The Adversarial Resilience Learning Architecture for AI-based Modelling, Exploration, and Operation of Complex Cyber-Physical Systems

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Abstract

Modern algorithms in the domain of Deep Reinforcement Learning (DRL) demonstrated remarkable successes; most widely known are those in game-based scenarios, from ATARI video games to Go and the StarCraft II real-time strategy game. However, applications in the domain of modern cyber-physical systems (CPS) that take advantage of a vast variety of DRL algorithms are few. We assume that the benefits would be considerable: Modern CPS have become increasingly complex and evolved beyond traditional methods of modelling and analysis. At the same time, these CPS are confronted with an increasing amount of stochastic inputs, from volatile energy sources in power grids to broad user participation stemming from markets. Approaches of system modelling that use techniques from the domain of Artificial Intelligence (AI) do not focus on analysis and operation. In this paper, we describe the concept of Adversarial Resilience Learning (ARL) that formulates a new approach to complex environment checking and resilient operation: It defines two agent classes, attacker and defender agents. The quintessence of ARL lies in both agents exploring the system and training each other without any domain knowledge. Here, we introduce the ARL software architecture that allows to use a wide range of model-free as well as model-based DRL-based algorithms, and document results of concrete experiment runs on a complex power grid.

1 Introduction

A cyber-physical system (CPS) is constituted of two components: On the one hand a physical-component, in which sensors perceive the system’s environment and actuators exert actions on that environment. On the other hand a cyber-component, where Information and Communication Technology (ICT) connects the distributed sensor and actuator components of the CPS to a computerized decision-making engine. Artificial Intelligence (AI) technologies have become an essential part in almost every domain of CPS. Reasons include the thrive for increased efficiency, business model innovations, or the necessity to accommodate volatile parts of today’s critical infrastructures, such as a high share of renewable energy sources. Over time, AI technologies evolved from an additional input for an otherwise solidly defined control system, through increasing the state awareness of a CPS, e.g. Neural State Estimation [5], to fully decentralized but still rule-driven systems, such as the Universal Smart Grid Agent [37]. All the way to a system where all behavior is based on machine learning, with AlphaGo, AlphaGo Zero and MuZero probably being the most widely-known representatives of the last category [32, 29].

Numerous systems are nowadays considered CPS, from most of today’s cars, trains, aircrafts, to, in particular, most of today’s critical infrastructures. In a recent survey we found that there is no
methodology for a comprehensive full-system testing [39]: Traditionally, CPS analysis is based on sound assumptions, e.g., employing models and assertions formulated in Metric Interval Temporal Logic (MITL), abstracting complexity through contracts, or employing simulation to check whether pre-defined invariants hold. While CPS are complex, the AI domain, in particular Deep Learning (DL) algorithms, lacks reliable guarantees; there is no definitive way to debug a neural network. When definite assertions cannot be given, falsifying the proposed properties of a system is a valid tactic. Hence, researchers are concerned with ways to “foil” the system, i.e., attacking it through adversarial samples or by simply finding loopholes in its rule sets [22, 36, 21, 18].

How much system analysis can benefit from a Deep Reinforcement Learning (DRL)-based agent exploring the system has been documented by Baker et al. [2], where a simulation of hide-and-seek games has uncovered bugs in the underlying 3D engine as an unintentional side effect. Many attack vectors against CPS exist, research consequently advances the hardening of Artificial Neural Networks (ANNs) as CPS controllers or analyzes the behavior of ANNs in the face of certain activations to counter malicious inputs. But a vast research gap exists in using AI for model building and, subsequently, resilient operation strategies. This gap lies in exploring a complex CPS, uncovering of previously undescribed or unexpected interrelation between entities in the environment, and subsequently provide training data for a resilient operation of the same CPS.

