

# Testing Cyber-Physical Systems Against Adversarial Attacks

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## ABSTRACT

The constant threat of attack faced by cyber-physical systems (CPSs) in critical infrastructure has motivated research into a multitude of attack detection mechanisms, such as *anomaly detectors* based on underlying neural networks. The effectiveness of such a detector can be assessed by subjecting it to test suites of attacks, whether from benchmarks, or tools such as network fuzzers. While studies have shown that neural network-based detectors perform well against these conventional attacks, limited consideration has been given to testing their effectiveness against *adversarial attackers* that possess knowledge of the underlying model. In this paper, we present an adversarial attack for testing recurrent neural network (RNN) anomaly detectors of CPSs. Inspired by some white-box gradient-based approaches, our adversarial attacks produce *noise* (or *perturbations*) with the aim of causing an incorrect classification. We implement it against detectors for two real-world critical infrastructure testbeds, successfully reducing their classification accuracy. Finally, we demonstrate that the detectors of the testbeds can be successfully adapted to detect attacks that utilise such noise.

## KEYWORDS

Cyber-physical systems, testing attack detection mechanisms, anomaly detectors, adversarial attacks, neural networks.

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## 1 INTRODUCTION

Cyber-physical systems (CPSs), in which software components are deeply intertwined with physical processes, are ubiquitous in critical public infrastructure. The potential disruption that could result from a compromised system has motivated research into a multitude of CPS attack detection mechanisms, including techniques based on invariant checking [41], physical attestation [18], and fingerprinting [26]. A particularly popular solution is to build *anomaly detectors* [16, 21, 27, 38, 62], in which an underlying machine learning (ML) model is trained on streams of the system's physical data in order to judge when it deviates from the norm. Typically, this would be a form of neural network, a model that is powerful enough to learn and recognise the complex patterns of behaviour that CPSs exhibit.

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The effectiveness of an anomaly detector can be assessed by subjecting it to a test suite of attacks, and observing whether it can correctly identify the anomalous behaviour. These tests can be derived from benchmarks [40], hackathons [4], or tools such as fuzzers [20], and typically involve manipulating or spoofing the network packets exchanged between CPS components. While studies have shown that neural network-based detectors perform well against these conventional attacks [36, 40, 42, 56], limited consideration has been given to testing their effectiveness against *adversarial attacks*, in which an attacker with knowledge of the model crafts *noise* (or *perturbations*<sup>1</sup>) on the data to specifically cause the neural network to misclassify it. Such attacks have been successfully demonstrated in several different classification domains (e.g. images [45], audio [15], malware [32]), raising the question as to whether anomaly detectors in critical infrastructure are susceptible too. If an anomaly detector fails to detect adversarial tests, then its CPS is potentially at risk of a much broader range of attacks since they can simply be masked by crafted noise.

In this paper, we present an adversarial attack for testing recurrent neural network (RNN) anomaly detectors of CPSs. Our approach is inspired by the white-box gradient-based approach previously applied to deceive the classifiers of audio files [15], but adapted to meet the unique challenges posed by the critical infrastructure. First, while we can craft noise on sensors in the continuous domain, actuators typically fall into a small number of discrete states (e.g. 'open' or 'closed'). Second, in addition to anomaly detectors, the logic of these CPSs often also includes some built-in mechanisms for *rule-checking* (e.g. testing that a tank's valve is open if its level is low) to add another level of certainty that the system is operationally normal. We address these issues by using genetic algorithm to select optimized combination of actuator values.

We evaluate the effectiveness of our adversarial attacks by implementing them against RNN-based anomaly detectors for two real-world critical infrastructure testbeds: Secure Water Treatment (SWaT) [49], a multi-stage water purification plant; and Water Distribution (WADI) [8], a consumer distribution network. We demonstrate that our adversarial tests successfully and substantially reduce the classification accuracy of their anomaly detectors, thus revealing a security flaw that could be exploited. We show that a rule-checking mechanism in SWaT has weakened our threat model, but with the application of a genetic algorithm, we can still achieve a similar accuracy reduction for the anomaly detectors. Finally, we go a step further and show that by training the RNNs on some noisy data, the anomaly detectors of SWaT and WADI can successfully identify that an adversarial attack is in progress.

**Our Contributions.** Our contributions are summarised as follows:

- We define a threat model for CPS adversarial attackers, and propose a white-box gradient-based attack to construct adversarial tests for deceiving RNN-based anomaly detectors.

<sup>1</sup>We will use noise and perturbation interchangeably.

- We re-implement SWaT’s RNN-based anomaly detector [27], extending it to cover the whole CPS, and learning another in parallel to cover WADI.
- We implement our adversarial attacker, and test it against the SWaT and WADI RNN-based anomaly detectors.
- We find that our approach significantly reduces the accuracy of the detectors to the point that masking other attacks is feasible.

**Organisation.** In Section 2, we provide the necessary background and present our threat model. In Section 3, we introduce our experiment design and methodologies to construct adversarial examples. We show our empirical study results on SWaT and WADI in Section 4. Finally, we review related works in Section 5 and conclude in Section 6.

## 2 BACKGROUND

In this section, we state our assumptions about the structure of CPSs, and introduce two real-world examples that our work will be evaluated. Following this, we define the threat model that our tests will be based on, as well as what constitutes a conventional and adversarial attack. Finally, we provide some background about the anomaly detectors we are testing, as well as the rule-checking mechanisms that may guard them.

### 2.1 Cyber-Physical Systems

In general, we assume that CPSs consist of two interconnected parts. First, a ‘physical’ part, in which various physical processes are monitored by sensors and acted upon by actuators. Second, a ‘cyber’ part, consisting of software components such as Programmable Logic Controllers (PLCs) [11] that implement some control logic. We assume that sensors, actuators, and PLCs are connected over a network, with PLCs taking sensor readings as input and computing commands to be returned to the actuators. Furthermore, we assume the presence of a Supervisory Control and Data Acquisition (SCADA) system built on top of the PLCs, that can supervise the control process and issue commands of its own.

