Data-driven modeling of cooling demand in a commercial building

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Overview

Background

Cooling System Design

Data and Modeling Approach

Results

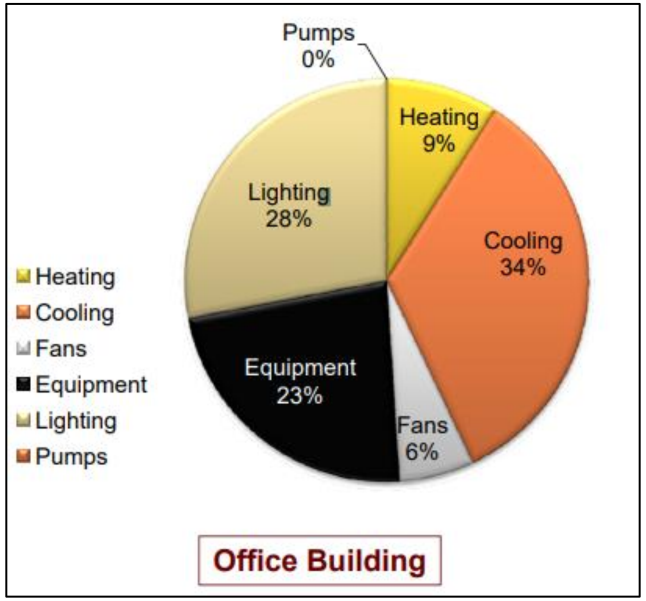
Discussion

Motivation

Heating, ventilation and air conditioning systems (HVAC) - ~30% of energy[1]

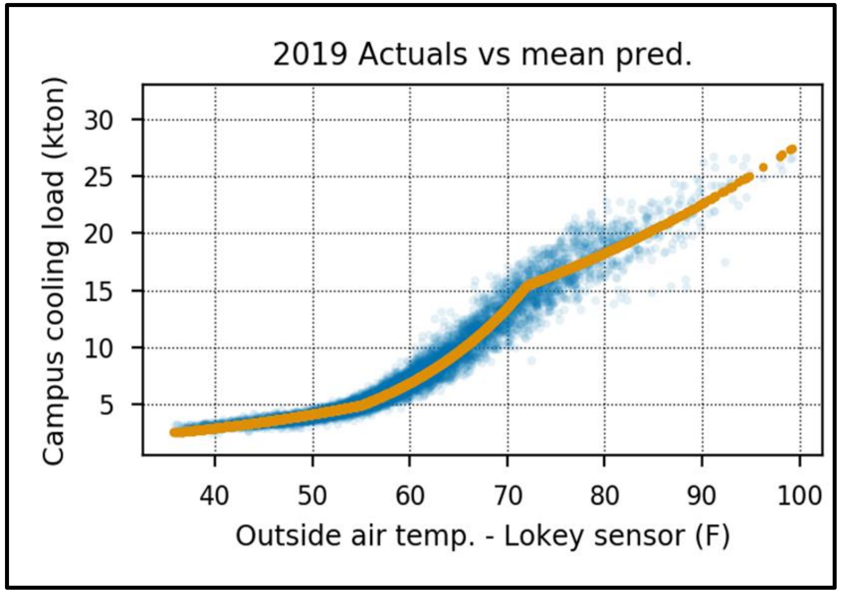
Extreme climates – demand increases

(a) Typical Energy Consumption



Source: [2]

(b) Relationship between cooling demand and outside air temperature

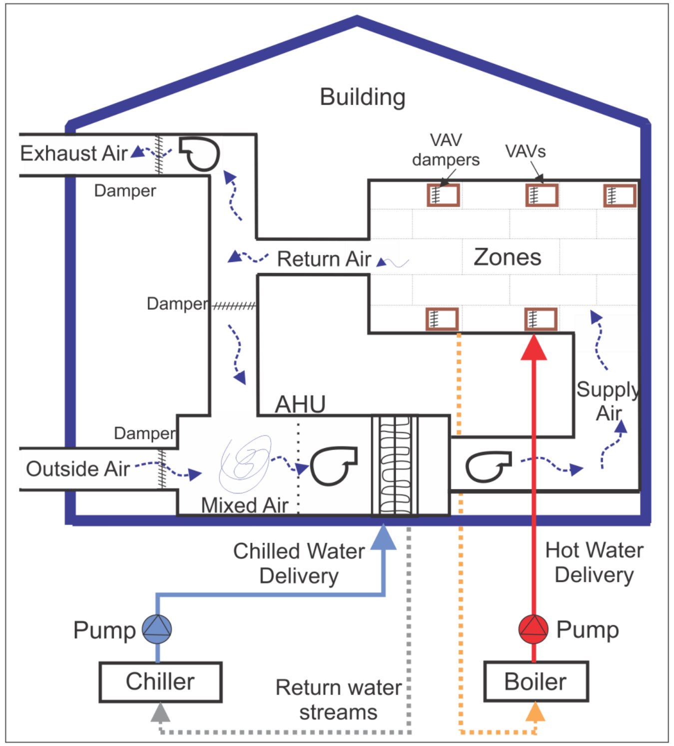


Source: [3]

[1] Manjarres et al. (2017), 'An energy-efficient predictive control for HVAC systems applied to tertiary buildings based on regression technique'
[2] Online. (2018) https://energy.stanford.edu/sites/g/files/sbiybj9971/f/energy_seminar_march_28_final.pdf s

