ICT for Building Design: Data Driven Prediction models in Buildings

POLITECNICO
DI TORINO

Lorenzo Bottaccioli

DIST - Interuniversity Department
of Regional and Urban Studies and Planning

- Buildings represent 40 % of primary energy consumption
- IoT devices: collecting energy-related data
- Data-driven models: forecasting indoor energy and air-temperature trends
- Machine Learning Techniques: learning unknown building parameters

→ Smart building management to optimize energy consumption

Grey-box models: statistical information are blended with physical phenomena

→ Partial knowledge of the physic phenomenon used to simplified the model I learn the parameters (e.g. Kalman Filter)

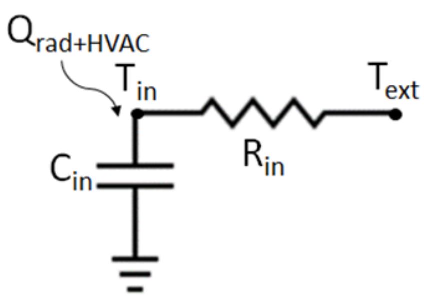
Black-box models: empirical model based on statistical data

→ Needing of a consistent data-set to validate and no knowledge of what is appending in the model (e.g neural network)

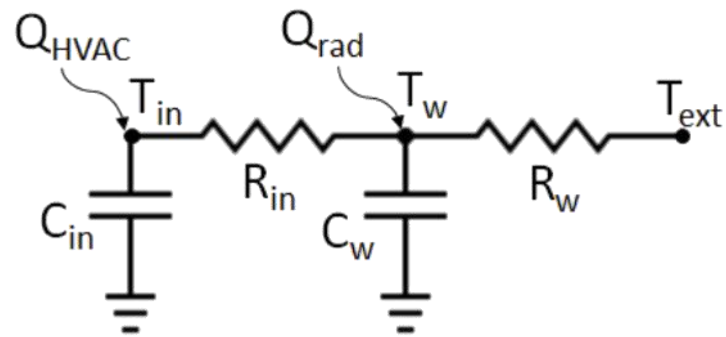
A Grey-box Model Based on Unscented Kalman Filter to Estimate Thermal Dynamics in Buildings

Building's thermal system can be approximated with RC electric circuit

1-NODE



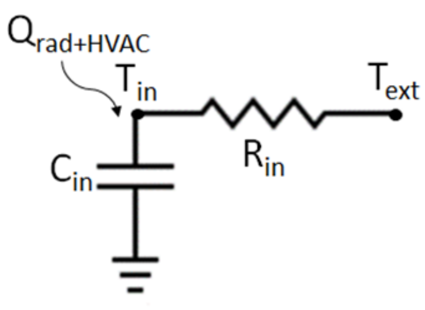
2-NODE



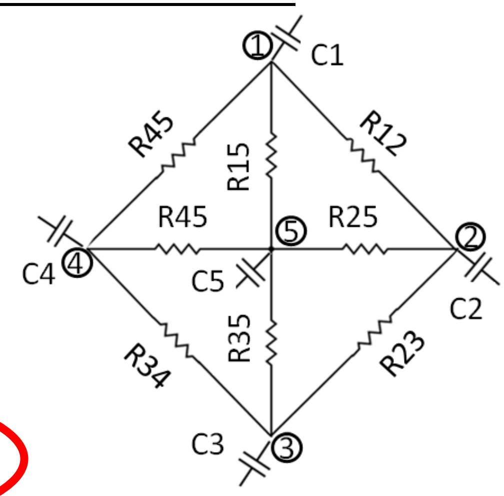
$$C_i \frac{dT_i}{dt} = \sum_j \frac{T_j - T_i}{R_{i,j}} + A_i Q_{rad_i} + \dot{Q}_{int_i}$$

Building's thermal system can be approximated with RC electric circuit

SINGLE-ZONE



MULTI-ZONE



$$C_i \frac{dT_i}{dt} = \sum_j \frac{T_j - T_i}{R_{i,j}} + A_i Q_{rad_i} + \dot{Q}_{int_i}$$

Kalman Filter

Recursive optimal estimator that produces estimates of unknown variables from a series of measurements observed over time

→ Detect Process Disturbances:
- Solar Radiation
- Heating Systems
- Opening of windows
- Human heat

→ Possible Uses:
- Demand Side Management
- Optimization of Scheduling
- Identification of low efficiency areas

- State Space Continuous Time Differential Equation

$$\dot{x} = f(x, u, d, p)$$

$$z = h(x, u)$$

- State $\bar{x}$ has been augmented combining together Temperatures, uncertain Parameters and Disturbances

$$\bar{x} = \begin{bmatrix} \bar{T} \\ \bar{p} \\ \bar{d} \end{bmatrix} \rightarrow \quad \text{function } f(\cdot) \text{ becomes non-linear}$$

- Equation discretized with 1-min Euler integration

FILTER LOOP:

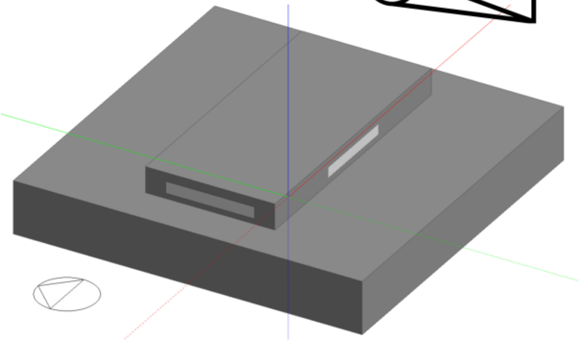
- 3-day-runs during night-time: disturbances (Solar Gain + HVAC) OFF

  → better estimate RC parameters

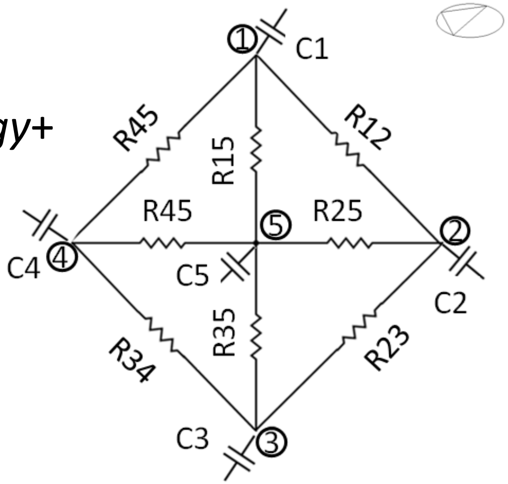
- 4-day-runs during whole day-time: disturbances ON

  → estimate both RC parameters and disturbances

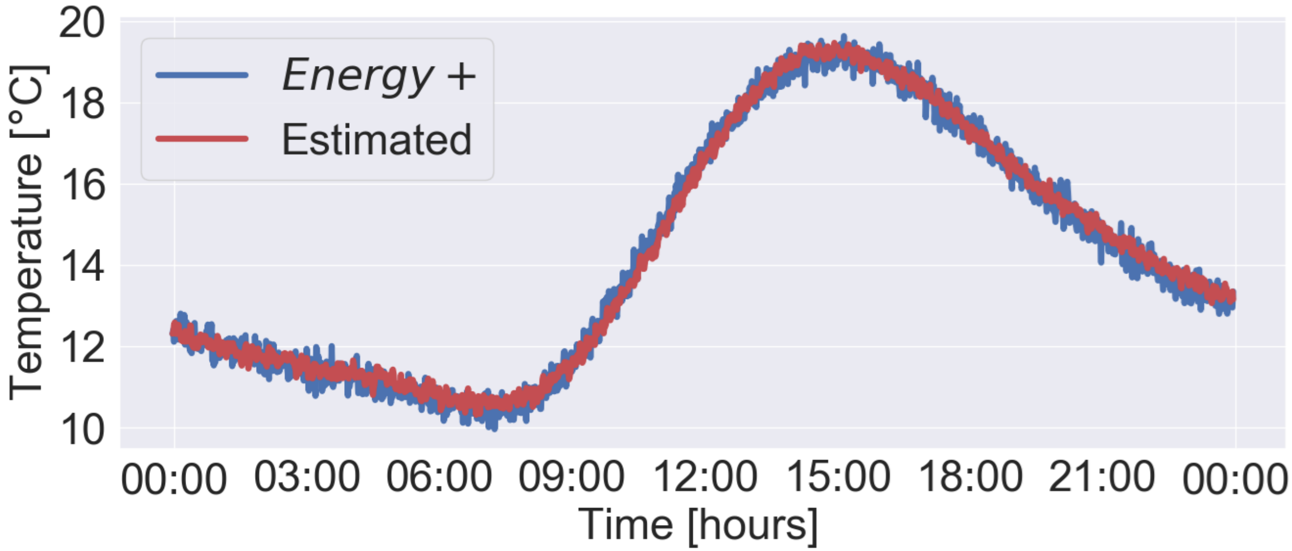
→ Obtained RC parameters and disturbance pattern are used to predict indoor air-temperature trends for next 24-hours



- Industrial-like building, base surface of $10000\ m^2$
- Weather file from Turin
- Measured values obtained with *Energy+*
- 5-zone discretization

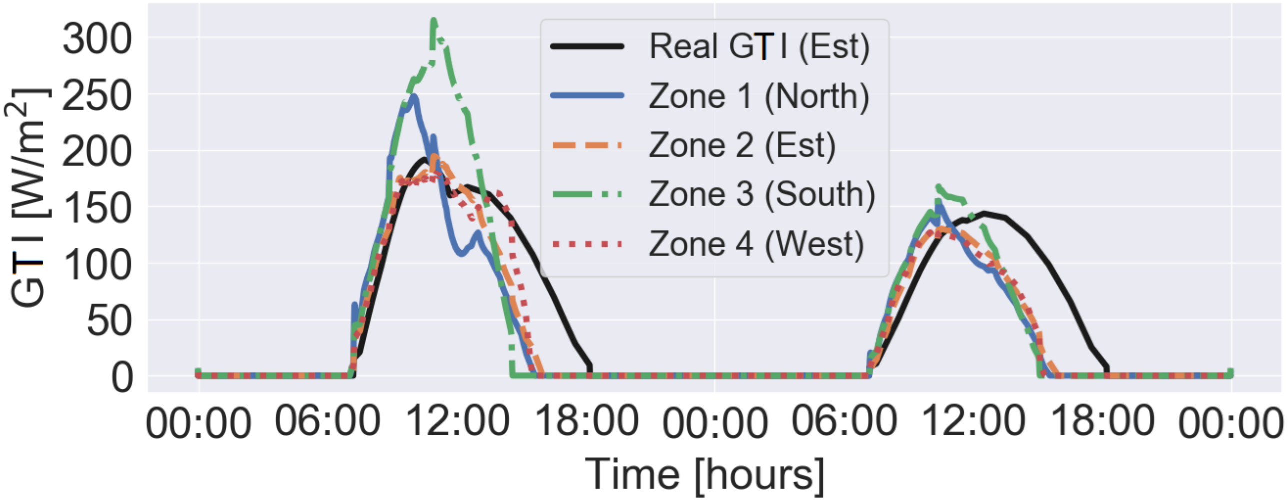


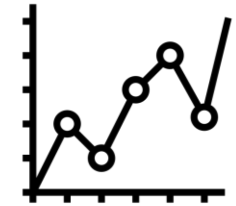
- SCENARIO 1: only GTI as a disturbance



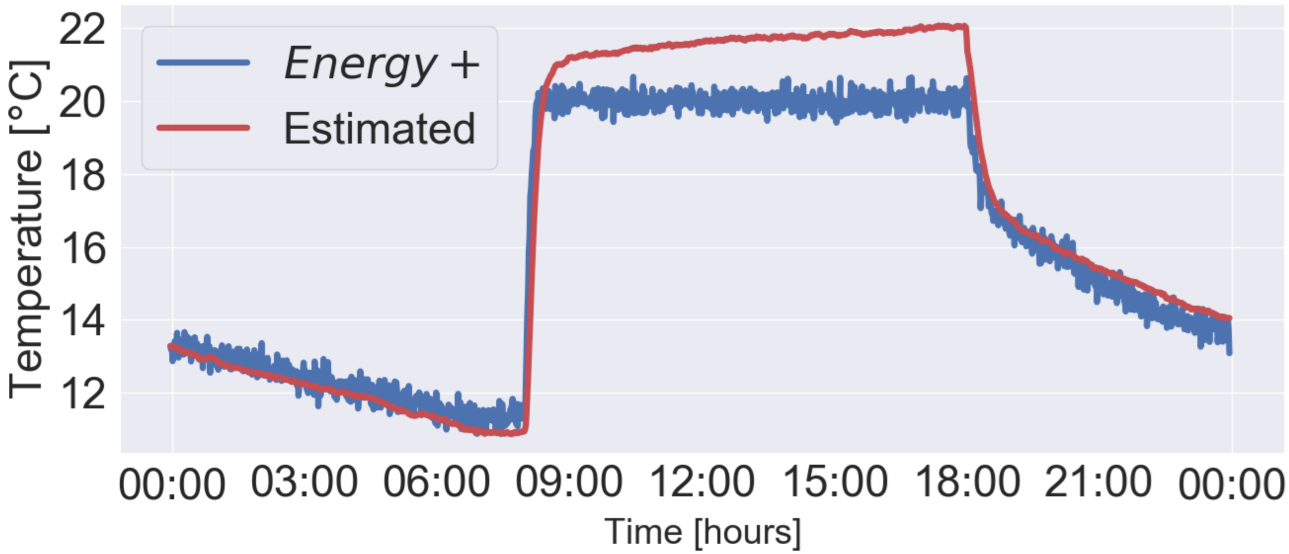
RMSE = 0.370 °C
MAE = 0.295 °C
CORR = 99.1 %