We assume that CPSs contain two different types of countermeasures against attacks. First, the PLCs may contain some rule-checking mechanism [10], for checking that the sensor and actuator states pertain to some invariant properties (e.g. if a certain sensor is below a certain range, then a certain actuator should be disabled). Second, we assume that a neural network-based anomaly detector [16] is present in the SCADA.

**SWaT and WADI Testbeds.** We carry out our studies on two modern, real-world critical infrastructure testbeds: Secure Water Treatment (SWaT) [49], a water purification plant capable of producing five gallons of safe drinking water per minute; and Water Distribution (WADI) [8], a consumer supply distribution system. SWaT is a six-stage plant including processes such as ultra-filtration, de-chlorination, and reverse osmosis. WADI consists of three stages, across which water is moved into elevated reservoirs, then supplied to consumer tanks on a pre-set pattern of demand.

**Sensors and actuators.** In total, SWaT contains 68 sensors and actuators. Its sensors variously read the level of tanks, pressure, and flow across the system, whereas its actuators include motorised valves and pumps. Sensor readings are typically continuous values, whereas actuators are typically discrete (e.g. ‘open’ or ‘closed’; ‘on’ or ‘off’). Note that a number of SWaT’s actuators are ‘standbys’ that are intended to be used only when the primary actuator fails. These are not considered in our work. After filtering such actuators, there are a total of 25 sensors and 26 actuators which are targeted in our study. WADI contains 70 sensors and 51 actuators, of a similar kind to those seen in SWaT.

The physical state of a testbed is a fixed ordering of all the sensor readings and actuator configurations at a particular timepoint. Table 1 illustrates four such states from the first stage of SWaT (handling supply and storage). There are two sensors covering water flow (FIT101) and the tank level (LIT101), as well as a motorised valve (MV101) controlling at the inflow pipe of the tank, and a primary pump (P101) and secondary pump (P102) for pumping water out of the tank. The logged data over four seconds indicates that water is flowing into the tank and thus the level is increasing.

Formally, we will use  $x$  to denote a system state, consisting of a fixed order of actuators and sensors:

$$x = [x_{a1}, x_{a2}, x_{a3} \dots x_{s1}, x_{s2}, x_{s3} \dots]$$

Here, each  $x_a$  represents an actuator value and each  $x_s$  represents a sensor value.  $X$  is the set of all possible system states. Let  $S$  be a sequence of system states. We use  $S[i]$  to denote the  $i$ -th state in the sequence,  $S[i : j]$  to denote the sequence of system states from time  $i$  to  $j$ , and  $S[i : ]$  to denote the sequence of states from time  $i$  to the present.

**Communication and control.** SCADA workstations are located in the plants’ control rooms. A Human Machine Interface (HMI) is also located inside each plant and can be used to view the process states and set parameters. Control code can be loaded into the PLCs via the workstations. We can also acquire data logs (as well as network packet flows) from the historian at preset time intervals.

A multi-layer network enables communication across all components of SWaT and WADI. A ring network at Layer 0 of each stage enables the responsible PLC to communicate with sensors and actuators, whereas a star network at Layer 1 of the network enables communication between the PLCs. Supervisory systems such as the workstation and historian sit at levels further above.

### 2.2 Threat Model for Testing

Given that we are testing the security of CPSs, we define a threat model that states our assumptions of what an attacker knows about the system and is capable of doing within it.

As depicted in Figure 1, our threat models assumes a white-box setting where an attacker has the following capabilities:

- the attacker is able to compromise the data transmitted from the physical part of the CPS to the PLCs at Layer 0 of the network;
- the attacker has full access to the RNN-based anomaly detector, including the network architecture, parameters, inputs, outputs, and other attributes;

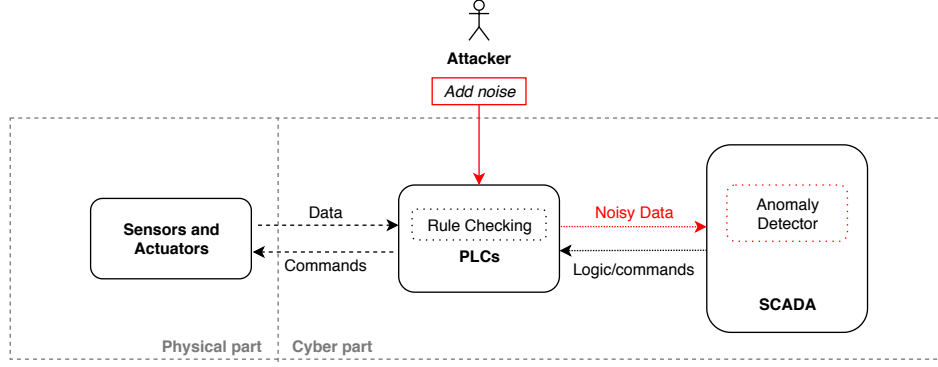


Figure 1: Overview of a cyber-physical system and an adversarial attacker

Table 1: Example of log data from the SWaT historian

Timestamp	FIT101	LIT101	MV101	P101	P102	Normal/Attack
28/12/2015 10:00:00 AM	2.427057	522.8467	2	2	1	Normal
28/12/2015 10:00:01 AM	2.446274	522.886	2	2	1	Normal
28/12/2015 10:00:02 AM	2.489191	522.8467	2	2	1	Normal
28/12/2015 10:00:03 AM	2.53435	522.9645	2	2	1	Normal

- the attacker is aware of the presence of a rule-checking mechanism, but cannot access any information about it other than inputs and outputs.

## 2.3 Attacks and Detection Mechanisms

**CPS Attacks.** With the capabilities given by the threat model, *conventional* CPS attacks are carried out by spoofing the sensor values that are transmitted from the physical part of the system to the PLCs, causing the control logic to issue the wrong actuator commands. For example, if a tank is near-empty, but an attacker spoofs a tank level sensor that is critically high, the pump could incorrectly be activated and lead to some underflow damage. Other examples are given in Table 2. The SWaT and WADI testbeds are equipped with benchmarks [40] containing multiple different attacks of this kind, which have been used to test the effectiveness of different countermeasures [36, 40, 42, 56]. Furthermore, data sets [40] are available containing several days of physical data resulting from subjecting the testbeds to these attacks. This data is suitable for training complex ML models such as RNNs and other kinds of neural networks.

