Learning to Attack Powergrids with DERs

Eric MSP Veith\textsuperscript{1}\textsuperscript{*}, Nils Wenninghoff\textsuperscript{1}, Stephan Balduin\textsuperscript{1}, Thomas Wolgast\textsuperscript{2} and Sebastian Lehnhoff\textsuperscript{1}

\textsuperscript{*}Correspondence: eric.veith@offis.de
\textsuperscript{1}OFFIS – Institute for Information Technology, R&D Division Energy, Escherweg 2, 26121 Oldenburg (Old.), Germany
Full list of author information is available at the end of the article

Abstract

In the past years, power grids have become a valuable target for cyber-attacks. Especially the attacks on the Ukrainian power grid has sparked numerous research into possible attack vectors, their extent, and possible mitigations. However, many fail to consider realistic scenarios in which time series are incorporated into simulations to reflect the transient behaviour of independent generators and consumers. Moreover, very few consider the limited sensory input of a potential attacker. In this paper, we describe a reactive power attack based on a well-understood scenario. We show that independent agents can learn to use the dynamics of the power grid against it and that the attack works even in the face of other generator and consumer nodes acting independently.

Keywords: Voltage Control; Deep Reinforcement Learning; Attack Vectors; Distributed Energy Resources; Vulnerability Analysis; Cyber-Physical System

Introduction

The attack on the Ukrainian power grid has shown that power grids have become valuable targets \cite{1, 2}. Cyber-attacks against this critical infrastructure had previously been discussed in theory, but were not considered an imminent threat yet. Nowadays, it is considered entirely possible that an attacker gains access to the Supervisory Control and Data Acquisition (SCADA) system—either physically or by virtually exploiting a bug that leads to a privilege escalation—and is subsequently able to control the physical asset \cite{3}. This is especially important considering that power grids world-wide transition from well-controlled, central power generation and simple consumers to a distributed architecture, in which nodes become prosumers and Distributed Energy Resources (DERs) are the norm. Not only has the number of nodes that influence the power grid increased, but also the parties involved.

A well-understood analysis of how an inverter-based generator can attack the power grid has been published by Ju and Lin \cite{4}. Their analysis considers DERs as potential attack vectors, assuming that an attacker has taken over control of one or many inverters (e.g., wind turbines or Photovoltaic (PV) systems). Without knowledge of the grid’s architecture, the authors show analytically that the attacker is able to use the reactive power control scheme of other nodes against the grid by introducing a oscillating maximum reactive power feed-in/consumption behavior. This way, an attacker can do damage of nearly twice its own reactive power feed-in/consumption capability by ‘leveraging’ other generators.

Ju and Lin’s paper is a prime example for what we call excellent first-generation analyses: They focus on an isolated issue and treat the power grid as a still object. I.e., while stringent in their analysis, Ju and Lin do not consider normal power grid operation: While the attacker does its work, other generators react according to
their voltage control scheme, but no other nodes are active. During a normal power grid operation, other consumers and generators would still follow their schedule. In general, one cannot easily deduce from the “petrified” grid how the influence of time series for weather or consumption influence the effectiveness of the attack. Two scenarios are equally possible: That the attack is mitigated by other nodes as their feed-in or consumption provides enough background noise that renders the attack ineffective, or that an attack might eventually synchronize with the behavior of other nodes as to leverage at least momentarily their feed-in or consumption for the attack, too.

In this paper, we argue that a learning agent based on Deep Reinforcement Learning (DRL) can learn to discover this attack. We base our research on the same premisses as Ju and Lin, namely no knowledge of the power grid structure, sensory data limited to the local attacker node only, and the same reactive power control scheme as Ju and Lin used and [4, 5] introduced. However, we extend the scenario by providing a full simulation of a realistic power grid with acting independent nodes. Thus, our hypothesis is that a “live” power grid will foil the attack in its original, obvious fashion, but a variant of the original attack can still be discovered by a learning agent without knowledge of the rest of the grid. Hence, this paper can serve as a blue-print for a second generation of more realistic weakness analysis examples.

