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Developing a Disaster-Ready Power Grid Agent Through Geophysically-Informed Fault Event Scenarios

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Abstract—Management of the nation’s power grid over the coming decades will need to consider multiple climate-driven threats to the power system that can be stressful or even detrimental to its operations. During disasters, grid operators suffer from cognitive overload where the electric grid is severely impacted by the weather, yet grid operators have limited awareness of these factors. Meanwhile, the electric grid is facing an explosion of data coming from a variety of sources which can enable the operator to evaluate the risks and develop mitigation strategies against hazardous events. In this work, we processed heterogeneous environmental and power grid data to learn and model grid behaviour caused by extreme weather events. In this study, we focused on two weather-driven hazards, hurricanes and wildfires, which were analysed for the electric grid of Texas. We then used this data to train a Reinforcement Learning (RL) agent by analysing and predicting future behaviour of the grid during those hazard events. All these parts are incorporated in one framework to have a geophysically informed power simulators that can be used to train RL agents.

Index Terms—electric grid, reinforcement learning, climate adaptation, energy equity

I. INTRODUCTION

The power grid is the collective network of electric generators, transmission lines, towers, and distribution systems that have the ultimate goal of delivering usable electricity to consumers. An envirotechnical system, the United States power grid faces simultaneous challenges in the 21st century, including rising electricity demand and energy source heterogeneity, while operating in a hostile physical environment of increasingly frequent and more severe extreme weather events.

Extreme weather is the primary cause of wide-area electrical disturbances due to its keen threat to any vulnerabilities in

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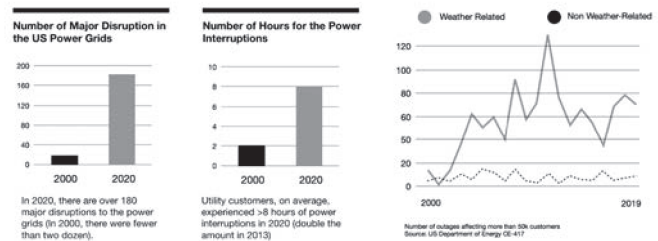


Fig. 1. Power grid disruption statistics since the turn of the century [1]. Major power disruptions are on the rise in recent years, and largely attributable to weather events.

critical infrastructure, as shown in Fig. 1. Wind, water, and fire each pose unique yet often compounding risks to various grid structures. Windthrow of trees via high winds cause overhead lines to swing and break. Prolonged heat waves or lightning strikes overheat and inflame cables, which raises resistance if not destroying the line entirely. Rainfall augments wind risk to the familiar steel lattice transmission towers [2]. These environmental threats have spurred an acute interest in natural disaster prediction among the natural, civil, and electrical sciences and engineering research circles.

As the planet warms, climate projections and observations confirm an increase in the frequency, intensity, and duration of many severe weather events. Historically, the proportion of most intense hurricanes (Category 4 or 5 on the Saffir-Simpson scale) has increased 25-30% for every 1 degree Celsius in global temperature [3]. As for wildfire risk, which is amplified in both hotter and drier conditions, climate change is attributable to over half the increase in forest fuel aridity since the 1970s, and nearly double the cumulative area burned since 1984 [4]. Implications of these extreme events on the power grid have already been dire. National power outage data reveal a tenfold increase in major weather-related power

outages between the mid-1980s and 2012 [5]. In response to these incidents, alongside long-term infrastructure and planning efforts, we must improve short-term management of our grid, including advances to monitoring and control operations, over the coming decades.

Effective tools must ultimately be tailored to the humans it aims to assist. The available devices and data to support grid operators may be overwhelming and disregarded in favor of more familiar, conservative approaches in disaster response. Merging various contextual data and environmental threats to support grid operators requires an interdisciplinary team of experts spanning physical infrastructure, atmospheric hazards, artificial intelligence (AI) and machine learning (ML) methods, and human-centric AI to augment the user's capabilities.

We here propose a framework to train machine learning models that autonomously operates a power grid by geospatially synchronizing and processing heterogeneous geophysical and topological data. This model can assist grid operators in monitoring and controlling power grid assets, further increasing grid resilience. By incorporating various infrastructure-relevant data sources, such as near-surface atmospheric developments and socioeconomic conditions, the agent can leverage contextual information that affects the grid (and thus people) beyond what human operators normally process.