In this paper, we aim to test CPSs against more than just these conventional attacks, by expanding the repertoire of attackers to include *adversarial attacks*. Using their knowledge of underlying RNN of the anomaly detector, adversarial attackers focus on crafting *adversarial examples* that maximise some measure of harm, while masking their true effects from detectors by using carefully applied noise that deceives them.

To judge the success of a conventional attack, we can check whether at a certain time point  $t$  there is an *observable impact* in the physical state,  $S[t]$ , i.e. the physical state differs from what it would have been in normal operational conditions. As this is not

simple to conclude in general, instead, we leverage the operator-specified acceptable ranges of sensor values to identify that the system has been successfully attacked. For example, in SWaT, LIT101 indicates the water level in the first stage. If the reading is above 1100mm, then while it might not yet have overflowed, it is outside its acceptable range, and thus we conclude that the system is under attack.

To judge whether an adversarial attack is successful is somewhat more complicated. Essentially, the goal is to deceive the anomaly detector and cause it to give an incorrect classification. For example, if the system is behaving normally and is being classified as such, the goal is to apply a minimal amount of noise such that the net behaviour of the system *doesn't* change, but the anomaly detector classifies it as anomalous (i.e. a false alarm, decreasing confidence in the detector). On the other hand, if the attacker is spoofing sensor values and causing the behaviour to be classified as anomalous, the goal is to craft noise that *doesn't* affect the net behaviour (i.e. it remains anomalous in the same way) but causes the detector to classify it as normal. As a result, for the purposes of experimentation, it is important to be able to conclude that physical effects on the system *before* the noise is applied are the same *after* it is applied too.

As the definition of the attacks is dynamic with changes of input data, so for every prediction of  $f$ , we have to generate the status labels as the ground truth, Figure 2 shows an overview of how results generated. Vertically, Data S is the original attack data, Data S' is noisy data after gradient-based attack by model N, and S'' is GA selected data to pass rule checker R. Horizontally, from each data set (S, S' and S''), we calculate  $Y_T$  as the ground truth to compare with the anomaly detector results  $Y_C$  and get outputs. The *Output* inside figure refers to a lists of standards such as precision, *recall* *f1*, etc.

Table 2: Example of modifications

Start Time	End Time	Attack Point	Start State	Modification
10:29:14	10:44:53	MV-101	MV-101 is closed	Open MV-101
10:51:08	10:58:30	P-102	P-101 is on where P-102 is off	Turn on P-102
11:22:00	11:28:22	LIT-101	Water level between L and H	Increase by 1 mm/s

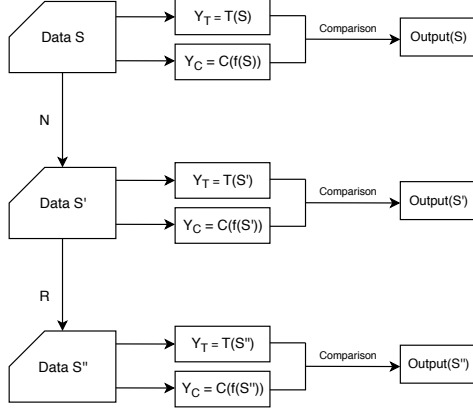


Figure 2: An overview of input vs output

**Attack Detection Mechanisms.** Finally, we describe in more detail two different kinds of attack detection mechanisms, both in the context of SWaT: a rule checker [3], and an RNN-CUSUM anomaly detector [27].

*Rule checking.* Adepu and Mathur [3] have systematically derived a set of invariants, consisting of 23 rules that describe the relationship between sensor and actuator values of SWaT. The idea of rule checking is to implement a set of pre-defined rules in the PLCs that should never be violated. For instance, a sensor value should never exceed its operation range, or regulations that the system should follow under normal operation. We use  $R$  to denote the set of rules implemented in PLCs for checking. Once a rule  $r \in R$  is violated, the system will raise an anomaly alarm to report that the system is in an abnormal state. Some rules are shown in Table 3. Let us take rule 1 as an example. The rule specifies that under the condition that sensor “LIT101” is equal or smaller than 500, the actuator “MV101” is supposed to be 2 after 12 seconds.

*RNN-based anomaly detectors.* The idea of learning-based anomaly detectors is to model the normal behaviour of the system from a piece of data historian  $S$  using a machine learning model (denoted by  $f$ ). At run time, the system looks at the historian data (of a window-size length), use  $f$  to predict the system state  $x'$  and compare it with the actual system state  $x$ . If the difference is beyond a threshold, the system is likely to be abnormal. In the work from Goh et al. [27], a RNN with LSTM architecture [35] is used as the prediction model and a CUSUM algorithm (denoted by  $C$ ) is used to calculate the differences between the actual value and the predicted value. This approach has been applied to the first stage of SWaT, and is shown to be effective for it. In our work, we re-implement

their approach but for all six stages of SWaT, and all three stages as WADI, as the defence mechanism for us to test.

### 3 EXPERIMENT DESIGN AND METHODOLOGY

Under the mentioned threat model and attack scenarios in section 2.2, we aim to answer the following questions: 1) Is our adversarial attacks effective on real-world CPS? 2) how should the attacker compromise the original data to deceive the rule checking system and the anomaly detector? 3) how can we design a defence against such adversarial examples? Experiments are designed to answer the research questions. To descent the performance of the anomaly detector of CPSs, there are some difficulties to complete the testing experiments.

- There are limited works on adversarial attacks on CPS, especially for anomaly detector with RNN, thus we do not have many references.
- There could be more than one anomaly detection system inside the CPS, to complete an adversarial attack, we need to consider all defences.
- A CPS system is normally complicated and composed with sensors and actuators, and for different physical components, the data type and range are different.
- Unlike statistical attacks, CPS is dynamic and hard to predict, a minor change may lead to the whole system break down.

For a basic set up of CPSs, data from sensors and actuators go directly to RNN predictor for attack detection, we apply a thread model with gradient-based adversarial attack to deceive the anomaly detector directly. While for many CPSs, a rule checking system as we described in 2.3 is implemented to check if data obey the rule (difficulty 2). For those systems, if the adversarial attack is able to deceive RNN predictor but detected by the rule checking system, we use generative algorithm to overcome the rule checker. Figure 3 provides an overview of the thread model and algorithm 1 show the logic to generate the adversarial examples.

