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# Smart Energy Systems Modeling

## Component Exchange during simulation

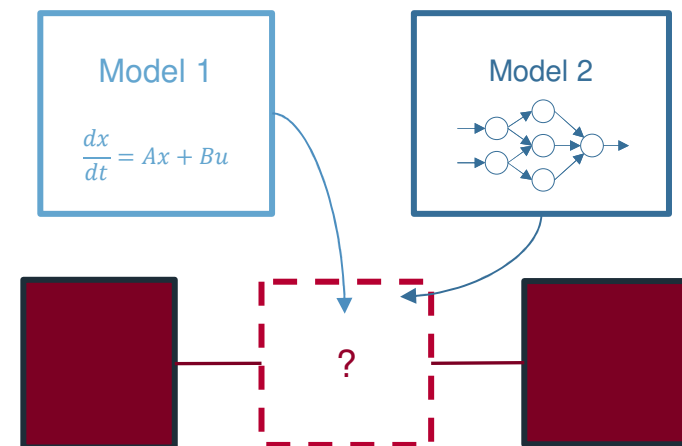
Sandra Wilfling, Basak Falay, Qamar Alfalouji, Johannes Exenberger, Thomas Schranz, Mina Basirat,  
Gerald Schweiger

# Motivation

- Application: Energy Systems Modeling
- Combination of strengths of different modeling methods
- Exchange model components during simulation depending on different criteria

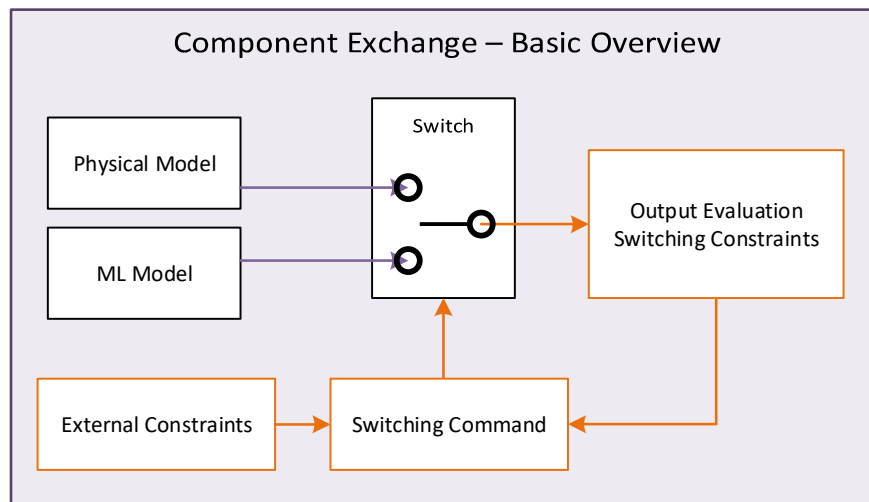


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## Method

### Simulation – Co-Simulation Approach



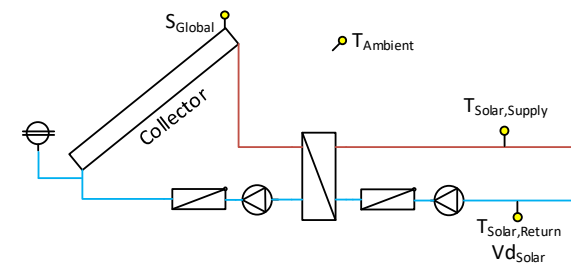
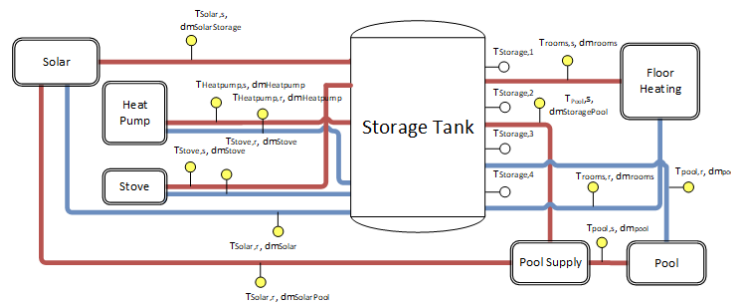
- Physical modeling in Dymola
- Data-driven modeling in Python
- Combination of Dymola and Python through co-simulation
- Evaluation of different models during simulation
- Component exchange during simulation run

