FRESCO: FEDERATED REINFORCEMENT ENERGY SYSTEM FOR COOPERATIVE OPTIMIZATION

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Paper under double-blind review

ABSTRACT

The rise in renewable energy is creating new dynamics in the energy grid that promise to create a cleaner and more participative energy grid, where technology plays a crucial part in creating the required flexibility to achieve the vision of the next-generation grid. This work presents FRESCO, a framework that aims to ease the implementation of energy markets using a hierarchical control architecture of reinforcement learning agents trained using federated learning. The core concept we are proving is that having greedy agents subject to changing conditions from a higher level agent creates a cooperative setup that will allow for fulfilling all the individual objectives. This paper presents a general overview of the framework, the current progress, and some insights we obtained from the recent results.

1 INTRODUCTION

Climate change has emerged as one of our planet's most pressing challenges. It is causing various environmental, economic, and social impacts, including rising sea levels, more frequent extreme weather events, and threats to global food security IPCC (2018). One way to address the challenges of climate change is by promoting the use of renewable energy sources, such as solar and wind power, to reduce greenhouse gas emissions from the energy sector. Deploying renewable energy technologies often involves using microgrids and small-scale power systems that can operate independently or in conjunction with the main grid. Hierarchical control systems ensure microgrids' efficient and effective operation by coordinating the various components and managing the energy flow Yang et al. (2020). However, as with any technology, there are also privacy concerns associated with microgrids, such as collecting and using data about energy consumption. It is important to address these issues proactively to ensure that the benefits of microgrids are maximized while also protecting the privacy of individuals and communities Tyav et al. (2022). In this work, we present a hierarchical control system composed of reinforcement learning (RL) agents, which includes federated learning (FL), to build a framework that can scale without risking the information from participants. The scenario we develop is formed by microgrids cooperating to reduce the collective carbon footprint; thus, we called this framework FRESCO.

2 METHODS

FRESCO comprises three components: 1) An OpenAI Gym environment that represents different microgrid setups, 2) a hierarchical structure of RL agents that control the microgrid at different scales, and 3) a training stage using FL. We modeled this framework to represent the real case scenario in which agents tend to pursue individual objectives, namely, are greedy; however, agents in the same label end up following a common objective dictated by a higher layer agent. Figure 1 presents a general view of our research scenario.

Our environment allows us to generate any microgrid scenario from a configuration file as we generate the data synthetically, allowing us to control our experiments' stochasticity. We turn off the noise to find solutions using optimization techniques to use them as the baseline for FRESCO. Then, we focused on finding the appropriate reinforcement learning methodology according to each layer's priority. Agents in layer 1 will seek to reduce their energy bill by managing a storage system at home. In Layer 2, the agents define trading prices in a microgrid, aiming to reduce the carbon

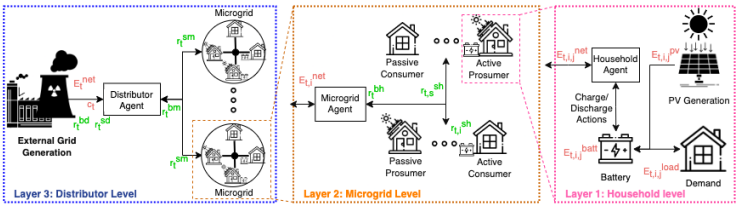

Figure 1: Three-layer architecture of our hierarchical microgrid control

	CVXPY	A2C - No FL	FRESCO
Train reward	-0.915	-0.993	**-0.81**
Train price score	**-0.103**	-0.097	-0.10
Train emission score	**-0.223**	-0.1522	-0.18
Test price score	-0.0889	-0.064	**-0.099**
Test emission score	-0.19	-0.097	**-0.28**

Table 1: Average performance of households. Lower is better for all except reward.

footprint by promoting energy exchange within neighboring houses. Finally, layer 3 will encourage energy exchange between microgrids by setting those prices and ensuring that the distribution system's physical constraints are respected. We propose a metric that evaluates two scenarios: one without batteries and one with FRESCO. It assesses the contribution of each household individually and aggregates the results at the microgrid and distributor levels, allowing for a comprehensive evaluation of the system's overall performance.

$$P_{delta} = P_{base} - P_{FRESCO}, \tag{1}$$

$$C_{delta} = C_{base} - C_{FRESCO}. \tag{2}$$

3 Experiments and Results

Currently, we have completed the experimentation for Layer 1 agents. We implemented our version of the Advantage Actor-Critic algorithm (A2C) using the causality trick as the core of the household agents. These agents' actions are defined in the $[-1, 1]$ range, where -1 means fully discharging the battery, and 1 means fully charging it. We trained the agents to be greedy in their objective of reducing bill price at the same time that they can adapt to external stimuli, like changes in the energy price or local energy availability coming from neighboring houses. The training set consists of 6 houses, the validation set of 6 other houses, and the testing set of 10 new houses. The baseline to compare the performance of FRESCO is the values obtained when solving the same case with a linear solver. Every 200 episodes, the neural network parameters for both the actors and critics are synchronized using the FedAVG approach introduced by McMahan et al. (2016). We utilized CVXPY, a linear solver, to establish the theoretically best possible result for the given scenarios. The results in table 1 demonstrate better results than the normal RL approach.

