A Solar Micro-Grid as a Community Resource Through Market Participation Using Optimal Time-Switching

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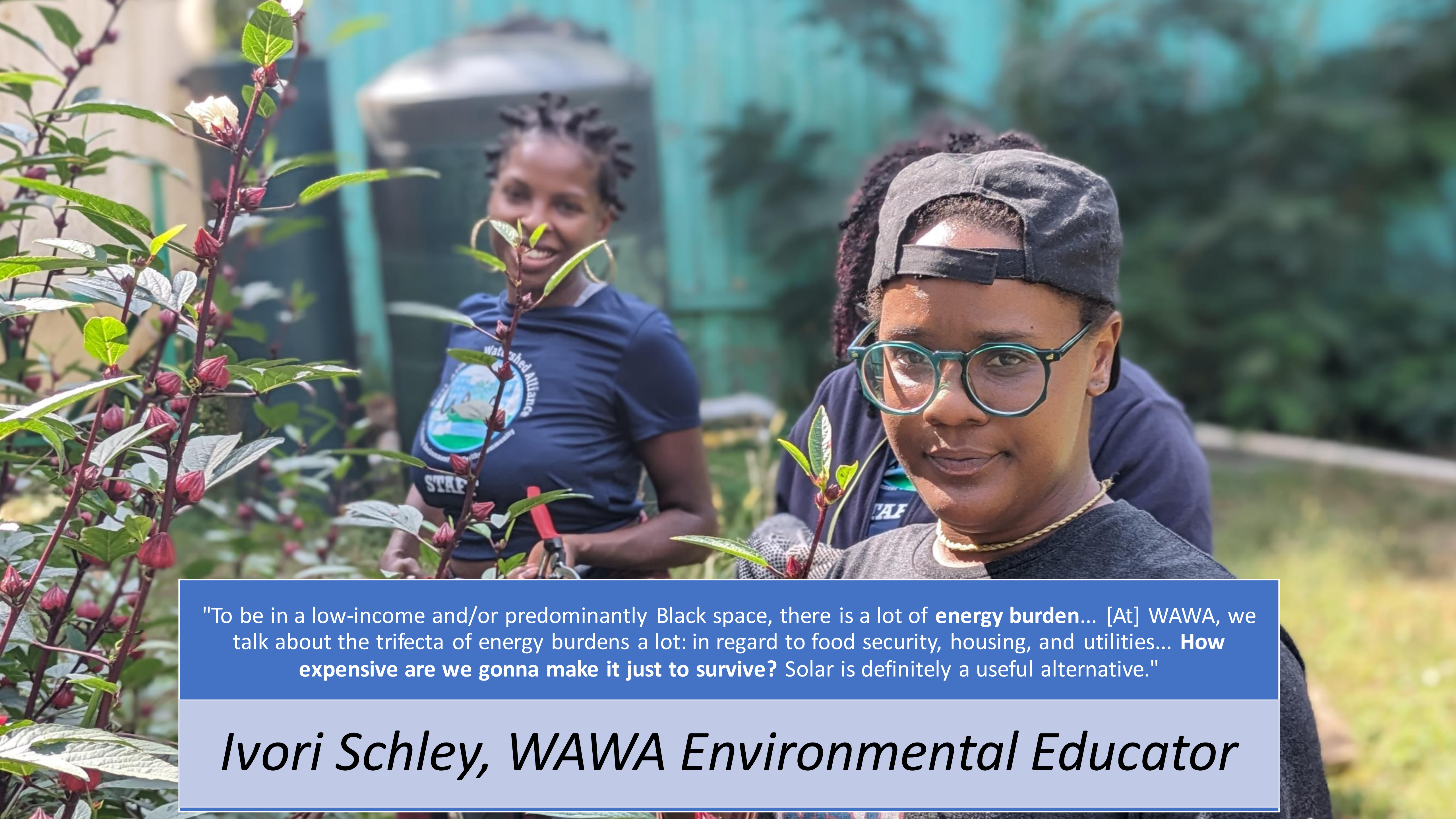
Microsoft

WAWA: Our Grassroots Community Partner

- West Atlanta Watershed Alliance (WAWA) serves environmental justice goals for over 18,000 residents
- Collaboration goals:
  - Bring free, renewable electricity to outdoor activity center and community farm with a solar micro-grid
  - Revenue from market participation can fund WAWA projects and community-building activities

Historic Hartnett Community Garden

- 1-acre urban farm in a historically Black community
- Produce and herbs grown for local seniors and midwives
- Future plans include an artist residency and training facility
- Solar micro-grid to power farm



"To be in a low-income and/or predominantly Black space, there is a lot of **energy burden**... [At] WAWA, we talk about the trifecta of energy burdens a lot: in regard to food security, housing, and utilities... **How expensive are we gonna make it just to survive?** Solar is definitely a useful alternative."