# Application – Use Case

## Single Family House Heating System - Solar Collector

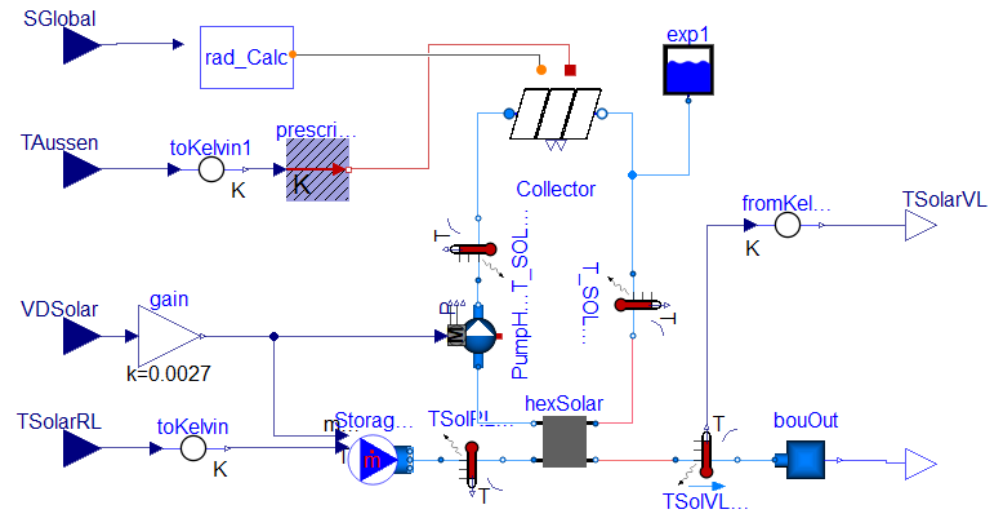
Single Family House Heating System:

- Combined Solar Collector – Storage Tank – Heat Pump System
- 46 m<sup>2</sup> Solar Collector



