Real-time Evasion Attacks with Physical Constraints on Deep Learning-based Anomaly Detectors in Industrial Control Systems

Alessandro Erba¹, Riccardo Taormina†, Stefano Galelli†, Marcello Pogliani‡, Michele Carminati †, Stefano Zanero‡, Nils Ole Tippenhauer *

*CISPA Helmholtz Center for Information Security 
{alessandro.erba, tippenhauer}@cispa.saarland
†Singapore University of Technology and Design 
{riccardo_taormina, stefano_galelli}@sutd.edu.sg
‡Politecnico di Milano
{marcello.pogliani, Michele.carminati, stefano.zanero}@polimi.it

Abstract—Recently, a number of deep learning-based anomaly detection algorithms were proposed to detect attacks in dynamic industrial control systems. The detectors operate on measured sensor data, leveraging physical process models learned a priori. Evading detection by such systems is challenging, as an attacker needs to manipulate a constrained number of sensor readings in real-time with realistic perturbations according to the current state of the system. In this work, we propose a number of evasion attacks (with different assumptions on the attacker’s knowledge), and compare the attackers’ cost and efficiency against replay attacks. In particular, we show that a replay attack on a subset of sensor values can be detected easily as it violates physical constraints. In contrast, our proposed attacks leverage manipulated sensor readings that observe learned physical constraints of the system. Our proposed white box attacker uses an optimization approach with a detection oracle, while our black box attacker uses an autoencoder (or a convolutional neural network) to translate anomalous data into normal data. Our proposed approaches are implemented and evaluated on two different datasets pertaining to the domain of water distribution networks. We then demonstrated the efficacy of the real-time attack on a realistic testbed. Results show that the accuracy of the detection algorithms can be significantly reduced through real-time adversarial actions: for the BATADAL dataset, the attacker can reduce the detection accuracy from 0.6 to 0.14. In addition, we discuss and implement an Availability attack, in which the attacker introduces detection events with minimal changes of the reported data, in order to reduce confidence in the detector.

I. INTRODUCTION

Computational and physical infrastructures are nowadays interconnected. Computers, communication networks, sensors and actuators allow to control physical processes. Data are retrieved from the sensors and communicated to computers, where they are analyzed, and decisions are made. Finally, these decisions are sent from computers back to the physical infrastructures as commands to actuators. Such systems are commonly referred to as cyber-physical systems (CPS). Examples of such systems are industrial control systems (ICS), autonomous vehicles, smart grids and, more in general, all systems falling under the umbrella definition of “Internet of Things” [1]. Since these systems operate in the physical world, they should guarantee security, safety and reliability in order to succeed in their tasks without harming the environment in which they operate. Moreover, CPS can have a strategic role, such as controlling interconnected critical infrastructures like power grids [2] and water supply systems [3].

The integration of modern security features into existing ICS is challenging, as industrial devices are resource constrained, and protocols need to be legacy compliant (i.e., they have to be backward compatible to decades old devices in the field, which do not support authentication or encryption). For that reason, complementary security solutions such as passive process data monitoring are promising. In recent years, a number of authors have proposed such solutions, and implemented anomaly detection approaches based on a broad range of techniques, including control theory [4] and Machine Learning (ML) [5]–[11]. In general, the goal of such systems is to leverage reported sensor data in order to detect attacks and anomalies that affect actuators.

Adversarial Machine Learning (AML) plays and important role to explore the robustness of machine-learning based anomaly detectors against manipulations. So far, the potential of AML has been explored in a few areas of computer science—e.g., image or speech recognition—, but little is known about the potential of AML approaches to evade attack detection in ICS. Evasion attacks in our context are challenging as they need to manipulate (in real-time) reported data from one or multiple sensors to induce a wrong classification of the system’s state, while matching physical laws imposed by the system. While in other contexts, universal adversarial perturbations [12], [13] are used to perform real-time manipulations (using precomputed patterns), manipulations in ICS cannot be precomputed as they need to be consistent with the current dynamic conditions of the system (with a large potential state space). In particular, successful application of AML algorithms in the ICS domain must account for two

A major part of this work was done while Alessandro Erba * was student at Politecnico di Milano, visiting SUTD.
key features characterizing process-based anomaly detectors. First, process-based anomaly detectors typically account for the underlying physical correlation characterizing the underlying physical processes [14]. Second, detectors in the ICS domain are trained to detect not only outliers, but also contextual anomalies (i.e., observations classified as abnormal only when viewed against other variables that characterize the behavior of the process [15]). In contrast to related work that assumes unlimited computational power to compute perturbations [16], AML algorithms for ICS will also need to produce adversarial examples in real-time[1] to react to the dynamic system.

In this work, we propose and evaluate attacks on process-based anomaly detectors for simulated and real world ICS, and propose two techniques to craft adversarial examples[2] in real-time. In particular, the classifier under attack is the anomaly detection system, while the samples are the sensor readings that the classifier uses to decide if the system is 'safe' or 'under attack'. The attacker's goal is to change the classification outcome by manipulating a subset of sensor readings, in order to hide an ongoing manipulation over the physical process (called Integrity attack in [17], described as 'Integrity attacks result in intrusion points being classified as normal'). We explore attacks on such detectors in two settings with different information available to the attacker, and compare them against replay attacks on a subset of sensors. Our results show that a) constrained replay attacks are easily detected as they violate physical correlations, b) using our white box model a powerful attacker can leverage knowledge on the system to perform efficient (but computationally expensive) attacks, and c) using our proposed black box attacks it is possible to craft effective adversarial samples in real-time.

In addition, we explore Availability attacks [17] ('availability attacks cause so many classification errors, both false negatives and false positives, that the system becomes effectively unusable'), in which the attacker looks for small perturbations to legitimate features that will—seemingly incorrectly—trigger ML-based attack detection schemes. This is useful to force the defender to increase detection thresholds (reducing its detection rate), or to eventually ignore alarms.

