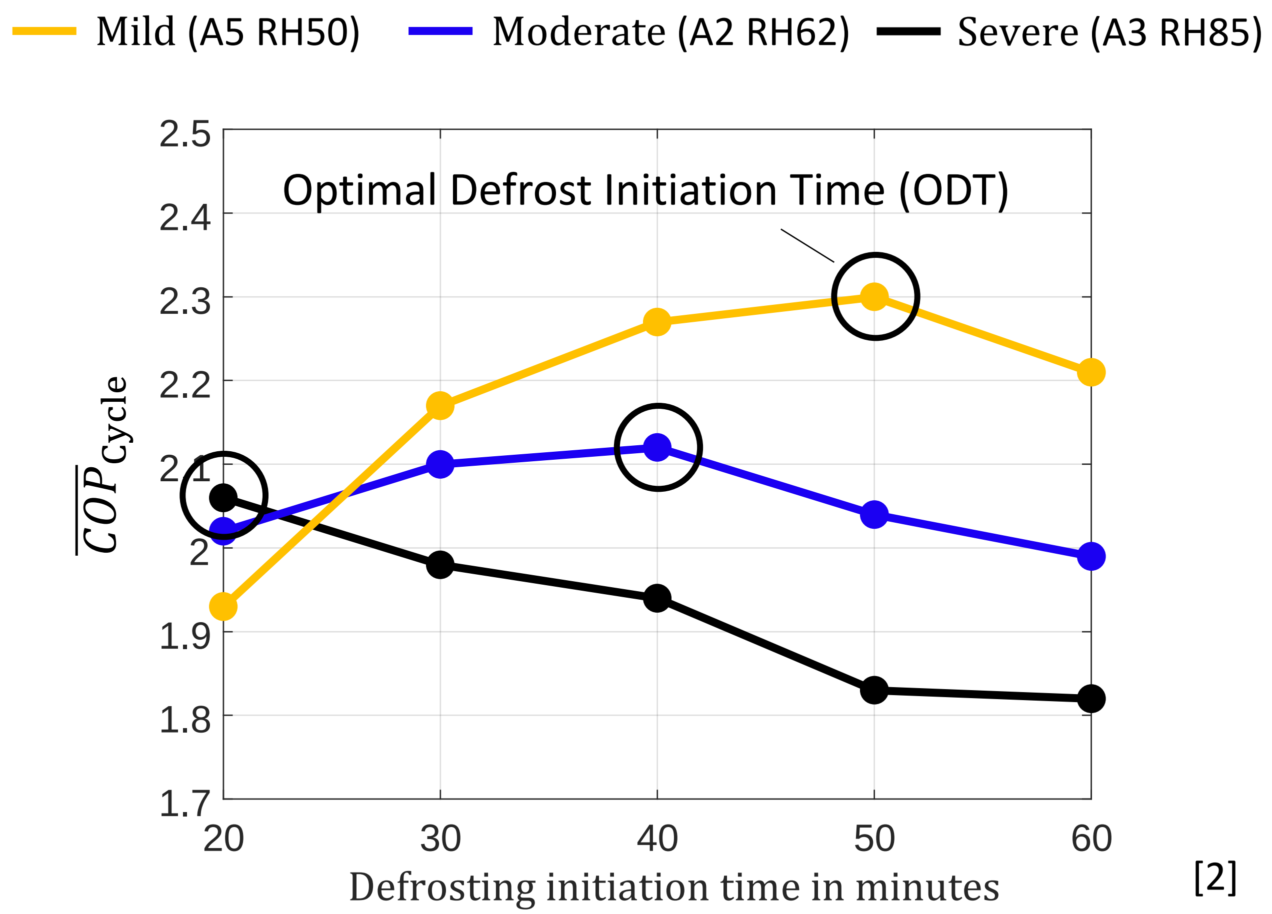


[1]



[2]