The goal to center equity in various weather resources, particularly in predicted and felt impacts, has exploded in recent years as a counter to generations of both explicit and subtle policy decisions disenfranchising lower-income and minority communities [6]. Approaches to power systems intelligence (i.e., smart grids) with AI tools such as deep and reinforcement learning have been developed and deemed viable for its exploration and verification stage, though not yet commercially ready [7]. And furthermore, utilizing ML such as artificial neural networks (ANNs) in weather-based fault prediction applications has been studied in the context of the Finland electricity network [8]. Our work builds upon these past investigations by developing a framework for a reinforcement learning power grid agent applicable to the U.S. power grid. This vision is hereby referred to as GridWorld.

The contributions of this work are (1) integrate datasets of extreme weather generation and fault event prediction with socioeconomic data, and (2) develop a reinforcement learning training framework to optimize grid fault response. This framework utilizes the generation and consumption time series data, but further adapts the grid for extreme weather adversary studies over the geographic area of interest. In addition, managing power delivery under time sensitive constraints without incorporating contextual information, like socioeconomic data, is beyond what human operators can normally process and act upon. Our project here is aimed to fill these gaps.

II. RISK ANALYSIS ON THE GRID

Electric power grids are complex, cyber-physical control systems that are subject to quick decision making and have real-world impacts on various energy-consuming assets. The consequences of power grid decisions can be directly and

immediately realized, as lack of electricity to certain safety-critical operations (e.g., hospitals) risk loss of human life. In our analysis, we have focused on the short-term operation of the grid in real-time, as opposed to long-term investments and decisions for the nation's energy infrastructure [9]. We recognize the importance of future decision making and policies for the grid, and hope our findings in real-time operation of the grid can shed light on vulnerable features of the nation's current grid health and influence future decisions.

III. REINFORCEMENT LEARNING FOR GRID CONTROL

The area of ML concerned with decision-making is referred to as reinforcement learning (RL). Optimal course of action for an intelligent agent is determined by a maximum reward. Since there is no correct answer in reinforcement learning, the reinforcement agent selects the optimal action available. This is distinct from supervised learning, where the training data includes the solution key and the model is trained with that answer. Here, the agent is obligated to gain knowledge from its experience in the absence of a training dataset.

RL has seen recent advancements and applications to power grids [10]. Specifically, the control of power grids with methods of RL have been proposed to handle the increasingly challenging problem of handling complex, smarter grids. The RL problem for power grid control can be defined by some main high-level characteristics as follows: (i) action space—what actions the agent can take on the grid; (ii) observation space—which grid measurements and parameters the agent processes; (iii) learning algorithm—how the agent can translate observations into actions and iteratively learn optimal decisions; and (iv) reward function—a function that defines the feedback the agent receives based on the grid's current operating state due to the last set of actions applied. For an RL agent to effectively perform power grid control, it trains on many simulations, or games, in which it attempts to operate the grid for as long as possible while updating the model weights within its learning algorithm.

IV. GRID2OP FRAMEWORK

The Grid2Op framework [11] is an open source Python package for modeling and simulation of reinforcement learning agents operating on power grids. Grid2Op features many levels of customization as users can define grid topologies and their time series data for loads and generators, while generating grid attack profiles to evaluate cascading failures. Uniquely, Grid2Op integrates reinforcement learning agents to operate on the grid and perform actions. Grid2Op's ability to interact with the OpenAI Gym [12] interface allows for training and evaluating of reinforcement learning agents. Grid2Op also allows for selection of various power-flow solvers that calculate flow across the grid (e.g., PandaPower [13]). Figure 2 outlines the sequential decision making process available in Grid2Op. The grid and its underlying state at time step t create observations passed on to an agent. The Agent, a reinforcement learning agent or any power grid controller, outputs an action or set of actions to take on the grid.

These actions are simulated on the grid within its respective environment before arriving at its new state, $t + 1$. To see a more in depth description of main steps in the Grid2Op architecture, please reference [11].

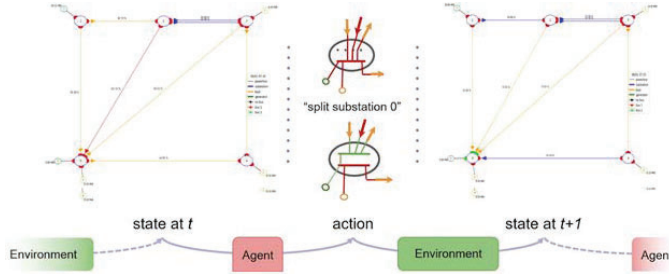


Fig. 2. Demonstration of sequential decision making in the Grid2Op [11].