We summarize our main contributions as follows:

- We practically implement and demonstrate the attacks in real-word Industrial Control System testbed, and show that they are possible in real-time.
- We also show that it is possible to use our framework for Availability attacks, i.e., to produce false positives, causing the detector to raise alarms without any actual physical process manipulation.

The remainder of this work is structured as follows. Background concepts are introduced in Section II. We present the problem of adversarial learning attacks on ML-based detectors in Section III. Our design of attacks is proposed in Section IV and their implementation and evaluation is presented in Section V. We discuss our work and next steps in Section VI, and summarize related work in Section VII. The paper is concluded in Section VIII.

II. BACKGROUND ON Evasion Attacks

In this section, we provide a brief overview on Evasion Attacks. A more complete review of related work is presented in Section VII. In Adversarial learning, an evasion attack is launched by an adversary to control the output behavior of a machine learning model through crafted inputs, called adversarial examples. Several evasion attack and defenses mechanisms have been proposed in the context of image, speech recognition and malware detection. The attacker scope and constraints vary from context to context [18].

In the case of image recognition, the attacker's goal could be the misclassification of the sample, either on a random target class or on a desired target class. In both cases, a constraint over the sample is the human indistinguishability of the sample (e.g., an attacker aiming to craft a dog sample (to have it classified as a cat) should not change the human perception of it. This is achieved by solving an optimization problem that minimizes distance between the sample and the adversarial example e.g. by minimizing norms: $L_0$, $L_2$, $L_{\infty}$. The work by [19] is the first that specifically studies adversarial manipulation to image classification using neural networks. The authors found that only a small portion of the image needs to be modified to achieve the attacker's goal.

In the case of malware detection, the task is binary (malware vs. benign software), so the attacker's goal is the misclassification of a malware sample. The constraint over the adversarial example is to leave malware behavior unchanged, meaning that the distortion introduced to the malware should not eliminate its malicious properties. Works such as [20] craft highly effective adversarial examples for neural networks used for malware classification.

The authors of [18] characterize attacks on machine learning models using a 4-tuple representation of the system under attack. The tuple is characterized by the training dataset $D$, the feature set $X$ (e.g., the set of features used to train the model), the learning algorithm $f$, and the trained parameters $w$. In an adversarial setting, an attacker can have complete or partial knowledge of each component of the system; limited knowledge of a component is denoted with the symbols $\hat{D}$, $\hat{X}$, $\hat{f}$ and $\hat{w}$ respectively. In particular, the authors characterize three types of attack scenario: Perfect-knowledge white box.
attackers characterized by the tuple \((\mathcal{D}, \mathcal{X}, f, w)\), Limited-knowledge gray box attacks \((\hat{\mathcal{D}}, \hat{\mathcal{X}}, \hat{f}, \hat{w})\) and Zero-knowledge black box attacks \((\hat{\mathcal{D}}, \hat{\mathcal{X}}, \hat{f}, \hat{w})\). In Section III we use that notation to introduce our proposed solution and position it within the related literature.

III. Evasion Attacks on Process-based Anomaly Detection

In this section, we introduce our system and attacker model, and our general problem statement for concealment and Availability Attacks. Then, we present our abstract approach for the white and black box attacker.

A. System Model

We consider a system under attack (Figure 1) consisting of a number of sensors and actuators, connected to one or more PLCs, which are in turn connected to a SCADA system that gathers data from the PLCs. In our work, we assume that the SCADA is passive, so it does not send control commands to the PLCs (e.g., to actively probe for manipulations). The SCADA feeds an attack detection system, whose goal is to accurately identify the instances in which the attacker manipulates the physical process, while minimizing the number of false detections. The attack detection system generally consists of two main components: a system model, which is used to generate additional features, and a classifier, which, for each time step, classifies the system as either under attack or under normal operating conditions (see Section VII for more details on prior work on classifiers in this context).

B. Attacker Model

Attacker Goal andCapabilities. In an ICS environment, an attacker can perform an evasion attack to achieve one of the following goals.

A first goal (Integrity Attack) is to conceal ongoing manipulations of the physical process, which requires changing the commands sent to the actuators. We assume that the attacker is already able to precisely control a subset of the actuators, and that the attacker manipulates a subset of traffic signals from the PLCs to SCADA (i.e., the sensor data) to conceal this attack from the detector.

An alternative second goal is Availability attack: The attacker aims to introduce alarms into the detection system with minimal changes in the reported sensor data (and no change in the underlying process). When such alarms would be investigated, the reported sensor data would be sufficiently close to the state of the process, and thus the efficacy of the detection system would be questioned, potentially allowing for future alarms to be taken less seriously.

Attacker Knowledge. Using the notation introduced in Section III, an evasion attack is characterized by the knowledge of the attacker about the training dataset \(\mathcal{D}\), feature set \(\mathcal{X}\), learning algorithm \(f\), and trained parameters \(w\). In particular, we classify attacks as white box, black box, and replay. For all attacks, we assume that the attacker aims to manipulate the subset of sensor readings that will change the detector’s classification label, knowing them explicitly (white box) or not (replay and black box).

The attacks are conducted in real time (i.e., per time step), not a posteriori (i.e., applied retrospectively to a longer sequence of sensor readings after they are fully received by the attacker).

White Box attack. In a white box attack, the attacker knows the exact system model and its variables (such as the currently estimated system state), and the exact thresholds of the classification system. Thus, the white box attacker is characterized by the tuple \((\mathcal{D}, \mathcal{X}, f, w)\). With that information, the attacker could either run basic exhaustive search, basic optimization strategies, or more complex approaches (especially solutions that use the gradient signal from the attacked model).