Ivori Schley, WAWA Environmental Educator

A greener Microsoft and corporate America

Ease of integrating renewables brings zero-carbon closer

Electrification of fleet can be an energy burden, renewable micro-grids are a solution

Prior work by RFI team provides POC for micro-grids as a datacenter resource

Towards the Smart Grid of Tomorrow

Production

- **Improved capability** to implement intermittent renewable energy sources
- **More resilient** power grid via decentralization of energy sources and storage

Markets

- Multi-time scale forward markets with **green incentives**
- Commit to delivering a certain amount of energy at a certain time

Transmission

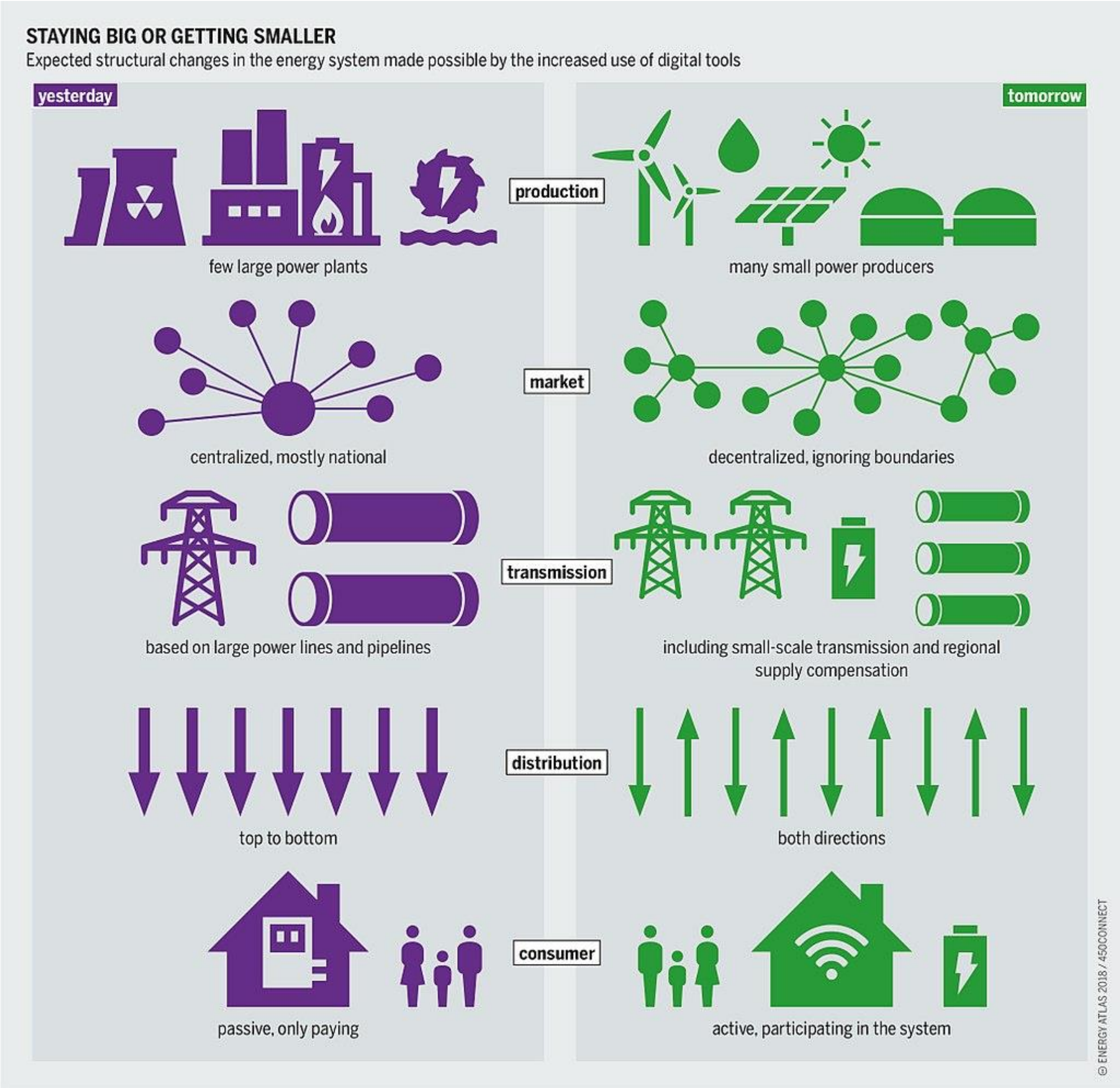
- **Localized transmission** for micro-grids

