Building Energy Management System (BEMS)

Literature Survey + Datasets Exploration

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Literature Survey (Part A)

Industry standards, reports, ML applications

Intelligent Building (IB), definitions, factors and evaluation criteria of selection

- Standardize criteria of IB design based on:
  - Quality Environment Modules (QEM)
    - **M1: Environmental friendliness**
    - M2…
    - **M4: Human comfort**
    - M5…
    - M10: Health and sanitation
  - Architectural point of view: see →
- Three main targets:
  - Safety & security, **User comfort**, Environment & **energy (reducing CO2)**

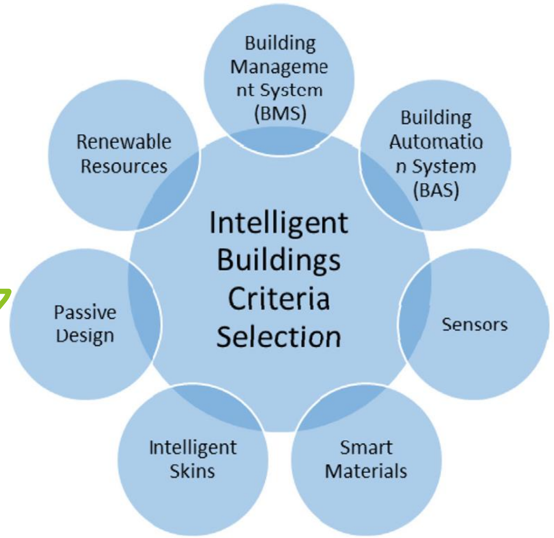


Fig. 5 Intelligent Buildings Criteria Selection with Main Factors (By Author). (Architectural point of view)

Reports

Mid-tier commercial office buildings in Australia

- Definition:
  - Buildings classified as premium, Grade A, B, C, D (defined by PCA)
  - Mid-tier buildings: Grades B/C/D (~50%)
- **Challenges**: Owners/tenants lack energy saving **motivation**
- **Pathway**:
  - Goals/Outcomes to motivate tenants
    - e.g. **higher standards** in new equipment, self-sustaining capital **investment**
  - Actions to achieve the outcomes
    - e.g. **equipment replacement**, innovative financing mechanism (**incentivization**)

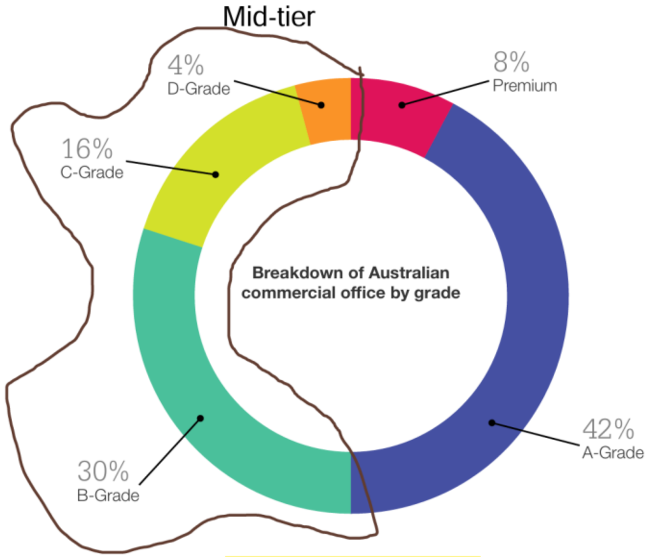


Figure 1: Breakdown of Australian commercial office by PCA grade, 2015 PCA Office Market Report

Reports

Project report: new generation intelligent building platform techniques

- **General purpose** control system design for different buildings
  - **Versatile**: suits building-specific requirements

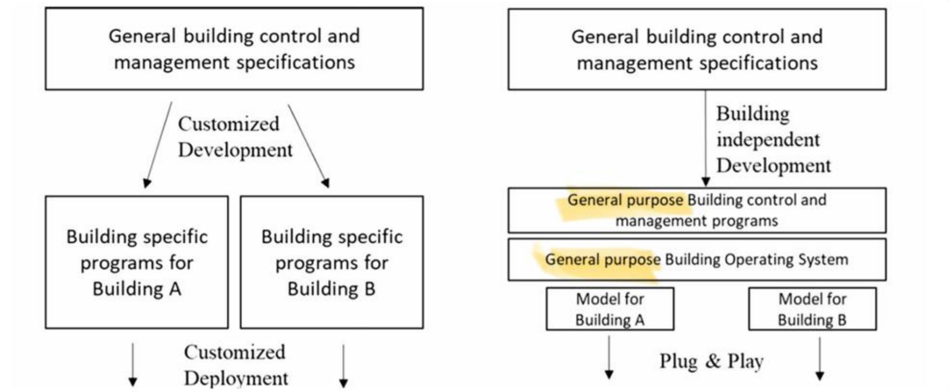


Fig. 3 a Customized Building Control System (left). **b** New Platform of Building Control System (right)

- **Decentralized** control and optimization for different buildings

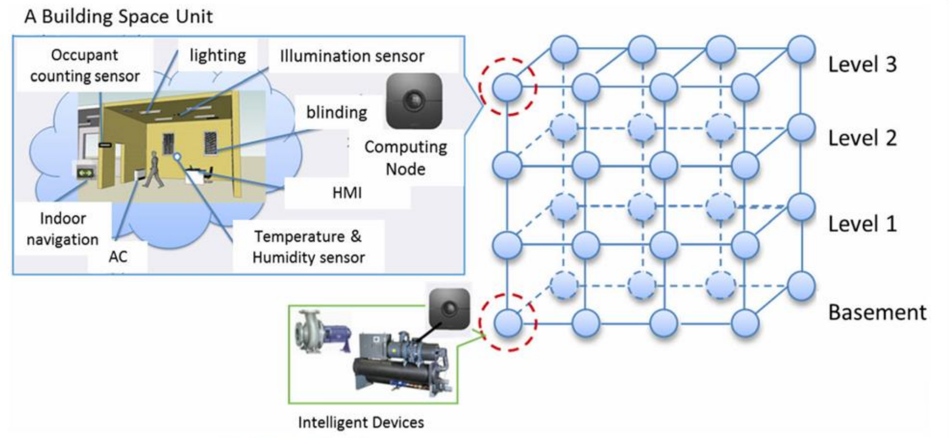


Fig. 2 An illustration of the decentralized control system in buildings

An overview of Machine Learning (ML) applications for smart buildings

- Part 1: Learning ability and goals of smart buildings

Table. 1
Examples of BAS improvements due to AI training.

Function	Status before training	Status after training
Observe	The BAS does not recognize one of the measured indoor temperatures as unexpectedly high.	The BAS recognizes unexpectedly high a room temperature.
Predict	The BAS mispredicts the building's energy demand for the next 24 h.	The BAS is able to predict the energy demand with a reasonable accuracy.
Adjust	The BAS follows a pre-defined control strategy without considering unpredicted changes in the occupancy.	The BAS introduces a new control strategy on the basis of up-to-date occupancy data.
Manage (data)	The BAS mispredicts the energy demand due to the gaps in acquired weather data.	The BAS predicts the energy demand accurately due to a reconstructed weather data set.
Interact (with humans)	The BAS calls service without a reason due to a misinterpreted temperature.	The BAS recognizes an unexpected temperature and calls the service if needed.

Our focus

An overview of Machine Learning (ML) applications for smart buildings

- Part 2: ML applications in BEMS, focusing on Reinforcement Learning (RL)
- RL key components (in BEMS context):
  - State: indoor (zone-specific) & outdoor temperatures, ambient light, #occupants
  - Reward: reduction in energy use (electricity)
  - Action: setpoint level (e.g. HVAC)
  - Environment (building energy model): Simulator-based / Data-driven → Our focus
    - This survey favours simulator (controllable settings) over data-driven

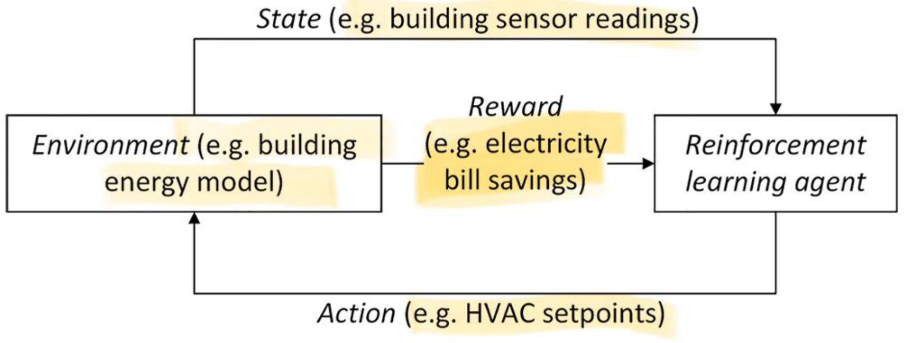


Fig.. 1. Key concepts of reinforcement learning.

An overview of Machine Learning (ML) applications for smart buildings

- Part 2: ML applications focusing on RL
- Papers on ML methods:
  - [1] Adjust lower-level HVAC setpoints
  - [2] Room-specific adjustment
  - [3][4] Consider variable electricity price
  - [5] Maximize rooftop photovoltaic generated electricity consumption
    - with occupants comfort as hard constraint
  - [6] Consider occupants behaviours e.g. adjust thermostat, change clothes

Literature Survey (Part B)

Methods (with/without codes) and toolset

Methods (with codes)

HVAC-using-Reinforcement-Learning

- https://github.com/UmeshRaval/HVAC-using-Reinforcement-Learning
- **Simplistic Q-Learning** agent in a **single HVAC** (not building) model
- QLearningAgent:
  - Q table = matrix of [**Actions** x **StateSpace**]
  - **Actions** = AC/Heating/Ventilation modes with Off/Eco/Performance levels
  - **StateSpace** = discrete permutation of (temp, humidity, watts, occupancy)
- HVACEnvironment:
  - Reward = weighted sum of reduction in **Temperature oscillation** and **Power** consumption
  - **Temperature oscillation** = Difference between current and target temperature
  - **Power** = Lookup table based on Off/Eco/Performance modes from Actions
- Packages: Most basic (e.g. numpy)

RL_HVAC_Ctrl

- https://github.com/RuiVieira89/RL_hvac_ctrl
- Another lightweight HVAC control model in a **car** (not building)
- Outdoor thermal data contains solar (radiance/irradiance), temperature and humidity
- **Rewards** occupants' (driver's / passengers') **comfort** by optimal dew point temperature as a function of humidity
- Packages: PyTorch

Automated_HVAC_System_using_Deep_Reinforcement_Learning

- https://github.com/JoshuaRaymondFernandes/automated_hvac_system_using_deep_reinforcement_learning
- **Deep** Q-Learning, controls heating/cooling power of a **building** (Building model defined)
- Aims to **minimize costs** while fulfilling custom-defined requirements
- Packages: Tensorflow 1.x