In this work, we focus on applying the grid topology and data available in the 2022 Learning to Run a Power Network Challenge [14]. As the title of this 2022's challenge, *Energies of the future and carbon neutrality*, suggests, the focus is a futuristic grid aimed at emulating a nearly carbon-neutral 2050 electric grid. The grid network topology (Fig. 3) consists of a 118-bus system with 62 power plants, 91 consumption nodes, and 7 batteries capable of storing energy. We utilized the generation and consumption time series data that was provided for the challenge, but further adapted the grid for our specific study on extreme weather adversaries over the geographic region of Texas.

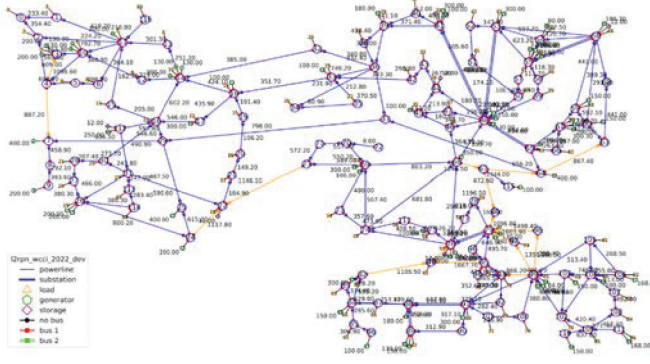


Fig. 3. Visualization of the power grid used in the 2022 challenge [14].

V. DATA PROCESSING & THE TEXAS CASE STUDY

Our pipeline (Fig. 4) consists of three dataset clusters: power grid data, meteorological data, and socioeconomic data. For our test case model region, we select Texas, home to the Electric Reliability Council of Texas (ERCOT) electric grid, due to its discontinuity from the national grid and susceptibility to multiple natural hazards.

The raw topology is not georeferenced, and thus requires placement and adaptation to a pseudo-realistic simplified grid network. Extreme weather events are then simulated from historical data to inform outage events. Numerous fault scenarios are generated to capture the probabilistic nature of conversion

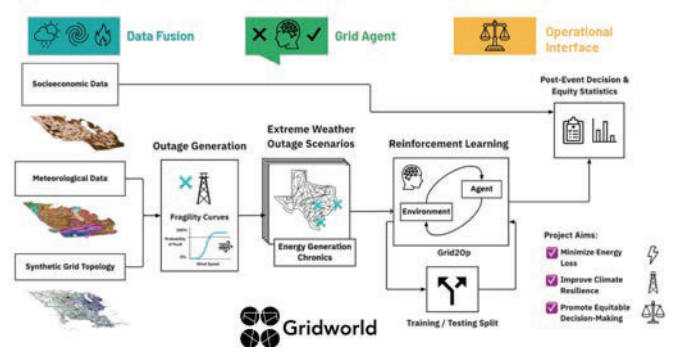


Fig. 4. GridWorld workflow.

from geophysical data to infrastructural collapse. The array of generated fault event scenarios are then split into training and testing groups before being evaluated and acted upon by the Agent within the power grid simulator.

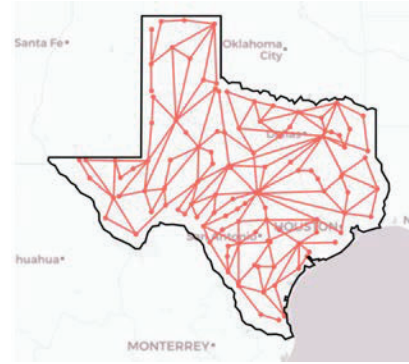


Fig. 5. IEEE 118-bus system used to represent Texas grid.

The current capabilities of the GridWorld design include meteorological considerations of hurricanes (winds) and wildfires. For wind-based threats, historical ERA5 reanalysis data for 8 Texas-landfalling hurricanes since 1960 was used to supply an hourly 10 m a.g.l. wind field [15]. For wildfire threats, we import thousands of wildfire records throughout Texas from 1992 to 2015, only a couple hundred of which impact the grid topology. The variety of outages caused by wildfires are demonstrated in Fig. 6.