Distribution

- **Bidirectional flow** of energy, blurs line between producer and consumer

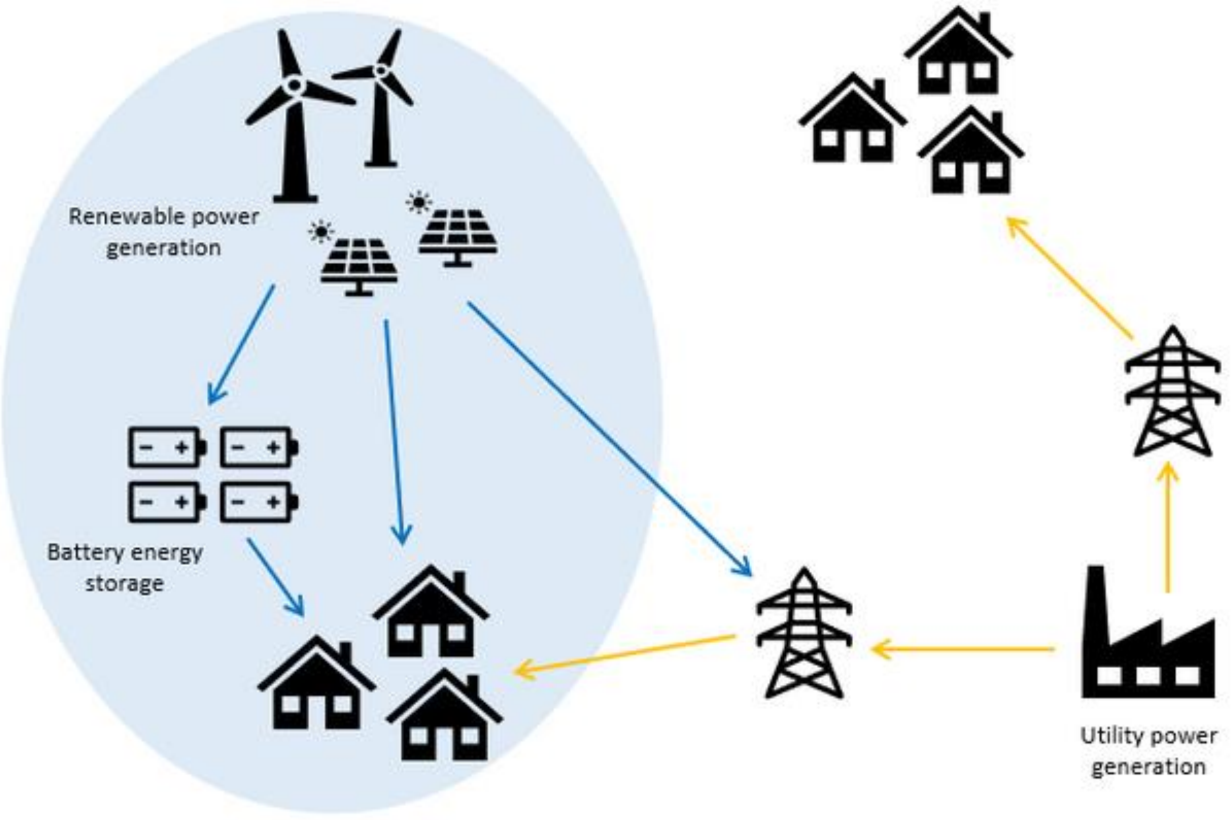
Consumption

- Consumers are moved to **active prosumers**
- Can further incentivize and simplify **demand shifting**



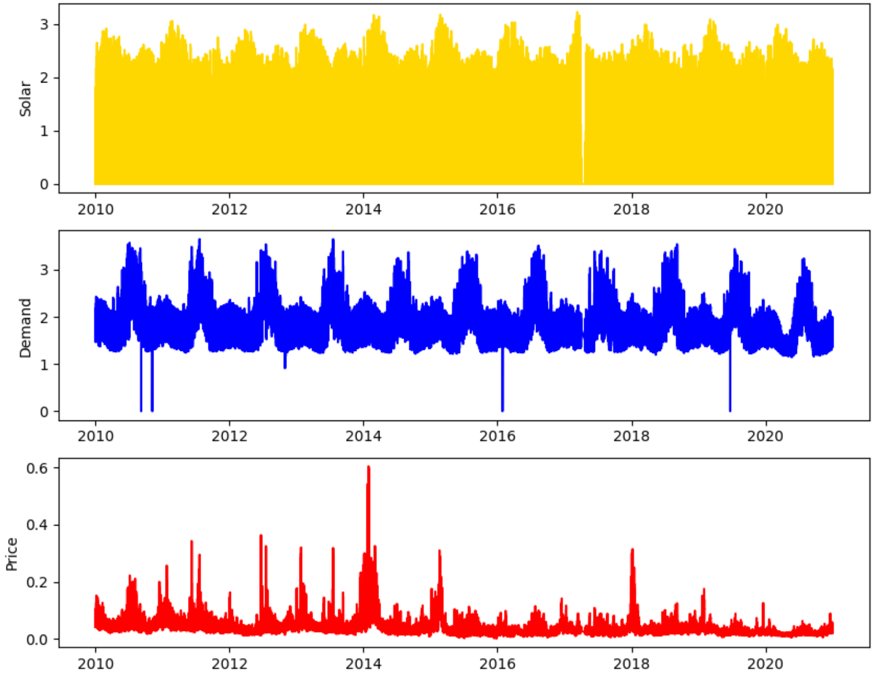
Methodology

Micro-grid system-of-systems



Prototyping goals

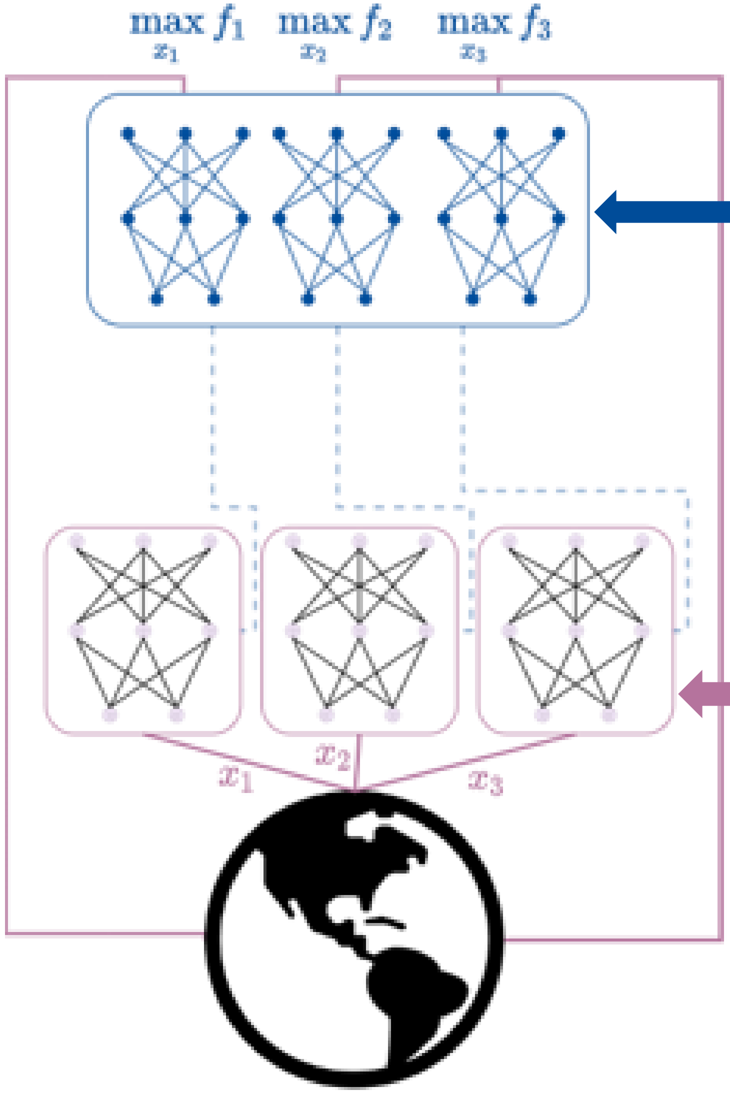
- Technical side: optimize for market profit while guaranteeing local power availability, i.e. **buy and sell power at the right time**
- Want end-product to be **accessible to non-technical users**
- Create **proof-of-concept for control mechanism** demoing hardware control and ability to handle complex/stochastic fluctuation in inputs



