
Adversarial poisoning attacks on reinforcement learning-driven energy pricing

Sam Gunn *

Department of Computer Science
University of California, Berkeley
gunn@berkeley.edu

Doseok Jang *

Department of Computer Science
University of California, Berkeley
djang@berkeley.edu

Orr Paradise *

Department of Computer Science
University of California, Berkeley
orrr@eecs.berkeley.edu

Lucas Spangher

Department of Computer Science
University of California, Berkeley
lucas_spangher@berkeley.edu

Costas J. Spanos

Department of Computer Science
University of California, Berkeley
spanos@berkeley.edu

Abstract

Complex controls are increasingly common in power systems. Reinforcement learning (RL) has emerged as a strong candidate for implementing various controllers. One common use of RL in this context is for prosumer pricing aggregations, where prosumers consist of buildings with solar generation and energy storage. Specifically, supply and demand data serves as the observation space for many microgrid controllers who are passed on a policy from a central RL agent, who is learning online. Each controller outputs an action space consisting of hourly “buy” and “sell” prices for energy throughout the day; in turn, each prosumer can choose whether to transact with the RL agent or the utility. The RL agent is then rewarded through its ability to generate a profit.

RL is known to be effective for this task. We ask: what happens when some of the microgrid controllers are compromised by a malicious entity? We demonstrate a novel attack in RL and a simple defense against the attack.

At a high level, our attack perturbs each trajectory to reverse the direction of the estimated gradient. We demonstrate that if data from a small fraction of microgrid controllers is adversarially perturbed, the learning of the RL agent can be significantly slowed. With larger perturbations, the RL aggregator can be manipulated to learn a catastrophic pricing policy that causes the RL agent to operate at a loss. We demonstrate other environmental characteristics are worsened too: prosumers face higher energy costs, use their batteries less, and suffer more transformer power violations when the pricing aggregator is adversarially poisoned.

We address this vulnerability with a “defense” module; i.e., a “robustification” of RL algorithms against this attack. Our defense identifies the trajectories with the largest influence on the gradient and removes them from the training data. Intuitively, it works because the non-poisoned trajectories are not expected to have out-sized gradients. It is computationally light and reasonable to include in any RL algorithm.

Acknowledgements

We are very thankful to Sergey Levine for thoughtful comments and guidance throughout all stages of this work. This research is supported by the *Simons Collaboration on the Theory of Algorithmic Fairness*, the *DARPA GRAIL project*, and by the *National Research Foundation, Prime Minister’s Office, Singapore* under its *Campus for Research Excellence and Technological Enterprise (CREATE) programme*.

*Equal contribution

1 Introduction

Artificial Intelligence (AI) heralds great benefits to power system operation. In the future, AI-based controls could manage the use of passive appliances [19, 3], orchestrate demand response [2], and optimize power flow throughout networks [4, 5]. In the context of energy grids, local grid networks (i.e., microgrids) enable refined control at the cost of increased complexity, necessitating adoption of complex controls at scale.

At the same time, energy grids are known to be lucrative targets for cyberattacks (e.g., [8]). Our work investigates the robustness of an AI-based microgrid controller to malicious actors. We present a novel attack that enables a few compromised microgrid controllers to adversely affect the behavior of connected controllers by *poisoning the data* on which it is trained. This expands on a recent explosion of interest in adversarial attacks [10, 12, 6]. We pair this finding with a gradient-based defense that eliminates the threat of this attack.

More concretely, we examine a setting in which a network of microgrid controllers collect supply and demand data that are continually aggregated by a central agent. The agent uses online reinforcement learning (RL) to optimize its profits. In our attack, a few microgrid controllers are compromised by a malicious adversary. The adversary applies a perturbation to the collected data, severely impacting the provider and *the entire network* of controllers. The provider is made to operate at a loss, and all prosumers are made to pay higher energy costs, use their batteries less, and violate more transformer power constraints.

Our work is set against a backdrop of developments in energy grid control that hold both promise and peril: RL-based controllers allow for sophisticated control in unprecedented granularity. Yet, we must be careful to minimize risk enabled by the opaque nature of deep learning. Our attack stands out in its subtlety and its scope. Other forms of large-scale interference such as blackouts and line disruptions are, by definition, easily detectable and local. Yet our attack causes harm by interfering with the agent’s learning, and may not be detected until significant financial damage has been incurred. Furthermore, by interfering with the central agent’s learning, our methods can damage systems that are physically disconnected from the energy grid under attack.