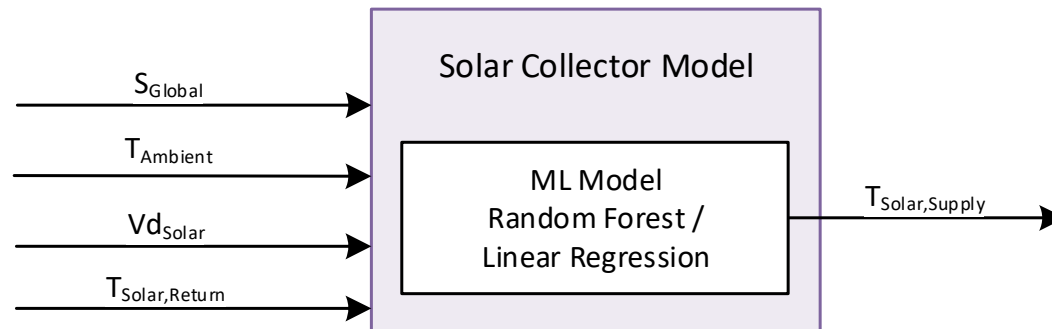
# Physical Modeling

## Solar Collector Model - Dymola



# Data-driven Modeling

## Machine Learning Models - Python



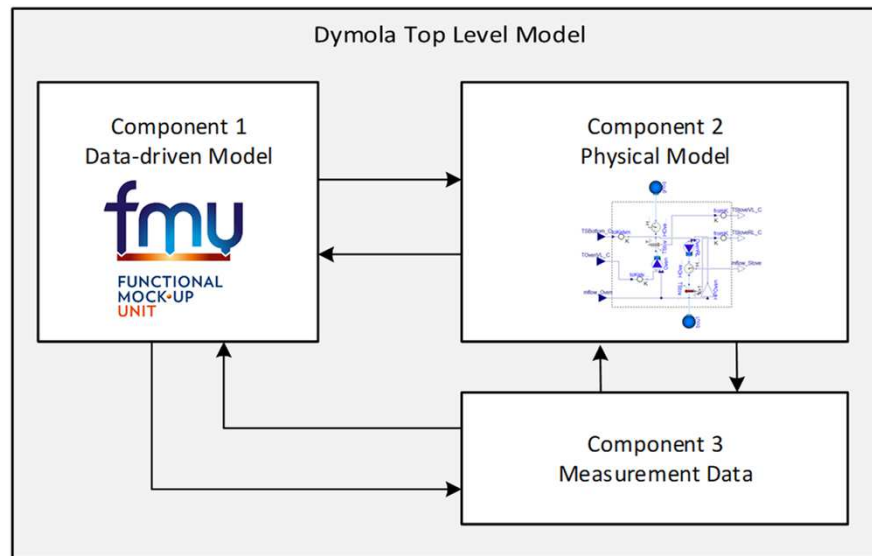
### Model Architectures:

Linear Regression, Random Forest

Training Data: 2019/02 – 2019/11 (80% training, 20% validation)

