Energy Sharing and Management System
209AS Final Project Presentation

Jingjing Xu (jingjing9160@g.ucla.edu)
Mindy Saylors (mindysaylors@gmail.com)
Chaohao Li (uclalch@ucla.edu)
Satvik Anand (satvik.anand029@gmail.com)

University of California, Los Angeles
Dec 10, 2020

Introduction - Project Background and Motivation

Problem Addressing

- Home renewable generation utilization
- Lowering the cost of energy

Common Implemented Approaches Today

- Various optimization techniques for energy generation and storage to meet single home demand
- Static pricing for Peer-to-Peer Trading schemes

https://www.ohmconnect.com/new-features/energy-sharing-the-newest-addition-to-the-sharing-economy

Current Research in Energy Management Systems using AI

- Using reinforcement learning variations or deep learning on energy management systems modeled as MDPs
- Research focus: How to trade energy between homes, how to set prices
- Goal: Make optimum energy usage decisions, lower cost for users
- Bibliometric analysis research: showing the trend of increasing publications in energy management area with Q-learning approach.

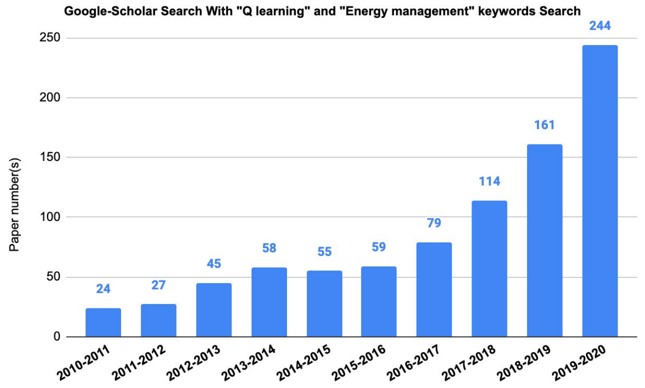


Fig.2 Google-Scholar Search With "Q learning" and "Energy management" keywords Search

Literature review

[1] Artificial intelligence based smart energy community management: A reinforcement learning approach

- **Brief environment/problem**

Smart community energy management in a P2P energy trading system between households

- **Methods used**

1. MDP
2. Fuzzy Q-learning
3. Fuzzy rules

[2] Deep reinforcement learning for energy management in a microgrid with flexible demand

- **Brief environment/problem**

Microgrid with its own wind-turbine energy generation mechanism that buys from and sells to the electricity market

- **Methods used:**

1. DRL methods
2. Deep Q-learning (DQN)
3. REINFORCE algorithm
4. Actor–critic algorithm
5. Proximal policy optimization (PPO) algorithm

[3]A smart community energy management scheme considering user dominated demand side response and P2P trading

- **Brief environment/problem**

P2P energy trading system with a local energy pool and pricing mechanism

- **Methods used:**

1. Battery energy storage system BESS model
2. UDDSR optimization approach Since

Problem Statement

Smart residential community concept is proposed consisting of domestic users and a local energy pool, in which users are free to trade with the local energy pool and enjoy cheap renewable energy.

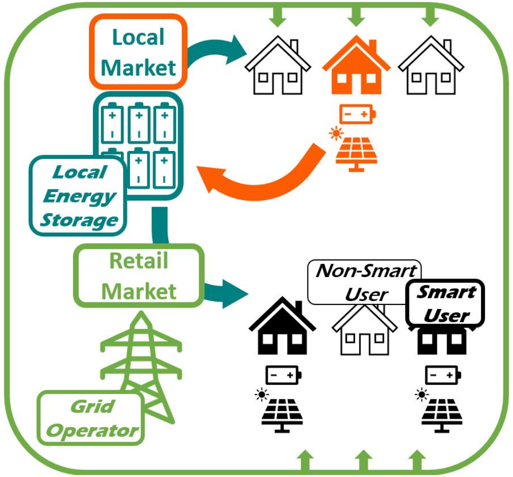


Fig.3 Smart energy sharing community scheme

Four parties for this system:

The smart homes with ESS: Equipped with Energy storage system

sell/buy their surplus energy

Non-intelligent homes: Buy the energy from the energy pool/retail market

Agents: Make decisions for charging/discharging for Energy storage system,

buying/selling energy for neighborhoods

The local energy pool Harvest surplus energy from users and renewable resources

sells energy between Feed-in-Tariff (FIT) and the retail price

Problem Statement Cont.