Outline. In Section 2 we briefly contextualize our work within RL and energy controls. In Section 3 we describe the threat model, attack, and defense. In Section 4 we introduce our experimental setup, which is used in Section 5 to evaluate the efficacy of our attack and defense in an energy grid environment. Finally, in Section 6 we discuss limitations and future work.

2 Background: RL for prosumer energy pricing

RL has been applied to a number of demand response situations in prosumer microgrids; most work centers on agents that directly schedule resources [15, 16] or control appliances [19, 11, 20]. Recent works have used an RL controller as a price setter in a market: RL has been used to estimate dynamic prices in a multi agent environment of demand response assets in [9], as well as [7, 1, 18].

Demand response, an incentive mechanism geared towards moving consumption, is a no-material solution to variable wind and solar generation and is thus seen as an important technique in the energy transition. It has been demonstrated that learning local price controls is an effective demand response mechanism due to its generalizability and optimal local battery resource utilization [14, 13].

The literature on adversarial attacks for RL in demand response focuses on *responding* to prices [17] rather than *setting* them. To our knowledge, there are no works on adversarial attacks on dynamic price setting for demand response.

3 Techniques

3.1 Threat model

In our setting, N controllers continuously collect data to be aggregated by a centralized agent. Learning takes place over multiple *iterations*; in each iteration, each controller collects a trajectory $\tau := (o_i, a_i, r_i)_i$ collected according to the agent policy π_θ . The agent’s policy π_θ is described by a neural network. Nodes are required to feed observations through π_θ so as to collect policy-specified actions (pricing schemes), so we assume that the network parameters θ and architecture are shared with the controllers.

The attacker’s power is determined by a fraction of *corrupted controllers* $\varepsilon \in (0, 1)$, and a *perturbation bound* $\rho > 0$, as follows: An attacker controls $\varepsilon \cdot N$ of controllers. The attacker *perturbs* the trajectories collected by each compromised controller, causing it to report back a trajectory $\tilde{\tau}$ instead of the collected trajectory τ . Crucially, these perturbations are

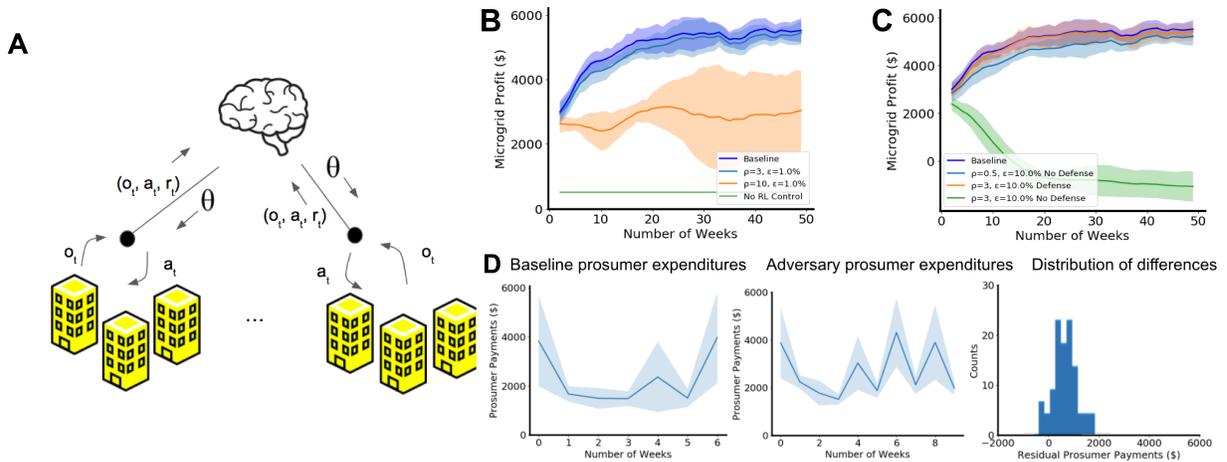


Figure 1: **A.** A description of the microgrid environment. In this figure, the brain is the RL agent, the black dot is the microgrid controller, and the adversary attacks the a_t that is sent back to the RL agent. **B.** Effect of the adversary on the agent’s learning. Note that $\epsilon = 1\%$ corresponds to only one adversarial microgrid. **C.** Effect of our defense in the presence of an adversary. **D.** Characterization of prosumer costs in the baseline and adversarial scenarios. The prosumer consistently pays more in energy when the adversary interferes.

of small norm, that is,

$$\|\tilde{\tau} - \tau\|_{\infty} \leq \rho$$

for some *perturbation bound* $\rho > 0$. Note that our attacker adheres to the suggested policy π_{θ} , but lies about the result to the agent.