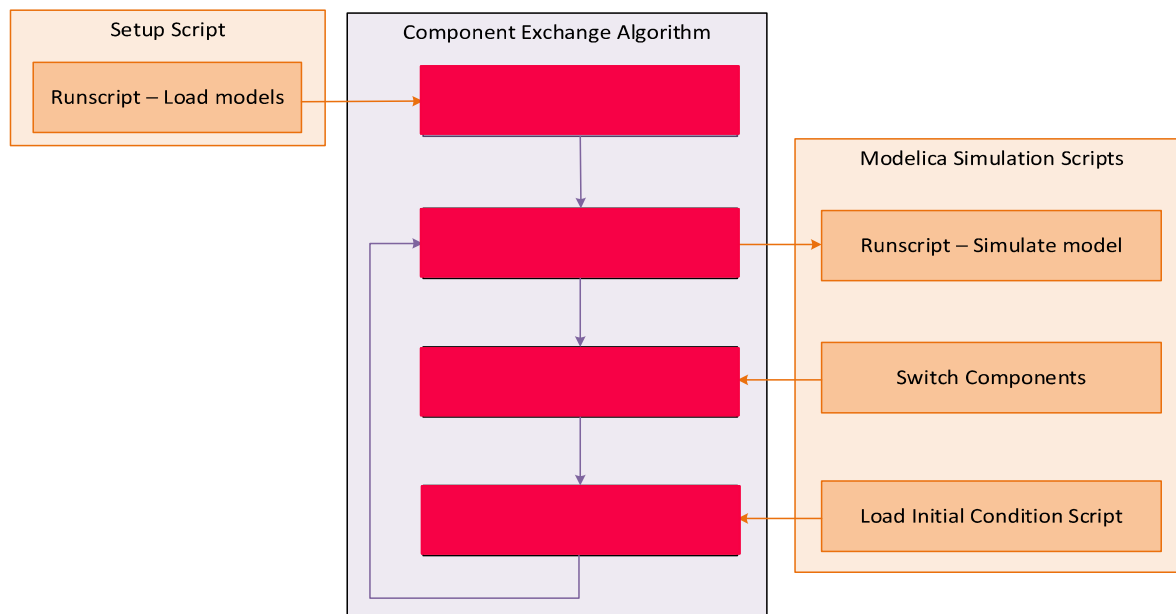
# Co-Simulation

Combination of physical and data-driven models



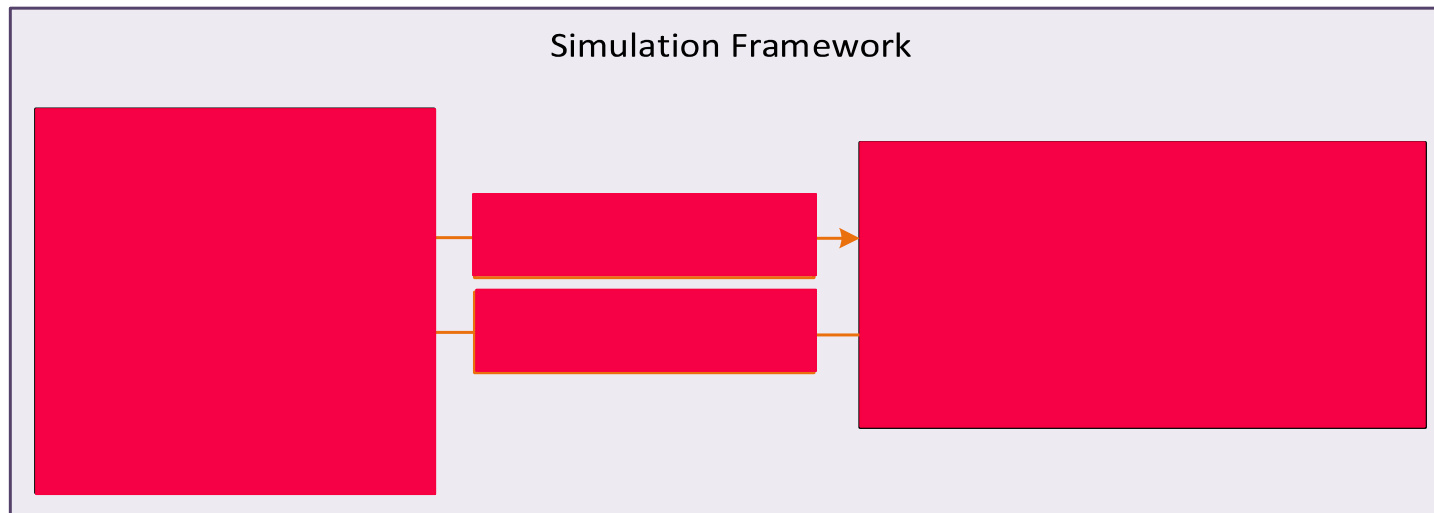
- Co-Simulation: Dymola-Python
- Simulation Master: Dymola
- Interfacing: FMI 2.0

# Component Exchange Algorithm



## Implementation

### Dymola-Python Framework

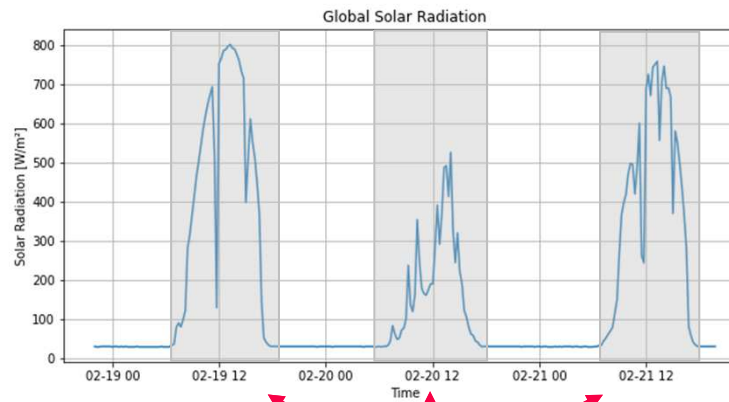


# Component Exchange - Application

## Solar Collector Use Case

Component exchange based on active and inactive period of solar collector – **active** and **supporting** model  
 Selection based on solar radiation  $S_{global}$