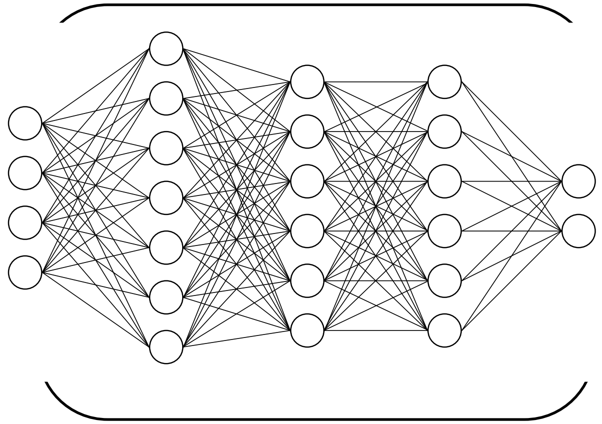
Using machine learning to predict defrosting necessity

Ambient Conditions

- T_{Air}
- φ_{Air}

ASHP

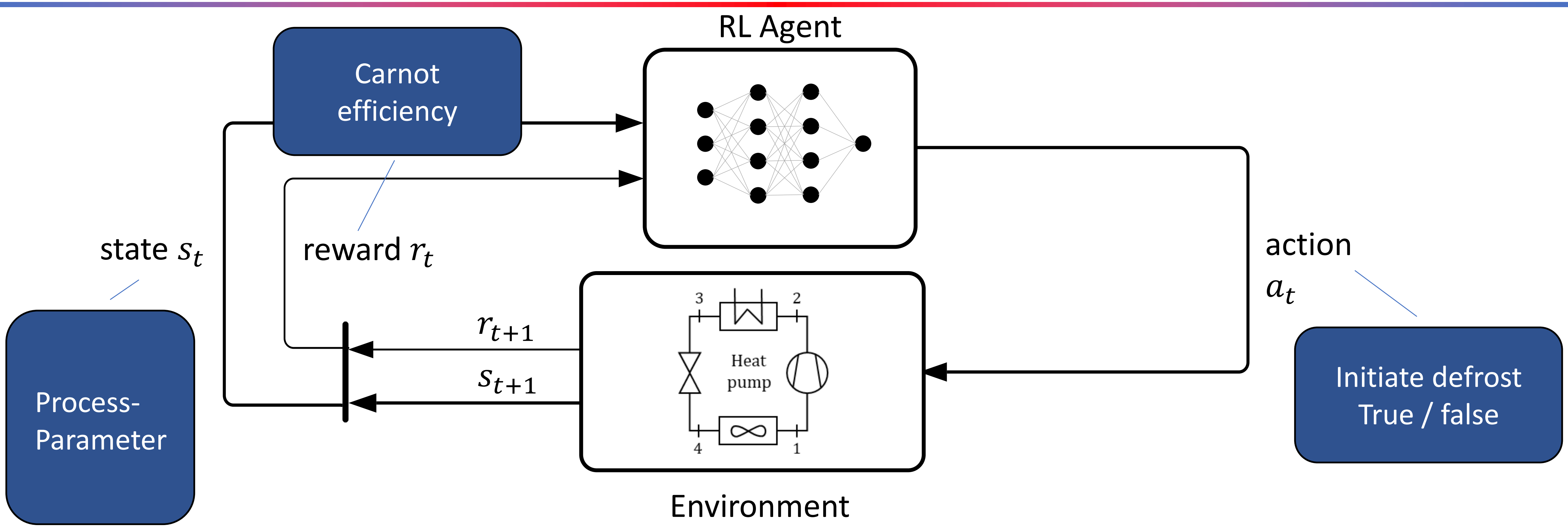
- Geometry
- Compressor speed
- Fan speed
- $\text{T}_{\text{Superheat}}$



Artificial Neural Networks as function approximator

Optimal Defrost Initiation Time (ODT)