The remainder of this paper is structured as follows: We review the relevant literature in Related Work. The section on Experiment Design discusses the environment, sensor-actuator assignments of the attacker agent, as well as the time series and learning algorithms employed. Simulation Results shows results of our simulation and the validation of our theory. Our Conclusion also offers an outlook to future work.

Related Work
The literature that covers attacks on power systems can roughly be divided into two groups: cyber attacks and physical manipulation of the power system [6]. Especially cyber attacks are investigated extensively. The most important class of cyber attacks are false data injection attacks to manipulate state estimation [7]. However, also false data injection attacks to manipulate load forecasting [8] or automatic voltage control [9] are possible. Further, time delay attacks, replay attacks, and theft attacks in the power system are investigated in literature [10]. For a comprehensive review of cyber attacks refer to Mehrdad et al. [10].

However, physical manipulation of the power system attracts more and more research interest in recent years. One or multiple compromised generators can manipulate the decentralized voltage control by leveraging the voltage control behavior of other non-attacking generators [4]. Such publications present an analytical approach that focuses on the feasibility or impact of a specific attack. However, in a previous literature survey, we found that analyzing Cyber-Physical Systems (CPSs) with learning agents is a necessary research topic that allows to uncover new weaknesses despite the complexity of modern power grids [11]. This is backed up by other scientists’ research. E.g., Ni and Paul use Q-learning to identify the minimum number of line switchings to achieve a blackout scenario, under the assumption of knowledge
about branch status [12]. Later, they have expanded their approach to sequential attacks [13]. Wolgast et al. demonstrate how DRL can be used to identify unknown attack strategies that maximize profit on ancillary service markets [6].

While most previous publications focus on specific attack strategies or vulnerabilities—e.g., cyber attacks, manipulation of the powerflows, energy markets—we have previously presented an approach called Adversarial Resilience Learning (ARL) [14] that allows the agents to explore a system while maintaining a pressure to learn through an adversarial agent. A complex co-simulation set-up including a power grid, an energy market, and a corresponding Information and Communication Technology (ICT) network is based on this methodology [15].

DRL lends itself very well for these analysis approaches, inspired by the “superhuman” performance in the game of Go. From the resurrection of (model-free) reinforcement learning with the 2013 hallmark paper by Mnih et al. [16], to the publicly-noted achievements of AlphaGo, AlphaGo Zero, AlphaZero, and (model-based) MuZero [17, 18, 19, 20, 21, 22], DRL has attracted much attention outside of the Artificial Intelligence (AI) domain. Much of the attention it has gained comes from the fact that, especially for Go, DRL has found strategies better than what any human player had been able to, and this without human teaching or domain knowledge. Baker et al. underpin the usefulness of DRL, specifically with competing agents, as an analysis tool: They describe how agents are able to uncover loopholes in the underlying simulation software, thus discovering a new class of strategies to achieve their goals [23]. Such modern DRL-based experimentation approaches seldom use classic Q-learning [18] or A2C [24] algorithms, but use modern variants such as Soft Actor Critic (SAC) [25] instead.

**Experiment Design**

**Environment**

For our experiment, we employ the MIDAS software suite. It incorporates the PySimMods software package that contains numerous models for power grid units, such as batteries, PV or Combined Heat and Power (CHP) power plants. The grid model is a CIGRE Medium Voltage (MV) grid model as show in fig. 1.

Each node has a constant load of $560 + j320 \text{kVA}$ attached to it in order to account for this real power feed-in that occurs naturally because of the inverter model. The goal is to maintain a voltage magnitude close to 1.0 p.u on every bus if no action is taken. The grid has a number of PV plants as inverter-based generators attached, as well as a super market and a small hotel that serve as consumers. These consumers follow standard load profiles according to their roles. The PV plants’ output is dependent on the solar irradiation, which is governed by a multi-year weather dataset from Bremen, Germany. Each PV has apparent power output of 50 MVA. We deliberately chose this high value in order to demonstrate the attack within a short simulation time frame. For the sake of realism, one could readily assume the inverter nodes to represent wind farms. To ease modelling and without weakening the argument, we have resorted to PV plants instead.

