Multi-agent Deep Reinforcement Learning for Zero Energy Communities

Amit Prasad and Ivana Dusparic
School of Computer Science and Statistics, Trinity College Dublin
prasada@tcd.ie, ivana.dusparic@scss.tcd.ie

Abstract. Advances in renewable energy generation and introduction of the government targets to improve energy efficiency gave rise to a concept of a Zero Energy Building (ZEB). A ZEB is a building whose net energy usage over a year is zero, i.e., its energy use is not larger than its overall renewables generation. A collection of ZEBs forms a Zero Energy Community (ZEC). This paper addresses the problem of energy sharing in such a community. This is different from previously addressed energy sharing between buildings as our focus is on the improvement of community energy status, while traditionally research focused on reducing losses due to transmission and storage, or achieving economic gains. We model this problem in a multi-agent environment and propose a Deep Reinforcement Learning (DRL) based solution. Each building is represented by an intelligent agent that learns over time the appropriate behaviour to share energy. We have evaluated the proposed solution in a multi-agent simulation built using osBrain. Results indicate that with time agents learn to collaborate and learn a policy comparable to the optimal policy, which in turn improves the ZEC’s energy status. Buildings with no renewables preferred to request energy from their neighbours rather than from the supply grid.

Keywords: Zero Energy Community · Energy sharing optimization · Deep Reinforcement Learning.

1 Introduction

Advances in renewable energy generation, lower cost of the required hardware and increased storage capacity have made energy users increasingly self-sustainable. A user may be defined as a home or a building. Here we use the term user to refer to a building or an independent house. If the net energy usage of such self-sustainable buildings over a period of one year is zero they are called Zero Energy Buildings (ZEBs). However, practically achieving the exact net zero status is difficult, and hence the term nearly ZEB (nZEB) is used. The definition of nZEB states that, the net balance between export and import of energy over a period of time must be zero or even positive [14]. ZEBs are receiving increased attention in the recent years due to increasing demand and thus pressure on non-renewable sources of energy. European Union(EU) has stated in its 2010[12] recast that
by year 2020 all new buildings have to consume nearly zero energy. Similarly,
the Japanese government too has set the same target for 2030 [5].

This concept of nZEB, when extended to group of buildings, is called a nearly Zero Energy Community (nZEC). [6] introduces the concept of cooperative ZEC (CNet-ZEC) and defines ZEC as a collection of only ZEBs having its annual energy balance as zero. However, this might not be accurate. The definition above describes a ZEB community, as opposed to a ZEC. We maintain a subtle distinction between a ZEB community and a ZEC. The former is a community in which all buildings satisfy the nZEB status whereas in the latter some buildings might not, but as a group they have net zero energy balance. All nZEB communities are nZECs but the reverse might not be true. We redefine nZEC formally as –

A micro-grid that has distributed generation, storage, delivery and consumption having net annual energy balance as nearly zero.

There is high uncertainty of energy production in an nZEC due to distributed generation that causes some buildings to produce insufficient energy with respect to their energy demand. Such buildings then request for additional energy from the supply grid at a higher cost. As an alternative to this, buildings can request additional energy from the nearby buildings. This reduces the losses due to transmission and promotes green energy. Moreover, buildings with surplus energy may also benefit economically by sharing with neighbours. In this work, we address the problem of energy sharing in such an energy community. We model this community as a multi-agent environment where each individual agent represents a building. As previous work showed that deep reinforcement learning (DRL) is an effective technique for energy management in a single building management system (i.e., single agent), we use it as a basis of our multi-agent solution. We therefore proposed a DRL-based solution to optimize energy sharing between these buildings. Intelligent agents representing buildings learn over time the appropriate behaviour to share energy in order to achieve a nearly zero energy status as a community.

The rest of the paper is organized as follows. We firstly discuss the existing work done in energy sharing between buildings in section 2. In section 3 we present the design and implementation of our proposed intelligent energy sharing solution. In section 4 we evaluate and present the results of our solution. Finally, in section 5 we conclude the paper and discuss the issues that remain open along with avenues for future work.