Black Box attack. In a black box attack, the attacker is aware of the general detection scheme (e.g., type of system model), but unaware of internal variables of the system model and exact thresholds used in the classification. We note that our black box attack is different from the one defined in [18], \((\hat{\mathcal{D}}, \hat{\mathcal{X}}, \hat{f}, \hat{w})\), from a threefold perspective:

First, our attack does not require the knowledge of \(f\) or its approximation \(\hat{f}\). In the usual setting, even if the attack does not require to build a surrogate model \(\hat{f}\), the attacker is assumed to be able to query the classifier under attack in a black-box fashion. This allows him to get feedback on the provided labels or confidence scores (this is done for example in [21–24]).

However, in our case, the nature of the environment imposes that the attacker cannot query the system even in a black-box manner, as this would mean potentially raising the alarm. Thus, we consider that the only assumption of the attacker with respect to \(f\) is that Deep Learning techniques are used for anomaly detection.

The second difference imposed by the ICS environment is the knowledge of the feature set (sensor readings). In order to detect anomalies using information coming from sensors, the defender is likely to use all the information he has. Under this assumption, the attacker crafts adversarial examples leveraging the complete set of features that he intercepts between PLC
and SCADA. Referring to $\mathcal{X}$ or $\hat{\mathcal{X}}$, it is the same, since the attacker assumes that the best case for the defender is to use all available features.

Finally, we assume that the attacker can collect an approximation of the training dataset (i.e., network traffic captured and decoded during the normal operation of the system). In the ICS case, recording normal operations at different time steps gives samples from the same dynamical physical process (assuming overall periodic operations with multiple stages). The more data the attacker collects, the better the training dataset is approximated. In fact, collecting more data will bring the attacker to see the realization of different stages of the ICS (potentially all stages involved in the ICS normal operations).

In general, we can say that the attacker is able to collect $D$, but, according to time spent collecting data, the attacker can reach the complete knowledge of $D$. Thus, we can define our black box attacker as $(D, \mathcal{X}, \hat{\mathcal{X}}, \hat{\mathcal{H}})$, since the attacker does not need the usage of these elements.

**Replay Attacks.** In this work, we use replay attacks (proposed in related work [25]) as a baseline to compare to. In a replay attack, the attacker records sensor readings for a certain amount of time and repeats them afterwards, e.g., while manipulating a physical process by sending an exogenous control input [25]. By doing so, the attacker aims to avoid detection by a monitoring system based on reported sensor data. In this work, we assume that the attacker was able to record selected data in the system over a certain length of time (e.g. one day), and will then replay that data at the start of the attack. In this kind of attacks there is no adversarial learning involved. The resulting tuple of a replay attack is $(\hat{D}, \mathcal{X}, \hat{\mathcal{X}}, \hat{\mathcal{H}})$, that corresponds to the one of black box attack.

**C. Problem Statement**

The goal of the attacker is to launch an evasion attack on an ICS to hide the true state of the process from an anomaly detector. In particular, we assume that the anomalous physical process results in a feature vector $\vec{x}$, which triggers the detection system. The attacker thus needs to find an alternative vector $\vec{x}'$, which prevents detection of the attack.

**Integrity Attack.** We formalize the integrity attack as follows: given a feature vector $\vec{x}$ and a classification function $y()$ s.t. the detector correctly classifies $y(\vec{x})$ = ‘under attack’, the attacker is looking for a perturbation $\vec{x} + \delta$ s.t. $y(\vec{x} + \delta)$ = ‘safe’. We assume two different settings for the attacker. **Unconstrained attack**, that the attacker can manipulate all the $n$ features in $\vec{x}$, and her perturbations are limited in terms of $L_0$ distance to be at most $n$. **Constrained attack** we assume that the attacker is constrained to perturb a subset of $k$ out of $n$ variables in $\vec{x}$, and her perturbations are limited in terms of $L_0$ distance to not exceed distance $k$.

**Availability Attack.** We formalize the availability attack problem as follows: given normal operations sensor readings correctly classified as ‘safe’, the attacker aims to distort them in order to cause false alarms by the detector. More formally, given a feature vector $\vec{x}$ and classification function $y()$ s.t. the detector correctly classifies $y(\vec{x})$ = ‘safe’, the attacker is looking for a modification $\vec{x} + \delta$ s.t. $y(\vec{x} + \delta)$ = ‘under attack’. As in the Integrity Attack, we consider $L_0 < k$ attacks.

**D. Example of an Integrity Attack**

We now illustrate an example of concealment over one time step of a water distribution system. Consider an attacker that aims to empty a water tank by changing the control signal to the pumps, i.e., by forcing them to be OFF even after the water in the tank falls below the level triggering their activation. An anomaly detection system could detect this anomalous condition by comparing the resulting sensor data with the readings realized during normal operations. In order to hide the attack, the adversary has to modify some sensor readings that will bring the system state to be classified as ‘safe’.

Since the data reflect a physical process, the effect of a control command over an actuator affects different system components—so, not only the components that are the target of attacker’s manipulation will be affected. In our case, manipulating only the sensor readings related to the target water pumps and tank does not assure to remain stealthy. For example, as illustrated in the simplified example of Figure [2] even if the attacker’s process manipulation is only targeting Tank 2, in order to remain stealthy, the attacker needs to manipulate four sensor readings. Two of them (Tank 2, Pump 2) are explicitly related to the actuator manipulation, while the other two are consequently modified to be consistent with the learned physical model, even if the corresponding physical process is not manipulated.

**E. Proposed Framework for Attack Computation**

For both the white box and black box case, the attacker is assumed to intercept and manipulate sensor readings in real time. The white box attacker is able to interactively query a classification oracle to determine which features to manipulate, and to which values to set those features. For the black box attacker, the target features to manipulate and their manipulated value are computed without oracle’s feedback.