#### 3.1 Dataset

Our study is based on the SWaT dataset [40], which is a publicly available dataset [39] and has been used in multiple projects [27, 61]. The dataset records the system state of 26 sensor values and 25 actuators (in total 51 features) every second. The sensor values are integer or float while the actuator values are discrete with 0 (actuator is opening/closing), 1 (actuator is closed) or 2 (actuator is open). The dataset consists of two types of data:

- *Normal data:* The normal dataset  $S_n$  is collected for 7-days (a total of xxx records) when the system is under normal operation. The data is used to train the LSTM anomaly detector.



Table 3: Examples of rules

Num	Condition	Rule	Time
1	LIT101 $\leq$ 500	MV101 = 2	12
2	LIT101 $\leq$ 250	P101 = 1 AND P102 = 1	2
3	LIT301 $\leq$ 800	P101 = 2 OR P102 = 2	12
4	AIT201 > 260 and FIT201 > 0.5	P201 = 1 AND P202 = 1	2

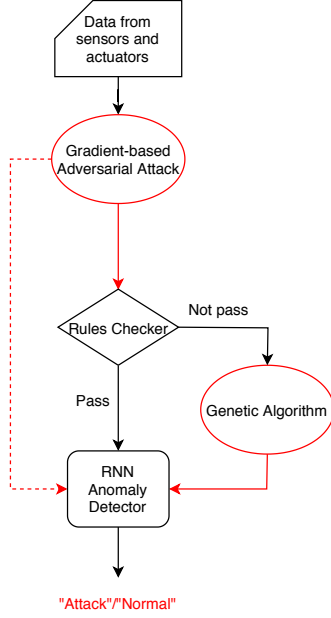


Figure 3: An Illustration of Data Flow for Adversarial Attack Scenario

**Algorithm 1: Overall Algorithm**

**Input:** Data  $S_i$ ; RNN predictor model  $f$ ; rule Checker  $R$ ; noise level  $\delta$

**Output:** adversarial examples

- 1 Get gradient direction from  $f$  of loss r.p.t inputs data  $S_i$ ;
- 2 Apply the noise  $\delta$  to  $S_i$  along or opposite the sign of gradients to get  $S'_i$ ;
- 3 **if**  $S'_i$  cannot pass rule checker **then**
- 4    $S''_i = GA(S'_i[i]);$
- 5 **else**
- 6    $S''_i = S'_i;$
- 7 **end**
- 8 **return**  $S''_i$

- **Attack data:** The attack dataset  $S_a$  is collected for 4-days (a total of 449909 records) by 36 attacks with labels (normal or attack). The data is used as testing data for the trained anomaly detector.

**3.2 RNN predictor**

We train a RNN in LSTM architecture from normal data as the prediction model. The trained model is a many-to-one prediction model  $f : S \rightarrow X$  which takes a certain sequence (parameterized by window size) of data historian as input and makes the prediction of the output of the coming timestamp. For example, a window size of 10 represents a sequential input of the past 10 timestamps.

Once we obtain the predicted output at each timestamp, we then adopt the CUSUM algorithm [13] to decide whether the system is in abnormal state as follows. The difference  $d$  at timestamp  $i$  (denoted as  $d[i]$ ) is calculated from the predicted value  $x'[i]$  by the RNN model and the actual value  $x[i]$ , the difference  $d$  will then be added cumulatively with an allowable slack  $c$ . We calculate the CUSUM for each sensor with both positive and negative value by the following formula:

$$\begin{aligned}
 SH[i] &= \max(0, SH[i-1] + d[i] - c) \\
 SL[i] &= \min(0, SL[i-1] + d[i] + c) \\
 d[i] &= X'[i] - x[i],
 \end{aligned} \tag{1}$$

where  $SH$  represents the set of high cumulative sum and  $SL$  represents the low cumulative sum,  $d$  is the difference between the predicted value  $x$  and actual value  $x'$ , and  $c$  is the allowable slack which is defined as 0.05 multiplied by the standard deviation of  $S$ . Besides, two thresholds, i.e., a Upper Control Limit (UCL) and a Lower Control Limit (LCL) for  $SH$  and  $SL$  to compare with respectively are required to check whether the system is in abnormal state. Normally, UCL and LCL are defined according to the experiment validation of the training data. Table 4 shows the UCL and LCL from stage 1 as an example.

**3.3 Adversarial Attacks**

Our next step is to construct adversarial examples which aim to deceive the anomaly detectors. We consider two cases. Firstly, we construct adversarial examples only to deceive the RNN predictor. Secondly, we take a step further to deceive both the RNN predictor and the rule checking system, which is more challenging. In both cases, we assume a white-box attack that the attacker could access the trained RNN model (and its parameters) and the attacker is able to compromise the data transmitted to the PLCs. The goal of the attacker is thus finding a minimum perturbation  $\delta$  on the original input  $\mathbf{x}$  such that the detector will make a different decision from the original one. Formally, given the input  $\mathbf{x}$  at each timestamp and the RNN detector  $f$ , the objective of an attacker is to:

$$\begin{aligned}
 &\min \delta \\
 &\text{s.t., } f(\mathbf{x}) \neq f(\mathbf{x} + \delta) \text{ and } \|\delta\| \leq \tau
 \end{aligned} \tag{2}$$

Table 4: Upper and Lower control limit

Senor	Upper Control Limit	Lower Control Limit
FIT101	2	-1.5
LIT101	50	-2

where  $\tau$  is a small value which restricts the manipulation range of  $\mathbf{x}$  according to a certain norm  $\|\cdot\|$  (to measure the distance of the modification). The success of such an attack will deceive the detector in two folds. In the case that the detector detects an actual anomaly, the adversarial attack will be able to bypass the detector and put the system in danger (without noticing that the system is in the abnormal state). In the case that the detector detects an actual normal status, the adversarial attack will deceive the detector to raise false alarms. We remark that how to construct adversarial examples using Eq. 2 has been extensively investigated in multiple domains [29, 37, 48, 60]. In the following, we introduce in details how we solve the problem in our setting.