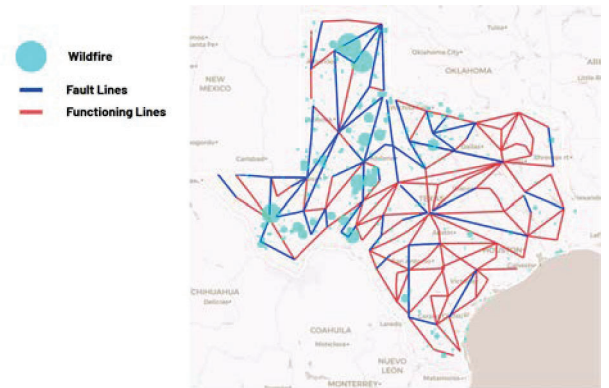


Fig. 6. Historical wildfires from 1992 to 2015 at a spatial resolution of 1 square mile.

While both environmental hazard types are georeferenced on the grid map, only hurricane-related events are capable of generating different fault outcomes for a single historical simulation due to the probabilistic nature of fragility curves (see Fig. 7). This results from assuming that wildfire-induced faults arise only if intersection with infrastructure occurs, whereas wind-induced faults are highly dependent on intensity. In the case of hurricane events, single parameter fragility curves on each component of the network (Fig. 6) determine the probability if an individual element becomes inactive. From here, a Monte Carlo method is used to derive the time-variant fault. A single sample snapshot of the results of applying this fragility curve on historical hurricane Carla (Cat 4) in 1961 is shown in Fig. 8.

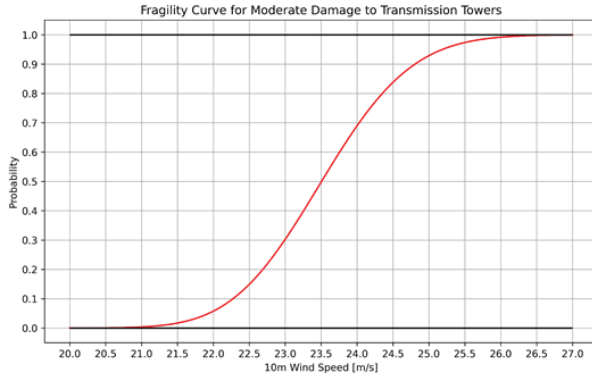


Fig. 7. Fragility curve for transmission towers adapted from [2].

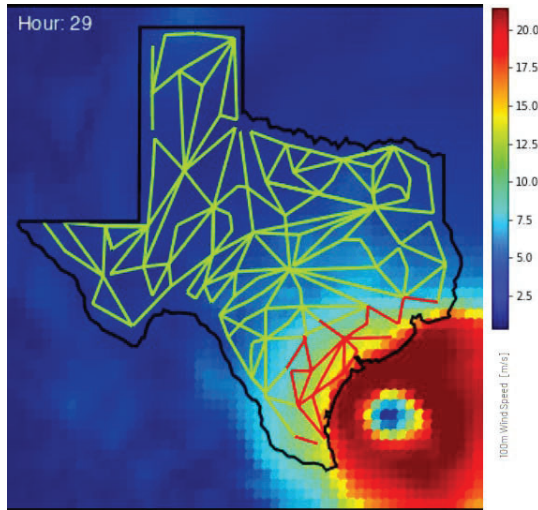


Fig. 8. Hurricane Carla 1961 outage example on Texas grid.

VI. TRAINING RL AGENTS

RL agents are then trained on the data from the extreme weather events detailed in the previous section. GridWorld enables the training of a variety of RL agents with varying learning parameters. These capabilities are summarized in Table I. RL agents within Grid2Op are allowed to perform

TABLE I
GRIDWORLD RL AGENT TRAINING CAPABILITIES

Parameter	Description
Learning Algorithm	the RL model type (e.g., Proximal Policy Optimization [16])
Network Architecture	dimensions of the model (number of layers and neurons)
Action Space	the allowable set of actions the agent can perform (e.g., dispatch, line disconnection)
Observation Space	the set of measurements used as inputs by the agent (e.g., active/reactive power flow)
Reward Function	customizable function of energy losses, grid fragility curves, equity impact
Opponent	natural disaster to simulate (e.g., hurricanes, wildfires)
Training Parameters	learning rate, episode iterations, number of scenarios, etc.
Safe Operation Limit	maximum electrical line capacities

a distinct set of discrete and continuous types of actions on the grid. These potential action types are: (i) switching lines on/off; (ii) grid topology adjustments through bus configuration changes; (iii) dispatching a power substation; (iv) increasing/reducing power generation; and (v) load reduction. The Grid2Op environment specifies internal limits and constraints for the agent's actions that are enforced by physics models for the generators, transmission lines, etc. [11].