[1] https://gitlab.com/midas-mosaik/midas
[2] https://gitlab.com/midas-mosaik/pysimmods
[3] Publicly available from https://opendata.dwd.de/climate_environment/CDC/observations_germany/climate_urban/hourly/.
The attacker controls the buses 3, 4, and 8. Buses 5 to 7, 9, 11, and 13 are voltage controlled. Each benign voltage controller applies the distributed control law [27]:

\[ q(t + 1) = [q(t) - D(V(t) - 1)]^+, \]

where the notation \([\cdot]^+\) denotes a projection of invalid values to the range \([q^l, q^u]\), i.e., to the feasible range of setpoints for \(q(t + 1)\) of each inverter. \(D\) is a diagonal matrix of step sizes. We have chosen a step size of 15 for each Q controller.

**Scenarios**

The experimental validation of our hypothesis rests on the following consecutive scenarios. We define these scenarios to work from the known, working attack scenario [4] towards a scenario that implements our hypothesis. For each of the three consecutive scenarios, we change only one characteristic.

Scenarios are defined through three properties: Its **goal** describes the purpose of the scenario; **setup** offers a concise description of the experiment setup and simulation environment; **expected result** allows to build a chain of arguments that interconnects the three scenarios.

This section contains only the description; evaluation of the actual results is offered in the **Simulation Results** section.
Scenario 1: Reproduction of an Original Paper

**Goal** Reproduce the original paper by Ju and Lin to note the characteristics of the simulation environment and to verify the effectiveness of the originally described attack [4].

**Setup** Consumers are not connected to the power grid. The weather provider offers weather data for a sunny summer day at noon, for each simulation step. I.e., the PV plants can be operated at peak capacity.

**Expected Result** The oscillating behavior of the attacking PV plants forces the Q controllers into a similar pattern, leading to a voltage band violation.

Scenario 2: Original Attack, with Time Series

**Goal** Evaluate the influence of time series data on the original attack

**Setup** Consumers and PV plants are connected to the grid. All nodes are influenced by the available time series data, i.e., the PV plants by the weather data, the consumers by their load profiles.

**Expected Result** The effectiveness of the original attack will depend on the current weather; the resulting data will show a clear yearly pattern.

Scenario 3: Learn to Attack, with Time Series

**Goal** Employ a learning agent to re-discover the attack described for Scenario 2.

**Setup** As in Scenario 2. However, the attacker is now a learning agent that employs a DRL algorithm to learn to attack the power grid.

**Expected Result** The agent learns to create voltage band violations. We expect the learning attacker to cope better with the influence of the weather data than the original attacker.

Reward Design

In DRL, the design of the reward function is one of the most important steps. Our experimenting framework, palaestrAI, separates reward from the objective of an agent. This is motivated by a shortcoming of simpler DRL experiments such as cartpole: The reward of an agent is given by the environment because of a state transition. E.g., for Q-learning, we commonly define the best action in a given state \(s\) as its Q value:

\[
Q(s, a) = r_{s,a} + \gamma \max_{a' \in A} Q(s', a') .
\] (2)

Simple, single-agent DRL setups assume that the reward is given by their environment and relates to the agent’s goal. In multi-agent environments, this is not the case. Here, we have to distinguish between the performance of the environment and the performance of the agent [14]. I.e., if \(r_{s,a}\) is equivalent to the environment’s performance when transitioning from state \(s\) given action \(a\), then the evaluation of a particular agent that considers this state transition should be denoted as \(p(r_{s,a})\).