In this paper, we describe the software architecture of Adversarial Resilience Learning (ARL). ARL [8] is our proposed methodology in which independent agents explore an unknown system, either probing for weaknesses or deriving strategies for a resilient operation. It works by two agents, an attacker and a defender, competing against each other for control of a CPS model. Therefore, we begin by describing related work for AI-based modelling and analysis of complex systems in section 2 to describe the broader context of ARL. In section 3, we give a brief introduction to ARL itself, as it is a rather young methodology. Section 4 describes the software architecture proper, focusing on how we incorporate different DRL methodologies and ensure a reliable experimental process. We then show results of ARL runs in a Capture The Flag (CTF)-like setting in section 5. A discussion of approach and results in section 6 as well as an outlook for future development in section 7 concludes this paper.

2 Related Work

ARL builds heavily on the various methodologies that have been developed in the domain of DRL. The first revival of DRL research with (end-to-end) Deep Q-Learning is marked by the hallmark publication by Mnih et al. [26] that focused on the idea that the sequence of observations is non-stationary and updates to the DRL policy network are highly correlated. As a result, the variations of Deep Q-Learning have seen numerous advances. The “rainbow paper” by Hessel et al. [16] is a good compilation of advances in this regard. Other approaches contributed to a healthy community research in and applying Deep Q-Learning, such as the Action-Branching Architectures by Tavakoli, Pardo, and Kormushev [35], who address the curse of dimensionality experienced in Deep Q-Learning.

One reason for the curse of dimensionality is the inability of Q-Learning to cope with continuous action spaces [23]. Policy gradient methods that combine reward and policy directly, are architecturally more fit to cope with continuous action spaces as they are often present in real-world scenarios. One of the early algorithms in this regard is REINFORCE [41]; modern approaches are represented by the actor-critic family, in particular Asynchronous Advantage Actor Critic (A3C) [25], Advantage Actor Critic (A2C) [24], or ACKTR [42].

All DRL methodologies, be it model-free ones like Q-Learning or policy gradient algorithms, or modern model-based approaches, such as MuZero by Schrittwieser et al. [29], have established a series of benchmark-like scenarios, from the ATARI games to beating Go world champions [32, 31, 29] to using race driving simulators [23].

Besides “benchmark-like” scenarios, DRL already finds application in simulations of critical infrastructures and interconnected markets. When leaving the realm of “pure” AI research towards that of CPS analysis and operation, the selection of DRL methodologies becomes more conservative. Predominantly the application of DRL is the subject of research, less the research on DRL itself. Examples, specifically from the domain of power systems, are the adaptive emergency control system by Huang et al. [19] or voltage control systems such as “Grid Mind,” presented by Duan et al. [6]: They focus on Q-Learning—often without the advances from the Rainbow Paper—or Deep
Deterministic Policy Gradient (DDPG), as they are more readily available from go-to libraries. Tang, Fang, and Zio [34] incorporate the idea of two agents competing against each other in a CPS setting; this attack-defender scenario is an idea parallel to our ARL [8] concept. However, the former have deliberately chosen a game-theoretic approach, whereas ARL uses any CPS simulation without restricting itself to a formal method of environment modelling.

However, all of these approaches treat the underlying DRL methods as a tool, opting to avoid a design in which algorithms, from simple Q-Learning to complex, distributed A3C and MuZero approaches, can be transparently combined and even benchmarked against each other. In contrast, the well-known OpenAI Gym environment and its extensions bring well-known, classic or extended settings, but have no equivalent for CPS analysis and operation [4, 1, 43, 12]. Bridging the two worlds—i.e., DRL research, and CPS analysis and operation research—and allowing for a transparent utilization and further development of many advanced DL and DRL methodologies (including, e.g., Meta-RL [40] or Neural Turing Machines [15]), is the goal of the ARL approach and the subsequently developed framework we present here.

3 The Adversarial Resilience Learning Concept

In ARL, we define classes of agents, of which two disjoint are most prominent: attacker agents and defender agents. The attacker’s goal is to de-stabilize a CPS, the defender’s utility function is based on robust or resilient operation of that CPS. ARL agents have no knowledge of each other, which makes sense in many real-world cases, e.g., in the power grid, where a deviation from nominal parameters can be caused by large-scale Photovoltaic (PV) feed-in, accidents, or an actual (cyber-) attacker. As such, agents perceive their world through the sensors they possess and act upon their environment through actuators.