For the white box attack, we propose to compute the manipulations using an iterative algorithm (without using a
more complex machine learning based approach). This algorithm calculates solutions that are ‘safe’ from the detector perspective. This algorithm is tunable, i.e., the attacker can act on some algorithm parameters that impact over time the computation and, consequently, the evasion efficacy. Moreover, the algorithm is constraintable, i.e., the attacker can decide the maximum number of features to be modified for each time step. Again, this speeds up computation but can impact the solution quality. Keeping the solution simple underlines the fact that, if the attacker steals the model, he does not strictly need a strong theoretical background to succeed. As we shall see later, even such simple white box attacks will be quite effective (although expensive).

For the black box attack, we propose the use of a Deep neural network that is capable of outputting concealed sensor readings. The attacker is adversarially training the neural network to learn how the detector expects the ICS to behave. This trained neural network then receives the traffic coming from the PLC. When the attacker manipulates the commands sent to the actuators, the neural network adjusts the anomalous data to resemble ‘safe’ data. This manipulated version is sent to the SCADA. This method can also be used for Availability Attack: first, we learn how the system behaves when targeted by an attack to the actuators; then, we use the network to transform sensor readings to resemble ‘under attack’.

IV. REPLAY, BLACK BOX, AND WHITE BOX EVASION

We now present a detailed design for the three attacks that we consider. We start with details on the autoencoder-based attack detector (proposed in prior work [11], then introduce the replay attack (proposed in prior work [25]). We provide details on the white box attack (which uses a classification oracle to optimize the manipulations). We then conclude with the black box approach, which leverages an online concealment method without any prior knowledge about the physical process that generates the sensor readings and the detection scheme (except that it uses Deep Learning). Given these premises, we note that, while adversarial examples found using the white box approach depend on the internal structure of the attacked anomaly detector, examples crafted through the black box approach are independent from the addressed detection scheme.

A. Deep Learning-based Attack Detector

In this work, we focus on the anomaly detection systems proposed in [7], [10], [11], which are based on the same underlying idea (see Section VII). The anomaly detector consists of two parts, namely a Deep Learning model (with \( n \) features as input and output) trained over the normal operation sensors readings of an ICS, and a comparison analysis between the input and output of the model. The idea is that the deep model has learned to reproduce the system behaviour under normal operating conditions with a low reconstruction error, so it reproduces a higher reconstruction error when fed with anomalous sensor readings (sensor readings are anomalous either if sensor values are outside normal operation ranges or if there are contextual anomalies among values). The comparison between input and output of the deep model is used to decide if the system is ‘safe’ or ‘under attack’.

In particular, we use the specific autoencoder proposed in [11], which is available as open source [26]. The autoencoder (AE) receives as input \( \vec{x} = [r_1, r_2, ..., r_n] \) the \( n \)-dimensional vector of sensor readings. AE outputs an \( n \)-dimensional vector \( \vec{o} = [v_1, v_2, ..., v_n] \), where \( v_i \) s.t. \( i \in \{1, ..., n\} \) represents the reconstructed value w.r.t. the input reading \( r_i \). In order to decide if the system is under attack, the mean squared reconstruction error between observed and predicted features are computed. If the mean squared reconstruction error exceeds a threshold \( \theta \), the system is classified as under attack. The authors chose \( \theta \) as 99.5 percentile (Q99.5) of the average reconstruction error over the training set.

We formalize this as follows. Given an input \( \vec{x} \in X \), we define: \( \vec{e} = \vec{x} - \vec{o} = [d_1, ..., d_n] \) as the reconstruction error \( n \)-dimensional vector, \( \varepsilon(\vec{e}) \) as the corresponding average reconstruction error:

\[
\varepsilon(\vec{e}) = \frac{1}{n} \sum_{i=1}^{n} d_i^2, \tag{1}
\]

and \( y(\vec{x}) \) as the classified state of the water distribution system out of AE Intrusion Detection System. Given an input \( \vec{x} \), \( y(\vec{x}) \) is ‘under attack’ if \( \varepsilon(\vec{e}) > \theta \):

\[
y(\vec{x}) = \begin{cases} 'under attack' & \text{if } \varepsilon(\vec{e}) > \theta \\ 'safe' & \text{otherwise} \end{cases} \tag{2}
\]

Moreover, the authors propose a window parameter that takes into consideration the mean of \( \varepsilon(\vec{e}) \) of the last window time steps to decide if the current tuple is ‘safe’. This helps diminish the amount of false positives, since an alarm is raised only if in the last window time steps the mean of \( \varepsilon(\vec{e}) \) is above \( \theta \).

B. Replay Attack

In the replay attack setting (prior work, used here as baseline), the attacker does not know how detection is performed. In order to avoid detection, the attacker is able to replay sensor readings that have been recorded while no anomalies were occurring in the system. In particular, we assume that the attacker was able to record selected data occurring exactly \( n \) days before. I.e., if the evasion attack starts at 10 a.m., the attacker starts replaying data from 10 a.m. one day before.

C. White Box Attack

In the white box setting, the attacker knows how detection is performed, all thresholds and parameters of the detector, as well as the normal operations ranges for each one of the model features. For example, the attacker knows which sensor readings are common during normal operation of the physical process. As a result, the attacker essentially has access to an oracle of the autoencoder, where the attacker can provide arbitrary \( \vec{x} \) features and gets the individual values of the reconstruction error vector \( \vec{e} \).

