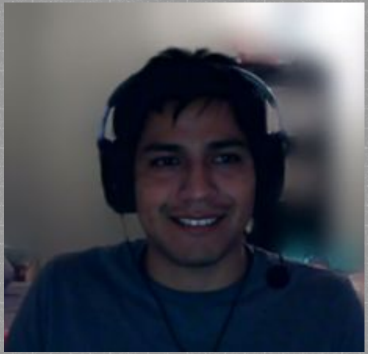
Optimizing an Electric Home

Meet the team!

Janelle Domantay

Nicholas Rui

Rebecca McCabe



Alvaro Carbonero

PROBLEM:

Design a control strategy for a fully electric home on a 100A electrical service

THE CHALLENGE:

MODEL OF THE HOME

- How much will power appliances turn on?
- When will they turn on?
- How to measure the impact of shifting load?

CONTROL ALGORITHM

- How should an ideal energy management controller shift power to keep demand with 100A with minimal impact?

SYSTEM DESIGN

- What sensors, actuators, communication flows, and appliance integrations would you implement?

THE SOLUTION:

MODEL OF THE HOME

- Determine appliance usage on an hourly basis
- Determine appliance usage based on user inputted values

CONTROL ALGORITHM

- Turn Shiftable Load (SL) appliances on/off based on **priority ranking** and appliance Unshiftable Load (UL) usage

SYSTEM DESIGN

- Temperature
  - Water Heater
  - Internal
  - External
- Power Draw
  - Unshiftable Loads

RELEVANT BACKGROUND:

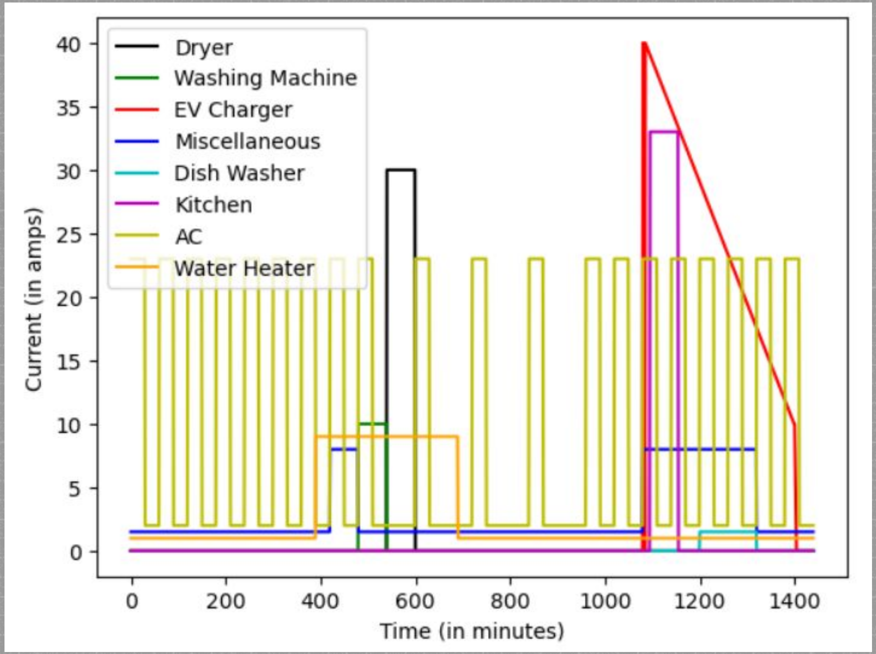
- Trajectory Optimization [3][4]
  - Online Trajectory Optimization
  - Direct Shooting Method