- SCENARIO 1: only GTI as a disturbance





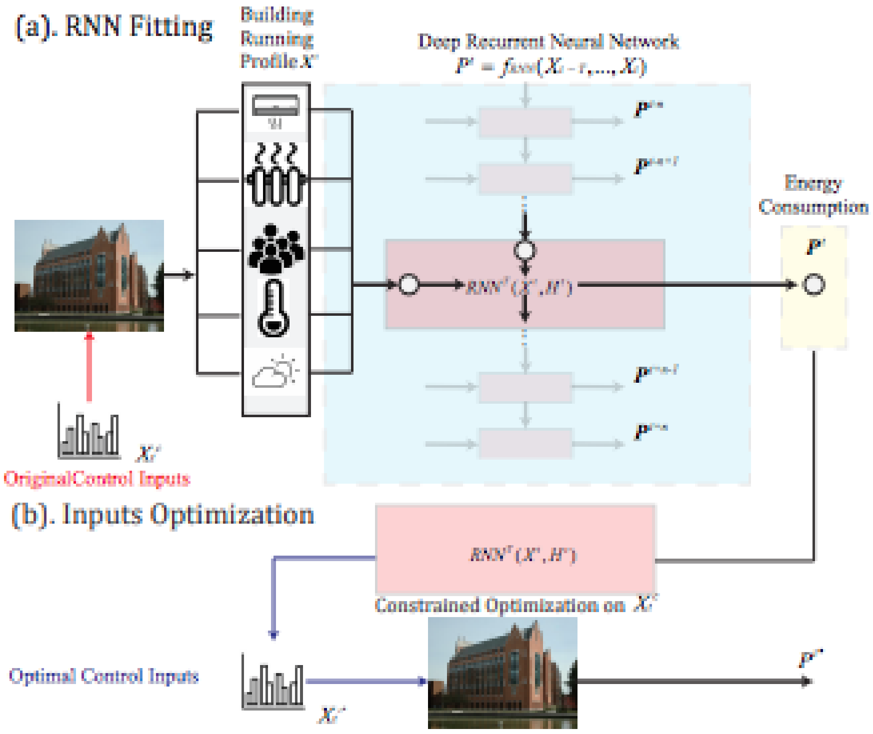
SCENARIO 2: GTI+ HVAC as a disturbance

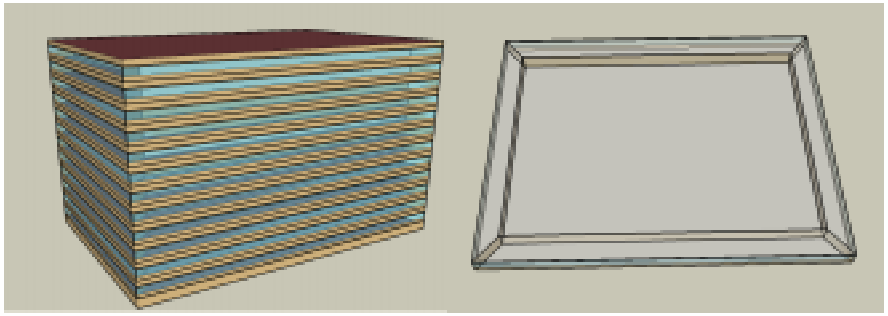


RMSE = 1.24 °C
MAE = 0.90 °C
CORR = 98.3 %

TEST	RMSE [°C]	MAE °[C]	CORR
1-node, GTI	0,370	0,295	99,1
1-node, GTI + HVAC	1,24	0,90	98,3
2-node, GTI	0,73	0,63	98,9
2-node, GTI + HVAC	1,09	1,32	91,2

In this work, a data-driven method which closes the loop for accurate predictive model and real-time control is presented.





At time t the building's running profile Xt := [Xuc_t , Xc_t , Xphy_t] is provieded.

Where Xuc_t denotes a collection of uncontrollable measurements such as zone temperature measurements, system node temperature measurements, lighting schedule, in-room appliances schedule, room occupancies and etc;

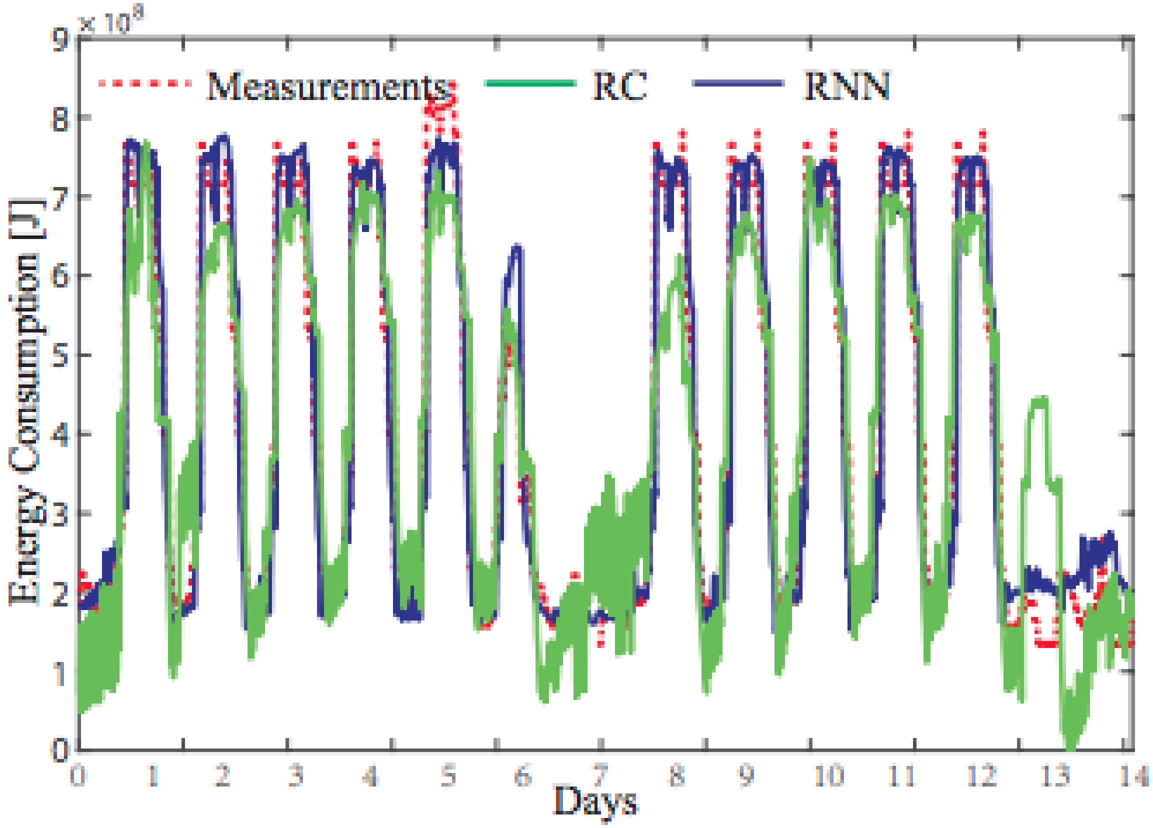
Xc_t denotes a collection of controllable measurements such as zone temperature setpoints, appliances working schedule and etc;

X_phy_t denotes the set of physical measurements or forecasts values, such as dry bulb temperature, humidity and radiation volume

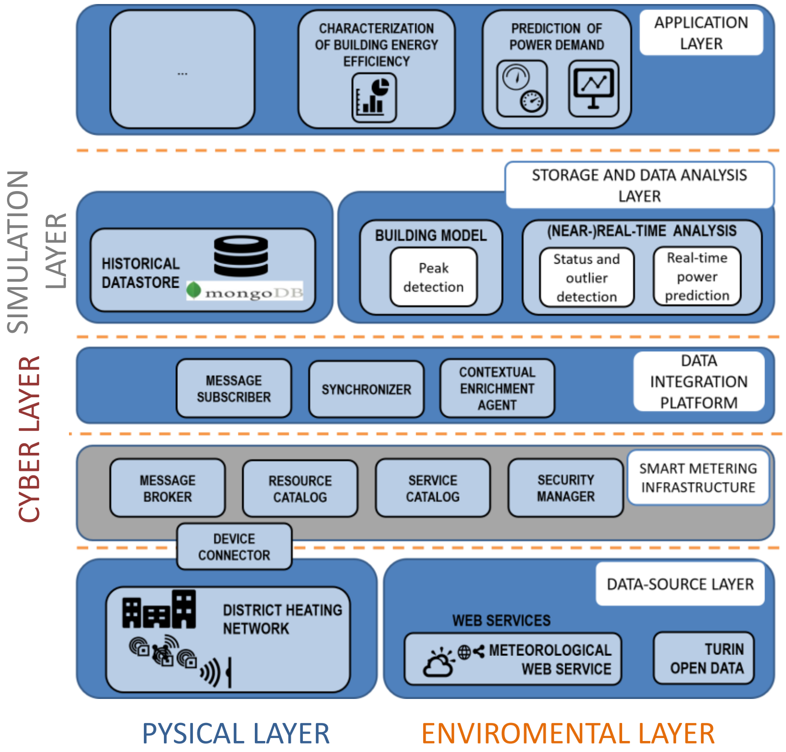
RNN automatically learn the relationship between sequential input xt, t = 0, , ..., T and output oT .

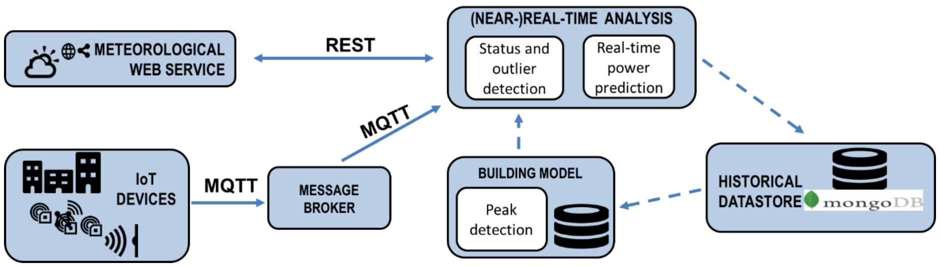
At timestep t, RNN is provided with hidden state vector ht and input vector xt, and outputs its computation vector oˆt. The t-step RNN cell is composed of three group of neurons, θx,t, θh,t, θo,t

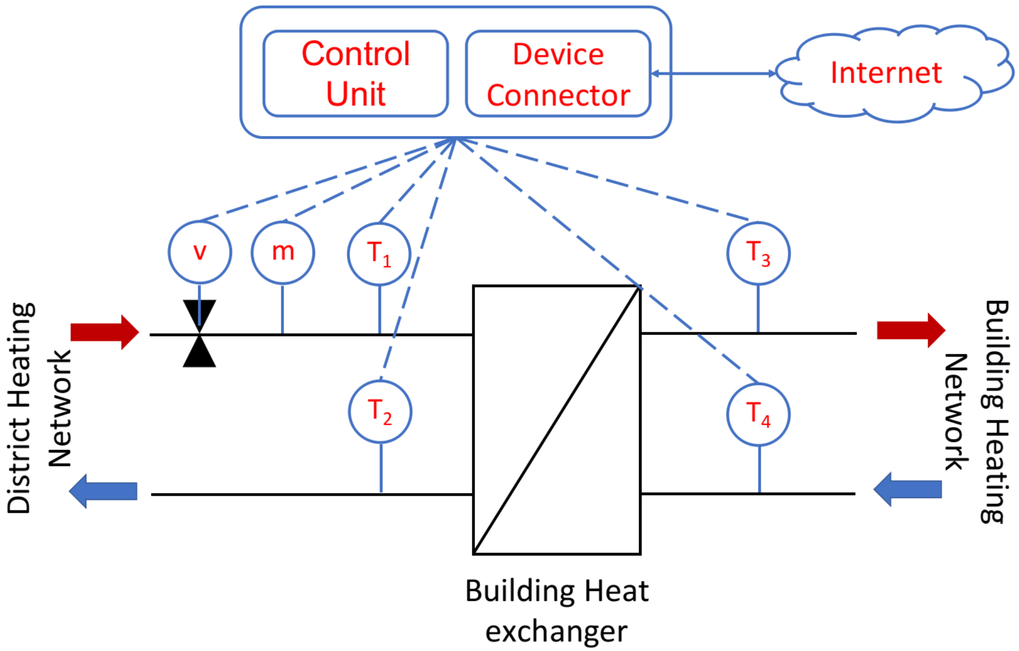
The RNN model is composed of 1 recurrent layer with 3 subsequent fully-connected layers. Authors have adopt rectified linear unit (ReLU) activation functions, dropout layers and Stochastic Gradient Descent (SGD) optimizer to improve our neural network training.