2 Related Work

More efficient usage of energy can be done if the excess energy produced on-site can be shared with other homes that require it. This can benefit the seller economically, it reduces the transmission losses that would have occurred if energy was requested from supply grid, or conversion losses if it was stored in batteries. To enable this, various strategies for energy sharing amongst homes exist.
The authors of [10] define a Central Energy Sharing (CES) systems as the one that consists of a central controller that has information of all the distributed energy resources in the micro-grid as well as the forecasting systems, and schedules resources accordingly. This type of system allows broad observability but reduces the flexibility. Work in [23] introduces a CES system that classifies homes into sets of suppliers and consumers, and then uses a greedy strategy to initiate energy exchange between homes. Another interesting system - IDES [22] uses a sophisticated distributed energy generation and sharing approach (DES) with a novel pricing model to incentivize energy sharing between homes.

There have been other works that focus on energy sharing between buildings but no direct work has been done on intra-nZEC energy sharing for community benefit. Previous works on only energy sharing between buildings focus on economic gains [15,22], optimizing transactions [18,24] and thereby reducing transmission and storage loses at the individual building level. [6] defines nZEC as a collection of only ZEBs having its annual energy balance as zero. However, [5] argues that achieving a ZEB status without a grid is very difficult. The authors propose a solution by defining energy communities using a basic energy matching algorithm and conclude that energy sharing can help achieve ZEB status for individual buildings. Additionally, in the previous section, we have argued that in a ZEC buildings may have varying generation capacities and some may even have none, as in reality, very few communities have all buildings exhibiting energy autonomy.

Previous related works in energy sharing, energy and cost optimization have used techniques like linear programming, dynamic programming, heuristic methods such as particle swarm optimization, game theory, and so on [4,22,23]. The general problem with majority of the algorithms is that, for optimization they compute partial or the entire solution space to choose the best one, and hence are time consuming. [7] explores an interesting approach that avoids computing the entire search space using Deep Reinforcement Learning (DRL) to optimize schedules for building’s energy management systems. The authors investigate two DRL based algorithms, Deep Policy Gradient (DPG) and Deep Q-Learning (DQN) for building a on-line large scale solution and conclude it to be more effective than traditional solutions. [3] uses DRL to model a solution that optimizes activation of energy storage devices considering the uncertainty of energy generation and consumption. [8] uses DPG to optimize the schedule of energy consuming devices in a dynamic energy pricing environment and reports great results.

To build on its success in single-house scenarios and considering the effectiveness to build on-line large scale solutions, we propose a DRL-based energy sharing solution to address the issue of energy sharing between buildings.

3 Design of DRL-based nZEC

We propose modelling an nZEC community as a multi-agent environment, where each agent represents a building. Every agent learns the optimal behaviour inde-
pendently and is entirely responsible for making energy transactions on behalf of that building. We identify two main components that are central to building a solution for this - the DRL agent, which learns the behaviour of an individual household and a Community Monitoring Service to enable collaboration between the agents. The first component takes care of learning the optimal actions that an agent needs to take with consideration of its energy state and the community’s energy state. The second component ensures that all agents can communicate with each other to request energy and have a consistent view of the community’s energy balance at any given moment. In the following sections we present details of each.

3.1 DRL-based Energy Management Agent

Reinforcement Learning (RL) is a machine learning approach that enables intelligent agents to learn the optimal behavior via trail-and-error [17]. RL is particularly suited for implementation of self-organizing behaviours in large scale systems as it does not require a predefined model of the environment [2,19]. Q-learning is one such model-free RL algorithm that allows intelligent agents to learn to associate actions with expected long term rewards of taking that action in a particular state [20]. DRL is an extension of the traditional RL algorithm and uses Neural Networks (NN) at its core to discover non linear solutions. This paper uses a DRL based algorithm called DQN to approximate Q-values. Q-value is the expected value of taking an action in a particular state while considering the expected long term reward of taking that action in that state. DQN is a Q-learning algorithm that uses two NNs internally. The first network estimates the Q-value and the second network estimates the target Q-value which is used to calculate the error between the observed and expected Q-values. This helps with the stability of the algorithm that otherwise has problems with convergence.

We use the following network configuration for both the networks after experimenting with various models –

- **Input Layer** with 63 neurons representing the encoded State, Action and Reward.
- **2 x Hidden Layers** with 100 neurons each and the activation function as sigmoid.
- **1 Output neuron** representing the Q-value with linear activation function.