In ARL, agents have no domain knowledge. More than that, their sensors do not provide them with any domain-specific information. All sensors and actuators are unlabeled; they return or accept values within a mathematical space definition, such as Discrete \( \{n\} \) for a range of discrete values \( 0, 1, \ldots, n \), or Box \( \{l_1, l_2, \ldots, l_n, h_1, h_2, \ldots, h_n\} \) for a bounded, \( n \)-dimensional box \( [l; h] \in \mathbb{R}^n \) [4]. These agents also gain rewards; the reward function turns them into attacker and defender, or something more nuanced in between, depending on the form of the function. However, the reward function is unit-less and conveys no direct domain-specific knowledge. The general direction of such an approach has already been verified: Ju and Lin [21], for example, show that little to no topographic knowledge is necessary for an effective attack against the power grid. The experiment results we show in this paper also verify that no domain-specific information needs to be conveyed at all for an effective functioning of the ARL agents.

We note that ARL has no connection to Adversarial Learning (AL). In AL, the subject of research is how to “foil” ANNs, i.e., made to output widely wrong results in the face of only minor modifications to the input. Even though seemingly similar by name, ARL should not be confused with AL, as the core problem of ARL is not the quality of sensory inputs, but the unknown CPS being subject to ARL execution. A second concept that is potentially similar in the name only is that of Generative Adversarial Networks (GANs): Here, one network, called the generator network, creates solution candidates—i.e., maps a vector of latent variables to the solution space—, which are then evaluated by a second network, the discriminator [13, 14]. Ideally, the results of the training process are results virtually indistinguishable from the actual solution space, which is the reason GANs are sometimes called “Turing learning.” The research focus of ARL is not the generation of realistic solution candidates; this is only a potential extension of the attackers and defenders themselves. ARL, however, describes the general concept of two agents influencing a common model but with different sensors (inputs) and actuators (output) and without knowing of each others presence or actions.

4 ARL Software Architecture

The ARL framework is intended to enable the training of DRL agents based on the ARL concept and to evaluate environments for possible vulnerabilities, as well as to develop strategies for a resilient operation for these environments. In order to guarantee the domain independence of the framework, ARL was designed to be as modular and therefore extensible as possible. The framework has four functional components; each component can be individually adapted, extended or replaced.
The design of experiments (DoE), as well as the setup of an experiment and the initialization of the individual experiment runs, are combined in the experiment component. The agent component embodies the DRL agents and works on an environment which serves as an interface to one or more simulations. The encapsulation into individual components with defined interfaces allows a separation of concerns in development and usage. This way, the ARL architecture can be transparently used to develop and test new DRL algorithms; the evaluation can then be performed on already implemented benchmark environments.

As the goal of the ARL methodology that is accommodated by the framework is the analysis and operation of CPS systems, the experimental environment is also a major part of the architecture. For sound and repeatable experiments, an abstract description language is used to define an experiment plan—including primitives for DoEs—and setup an environment. This includes the number and configuration of agents used as well as their integration into the environment. An experiment generator is used to derive concrete experiments from the experiment plan. Each experiment is then executed. Since the number of experiments increases strongly with increasing complexity, a decentralized execution architecture is used. ZeroMQ [17, 7] scales ARL horizontally over a distributed system.

### 4.1 ARL Experiment

The ARL architecture enables to execute comparable runs with different configuration settings, i.e., a series of soundly defined experiments. All the data required for an experiment plan are gathered in the CPS Abstract Ontology (CPS-AO). This includes references to models of the CPS, as well as to raw data for simulation, a co-simulation setup for execution, and settings for the parameters to be investigated. The CPS-AO allows a domain-independent description of the environment in a human-understandable format. Important settings, in addition to configuration settings of the CPS itself, are parameters for the DRL agents, such as the strategy, the reward function, or predefined access to sensors and actuators that is given in each and every experiment run. Finally, the CPS-AO describes sensors and actuators in the environment, but the space definitions introduced in section 3 are the only information attached to them.