For the simulation, we define the reward as a vectorized function of all bus voltage magnitudes after all agent actions are applied:

\[
\mathbf{r}_{s,a} = [V_1, V_2, \ldots, V_n]^T .
\] (3)
Let $i_A$ denote the vector of sensors (inputs) the attacker has access to. We can then assume a function $filter : (r_{s,a}, i_A) \mapsto r'_{s,a}$ that reduces the vector $r_{s,a}$ such that it includes only those bus voltage magnitudes the attacker has sensor access to. Then, we express the objective function of the attacker as:

$$p_A(r'_{s,a}) = 2 \left[ A \cdot \exp \left( -\frac{\frac{1}{2} \sum_{r' \in r'_{s,a}} (r')^2 - \mu}{2\sigma^2} - C \right) \right].$$  \hspace{1cm} (4)

We set $\mu = 1$, $\sigma = -0.05$, $C = -1.2$, and $A = -2.5$. The objective function is inspired by a Gaussian PDF. Figure 2 shows that, essentially, the attacker is rewarded for a voltage band violation, while a mean voltage close to 1.0 pu yields a negative value. This essentially encourages the attacker to force an extreme state with regards to the voltage magnitude; moreover, the influence of the weather data will drive the attacking agent towards the voltage magnitude boundaries it can easily enforce.

**Simulation Results**

**Scenario 1**

Scenario 1 serves as baseline in order to reproduce and ascertain the attack documented by Ju and Lin [4]. Figure 3(a) shows how the regular Volt/VAr controller within an acceptable boundary close to 1.0 pu. Figure 3(b) shows the same buses after the attacker has begun the oscillating VAr behavior. Clearly, the oscillation of the $V(t)$ curve is visible. In addition, the second peak is higher as the first one. The attacker’s behavior is always the same: It alternates between 100 % and $-100 \%$ of its possible reactive power injection/consumption. It confirms the general effectiveness of the attack, sans realistic time series.
Figure 3: System behavior for the simple alternating attacker

(a) Voltage magnitudes on targeted buses before attack

(b) Voltage magnitude at benign buses during attack
Scenario 2

Scenario 2 enables time series for weather and (regular) consumers, but does not change the configuration of the Volt/VAr controller or the attacker.

Figure 4 shows data from the month of July. The voltage magnitude has much higher values, even exceeding 1.25 pu. The oscillating behavior can still be observed, but the attacker can force only 2 to 3 oscillation periods on the Volt/VAr controllers before the load flow calculation does not converge anymore.

The simulated month of July is exemplary in showing that weather or consumer effects can lead to an increased impact of the attack. Comparing the voltage magnitude in fig. 4(a) with the solar irradiation plot in fig. 4(b), we correlate the increased voltage magnitude with the increase solar irradiation of the course of the day. Considering the distributed VAr control scheme eq. (1), we see that the controller considers the current voltage magnitude as well as the previous VAr setpoint. Since the VAr setpoints are given as values relative to the inverter’s current maximum, the controller overshoots the target, thereby amplifying the attack.

Scenario 3

Scenario 3 introduces a learning agent as attacker in addition to scenario 3. To summarize, the third scenario then employs the CIGRÉ network with PV feed-in, time series both for weather and for consumers, the Volt/VAr controller logic eq. (1) defines, as well as a learning attacker. The attacker uses SAC as learning algorithm.

Figure 5(a) confirms that the agent has learned to reproduce the attack. Note, that the agent was given no indication that the alternating setpoints behavior would lead to this result.

In fact, the denser nature of the plot in fig. 5(a) shows that the attacker learns to alternate the setpoints in a much quicker succession. Had the deterministic attacker in scenarios 1 and 2 a holdoff time of 25 steps, none such was implemented for the SAC-based attacker. This allowed the attacker agent to learn the value of $D$, i.e., the step size of the defender.

That the oscillating Volt/VAr control leads to the desired attack becomes evident from fig. 5(b). It shows the attacker’s objective (cf. fig. 2). The objective incentivizes a voltage band violation and punishes values close to 1.0 pu. Equation (4) therefore does not provide an immediate incentive for the attacker to adapt the oscillating behavior; in rather disencourages it. However, in face of the Volt/VAr control regime eq. (1), the attacker learns that the oscillating behavior is the only sensible course of action.

Discussion and Limitations

Volt/VAr controllers do not provide protection against malicious network actors. Deterministic Volt/VAr control schemes are vulnerable: Once known, it can be exploited in theory with any deterministic attacker. However, we show that even in absence of any knowledge about the grid topology or the control scheme, attacks are possible.