Model-based Reinforcement Learning for Building HVAC Control

- https://github.com/vermouth1992/mbrl-hvac
- https://doi.org/10.48550/arXiv.1910.05313 (Zhang et. al. 2019)
- Model-based approach, adopts **Model-Predictive-Control (MPC)** (not RL)
- Packages: EnergyPlus 9.1.0, Gym (OpenAI), PyTorch
  - Paper first published in 2019, packages are out-dated (EnergyPlus 9.x, Gym)

A Multi-Agent Reinforcement Learning Approach to Price and Comfort Optimization in HVAC-Systems

- https://github.com/ChrBlad/MARL_data
- "Data-driven Offline Reinforcement Learning for HVAC-systems" (https://doi.org/10.1016/j.energy.2022.125290) (Blad et. al. 2022)
  - Offline RL pretraining with **simulated data** from traditional control policies
  - Simulated data using Dymola (by Dassault Systèmes): Resembles Danish domestic house
  - Controls **Under-Floor-Heating (UFH)** system with heat pump (heating only, not HVAC)
- "A Multi-Agent Reinforcement Learning Approach to Price and Comfort Optimization in HVAC-Systems" (https://doi.org/10.3390/en14227491 Blad. 2021)
  - Focus on RL agents and environment design, modeled as a Markov Game process
  - Aims to reduce training time, heating costs and temperature oscillations
- Packages: Gym (environment), Tensorflow Keras (model)

Method (state-of-the-art!) (no codes)

A Multi-Agent Deep Constrained Q-Learning (MADCQ) Method for Smart Building Energy Management Under Uncertainties (Saberi et. al. 2024)

- Summary + innovations:
  - Online optimal solutions for BEMS under uncertainties and avoiding reward shaping
  - **Multi-agent** approach satisfies both individual and system-wide constraints
  - Performance evaluated by convergence (#iterations) and daily **energy cost**
  - Proposed method (MADCQ) superior to conventional DDQN
- Model, data, codes and toolset:
  - Building energy model: mathematically simulated
  - DNNs training data: Monte-Carlo simulated
    - based on historical outdoor temperature, solar irradiance etc.
  - Tensorflow (build DNNs), Pyomo (define optimization), GUROBI (solve the problem)

RL Agent, Environment, Evaluation (Single building settings)

- Gym by OpenAI (https://openai.com/index/openai-gym-beta/)
  - **General purpose** RL environment + evaluation framework
  - Gymnasium: Python library of Gym
- EnergyPlus (https://energyplus.net/)
  - A simulation framework **specifically built for building** energy simulation
  - Program funded by US Dept-Of-Energy's (DOE) Building-Technologies-Office (BTO)
- **Sinergym** (https://github.com/ugr-sail/sinergym)
  - A wrapper of **Gymnasium** for simulation in **EnergyPlus**
  - "An experimental evaluation of Deep Reinforcement Learning algorithms for HVAC control" (https://github.com/ugr-sail/paper-drl_building):
    - An algorithms' evaluation framework using Sinergym framework

For other purposes…

- HV-Ai-C (https://github.com/VectorInstitute/HV-Ai-C):
  - Implemented by Vector Institute (Toronto) and TELUS for HVAC temperature control
  - Aims to boost computational efficiency **for efficient deployment**
- CitySim (https://www.epfl.ch/labs/leso/transfer/software/citysim/)
  - Energy simulator for a set of **(multiple) buildings**
  - “Fusing TensorFlow with building energy simulation for intelligent energy management in smart cities” (https://doi.org/10.1016/j.scs.2018.11.021)
    - Integrates CitySim + Tensorflow/Keras

Dataset Exploration (Part A)

Building Overview, Metadata, Mapping to RL components

Building Overview

- Office building in Berkeley, California, constructed in 2015
- Vertical view:
  - Ground, Second floor
- Horizontal view:
  - North wing, South wing
  - HVAC Roof-Top-Unit: RTU 1, RTU 2, RTU 3, RTU 4
  - Zones:
    - Exterior zones (with exterior walls, 51 wall-mounted sensors)
    - Interior zones (16 digital sensors above/under workstation desks)

Building Schematic – Vertical View

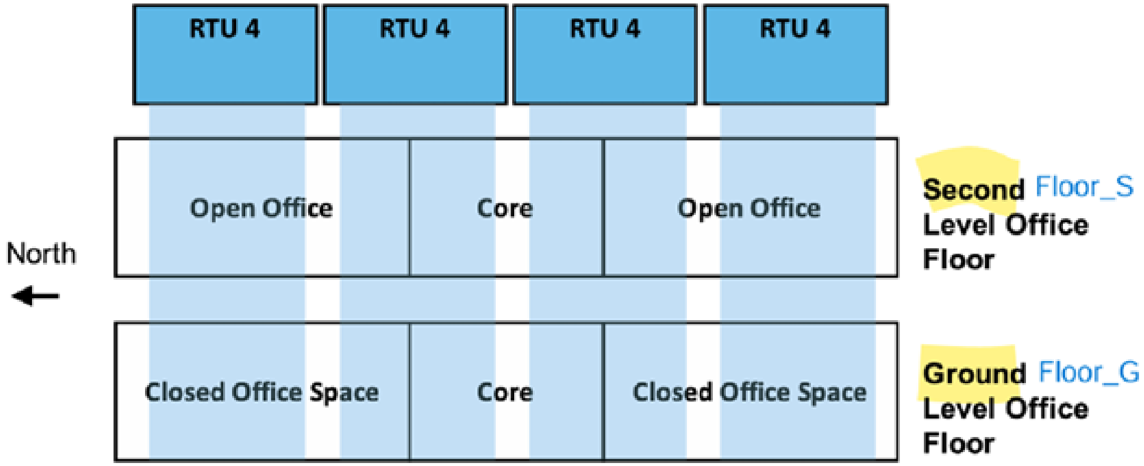


Fig. 3 Elevation schematic of RTU service coverage of the office levels.

Building Schematic – Horizontal View

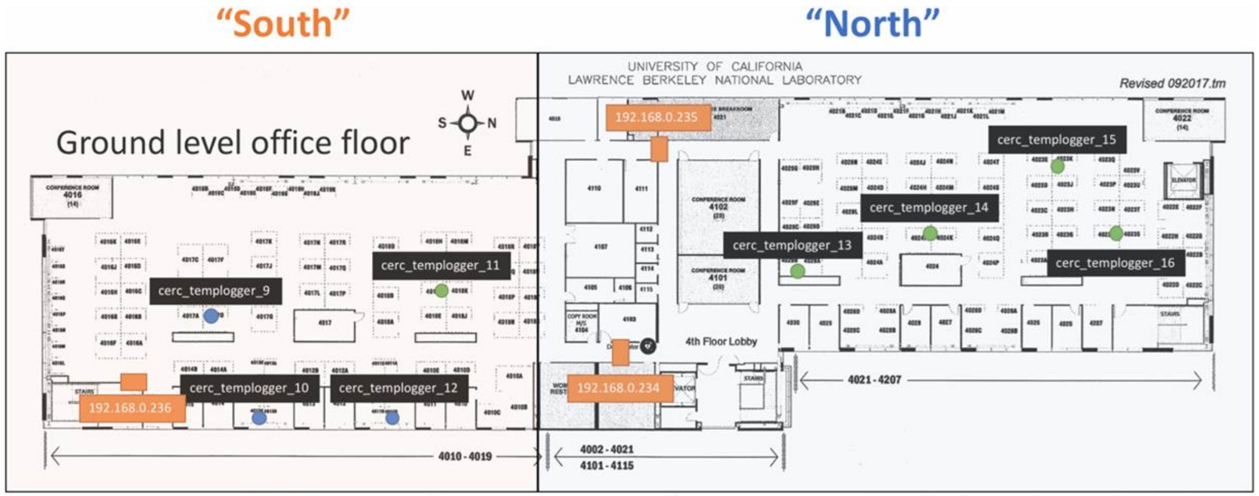


Fig. 2 Location of temperature sensors and occupant sensors.

Temp Sensors – Under Desk
Temp Sensors – Above Desk
Occupancy Sensors

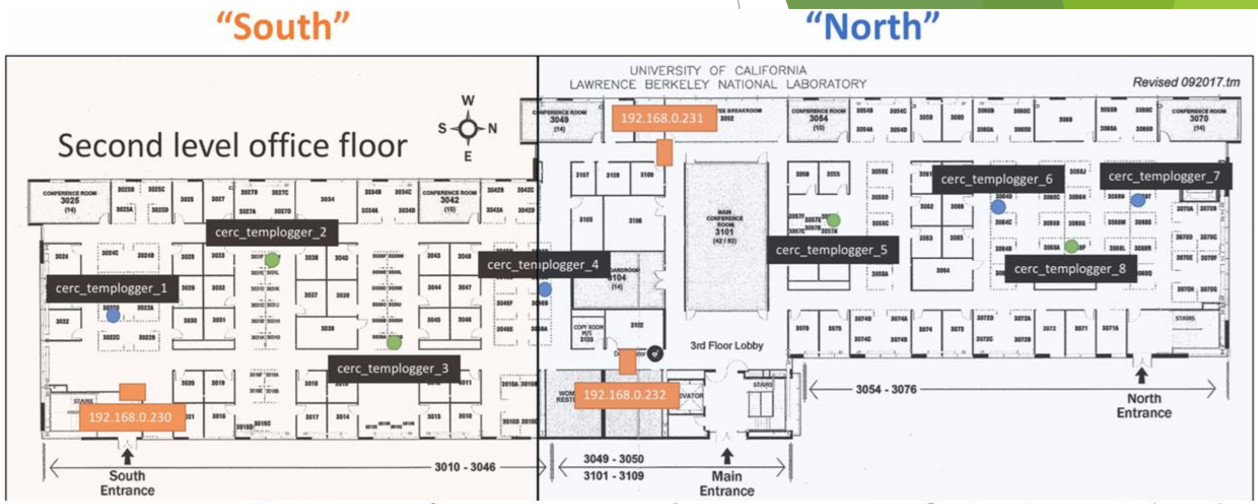


Fig. 2 Location of temperature sensors and occupant sensors.

Temp Sensors – Under Desk
Temp Sensors – Above Desk
Occupancy Sensors

Fig. 13 The floor map of (a) ground and (b) second floor about the location of each thermal zone.

Fig. 13 The floor map of (a) ground and (b) second floor about the location of each thermal zone.