The attacker then computes \( \max_i \varepsilon_i \) and finds the sensor reading \( r_i \) with the highest reconstruction error from \( \vec{x} \).
In order to satisfy $\varepsilon(\vec{e}') < \theta$, the attacker attempts to decrease the reconstruction error $d_i$ by changing $r_i$. Sensor readings $r_i$ are modified in the range of normal operating values; this guides the computation to a solution that is consistent with the physical process learned by the detector. For example, if normal operations of sensor $r_i$ are in the range $[0, 5]$, the attacker tries to substitute the corresponding value of $r_i$ according to its range to see if the related reconstruction error decreases. This results in $\vec{x}' = [r_1, \ldots, r'_i, \ldots, r_n]$, where $d'_i < d_i$ and, accordingly, $\varepsilon(\vec{e}') < \varepsilon(\vec{e})$. Figure 3 shows the steps followed by the attacker in such context, while Algorithm 1 is the pseudo-code applied to compute sensor readings modifications.

In order to find the value of $r_i$ that decreases $\varepsilon(\vec{e})$ the most, we can introduce $X$ as the matrix containing the mutations of $\vec{x}$ w.r.t. $r_i$.

$$X = \begin{bmatrix} r_1 & \ldots & r'_1 & \ldots & r_n \\ r_1 & \ldots & r'_i & \ldots & r_n \\ \vdots & & \vdots & & \vdots \\ r_1 & \ldots & r'_m & \ldots & r_n \end{bmatrix}$$

were $r'_i \in$ normal operations values for sensor $i$. Among the all mutations, we select the one that generates the lower reconstruction error $\varepsilon(\vec{e})$. After choosing the best value over the variable $r_i$, the algorithm repeats until a solution with average reconstruction error lower than $\theta$ is found.

Two stopping criteria are put in place: patience and budget. It could happen that no lower reconstruction errors $d_i$ are found by changing the value of a chosen reading $r_i$. In this case, we try to change the other readings in descending order of reconstruction error. patience mechanism is put in place to avoid wasting of computation. If no improved solutions are found in patience iterations, the input is no more optimized.

According to the communication mechanism between PLCs and SCADA, the attacker may be constrained to send the data in a certain amount of time. budget is the maximum amount of times that loop at Line 8 (Algorithm 1) can be performed. After budget attempts without finding a set of modified readings that satisfies $\varepsilon(\vec{e}') < \theta$, the input is no more optimized, and no solution is found.

Exiting the loop at Line 8 due to a stopping criterion is not providing a misclassified example. Even though a solution such that $\varepsilon(\vec{e}') < \theta$ is not found, the resulting tuple is likely to have a lower $\varepsilon(\vec{e})$, i.e., $\varepsilon(\vec{e}) > \varepsilon(\vec{e}') > \theta$.

### D. Black box attack

In the black box setting, the attacker does not know anything about the detection mechanism except the fact that it relies on a Deep Learning Model: the attacker can only intercept and manipulate the communication between the PLCs and the SCADA. However, the nature of the ICS environment allows us to assume that a detection mechanism trained over a specific CPS should represent its physical rules in order to spot anomalies.

In this case, a reasonable attack scheme could be divided into five steps (Figure 5). The attacker first intercepts traffic from PLCs to SCADA in order to collect information on how the ICS behaves under normal conditions. Second, collected data are used to learn how the system behaves normally and train a Deep Learning model. Third, the attacker manipulates the physical process; anomalous data are generated as a consequence. Fourth, the adversarial trained model is used to conceal anomalous readings, by morphing them into concealed data that will be classified as ‘safe’; the concealed data is forwarded to the SCADA.

### Autoencoder-based Generator.

We implement the black box attack using an autoencoder network to generate concealed data (the word generator is used with a different meaning than the usual one. In our case the input is not random noise that is going to be crafted by the network). The autoencoder is trained while intercepting normal traffic; the network learns to output tuples that are classified as being normal with high confidence. Forwarding the output of the adversarial network—regardless of how detector is built—forces it to misprediction, because the adversarial examples have been adjusted to resemble normal operations. Note that the autoen-

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**Algorithm 1 White Box evasion attack**

```plaintext
1: procedure CONCEAL($\vec{x}$)
2:   $c \leftarrow 0$ \quad \triangledown \ number of changes
3:   $i \leftarrow 0$ \quad \triangledown \ last optimization
4:   solved $\leftarrow$ False
5:   $\vec{e} \leftarrow$ compute_reconstruction_errors($\vec{x}$)
6:   previous_best_error $\leftarrow$ $\varepsilon(\vec{e})$ \quad \triangledown \ access oracle
7:   $\vec{e} \leftarrow$ sort_descending($\vec{e}$)
8:   while ($\neg$ solved) \&\& ($c - i <$ patience) \&\& ($c <$ budget)
9:     $f \leftarrow$ choose_feature_to_optimize($\vec{e}$)
10:    $X \leftarrow$ compute_matrix_of_mutations($\vec{x}, f$)
11:    $\vec{x}', \vec{e}' \leftarrow$ find_best Mutation($X$)
12:    if $\varepsilon(\vec{e}') <$ previous_best_error then
13:       previous_best_error $\leftarrow$ $\varepsilon(\vec{e}')$
14:       new_best $\leftarrow$ $\vec{x}'$
15:    else
16:       $i \leftarrow c$
17:     end if
18:    if $\varepsilon(\vec{e}') < \theta$ then
19:       solved $\leftarrow$ True
20:     end if
21:    $c \leftarrow c + 1$
22:    $\vec{e} \leftarrow$ sort_descending($\vec{e}'$)
23:  end while
24:  return new_best
25: end procedure
```
A number of approaches are feasible to reach our alternative goal of Availability Attack. For example, it is easy to cause a false alarm by replacing sensor readings with random values. We argue that such an attack would be noisy and likely attributed to bad sensor readings by the operator, and not be blamed on the detection system. Instead, the attacker should raise the alarm while concealing readings in a physically plausible way.