In practice, the impact of these attacks is mitigated by many other influencing factors. Usually, a power grid’s design provides enough robustness against these kind of attacks. However, the vulnerability remains and can be exploited. With the
Figure 4: System behavior for the simple alternating attacker with time series.
Figure 5: System behavior for the simple alternating attacker with time series
general tendency to eschew physical grid extension in favor of a more intelligent grid control, the grid’s inherent “buffer” against these kind of attacks grows ever smaller. While efficient grid control instead of physically deploying more cabling and assets is generally favorable since it is more sustainable, it also works in favor of these kinds of attacks.

The threat to the power grid depends on the degree of influence of the attacker. Our experiment design (cf. ??) forms a limitation in this regard: In order to pose a consistent threat against the CIGRÉ benchmark grid, the inverter-based generators have been scaled to 45 MVA peak output. Without loss of generability, we argue that our PV plant model can be replaced by wind farms, where 45 MW peak output constitute a reasonable value.

Loads can both strengthen and weaken the deterministic attack. If loads and attackers act in the same direction at the same time, the effect is additionally amplified; if the attacker acts against the load, it weakens the attack as the attacker effectively acts like a benign Q controller. Both effects have an impact on the reaction of the voltage regulator, because it does not react to the action of the attacker, but to the bus voltage.

Due to the design of the objective and the configuration of the power grid, the voltage only oscillates in the range above overvoltage. The objective of the agent evaluates voltages close to 1.0 pu poorly. The grid tends to have an overvoltage due to the configuration. Undervoltage would only be possible by an action of the agent. During exploration, a sufficiently large undervoltage does not occur, so the agent only learns to generate an overvoltage. In a different network configuration, oscillation between overvoltage and undervoltage would also be possible. Adjusting the objective could also bring this about. However, this could minimize the damage, since the oscillation would have to be larger to get into critical areas. The attack could also be implemented in a network configuration with a tendency to undervoltage.

DRL can reproduce the attack and exploit the Q controller’s vulnerabilities. Since the Volt/VAr control scheme employed has the vulnerabilities demonstrated in scenario 1 and 2, a learning agent can find and exploit them. In addition, by exploring the solution space and adaptive properties, the agent is able to optimize the attack.

The adaptive capability gives the attacker an unfair advantage over the defender. If the defender has a vulnerability, the attacker can search for it, find it, and exploit it, given enough time. The defender lacks an adaptive and adequate way to react. Past publications in DRL research have shown that especially multi-agent autocurricula—our setup also being one—can find any possible solution vector and even explore and exploit weaknesses in the underlying simulation environment to this end [23].

This attack shows that adaptive controllers are needed that can react depending on the situation and adapt to new attack patterns. The task of defending the power grid against attacks is more complex, since all possible attack vectors must be covered. However, in the case of learning attackers, the defender also represents a possible attack vector, as these experiments show. Complete coverage is therefore difficult to implement, due to the possible further exploration of the attacker. Instead, robustness should be pursued through continual adaptation. The continual
adaptation and self-optimization of the defender reduces the risk of becoming a target of the attack itself.

Like the work of Ju and Lin [4], simplifying assumptions were made in this scenario. There is no inertia in the power grid; grid codes concerning, e.g., voltage gradients, are also absent. A Distribution System Operator (DSO) would have the attacker disconnected after the first oscillation due to violation of these codes. As future work, we will extend our scenarios with exactly these grid codes, posing the attacker to find a new attack vector.

This work shows that theoretical attack scenarios can have an impact even as the degree of realism increases. The identified vulnerabilities should be addressed in future work. However, due to the abstraction required and the still very sterile simulation environment, the threat of the identified attack vector to real power systems is low. However, it demonstrates very clearly how more realistic, complex simulations and scenarios are urgently needed to identify potential real-world vulnerabilities and develop countermeasures at an early stage.