× 10^8
Measurements
RC
RNN
Energy Consumption [J]
Days
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14

Forecasting Heating Consumption in Buildings: A Scalable Full-Stack Distributed Engine

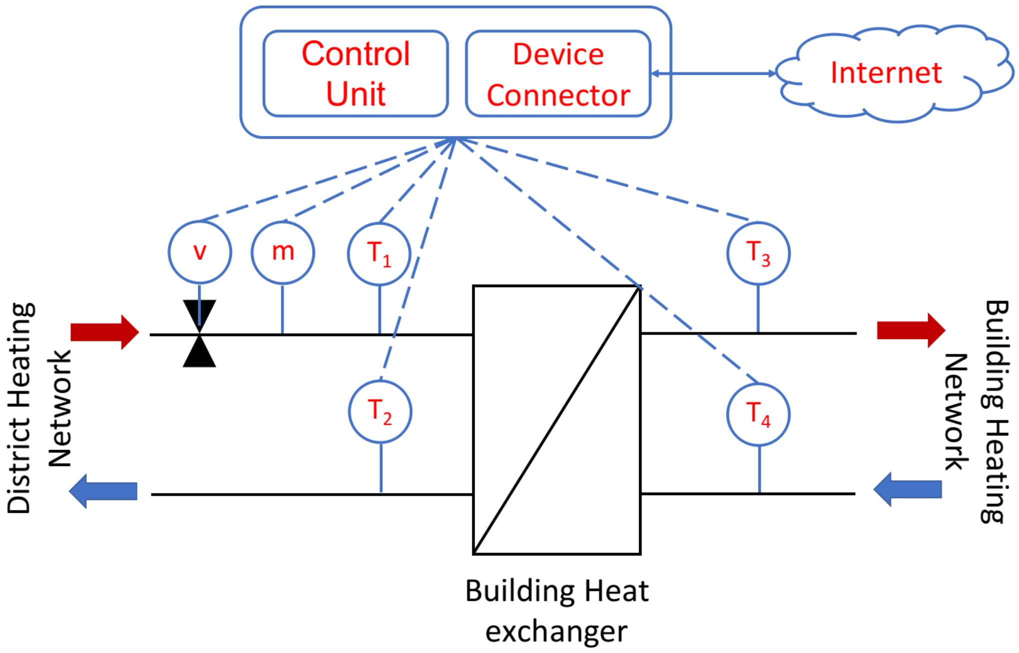


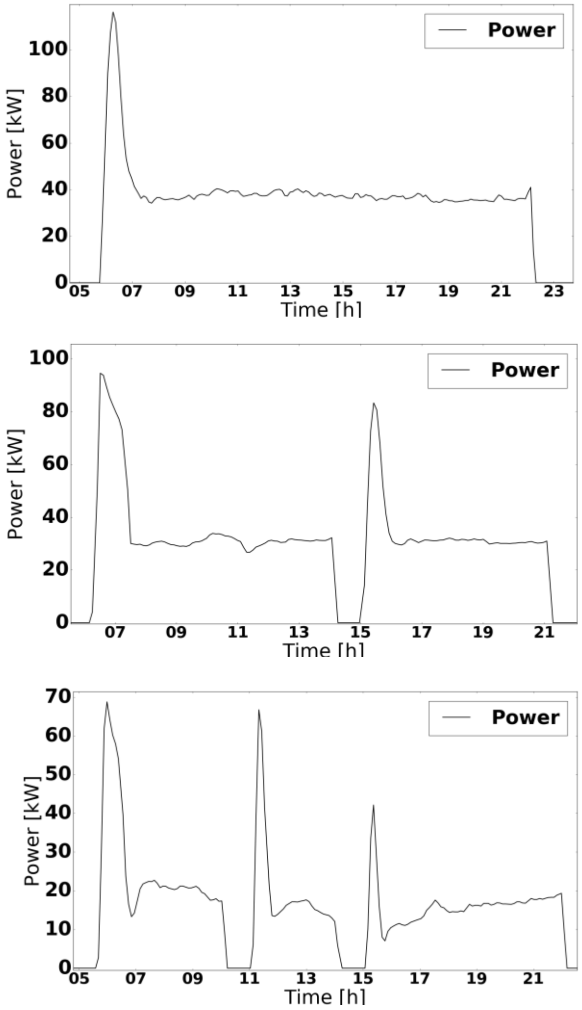




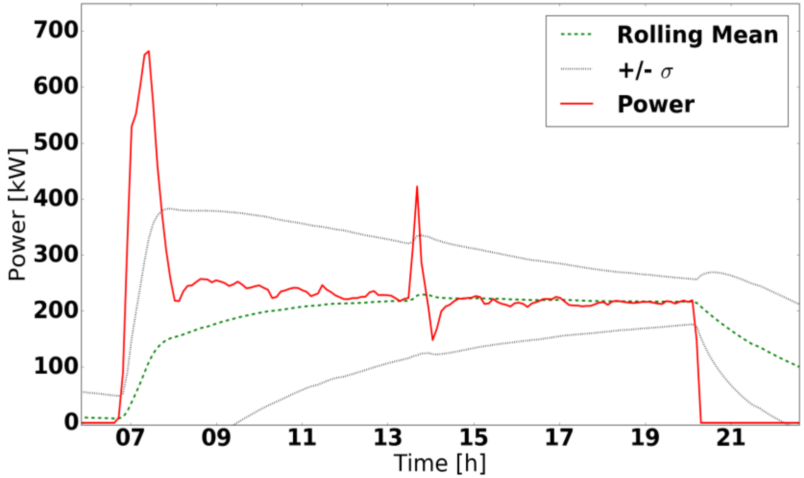
Turin District Heating:

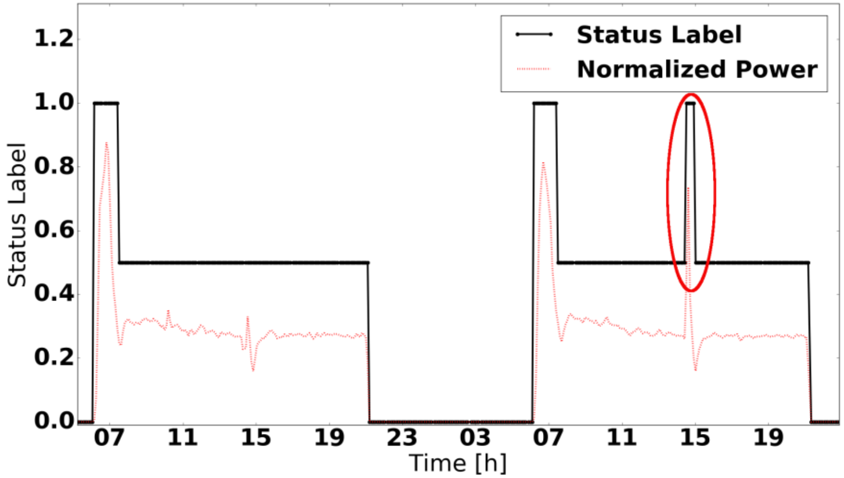
300 Monitored Buildings


Control Unit
Device Connector
Internet
v
m
T_1
T_2
T_3
T_4
District Heating Network
Building Heating Network
Building Heat exchanger

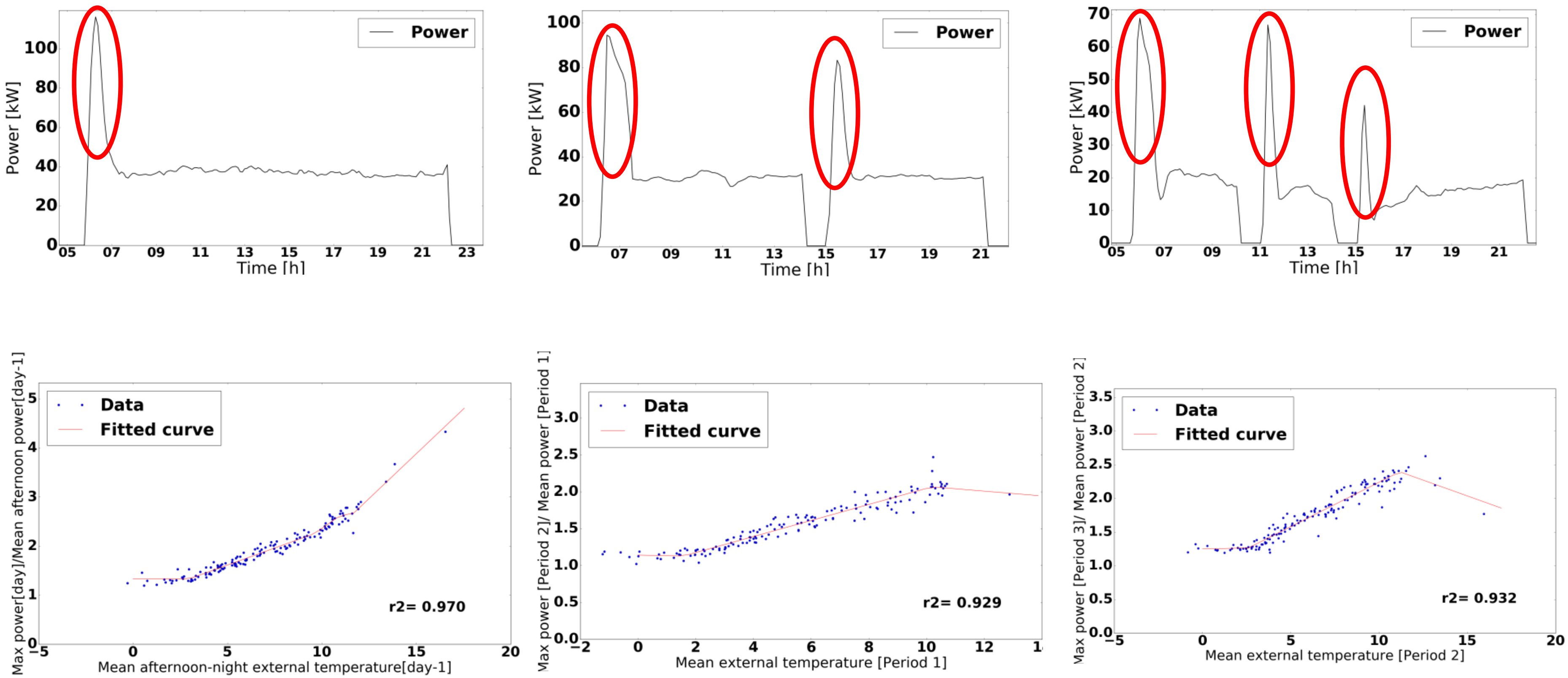

Power
Power [kW]
Time [h]

Status Identification and outlier algorithm (SOD)



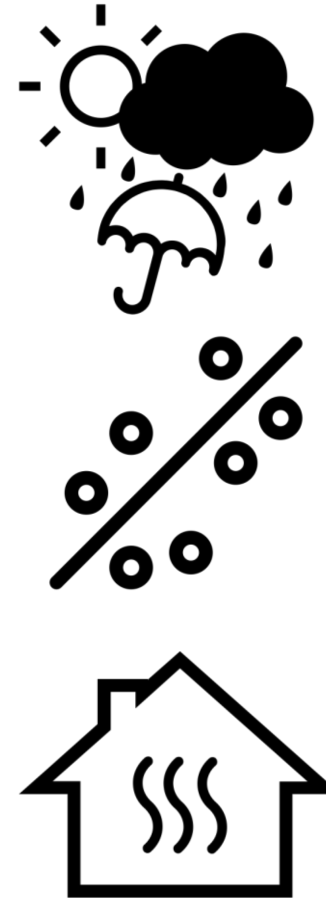


Peak Power identification algorithm (PD)



Power Prediction algorithm

On the basis of the outcomes of the **SOD** and **PD** algorithms, the **Power Prediction** algorithm exploits the multiple version of the **Linear Regression with Stochastic Gradient Descent**