Control mechanism: DDPG agent

- Deep deterministic policy gradients (DDPG) are an **actor-critic** reinforcement learning method
- Suited to continuous or discrete state spaces, and continuous action spaces
- Scales well with # of decision variables
- Research shows DDPG agents are successful at controlling a microgrid battery and energy arbitrage

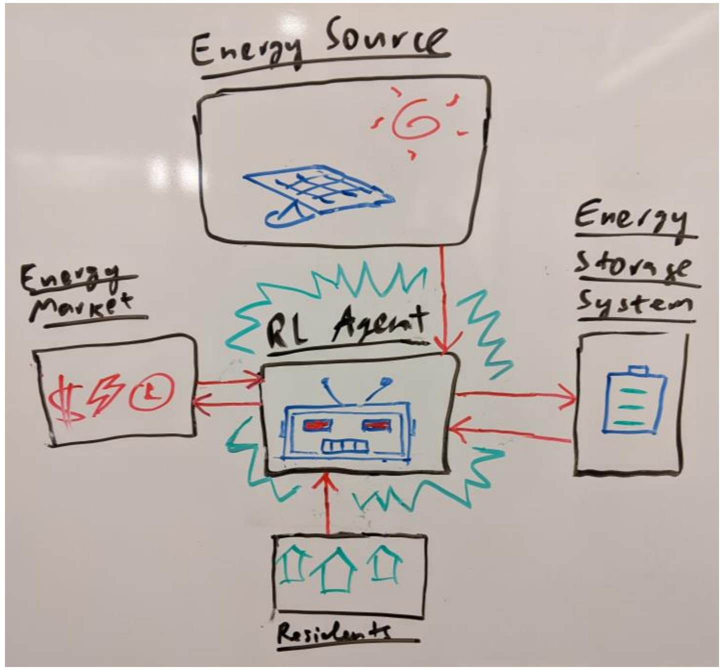
The Actor-Critic RL paradigm



The actor neural network's hyper-parameters are updated by another neural network – the **critic**. The critic evaluates the action chosen and gives the expected long-term reward.

In actor-critic methods, each decision policy corresponds to a distinct neural network – the **actor**. It takes in the environment state and outputs the agent's action.

DDPG implementation



State inputs: renewable generation, demand, energy price, forecasted values, battery level, current time

$$\hat{\mathbf{s}}_t = [r_t, r_{t+1}, d_t, d_{t+1}, p_t, d_{t+1}, q_t, h_t^d, h_t^w]$$

Output actions: toggle power source (solar vs battery); discharge/charge battery; buy/sell power

$$\hat{\mathbf{x}}_t = [R_t, D_t, C_t, B_t, S_t]$$

Reward function: maximize expected profit under microgrid operation constraints; project infeasible actions into feasible range

$$\max_{\hat{\mathbf{x}}_t} \frac{1}{T} \sum_{t=1}^{T} \mathbb{E}[f(\hat{\mathbf{x}}_t; \hat{\mathbf{s}}_t)]$$

$$f(\hat{\mathbf{x}}_t; \hat{\mathbf{s}}_t) = p_t(S_t - B_t)$$

DDPG implementation: action constraints

1. **Demand:** agent should not sell power needed to fulfill local demand, or refuse to buy if local power is insufficient
2. **Battery capacity:** cannot charge battery above capacity, or discharge below empty