Remark 1. In our setting, the attacker may only perturb the actions of each trajectory. Observations and rewards remain unperturbed, because such perturbations would be expensive or easily noticed. This is in contrast to previous work in RL poisoning in which only rewards are poisoned [12].

3.2 The attack

At a high level, our attack aims to perturb each trajectory to reverse the direction of the estimated gradient $\nabla_{\theta} f(\theta)$. Let τ_P be the parameters of the agent’s policy, τ_P be the unperturbed set of compromised trajectories (the trajectories collected by compromised controllers), $\tilde{\tau}_P$ be the set of perturbed adversarial trajectories (reported back to the agent), and τ_H be the set of honest trajectories (unaffected by the adversary). Our adversary minimizes the correlation of the gradient post-perturbation with the honest one by solving the following constrained optimization problem:

$$\begin{aligned} \min_{\tilde{\tau}_P} \quad & \langle \nabla_{\theta} f_{\theta}(\tilde{\tau}_P), \nabla_{\theta} (f_{\theta}(\tau_P) + f_{\theta}(\tau_H)) \rangle \\ \text{such that} \quad & \|\tilde{\tau}_P - \tau_P\|_{\infty} \leq \rho. \end{aligned} \quad (1)$$

Since the compromised controllers report $\tilde{\tau}_P$ to the agent instead of τ_P , the agent will take gradient steps according to $\nabla_{\theta} (f_{\theta}(\tilde{\tau}_P) + f_{\theta}(\tau_H))$. Therefore, choosing $\tilde{\tau}_P$ to minimize Equation (1) should maximally mislead the gradient towards a sub-optimal policy. Equation (1) is optimized by the adversary using the Fast Gradient Sign method (FGSM) [6]. Interestingly, we find that our adversaries can obtain nearly identical results by solving Equation (1) without the τ_H term, meaning that the adversary does not require any information about the honest (uncompromised) controllers.

3.3 The defense

We propose a defense to protect an online deep RL agent from the attack described in Section 3.2. Our defense works by identifying and removing the trajectories which have the largest influence on the gradient from the training data. Intuitively, this defense works because the honest trajectories are not expected to have out-sized gradients. Note that the poisoned trajectories are not easily identifiable without calculating the gradient through the policy; while the adversarial perturbations significantly influence the gradient estimate, the perturbations themselves are small. More formally, if the RL agent suspects that some fraction $\hat{\epsilon}$ of the microgrids are adversarially controlled, then, when estimating the gradient $\nabla_{\theta} f(\theta)$, it ignores the $\hat{\epsilon}$ -fraction of trajectories τ with large $\|\nabla_{\theta} f_{\theta}(\tau)\|_2$.

4 Experimental setup

4.1 The Price-Setting Microgrid Problem

Consider a setting of 100 microgrids. One RL agent sets the policy parameters θ of all 100 microgrid controllers, which transacts locally within each microgrid. Each microgrid consists of 7 prosumer office buildings. Every prosumer has a battery, solar panel array, and baseline energy consumption; each wants to minimize their energy cost. Prosumers see both grid-set hourly energy buy and sell prices and local microgrid controller-set hourly energy buy and sell prices. Prosumers choose to transact with either the grid or the RL aggregator at each hour. Prosumers also decide when to discharge their battery according to both their demand and the energy prices. The microgrid controller accepts all transactions the prosumers request of it. It does not produce or store energy, but sells energy it has bought from prosumers producing energy in a timestep to prosumers demanding energy in the same timestep. The aggregator balances the net load by purchasing from or selling to the energy utility under which they sit, usually at a loss. As the manager of the RL-aggregator, you see the grid’s buy and sell prices, and wish to learn an automatic pricing strategy such that you consistently turn a profit. See Figure 1.A for a graphical depiction of the environment.