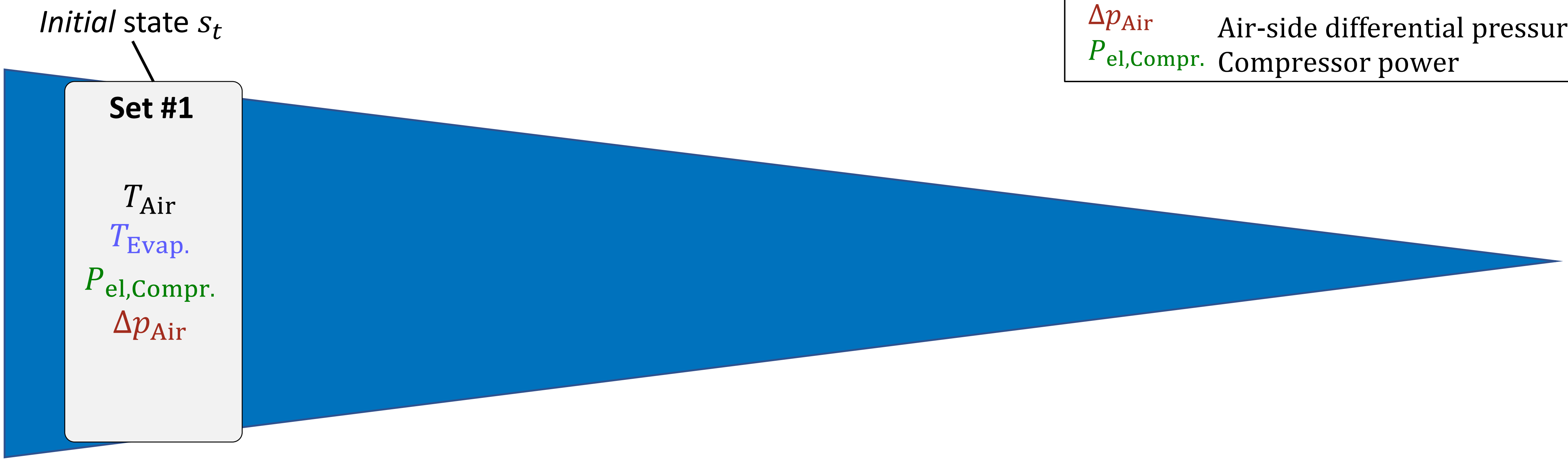
Deep Reinforcement Learning: A Self-optimizing control algorithm



A trained RL agent performs actions, which maximize the future expected reward

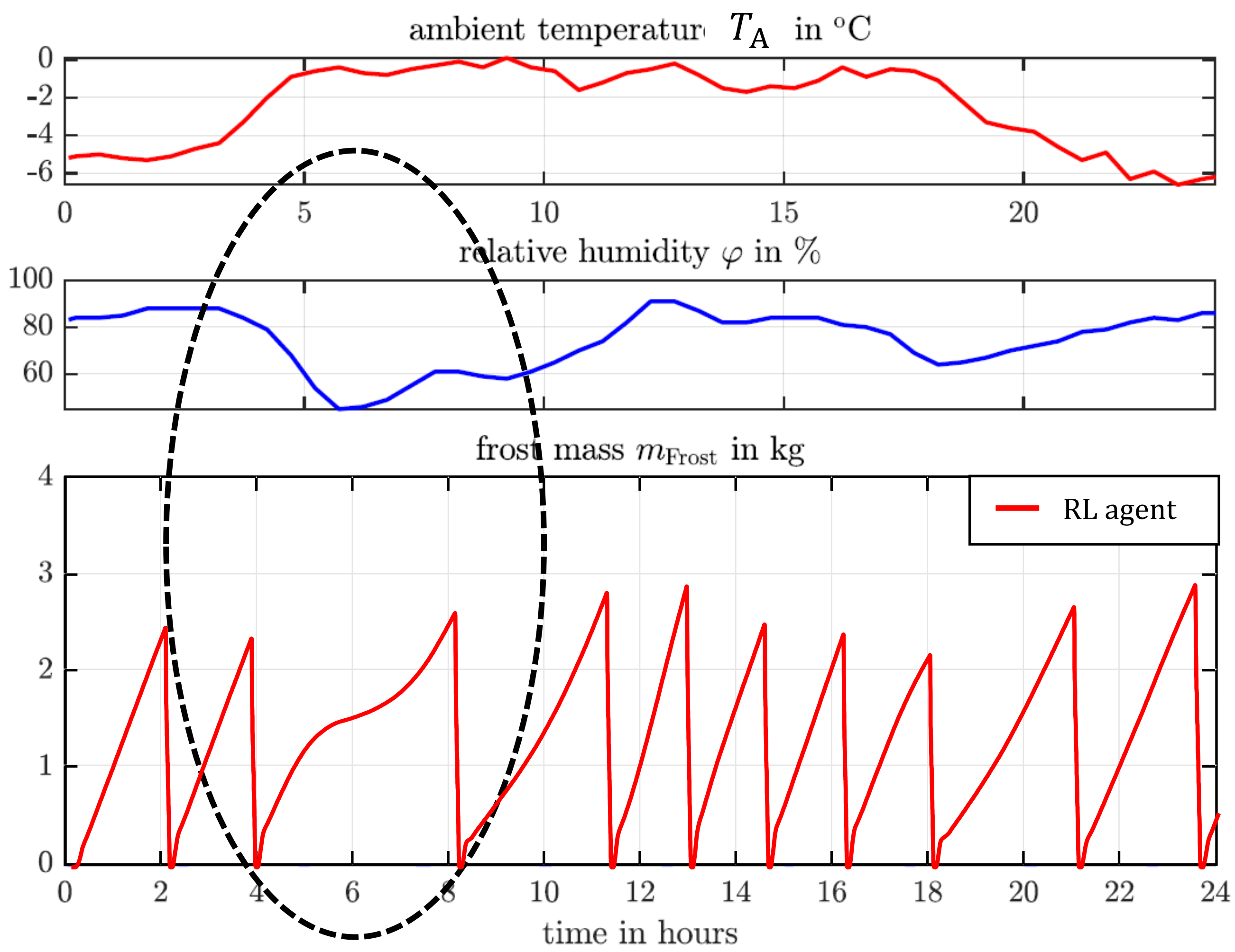
What information does the agent need to detect frost formation?