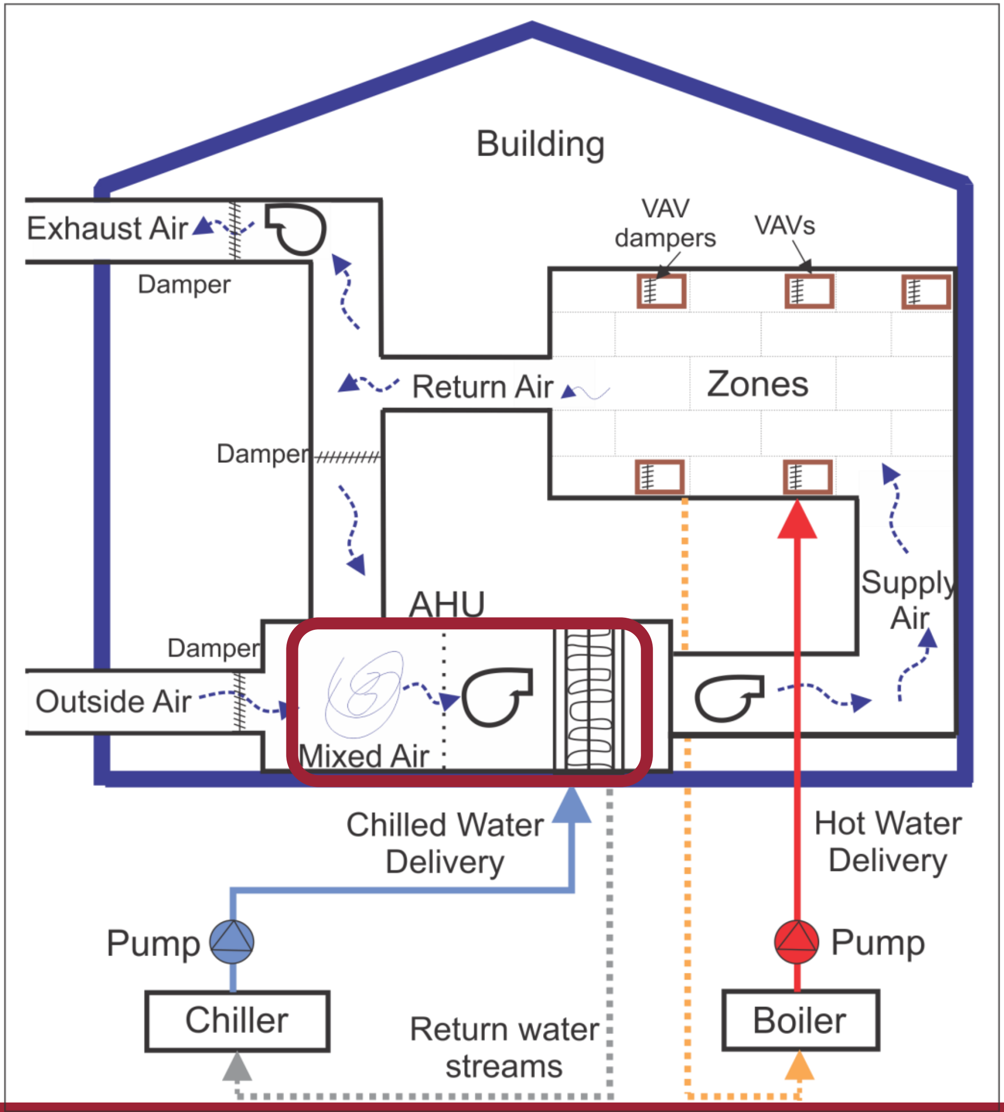
Background

- **Identification** of the thermal response of the building to relevant control inputs
- **Integral components of HVAC**: AHUs and VAVs characterize the thermal dynamics
- **Data-driven** modeling approach
- **System identification model**
  - Control variables: zone-level temperature setpoints
  - Cooling demand across AHU is a function of
    - Temperature setpoints (TSPs)
    - Outside Air Temperature (OAT)
    - Return Air Temperature (RAT)

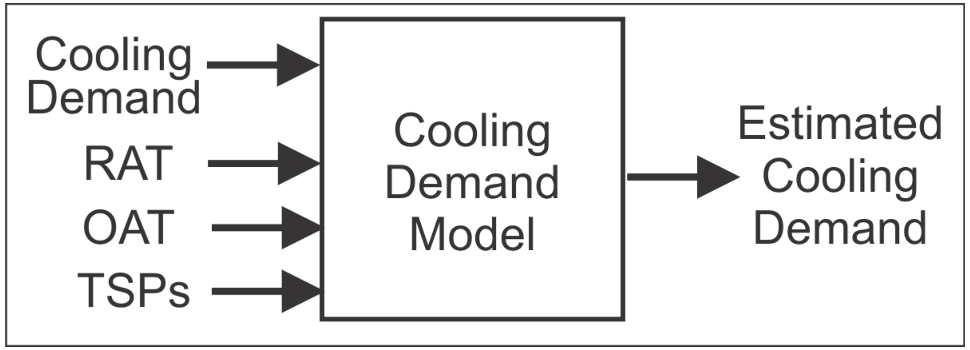


Cooling System Design

Inputs to AHU: Outside air (OA) and Return air (RA)
Output of AHU: Chilled supply air
Assumption: Cooling demand is a function of Temperature setpoints (TSPs) and input air temperature

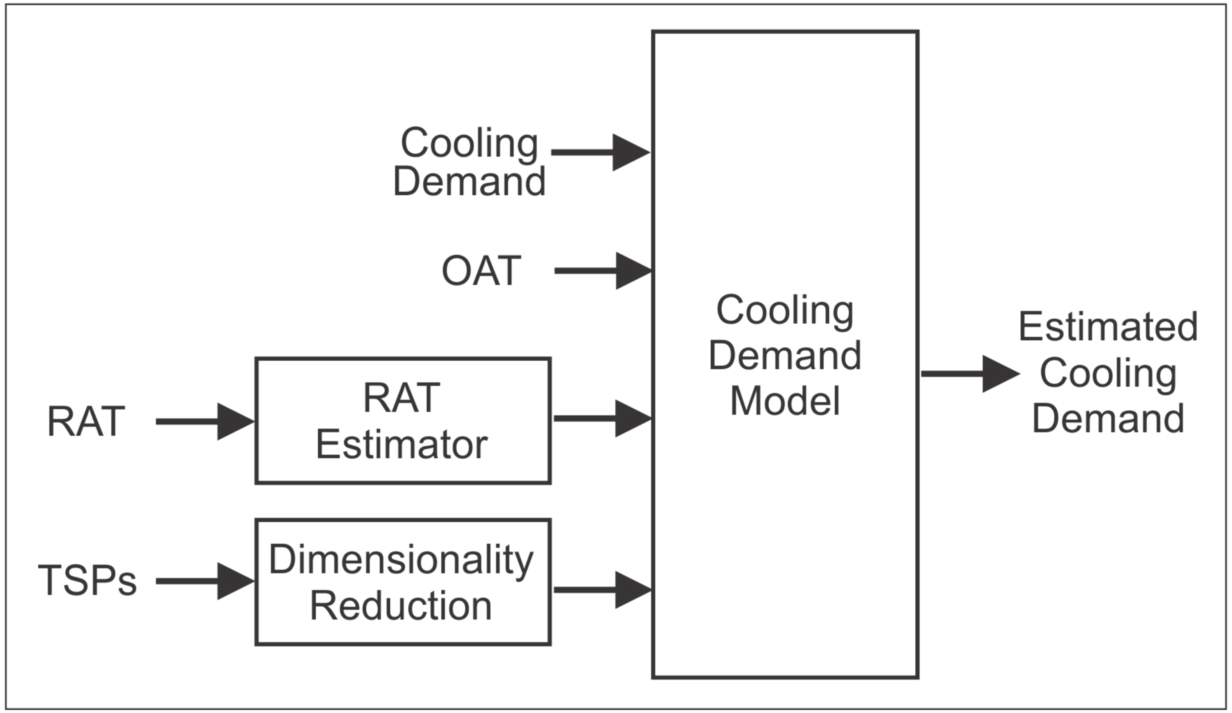


Modeling Approach



- Challenges and proposed solutions
  - RAT measurements for the future are not available – Estimate them first
  - OAT forecasts from a local weather station – treated as exogenous variable
  - TSPs are collinear variables – dimensionality reduction