Projecting actions for demand constraint

Calculates remaining demand after battery discharge

Agent forced to buy to fulfill leftover demand, reward calculated accordingly

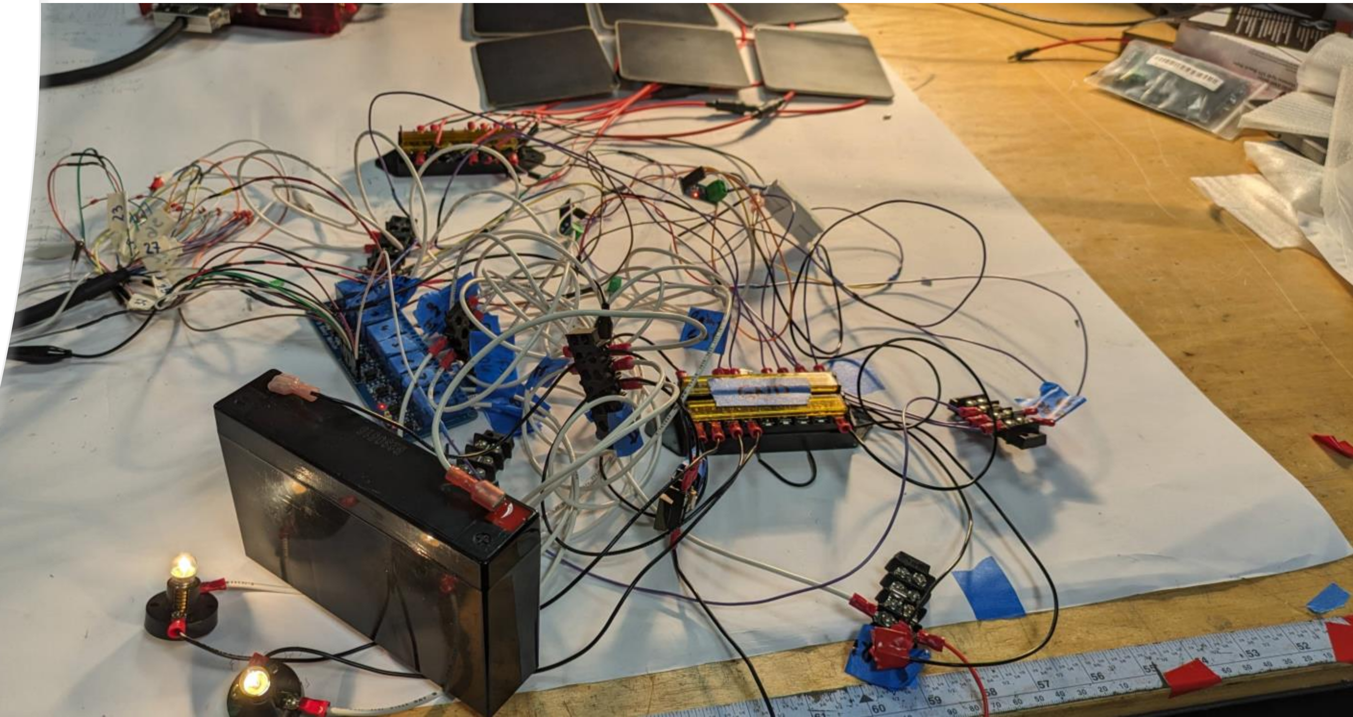
```
if DISCHARGE > 0.5:
    actual_discharge, leftover_demand = self.battery.discharge(leftover_demand)
    if leftover_demand > 0:
        adj_demand_diff = leftover_demand / self.battery.efficiency
    else:
        adj_demand_diff = 0
else:
    adj_demand_diff = 0
```

Agent **learns to output actions within constrained space**, and is automatically redirected when needed