To reduce correlation between the data used (i.e. state-action pair and reward received) for training the NNs and also to overcome issues with convergence we have used a technique called Combined Experience Replay [21] that adds the latest experience to the mini-batch of random experiences.

Overall learning process of a DRL agent is summarized in the Algorithm 1. Agent senses the environment conditions (energy consumption and generation) and translates them into a state, from which it selects a suitable action. We describe available states and actions below.
Algorithm 1: Agent Learning Algorithm

1. env ← Environment() /* env is an instance of the environment */
2. while true do
3.   consumption ← env.preceptEnergyConsumption()
4.   generation ← env.perceptEnergyGeneration()
5.   state ← updateEnergyBalance(consumption, generation)
6.   legalActions ← getLegalActions()
7.   chance ← generateRandomNumber()
8.   if chance ≤ ϵ then
9.     action ← chooseRandomAction(legalActions)
10.   else
11.     action ← selectBestActionFromPolicy(legalActions)
12.   end
13.   nextState, reward ← env.takeAction(action)
14.   updateAgentLearning(state, action, reward)
15. end

State space – Every agent has a State (line 5 - Algorithm 1) object that contains AgentState and EnvironmentState objects embedded in it. This helps an agent to keep track of its own internal state and its perspective of the world. The AgentState object keeps track of the energy consumed, generated and stored by that agent at a particular time instant. Similarly, the EnvironmentState object keeps track of the energy balance of the community. This state information along with time of the day (discretized into 48 intervals of half hour each), and day of the week is encoded and fed into the NNs for training. Continuous energy values in the State object are also discretized to values 0, 1, 2 and 3 representing none, low, medium and high energy states respectively before they are fed into the NN.

Action set – In the simplest scenario, in an energy sharing environment an agent representing a energy user faces following choices to manage its energy requirements –

- Consume and store excess energy (CONSUME_AND_STORE)
- Request neighbour for additional energy (REQUEST_NEIGHBOUR)
- Request supply grid for additional energy (REQUEST_GRID)
- Grant energy request from a neighbour (GRANT_REQUEST)
- Deny energy request from a neighbour (DENY_REQUEST)

Not all actions listed above are physically possible at every time instance, and only a subset of them is "legal" at each time step (line 6 - Algorithm 1). We therefore group these actions into a sets of actions exclusive of each other –

1. \{CONSUME_AND_STORE\}
2. \{REQUEST_NEIGHBOUR, REQUEST_GRID\}
3. \{GRANT_REQUEST, DENY_REQUEST\}
These sets of actions along with the encoded state information and reward is passed to the DRL engine that returns an appropriate action whenever requested for. The reward function generates a reward for taking an action in a particular state based on the feedback from the environment (line 13 - Algorithm 1). As agents in our system have a common goal to achieve zero energy status as a community, they receive similar rewards based some global information discussed in the next section.

### 3.2 Community Monitoring Service

Agents in a ZEC have a common goal to achieve a zero energy status and therefore they need to do this in collaboration with the other agents. Literature in cooperative strategies [1,13,16] suggests the use of shared rewards or global rewards to enable cooperation between individual learners.

**Reward model** – In the simplest form, a negative of the community energy status can used as a global reward.

\[
reward = -\left( \sum_{i=1}^{n} c(h_i) - g(h_i) \right)
\] (1)

where:

- \( c(h_i) \) = energy consumed by the \( i^{th} \) house
- \( g(h_i) \) = energy generated by the \( i^{th} \) house

To enable this, we introduce a *Community Monitoring Service (CMS)*. The CMS acts as a agent group membership management service with functionalities like agent joining the group, agent leaving the group and maintaining a list of active agents. Apart from this, CMS also collects individual energy status’ from all agents at regular intervals and calculates the community energy status. This information is made available to all agents via an HTTPS call. Intelligent agents use this information to calculate their rewards based on the action taken. We tried experimenting with only local rewards based on energy balance of individual agents, but this resulted in a nZEB community (described in section 1) as agents started behaving selfishly to maximize their own gains.