Modeling Approach



- RAT Estimator
  - Future RAT values are a function of past RAT measurements, current OAT and current TSPs
- Dimensionality Reduction Technique
  - Principal component analysis (PCA)
  - Extracted PCs from TSPs
- ARX models

Modeling RAT

Lag order

# of PCs

α_j : Model Coefficients

$$\hat{T}_{RA}(t+1) = \sum_{i=1}^{p_r} \alpha_{1,i} T_{RA}(t-i+1) + \sum_{k=1}^{n_r} \alpha_{2,k}\phi_k(t) + \alpha_3 T_{OA}(t) \qquad (1)$$

Past values of RAT

PCs of Temperature setpoints

Outside Air Temperature

Modeling Cooling Demand

Lag order

\# of PCs

\# of AHUs

β_j : Model Coefficients

$$\hat{X}(t+1) = \sum_{i=1}^{p_x} \beta_{1,i} X(t-i+1) + \sum_{k=1}^{n_x} \beta_{2,k} \phi_k(t) + \sum_{k=1}^{m_x} (\beta_{3,k} T_{RA,k}(t) + \beta_{4,k} T_{OA,k}(t)) \quad (1)$$

Past values of demand

PCs of Temperature setpoints

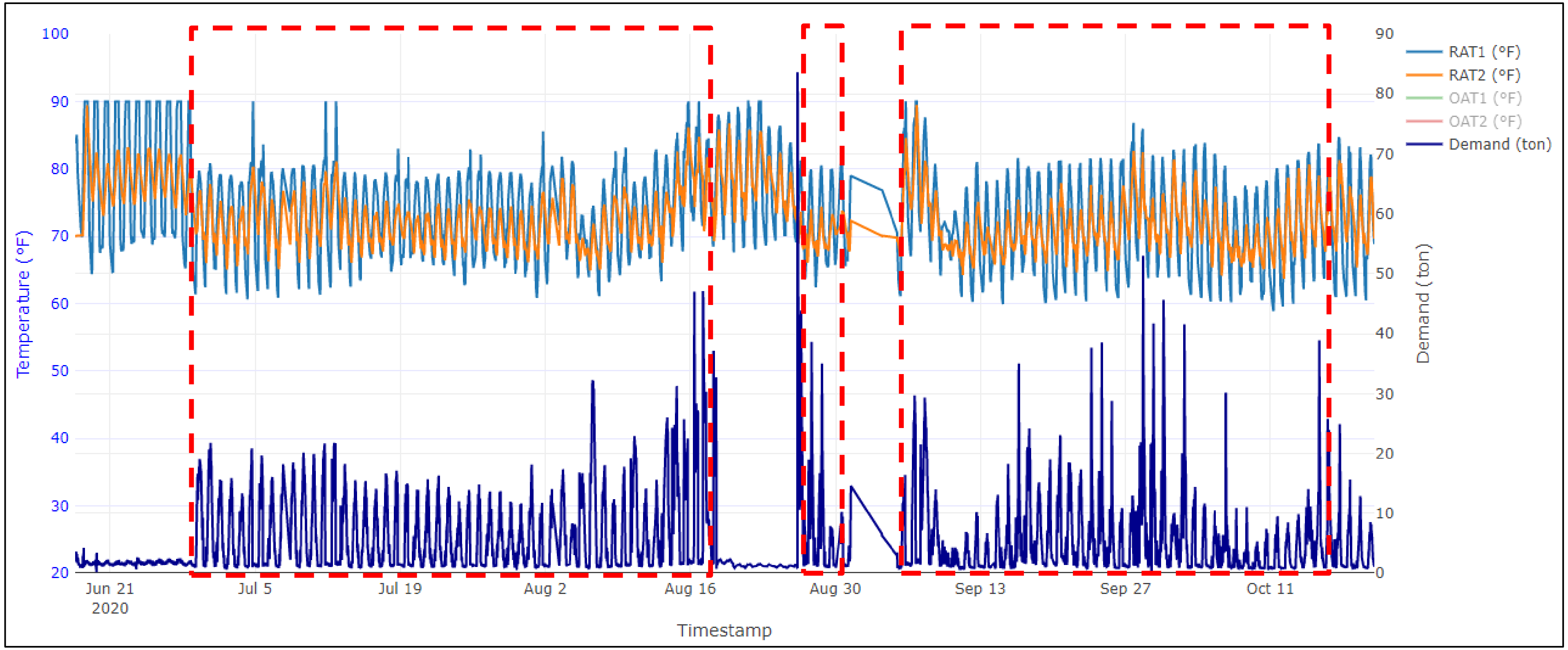
Return Air Temperature

Outside Air Temperature

Data

George Havas Building

- Two AHUs
- Multiple zones (15, 18)
- Time resolution: 5 min
- Period: June – October
- Three sets for training (30th June – 15th Oct)
- Prediction: 16th – 18 Oct



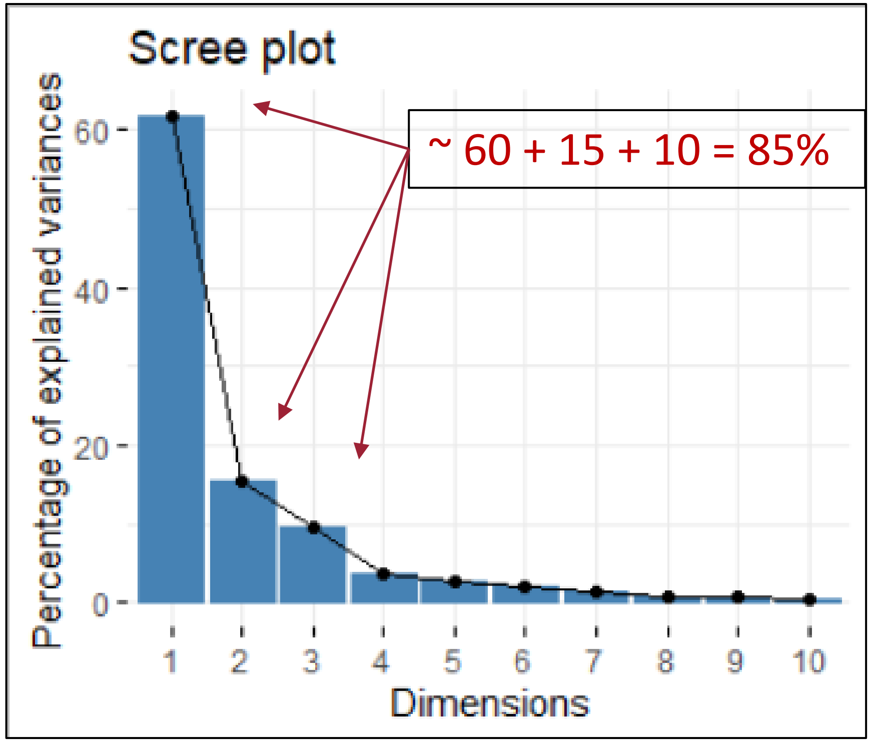
Data Preparation and Analysis – Dimension Reduction (PCA)