Results

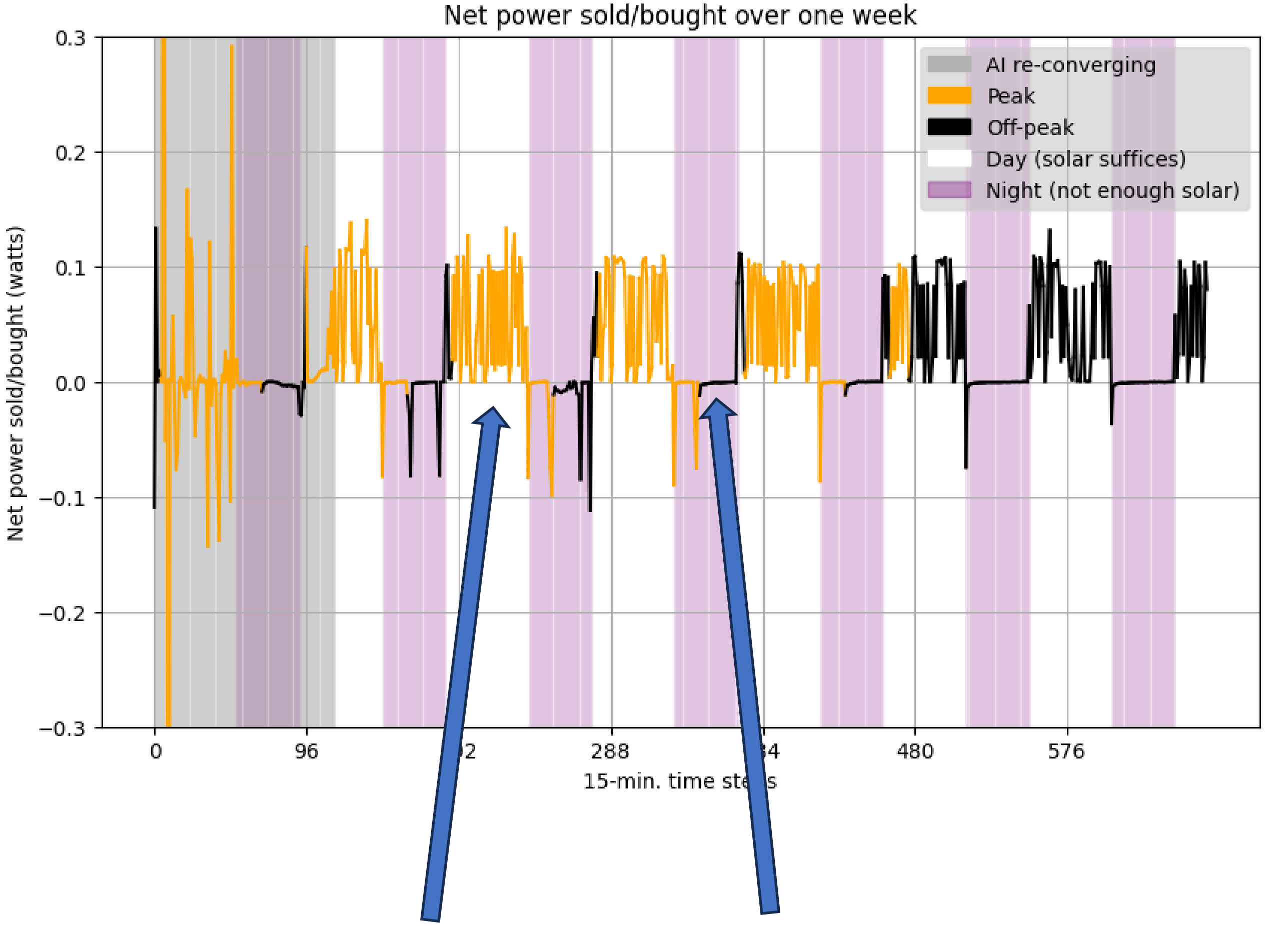
Hardware schematic

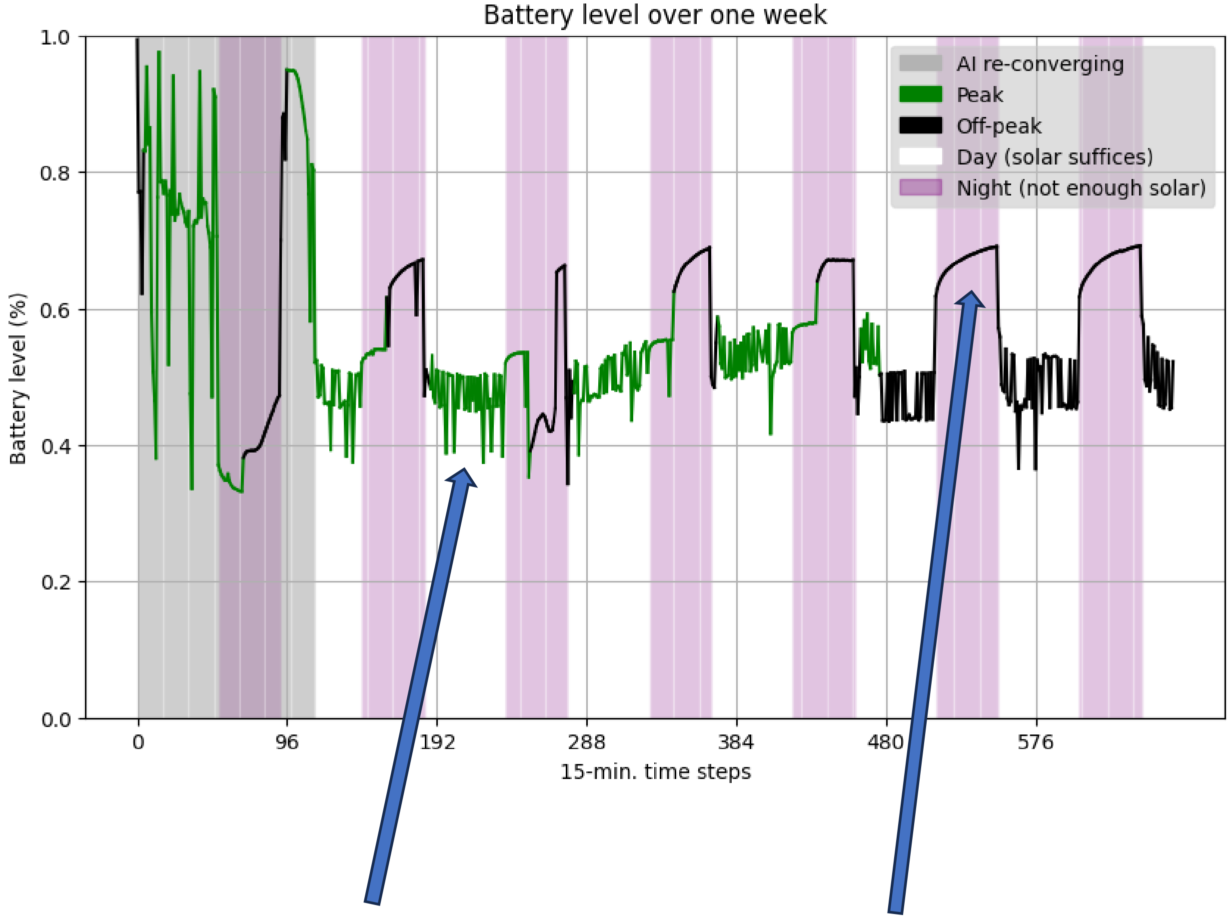
- Simplified day/night with 12 hours of direct sunlight and 12 hours of no sunlight
- Incorporates peak pricing (2x reg.) from 7am – 11pm on weekdays
- Train the model on simulated hardware, then test on a simulated week on real hardware (scaled to 30 minutes)