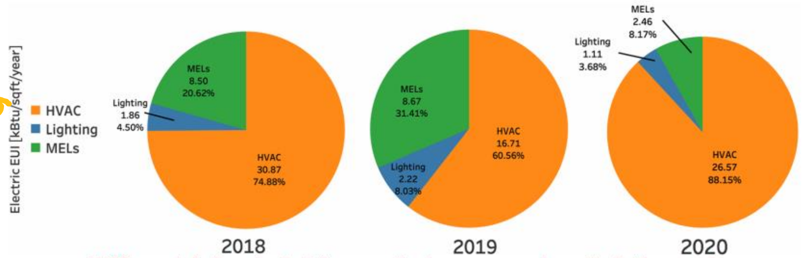
Building Zone Mapping

Horizontal view		Vertical view		Horizontal view					
				Exterior Zones			Interior Zones		
Building wings	HVAC RTU	Floor	Occupancy data	Temperature sensors	Zone numbers	Data field names	Zone numbers	Temperature sensors	Data field names
North wing	RTU 1	GF	-	Wall-mounted sensors	064,065,066,067,068,069,070	zone_*_temp	-	Digital sensors mounted above/under workstation desks	cerc_templogger_[13,14,15,16]
		2F	-		036,037,038,039,040,041,042		-		cerc_templogger_[4,5,6,7,8]
	RTU 2	GF	-		049,057,058,059,062,063,071,072		050,060		cerc_templogger_[13,14,15,16]
		2F	-		019,027,028,030,032,033,035,043,044		020,029,031,034		cerc_templogger_[4,5,6,7,8]
South wing	RTU 3	GF	occ/wifi_third_south		048,055,056,061		-		cerc_templogger_[9,10,11,12]
		2F	occ/wifi_fourth_south		018,025,026,045		-		cerc_templogger_[1,2,3]
	RTU 4	GF	occ/wifi_third_south		046,047,051,052,053,054		-		cerc_templogger_[9,10,11,12]
		2F	occ/wifi_fourth_south		016,017,021,022,023,024		-		cerc_templogger_[1,2,3]

A three-year dataset supporting research on building energy management and occupancy analytics

Data Overview

- Three years (from 2018 to 2020), consisting of:
  - Energy use data
    - <u>HVAC</u> (every 15mins), Lighting (South wing only), Miscellaneous
  - Outdoor environmental data
    - Sensors for **<u>temperature</u>**, humidity, solar radiation
  - Indoor environmental data (temperature)
    - **<u>Exterior zones</u>** (51 zones): Every 1min, complete period
    - Interior zones (16 sensors): Every 10mins, missing Jan 2018
  - HVAC operational data
    - RTUs supply air **<u>temperature setpoints</u>**, RTUs supply **<u>fan speed</u>**, Zones cooling/heating temp. setpoints
    - Hydronic (water) heating coils valve position (44 exterior zones only)
  - Occupant data: South wing only, floor-level (not zone-level) only
    - #occupants: May 2018 to Feb 2019 only, #Wifi-connections: May - Jul 2018, Feb - Dec 2020 only



HVAC accounts for the major electricity consumption, hence, we may only consider that for research.

Fig. 9 Electric EUI of major end uses from 2018 to 2020.

Data Mapping to MADCQ RL method

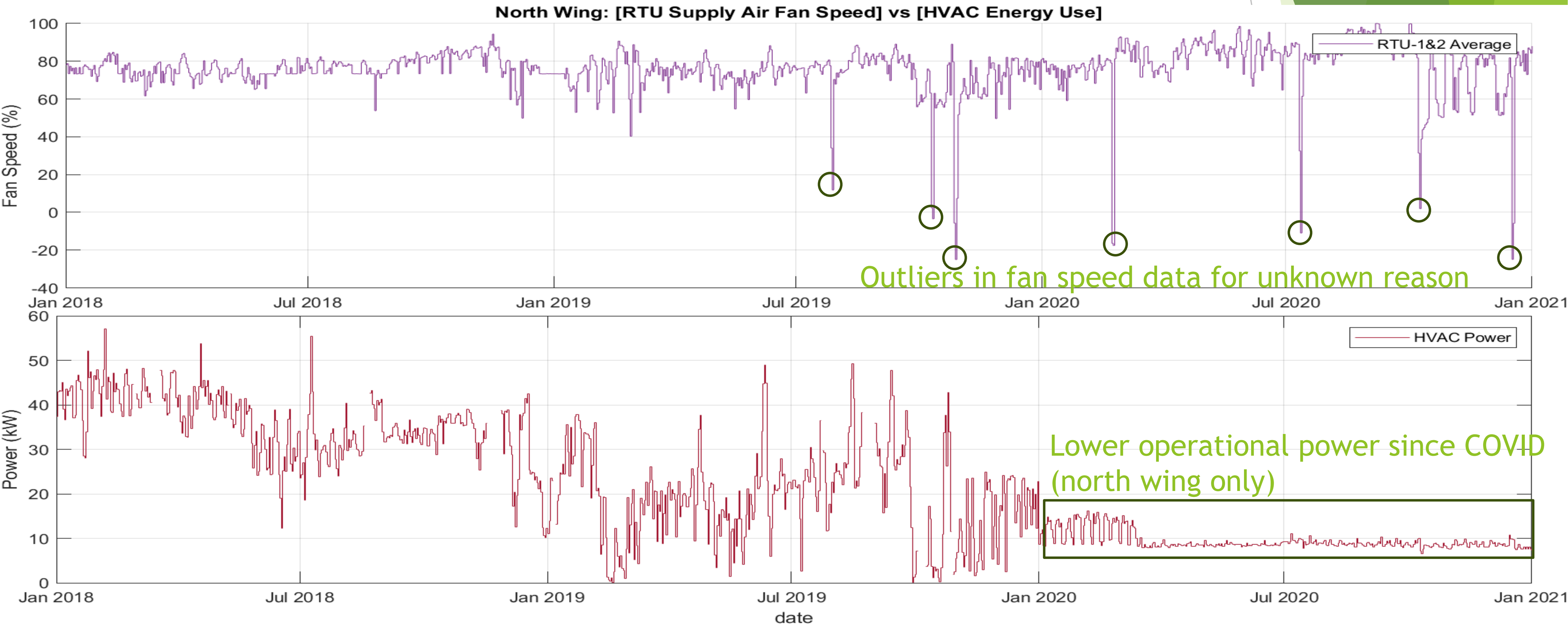
RL components	MADCQ data-driven approach	Berkeley building dataset
Actions	HVAC temperatures, divided into: 1. AC, the air temperature 2. H, heating temperature (by water)	rtu_sa_t_sp.csv > rtu_*_sat_sp_tn (*:001...004)
		rtu_fan_spd.csv > rtu_*_sf_vfd_spd_fbk_tn (*:001...004)
		zone_temp_sp_c.csv > zone_*_cooling_sp (*:exterior_zone_numbers)
		zone_temp_sp_h.csv > zone_*_heating_sp (*:exterior_zone_numbers)
		uft_hw_valve.csv > zone_*_hw_valve (*:016...072 excl. 019,020,029,030,031,032,033,034,049,050,059,060,062)
		rtu_oa_damper.csv > rtu_*_oadmpr_pct (*:001...004)
		rtu_econ_sp.csv > rtu_*_econ_stpt_tn (*:001...004)
	Water heater (WH) temperature controllers	- (no hot water supply in this dataset, to be distinguished from hydronic floor heating.)
	EV charger temperature setpoints	-
States	Indoor temperatures	zone_temp_exterior.csv > zone_*_temp (*:016...072 excl. 020,029,031,034,050,060)
		zone_temp_interior.csv > cerc_templogger_* (*:1...16)
	Outdoor temperature	site_weather.csv > air_temp_set_* (*:1,2)
	-	site_weather.csv > relative_humidity_set_1
	-	site_weather.csv > solar_radiation_set_1
	-	occ.csv > occ_*_south (*:third,fourth)
	-	wifi.csv > wifi_*_south (*:first,second,third,fourth)
Rewards	Reduction in energy consumption	ele.csv > hvac_S
		ele.csv > hvac_N
Constraints (users comfort)	Room-specific T_min < T < T_max	See indoor temperatures
	-	zone_co2.csv > zone_*_co2 within thresholds

Dataset Exploration (Part B)

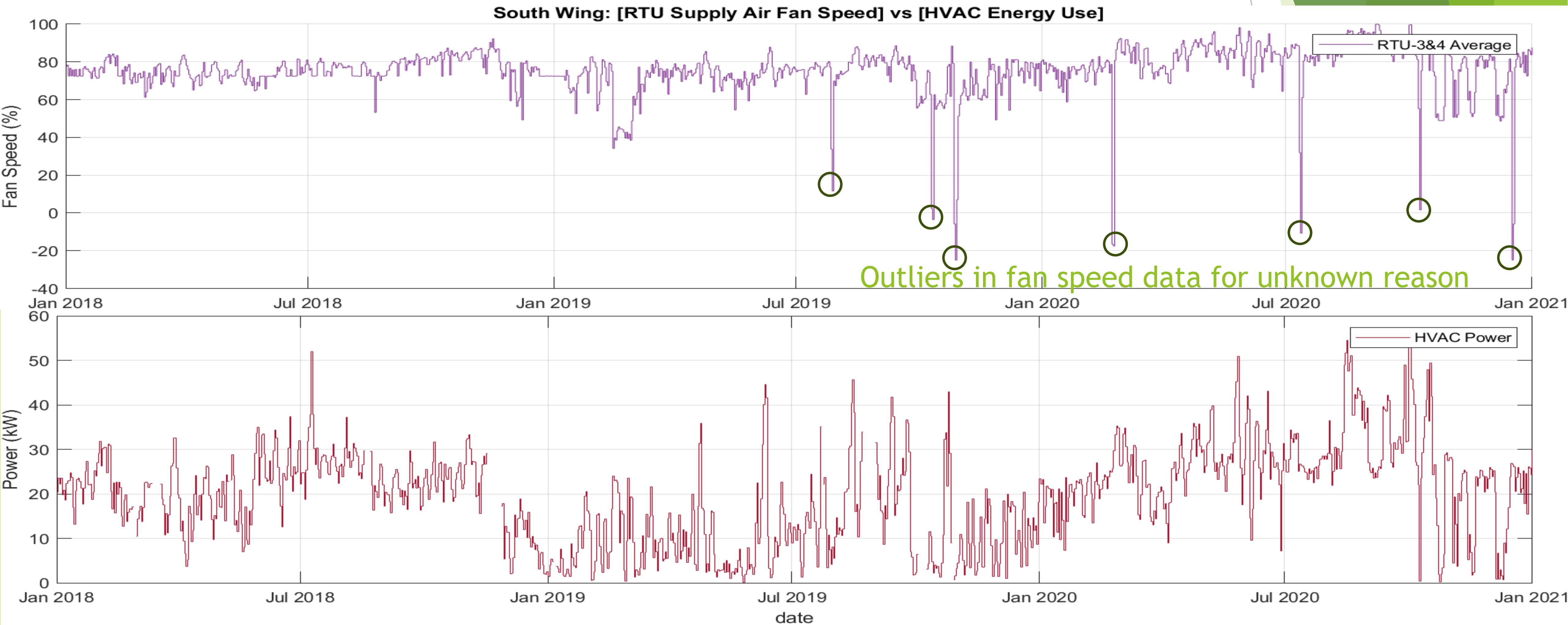
Visualization

Energy consumption (daily average)