Battery Capacity(ESS) Model

$$E_{t+\Delta t}^{Bt} = \begin{cases} E_t^{Bt} + P_t^b * \eta^c * \Delta_t & if P_t^b >= 0 \\ E_t^{Bt} + frac P_t^b \eta^d * \Delta T & if P_t^b < 0 \end{cases}$$

$$P_d^b \leq P_t^b \leq 0 if P_t^b < 0$$

$$0 \leq P_t^d \leq P_c^b if P_t^b \geq 0$$

$$0 \leq E_t^B t \leq E^B t$$

E_t^{Bt}: capacity of Battery Energy Storage system (BESS) at time t, kW

P_t^b: the charging/discharging rate of BESS at time t, kWh

η^c : charging efficiency, kWh

η^d : the discharging efficiency, kWh

P_c^b: the BESS maximum charging rate, kWh

P_d^b : BESS maximum discharging rate, kWh

E^{Bt}: the maximum BESS capacity, kW

The community pricing model:

$$q(t, \gamma_1(t)) = a(t) * \gamma_1(t)^2 + b(t) * \gamma_1(t)$$

$$q(t, \gamma_1(t)) + p^F < r(t)$$

$$\gamma_1(t) = \frac{e_m(t) + S_{pv}(t) + s_m(t)}{s_n(t)}$$

$$p(t, \gamma_1(t)) = r(t) - q(t, \gamma_1(t))$$

ρ : real-time market price, $

$\gamma_1(t)$: the ratio of the energy in the pool, kW

$\gamma_2(t)$: Discount factor

a(t) and b(t) are time-dependent non-negative parameters

$s_m(t)$: the amount of energy that smart users sell to the pool at time t, kW

$e_m(t)$: the rest of the energy in the pool before time t, kW

$s_{pv}(t)$:the solar energy at time t, kW

$s_{n(t)}$: the aggregated demand amount of users that are requesting energy from the pool, kW

p^F : the Feed-in-Tariff (FIT), $

Project Scope

Goals:

The robot/agent can computationally reach the optimal state in real time for the energy sharing community to achieve higher consumers' profits and more optimized utilization of renewable energy.

Deliverables:

1. Table/Graph should show agent dynamically make optimal charge/discharge decisions to optimize the consumption of renewable energy;
2. Table/graph should show agent can dynamically help the neighborhoods make the trading decisions to minimize the cost in trading.
3. Cost comparison graph/data should present the evident differences in cost with/without algorithm.

Approaches

1. MDP
2. Fuzzy Q learning
3. Gaussian Process Regression

Mathematical Formulation - Markov Decision Process (MDP)

State Space:

S = {[S_1: Battery capacity, S_2: Real-time retail prices, S_3: Market price]}

$$S = \{[s_1, s_2, s_3] : s_1, s_2, s_3 \in \Re\}$$

Action Space:

$$A = \{[a_s, a_t] : a_s \in A_s, a_t \in A_t\}$$

$$A_s = \{-1, -0.9, -0.8, ..., 0, ..., 0.8, 0.9, 1\}$$

A_s: The battery charge (+) / discharge (-);

$$A_t = \{-1, -0.9, -0.8, ..., 0, ..., 0.8, 0.9, 1\}$$

A_t: The agent buy/sell a_t of the maximum electricity trade rate from the local energy pool.

System Dynamics and Sensor Model:

In this problem we are unaware of the system dynamics/transition probabilities and we don't need to know them for our Q-learning algorithm. We also do not have a sensor model so we formulate our problem without belief states.

Horizon:

$$H = \infty$$

Mathematical Formulation - Markov Decision Process (MDP) Cont.