Scheduling Criterion: Collector active during defined timespan



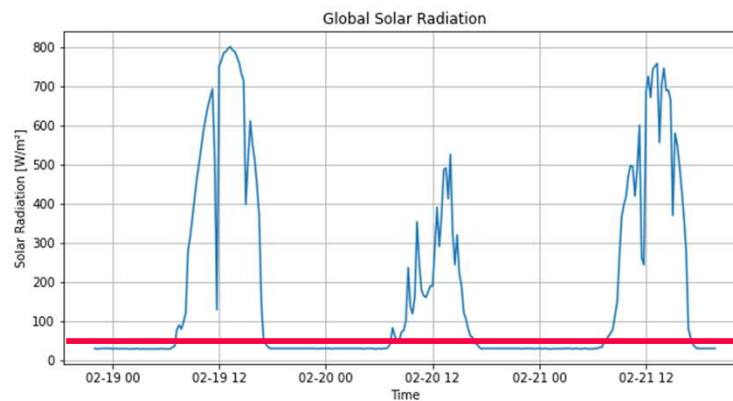
Active Collector: 8:00 – 18:00

# Component Exchange - Application

## Solar Collector Use Case

Component exchange based on active and inactive period of solar collector – **active** and **supporting** model  
 Selection based on solar radiation  $S_{global}$

Threshold Criterion: Collector active when radiation above threshold value



$S_{Threshold} = 30 \text{ W/m}^2$

Active Collector:  $S_{Global} > S_{Threshold}$

## Experiments

### Experiment Setup

Parameter	Value
Co-Simulation Timestep	15 min
Simulation Duration	25 – 32 days

### Exchange Criteria

Method	Criterion
Scheduling	Active Model: 8:00 – 18:00
Threshold	Active Model: $S_{\text{global}} > 30 \text{ W / m}^2$

### Model Selection

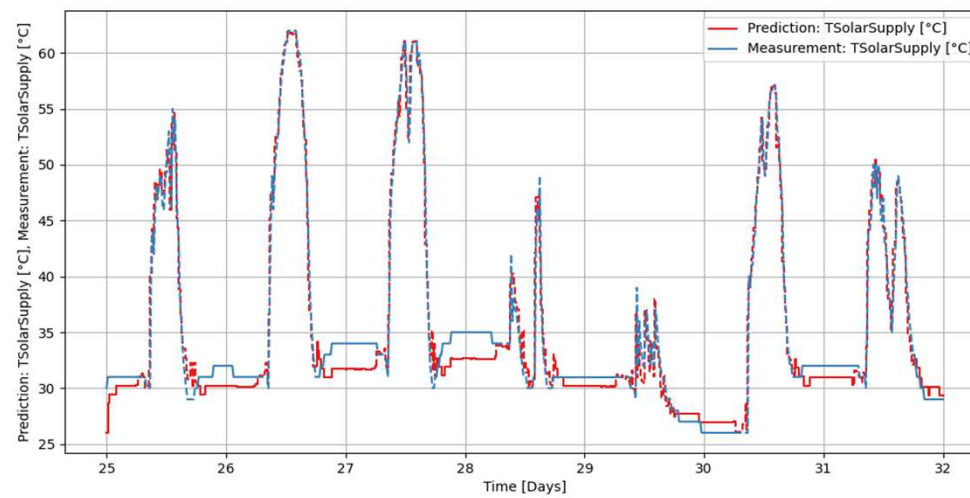
Active Model	Supporting Model
Linear Regression	Random Forest
Random Forest	Linear Regression
Random Forest	Physical Model