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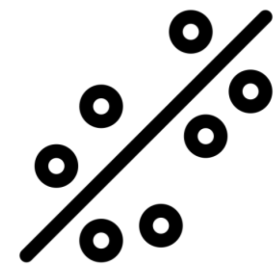
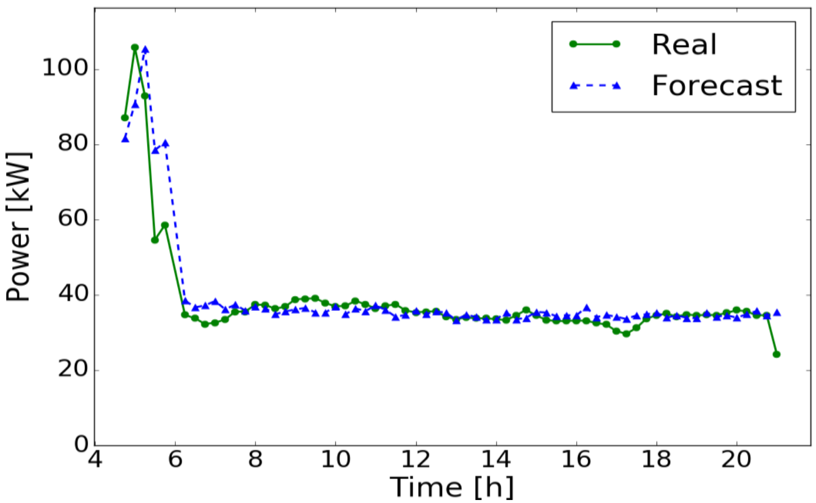
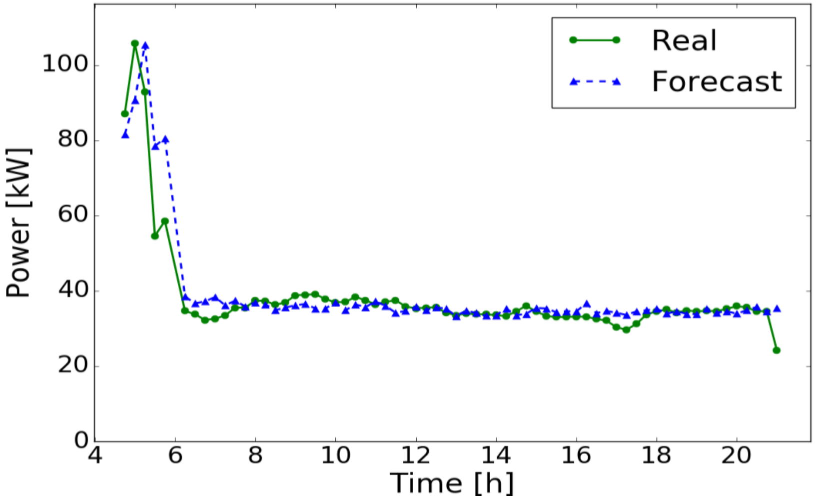


Power Prediction algorithm defines a building model based on **a linear dependency** between **weather data** and **power level**. PP relies on the **assumption** that the **average power exchange** for a building heating system at a given time instant is **likely to be correlated** with the **surrounding weather conditions**.

Results of Power Prediction



Results of Power Prediction



Heating cycles	Building ID	Overall MAPE	Overall SMAPE	First cycle MAPE	First cycle SMAPE	Second cycle MAPE	Second cycle SMAPE	Third cycle MAPE	Third cycle SMAPE
Single	1	15.56	6.78	15.56	6.78	-	-	-	-
	2	18.58	7.95	18.58	7.95	-	-	-	-
	3	20.48	8.35	20.48	8.35	-	-	-	-
	4	22.38	9.32	22.38	9.32	-	-	-	-
	5	20.42	8.46	20.42	8.46	-	-	-	-
Double	6	23.24	9.62	28.81	10.95	20.58	8.06	-	-
	7	22.02	9.56	36.98	13.35	15.52	7.10	-	-
Triple	8	23.11	9.72	35.35	13.90	17.38	7.67	18.33	7.63
	9	27.96	10.62	28.46	10.90	24.73	10.14	25.87	10.85
	10	33.75	11.64	39.70	14.40	38.44	14.49	26.53	10.21
	11	29.05	11.83	31.89	11.98	37.53	13.99	23.23	9.58
	12	27.26	11.56	32.62	13.26	28.39	11.42	23.01	9.27

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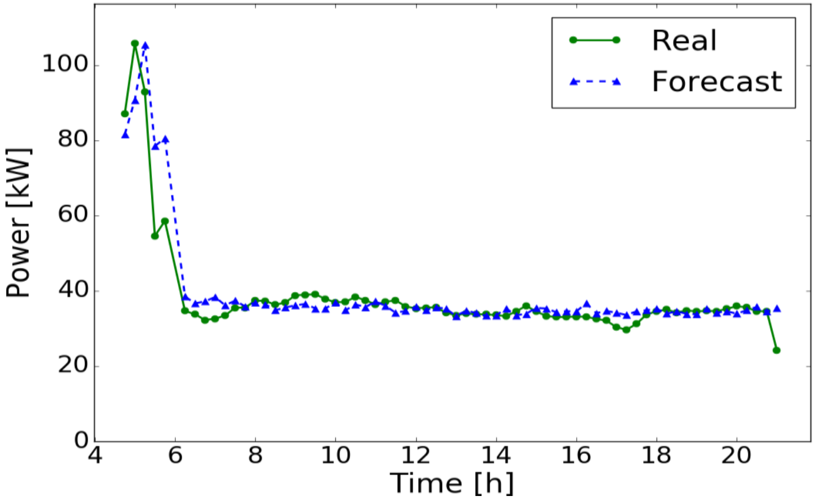

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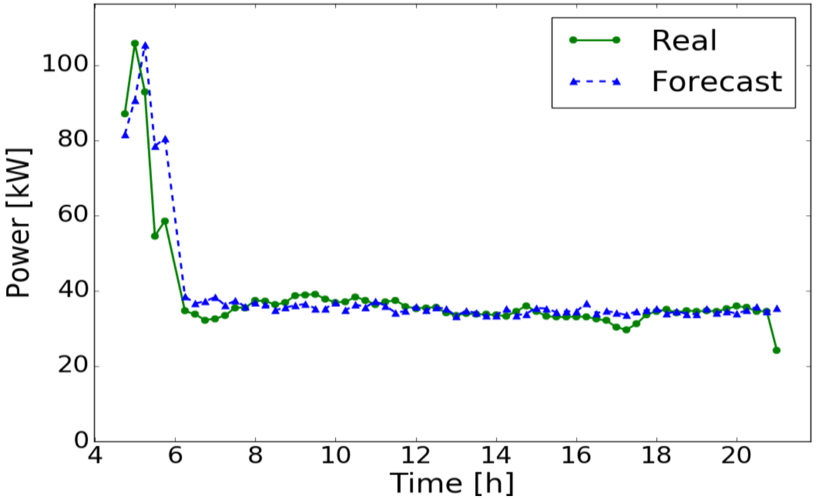

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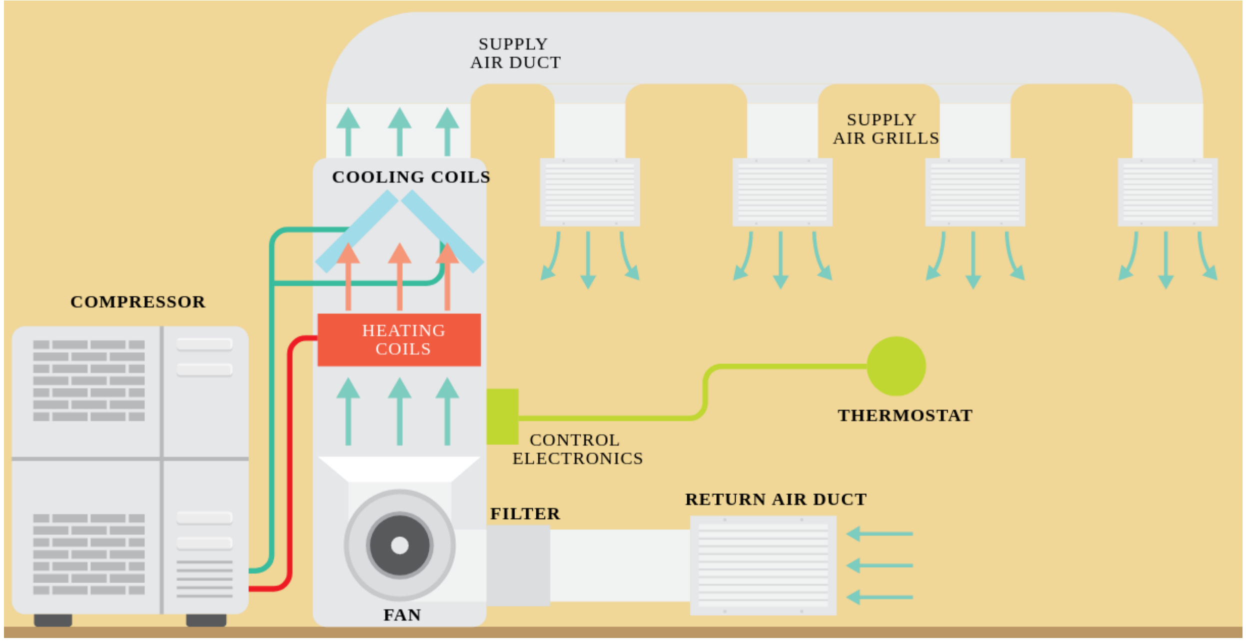
The Problem: Energy Optimization in HVAC Systems

- Use of temperature **setpoints**, as measured by a thermostat
- **PID controller** to manage the distribution of hot/cold air
- It is hard to optimize both **energy consumption and thermal comfort**
- Great research effort has been put to **develop more efficient strategies**



State of the Art

Traditional PID controller

- A PID controller receives f**eedback from a thermostat** and manages the distribution of hot/cold air
- Has to be **scheduled** in advance for the whole heating/cooling season
- Does not take into account **external dynamic factors**, so not very efficient

Model Predictive Control (MPC)

- Solves an **optimization problem**, where both energy consumption and comfort can be taken into account
- Considers **external factors** (i.e. ext. temperature, solar radiation)
- Needs a thorough **simulation** of the building thermal dynamics (E+)

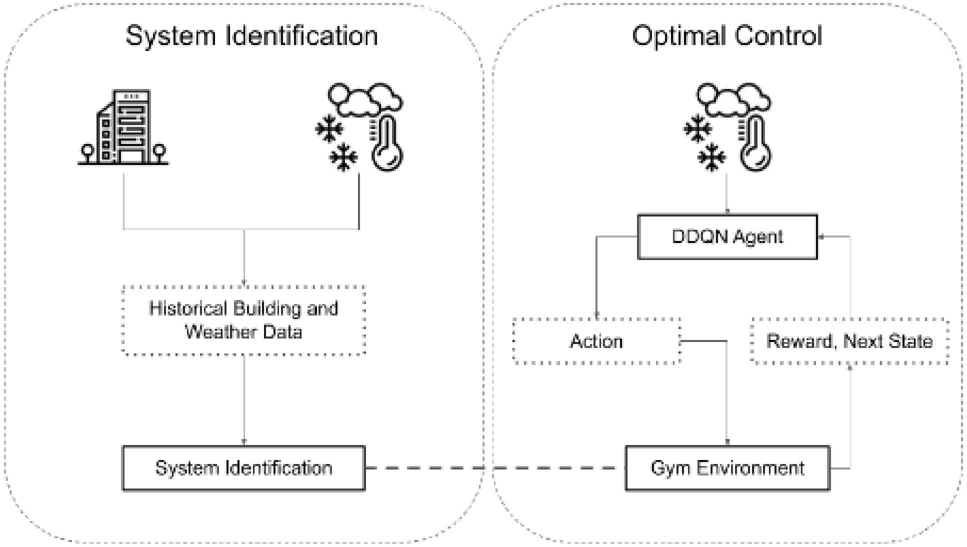
Model-free Reinforcement Learning

- A **self-learning agent** interacts with the environment without previous knowledge of the system, receiving a reward and learning the optimal control policy
- Not viable to train the agent directly on the building, as it would select **poor strategies** in the beginning of training.
- Again, a building **simulation** is needed.

Our Approach

Hybrid approach based on a two-steps methodology

- Instead of a White-Box (E+) simulation, a Black-box **System Identification** is performed, using Supervised Machine Learning on historical building and weather data.
- A **model-free RL** agent is trained, using the system identification model instead of a simulation to determine the environment's response to the agent's actions.
- For this reason, this approach can be **easily applied to any building**, as long as historical data is available.



System Identification: Supervised Learning

Input

- **Historical Building Data**: initial indoor temperature and control action

- **Historical Weather Data**: a set of external disturbances (ext. temperature, solar radiation etc.)