4 Conclusion

FRESCO framework demonstrates how a federated reinforcement learning (FRL) approach can enable effective communication and cooperation among entities as smart grids move towards decentralization while keeping private the end user's private information. The framework proposed in this paper considers external grid CO2 impact and prices, temperature, different distributed energy resources, and the heterogeneous nature of households. The approach enables stakeholders to trade energy optimally and in an automated manner without sharing consumer energy data. Results show that using FRL can speed training, quickly adapt to grid changes, and improve optimal policy convergence. Our approach applies to multiple interconnected microgrids and benefits all stakeholders by lowering energy bills, reducing electricity transmission rates, decreasing CO2 impact, and increasing participation in the energy market.

URM STATEMENT

The authors acknowledge that at least one key author of this work meets the URM criteria of the ICLR 2023 Tiny Papers Track.

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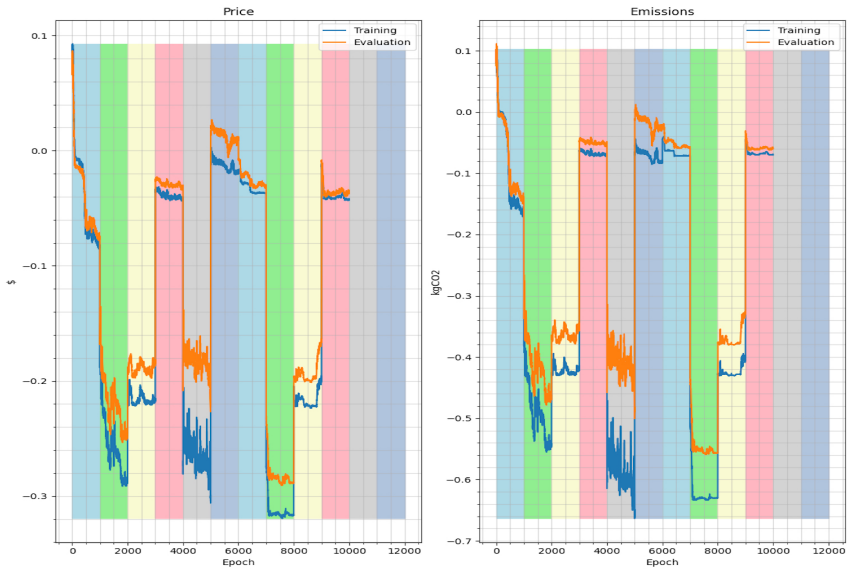

Figure 2: Reinforcement learning A2C run

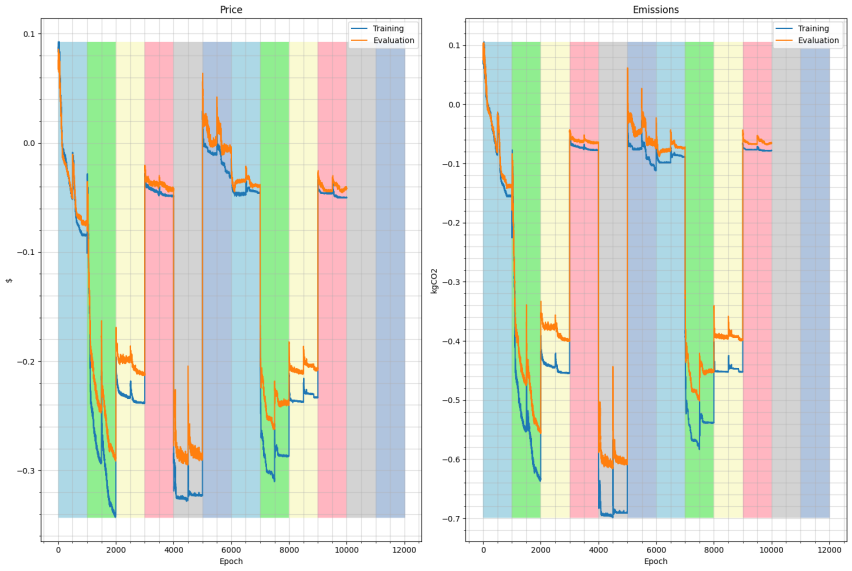

Figure 3: Federated Learning Run