# Results

## Model Selection – Scheduling Algorithm

Active Model: Random Forest Regression - Supporting Model: Linear Regression

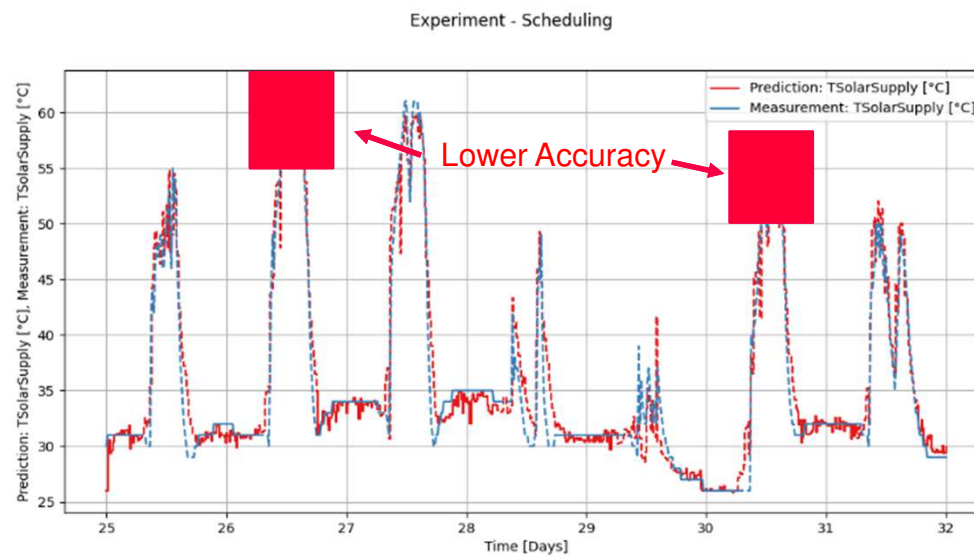
Experiment - Scheduling



# Results

## Model Selection – Scheduling Algorithm

Active Model: Linear Regression - Supporting Model: Random Forest Regression



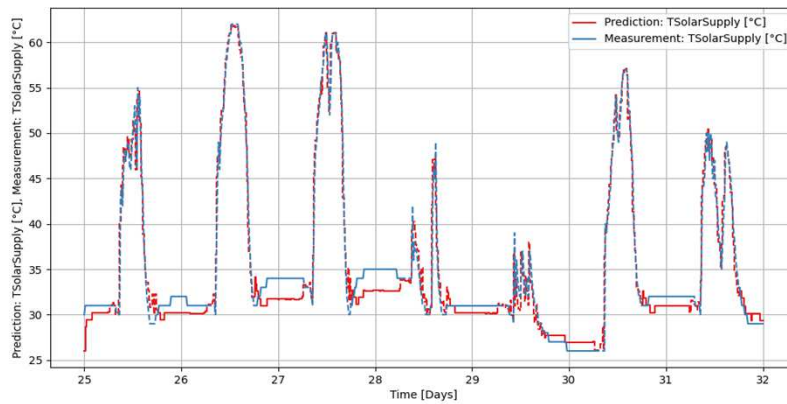
# Results

## Model Selection – Scheduling Algorithm

### Scheduling Criterion

Active Model	Supporting Model
Random Forest	Linear Regression

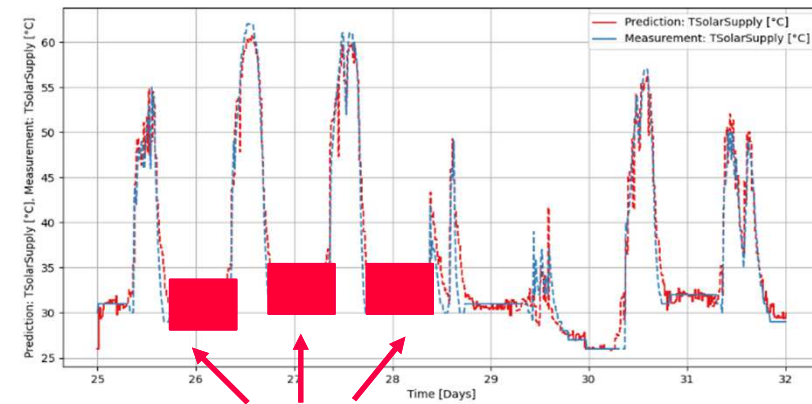
Experiment - Scheduling



### Scheduling Criterion

Active Model	Supporting Model
Linear Regression	Random Forest

Experiment - Scheduling



Value Fluctuations

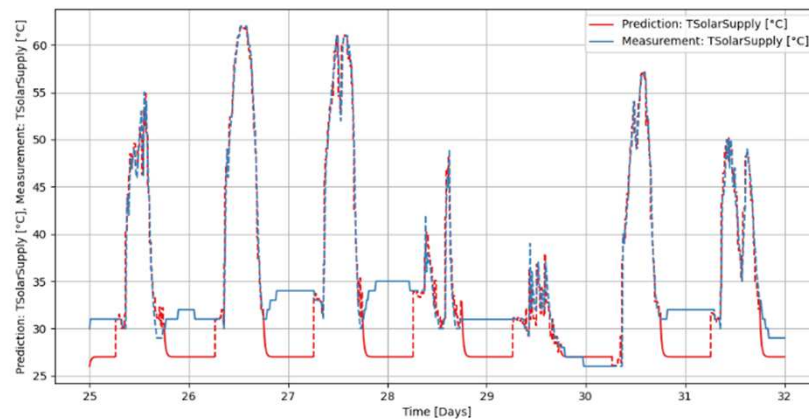
# Results

## Scheduling and Threshold Criterion

### Scheduling Criterion

Active Model	Supporting Model
Random Forest	Physical Model

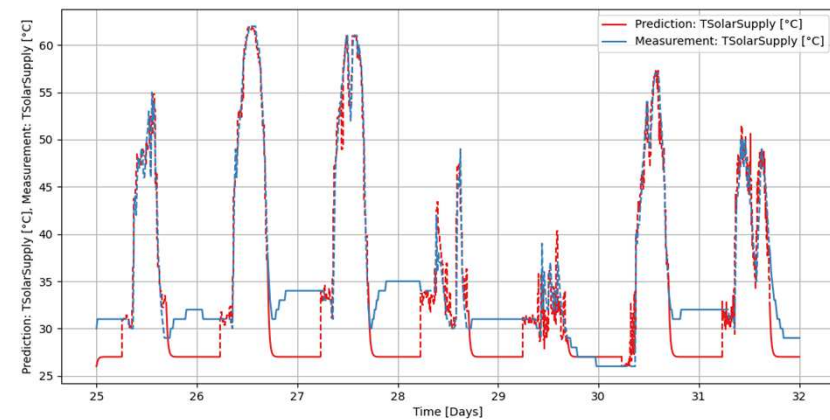
Experiment - Scheduling



### Threshold Criterion

Active Model	Supporting Model
Random Forest	Physical Model

Experiment - Threshold



## Results

### Performance Metrics

#### Scheduling Criterion

Active Model	Supporting Model	Exchange Criterion	$R^2$	CV-RMSE	MAPE
Linear Regression	Random Forest	Scheduling	0.936	0.062	3.87 %
Random Forest	Physical Model	Scheduling	0.921	0.094	7.94 %

#### Threshold Criterion

Active Model	Supporting Model	Exchange Criterion	$R^2$	CV-RMSE	MAPE
Linear Regression	Random Forest	$S_{\text{Global}} > 30 \text{ W/m}^2$	0.947	0.053	3.58 %
Random Forest	Physical Model	$S_{\text{Global}} > 30 \text{ W/m}^2$	0.912	0.086	7.26 %

## Conclusion

### Future Work

- Different applications / use cases
- Different criteria / combined criteria

### Acknowledgements

The project NextHyb2 (881150) is funded by the Austrian Climate and Energy Fund within the program “Energieforschung”.





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# Thank you for your attention!

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