Output

- **Predicted indoor temperature** one step in the future

System Identification Equation

$$f_\theta(x_t, u_t, d_t) = \hat{x}_{t+1} = Ax_t + Bu_t + Dd_t$$

- Parameters matrix *A*,*B* and *D* are trained with **stochastic gradient descent**

Training Loss

- **Mean-squared-error** between the predicted temperature and the historical temperature

Double Deep Q-Network (DDQN)

States

- A set of features: difference between indoor temperature and setpoint, difference between external temperature and setpoint, time to occupancy, solar radiation etc. (min-max normalised)

Action

- At each timestep, the agent selects one of 4 control actions, in the discrete set [0,2,4,6]

Reward

- Reward is given by the cost of the squared distance of the indoor resulting temperature from the setpoint, plus the control action

$$R(s,u) = r = -(\beta \cdot (x_t - x_{setpoint})^2 + \rho \cdot u_t)$$

Q values update rule

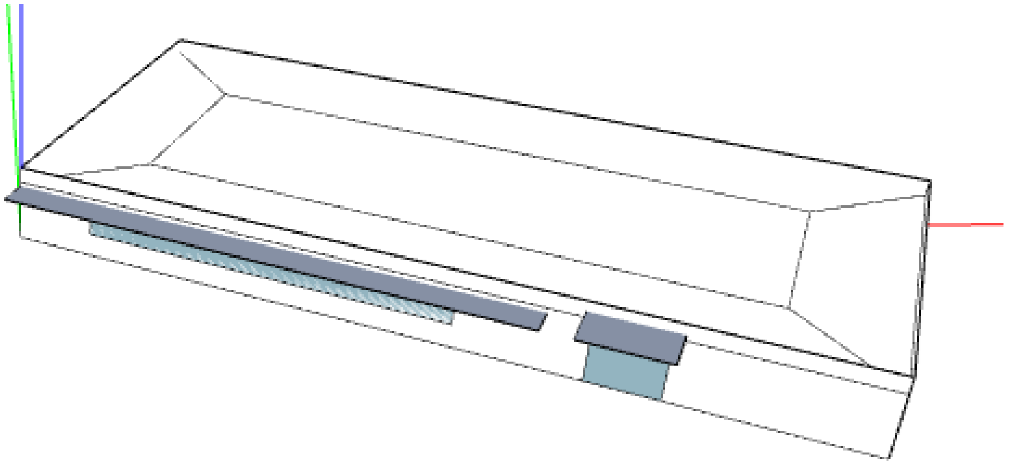
- Parameter γ influences whether the agent focus on short-term reward, or long-term expected reward

$$Q^*(s_t, u_t) = r_t + \gamma \cdot Q_\omega(s_{t+1}, argmax_u Q_{\omega'}(s_{t+1}, u_t))$$

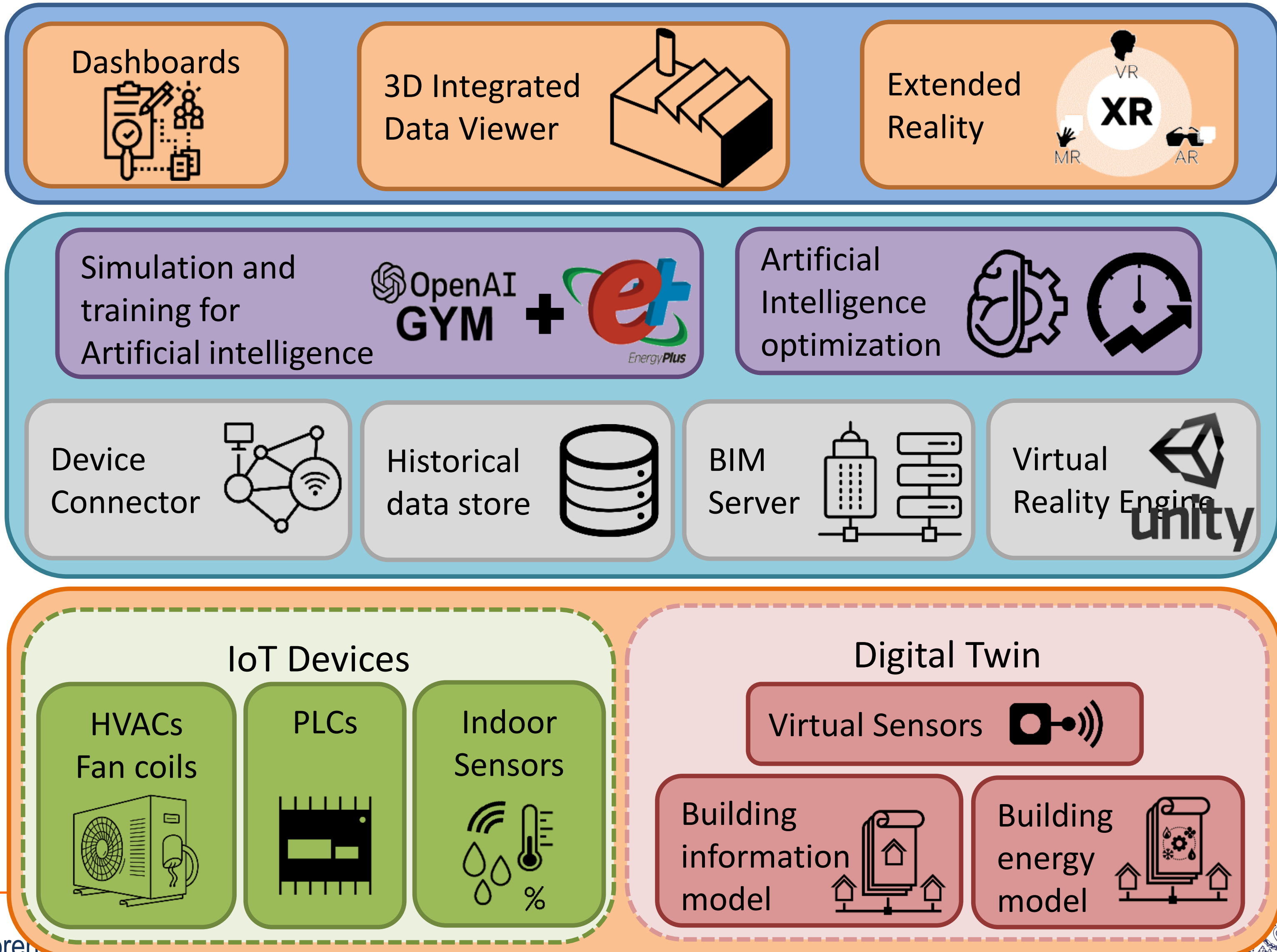
Use-Case Scenario

Building Dataset
- Historical data are gathered from an E+ simulation (but could come from a real building)
- 5 thermal-zones building, treated as a single zone (temperatures are averaged) for sake of simplicity

Weather Dataset
- Pittsburgh 3 months weather data, from Jan. to Apr. 2017
- Testing performed on 3 months data of the same period but different year



Digital Twin Platform for Facility management and AI test bed

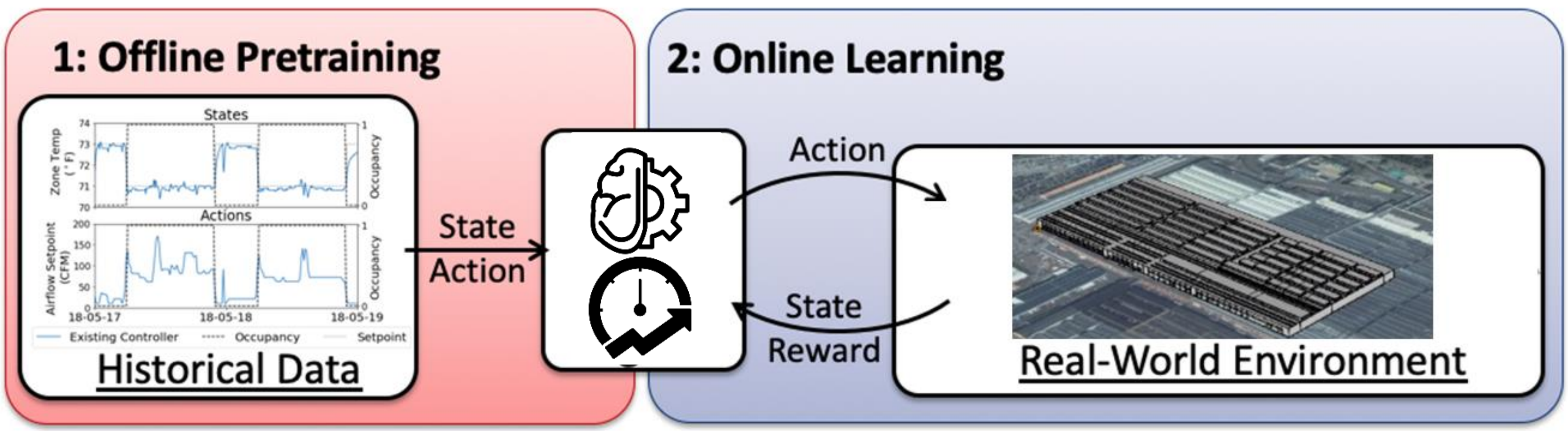


Model Predictive Control

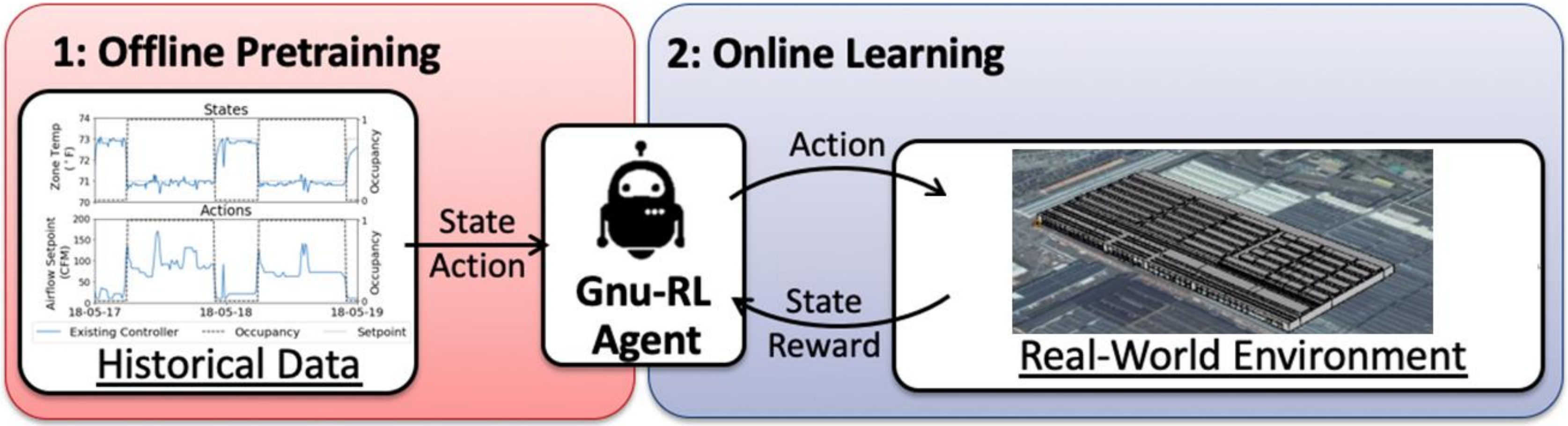
Simulation and training for Artificial intelligence