**3.3.1 Adversarial Attacks on RNN predictor.** In the primary setting, we only aim to construct adversarial examples for the RNN detector. Notice that the detector uses CUSUM to check the difference between the predicted output and the actual output. Thus, we need to minimize the difference between the predicted value and targeted value in order to deceive the CUSUM checker. On the other hand, we may need to minimize the loss of actual value and the targeted by RNN. Consider the RNN predicts sequential data, (2) is not suitable here as the output for this equation is for classification. Thus the equation should be modified with an adversarial target output  $y^*$  which is to be matched as close as possible with  $f(x')$  where  $x'$  is the adversarial example, thus the equation could be modified as:

$$\min_{\delta} \quad (3)$$

$$s.t., \quad \|f(\mathbf{x} + \delta) - y^*\| \leq \Delta \text{ and } \|\delta\| \leq \tau$$

where  $y^*$  is the desired output of the model,  $\Delta$  is the acceptable difference between the desired model output and adversarial output.

The key problem is to calculate the perturbation  $\delta$ . For this, we borrow the idea of the Fast Gradient Sign Method (FGSM) method in image domain, which perturbs the input *along* the gradient direction to *maximize* the change in the model prediction[30]. Consequently, if the perturbation is added *opposite* the direction of the Gradients, the change of the model prediction is *minimized*. Perturbations can be formalized as:

$$\mathbf{x}' = \mathbf{x} \pm \delta \quad (4)$$

$$\delta = \epsilon \cdot \text{sgn}(\nabla_{\mathbf{x}} l(\mathbf{x}, y'))$$

where  $\mathbf{x}'$  is the calculated adversarial examples,  $\epsilon$  is a constant representing the magnitude of the perturbation and  $l$  is the loss function. In our work, we choose Mean Square Error (MSE) as the loss function, which is the most commonly used for regression tasks. In our case, due to the target of deceiving the RNN predictor, we increase the loss with adding  $\delta$  if the actual status of the data point is "normal" ( $S_a = \text{"normal"}$ ) and decrease the loss by minus  $\delta$  if the actual status is "attack" ( $S_a = \text{"attack"}$ ). Besides, notice that in Eq. 4  $\epsilon$  is a constant, which is not suitable for CPS data set with a combination of different data types. To solve the two problems, we propose an adapted version of the Eq.4 in practice:

$$\mathbf{x}' = \begin{cases} \mathbf{x} + \delta, & \text{if } S_a = \text{"normal"} \\ \mathbf{x} - \delta, & \text{if } S_a = \text{"attack"} \end{cases} \quad (5)$$

$$\delta = \text{sgn}(\nabla_{\mathbf{x}} l(\mathbf{x}, y')) \cdot \vec{\epsilon},$$

where  $\vec{\epsilon}$  is a diagonal matrix, and the value of each element from  $\vec{\epsilon}$  is defined according to the data type of each feature which represents the magnitude of the perturbation for each feature. The smaller the  $\vec{\epsilon}$  is, the less is the perturbation.

We distinguish three different types of feature (to solve difficulty 3 in section 3), i.e., actuators, valves and pumps and add different perturbation on them. For sensors, we add a perturbation  $\lambda$ , which represents the percentage of the perturbation w.r.t. the original value. There are two types of actuators, valves and pumps. For valves, there are three values: 0 for opening/closing, 0.5 for close and 1 for open. For pumps, there are two values with 0 for close, and 1 for open. In order to follow the character of discrete values for actuators, we define the  $\epsilon$  of valves as 0.5 and the  $\epsilon$  of pumps is defined as 1. In summary, the value of the diagonal matrix  $\vec{\epsilon}$  can be defined as:

$$\vec{\epsilon}_{jj} = \begin{cases} \lambda, & \text{if } \vec{F}[j] \in \vec{U}, \text{ where } \vec{U} \subset \vec{F} \\ 0.5, & \text{if } \vec{F}[j] \in \vec{V}_m, \text{ where } \vec{V}_m \subset \vec{F} \\ 1, & \text{if } \vec{F}[j] \in \vec{V}_p, \text{ where } \vec{V}_p \subset \vec{F} \end{cases}$$

where  $\vec{F}$  is the set of all features,  $\vec{U}$  is the set of sensors,  $\vec{V}_m$  is the set of all valves, and  $\vec{V}_p$  is the set of pumps. For example, if we only consider data from stage 1,  $\vec{\epsilon} =$

$$\begin{bmatrix} 0.01 & 0 & 0 & 0 & 0 \\ 0 & 0.01 & 0 & 0 & 0 \\ 0 & 0 & 0.5 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

To make sure the modified data are following the formats of data set, we clip the adversarial examples to 0 to 1 as it supposed to be. In specific, for a pump value, if the sign of the gradient at  $V_p[i, j]$  is positive,  $V_p'[i, j] = S[i, j] + 1$ . where  $V_p'[i, j]$  is the adversarial example of  $S[i, j]$ . However, we get  $V_p'[i, j] = 2$  which is not acceptable if  $V_p[i, j] = 1$ . Thus clipping is necessary. In physical world,  $V_p[i, j] = 0$  means the pump is closed and after adversarial attack, it change to 1, means it is open after the attack.

We thus construct adversarial examples for the RNN detector by adding noise in the above way and algorithm 2

**3.3.2 Adversarial attacks considering rule checking.** The rule checking mechanism is widely used to detect anomaly of CPS by many works [10, 11, 19, 50]. An example rule from SWaT system could be that when the value of "LIT101" is smaller than 500, the value of "MV101" should always equal to 2 after 12 seconds, otherwise

**Algorithm 2: Adversarial examples**


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**Input:** Data  $S_i$ ; RNN predictor model  $f$   
**Output:** adversarial examples

```

1  $\delta \leftarrow \text{sgn}(\nabla_{\mathbf{x}} l(\mathbf{x}, y')) \cdot \vec{\epsilon}$ ;
2 if  $S_i$  is normal data then
3    $S'_i = S_i + \delta$ ;
4 else
5    $S'_i = S_i - \delta$ ;
6 end
7 if  $S'_i$  cannot pass rule checker then
8    $S''_i = \text{GA}(S'_i)$ ;
9 else
10   $S''_i = S'_i$ ;
11 end
12 return  $S''_i$ 
```

---

an alarm will arise to indicate anomalies. In this setting, we aim to construct adversarial examples to bypass both the RNN detector and the rule checking system.

