GAIA: Green AI Apprentice

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ABSTRACT

This paper introduces a novel formulation for optimization of the BESS (battery and energy storage systems) problem, a crucial component for driving the renewable energy production to profitability. We review the existing literature of several optimization methods and make a case for the need of this novel MDP formulation that will be a foundation to learning from human demonstrations and feedback, prioritizing different constraints and real-world situations in addition to optimizing for profitability.

KEYWORDS

Green AI, Reinforcement Learning, Social Good

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1 INTRODUCTION

In the pursuit of a sustainable and resilient energy future, the integration of energy storage solutions, alongside renewable energy sources, such as solar and wind, has become paramount. "Storage reduces total electricity system carbon dioxide emissions by utilizing overgeneration from zero-marginal emissions sources such as wind and solar to displace the generation from the coal and natural gas fleet" [12].

The emergence of Battery Energy Storage Systems (BESS) has played a pivotal role in addressing this challenge, offering a means to store excess energy during periods of high production and releasing it during times of increased demand. Optimizing BESS is a challenge in itself, involving the navigation of the intricate interplay of factors such as avoiding energy waste, meeting demand shortfalls, and maximizing revenue in volatile open energy markets, through long-term energy acquisition contracts such as pre-purchase agreements (PPA[1]) or participating in global grid stability with mechanisms such as frequency control ancillary services (FCAS[2]). Figure 1 describes a model of the system.

A significant complication arises from the unpredictability of external factors crucial to this optimization process, namely weather patterns that influence solar and wind energy production, context-driven variations in energy consumption, and fluctuating prices in energy markets similar to stock markets. Balancing these factors is further complicated by the multiplicity of objectives. For instance, it might be financially prudent to forego fulfilling a PPA in favor of a more lucrative open market option, but this might impact future contract negotiations. The delicate trade-offs extend to decisions such as exceeding recommended charging cycles of a battery system to enhance revenue, which might reduce its lifetime.

Navigating this multifaceted optimization challenge often falls on human operators who possess a nuanced understanding of the context and are empowered to make critical judgment calls. A robust BESS optimization system, therefore, should not only be sophisticated in its algorithms, but also be bidirectional, seamlessly incorporating human operator feedback into its decision-making processes.

Over the past few years, techniques to take human feedback into account have been developed on top of the reinforcement learning (RL) framework, namely the reinforcement learning from human feedback (RLHF) family of algorithms [7, 17]. In this work, we take a first step towards this direction by demonstration of the applicability of RL based methods to the BESS optimization problem.

We review the existing literature and propose a novel Markov decision process (MDP) formulation for the BESS system. We introduce an open-source environment and establish different baseline algorithms including heurisitc, reinforcement learning, and imitation learning algorithms. We foresee an active community of developers and researchers pushing the frontiers of this novel system to reduce carbon dioxide emissions and make clean energy more profitable.

2 RELATED WORK

With the increasing global adoption of renewable energy sources, driven by their inherent variability influenced by weather conditions, the electricity markets are experiencing increased volatility. Consequently, there is an increasing need to develop accurate simulations of power plants that participate in these markets. Such simulations facilitate the exploration of power generation management strategies aimed at achieving a more resilient power generation system, leveraging on-site power storage facilities to better align with market demand profiles. This tool is essential for maximizing the profitability of renewable energy producers, thus stimulating further growth in this sector in conjunction with other conventional power generation methods.

Formulating a mathematical problem to maximize the profit of a power plant entails integrating all pertinent aspects of the energy balance, encompassing electricity production and consumption dynamics, alongside associated supply and sale costs. The objective function typically quantifies the disparity between income and costs, subject to technical constraints governing the system's variables. Conventionally, addressing this optimization problem involves leveraging classical optimization techniques, including linear programming [1], [21], mixed-integer linear programming [19], [4], [29], nonlinear programming [2], [13] and mixed-integer nonlinear programming [22], [27].