As detailed in Section III, the reward function plays a critical role in defining the problem for the RL agent. GridWorld offers a high level of customization for users in the definition of the reward function. In our use case we focus on three aims (Fig. 4): (i) minimizing energy losses, (ii) improving climate resilience, and (iii) promoting equitable decision making. To implement these aims into a reward function, we propose a custom function that scales each aim by a user-defined weighted parameter. Energy losses on the grid are calculated by summing the cost of performing actions on the grid (either from dispatching and/or generation) and the cost of energy flow losses on the grid (total energy generated vs. consumed). Climate resilience is defined by probability of grid failure given the natural disaster which is derived from the fragility curve analysis as presented in Section V. Lastly, we propose that equitable decision making can be incorporated into the reward function by using socioeconomic data to model impacts of grid failures on under-represented geographic regions. Additionally, to promote equity, the user interface of GridWorld outputs impacted populations following decisions made on the power grid to increase awareness of impacts on already marginalized communities. Users of GridWorld can tune a set of parameters to weight each of these aims to varying degrees to fit their design decisions.

VII. RESULTS

The GridWorld platform allows for integration of socioeconomic data such as poverty rate from the 2020 Census Bureau to identify the lines serving vulnerable populations. Through a user-friendly interface (Fig. 9), one can see that many of the vulnerable lines serving low-income communities are also

those being affected by Hurricane Carla. With this analysis, we could predict the number of people being affected by a hurricane and plan intervention proactively, as the forecast evolves. An additional analysis can identify a group of critical lines in the power grid requiring fortification (Fig. 10). These lines, highlighted in red, lead to immediate game over or black out when disabled. This can inform long term interventions such as undergrounding, line doubling, or adding power storage in the area.

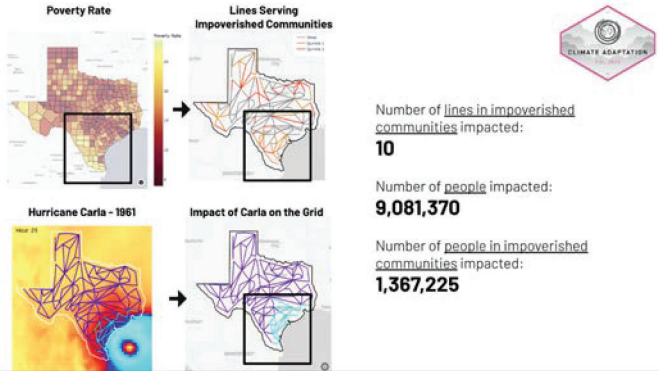


Fig. 9. Example live interface in GridWorld for equity analysis.

When evaluating the performance of our RL agents, we focus on two main metrics: grid operation time steps and cumulative reward gained by the agents. The longer the RL agent can operate the grid without failures, the better the RL agent can assist human grid operators in making real-time grid decisions during disasters. Larger cumulative rewards indicate successful agent learning as the agent's optimize their out-putted actions to maximize the user-defined reward function. During preliminary experiments, we found the performance of RL agents to be very sensitive to the parameters specific in Table I. For example, restricting an agent's action set to only energy dispatch, without discrete action operations like line connections and bus configurations, leads to early grid failures in the case of severe weather events that can disrupt a large number of power lines. Similarly, the reward function definition can heavily influence performance and requires careful tuning to allow the agent enough space for successful exploration.

The imagined future of GridWorld involves the grid operator receiving the Agent's recommendations through interactive data visualization, ensuring recommendations are explainable and actionable. The Agent would also predict the socioeconomic outcomes of the recommended actions, so the operator can be maximally informed of their actions. The system will likewise be usable for policy makers to determine long term development plans by identifying the most vulnerable areas on the grid.