As the rule checking system makes decisions depending on the actuators status, we propose to use genetic algorithm(GA)[28] to help us generate the ideal combination of actuator status. Due to the difficulty of different range for sensors, pumps and valves, we develop the genetic algorithm to generate values according to data types. The algorithm 3 give an overview of how genetic algorithm works in this project.

**Algorithm 3: GA**


---

**Input:** Data  $S'[i]$ ; fitness function  $G$ ; population size  $n$ ; mutation probability  $p_m$ ; rule Checker  $R$   
**Output:** adversarial examples

```

1 Generate initial population  $P$ ;
2 Compute fitness  $g$  for each candidate from  $P$ ;
3 repeat
4   Select parents from  $P$  with a probability of fitness
   distribution;
5   Apply crossover and mutation with  $p_m$  to get new
   candidates;
6   Select individuals from old and new candidates based on
   their fitness to participate in new  $P$ ;
7    $S''[i] \leftarrow$  fittest candidate from  $P$ ;
8 until  $R(S''[i]) = \text{True}$  or iteration = max iteration;
9 return  $S''[i]$ 
```

---

Inside the algorithms,  $R$  is a set of rule implemented in the system (for SWaT, there are in total 23 rule to monitor the system status.). Firstly, a set of random data points generated with population size  $n$ . Those data points should have the same data format with attack data set  $S$ , such as 26 sensor values with range from 0-1, 9 valve values from [0, 0.5, 1], and 16 pump values from [0, 1]. Afterwards, we calculate the fitness number with  $g = c1 * (1/c2)$ , where 1)  $c1 = 1$  if  $R(x) = \text{True}$ , which means the data point  $x$  has passed rule checker, and  $c1 = 0$  otherwise which indicating it is impossible to be chosen;

2)  $c2$  is the vector magnitude of the difference between the the candidate and its original value. The lower  $c2$  is, the fewer modification on original data, which has a higher possibility to be chosen. Then we start to look at the repeating part, where the new population generated. Each candidate is assigned a probability according to the roulette wheel selection [28], which means probability of each candidate being selected as parent is  $g_i / \sum_{j=1}^n g_j$ . From the selected parents, the generation is sampled with crossover and mutation, in details, a random point is chosen to divide the vector and swap the sub-vector with each other. Afterwards, we randomly mutate a point with fix mutation probability  $p_m$ . Next, the fitness score is calculated for all candidates and top  $n$  fittest candidates form the new population. The fittest candidate value pass to  $S''[i]$ . This iteration continues until  $S''[i]$  pass rule checker or timeout. Then we get the new adversarial example  $S''[i]$ .

Our experiment shows that this way works for passing most rules. We apply our methodology to construct adversarial examples in this setting and found that 461 out of 449909 data points have been caught by the rule checking system. After removing the noises accordingly, we obtain the results shown in the last row of Table 6. From the results we can see that we still achieve similar reduction in the performance of the anomaly detector as explained in the above section.

**3.4 Defence model**

Our next question is whether it is possible to detect the constructed examples efficiently as a defence. Our attempt is to create a binary classifier of different model types (e.g., def-NN and random forest) trained from a set of original data points and an equal number of adversarial examples. We then use the trained classifier to test whether the classifier can detect adversarial examples constructed from other data points. We focus on the defence neural network (def-NN) performance and use the random forest as a comparison.

**4 EVALUATION ON PHYSICAL SYSTEM**

We evaluated our experiment to the full data set of real world cyber-physical systems, SWaT system that we have introduced in Section2 background. The experiments are done on a purpose to answer our research questions raised in section 3.

**4.1 Experiment setting**

We conducted our experiments on a GPU laptop with 1 Intel(R) Core(TM) i7-8750H CPU at 2.20GHz, 16GB system memory and GPU of NVIDIA GeForce GTX 1050 Ti with Max-Q Design.

The threshold selection for CUSUM is according to the validation of the attack data. We compared the cusum value for each sensor with attack labels, and set the threshold as the lowest peak of the CUSUM value that indicates an attack, so each sensor is possible to indicate 0 attacks or more than 1 attacks. Fig 4 presents a cusum value example for sensor "LIT101", the top graph is the negative cusum value  $SL$  of "LIT101". The bottom picture is the actual label of data, 1 means under attack and 0 means normal status. By comparing the two graph, almost each peak value from the  $SL$  indicated an attack, we choose the lowest peak value as the threshold and here it's indicated by the red dot line with value of  $-2$ . All thresholds are calculated with this methods.

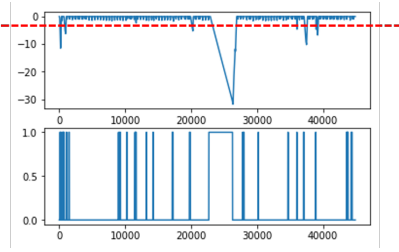


Figure 4: A CUSUM value example for sensor LIT101

The above CUSUM-RNN model proposed by J.Goh [27] is also evaluated on SWaT system, however only on stage 1 (Supply and Storage). We expand the model with all stages of the system to make sure our adversarial attack works on the completed system.

## 4.2 Research questions

We have three research questions to evaluate our experiments with SWaT and WADI system.

*RQ1: Is our adversarial attacks effective on real-world CPS?*

On SWaT system, the adversarial attack has been applied following the Eq.5. To balance the modification and effectiveness of the model, we design three experiments to find the optimized solution. Experiment #1 (noises to sensor 1%) and #2 (noises to sensor 10%) are to apply the noise to sensor data only with  $\lambda = 0.01$  and  $\lambda = 0.1$  to check the influence for different noises. Experiment 3 and 4 are based on experiment #1 (noises to sensor 1%) and #2 (noises to sensor 10%), but we also change the actuator values along the sign of calculated gradient. In details,  $\vec{e}$  is defined with 26 elements with  $\lambda = 0.01$  for sensor value for experiment #3 (noises to all data 1%) and  $\lambda = 0.1$  for sensor value for experiment #4 (noises to all data 10%), with 6 elements with 0.5 for actuator valves and 19 elements with 1 for actuator pumps value with locations responding to each feature, and the same logic has been applied to WADI system. A summary of parameters is shown at Table 5.