Reduce dimensionality

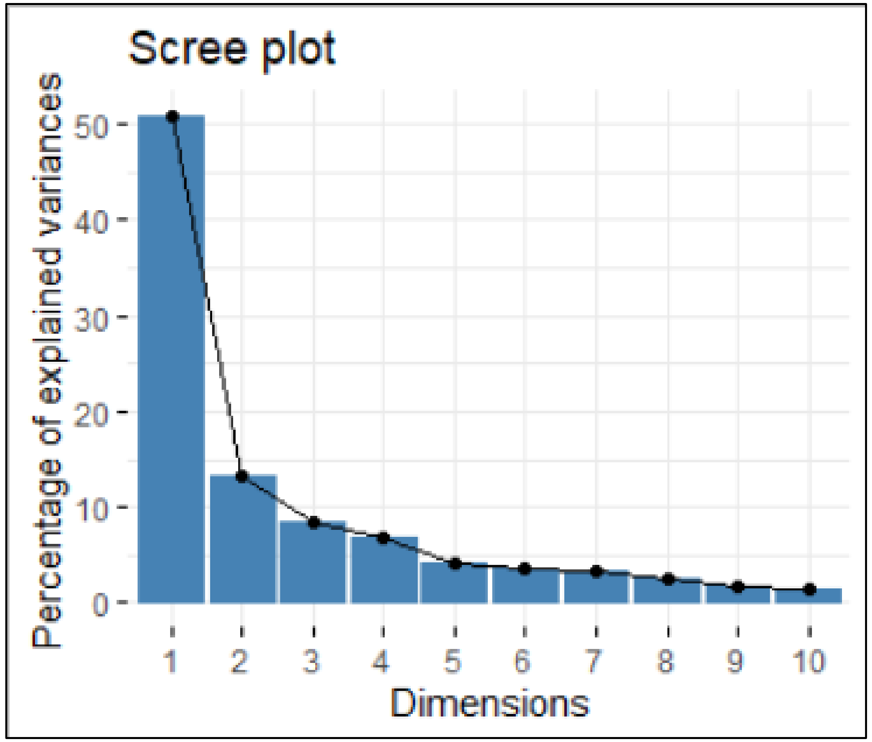
Principal components capture the underlying structure

Linear transformation

AHU-1



AHU-2



RAT Estimation Prediction Errors (3 days)

Table 1: RAT1 Estimation (Exogenous: OAT1 and TSPs)

	ME	RMSE	MAE	MPE	MAPE
Test set	1.807	2.412	1.931	2.253	2.418

Table 2: RAT2 Estimation (Exogenous: OAT2 and TSPs)