Reward

Our reward function is formulated as follows for an action combination $a_t = a_t \times a_s$ at state $s_t = s_1 \times s_2 \times s_3$:

$$R(s, a, s') = -p_n * \Delta\zeta(s) - \Delta p * \Delta\theta(s)$$

$$\Delta p = (p_d + p_b - p_n)$$

$$\Delta\theta(s) = \theta(s) - \theta(s')$$

Here p_n is the the amount of trade electricity with the local pool; $\zeta(s)$ is the community market price at state s; $\theta(s)$ is the retail price at state s; p_d denotes the home energy demand; p_b denotes the amount of electricity the battery charge/discharge. $R(s, a, s')$ is normalized in the range [1,0].

Discount factor

$$\gamma = 0.9$$

Design Process and Decisions

- **Generating framework of Peer-to-Peer trading system**
  - Modeling the MDP - state space, action space, system dynamics, reward and horizon

- **Implementation of Fuzzy Q-learning**
  - Based system on [1] but later changing reward function drastically
  - Applied out model to a small community
  - Q-learning could be applied to model-free, ongoing tasks with excellent performance.
  - Fuzzy logic can obtain continuous variables from the discrete fuzzy set.
  - Use of fuzzy rules help
- **Gaussian Process Regression (to do)**
  - Choice of appropriate model
  - Calculate the predictive posterior distribution
  - Measure the performance of the GPR

Methods and Algorithm

Fuzzy Q-learning Approach - based on Q-learning

- Obtain current state s
- Find optimal action combination
- Compute the corresponding Q-value table
- Apply and select action combination to obtain new state s’
- Calculate value function V and Q-value variation
- Update the q-value
- Exploration and Exploitation algorithm

Algorithm: Fuzzy Q learning

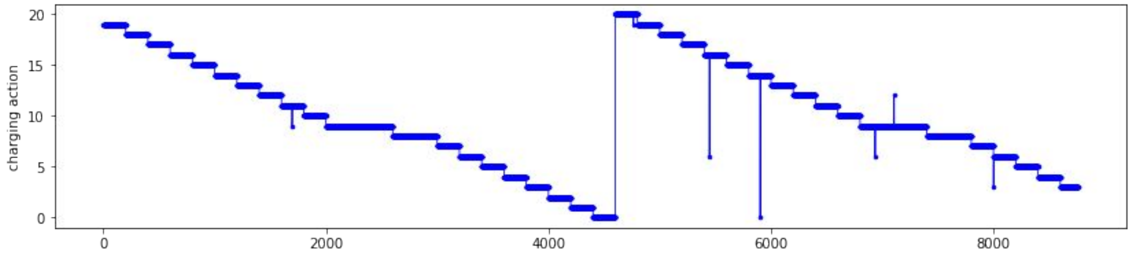
Pseudo Code

```
for iteration $[1, max+1]$
        for S(s_1,s_2,s_3),do
                compute fuzzy output set w(s)
        end

        for fuzzy value from w(s) do:
                convolution --> caculate reward[i]
        end

        for i = 1,2,..27 do:
                $updatingQ - value \leftarrow Q + q(1 \times a_s, a_t) * r(i)$
                $updatingV - value \leftarrow V + max_{a_s i, a_t i} q(i \times a_s i \times a_t i) * r(i);$
        end
        Normalizing Q and V:
        $Q \leftarrow \frac{Q}{\sum^2 7_{i=1} r(i)}$
        $V \leftarrow \frac{V}{\sum^2 7_{i=1} r(i)}$
        $\Delta Q = R(s, a, s^{(\prime)}) + \gamma * V - Q$
        $q[i^*][a_s][a_t] \leftarrow q[i^*][a_s][a_t] + \alpha * \Delta Q * r(i^*)$
        for i = 1,2,....27 do:
                $if e < \varepsilon :$
                        $a_s, a_t = max_{a_s a_t} q(i \times a_s \times a_t)$
                        $s \leftarrow s'$
                $else$ :a_s,a_t = random
        $end$
$end$
```