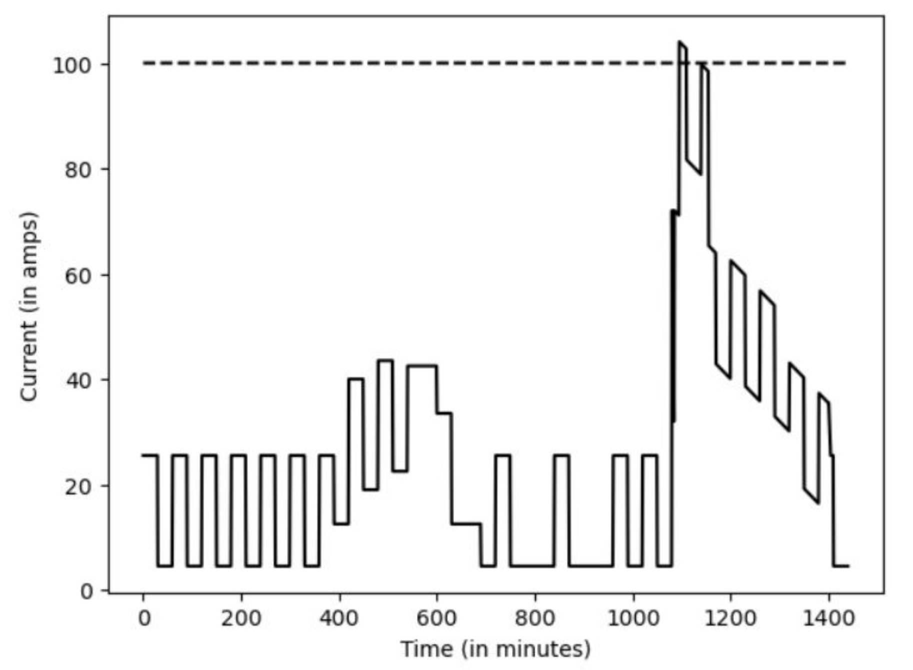
- Adaptive Control for improving home thermal model
- Machine Learning for predicting energy consumption [1][2]

HOUSE TOY MODEL:

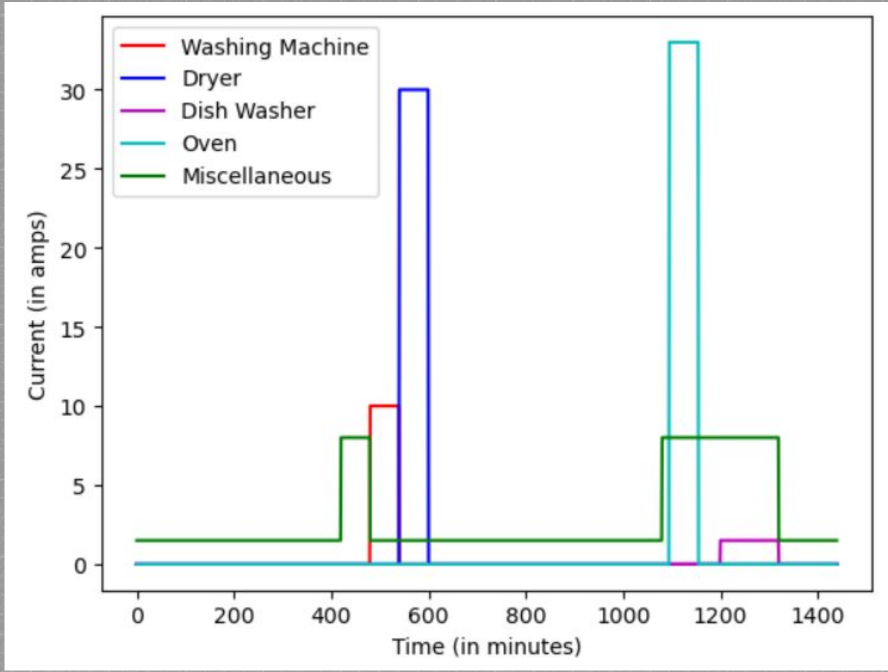
- Realistic, data-informed model with dominant power-demand contributions from:
  - HVAC
  - Water heating
  - Level 2: Electric vehicle charging
  - Other appliances
- Name of the game: minimize user “unhappiness” under maximum load constraint
- Training on fiducial model parameters, with plans for robustness testing on perturbed model parameters with real-time control