The CPS-AO describes only the components relevant for the experiment, but not the topology. This is already implemented in the used simulation and thus the description of an experiment remains clear. I.e., the CPS-AO does not claim to be a universal description language for any CPS, but a format to describe the connection of existing models, simulators, and the ARL agent code. Hence, the term abstract ontology. The CPS-AO document is the source for the CPS Experiment Generator (CPS-EG) that generates concrete experiments with all necessary information to reproducibly run them.

The fan-out/fan-in type of parallelization that can be employed for multiple experiment runs is handled by the CPS Experiment Executor (CPS-EE). Each individual run is handled by a governor. Since some DRL algorithms rely on parallel and partly asynchronous execution of worker instances, such an experiment run can consist of a multitude of simulation environments, whose handling is also the task of the governor. The handling of parallel workers, including the distribution of weight updates between the workers, is the task of an agent conductor. It is also responsible to clone agents using DRL strategies that do not rely on such a parallel execution, such as simple Q-learning. This way, Q-learning agents can compete with A3C workers. Finally, the environment class serves as control and data interface for the agents, i.e., the agents never communicate directly with a domain model, but always with a co-simulated, abstracted environment.

All data from the stages of the experiment process, from raw data to software version references to experiment descriptions and parameters, to execution logs, are stored in a database as to ensure reproducibility and also allow later analysis. The whole flow of execution is depicted in fig. [1] while the more detailed class and package diagram is shown in fig. [2].

### 4.2 ARL Agents

ARL agents harbor the implementation of DRL algorithms as well as other methodologies, such as neuro-evolutionary approaches [33], or Neural Turing Machines. The overall agent is divided into a conductor and one or more agents/workers. But when a new algorithm is implemented, the implementer needs to adapt only two classes: The strategy and the strategy mutator.
The strategy contains the execution component of the DRL algorithm: A strategy has one public method, called `propose_actions(·)`. Its purpose is to map sensory inputs to actuator setpoints. For DRL algorithms, this encapsulates ANN, but it can as well be any simple replay, a decision tree, or any other method. The strategy also references an agent’s reward function.

However, the training is implemented in the strategy mutator as to allow asynchronous and parallel execution by more than one worker and to aid in clustering simulation approaches where machines with different hardware setups are used. For this purpose, the mutator receives both, the input values and the outputs including the rewards of all workers. It implements how a strategy’s parameters should be modified. Parameter distribution is delegated to the agent conductor, who also implements all low-level communication facilities. This way, weight updates of the mutator are first adopted in the global network of the Agent and then distributed according to the strategy. Thus, both synchronous and asynchronous procedures are possible.

The communication between the conductor, its workers, the governor, and between agents and environment is done via message passing on a ZeroMQ bus as to decouple all modules for large-scale parallelization. The instantiation of new agents is controlled by the run governors. At the beginning of an experiment, each run governor connects one or more agents/workers with one environment instance. Once a run is complete, e.g., because the CPS was successfully de-stabilized by an attacker, the run governor asks the conductors to spawn new workers, if necessary.

### 5 Experimental Architecture Verification Setup

In order to verify the general feasibility of the ARL concept and its software architecture, we have chosen a game-like setting: A CTF contest. CTF contests have their origin in the cyber-security scene, where two teams both control a set of servers with services they need to defend against the respective other team, i.e., both teams need to protect their “bases” as well as capture the “flag” from the contesting team. In the cyber-security scene, these flags are tokens that can be read once a service has been compromised. The DARPA Cyber Grand Challenge was the first to incorporate AI into this setting [10].

To test ARL, we chose a coin defense scenario: The defender starts with 10,000 points, called “coins,” which are being taken by the attacker when it succeeds in bringing elements offline. The number of coins a generator ($c_G$) or load ($c_L$) yields, depends on its nominal real power characteristic $P_N$ and the number of time steps $t$ it remains offline over the course of the whole simulation, denoted as $T$:

\[
    c_G = c_L = 0.1 P_N \frac{t}{T}.
\]  

(1)
A transformer that is being brought offline yields 20 coins, a power line 10 coins. The attacker wins when it has gained all coins from the defender over the course of the simulation.