In order to achieve this result, we propose to use the black box approach. In this case, the attacker needs first to generate some ‘under attack’ traffic (e.g., by simulation or her own testbed). Given that traffic, the attacker can train a network to predict ‘under attack’ tuples. Then, the attacker uses the trained network to manipulate the normal traffic to resemble ‘under attack’ traffic.

V. Evaluation

In this section, we experimentally evaluate the two proposed attack mechanisms. We assume different attacker settings to study the behavior of our contribution.

First, we introduce the datasets we used for our experiments: the BATADAL dataset and data coming from a real industrial process (WADI dataset). Then, we show and analyze the results of the evasion attacks carried out over ICS datasets. We discuss Integrity Attacks (in which the attacker tries to misclassify the ‘under attack’ samples) by investigating the impact along $X$ dimension and comparing them to replay attacks. Moreover we evaluate the behavior of black box Integrity Attack along $D$ dimension. We then evaluate the usage of our black box approach to generate Availability Attack (leading to misclassification of the ‘safe’ samples). Finally we conduct the evaluation of our contribution in real-time over TestbedX testbed.

A. Dataset 1: BATADAL

The first dataset was generated with epanetCPA [27], an open-source object-oriented Matlab toolbox for modelling the hydraulic response of water distribution systems to cyber-physical attacks. The dataset was originally generated for the BATADAL [14] competition, which ran between 2016 and 2017. The goal of BATADAL was to objectively compare the performance of algorithms for the detection of cyber attacks in
water distribution systems. The system considered for the competition is C-Town, a medium-size water distribution network (i.e., about 400 nodes and 420 arcs) first presented in [28]. The BATADAL competition was based on three datasets: the first contains data coming from the simulation of 365 days of normal operations, while the second and the third contains 14 attacks (7 attacks each). The details of the attacks can be found in [14]. Each dataset contains readings from 43 C-Town sensors read every 60 minutes. These variables contain: tank water levels (7 variables), inlet and outlet pressure for one actuated valve and all pumping stations (12 variables), as well as their flow and status (24 variables). All variables are continuous, with the exception of the status of valve and pumps, represented by binary variables.

The original attack dataset (from http://www.batadal.net/data.html) contained sensor data readings that were manually concealed. For that reason, we could not use the original attack dataset directly (as we wanted to add concealment ourselves). Instead, we re-created the attacks (and resulting sensor data) from the BATADAL dataset for this work using the original setup, without any manual concealment. In our new version, the data are collected from sensors every 15 minutes instead of hourly as in the original setting.

### B. Dataset 2: WADI

Our second dataset is based on the Water Distribution (WADI) testbed, a real-world ICS testbed located at Singapore University of Technology and Design [29]. It is composed by two elevated reservoir tanks, six consumer tanks, two raw water tanks and a returned tank. It contains chemical dosing systems, booster pumps and valves, instrumentation and analyzers. WADI is controlled by 3 PLCs that operate over 103 network sensors. Moreover, the testbed is equipped with a SCADA system. WADI consists of three main processes: P1 (Primary supply and analysis), P2 (Elevated reservoir with Domestic grid and leak detection), and P3 (Return process).

For anomaly detection purposes, we consider sensor data from P1 and P2, since the return process is only implemented for water recycle purposes. Considering stages P1 and P2, we have data coming every second from 82 sensors. In this work, we use two WADI datasets. The first dataset contains data of 14 days of normal operations, the second contains 15 attacks to physical processes spanned over two days of operations. This dataset is available on request from its authors [30].

We primarily use the WADI dataset for two reasons: i) to show that the discussed detection mechanism is applicable to real world ICS data, and ii) to see whether our attack methodology is transferable from a scenario in which simulated data are used to another scenario in which real data are used.

### C. Evaluation Setup

We evaluate the detection accuracy over datasets under original conditions (i.e., no Integrity Attacks), the White Box, AE Black Box, and CNN Black Box Integrity Attacks. The **Accuracy** is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN},$$  

where $TP$ stands for True Positive, $TN$ for True Negative, $FP$ for False Positive and $FN$ for False Negative. The attacker’s concealment goal can be expressed in term of **Accuracy**: the Integrity Attack is successful if the detector accuracy over the concealed tuples goes to 0. The closer the accuracy comes to 0, the higher the amount of misclassified tuples.

Both white and black box attacks are implemented using Python 3.6.5, neural networks are implemented and trained using Keras 2.2.4 with TensorFlow 1.11.0 backend. Experiments were performed on a laptop equipped with Intel i7-7500U CPU, 16GB of RAM, and NVIDIA GeForce 940MX GPU 4GB.

**Training of Attack Detector.** For both BATADAL and WADI, we trained the attack detector [11] on sensor readings occurring during normal operational data (first dataset). Then we tuned window parameter using the attack datasets. These datasets contains both instances of normal operations and attacks to the physical process. Each attack recorded in both datasets is preceded and followed by instances of normal operations. The effect of a manipulation over a water distribution system can take a while before being detected and it can last over time even if the manipulation is not occurring anymore (i.e., if a pump is turned on to increase level in a water tank, it takes a while to bring the water to an anomalous value and when the pump is turned off the level in the tank takes a while before returning to normal operating conditions). Tuples of sensor readings have a related ground truth that report if any manipulation was occurring in the physical process. As the attack datasets are highly unbalanced, there are more instances of normal operations (negative class) than instances of manipulations of the physical process. The ground truth reports whether manipulation was occurring, but the effect in the data may not be seen immediately.

In order to select window parameter we considered the precision and recall of the detector, taking care also of the False Positive Rate (FPR). We are interested especially in raising a little amount of false positives (ideally no False Positives) while being able to classify correctly the attacks.