T_{Air}	Air temperature
$T_{\text{Evap.}}$	Evaporation temperature
Δp_{Air}	Air-side differential pressure
$P_{\text{el,Compr.}}$	Compressor power



Simulation Results: Benchmark Comparison

- Calibrated simulation model
- Evaluation for 24h (dynamic load profile)
- Varying frosting interval lengths
- RL Agent initiates defrosting based on demand



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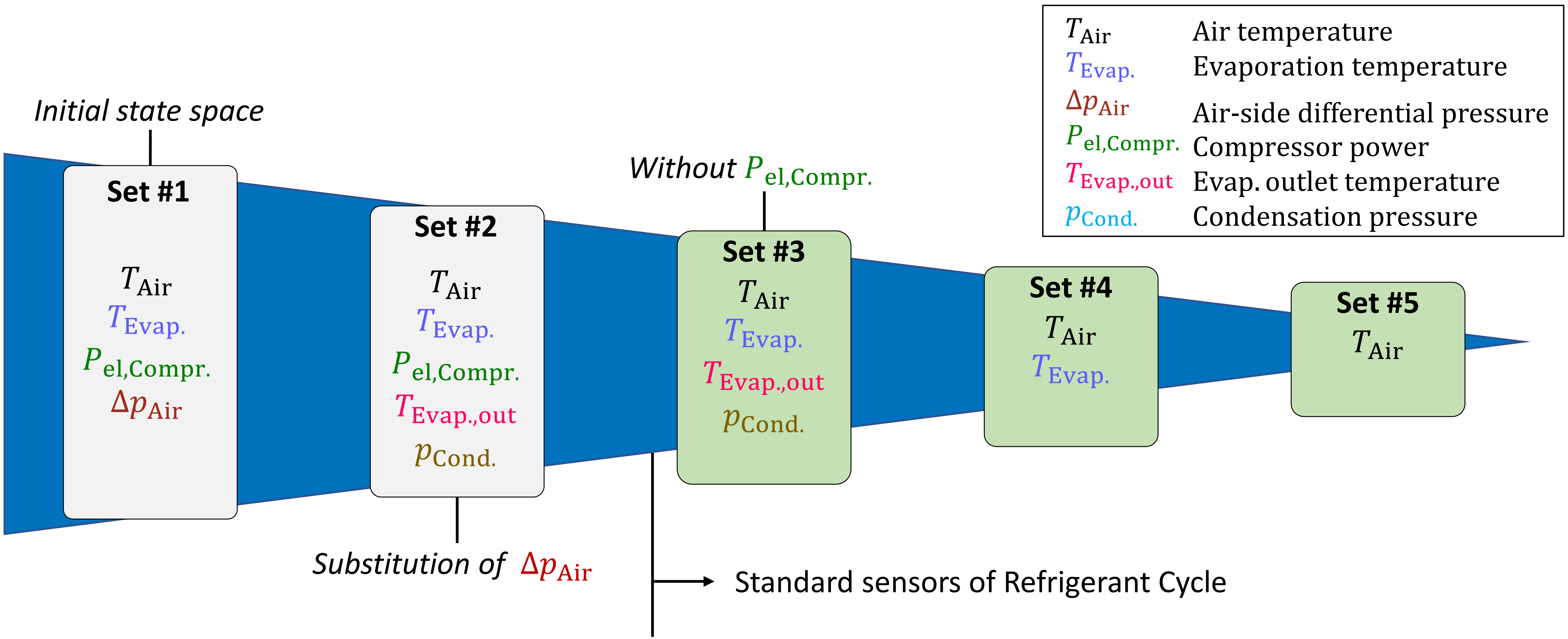
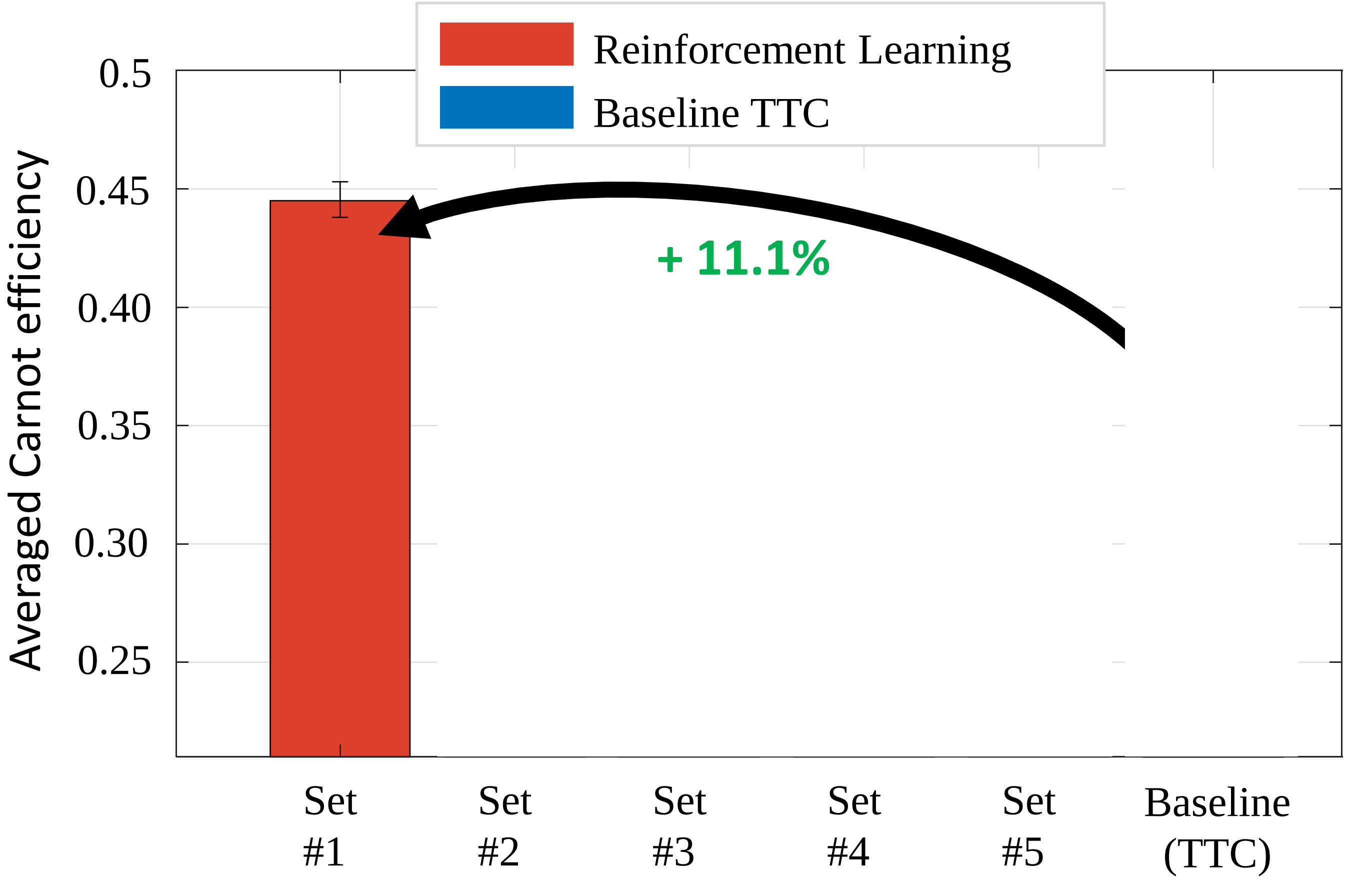