[1]https://www.engie.com/en/news/ppa-power-purchase-agreement-what-is-it
[2]https://aemo.com.au/en/energy-systems/electricity/national-electricity-market-nem/system-operations/ancillary-services

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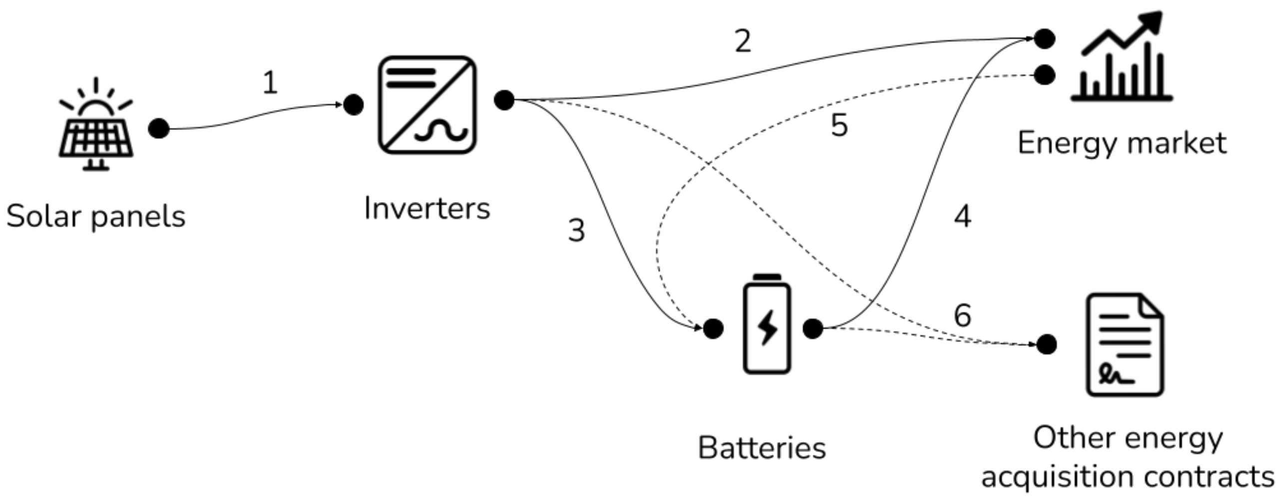

Figure 1: Solar energy production & storage simplified system diagram. The solar panels generate direct current (DC) electricity from sunlight, it is then converted (1) to alternative current (AC) electricity by inverters. DC electricity can then be sent (2) to the power grid and sold on the energy market. The introduction of batteries enables storing (3) the produced energy to sell it (4) later on, e.g. when the demand, hence the price, is higher. Energy can also be bought from the grid (5) to be stored and sold later on. Additionally to realtime "open" energy markets, energy producers can sell (6) their energy to other types of energy acquisition contracts. (5) and (6) are not covered in the current work.

Implementing these optimization strategies offers simplicity and rapid execution to identify optimal solutions. Presently, mainstream computational software incorporates proficient solvers capable of efficiently handling mixed-integer linear problems. However, challenges arise when nonlinear constraints are introduced into the power plant optimization problem, potentially yielding nonconvex feasible regions and complicating resolution. Some studies adopt various mathematical and heuristic methodologies to tackle these intricacies.

These mathematical methods attempt to converge towards optimal solutions, a crucial aspect of effectively managing energy resources. In linear programming models, the simplex method [23], [3] emerges as the preferred approach due to its broad applicability, ease of implementation, and computational efficiency. Conversely, for integer programming models, branch-and-bound techniques [16], [20] are predominantly used, enabling an intelligent search for optimal solutions by systematically evaluating feasible integer solutions while considering constraints and bounds. However, due to the complexity and computational demands of these methods, some studies advocate linearizing model equations before solving them.

Heuristic methods, on the other hand, such as Particle Swarm Optimization [22], [11] and Genetic Algorithms [28], offer efficient solutions for energy resource optimization. Particle swarm guides particles in the search space toward optimal solutions with minimal parameter adjustment. Genetic algorithms simulate biological evolution and natural selection, providing flexibility and exploring solution spaces intelligently. Selecting the appropriate parameters of the algorithm is crucial to achieve satisfactory results. However, these methods may not guarantee optimal results.

Deep reinforcement learning (DRL) is an alternative route to pursue to optimize power plant operations in renewable energy markets. Unlike traditional optimization techniques, which rely heavily on predefined models and assumptions, DRL learns directly from interactions with the environment, enabling it to adapt and improve over time. By iteratively exploring and exploiting the state-action space, DRL agents can discover complex strategies that may not be apparent through conventional methods alone. Compared to the classical optimization methods reviewed above, DRL approaches can learn from historical data, are self-adaptable, and learn a good control policy even in a complex environment of optimizing battery energy trading while limiting degradation costs using Deep Q-Learning (DQN) [6]. This inherent flexibility allows DRL to navigate dynamic and uncertain conditions more effectively, potentially unlocking new insights and strategies to optimize power plant operations in renewable energy markets. Double DQN was used in another study [5] to improve the over-optimistic value estimates of DQN by decoupling the selection from the evaluation of an action using a second neural network.