For the BATADAL dataset (where sensor readings are sampled every 15 minutes), we found that parameter window = 3 quarter of hours is a reasonable decision boundary to flag correctly attacks and do not raise False alarms. This gives an **Accuracy** = 0.93, **Precision** = 0.90, **Recall** = 0.58, **FPR** = 0.01. Changing window parameter we are able to increase the **Recall** at the price of decreasing **Precision** that means raising a higher number of False Alarms. With the considered window value we obtain a detector that gives a small number of false alarms, so even if not, an attack is detected for the whole duration of the physical manipulation, when an alarm is raised we are pretty confident that an anomaly is occurring.

For the WADI dataset, we found that parameter window = 60 seconds is a reasonable decision boundary to flag correctly attacks and distinguish them from False Positives. This gives a **Accuracy** = 0.97, **Precision** = 0.77, **Recall** = 0.57, **FPR** = 0.01. As in the BATADAL dataset, we preferred a window size that results in an higher **Precision** and consequently highly reliable alarms. Note that when we discuss accuracy in Section [V-D]...
we focus our attention to accuracy over the instances of data recorded during the manipulation over the physical process (ground truth ‘under attack’).

**Replay attack.** In this attack, the attacker replays for the whole duration of the physical manipulation the sensor readings as recorded at the same hour $s$ days ahead (assuming that process operations are often periodic within 24h). $s$ is chosen to let the replay contain only normal operations data. For example given a physical manipulation that last 50 hours, we replay sensor readings as happened 72 hours earlier (3 days earlier).

**White box attack.** In this attack, the attacker manipulates variables required to find a solution (according to the two stopping criteria introduced in Section IV.C and constraints over modifiable sensor readings). The result of this experiment highly depends on the detection mechanism. The attacker is using the oracle to determine if the concealment is successful. The detection scheme (as explained in Section IV.A) computes the mean of the reconstruction error over all the sensors, this results in the manipulation of only the sensor readings that contain anomalies (which are a small subset of sensors).

**Black box attack.** For the black box attack we conducted two different experiments. In the first, the attacker uses an autoencoder (AE) as generator and sends predicted readings to the SCADA. For the BATADAL dataset (43 variables), we train an autoencoder with 64 and 128 units for the first and second hidden layer respectively; for the WADI dataset (82 variables), we use 128 and 256 units. For the second experiment, the generator is a convolutional neural network (CNN) instead of the AE to show independence between the Deep Learning generator and the Deep Learning detector.

**D. Unconstrained Integrity Attack**

In this experiments we assume that the attacker is able to control all the reported sensor readings. We discuss the results of our evaluation of the detector for both datasets in several scenarios (see Table I). We evaluated the performance of our Integrity Attacks over the time steps with ground truth ‘under attack’ labels only, i.e. we exclude normal operation data time steps from computation of accuracy for this attack evaluation.

First row of Table I refers to Integritiy Attacks over WADI Dataset. In this case, for the white box parameters we choose $\text{patience} = 40$ and $\text{budget} = 300$. Result over this dataset shows that Replay attack can hide the anomaly occurring over the CPS. The performance of the white box approach equals the one of the Replay Attack. Finally, black box is underperforming the other methods. Despite this, detector’s accuracy reduces more than 50% black box using autoencoder.

**Computational Time.** Table I reports the average required time to compute the adversarial examples. Differently from white box and black box, replay attack does not require computation. White box approach requires an amount of time that depends from the algorithm $\text{budget}$ and $\text{patience}$ parameters. Black box approach requires a constant amount of time since it consists of a neural network prediction. Given our real-time constraints over the computation of adversarial examples, we can conclude that both white box and black box approach meets the requirements. In the BATADAL case (where the sampling time is 15 minutes), we do not require more than 2.28 seconds on average to compute an adversarial example. In WADI case (where sampling time is 1 second), on average we do not require more than 0.6 seconds to compute an adversarial example.

**Comments about Unconstrained Attacks.** When the attacker is free to manipulate all the sensor readings, results show that replay attacks are the best way to hide anomalies occurring over the physical process. First a replay attack does not require computation to find the manipulated set of sensor readings, second, the attacker does not need to be aware of the detection mechanism and third, the considered anomaly detector accuracy goes to zero since the replayed sensor readings do not contain (additional) anomalies. White box, even though achieves valuable results, requires computation and the attacker needs to be omniscient wrt. defense mechanism. Finally, we note that the black box attack is able to partially hide anomalies without having access to any oracle of the detector, with low computational effort (after training) and same knowledge wrt. the attacked model as the replay attack.

**E. Constrained Integrity Attack ($\mathcal{X}$ dimension)**

In the previous subsection, we found that full replay attacks can be a powerful and low cost way to evade (passive) anomaly detectors, if all features can be replayed. In this section, we demonstrate the impact on limitations on the attacker, e.g. if the attacker can only control a subset of the reported sensor values. For example, this can be the case if one PLC was compromised by the attacker.

**Definition of Constraints.** In order to study the impact of this kind of constraints, we selected $k$ features for every attack that can be modified. Then we studied how replay, white box, and black box attacks perform when these constraint are applied. We defined the constrains as follows: starting from the results of white box and black box attacks we determined the $k$ features that were changed most frequently (over the course of each attack). The intuition behind this is as follows: features that are modified most often in the unconstrained case are assumed to have the highest impact on the performance of
In the case of white box and black box attack, we limited the adversarial example exploration to the $k$ features extracted for the considered approach. In the case of replay attack we applied the same replay strategy introduced before but we replayed only the selected $k$ features extracted from the white box approach. We note that this choice (replay the features extracted from the white box approach) was made to reflect worst case scenario, i.e., an attacker that is able to replay exactly the $k$ features that a white box attacker would replay.