	ME	RMSE	MAE	MPE	MAPE
Test set	0.991	2.101	1.759	1.294	2.335

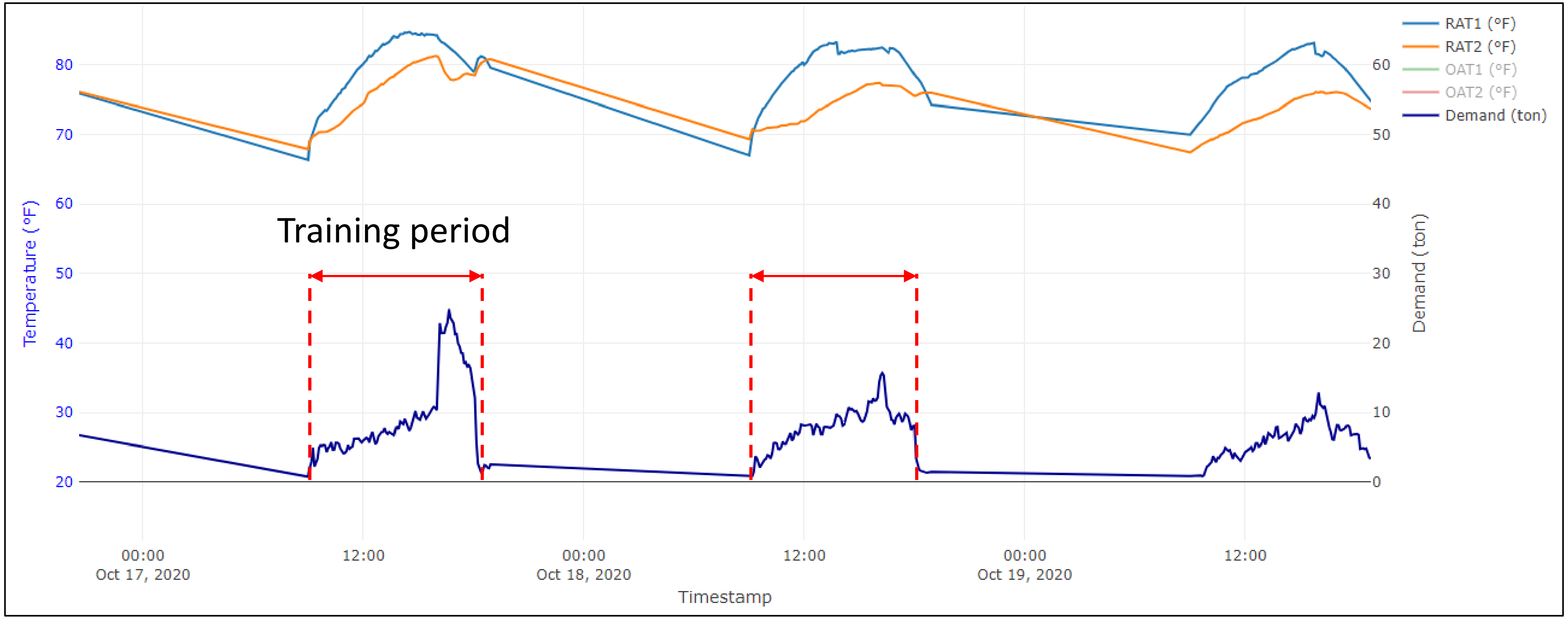
Experimental Data

Specifications

- Operating hours: 9am – 6pm
- Time resolution: 5 min to 1 hour interval

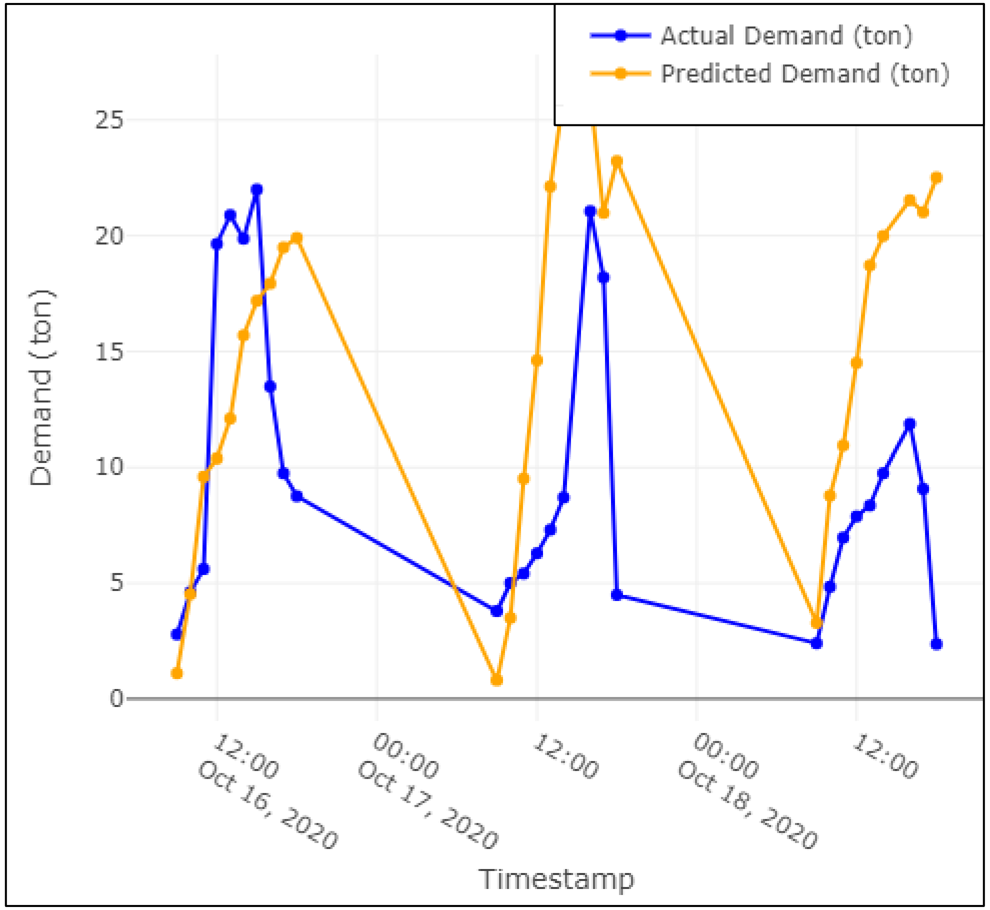
Scenarios

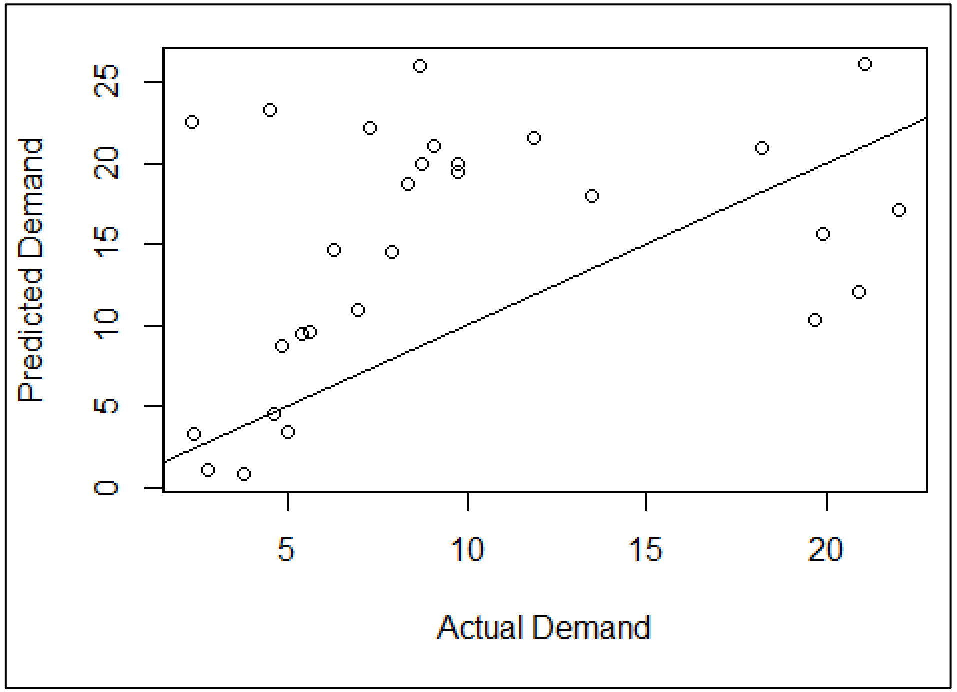
- A) Exclude the night time period from analysis
- B) Replace low demand by a constant
- C) Forecast using a rolling window



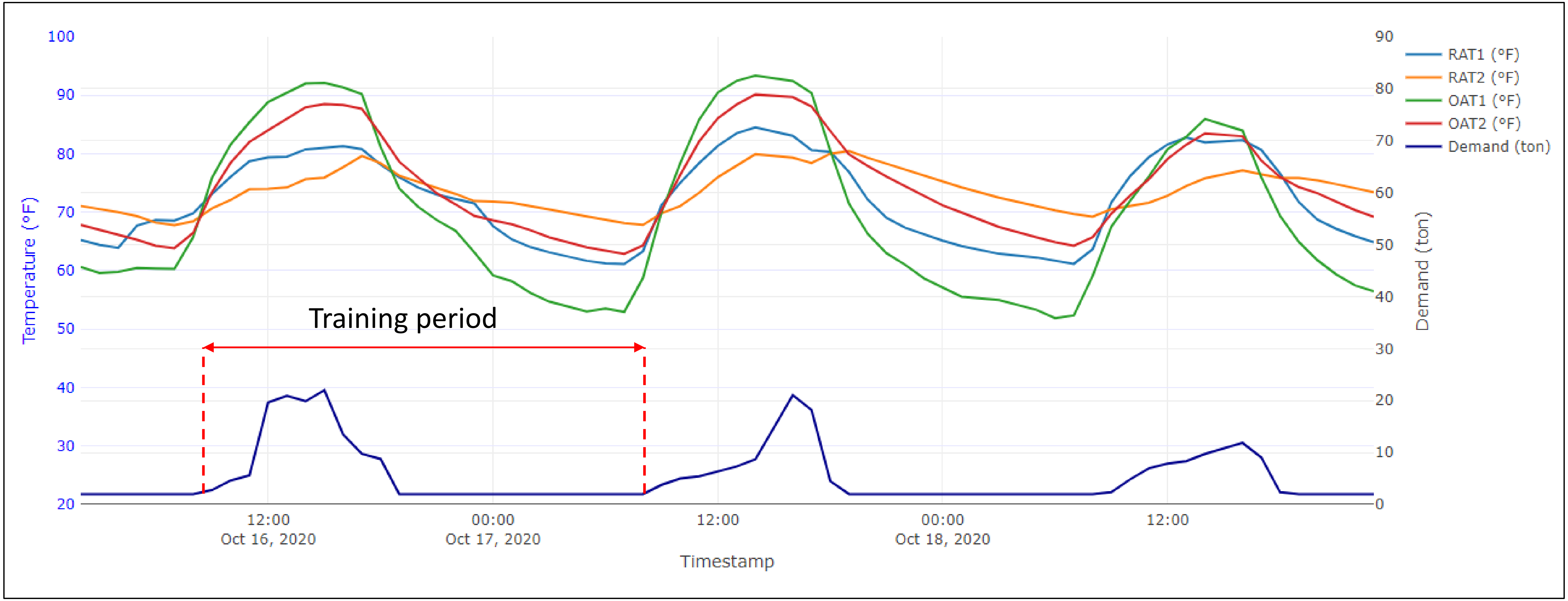
(A) Cooling Demand – removal of low demand periods