Fig.4 Algorithm for fuzzy Q learning for energy sharing system

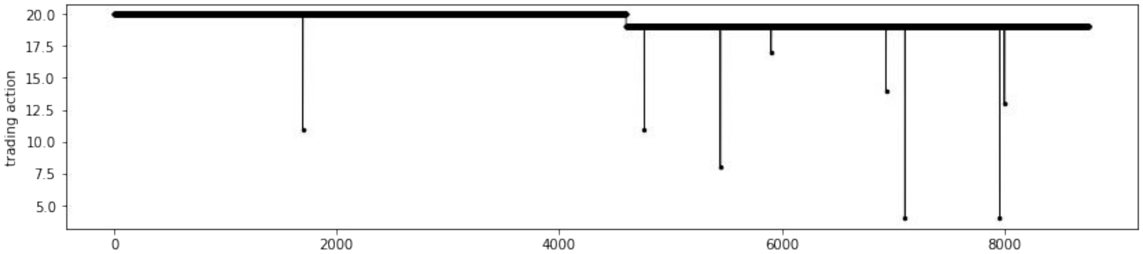
Current Results

Storage Action



Time/30mins

Trade Action

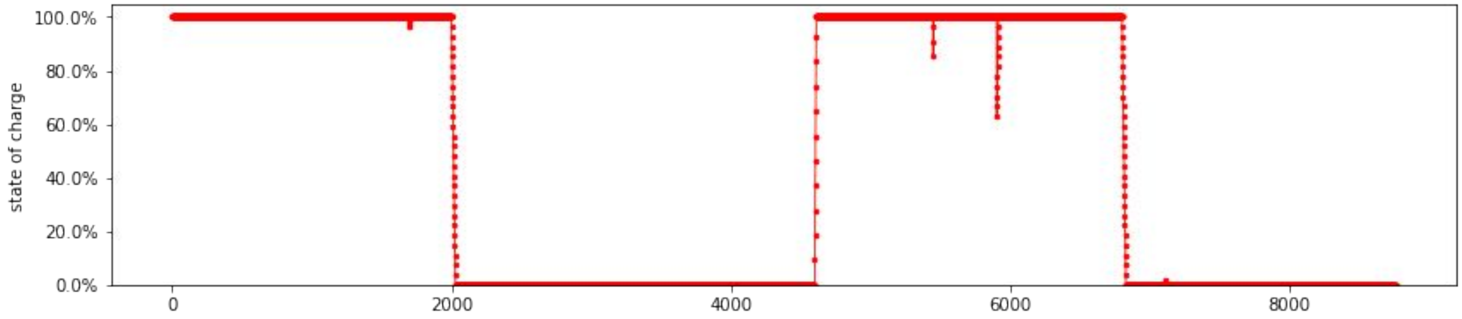


Time/30mins

Fig.5 Storage action and trade action at every 30 minutes

- Trade action with the local energy pool - solar energy generated plus the battery capacity > electricity demand
- More charges in the local energy pool, the community drops rapidly, and sometime goes to negative.
- Community price < the retail price - Able to charge and buy.

Current Results - Cont.



Time/30mins

Fig.6 State of charge/ battery capacity at every 30 minutes

- The storage action is somehow periodic
- The state of charge is only changing in responsive to the charge or discharge action, which doesn’t make a lot of sense.

Future Work

- Apply Gaussian Process Regression (GPR) to
    - Datasets: solar and home energy usage datasets
    - State space: state of charge
    - Action space: energy trade rate
- Analyze MSE for each application to evaluate GPR effectiveness
- Adjust price model for more realistic performance for community price
- Completely remake reward function based on:
    - Avg Price/kWh for Smart and Non-Smart Users with bias incentive for Smart User to encourage participation
    - Renewable Energy Penetration
- Creating a cost comparison showing the cost with or without algorithm applied
- Scaling of algorithm test

Expected Conclusions

- GPR: more realistic model, ability to add uncertainty measurements to prediction
- Analyze MSE for each application to evaluate GPR effectiveness
  - Datasets: relatively low MSE
  - State space: state of charge
  - Action space: energy trade rate
- Adjust price model to achieve a better performance for community price
- Reward function reconstruction:
  - Avg Price/kWh
  - Renewable Energy Penetration
- Cost and renewable penetration should show improvement with algorithm
- Scaling algorithm unsure of result

Citations & References

Image Citation:
C. Tongue, "'Energy Sharing' the newest addition to the sharing economy," 27-Apr-2018. [Online]. Available: https://www.ohmconnect.com/new-features/energy-sharing-the-newest-addition-to-the-sharing-economy. [Accessed: 09-Dec-2020].