HVAC RTU Fan speed vs Power (North wing)

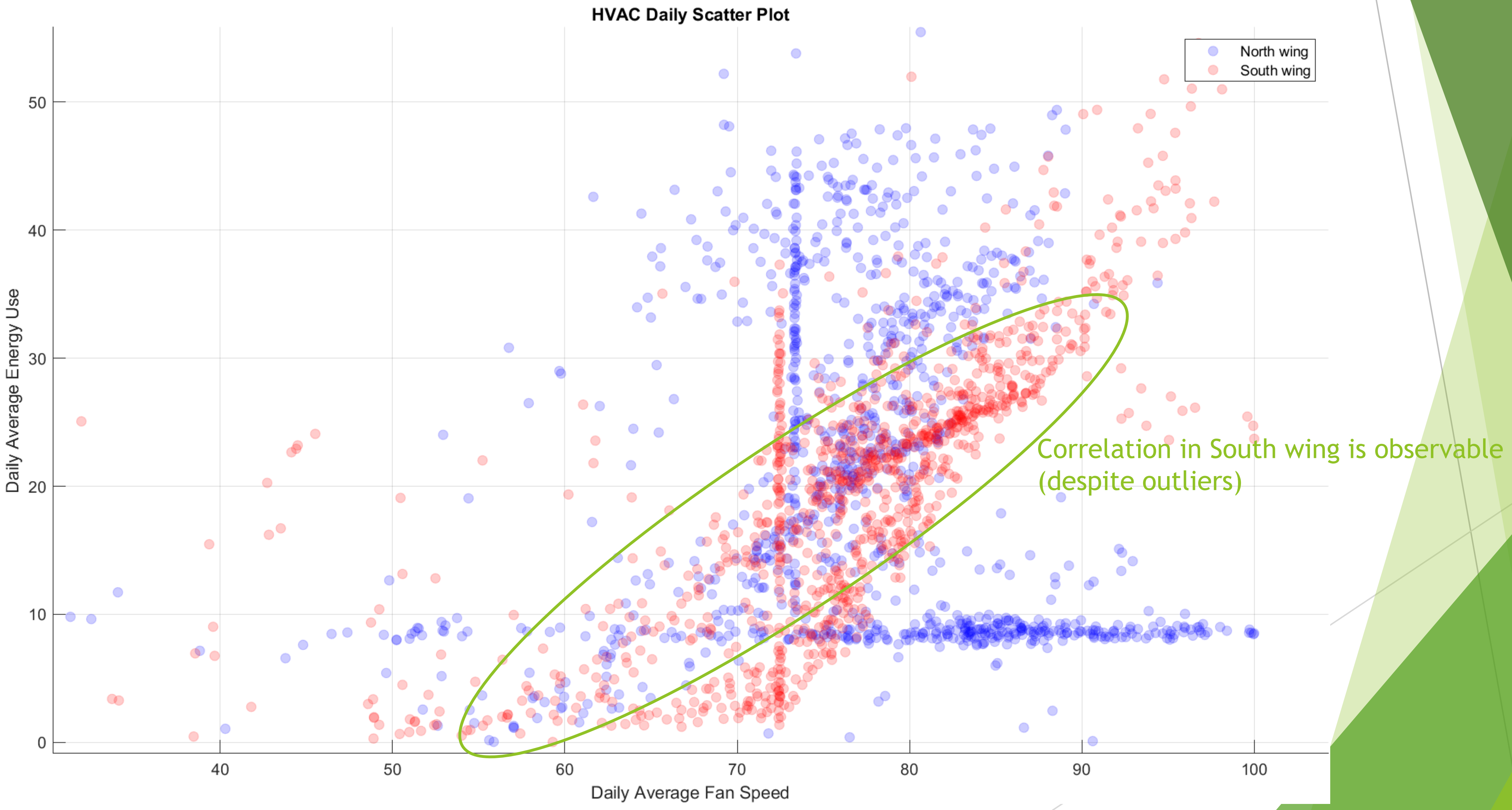


HVAC RTU Fan speed vs Power (South wing)



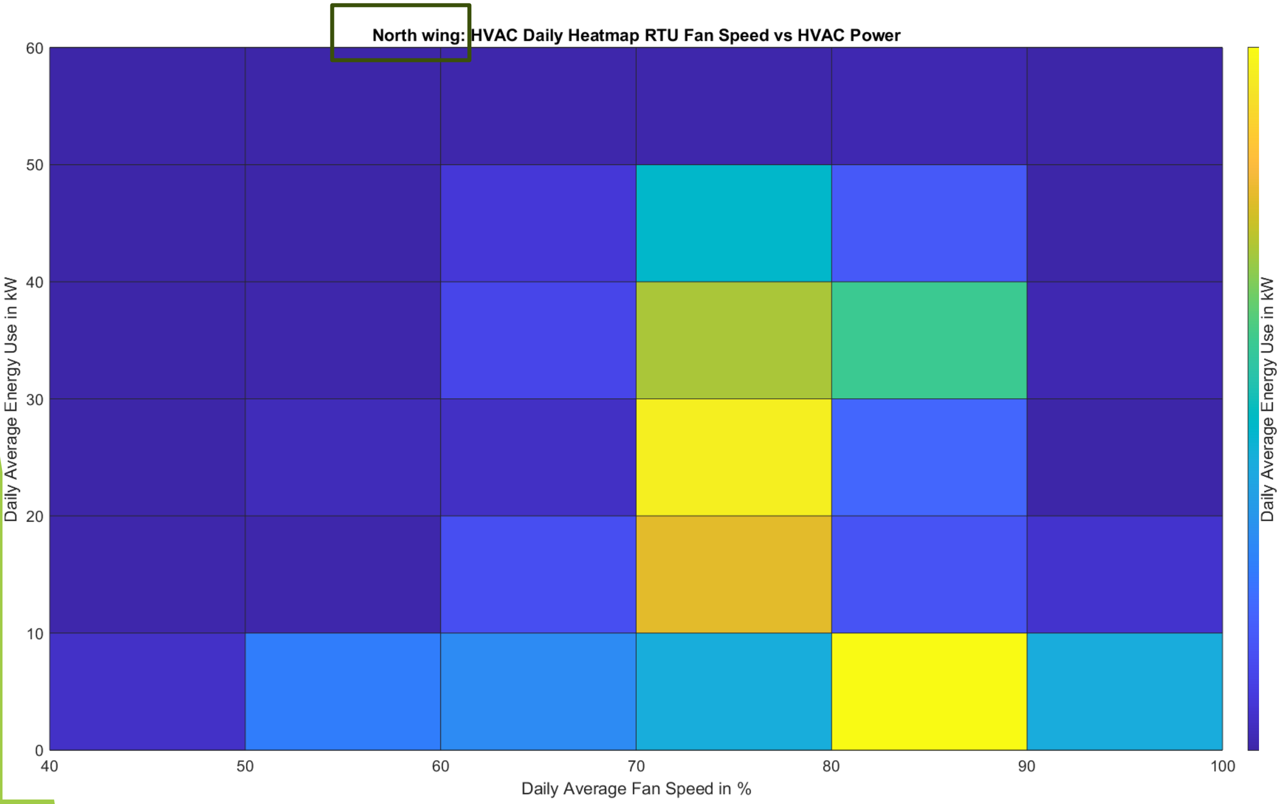
Energy consumption (daily average)

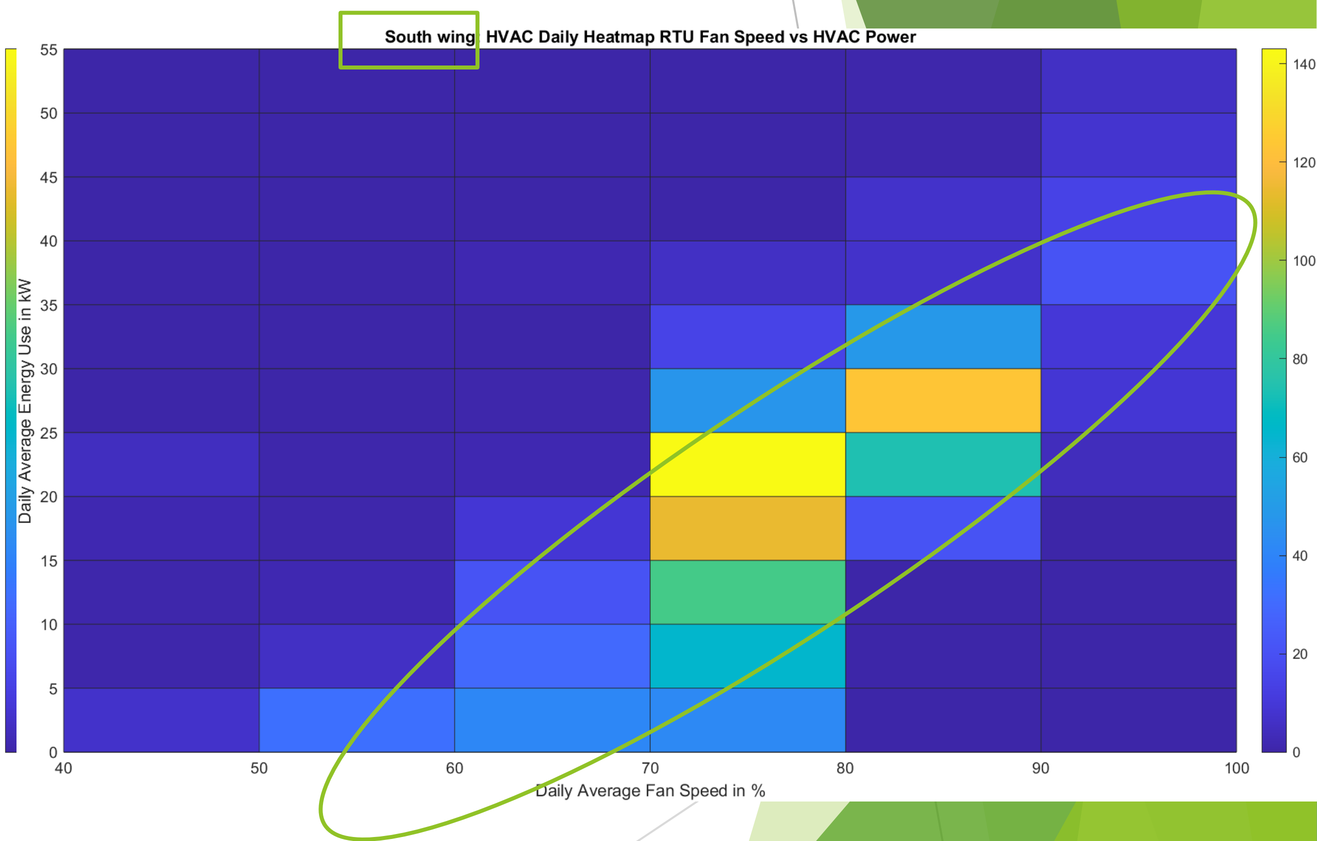
HVAC RTU Fan speed vs Power



Energy consumption (daily average)