- RMSE = 9.23



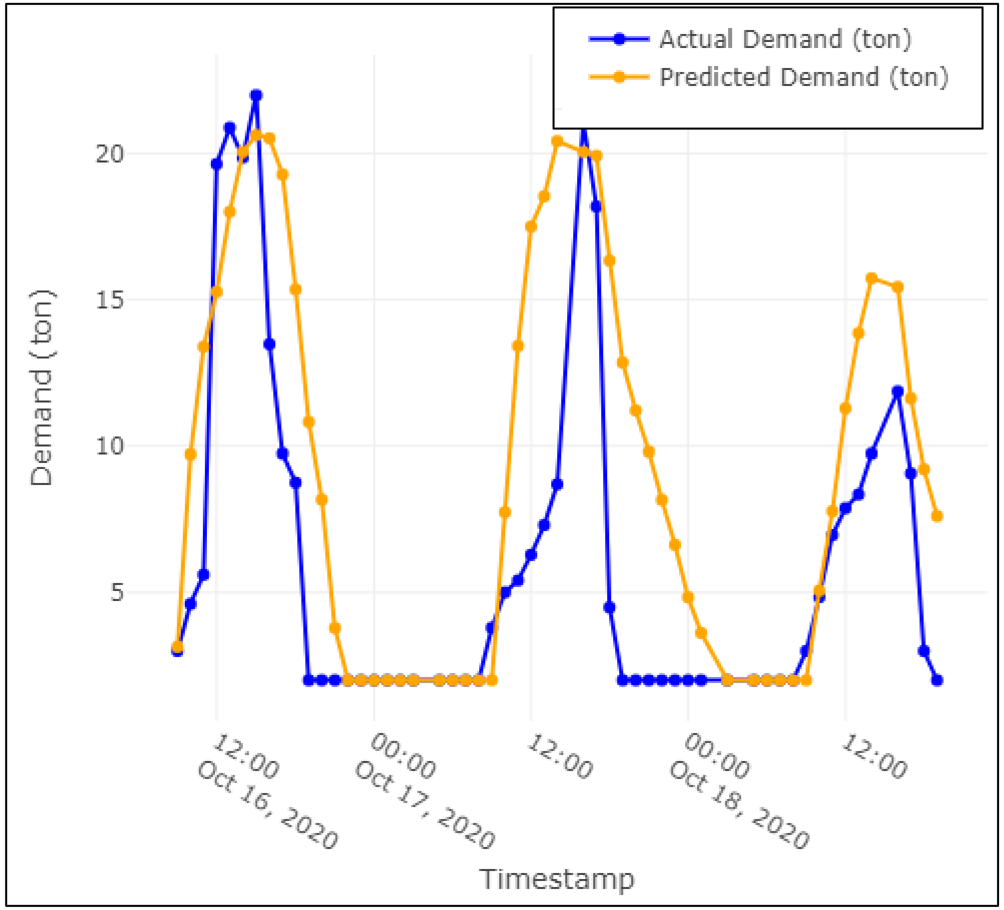


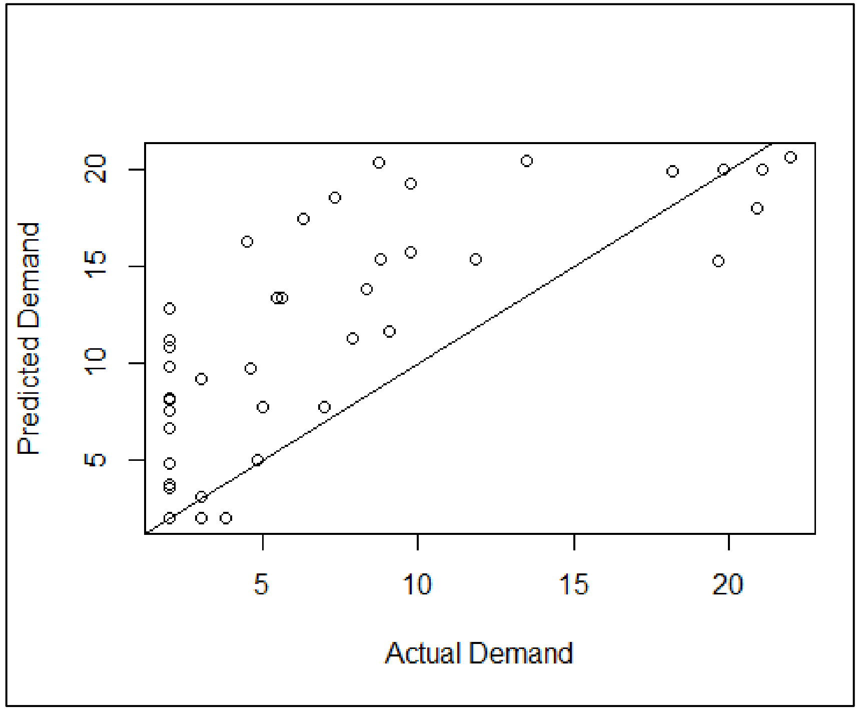
(B) Cooling Demand – low demand periods set to 2 ton