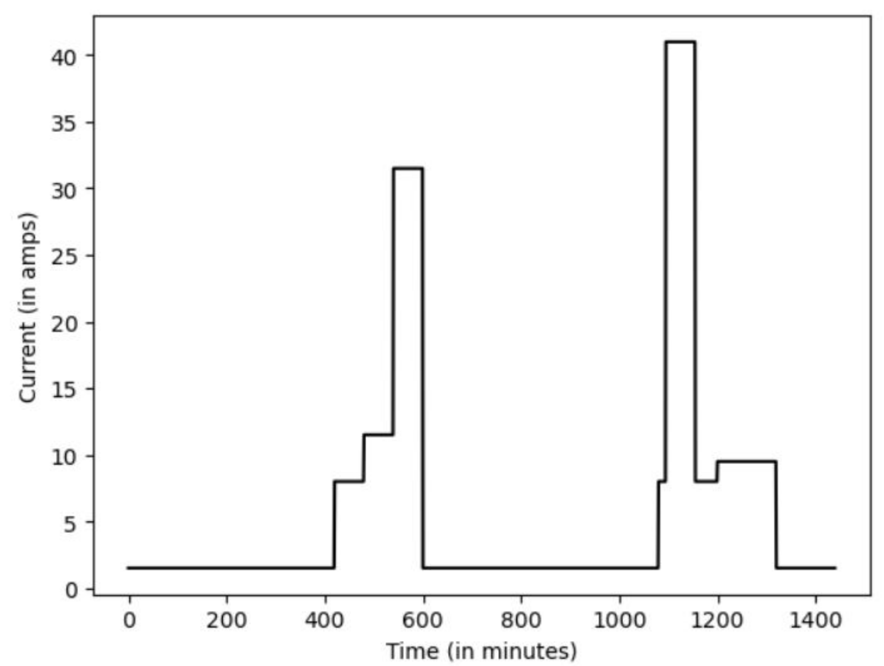
Initial Conditions:

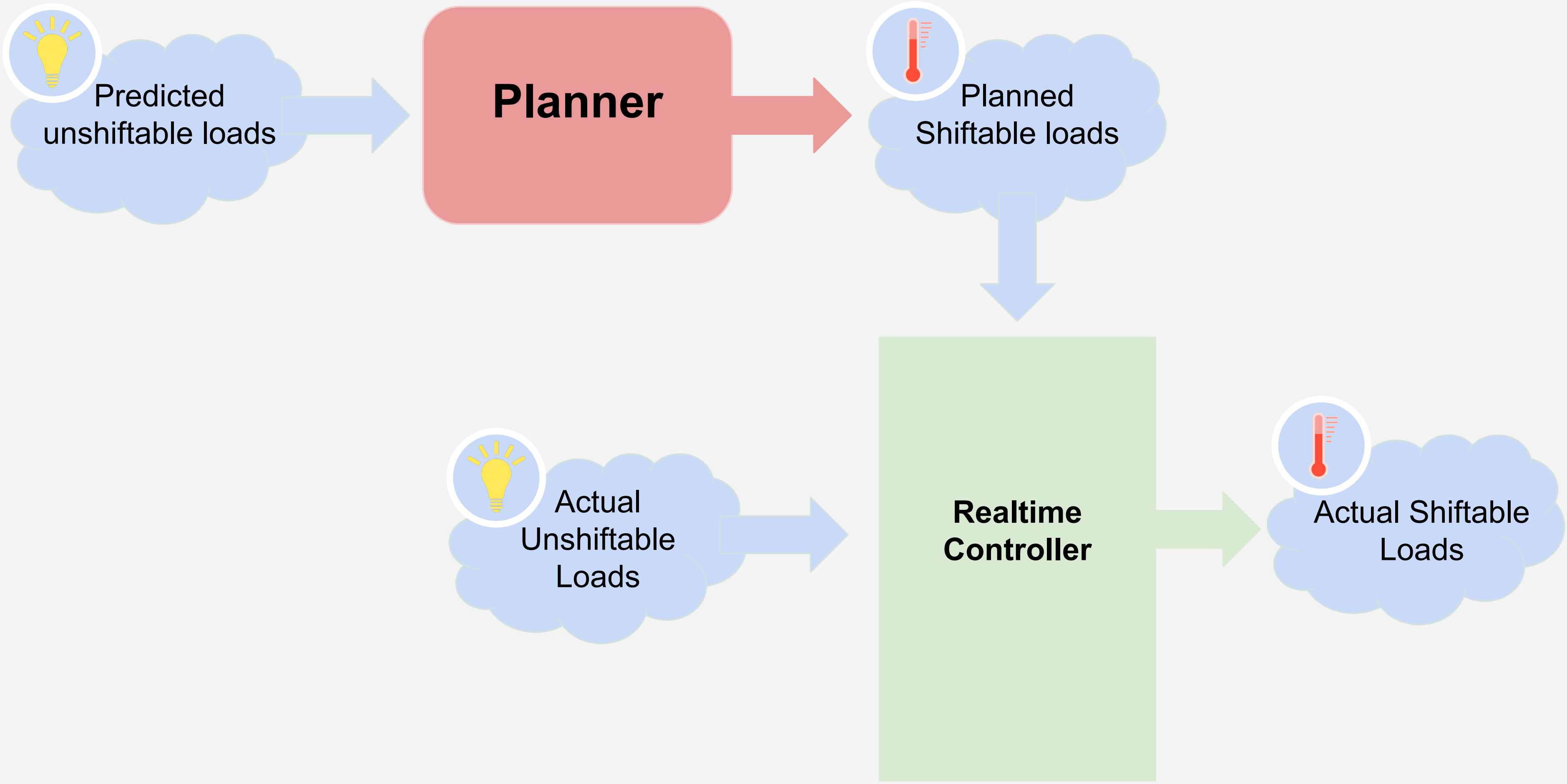




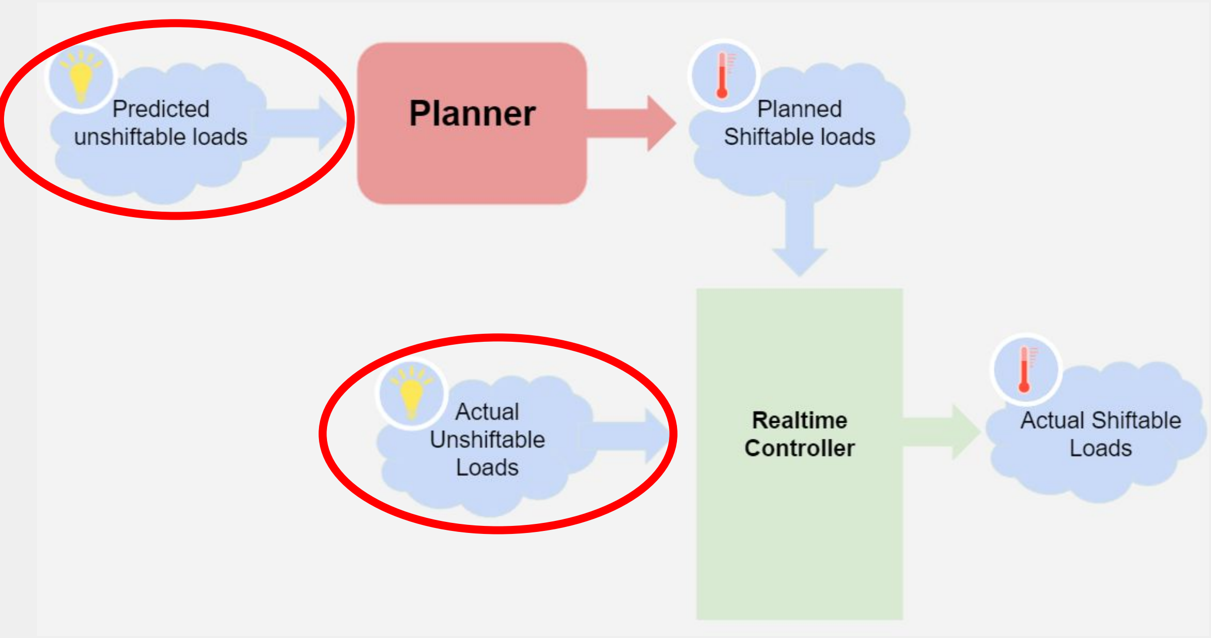
Predicted Unshiftable Loads:






Predicted unshiftable loads
Planner
Planned Shiftable loads
Actual Unshiftable Loads
Realtime Controller
Actual Shiftable Loads

How should the controller shift power?