For a more precise description of the convex optimizations governing prosumer battery behavior and the reward function training the RL-aggregator, see [1].

4.2 Adversarial microgrid poisoning “in the wild”

We briefly present a potential real-world example of our adversary in action.

Suppose that Eastern Gas & Electric (EG&E) is piloting a dynamic, local pricing program. To do this, EG&E instantiates an RL agent to train across a sample of building clusters (i.e. microgrids grouped locally). Unfortunately, there is an attacker who wishes to disrupt the functioning of EG&E, and they intercept the outflow of data from one of the local microgrid controllers. In one attack strategy, the attacker wishes to minimize the extent to which the outgoing prices are perturbed so as to escape detection. In another attack strategy, the attacker considers high perturbations in order to maximally disrupt profitability.

5 Results

Next, we present experimental results demonstrating the gradient-reversing adversary’s harmful potential, as well as the efficacy of the filtering defense.

All of our experiments used the MicrogridLearn environment [1] consisting of 100 microgrids of 7 buildings each. The RL agent is an Actor-Critic agent which updates every week over the course of one year.

The attack. Figure 1.B shows our attacker can significantly hinder the RL agent’s learning by co-opting a single microgrid controller. The maximal difference between successive actions taken by the true policy is around 6, so the strongest attack in the single-trajectory setting requires a relatively high perturbation budget $\rho = 10$. However in Figure 1.C, our attack utilizes a smaller perturbation budget of $\rho = 3$ with ten ($\varepsilon = 10\%$) compromised controllers to achieve significant damage.

The defense. We find that our defense recovers the original performance of the RL agent, even under generous ε and ρ . See Figure 1.C.

Characterizations of environmental response. We investigated several ways in which the environment responded to adversarial attack beyond the sheer profit: individual prosumer energy costs (the sum of the building’s energy expenditures with the adversary and without), battery utilization (the number of times batteries were charged and discharged, and the total capacities) and transformer power constraint violations. Under all measures, the environment performed worse with an adversary, even those not directly targeted: the prosumers paid on average *more* for the energy, the battery was used *less* when the microgrid controller was adversarially perturbed, and transformer power constraints were violated more. We present the prosumer prices in Figure 1.D and omit the rest due to space constraints.

6 Future Work

The goal of our work is to call attention to the threats made possible by adoption of RL in energy grid pricing. Towards this end, we focused on a narrow yet concrete setting, leaving much room for future work.

- The classical adversarial machine learning literature has an abundance of *targeted* attacks, in which the adversary is able to lead the agent towards a particular policy. One of our next objectives is to design an adversary to cause targeted damage, for example to lead the agent to learn a policy which puts the voltage constraints of the power grid at risk.
- Our proposed defense requires the RL agent to drop as many trajectories as could potentially be compromised. More sophisticated defenses could likely result in less dropped data and more robust learning.
- We would like to explore our attack in more environments. In parallel, we hope to achieve successful attacks with smaller settings of ρ and ϵ .