1. Zhou, S., Hu, Z., Gu, W., Jiang, M., & Zhang, X.-P. (2019). Artificial intelligence based smart energy community management: A reinforcement learning approach. *CSEE Journal of Power and Energy Systems*, *5*(1), 1–10. https://doi.org/10.17775/cseejpes.2018.00840
2. Nakabi, T. A., & Toivanen, P. (2020). Deep reinforcement learning for energy management in a microgrid with flexible demand. *Sustainable Energy, Grids and Networks*, *25*, 100413. https://doi.org/10.1016/j.segan.2020.100413
3. Zhou, S., Zou, F., Wu, Z., Gu, W., Hong, Q., & Booth, C. (2020). A smart community energy management scheme considering user dominated demand side response and P2P trading. *International Journal of Electrical Power and Energy Systems*, *114*(July 2019), 105378. https://doi.org/10.1016/j.ijepes.2019.105378

Additional References:

4. California Independent Electricity System Operator. *Realtime Market Price Report*, Toronto, ON: Independent Electricity System Operator, 2019. [Online]. Available: http://reports.ieso.ca/public/RealtimeMktPrice/. [Accessed: November 29, 2020].
5. Zhou, S., Zhuang, W., Wu, Z., Gu, W., Zhan, X., Liu, Z., & Cao, S. (2020). Optimized scheduling of multi-region Gas and Power Complementary system considering tiered gas tariff. *Energy*, *193*, 116677. https://doi.org/10.1016/j.energy.2019.116677

Citations & References

8. Berk Celik, Robin Roche, David Bouquain, Abdellatif Miraoui. Coordinated Neighborhood Energy Sharing Using Game Theory and Multi-Agent Systems. PowerTech, Jun 2017, Manchester, United Kingdom. Hal-02131024
9. Tsay, M. T., & Gow, H. J. (2005). Congestion influence on bidding strategies in an electricity market. *Proceedings of the IEEE Power Engineering Society Transmission and Distribution Conference*, *2005*(3), 1–6. https://doi.org/10.1109/TDC.2005.1546778
10. Glorennec, P. Y., & Jouffe, L. (1997). Fuzzy Q-learning. *IEEE International Conference on Fuzzy Systems*, *2*(3), 659–662. https://doi.org/10.1109/fuzzy.1997.622790
11. Li, X., Zang, C., Zeng, P., & Yu, H. (2012). Genetic based fuzzy Q-learning energy management for smart grid. *Chinese Control Conference, CCC*, 6924–6927.
12. Li, X., Hui, D., & Lai, X. (2013). Battery energy storage station (BESS)-based smoothing control of photovoltaic (PV) and wind power generation fluctuations. *IEEE Transactions on Sustainable Energy*, *4*(2), 464–473. https://doi.org/10.1109/TSTE.2013.2247428
13. De Sá Ferreira, R., Barroso, L. A., Lino, P. R., Carvalho, M. M., & Valenzuela, P. (2013). Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: A stochastic optimization approach. *IEEE Transactions on Smart Grid*, *4*(4), 2285–2295. https://doi.org/10.1109/TSG.2013.2241087
14. Yoon, J. H., Bladick, R., & Novoselac, A. (2014). Demand response for residential buildings based on dynamic price of electricity. *Energy and Buildings*, *80*(1), 531–541. https://doi.org/10.1016/j.enbuild.2014.05.002
15. Li, R., Wang, Z., Gu, C., Li, F., & Wu, H. (2016). A novel time-of-use tariff design based on Gaussian Mixture Model. *Applied Energy*, *162*, 1530–1536. https://doi.org/10.1016/j.apenergy.2015.02.063
16. Zhou, S., Wu, Z., Li, J., & Zhang, X. P. (2014). Real-time energy control approach for smart home energy management system. *Electric Power Components and Systems*, *42*(3–4), 315–326. https://doi.org/10.1080/15325008.2013.862322

Thank You!

Jingjing Xu (jingjing9160@g.ucla.edu)
Mindy Saylors (mindysaylors@gmail.com)
Chaohao Li (uclalch@ucla.edu)
Satvik Anand (satvik.anand029@gmail.com)

University of California, Los Angeles
Dec 10, 2020