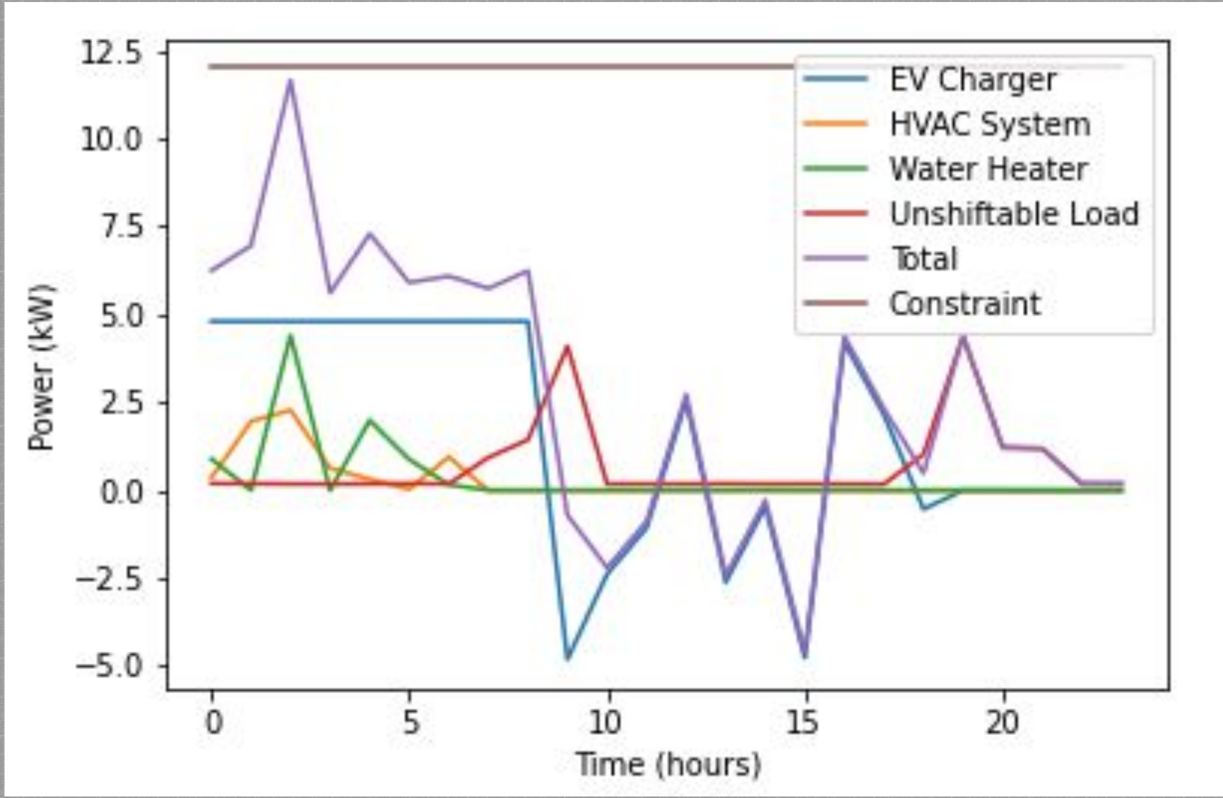
If pred UL < actual UL:

- Using more energy than expected
- Turn Down/ Off lowest priority SL
- Priority = impact and expected future impact