HVAC RTU Fan speed vs Power

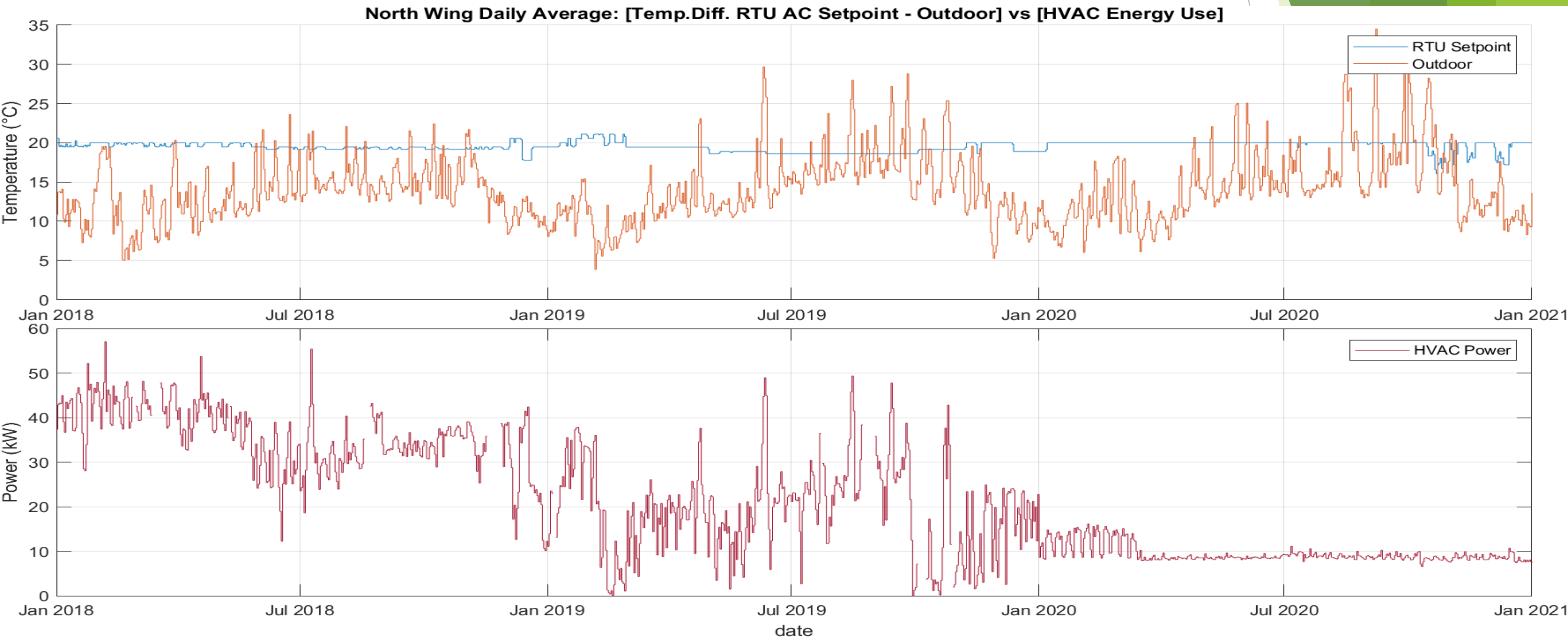




Correlation in South wing is more obvious than in North wing (despite outliers)

HVAC RTU Temp. Setpoint vs Power (N)

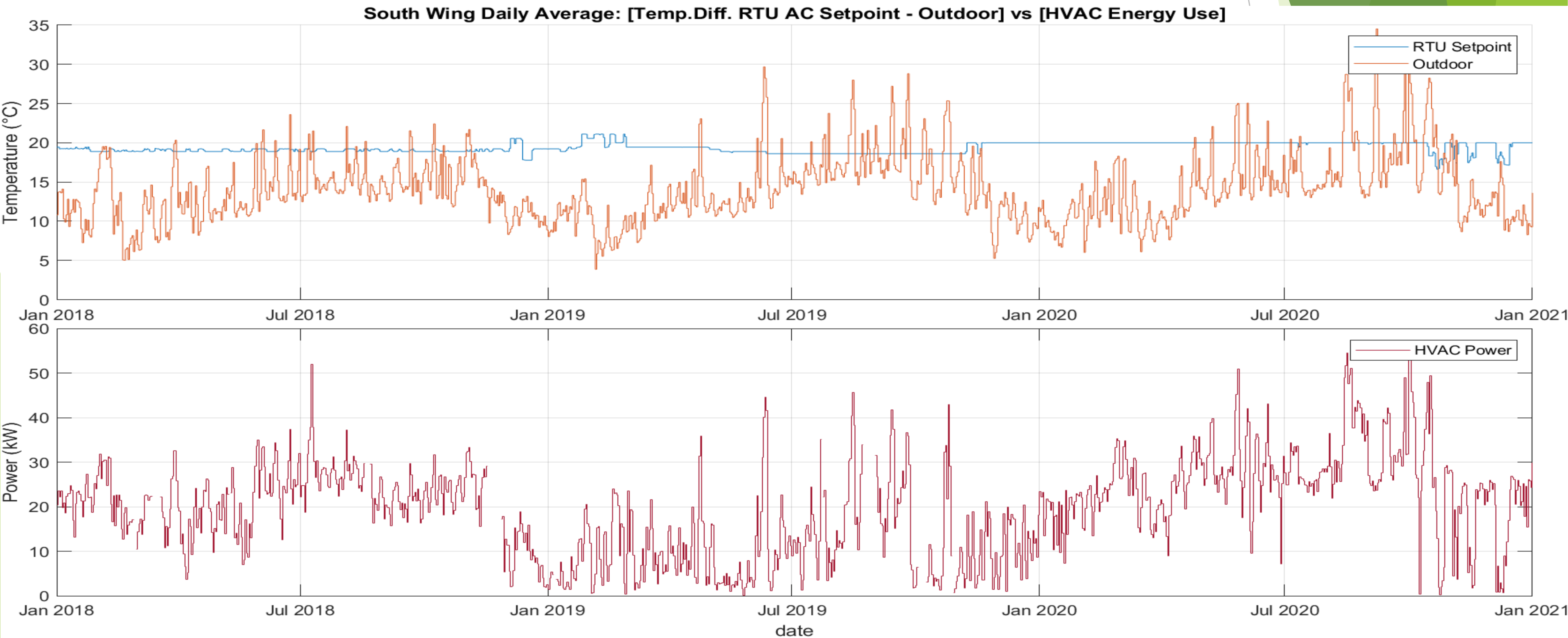
No observed correlation btw. temp. diff. (setpoint-outdoor) and HVAC power



Energy consumption (daily average)

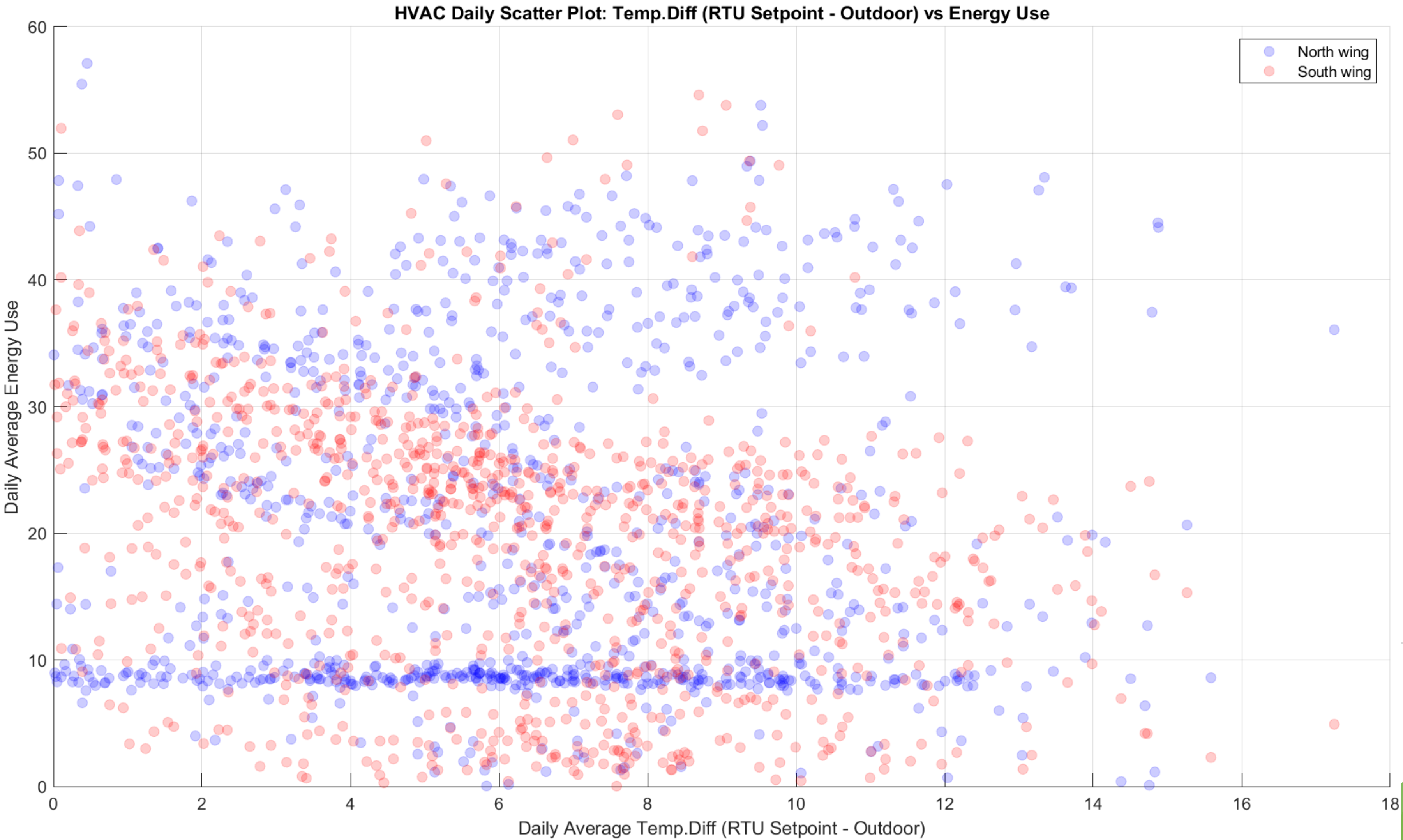
HVAC RTU Temp. Setpoint vs Power (S)