### 3.3 Hyperparameter Tuning

All agents are trained in an episodic manner and are rewarded at the end of each episode. The learning rate \( \alpha \) and the discount factor \( \gamma \) for DRL are set at the start of the experiment. We experimented with various values for \( \alpha \) and for further experiments selected \( 0.125 \times 10^{-3} \) that led to convergence. Similarly, we choose the value of \( \gamma \) to be 0.99 after experimenting with a range of values between 0.5 and 0.99. Discount factor decides the importance of future rewards and lower the value of \( \gamma \) the longer time its takes for the rewards to be propagated backwards.
To enable simulation and synchronize actions between all the agents, we introduce a separate process called \textit{Synchronizer} that sends energy consumption data to all agents corresponding to the building they represent. All buildings used for the simulation are residential. This is done purely for simulation purposes and can be easily removed in the actual system implementation. Every agent experiences a minimum of 144 states in each iteration. The number states experienced also depends on the number on interactions an agent has with other agents for energy sharing.

The energy consumption dataset used in this simulation was generated using Load Profile Generator [11], that models the behaviour of the people living in a house to generate consumption data. We have used the energy consumption values generated every half an hour during 3 weekdays for this simulation. We assume that every house may or may not be equipped with solar panels, but is the only source of on-site energy generation. For this, we have used NREL’s NSRDB [9] solar exposure dataset of Toronto City.

4 Evaluation and Results

4.1 Experimental Setup and Parameters

To simulate different generation and demand patterns, we have evaluated our approach in 2 sets of weather conditions: Winter and Summer. During winter, House 1, House 2 and House 3 have average daily consumption as 11.01, 9.49, and 10.03 kWh respectively. Similarly, during summer their average daily consumptions are 12.12, 11.68, and 8.27 kWh respectively. House 4 exhibits a similar energy consumption profile as House 1. As all these houses are part of the same community, we assume that they are present in the same geographical region and therefore experience similar solar exposure. The average daily solar exposure during winter is 11770 W/m² and during summer is 18850 W/m².

Further, in each set of conditions, we have evaluated 3 different scenarios representing different community configurations (i.e., combinations of initial stored energy value and the numbers of solar cells available to a household) and 3 different scales (i.e, different number of households). In all evaluation scenarios agents were trained for 3 simulated days, for 500 episodes. We progressively decreased the value of $\epsilon$ after every $(1/10^{th})$ training episodes and set it to 0 in the final 10 episodes for complete exploitation. This means, in the final 10 episodes the agents select only those actions that they have learnt to be good over the previous training episodes.

We begin training our agents at 00:00 hrs i.e. at midnight and as there is no solar exposure during that time all agents are forced to borrow energy from the supply grid. This introduces a bias that leads to problems in discovering the optimal policy. To overcome this bias, we provide agents with an initial battery charge. The batteries used in this simulation are have a maximum power voltage of 12V and a charge rate of 100 amps for 20 hours. We convert this into kWh for ease of calculation (calculates to 1.2 kWh). Each house is equipped with 6 such batteries and has a total storage capacity of (1.2 * 6 =) 7.2 kWh.
We have tested for the following scenarios:

- **Scenario 1** - 3 houses having varying generation capacity and initial battery charge
- **Scenario 2** - 4 houses having varying generation capacity and initial battery charge (with one of the houses having 0 generation capacity)
- **Scenario 3** - 10 houses having varying generation capacity and initial battery charge

Configuration for the houses in **Scenario 1** and **Scenario 2** is described in Table 1 below:

| House No. | Agent | n*(SCells) | Batt. Init (kWh) |
|-----------|-------|------------|-----------------|
| 1         | Alice | 72         | 7.2             |
| 2         | Bob   | 54         | 2.5             |
| 3         | Charlie | 12      | 5.0             |
| 4         | Dave  | 0          | 0               |

Table 1: Configuration for 3 and 4 houses having varying generation capacity.

### 4.2 Results and Analysis

Results are presented in Figures 1 to 3, with a figure per scenario. **Always Share**, **Random**, and **Never Share** labels represent the baseline strategies: always-share-energy strategy, random-action-selection strategy, and no-energy-sharing strategy. In our scenarios, to achieve zero energy status as a community, the optimal behaviour is to always share leftover energy with neighbours as there are no other components that will affect the decisions taken by agents. However, evaluating whether agents are capable of learning that to be the optimal strategy (versus not sharing, or charging local batteries), and to what extent, will enable integration of this approach into more complex energy balancing scenarios that include, for example, dynamic pricing models.