OpenAI GYM + EnergyPlus

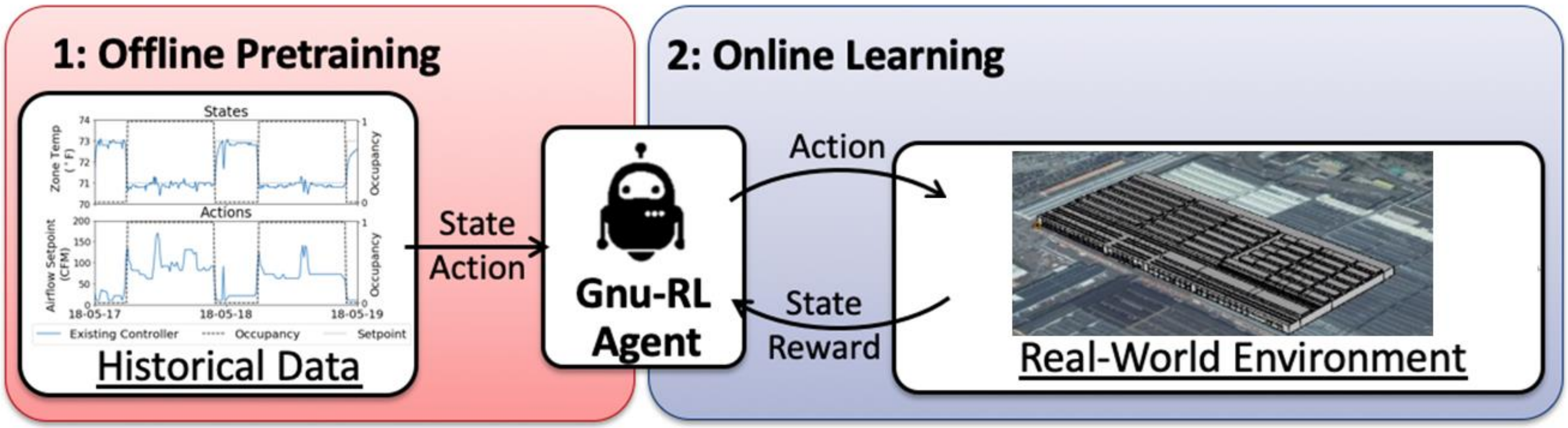
Artificial Intelligence optimization



Design of Model Predittive Control

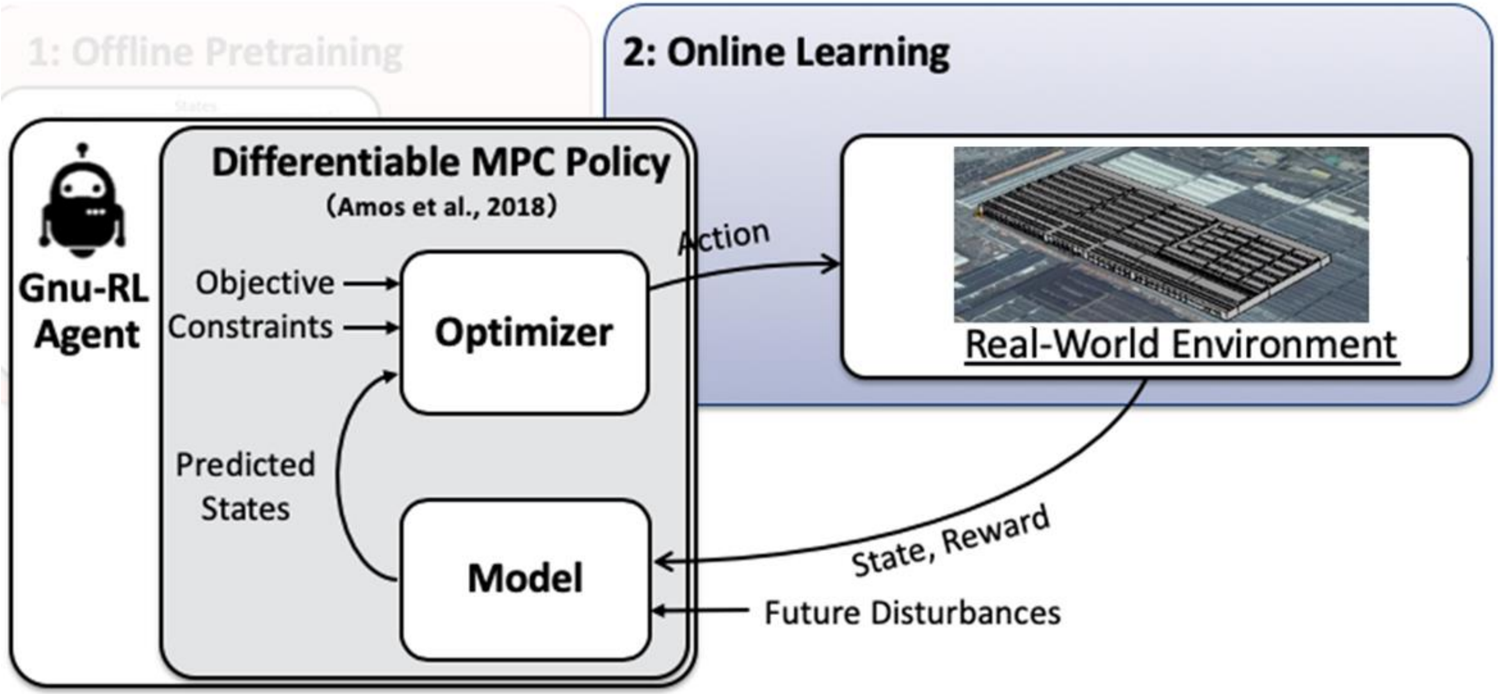


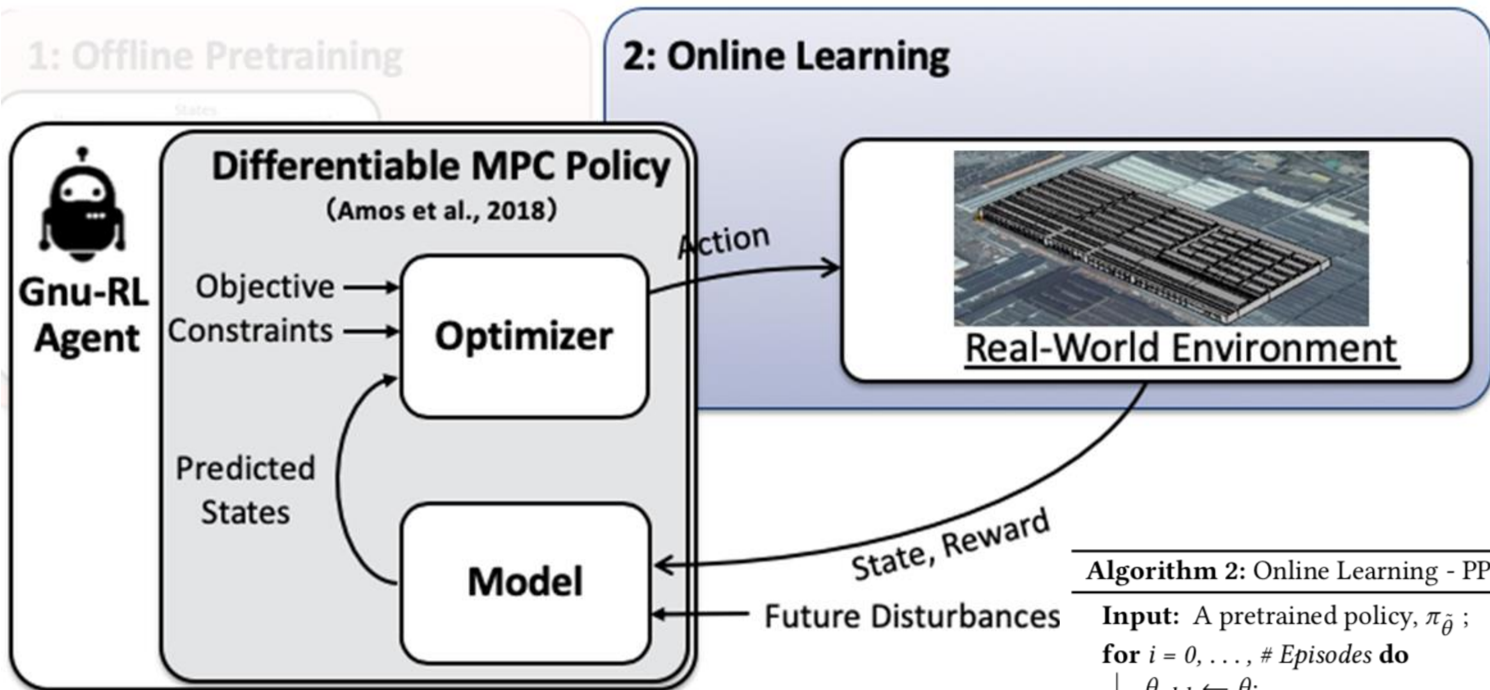
Design of Model Predittive Control



Algorithm 1: Offline Pre-training - Imitation Learning

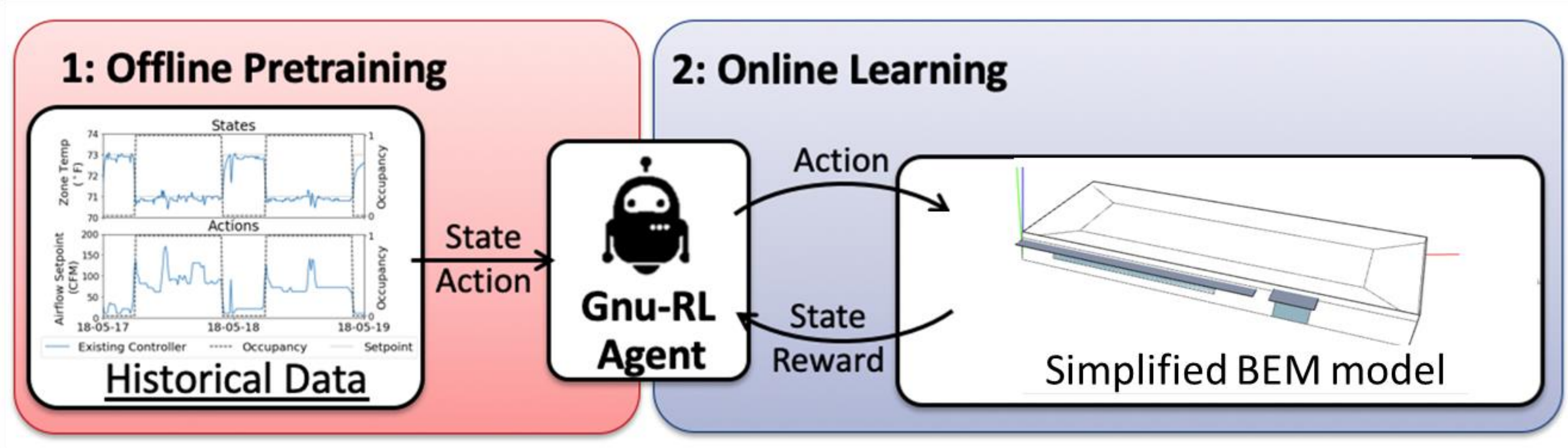
Input: A Differentiable MPC policy π_θ;
Expert demonstrations X, U;
Randomly initialize policy parameter $\theta = \{A, B_d, B_u\}$;
for $i = 0, \ldots,$ *# Episodes* **do**
  for $t = 0, \ldots,$ *# Steps* **do**
    $\hat{u}_t = \pi_\theta(x_t)$;
    $\hat{x}_{t+1} = f_\theta(x_t, u_t)$;
  end
  $\theta \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}_{\text{Imit}}(\theta)$;
end
Output: A pre-trained policy, $\pi_{\tilde{\theta}}$


1: Offline Pretraining
2: Online Learning
Gnu-RL Agent
Differentiable MPC Policy
(Amos et al., 2018)
Objective
Constraints
Optimizer
Predicted States
Model
Action
Real-World Environment
State, Reward
Future Disturbances



Algorithm 2: Online Learning - PPO (Modified from [43])

Input: A pretrained policy, $\pi_{\tilde{\theta}}$;
for i = 0, . . . , # *Episodes* **do**
  $\theta_{old} \leftarrow \theta$;
  for t = 0, . . . , # *Steps* **do**
    $\hat{u}_t = \pi_\theta(x_t)$;
    x_{t+1}, r_{t+1} = env.step($\hat{u}_t$);
  end
  Compute $\hat{A}_t$;
  With minibatch of size M;
    $\theta \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}_{PPO}(\theta)$;
end



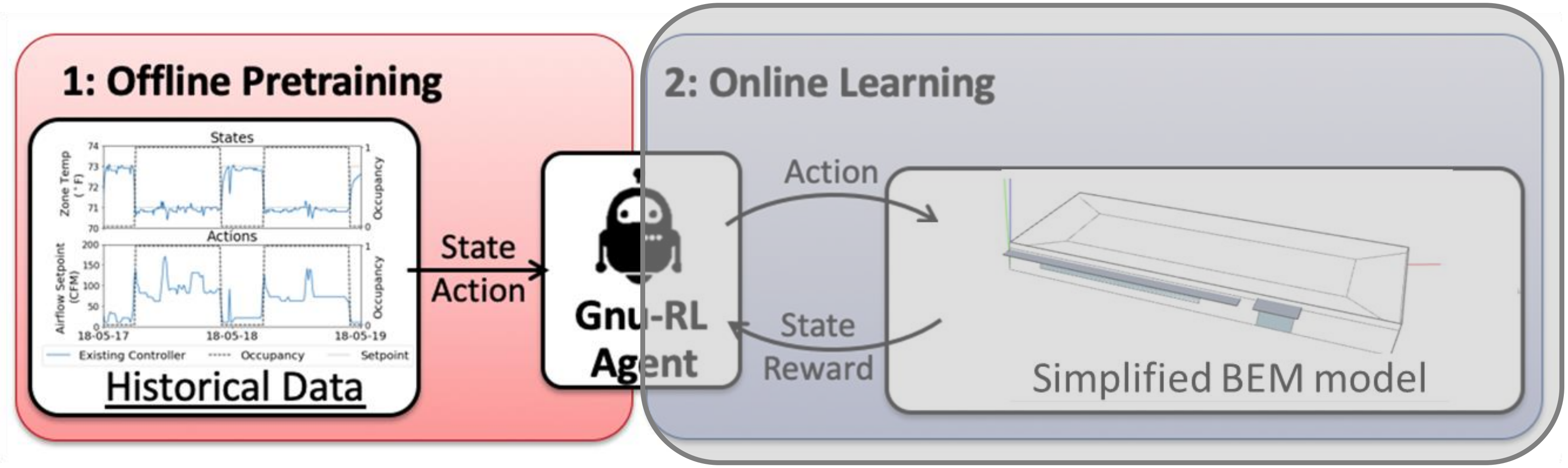
HVAC
The air conditioning to the simplified 5 zone building is supplied by an air handling unit (AHU) with a variable speed fan. The heating is provided by a main heating coil in the air handling unit. The terminal unit in each thermal zone controls the air flow rate based on single maximum control logic. That is to say, the only source of heating is the main heating coil.