References

- [1] Utkarsha Agwan, Lucas Spangher, William Arnold, Tarang Srivastava, Kameshwar Poolla, and Costas J. Spanos. 2021. Pricing in Prosumer Aggregations using Reinforcement Learning. In *e-Energy '21: The Twelfth ACM International Conference on Future Energy Systems, Virtual Event, Torino, Italy, 28 June - 2 July, 2021*, Herman de Meer and Michela Meo (Eds.). ACM, 220–224.
- [2] Donald Azuatalam, Wee-Lih Lee, Frits de Nijs, and Ariel Liebman. 2020. Reinforcement learning for whole-building HVAC control and demand response. *Energy and AI* 2 (2020), 100020.
- [3] Bingqing Chen, Zicheng Cai, and Mario Bergés. 2019. Gnu-rl: A precocial reinforcement learning solution for building hvac control using a differentiable mpc policy. In *Proceedings of the 6th ACM international conference on systems for energy-efficient buildings, cities, and transportation*. 316–325.
- [4] Bingqing Chen, Priya L Donti, Kyri Baker, J Zico Kolter, and Mario Bergés. 2021. Enforcing policy feasibility constraints through differentiable projection for energy optimization. In *Proceedings of the Twelfth ACM International Conference on Future Energy Systems*. 199–210.
- [5] Emiliano Dall'Anese, Hao Zhu, and Georgios B Giannakis. 2013. Distributed optimal power flow for smart microgrids. *IEEE Transactions on Smart Grid* 4, 3 (2013), 1464–1475.
- [6] Ian J Goodfellow, Jonathon Shlens, and Christian Szegedy. 2014. Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572* (2014).
- [7] Byung-Gook Kim, Yu Zhang, Mihaela Van Der Schaar, and Jang-Won Lee. 2015. Dynamic pricing and energy consumption scheduling with reinforcement learning. *IEEE Transactions on smart grid* 7, 5 (2015), 2187–2198.
- [8] Nir Kshetri and Jeffrey M. Voas. 2017. Hacking Power Grids: A Current Problem. *Computer* 50, 12 (2017), 91–95.
- [9] Renzhi Lu, Seung Ho Hong, and Xiongfeng Zhang. 2018. A dynamic pricing demand response algorithm for smart grid: reinforcement learning approach. *Applied Energy* 220 (2018), 220–230.
- [10] Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. 2018. Towards Deep Learning Models Resistant to Adversarial Attacks. In *6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings*. OpenReview.net.
- [11] Giuseppe Pinto, Marco Savino Piscitelli, José Ramón Vázquez-Canteli, Zoltán Nagy, and Alfonso Capozzoli. 2021. Coordinated energy management for a cluster of buildings through deep reinforcement learning. *Energy* 229 (2021), 120725.
- [12] Amin Rakhsha, Xuezhou Zhang, Xiaojin Zhu, and Adish Singla. 2021. Reward Poisoning in Reinforcement Learning: Attacks Against Unknown Learners in Unknown Environments. *CoRR* abs/2102.08492 (2021). arXiv:2102.08492
- [13] Lucas Spangher. 2021. Transactive multi-agent reinforcement learning for distributed energy price localization. In *BuildSys '21: The 8th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, Coimbra, Portugal, November 17 - 18, 2021*, Xiaofan Fred Jiang, Omprakash Gnawali, and Zoltan Nagy (Eds.). ACM, 244–245.
- [14] Lucas Spangher, Akash Gokul, Manan Khattar, Joseph Palakapilly, Akaash Tawade, Adam Bouyamourn, Alex Devonport, and Costas J. Spanos. 2020. Prospective Experiment for Reinforcement Learning on Demand Response in a Social Game Framework. In *e-Energy '20: The Eleventh ACM International Conference on Future Energy Systems, Virtual Event, Australia, June 22-26, 2020*. ACM, 438–444.
- [15] José R. Vázquez-Canteli, Jérôme Henri Kämpf, Gregor Henze, and Zoltán Nagy. 2019. CityLearn v1.0: An OpenAI Gym Environment for Demand Response with Deep Reinforcement Learning. In *Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, BuildSys 2019, New York, NY, USA, November 13-14, 2019*. ACM, 356–357.
- [16] José R Vázquez-Canteli and Zoltán Nagy. 2019. Reinforcement learning for demand response: A review of algorithms and modeling techniques. *Applied energy* 235 (2019), 1072–1089.
- [17] Zhiqiang Wan, Hepeng Li, Hang Shuai, Yan Lindsay Sun, and Haibo He. 2021. Adversarial Attack for Deep Reinforcement Learning Based Demand Response. In *2021 IEEE Power & Energy Society General Meeting (PESGM)*. IEEE, 1–5.
- [18] Hanchen Xu, Hongbo Sun, Daniel Nikovski, Shoichi Kitamura, Kazuyuki Mori, and Hiroyuki Hashimoto. 2019. Deep reinforcement learning for joint bidding and pricing of load serving entity. *IEEE Transactions on Smart Grid* 10, 6 (2019), 6366–6375.
- [19] Xiangyu Zhang, Xin Jin, Charles Tripp, David J Biagioni, Peter Graf, and Huaiguang Jiang. 2020. Transferable reinforcement learning for smart homes. In *Proceedings of the 1st International Workshop on Reinforcement Learning for Energy Management in Buildings & Cities*. 43–47.
- [20] Yuekuan Zhou and Siqian Zheng. 2020. Machine-learning based hybrid demand-side controller for high-rise office buildings with high energy flexibilities. *Applied Energy* 262 (2020), 114476