**Scenario 1**: Figures [1a] and [1b] present the results for **Scenario 1** during Winter and Summer, respectively. As seen in figure [1a] representing the Winter scenario, as agents train, they learn the optimal behaviour (indicated by the **Learned Behaviour** label) to always share energy. To achieve this optimal behavior agents learn to borrow more energy from their neighbours and less energy from the supply grid. This is evident from figures [1c] and [1d]. However, we also observe that (fig. [1d]) 2 agents (Alice and Bob) learn to request for additional energy to the supply grid. This is because agents learn to operate selflessly in order to support the third agent (Charlie) that has lesser renewable generation. This helps to improve the net zero energy balance of the community. Additionally, as houses share energy with each other, a deficit is introduced to their locally available batteries and they can now store the generated surplus energy which would otherwise have been wasted due to fully charged batteries.
Figure 1b shows a comparison of strategies used to achieve nZEC during Summer with 3 houses. The lines overlap with each other completely and therefore only a single line is visible. With the configuration in Table 1 during summer houses are entirely self-sustainable and therefore have no need to share energy with each other. As there is no energy sharing involved, no decisions are made regarding the choice of borrowing energy from grid or neighbours. Therefore, all strategies have similar nZEC status of -1.72 kWh. This minor negative status of 1.72 kWh is due to the initial bias introduced by the training data as agents start training at midnight and have no solar exposure to produce energy during that time.

Scenario 2: In the summer in Scenario 1 all houses were self-sustainable and therefore no learning behaviour could be observed. To evaluate the adaptive behaviour of agents in different climatic conditions, we introduce a fourth house with no source of renewable energy generation. We firstly evaluate this setup during Summer and then in Winter. This also helps simulate an environment with different levels of energy generation including no energy generation. We argued that such energy communities can exist (section 1) and hence the need for energy sharing in such communities. Figures 2a and 2b shows a comparison of nZEC statuses achieved for this scenario during Summer and Winter. During Summer, in comparison with the optimal behaviour i.e. *Always Share Energy*, the
Learned Behaviour strategy performs well. A difference of only 7 kWh in their nZEC statuses can be seen. This is not as close to optimal as the previous case with 3 houses, but at least it guarantees a lower bound (the worst case) on the nZEC status. When compared with the no-energy-sharing strategy the agents perform very well (difference of 64 kWh). Similarly to Scenario 1 during Winter, results of our DRL-based approach are much better than the no-energy-sharing and random-action-selection strategy but comparable to an always-share-energy strategy.

Scenario 3: In this scenario, we evaluate the ability of our system to learn the optimal solution when the number of agents grow. For this, we have considered 10 agents with varying generation capacities and initial charge. In both Seasons, we observe that our system performs better than a random-action-selection strategy and a no-energy-sharing strategy (Figure 5). During Winter, the distinction between Always Share, Random, and Learned Behaviour curves is very minor, however, we still can observe that our solution tends towards the optimal strategy.

Fig. 2: Scenario 2 - Results with 4 houses having varying generation capacities

Fig. 3: Scenario 3 - Results with 10 houses having varying generation capacities
4.3 Evaluation Summary

Results in this paper indicate that DRL is a suitable technique for building intelligent agents that are able to collaborate with each other to optimize energy transactions between buildings. This behaviour allows us to build a nZEC with varying levels of distributed generation. Agents representing houses learn over time to set aside their goals of self-optimization and take a community first approach. Evaluations indicate that our solution improves the nZEC status drastically when compared to a no-energy-sharing strategy and random-action-selection strategy. An improvement of $40\, \text{kWh}$ with 3 houses during winter and over $60\, \text{kWh}$ with 4 houses during summer over 3 days in the overall community’s energy balance was found when compared to a no-energy-sharing strategy. Similarly, with 10 houses a improvement of $97\, \text{kWh}$ during Winter and $156\, \text{kWh}$ during Summer was found. Additionally, as an indirect effect of energy sharing, houses were able to produce more energy that consequently increased the flow of energy generated from renewable sources in the community.