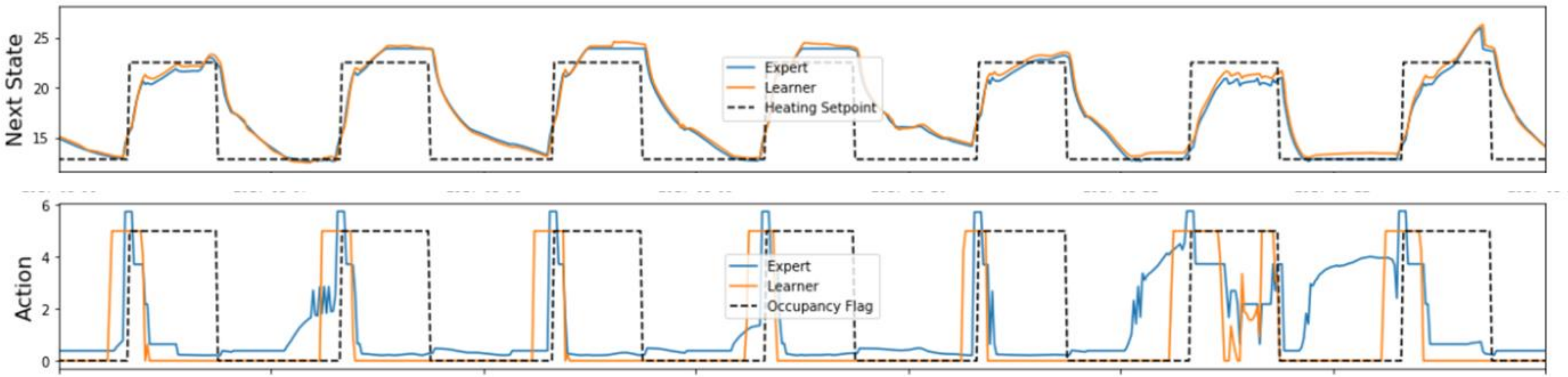
Control
In this demonstration, we control the supply air temperature of the main AHU and let the terminal units determine the airflow based on default EnergyPlus control logic.

In the Gnu-RL control, the action is defined as the difference between Supply Air Temperature and Mixed Air Temperature, which is proportional to the energy consumption of the heating coil.

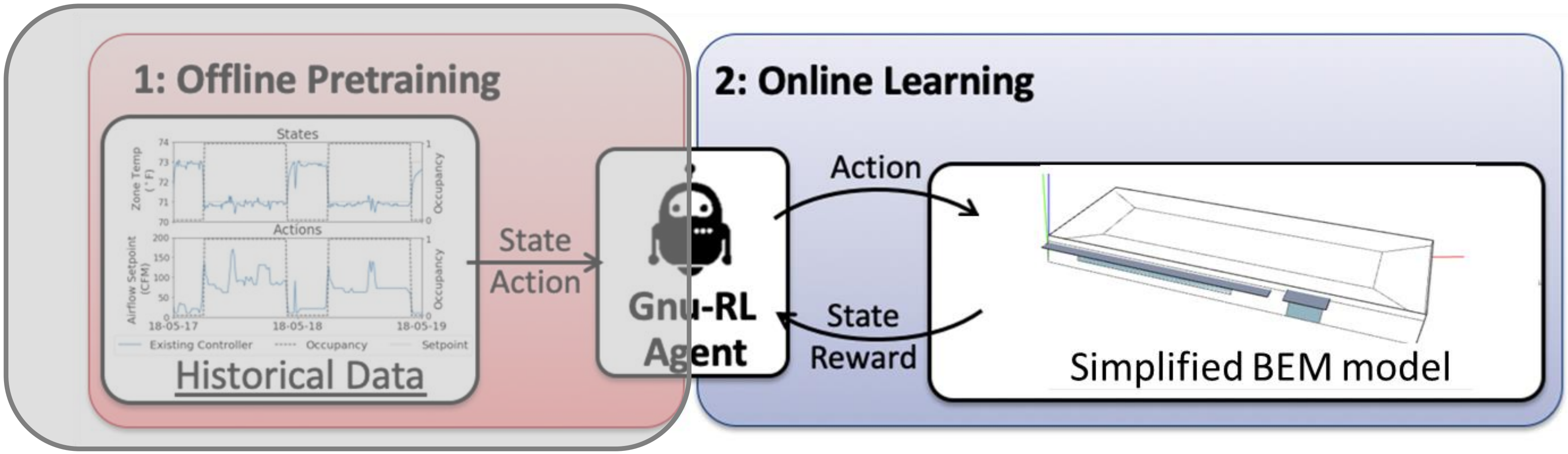
State	**Disturbance**
Zone Temp.	Outdoor Temp.
Setpoint	Outdoor RH
Zone Temp. Setpoint	Wind Speed
Action	Wind Direction
$\Delta T = T_{SA} - T_{MA}$	Diff. Solar Rad.
	Direct Solar Rad.
	Occupancy Flag

Test of Model Predittive Control

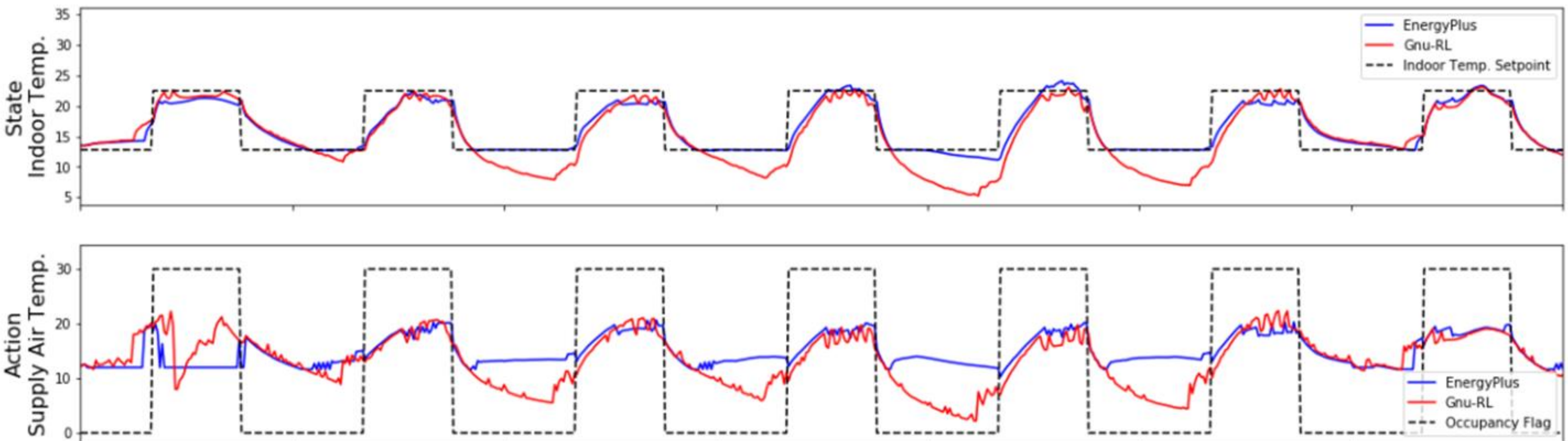




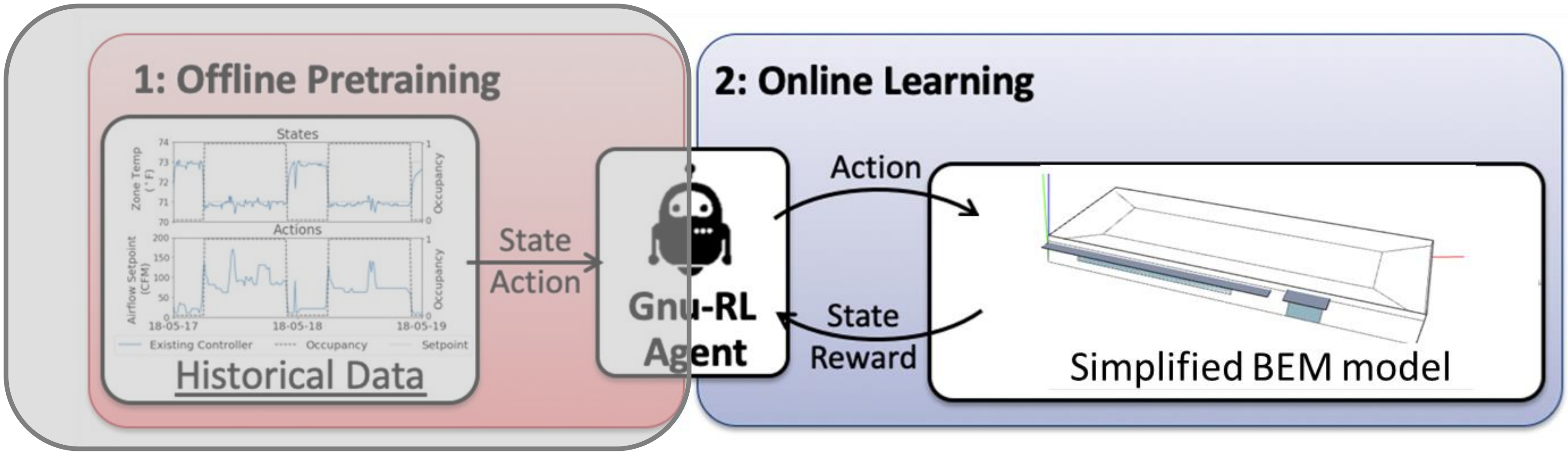
Test of Model Predittive Control



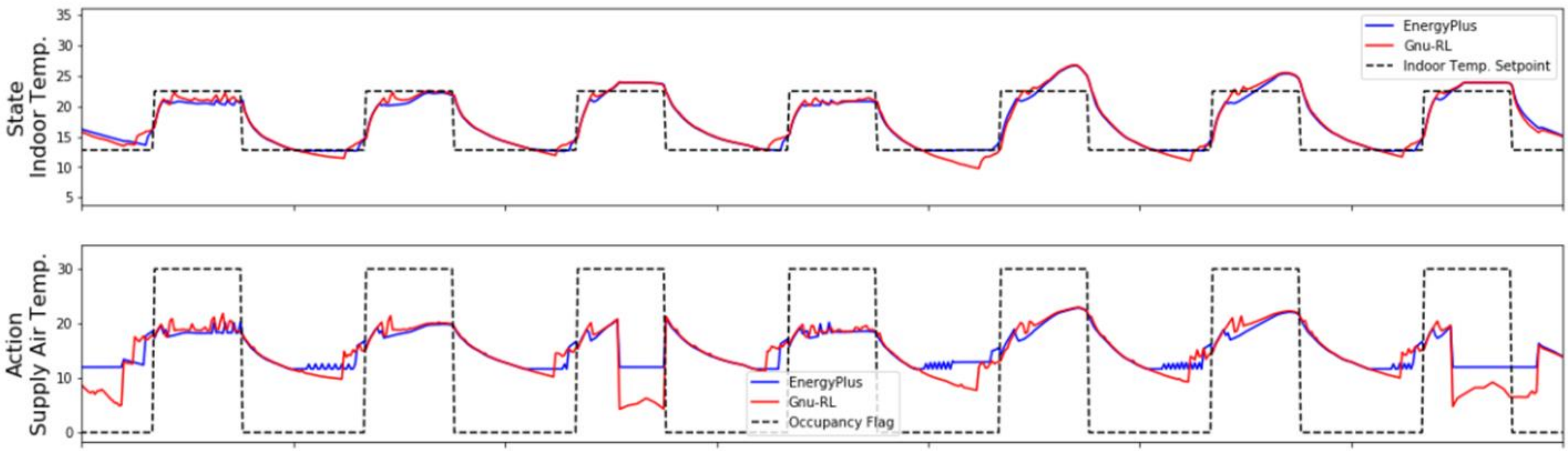
Actions Before online learning

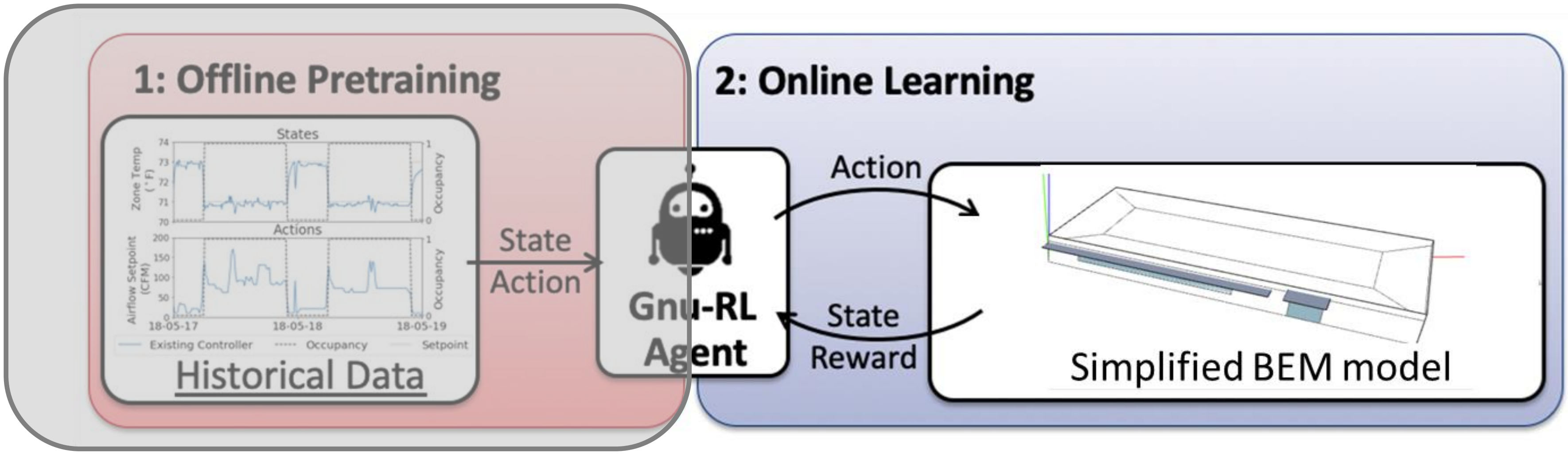


Test of Model Predittive Control



Actions After a period of online learning





EnergyPlus Baseline

```
Energy Consumed by the Heating Coil = 4413.17kWh
Energy Consumed by the HVAC System = 7482.66kWh
```