Hardware demo

Hardware results





Sells more power than bought when solar is available

Relies on battery to power load at night, makes fewer transactions

Battery reserves are sold during the day as solar can power load

Conserves power at night to avoid buying and maximize selling during the day

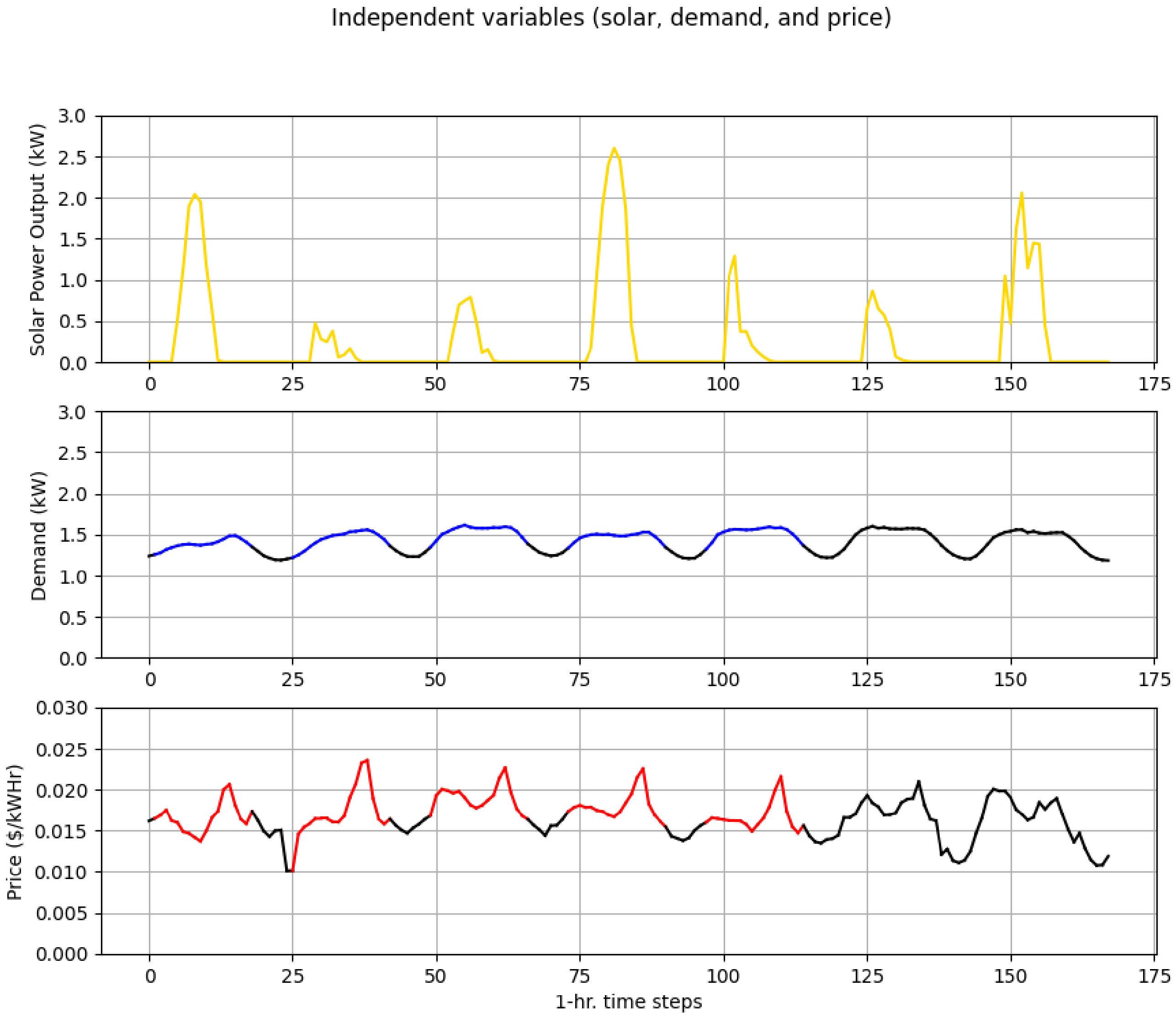
Software simulation

- Test our agent in an environment closer to real-world complexity
- Simulate patterns in solar, demand and price as well as unpredictable fluctuations

- Solar output simulated using pvlib based on NREL weather data
- Obtained NYISO demand and price data for an average household in Brooklyn, NY for 10 years