In our set up, we use a realistic city-state power grid. In this model, Power is consumed by 40 load nodes ($\cos \phi = 0.97$), 18 of which represent aggregated subgrids—i.e., whole districts with statistically modelled power consumption from households, bakeries, etc.—22 are large-scale industry loads. It contains 2 conventional power plants ($\cos \phi = 0.8$), 5 wind farms, as well as a number of small PV installations—mostly on domestic rooftops—that are aggregated to 18 nodes ($\cos \phi = 0.9$); in total, these nodes generate a nominal power output of 51 MW. The grid features a total of 22 transformers, 4 of which connect the city’s medium voltage grid to the high-voltage distribution grid; the remaining 18 connect the city’s medium voltage grid to the low-voltage grids, where households and other regular consumers connect.

A disconnect is triggered by a violation of the grid code (Technical Connection Rules, TCR [9]) or by constructional constraints of certain nodes [3, 30]. Every time an agent acts, a power flow study is conducted and the result is checked against these constraints. A disconnection means that the attacker has won coins; thus, from the grid model, the coin distribution rules become obvious, as there are multiple ways for an attacker to gain them. For example, disconnecting a transformer means also disconnection all connected consumers, i.e., the attacker wins not only the 20 coins associated with the transformer, but also all coins associated with the corresponding consumers that now fall dark. Similarly, disconnecting generators means that the city grid needs to be supplied from the external high voltage grid; once the connecting medium-high voltage transformer becomes overloaded, a whole district can fall dark. As such, the ARL attacker agent can explore many different strategies. Similarly, different potential strategies can be explored by the defender, too: For example, the transformer’s tap changer can be used to correct the voltage level to remain within the safe voltage.

Figure 2: The Adversarial Resilience Learning Software Architecture
band of [0.85; 1.15] pu, or big loads such as industries can be scaled down, generators used to counter fluctuating demand and supply or to control reactive power that is needed for voltage control.

All agents have sensors that provide the current voltage level at their respective connection point, expressed as a Box \((0.85, 1.15)\). Additionally, all loads and generators ‘sense’ their current power injection or consumption as a value relative to their nominal input/output (Box \((0.0, 1.0)\)). As actuators, loads and generators provide scaling setpoints; for DRL algorithms that are not able to natively represent continuous action spaces, they are discretized in 10% steps (Discrete \{11\}), otherwise, they are represented by Box \((0.0, 1.0)\). Tap changers describe their possible discrete tap positions, e.g., Discrete \{5\}. As described in section 3, no sensor or actuator contains direct domain knowledge. When agents need to assess their current performance and world state during play and before the CTF coins are distributed, they use a performance function modelled to the voltage values their sensors provide [8]:

\[
p_a(m(t)) = -1[a \in A_A] \exp \left[ -\frac{(\psi_a(m(t)) - \mu)^2}{2\sigma^2} \right] - c, \tag{2}
\]

where \(c\), \(\mu\) and \(\sigma\) parameterize the reward curve, \(-1[a \in A_A]\) negates the reward if \(a\) is an attacker [20], and \(\psi_a(\cdot)\) is the arithmetic mean of all inputs. Note that this reward function does not include any information specific to the energy domain. E.g., it treats the difference between 1.0 pu and 0.8 pu similar to a reduction to 0.5 pu, even though this would mean a tremendous success to the attacker compared to a reduction to 0.8 pu. This simplification was done deliberately as 0.8 pu usually provides a general disconnection point for hardware in the power grid, thereby already leading to a cascading blackout.

In our power grid scenario, the attacker controls all loads and static generators, while the defender also controls all loads, static generators, and the transformers. We have deliberately created a setting in which both agents can influence the same elements: After all, the attacker can realistically be a virus or botnet, which does not lock out the legitimate operator, but overrides actions.

6 Discussion

We have conducted numerous CTF tournaments—episodes organized in several rounds—to verify our assumption that agents can learn to meaningfully attack or operate a complex CPS, even when interfering with each other. Also, we wanted to verify that different algorithms can be pitched against each other, as to verify the benchmark-notion of the ARL architecture. Even though this publication does not offer an extended benchmark, we can nevertheless show the general feasibility of the ARL approach. Figure 3 shows averaged results for all runs.