During the experiments, firstly, the RNN predictors for the two systems had been created, all data are collected with a frequency of 1Hz, so we select 10 seconds as the window size for WADI due to slowly change of real systems. While we choose 12s as the window size of the SWaT system which is the maximum delay from the rule checking mechanism. As the system is dynamic and the ground truth is changing whenever the data is changing (difficulty 4 in section 3), we compare the results of ground truth model  $T(S)$  with the results from learning-based anomaly detector  $C(f(S))$  to calculate the original anomaly detector accuracy of data  $S$ , and the difference between  $T(S')$  and  $C(f(S'))$  to get accuracy of data  $S'$ .

We can see the results in Table 6 for SWaT and Table 7 for WADI, where the precision, f1 and accuracy has been apparently reduced after the adversarial attack. Results of experiments #1 (noises to sensor 1%) and #2 (noises to sensor 10%) are given from the second and third rows of the Table 6, if we only add noises on sensor values, the more noises we added, the lower accuracy of the anomaly detector. However, there is a possibility that the noises are added in an

extreme condition so that the noisy data has exceeded the threshold and defined as an attack by the model  $T$ . Thus the precision, recall and f1 for 10% noises are all higher than 1% noises. Comparing to the original performance of the anomaly detector, the reduced accuracy has shown that the anomaly detector is vulnerable and sensitive to the adversarial attacks.

The fourth (Noises to all data 1%) and fifth (Noises to all data 10%) row provide the results that we apply the noises to sensor and change actuator values at the same time. The accuracy has been reduced more than if we apply noises to sensors only, that could because the noises to all data give a stronger impact to the RNN predictor, and CUSUM calculation could emphasize this impacts to result in a much lower accuracy. The false negative values of 0.78 from SWaT table, Noises to all data (10%) row, and 0.99 from WADI, Noises to all data (1%) and Noises to all data (10%), imply that many false alarms have been generated by the anomaly detector, which indicating the changing of actuators is easy to be decided as an attack by the anomaly detector. However, the false negative of 0.46 from SWaT table, Noises to all data (1%) row, is not high comparing to the above, this could because less actuators were changed when we calculate the gradients (i.e. the gradient is 0 for most actuators).

As for row 2,4 and row 3,5, we can see if we apply the same noise range for sensor value, a manipulation of actuators could provide an extra decrease of model accuracy, as the RNN predictor make prediction according to all features from historical data, so actuator values also play a role to reduce the prediction accuracy.

We did the same experiment on WADI, and get the results as shown by Table 7. WADI is a bit different as we do not have its control points information to determine the ground truth, thus we calculate the operation range under normal conditions with a small tolerance to set the ground truth model  $T$ . As it has more features (121) than SWaT (51), the complexity is more apparent and behavior is more unpredictable.

*RQ2: how should the attacker compromise the original data to deceive the rule checking system and the anomaly detector?*

Rule checking system is commonly used in industrial CPS as a basic defence mechanism, as WADI has not established a rule checking system, so our second experiment is only applied to SWaT testbed. The rule checking mechanism is settled to monitor the condition and invariant in SWAT system, it will check in total 20 actuators status according to the 11 sensor values for SWaT system. Thus we design the experiment #5(Noises to all data + GA for actuator) to use GA to generate actuator data in order to pass the rule checker. We assume that the attacker does not have the access to the content of the rule, but knows whether the data could pass the rule checker or not. The rules include the relationship between the sensor and actuator values, so we divided a data point  $x$  into  $x_a = [x_{a1}, x_{a2} \dots]$  and  $x_s = [x_{s1}, x_{s2} \dots]$ , and use GA to generate possible  $x_a$  and keep  $x_s$  to combine back to calculate fitness score. As our goal is to generate adversarial attacks rather than break down the system, so we only use GA to replace those attacks that being detected by rule checker due to noises.

The results for experiment #5(Noises to all data + GA for actuator) can be found from the last row of Table 6. The accuracy has been slightly increased indicating that using GA for actuator value



Table 5: Parameter summary for SWaT and WADI experiments

	sensor	actuator	
	$\lambda$ for sensor	$\lambda$ for valves	$\lambda$ for pumps
Noises to sensor (1%)	0.01	0	0
Noises to sensor (10%)	0.1	0	0
Noises to all data (1%)	0.01	0.5	1
Noises to all data (10%)	0.1	0.5	1
Noises to all data + GA for actuator	0.1	0.5	1

Table 6: Before and after adding noises of anomaly detector for SWaT

	precision	recall	f1	accuracy	False negative	False positive
Original Anomaly Detector	0.96	0.86	0.91	89.40%	0.05	0.14
Noises to sensor (1%)	0.62	0.53	0.57	52.38%	0.48	0.47
Noises to sensor (10%)	0.65	0.58	0.61	48.78%	0.72	0.42
Noises to all data (1%)	0.52	0.50	0.51	51.85%	0.46	0.50
Noises to all data (10%)	0.12	0.84	0.21	28.84%	0.78	0.16
Noises to all data + GA for actuator	0.14	0.76	0.24	39.56%	0.62	0.34

Table 7: Before and after adding noises of anomaly detector for WADI

	precision	recall	f1	accuracy	False negative	False positive
Original Anomaly Detector	0.32	0.16	0.22	93.29%	0.02	0.84
Noises to sensor (1%)	0.43	0.65	0.52	52.85%	0.55	0.35
Noises to sensor (10%)	0.42	0.67	0.52	49.88%	0.62	0.33
Noises to all data (1%)	0.34	0.96	0.50	33.28%	0.99	0.04
Noises to all data (10%)	0.33	0.95	0.49	32.23%	0.99	0.04

selection may sacrifice the drop of accuracy which is reasonable, as GA generated values do not change following the sign of gradients. While the overall performance is almost the same comparing with the experiment #4 (noises to all data 10%) results from Table 6, so GA is effective to pass the rule checker without reduce the anomaly detector performance much.