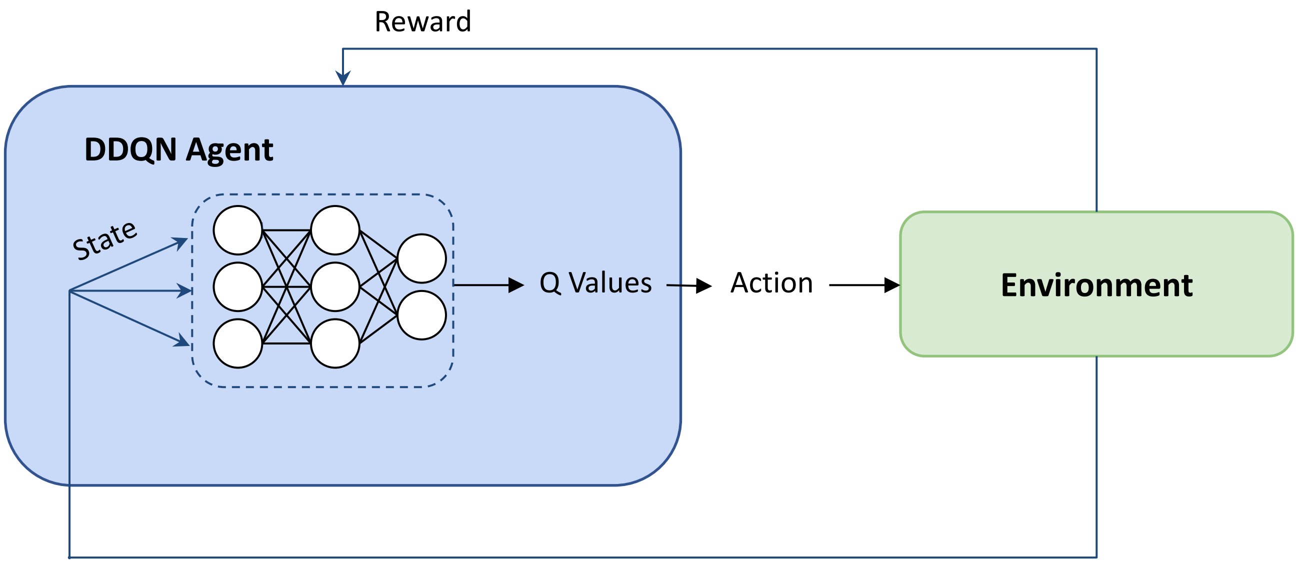
Gnu-RL

```
Energy Consumed by the Heating Coil = 3935.91kWh
Energy Consumed by the HVAC System = 7063.86kWh
```

10.8%

5.59%

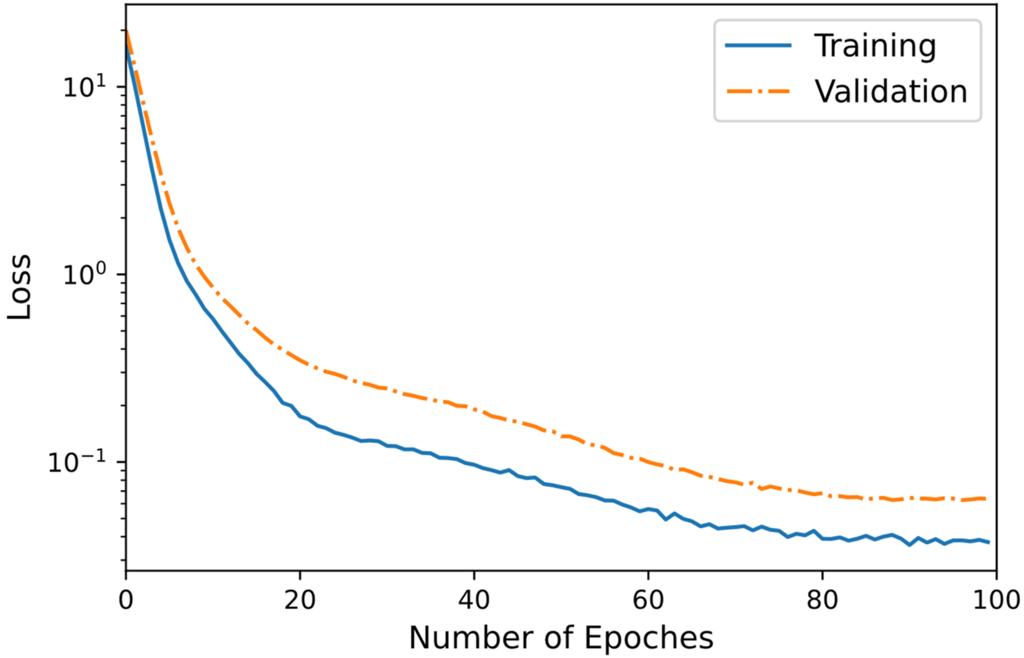
Double Deep Q-Network (DDQN)



System Identification Results

Loss Results

- Prediction Mean-Squared-Error on the test dataset gets as low as **0.06 °C** after 100 epochs and then stabilizes.
- The system identification is able to **correctly represent the building thermal dynamics**, so it can act as a substitute for a white-box model

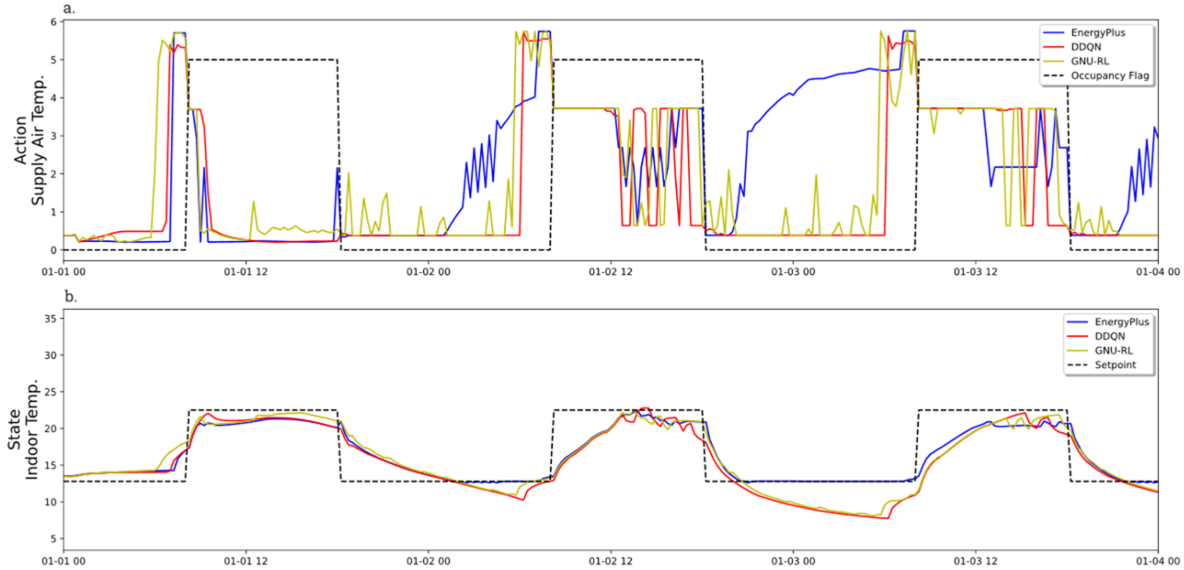


Optimal Control Results: Comparison

Energy Plus Controller
- E+ standard scheduled controller is adopted as a baseline.

GNU-RL (MPC)
- The GNU-RL implementation is based on an MPC and a similar system identification model

DDQN
- 3 different values of γ are tested, as its variation heavily affects the results.



Optimal Control Results: Performance Comparison

	$E+$	$GNU\text{-}RL$	$DDQN_{\gamma=0.8}$	$DDQN_{\gamma=0.9}$	$DDQN_{\gamma=0.99}$
PPD	17.75%	16.46%	16.61%	17.31%	**15.45%**
HVAC Power	4413kWh	4215kWh	4097kWh	**4093kWh**	5220kWh
Coil Power	7482kWh	7421kWh	7248kWh	**7228kWh**	8381kWh

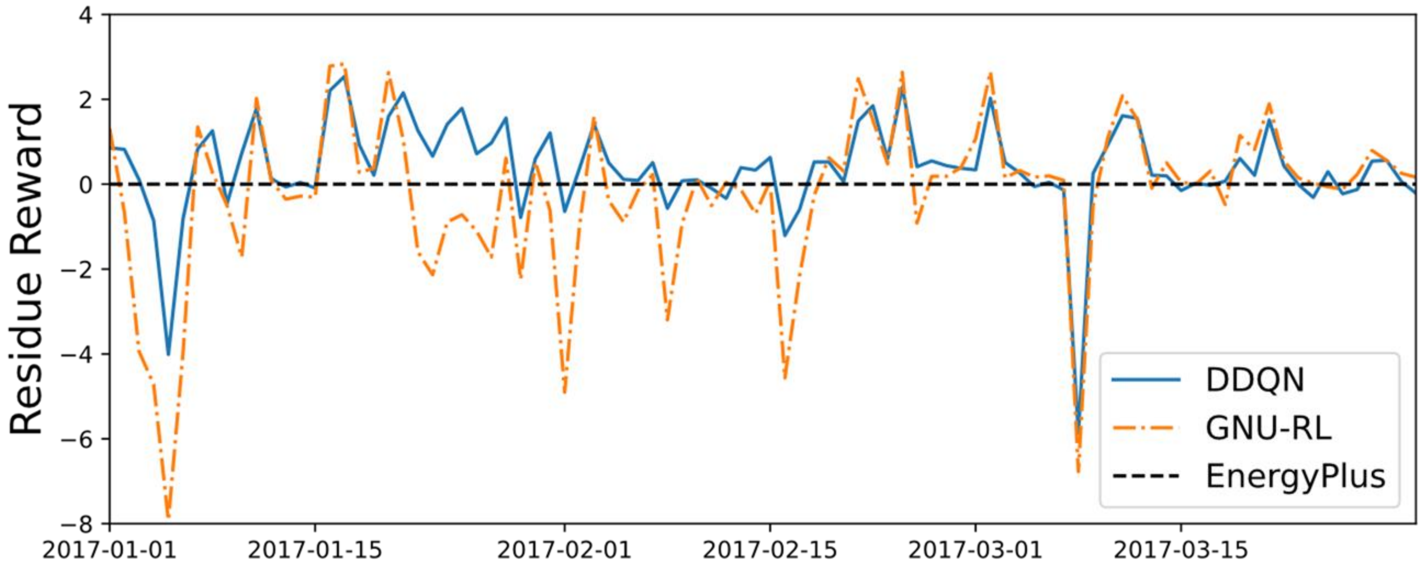
Evaluation Metrics

- Predicted Percentage of Dissatisfied (PPD): a common metric for measuring **thermal comfort;** the lower the better (anything below 20% is deemed acceptable).
- Power Consumptions: the total amount of **kWh consumed** by the HVAC system and its coil, during the considered period

Results

- Higher γ: the agent is more concerned with **thermal comfort** maximisation
- Lower γ: the agent is more concerned with **energy consumption** reduction

Optimal Control Results: Comparison Over E+ Baseline



References

Massano, Marco, et al. "A Grey-box Model Based on Unscented Kalman Filter to Estimate Thermal Dynamics in Buildings." *2019 IEEE International Conference on Environment and Electrical Engineering and 2019 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*. IEEE, 2019.

Chen, Yize, Yuanyuan Shi, and Baosen Zhang. "Modeling and optimization of complex building energy systems with deep neural networks." *2017 51st Asilomar Conference on Signals, Systems, and Computers*. IEEE, 2017.

Acquaviva, Andrea, et al. "Forecasting Heating Consumption in Buildings: A Scalable Full-Stack Distributed Engine." *Electronics* 8.5 (2019): 491.

Solinas et al. “An Hybrid Model-Free Reinforcement Learning Approach for HVAC Control” *2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*. IEEE, 2021.