No observed correlation btw. temp. diff. (setpoint-outdoor) and HVAC power



HVAC RTU Temp. Setpoint vs Power

No observed correlation btw. temp. diff. (setpoint-outdoor) and HVAC power



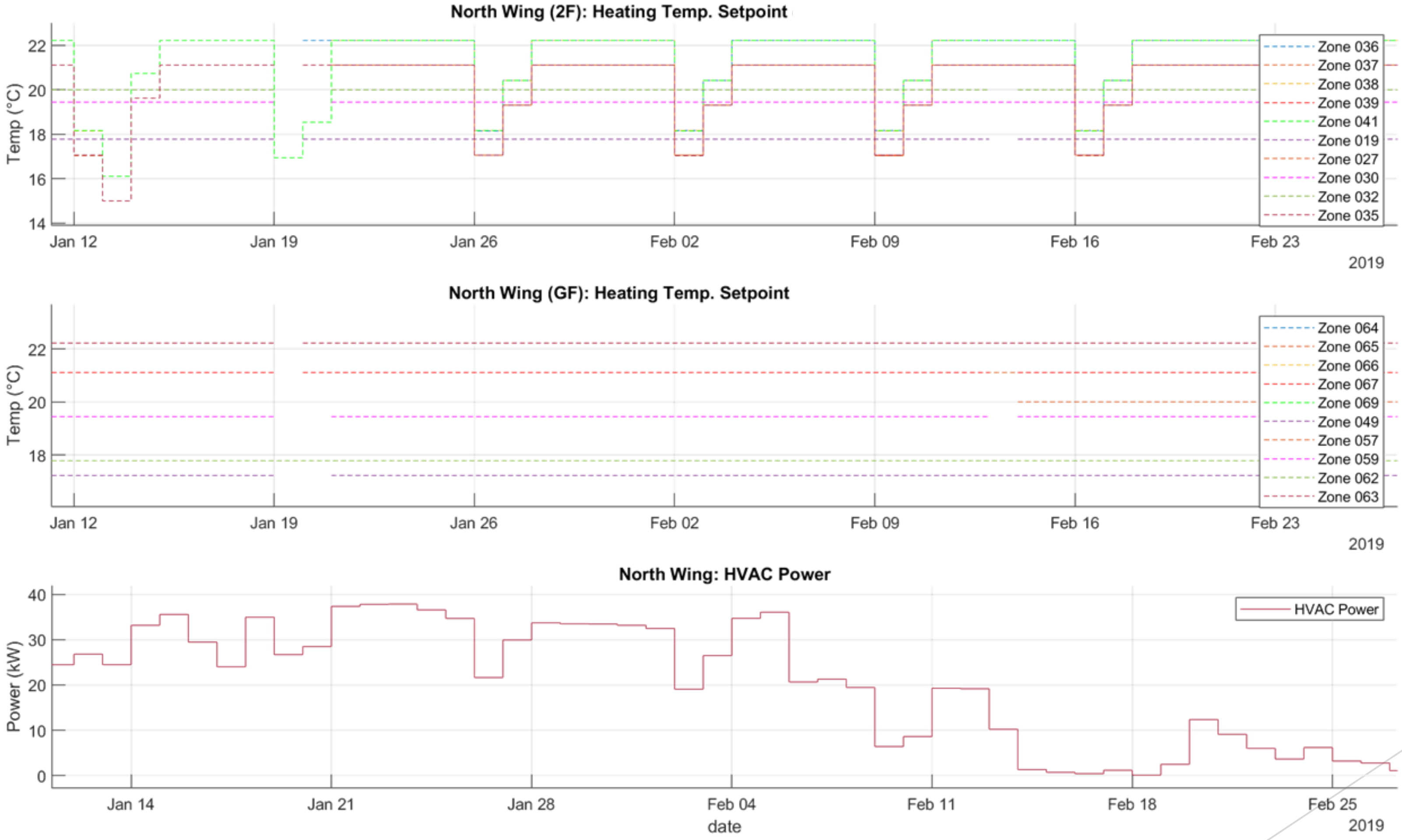
Energy consumption (daily average)

Zone Cooling Temp Setpoint vs Power (N)

- During summer 2019, cooling setpoints are only adjusted on 2F.
- No observable correlation between setpoint and energy consumption.

Zone Heating Temp Setpoint v Power (N)

- During winter 2019, heating setpoints are only adjusted on 2F.
- No observable correlation between setpoint and energy consumption.



Zone Cooling Temp Setpoint vs Power (S)

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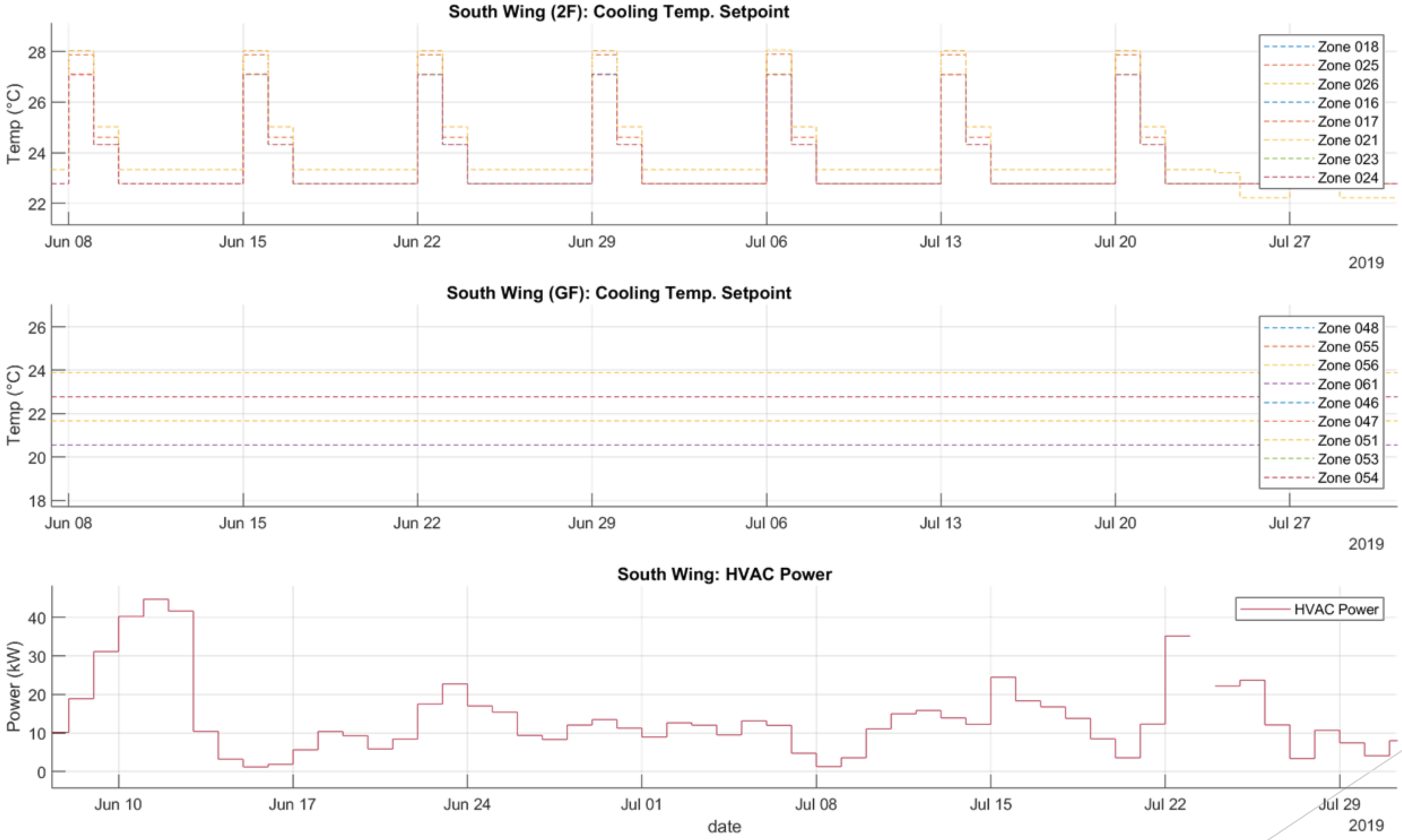

Zone Heating Temp Setpoint vs Power (S)