Simulation Results: Necessary Sensors

- Simulation Setup
  - Identical training procedure for all sets
  - Evaluation for 72h (dynamic load profile)
- Baseline: Time-temperature controlled defrosting (TTC)
  - Defrosting every 60 min
  - Air Temperature < 6°C



Simulation Results: Necessary Sensors

Set #1

T_{Air}
$T_{\mathrm{Evap.}}$
$P_{\mathrm{el,Compr.}}$
Δp_{Air}

Set #2

T_{Air}
$T_{\mathrm{Evap.}}$
$P_{\mathrm{el,Compr.}}$
$T_{\mathrm{Evap.,out}}$
$p_{\mathrm{Cond.}}$

Set #3

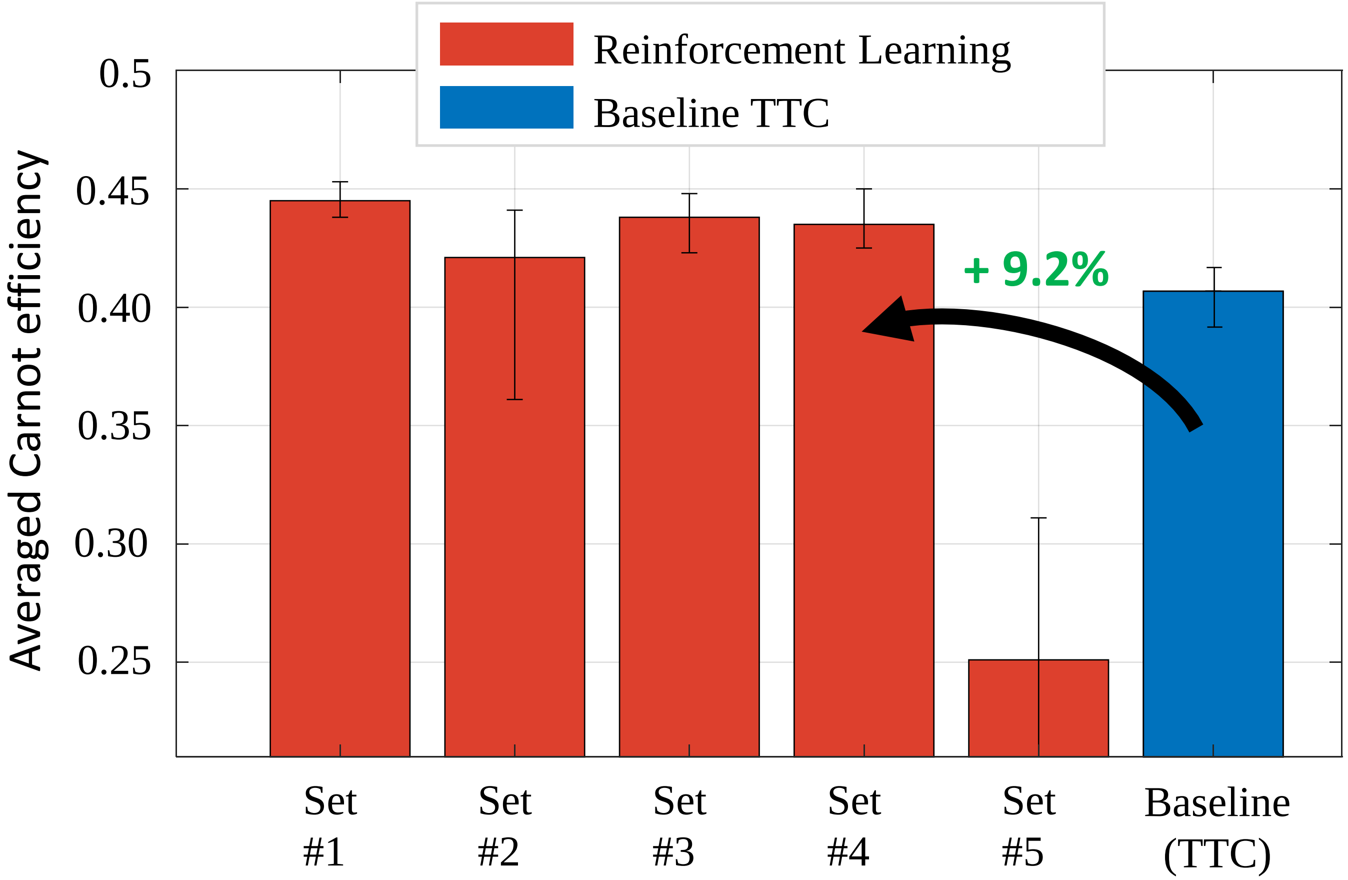
T_{Air}
$T_{\mathrm{Evap.}}$
$T_{\mathrm{Evap.,out}}$
$p_{\mathrm{Cond.}}$