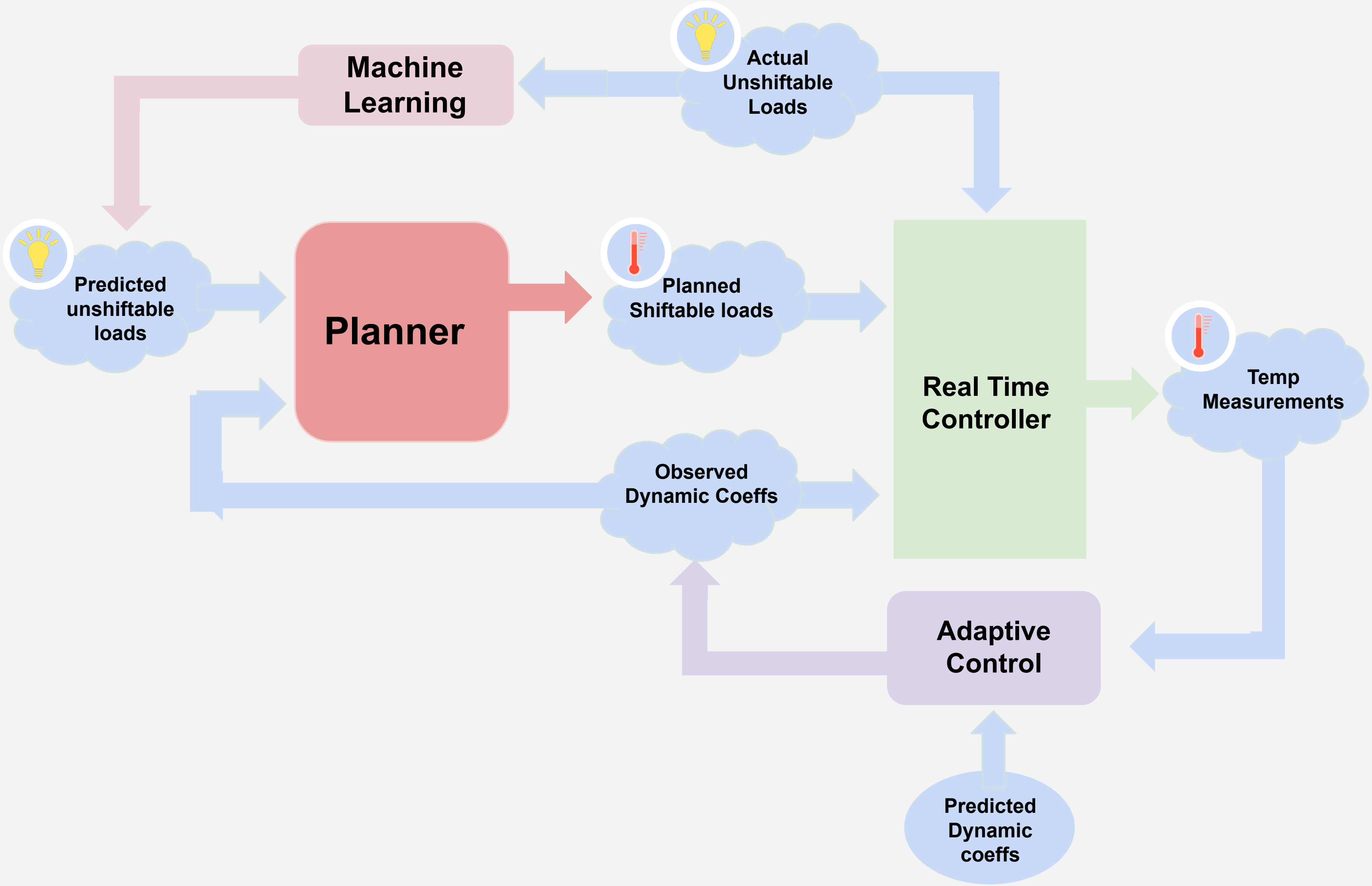
Else If pred UL > actual UL: (unexpected energy use)

- Using less energy than expected
- Turn Up/On highest priority SL

RESULTS



12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
Power (kW)
0
5
10
15
20
Time (hours)
EV Charger
HVAC System
Water Heater
Unshiftable Load
Total
Constraint



Machine Learning
Actual Unshiftable Loads
Predicted unshiftable loads
Planner
Planned Shiftable loads
Real Time Controller
Temp Measurements
Observed Dynamic Coeffs
Adaptive Control
Predicted Dynamic coeffs

REFERENCES:

[1] Bourhnane, S., Abid, M.R., Lghoul, R. et al. Machine learning for energy consumption prediction and scheduling in smart buildings. SN Appl. Sci. 2, 297 (2020). https://doi.org/10.1007/s42452-020-2024-9
[2] Kaustav Basu, Lamis Hawarah, Nicoleta Arghira, Hussein Joumaa, Stephane Ploix,A prediction system for home appliance usage,Energy and Buildings,Volume 67,2013,Pages 668-679,ISSN 0378-7788,https://doi.org/10.1016/j.enbuild.2013.02.008.
[3] Tedrake, R., Underactuated Robotics: Algorithms for Walking, Running, Swimming, Flying, and Manipulation. Course Notes for MIT 6.832, (2022)
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