In fig. 3(a), the attacker’s success becomes apparent, as it is able to gain coins from the defender in several CTF rounds. Figure 3(b) shows the defender’s reward curve that indicates training success for the defender, i.e., the agent is able to develop strategies to counter the attacks. Thus, each agent learns over the episodes; interfering agents do not necessarily form a chaotic system, which is important for ARL-like scenarios in general.

Figure 3(c) and 3(d) show how much the attacker exerted control over certain actuators, summed up and then averaged over all tournaments, with fig. 3(c) showing generators and 3(d) controllable loads. Similarly, fig. 3(e) show the defender’s actions on generators, and fig. 3(f) the defender’s actions on loads. This confirms that an attacker can leverage the potential damage of each node without requiring any topology knowledge by exploiting the other nodes’ behavior, as was shown by Ju and Lin [21]; also, this confirms that an attacker can cause most difficulties for an operator by exploiting simultaneity effects. In contrast, the defender prefers specific generators and loads for countermeasures; this confirms what an experienced operator would also do: Make use of system-relevant nodes to easily redeem the power grid.

Overall, this shows that the ARL architecture serves well to use different DRL algorithms to analyze and operate complex CPS.
7 Conclusion

Adversarial Resilience Learning (ARL) is a methodology that employs Deep Reinforcement Learning (DRL) algorithms to analyze and operate complex cyber-physical systems (CPS). We have detailed the ARL software architecture that allows the two ARL agents, attacker and defender, to work against each other in order to control the underlying CPS. During this, the two agents can employ different DRL algorithms, allowing to exploit and analyze the characteristics of these algorithms, as well as to compare advanced, but vastly different, DRL approaches. We have shown the feasibility of the ARL approach and the architecture in a Capture The Flag (CTF)-like tournament, with the ARL agents competing to control a realistic model of a complex power grid.

In the future, we plan to run a series of benchmarks on the same model, documenting and analyzing the effect of different DRL algorithms in the ARL setting, e.g., Rainbow Q-Learning against Advantage Actor Critic (A2C) or MuZero. We believe that the ARL framework can be used as a complex, real-world benchmark scenario for analysis and operation of complex critical infrastructures and other types of CPS, and even as a proving ground for complex, distributed control algorithms deemed as "robust" [11] [38] [27] for these infrastructures. We also hope to use it as a workbench to extract strategies for resilient operation of complex CPS from ARL runs, i.e., help to apply and advance explainable DRL [28].
**Broader Impact**

The ARL concept aims to be a methodology for Artificial Intelligence (AI)-based analysis and operation of complex CPS, specifically critical infrastructures. ARL explicitly ‘turns the tables’ on the problem of non-assessible Artificial Neural Network (ANN)- and DRL-based control schemes that can be prone to manipulation through adversarial samples, as in ARL, the attacker is already included. This system-of-systems-reinforcement-learning approach, where each agent learns not only to manipulate its environment, but to do so when another unknown party also does so, means that the agents become better with each round they play against each other as they continuously strive to develop better strategies.

This can be highly beneficial for operators of critical infrastructures: The attacker shows potential attack vectors against this infrastructure, which can be assumed to be realistic—depending on the model—as well as sophisticated, thanks to the defender. Furthermore, the attack scenarios can be used as training material for personnel. The defender’s use case is obvious—i.e., operation of the CPS—, but the domain-agnostic sensors and actuators can yield different use cases, such as in anticipatory design, where the operator’s user interface gets modified to highlight important information, present possible solutions, or assist in managing the flood of system messages from Supervisory Control and Data Acquisition (SCADA) systems by prioritizing or aggregating pieces of information.

We are fully aware that the system itself could be a valuable tool for defender and attacker alike; it does nothing to prevent a malevolent person from ‘throwing away’ the defender and utilizing the attacker on a real piece of critical infrastructure. We hope that, the more advanced our ARL concept evolves to be—e.g., by incorporating neuroevolution or similar strategies for full adaptivity—that we can also research a explainable deep reinforcement learning technique fitting for the ARL concept and, based on that, a hybrid architecture with a rule-based foundation that incorporates codified robotic laws into the ARL agents.

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