Conclusion

This paper has considered voltage attacks with distributed DERs and investigated a learning agent’s ability to discover and exploit a Volt/VAr control scheme. Through scenarios that build on each other, we experimentally verified that simple oscillating behavior of a malicious agent can cause a voltage disruption by forcing other benign agents into the same oscillating behavior, thus amplifying the attack; moreover, we verified that this behavior is still relevant even with time series for consumption and weather applied to the simulation; and finally, we showed that DRL can be used to uncover such a vulnerability.

We have seen that the DRL agent is able to drive a far more effective attack by uncovering the step size of the Volt/VAr control scheme. We assume that an adaptive Volt/VAr control scheme, possibly also backed by a learning agent, could mitigate the attack.

In the future, we will investigate this defender. We also plan to employ a more realistic grid by implementing grid codes and asset constraints.

Funding

This work was funded by the German Federal Ministry of Education and Research through the project PYRATE (01IS19021A).

Availability of data and materials

Relevant code and experiment definitions to reproduce all experiment runs for this paper are available at the following Gitlab repository: https://gitlab.com/Niwen/attack-paper

Author’s contributions

Eric MSP Veith conducted experiment runs, analysis, and wrote the corresponding sections. He is also one of the main contributors to the framework palaestraI that was used to carry out the analyses.

Nils Wenninghoff implemented the SAC learning agent. Together with Eric MSP Veith, he created the initial reward design and was responsible for the Q control scheme. He is also one of the main contributors to the framework palaestraI that was used to carry out the analyses.

Stephan Balduin contributed the power grid model, models for PV, and all time series. He is the main author of the simulation modelling framework MIDAS.

Thomas Wolgast sanitized the attack design and fine-tuned the scenario design.

Sebastian Lehnhoff was responsible for the overall plausibility and verification of the simulation models and testbed.

Competing interests

The authors declare that they have no competing interests.
25. Haarnoja, T., Zhou, A., Abbeel, P., Levine, S.: Soft actor-critic: Off-policy maximum entropy deep reinforcement learning. 1801.01290. Accessed 2021-12-22

22. Schrittwieser, J., Antonoglou, I., Hubert, T., Simonyan, K., Sifre, L., Schmitt, S., Guez, A., Lockhart, E., Lai, M., Lanctot, M., Sifre, L., Kumaran, D., Graepel, T., Lillicrap, T., Horgan, D., Piot, B., Azar, M., Dabney, W., Graepel, T., Hassabis, D.: Mastering the game of Go without human knowledge. Nature 550(7676), 354–356 (2018).

21. Silver, D., Hubert, T., Schrittwieser, J., Antonoglou, I., Lai, M., Guez, A., Lanctot, M., Sifre, L., Kumaran, D., Graepel, T., Lillicrap, T., Simonyan, K., Hassabis, D.: Mastering chess and shogi by self-play with a general reinforcement learning algorithm. 1712.01815

20. Silver, D., Schrittwieser, J., Simonyan, K., Hassabis, D.: A reinforcement learning approach for sequential decision-making processes in large and complex systems. In: Energy 2019, The Ninth International Conference on Smart Grids, Green Communications and IT Energy-aware Technologies, pp. 32–39. IARIA XPS Press, Athens, Greece (2019). 1811.06447

21. Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T., Hassabis, D.: Mastering the game of Go without human knowledge. Nature 502(7466), 484–489 (2016). doi:10.1038/nature12663

19. Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T., Hassabis, D.: Mastering chess and shogi by self-play with a general reinforcement learning algorithm (2017). 1712.01815

18. Hessel, M., Modayil, J., Van Hasselt, H., Schaul, T., Ostrovski, G., Dabney, W., Piot, B., Azar, M., Dabney, W., Graepel, T., Hassabis, D.: Rainbow: Combining improvements in DQN. The Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18), 3215–3222 (2018)

17. Lillicrap, T.P., Hunt, J.J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., Silver, D., Wierstra, D.: Continuous control with deep reinforcement learning. 4th International Conference on Learning Representations, ICLR 2016 Conference Track Proceedings (2016). 1509.02971

16. Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., Hassabis, D.: Human-level control through deep reinforcement learning. Nature 518(7540), 529–533 (2015). doi:10.1038/nature14236