To broaden the action space of the DRL agents from discrete to continuous, necessary for tasks like adjusting battery charge or discharge power, policy gradient techniques are being employed. The deep deterministic policy gradient method [14] initially facilitated the handling of such action spaces and has been further refined by the DRL research community since its inception to achieve better stability and performance. In their study, [10] employed Rainbow

DQN to oversee battery operations in a microgrid, enhancing energy arbitrage through solar and wind energy utilization, while integrating real-world dynamics of demand, renewable generation, and dynamic energy pricing sourced from wholesale markets, achieving superior performance compared to DDPG and a linear programming model with discrete optimization. Recently, these improved algorithms have been applied to the power management problem. [26] used the soft actor-critic (SAC), twin-delayed deep deterministic policy gradient (TD3), and proximal policy optimization (PPO) to control potentially millions of small-scale assets in private households. Their DRL algorithms outperformed common heuristic algorithms and fell short of the results provided by linear optimization, but by less than a thousandth of the simulation time.

In their study, [18] used battery storage for concurrent energy arbitrage and frequency regulation services, to maximize total revenue while adhering to physical constraints. By tackling the multi-timescale challenge through nested Markov decision process submodels and implementing a co-optimization scheme, their method effectively coordinated these actions. They used the TD3 with an exploration noise decay approach in simulations conducted with real-time electricity prices and regulation signal data, showcasing superior performance compared to DQN.

The studies mentioned above showcased the superiority of DRL in grasping the intricate patterns and uncertainties inherent in power generation and market dynamics, outperforming classical optimization techniques. What sets our work apart is the introduction of a novel MDP formulation designed to tackle the intricacies of energy storage optimization. By doing this, we offer a methodical and rigorous approach to model BESS operations, encapsulating crucial variables such as energy production, consumption, market dynamics, and storage constraints. This formulation not only provides a holistic representation of the optimization challenge, but also facilitates the development of streamlined algorithms for BESS management. We strongly advocate for the widespread adoption of our formulation as the benchmark for future research endeavors and industrial applications, as it lays a solid foundation for the promotion of advancements in sustainable energy management practices.

3 ENVIRONMENT

Our BESS model consists of one renewable energy source and one battery. The goal is to decide how much power should be sold to the grid and to charge or discharge or leave the battery idle based on the spot price and the LGC price. The system is represented in Figure 1. We model the MDP as follows: Each time step corresponds to an interval of 5 minutes. Each episode lasts for one day, that is, 288 time steps. The observation at each time step includes the power generation and price values for the last hour, the current and the next hour, the current state of the battery, and the number of time steps remaining until the horizon. The action is a scalar value that tells the total amount of power sold to the grid; this is represented as the edge (2) in Figure 1. If the action is less than the power generated, the additional power generated is used to charge the battery; this is represented as edge (3) in Figure 1. If this value is higher than the generated power, the remaining power is obtained by discharging the battery; this is represented as the edge (4) in Figure 1. However, if at any point during training the action indicates that the battery should be charged or discharged beyond its capacity, we classify it as an illegal action, penalize it heavily, and terminate the episode. During the evaluation phase, we emulate the real-world settings by ignoring the illegal actions, as the inverter is disconnected when the battery is full in the real-world (digital twin).

3.1 Generate data of multiple levels of difficulty

The environment is equipped with the capability to generate data (generated power and price) of varying levels of difficulty. This can be used to train agents through curriculum learning. After inspecting the real data of the generated power and the corresponding prices in 10 different provinces in Australia, we generated synthetic data, close to these real data.

At the foundational level, generated power is modeled by a cosine wave, and price is modeled by a sine wave (as they are inversely correlated — if the generated power is higher, the demand would decrease, and hence the price is lower. On the other hand, if the generated power is less, the demand will increase, and the price will be higher). When the value of the cosine wave is negative, it is clipped to zero, indicating zero power production during the night. For the corresponding duration, when the generated power is zero, the price is fixed to its maximum value. The generated power values are multiplied by a constant to match the distribution to the real power generation values of a power plant. Similarly, the prices are multiplied by a constant to make them similar to the actual prices.

Furthermore, a random noise sampled (at each time step) from a uniform distribution (with a fixed amplitude) can be added to every time step of the generated power and price values. Increasing the amplitude will make the task harder.

The real power generation curves are characterized by unusual spikes at arbitrary times. To mimic this behavior, we added the provision of adding spikes, i.e., a random noise sampled from a uniform distribution (but with much higher amplitude than the amplitude for noise at each time step) after every few time steps, again characterized by time period and additional position noise.