Set #4

T_{Air}
$T_{\mathrm{Evap.}}$

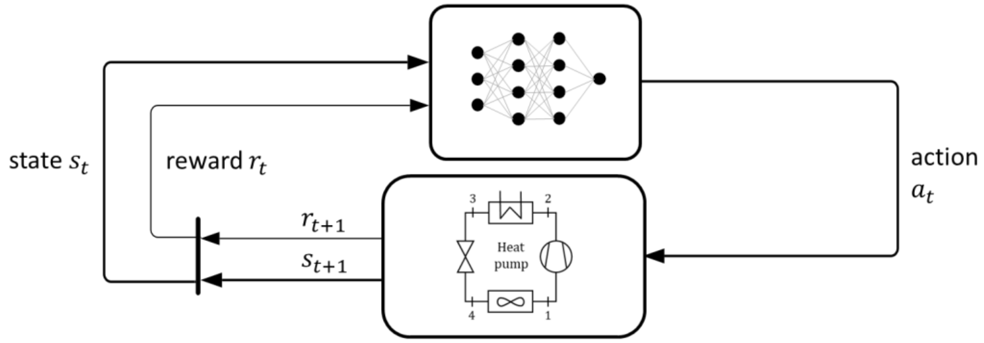
Set #5

T_{Air}

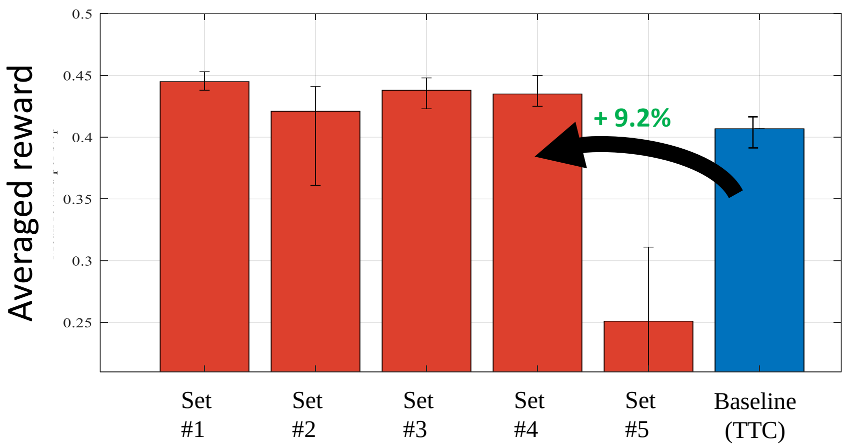


Conclusion and Outlook

- **Conclusion**
  - Validation of self-optimizing defrost controller based on Reinforcement Learning
  - Succesful implementation using only standard sensors of refrigerant cycle



- **Outlook**
  - Verify proposed control algorithm on test bench
  - Test robustness of control (e.g., measurement noise)



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