15. Veith, E.M., Balduin, S., Wenninghoff, N., Troschel, M., Fischer, L., Nietzsche, A., Wolgast, T., Sethmann, R., Allen Hamilton 12, 20 (2016)

14. Fischer, L., Memmen, J.M., Veith, E.M., Troschel, M.: Adversarial resilience learning—towards systemic vulnerability analysis for large and complex systems. In: ENERGY 2019, The Ninth International Conference on Smart Grids, Green Communications and IT Energy-aware Technologies, pp. 26–32. IARIA XPS Press, Athens, Greece (2019). 1811.06447

13. Ni, Z., Paul, S.: A Multistage Game in Smart Grid Security: A Reinforcement Learning Solution. IEEE Transactions on Smart Grid 8(4), 2630–2638 (2017). doi:10.1109/TSG.2015.2495133

12. Ni, Z., Paul, S., Zhong, X., Wei, Q.: A reinforcement learning approach for sequential decision-making processes in large and complex systems. In: ENERGY 2019, The Ninth International Conference on Smart Grids, Green Communications and IT Energy-aware Technologies, pp. 3–12. IARIA XPS Press, Lisbon, Portugal (2020). 2006.06074. http://arxiv.org/abs/2006.06074

11. Veith, E.M., Fischer, L., Troschel, M., Nieße, A.: Exploiting cybersecurity controls through adversarial attacks. In: Proceedings of the Third ACM Conference on Cyber Security. ACSAC '19, pp. 1–11. ACM Press, New York, New York, USA (2019)

10. Mehrdad, S., Mousavian, S., Madraki, G., Dvorkin, Y.: Cyber-Physical Resilience of Electrical Power Systems Against Malicious Attacks: A Review. Current Sustainable/Renewable Energy Reports 6(1), 14–22 (2018).

9. Chen, Y., Huang, S., Liu, F., Wang, Z., Sun, X.: Evaluation of reinforcement learning-based false data injection attack to automatic voltage control. IEEE Transactions on Smart Grid 10(2), 2158–2169 (2019). doi:10.1109/TSG.2018.2790704

8. Chen, Y., Tan, Y., Zhang, B.: Exploiting vulnerabilities of load forecasting through adversarial attacks. In: Proceedings of the Tenth ACM International Conference on Future Energy Systems - e-Energy '19, pp. 1–11. ACM Press, New York, New York, USA (2019)

7. Liang, G., Zhao, J., Luo, F., Weller, S.R., Dong, Z.Y.: A Review of False Data Injection Attacks Against Cyber-Physical Systems. IEEE Transactions on Smart Grid 8(4), 2648–2657 (2017).

6. Wolgast, T., Veith, E.M., Nieße, A.: Towards reinforcement learning for vulnerability analysis in power-economic systems. Energy Informatics 4(53) (2021)

5. Zhu, H., Liu, H.J.: Fast local voltage control under limited reactive power: Optimality and stability analysis. IEEE Transactions on Smart Grid 10(2), 2158–2169 (2019). doi:10.1109/TSG.2018.2790704

4. Ju, P., Lin, X.: Adversarial attacks to distributed voltage control in power distribution networks with DERs, S3 (2021). https://doi.org/10.1109/TSG.2015.2495133

3. E-ISAC: Analysis of the Cyber Attack on the Ukrainian Power Grid: Defense Use Case

2. Reuters: Ukrainian banks, electricity firm hit by fresh cyber attack. Reuters (2017)
26. Rudion, K., Orths, A., Styczynski, Z.A., Strunz, K.: Design of benchmark of medium voltage distribution network for investigation of dg integration. In: 2006 IEEE Power Engineering Society General Meeting, p. 6 (2006). doi:10.1109/PES.2006.1709447

27. Zhu, H., Liu, H.J.: Fast local voltage control under limited reactive power: Optimality and stability analysis. IEEE Transactions on Power Systems 31(5), 3794–3803 (2016). doi:10.1109/TPWRS.2015.2504419