3.2 Observation and Reward

In addition to the observation and reward described in Section 3, the environment is equipped with several other options. A 'mini observation' only includes the price and power generated at the current time step, current state of the battery, and the number of time steps remaining until the horizon. All these values are normalized by the corresponding normalization constants. An 'observation with noisy forecasts' allows adding additional noise to the forecast values of both prices and power generation.

Agents can be trained and evaluated with different kinds of rewards. 'just revenue' computes the revenue generated at each time step by mulitiplying the price at current time step with the total power to the market grid. 'Scaled revenue' scales the raw revenue by dividing with an appropriate normalization constant. 'Scaled revenue and penalty' adds a penalty of -1 for illegal actions in addition to the scaled revenue. 'Survival' gives a reward of -1 for illegal actions and +1 for legal actions.

In our experiments, mini observation along with survival reward were used as quick sanity checks to confirm that the agent can train. We then used standard observation with scaled reward and penalty for training. Both the scaled reward and penalty, and just revenue, were plotted for evaluation episodes.

3.3 Design principles

All implementations (algorithms) have the same input and output formats. For example, even though the output range of the TD3 algorithm (bounded by [-max-action, +max-action]) is different from that of the heuristic or no-battery baseline (which has an actual range of [0, max-action + sum-action]), we rescale the output of the heuristic and no-battery baseline to ensure that the environment can handle the actions coming from all the implementations in a similar way. Similarly, no-battery baseline only requires the power generated at the current time step, but we still send the complete observation as its input (the same as the input to RL algorithms).

4 IMPLEMENTATIONS

4.1 Heuristic Algorithms

Our first baseline is a scenario with no battery and all the power generated at every time step is sold to the grid.

As a second baseline, we propose a simple heuristic algorithm in which decisions are made based on the price forecasts. If the average forecast price for the next hour is less than the current price, it indicates that the price is decreasing. Therefore, we decide to sell all the power generated in the current time step and completely discharge the battery. On the other hand, if the average forecast price for the next one hour is greater than the current price, it indicates that the price is increasing. Therefore, we completely charge the battery and only the additional power generated is sold.

4.2 RL Algorithms

Twin Delayed DDPG (TD3): TD3 [9] is an off-policy algorithm for continuous control tasks. It builds on DDPG [15] and uses the following techniques to make the RL algorithm more stable: (1) Clipped Double Q-learning which maintains two Q-estimators and updates the loss functions using the smaller Q-value to avoid overestimation bias (2) delayed policy and target network updates compared to Q-function update (3) target policy smoothing as regularization by introducing noise to the target action value. The loss function of the critic is:

$$\mathcal{L}(\theta_i) = E_{(s,a,s',r)\sim B}[(Q_{\theta_i}(s,a) - y)^2] \tag{1}$$

In the above equation, θ_i refers to the parameters of the i^{th} Q-estimator for $i \in \{1,2\}$, B is the replay buffer, y is the target value computed as $y = r + \gamma \min_{i=1,2} Q_{\theta'_i}(s', \pi_{\phi'}(s') + \epsilon)$ where θ'_i refers to the parameters of the i^{th} target Q network, ϕ' is the parameter of the target actor network and ϵ is the policy noise. The actor loss is as follows:

$$\mathcal{L}(\phi) = \max_{\phi} E_{s\sim B}[Q_{\theta_1}(s, \pi_\phi(s)] \tag{2}$$

In the above equation, ϕ is the parameter of the actor-network.

TD7 [8] was originally proposed as an improvement over TD3 comprising the following four additions: the state-action representation learning method SALE, the checkpoint trick, prioritized experience replay, and a behavior cloning term.

Proximal Policy Optimization (PPO) [25] is an on-policy RL algorithm that shares the benefits of trust region policy optimization [24] and is more general and has better sample complexity (measured empirically on a wide range of benchmark tasks).

4.3 Imitation Learning Algorithms and RLHF

As an example of learning from human demonstrations, we train a policy network to imitate the behavior of a heuristic using behavior cloning. Furthermore, we developed a framework to continuously solicit human feedback and preferences for the actions and train a reward model that is used to further fine-tune the policy model. This is very similar to how the large language models (LLMs) are updated in some of the latest work.

5 CONCLUSION

In this work, we reviewed the current start of the art of optimization techniques for BESS and highlighted the need for better frameworks for taking human demonstrations and feedback into account and proposed a novel MDP framework and benchmarked heuristic, reinforcement learning, and imitation learning algorithms. We strongly advocate for the widespread adoption of our formulation as the benchmark for future research endeavors and industrial applications, as it lays a solid foundation for the promotion of advancements in sustainable energy management practices.

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