(B) Cooling Demand – low demand periods set to 2 ton

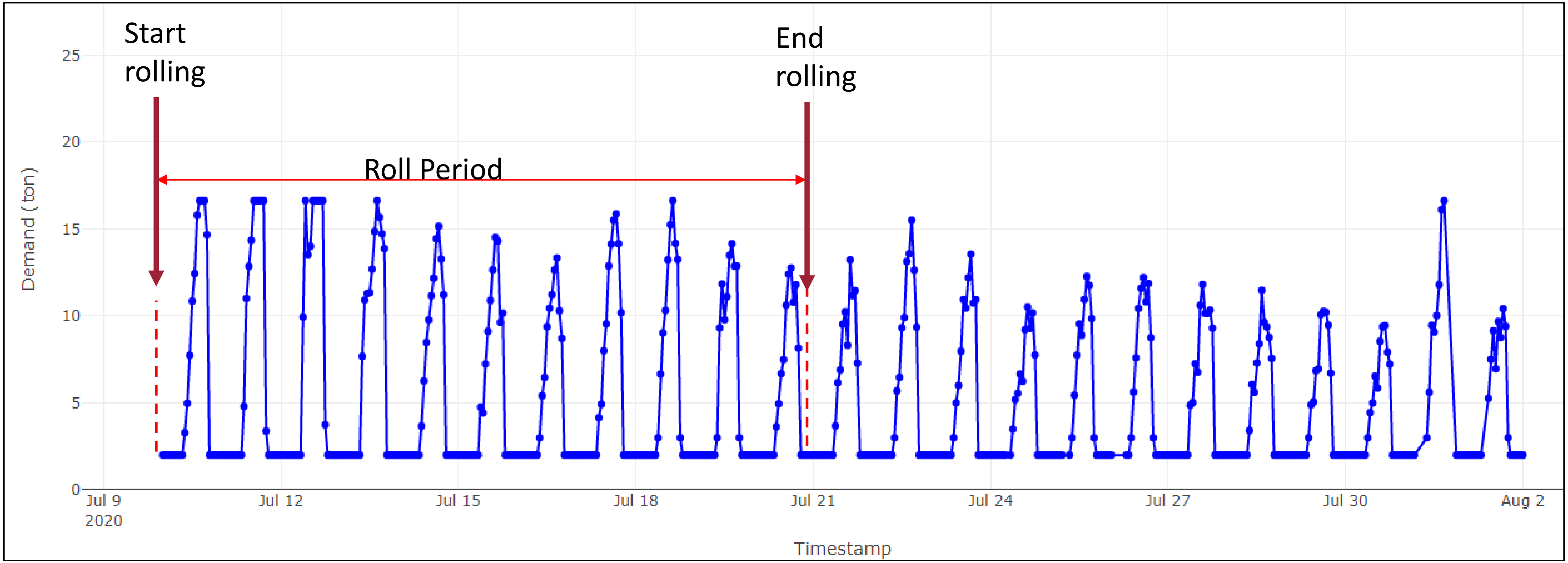
- RMSE = 5.323969





(C) Cooling Demand – rolling window forecast

- Roll period: 10th July – 20th July
- Training window: three weeks
- Prediction horizon: 1st Aug: 11th Aug



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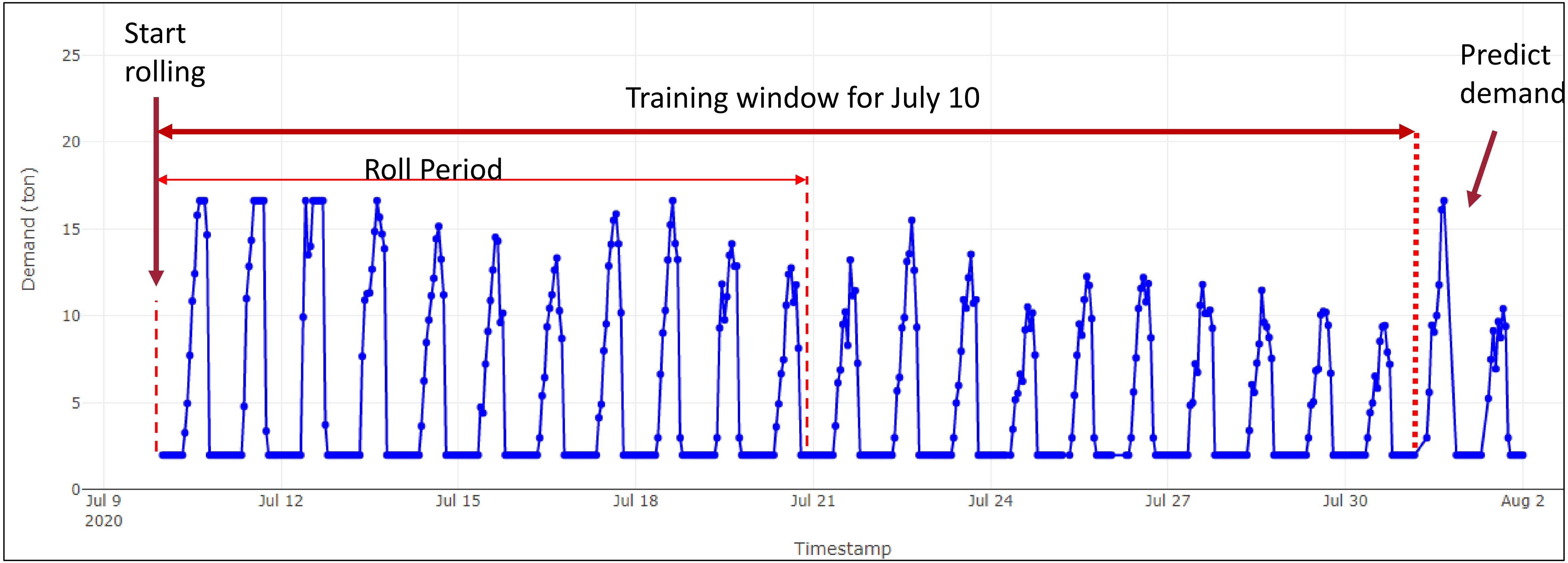
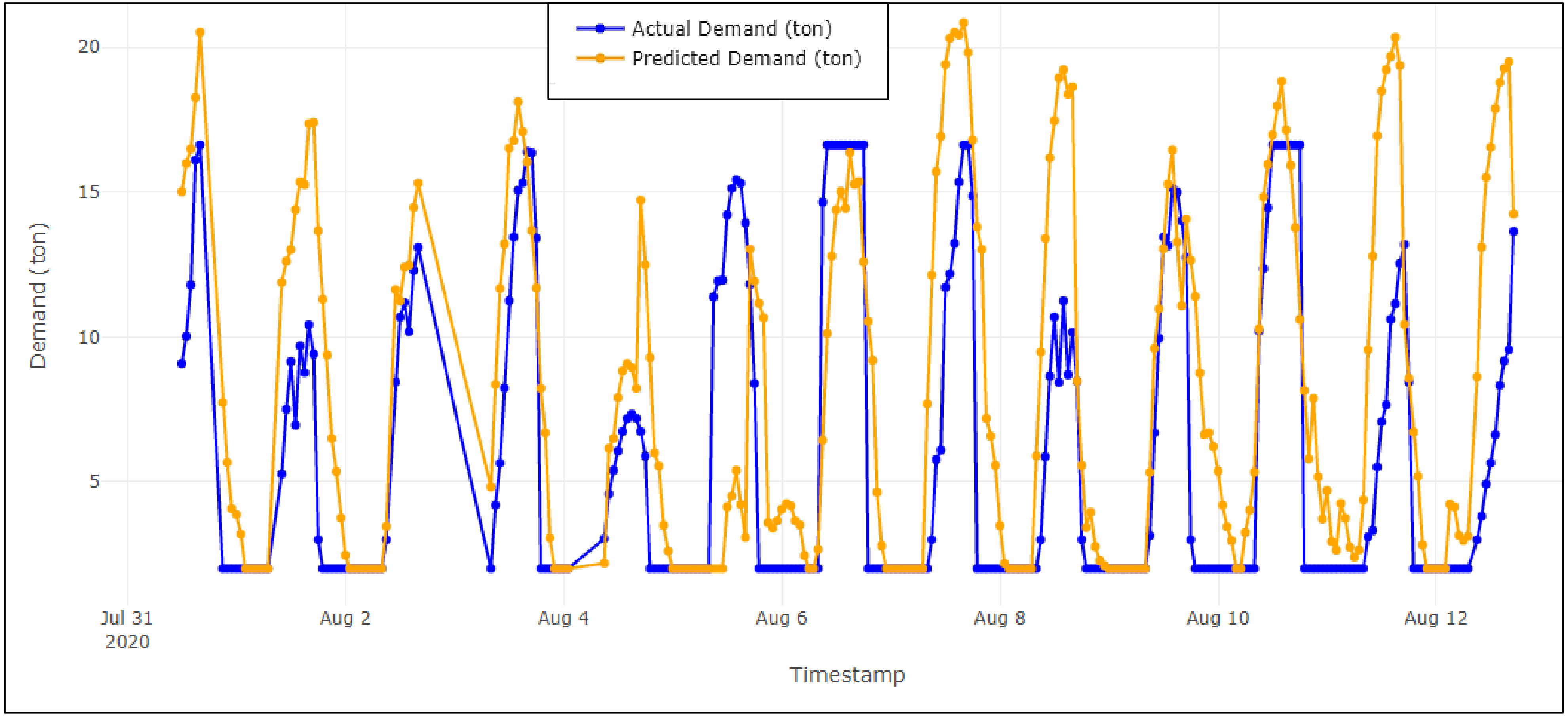