VIII. CONCLUSION

We developed a framework for an AI agent that could assist the grid operators in making more informed decisions by processing extreme weather events as well as socioeconomic

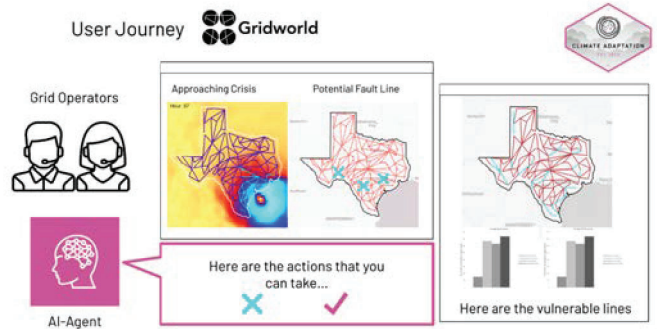


Fig. 10. Example live interface in GridWorld for critical line analysis.

data to ensure the security of our energy future. The actions recommended by the RL agent resulted in an increase in grid resilience by managing the grid to serve customers for longer periods during these events. Finally, we incorporated contextual information (like socioeconomic data) to advise grid operators on the impact of their control decisions beyond what they can normally process under time sensitive constraints.

REFERENCES

- [1] C. Capozziello, for The Wall Street Journal, "America's power grid is increasingly unreliable," Feb 2022. [Online]. Available: <https://www.wsj.com/articles/americas-power-grid-is-increasingly-unreliable-11645196772>
- [2] X. Fu, H.-N. Li, G. Li, and Z. Dong, "Fragility analysis of a transmission tower under combined wind and rain loads," *Journal of Wind Engineering and Industrial Aerodynamics*, vol. 199, p. 104098, 2020.
- [3] G. Holland and C. Bruyère, "Recent intense hurricane response to global climate change," *Climate Dynamics*, vol. 42, no. 3, pp. 617–627, 2014.
- [4] J. T. Abatzoglou and A. P. Williams, "Impact of anthropogenic climate change on wildfire across western us forests," *Proc. of the National Academy of Sciences*, vol. 113, no. 42, pp. 11 770–11 775, 2016.
- [5] A. Kenward, U. Raja *et al.*, "Blackout: Extreme weather climate change and power outages," *Climate central*, vol. 10, pp. 1–23, 2014.
- [6] A. Tripathi *et al.*, "Centering equity in the nation's weather, water and climate services," *EarthArXiv*, 2022.
- [7] Z. Zhang, D. Zhang, and R. C. Qiu, "Deep reinforcement learning for power system applications: An overview," *CSEE Journal of Power and Energy Systems*, vol. 6, no. 1, pp. 213–225, 2019.
- [8] C. Brester, H. Niska *et al.*, "Weather-based fault prediction in electricity networks with artificial neural networks," in *2020 IEEE Congress on Evolutionary Computation (CEC)*. IEEE, 2020, pp. 1–8.
- [9] U.S. Department of Energy, "Big data analytics: Recommendations for the u.s. department of energy," Feb 2021. [Online]. Available: https://www.energy.gov/sites/prod/files/2021/02/f83/EAC%20Big%20Data%20Analytics%20Work%20Product_Final.pdf
- [10] X. Chen, G. Qu, Y. Tang, S. Low, and N. Li, "Reinforcement learning for selective key applications in power systems: Recent advances and future challenges," *IEEE Transactions on Smart Grid*, 2022.
- [11] B. Donnot, "Grid2op-a testbed platform to model sequential decision making in power systems." <https://github.com/rte-france/grid2op>, 2020.
- [12] G. Brockman *et al.*, "Openai gym," *arXiv preprint arXiv:1606.01540*, 2016.
- [13] L. Thurner, A. Scheidler, F. Schäfer, J.-H. Menke, J. Dolichon, F. Meier *et al.*, "pandapower—an open-source python tool for convenient modeling, analysis, and optimization of electric power systems," *IEEE Transactions on Power Systems*, vol. 33, no. 6, pp. 6510–6521, 2018.
- [14] G. Serré, E. Boguslawski, B. Donnot, A. Pavão, I. Guyon, and A. Marot, "Reinforcement learning for energies of the future and carbon neutrality: a challenge design," *arXiv preprint arXiv:2207.10330*, 2022.
- [15] H. Hersbach, "The era5 atmospheric reanalysis," in *AGU fall meeting abstracts*, vol. 2016, 2016, pp. NG33D–01.
- [16] J. Schulman, F. Wolski, P. Dhariwal *et al.*, "Proximal policy optimization algorithms," *arXiv preprint arXiv:1707.06347*, 2017.