5 Conclusions and Future Work

This paper introduces a new definition of nZEC that encompasses a mixture of buildings with varying levels of energy generation building upon the previous definition of nZEB. It also introduces a multi-agent DRL based solution for energy sharing between houses in such an nZEC community. Results show that with time agents learn to collaborate with each other and achieve net zero energy balance as a community. We have trained the agents in an episodic manner and for the future work, it would be interesting to observe their behaviour if they were trained in an on-line fashion. Further, we were not able to test this system on scale with hundreds or thousands of houses due to the limitation on physical resources we had and other issues related to the implementation and framework. Our design is simple and the focus is mainly on motivating agents to share energy without any energy pricing scheme involved. However, in real world systems this is not true and such integration is necessary, and is a potential future research.

References

1. Claus, C., Boutilier, C.: The dynamics of reinforcement learning in cooperative multiagent systems. AAAI/IAAI 1998, 746–752 (1998)
2. Dusparic, I., Harris, C., Marinescu, A., Cahill, V., Clarke, S.: Multi-agent residential demand response based on load forecasting. In: Technologies for Sustainability (SusTech), 2013 1st IEEE Conference on. pp. 90–96. IEEE (2013)
3. Francois-Lavet, V., Taralla, D., Ernst, D., Fonteneau, R.: Deep reinforcement learning solutions for energy microgrids management. In: European Workshop on Reinforcement Learning (EWRL 2016) (2016)
4. Hurtado, L., Mocanu, E., Nguyen, P.H., Gibescu, M., Kling, W.L.: Comfort-constrained demand flexibility management for building aggregations using a decentralized approach. In: Smart Cities and Green ICT Systems (SMART-GREENS), 2015 International Conference on. pp. 1–10. IEEE (2015)
5. Kayo, G., Hasan, A., Siren, K.: Energy sharing and matching in different combinations of buildings, chp capacities and operation strategy. Energy and Buildings 82, 685–695 (2014)

6. Lopes, R.A., Martins, J., Aelenei, D., Lima, C.P.: A cooperative net zero energy community to improve load matching. Renewable Energy 93, 1–13 (2016)

7. Mocanu, E., Mocanu, D.C., Nguyen, P.H., Liotta, A., Webber, M.E., Gibescu, M., Slootweg, J.G.: On-line Building Energy Optimization using Deep Reinforcement Learning pp. 1–9 (2017), http://arxiv.org/abs/1707.05878

8. NREL: National solar radiation database (nsrdb) (2018), https://nsrdb.nrel.gov/nsrdb-viewer

9. Recast, E.: Directive 2010/31/eu of the european parliament and of the council of 19 may 2010 on the energy performance of buildings (recast). Official Journal of the European Union 18(06), 2010 (2010)

10. Stone, P., Sutton, R.S., Kuhlmann, G.: Reinforcement learning for robocup soccer keepaway. Adaptive Behavior 13(3), 165–188 (2005)

11. Sutton, R., Barto, A.: Introduction to reinforcement learning. mit press. Cambridge, MA (1998)

12. Swaminathan, G., Ramesh, V., Umashankar, S., Sanjeevikumar, P.: Investigations of microgrid stability and optimum power sharing using robust control of grid tie pv inverter. In: Advances in Smart Grid and Renewable Energy, pp. 379–387. Springer (2018)

13. Zhang, S., Sutton, R.S.: A deeper look at experience replay. arXiv preprint arXiv:1712.01275 (2017)

14. Zhong, W., Huang, Z., Zhu, T., Gu, Y., Zhang, Q., Yi, P., Jiang, D., Xiao, S.: Ides: Incentive-driven distributed energy sharing in sustainable microgrids. 2014 International Green Computing Conference, IGCC 2014 (2015). https://doi.org/10.1109/IGCC.2014.7039166

15. Zhu, T., Huang, Z., Sharma, A., Su, J., Irwin, D., Mishra, A., Menasche, D., Shenoy, P.: Sharing renewable energy in smart microgrids. In: Cyber-Physical Systems (ICCPS), 2013 ACM/IEEE International Conference on. pp. 219–228. IEEE (2013)
24. Zifa, L., Ya, L., Ranquin, Z., Xianlin, J.: Distributed reinforcement learning to coordinate current sharing and voltage restoration for islanded dc microgrid. Journal of Modern Power Systems and Clean Energy 6(2), 364–374 (2018)