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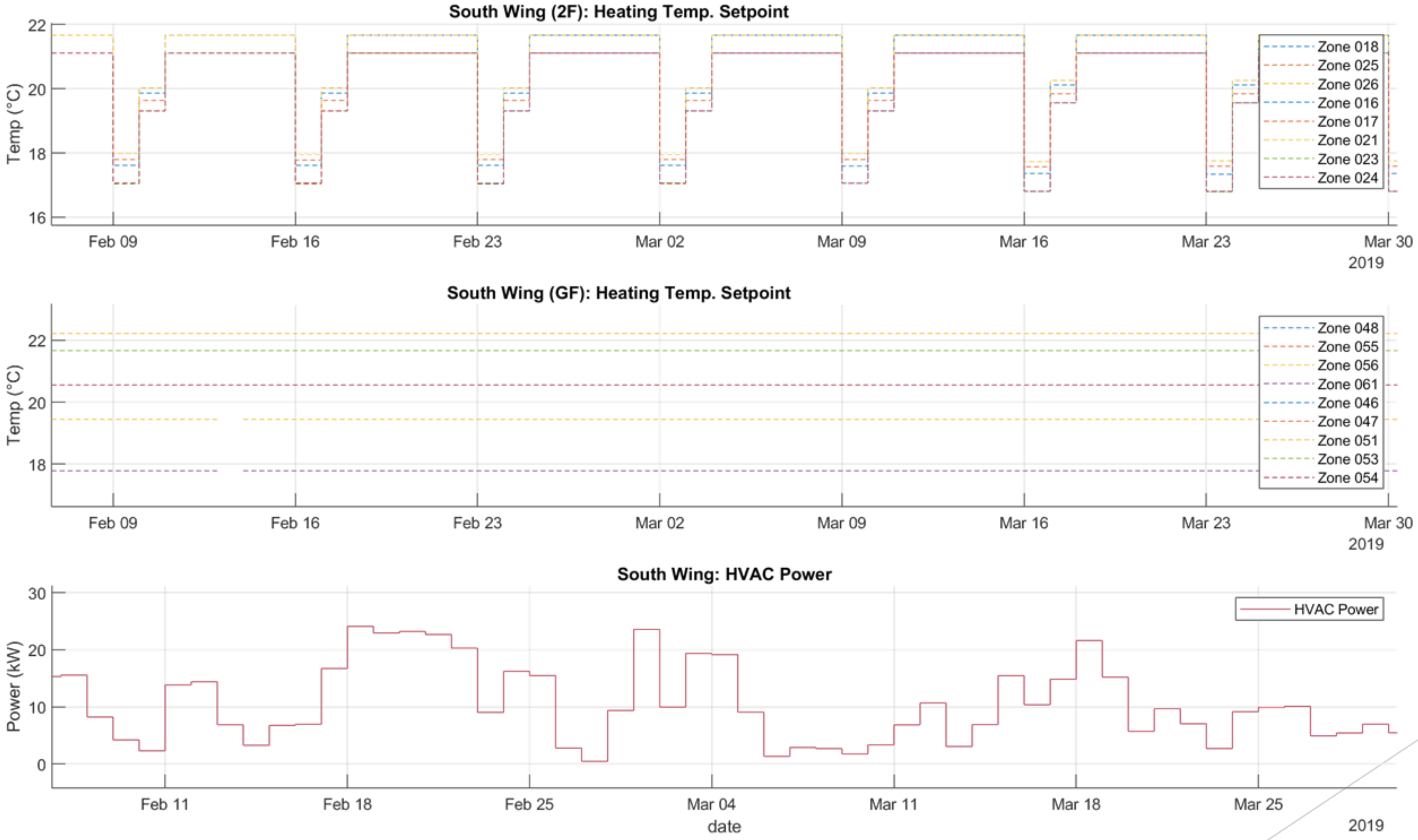
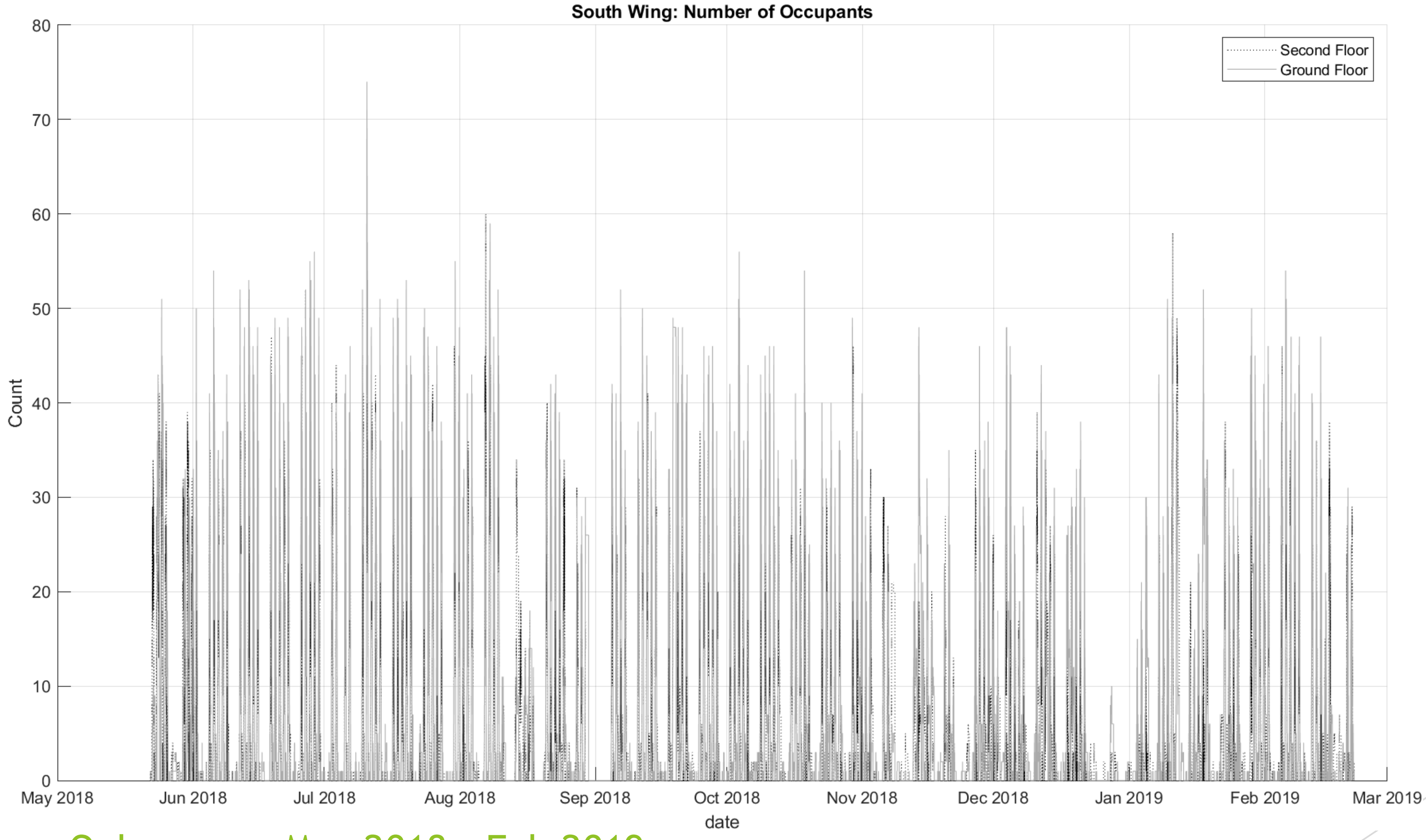


#Occupants (floor-level)

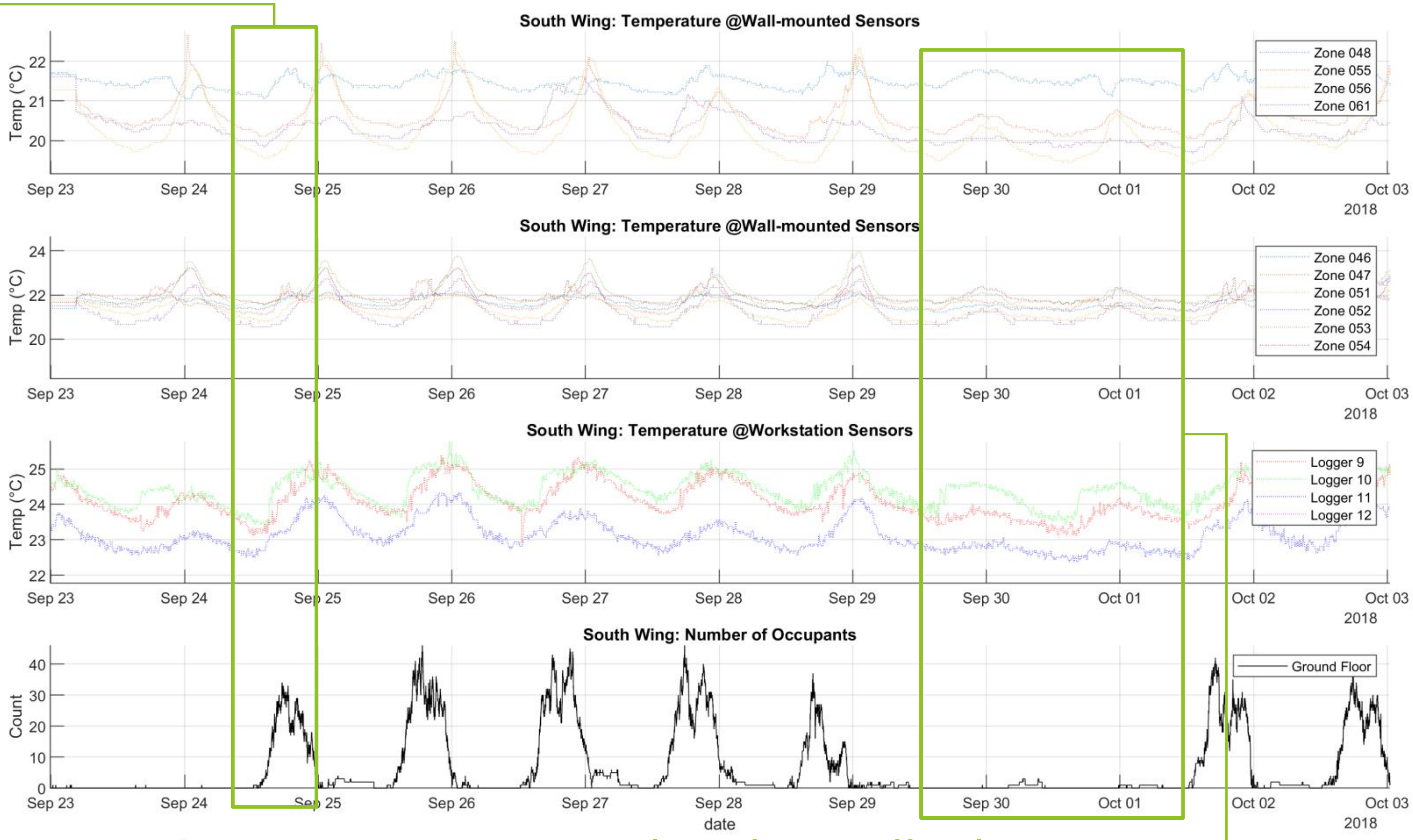


Only covers May 2018 – Feb 2019

Occupancy data (per minute)

Indoor (zone-level) Temperatures vs #Occupants (floor-level, GF)