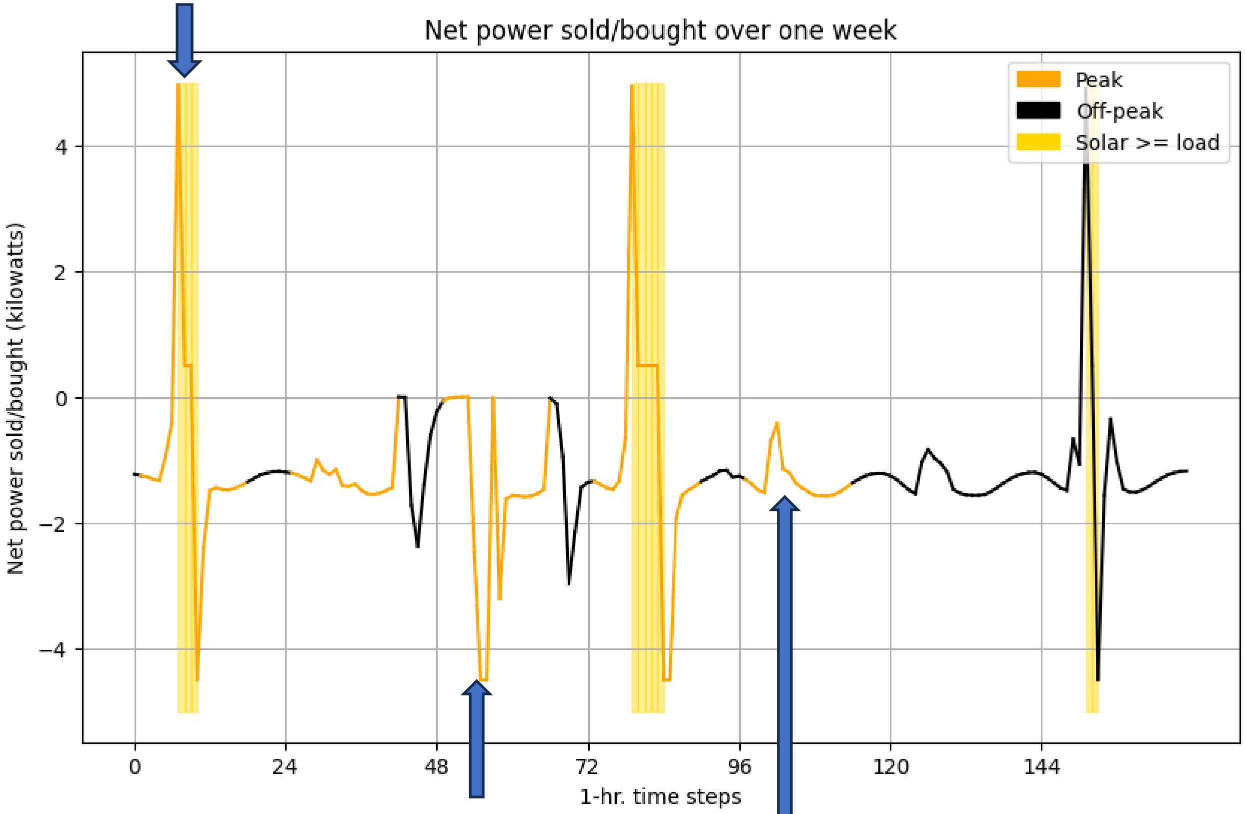
Simulation results

- Results for a representative week from last training epoch
- Data and simulated solar output for Brooklyn in April 2020



Simulation results

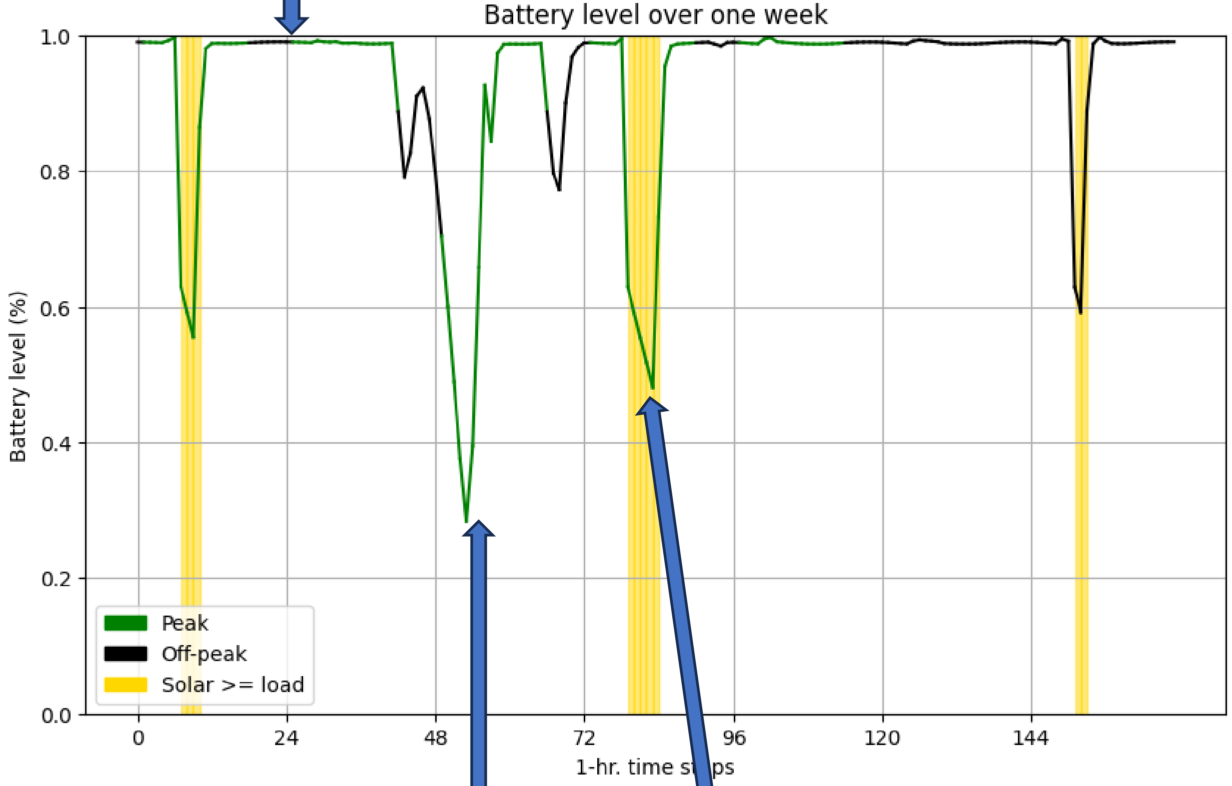
Looks for opportunities to maximize profit during energy abundance



Buying during peak is necessary to meet demand constraint

Minimizes cost by using solar to charge battery

Operating in an energy deficit, keeps battery charged



Responds to battery drain during high demand

Can sell reserves during solar surplus

Conclusions

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- DDPG agent successfully controls a scaled hardware prototype and data-based simulation, each representing a solar micro-grid
- Training on simulated hardware quickly translates to controlling real prototype
- Projecting actions into feasible range promotes learning and ensures constraints are met
- Agent is able to predict patterns and handle fluctuations in independent variables
- Prediction accuracy could potentially be improved by longer forecasts for independent variables

Future Work

- Creating an LLM-based frontend to generalize the control mechanism to arbitrary microgrids, and improve configuration accessibility
- Help WAWA implement a micro-grid in Atlanta!

Q&A

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