*RQ3: how can we design a defence against such adversarial examples?*

The adversarial examples have more noises comparing to original data, so we design a defence neural network (def-NN) and a commonly used classification model, a random forest (RF), to distinguish if the data are adversarial examples or original data from the system. The def-NN and RF perform as two basic binary classifiers. We train the model with half original data and half adversarial examples as training data and the rest half as testing data. The def-NN model is designed with three layers and 100 units for each layer, and we choose *binary cross entropy* as our loss function. The random forest is designed with 10 estimators.

The results can be found from Table 8 and Table 9, both def-NN and random forest model works well on detecting the noises, which indicates the original data has a certain pattern that the noises we added, though the noises are small but easy to change the pattern. Moreover, comparing to changing sensor values only, changing all data would be 100% detected by the defence models. As

for changing sensor values only, the larger value we modified, the easier to be detected. With such high accuracy defence mechanism, we could conclude that the adversarial attacks may perform harder with a extra well-trained binary classifier. However, to train such a classifier, the defender has to know the adversarial examples, which is hard in practice.

### 4.3 Threats to Validity

There are some limitations for the evaluation and application validity. First, though the two CPS systems are real and operational, they are still testing bed and not industrialized. Secondly, the data are collected and labeled due to manual work, there are some data points are not accurate and may increase the bias of the results. Finally, we only considered the recorded attacks to train and calculated ground truth, so the methods may not work well for non-recorded attacks. Similarly, the defence method (i.e. def-NN) has to be trained for each kind of adversarial examples (10% noises and 1% noises), and it does not work for un-known adversarial examples (e.g. 5% noises).

## 5 RELATED WORK

This work focus on adversarial attacks on LSTM-RNN which is implemented as a part of anomaly detector in a cyber-physical system. In this section, we discuss some researches with relevant themes such as adversarial attacks and some relevant works done on SWaT/WADI systems.

**Table 8: Defence for adversarial attacks on SWaT**

	def-NN			RF		
	precision	recall	f1	precision	recall	f1
Noises to sensor (1%)	0.98	0.99	0.99	1	0.99	0.99
Noises to sensor (10%)	0.99	0.99	0.99	1	1	1
Noises to all data (1%)	1	1	1	1	1	1
Noises to all data (10%)	1	1	1	1	1	1
Noises to all data + GA for actuator	1	1	1	1	1	1

**Table 9: Defence for adversarial attacks on WADI**

	def-NN			RF		
	precision	recall	f1	precision	recall	f1
Noises to sensor (1%)	0.5	1	0.67	1	1	1
Noises to sensor (10%)	1	1	1	1	1	1
Noises to all data (1%)	1	1	1	1	1	1
Noises to all data (10%)	1	1	1	1	1	1

*Anomaly detection on CPS:* A number of researches has explored the anomaly detection on CPS, these approaches [6, 12, 22, 33, 34, 38, 44, 46, 52, 55, 58] unusual monitor the changes or suspicious patterns from the logs of a CPS. Y.Harada et al [33] has proposed a statistical way to monitor the outliers from logs. This statistical methods can include machine learning or deep learning methods. J.Inoue et al [38] has provide an unsupervised machine learning methods to detect anomalies and M. Kravchik et al [44] proposed to use convolutional neural network to detect cyber attacks in control systems.

SWaT system as a typical cyber-physical system has been widely explore by researches, and there are many works including anomaly detection done on the public data set [39, 40]. These works includes unsupervised learning methods [27, 38, 44], which includes deep learning methods, and supervised learning methods [17, 18], who injected simulated faults to get attack data. Ahmed et al. [7, 9] has worked on fingerprinting the noises patterns to detect anomalies while Adepu and Mathur [2–5] has manually derived the invariants or what we call "rules" by monitoring the normal operation of the system. C. Feng [24] also tried to get invariants but using a systematic way to learn the invariants.

*Neural networks in CPS:* Neural networks as a state-of-art technique has been adopted in CPS as well. Lv et al. [47] have introduced a multiple layers neural networks for probabilistic estimation of brake pressure for electrified vehicles. Nanduri et al. [51] have applied RNN as a part of anomaly detector in aircraft data. Sargolzaei et al. [57] have designed a fault detector with neural networks to detect fault data injection for vehicular cyber-physical systems with wireless communications. Similar works with anomaly detection with Neural networks have been evaluate on smart grid [43] and gasoil plant [25], which use LSTM as predictor. Eiteneuer et al. [23] have applied LSTM neural networks to learn the behavior of a water tank.

*Adversarial attacks:* Papernot et al. have pointed out the limitations of deep learning in adversarial settings [54] and Nguyen et al. have pointed in their work [53] that it's easy to produce images that

completely unrecognizable by human but recognizable with 99.99% confidence by state-of-art neural networks. Adversarial attacks have many mature toolbox [1, 31?] to generate adversarial attacks. Adversarial attacks has been adopted in many applications in physical world [45] including image [59] and audio [14, 15]. However, there are few works on CPS.

## 6 CONCLUSION

In this paper, we introduce a case study of adversarial attack for real world cyber-physical systems, and we create possible defences for adversarial attack. Firstly, we propose a adversarial attacks for anomaly detector with LSTM-RNN as predictor in a cyber-physical system, we applied noises with different ranges and compare their impacts. Then we consider the condition with rule checking mechanism and provide a solution to overcome the checker, which is by using GA. Finally, we explore if there is any possible methods to detected the adversarial examples and tried def-NN and random forest for the experiments. Afterwards, we evaluate our methods on two testing beds, SWaT and WADI and get results to show that the thread model has effectively drop the performance of the pre-implemented anomaly detectors, and even though we consider the rule checking mechanism to weaken the assumptions of attackers, we can still achieve a similar results with our improved adversarial attack methods.

For future works, we will consider weaken the attacker model with black box adversarial attack, and we will explore other methods to overcome the rule checker such as SMT solver. The evaluation should be done with the actual system and real time attack application. Moreover, we will investigate possible solutions for adversarial example detection.

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