#Occupants increases → Indoor temperatures have a larger increase

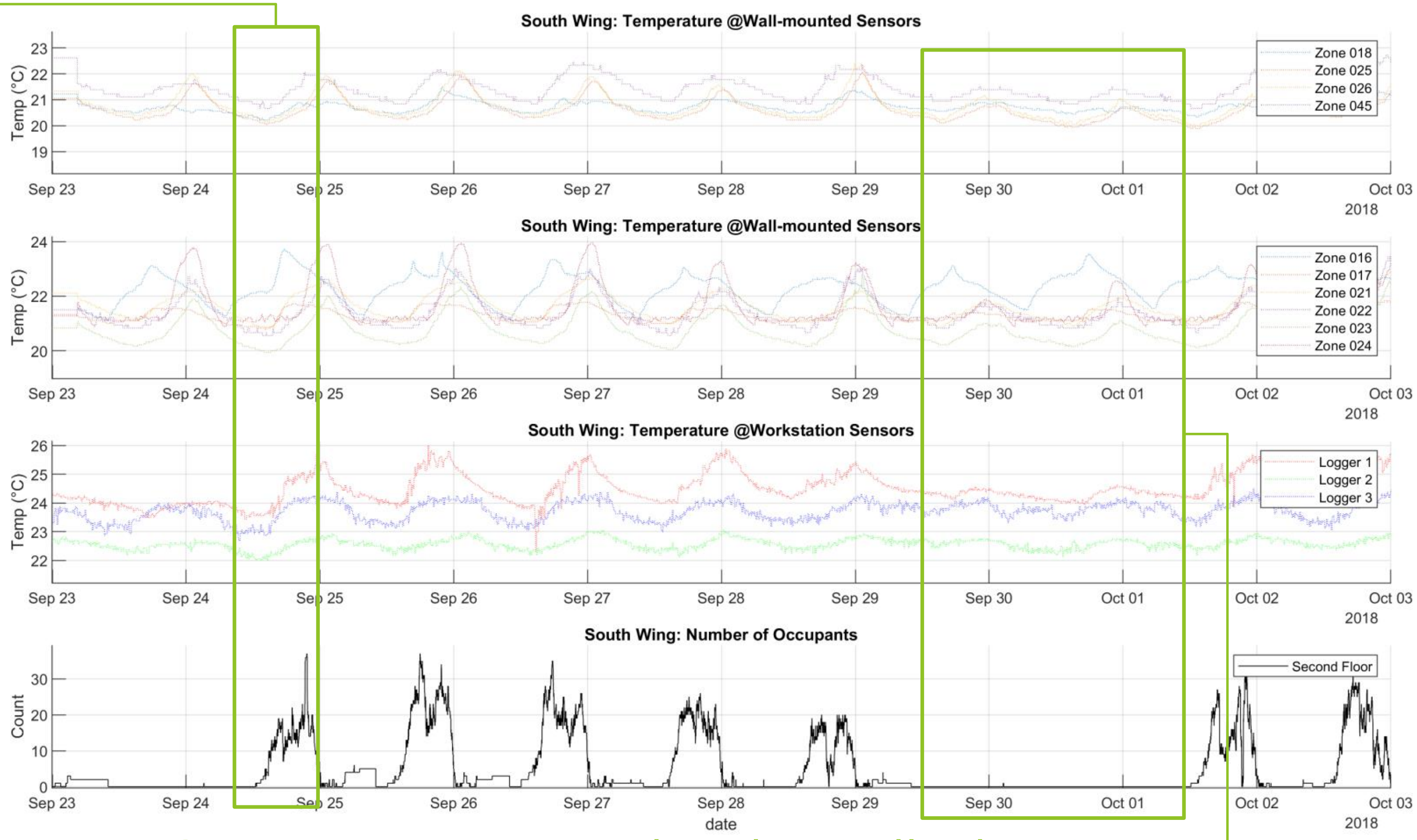


When no occupant: Room temperatures are less drastically changing

Occupancy data (per minute)

Indoor (zone-level) Temperatures vs #Occupants (floor-level, 2F)

#Occupants increases → Indoor temperatures have a larger increase



When no occupant: Room temperatures are less drastically changing

Summary – Literatures Survey

- Intelligent Buildings standards, design: General purpose, decentralized
- Energy efficiency: Challenges and pathways in Australia
- ML applications: Adjustment using RL
  - Formulate States, Rewards, Actions, Environment (simulation vs **data-driven**)
- Methods:
  - RL approach (with codes): Q-learning with/w.o. DNN, Single-to-Multi-Agent, HVAC vs UFH
  - RL approach (SOTA but without codes): **MADCQ**
  - Other approaches: MPC
- Toolset:
  - Gym, EnergyPlus, Synergym
  - HV-Ai-C, CitySim

Summary – Dataset Exploration

- Berkeley building, two floors, north/south wings, four HVAC Roof-Top-Units
- Exterior zones (with exterior walls), interior zones
- Information in data:
  - Energy use (mainly HVAC), Outdoor environment, Indoor temperatures, HVAC operations, Occupants
  - Data mapping to RL components (Actions, States, Rewards, Constraints)
- Findings in visualization:
  - Daily plots: time series, scatter, heatmap
    - Fan speed vs HVAC Energy: Correlation can be found
    - Temperatures setpoints (both RTU-level and zone-level) vs HVAC Energy: No correlation observed
  - Raw data plot (minutely): Time series
    - (Indoor) zone-level temperatures vs Floor-level #Occupants: Correlation can be observed

Suggested Next-steps

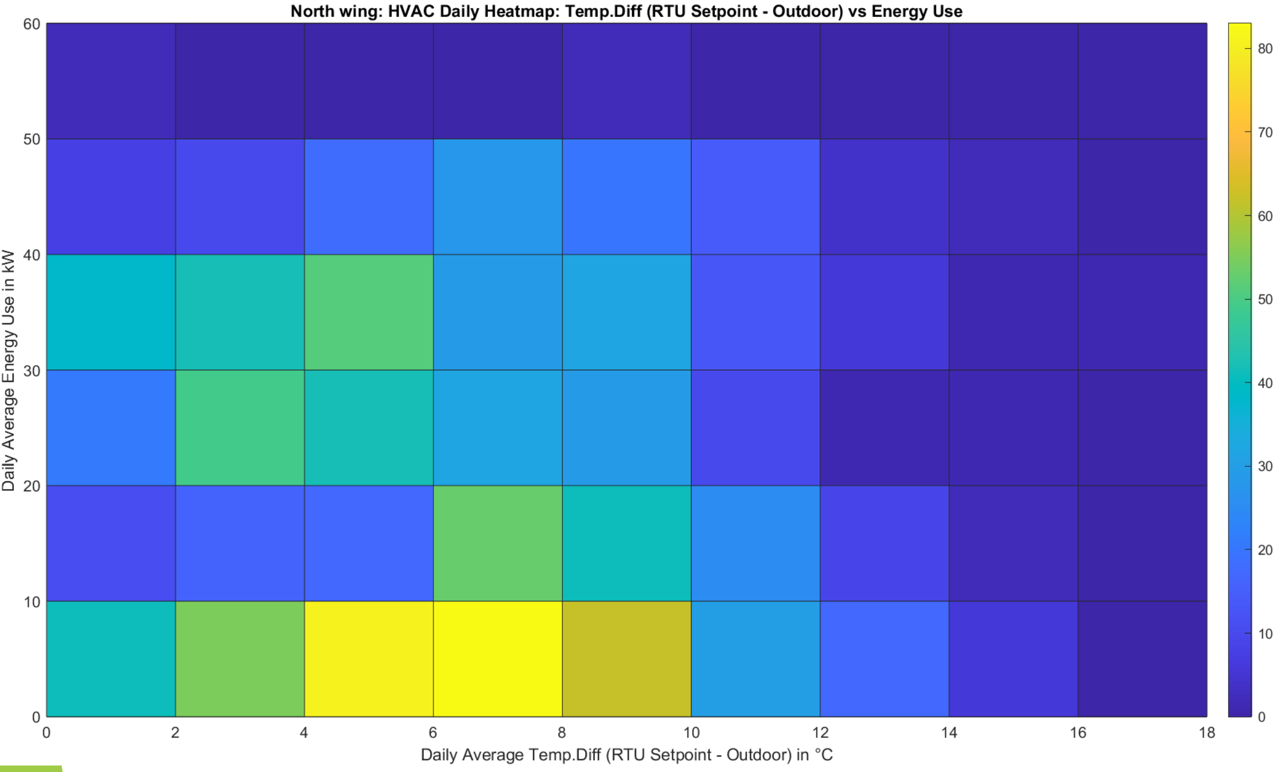
- Try any (simulator-based) workable codes on GitHub, without real-world dataset.
- Consider RL only (more popular than MPC).
- Wrap the codes settings to data-driven.
- Wrap input data to Berkeley dataset.

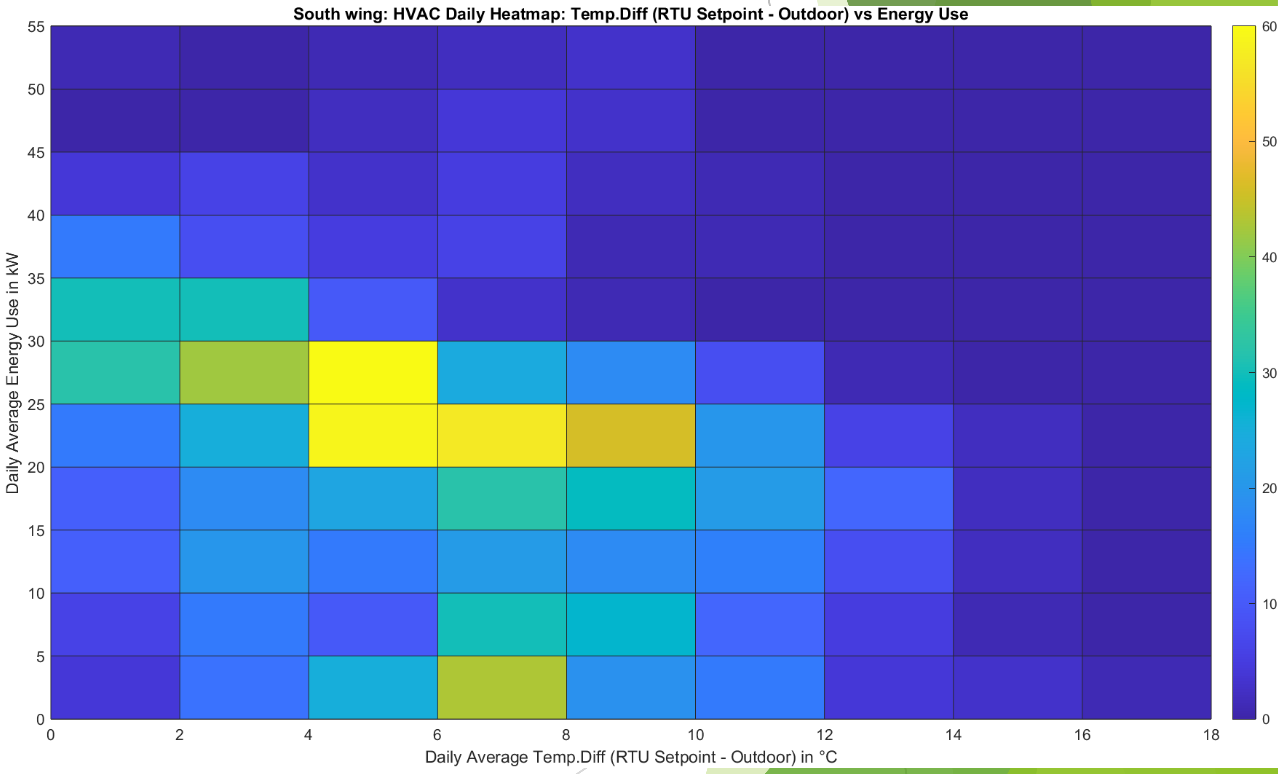
Backup

Energy consumption (daily average)

HVAC RTU Temp. Setpoint vs Power

No observed correlation btw. temp. diff. (setpoint-outdoor) and HVAC power





Other works mentioning data

- Occupant behavior, thermal environment, and appliance electricity use of a single-family apartment in Beijing, China
  - Temperatures collected using IoT (not sensors),
  - implicitly indicate setpoints (Actions) → no temperatures to construct RL State
  - → not suitable for data-driven approach
- Household electricity consumption in Greece: A dataset based on socio-economic features: Survey results (not dataset) of 104 households (non commercial building) in Greece
- Impact of occupancy rates on the building electricity consumption in commercial buildings: Dataset from Philadelphia with broken link
- Data driven occupancy information for energy simulation and energy use assessment in residential buildings: Dataset from Lyon, France with no explicit link