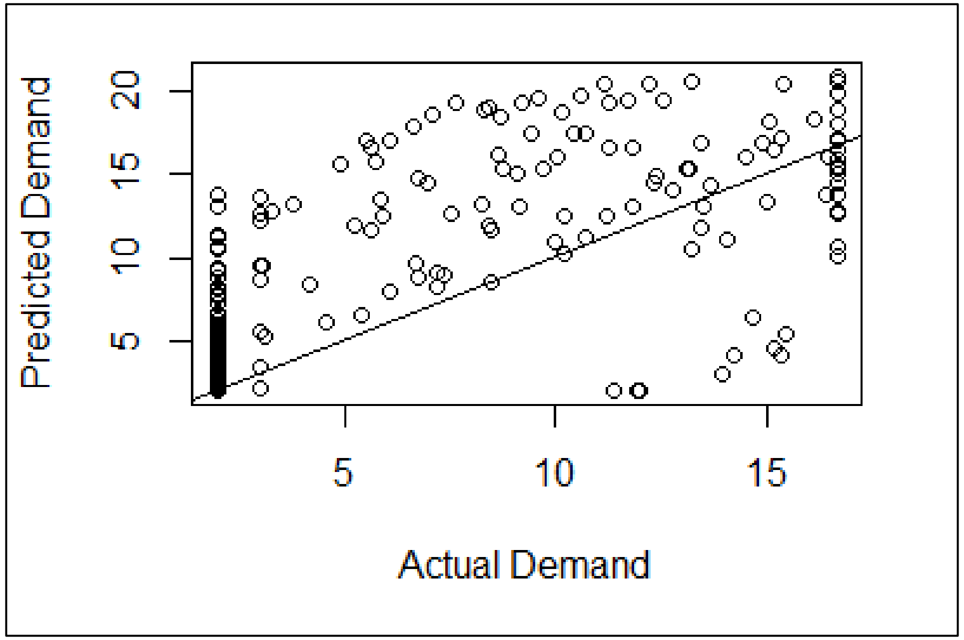
(C) Cooling Demand – rolling window forecast for August 2020



(C) Cooling Demand – rolling window forecast

Table 1: RMSE variations on each day of Aug

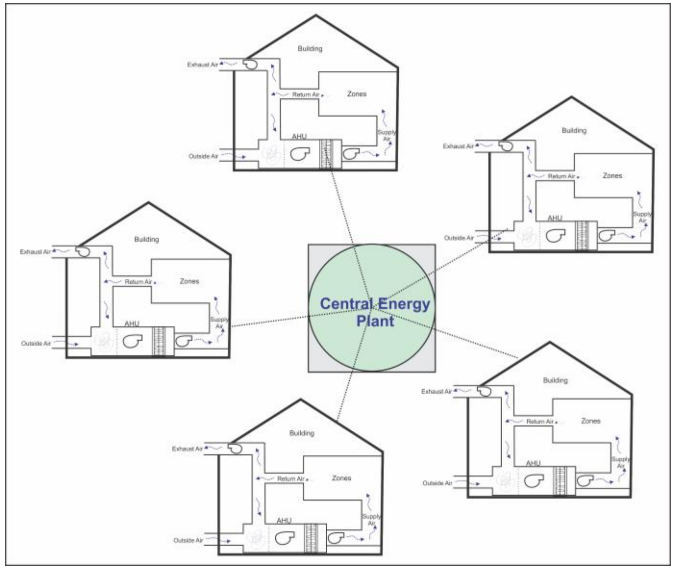
Day	1	2	3	4	5	6	7	8	9	10	11
RMSE	4.542	3.773	2.915	6.564	3.758	5.418	6.102	1.375	3.773	6.151	5.917



Takeaways

1. Testing/prediction horizon: Dynamic models are more accurate but may suffer from discontinuities in the data
2. Physical constraints: Buildings are shut down at night
3. Discarding the cooling demand and RAT values measured during the night may have a negative impact on the prediction of the demand for the first few minutes in the morning
4. Scalability

- Campus wide
- Building’s thermal response
- Occupancy mode
- Occupancy behavior
- Indoor environment
- Outside air temperature



Thank you!