**Impact of Constraints.** Table I reports the average result of the constrained attacks over BATADAL and WADI Datasets.

In the case of BATADAL Dataset, we note that the replay attack does not cope well with constraints. Since the anomaly detector is able to spot the presence of contextual anomalies, the replay of only $k$ features results in alarms, resulting in an average detection accuracy higher than in the benign case (i.e., no manipulation of sensors applied). In the case of white box and black box attacks we can notice that the detection accuracy is always lower than the original accuracy. In the white box case accuracy decreases with the number of features that can be modified. Black box accuracy is not monotonically decreasing with the number of features that can be modified, the minimum is found when the attacker can compromise 8 features. Certain set constraints match better the physical rules learned by the detector and allow the creation of more effective adversarial examples. In case of WADI, we can observe that the replay attack is able to diminish detector’s accuracy especially when the attacker manipulates 3 features. White box and attack is able to achieve the same accuracy as if in the Unconstrained Attack case when manipulating 15 features. In the case of black box attack, results show that for 20 manipulated features, the attack performing slightly better than in the unconstrained case.

Moreover, we investigated how the set of features that can be modified by the attacker changes the efficacy of black box attack. We constrained black box attack to search solutions in the set of features extracted from the white box attack. Result shows that black box attack benefits of this choice, i.e. detector’s accuracy drops to 0.21 when acting on 3 features in WADI case (details are provided in Appendix Table VII). This indicates that depending on which features are available to modify by the attacker, attacks might be even more efficient than our main results shown previously.

**Comments about Constrained Attacks.** This experiment showed that a replay attack performs worse in the case in which only a limited set of sensors can be manipulated. In particular, the detector’s accuracy is increased due to contextual anomalies that are inserted in the data. Our proposed White and black box approaches reduce detector’s accuracy in real-time without introducing contextual anomalies.

### F. Black Box: impact of $\mathcal{D}$ dimension

Another aspect that we investigated is the impact of $\mathcal{D}$ on the applicability of black box attack. Especially, we are interested in understanding how much normal operational data the attacker needs to conduct the proposed black box attack. We investigated the impact of less available normal data (i.e., a fraction of $\mathcal{D}$) on the achieved reduction in detection accuracy for the black box attacker. We performed a sensitivity analysis by random sampling normal operations data 10 times the for each one of the considered percentages of data. Then, we trained an adversarial network for each sampling of the data percentage (50 adversarial networks trained for each dataset). As result we computed the sample mean ($\mu_{\hat{\mathcal{D}}}$) and sample standard deviation ($\sigma_{\hat{\mathcal{D}}}$) of the resulted detection accuracy by using the different black box networks.

For BATADAL, the resulting mean detection accuracy ranges from 0.14 for 100% of $\mathcal{D}$ available for AE training to 0.44 for 5% of $\mathcal{D}$ available (compared to 0.59 without

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**TABLE I**

| Detection Accuracy | Dataset | Original | Replay | White Box | AE Black Box | CNN Black Box |
|--------------------|---------|----------|---------|-----------|--------------|---------------|
| BATADAL            | 0.60    | 0        | 0.14    | 0.14      | 0.27         |
| WADI               | 0.68    | 0.07     | 0.07    | 0.31      | 0.46         |

**TABLE II**

| Required computational time, mean($\mu_{\mathcal{D}}$) and std($\sigma_{\mathcal{D}}$) | Dataset | Replay | White Box | AE Black box | CNN Black box |
|---------------------------------------------------------------------------------|---------|---------|-----------|--------------|---------------|
|                                                                                   |         | $\mu_{\mathcal{D}}(s)$ | $\sigma_{\mathcal{D}}$ | $\mu_{\mathcal{D}}(s)$ | $\sigma_{\mathcal{D}}$ | $\mu_{\mathcal{D}}(s)$ | $\sigma_{\mathcal{D}}$ |
| BATADAL                                                                         | -       | 2.28    | 2.46      | 0.002        | 0.005         | 0.003         | 0.003         |
| WADI                                                                            | -       | 0.60    | 0.41      | 0.005        | 0.002         | 0.005         | 0.002         |
TABLE III
IMPACT OF THE NUMBER OF FEATURES CONTROLLABLE BY THE ATTACKER. BY DECREASING THE NUMBER OF FEATURES THAT THE ATTACKER CAN CONTROL, WE CAN NOTICE THAT REPLAY ATTACK IS NO MORE ABLE TO HIDE ANOMALIES. REPLAY ATTACK INTRODUCES CONTEXTUAL ANOMALIES WHILE BOTH BLACK AND WHITE BOX APPROACHES AVOID THIS PROBLEM.

| Dataset | Original Accuracy | Experiment Accuracy vs. # of Controlled sensors $k$ (43 features BATADAL/ 82 features WADI) |
|---------|------------------|---------------------------------|
| BATADAL | 0.60             | 43/82  | 20  | 15  | 10  | 9    | 8    | 7    | 6    | 5    | 4    | 3    | 2    |
|         |                  | replay | 0.00 | 0.93 | 0.90 | 0.78 | 0.69 | 0.79 | 0.77 | 0.77 | 0.71 | 0.68 | 0.78 | 0.73 |
|         |                  | white box | 0.14 | 0.22 | 0.22 | 0.22 | 0.25 | 0.25 | 0.25 | 0.25 | 0.27 | 0.35 | 0.51 | 0.52 |
|         |                  | black box | 0.14 | 0.38 | 0.38 | 0.35 | 0.35 | 0.24 | 0.27 | 0.32 | 0.34 | 0.49 | 0.55 |
| WADI    | 0.68             | replay | 0.07 | 0.87 | 0.85 | 0.65 | 0.64 | 0.62 | 0.62 | 0.62 | 0.60 | 0.44 | 0.40 | 0.49 |
|         |                  | white box | 0.07 | 0.07 | 0.07 | 0.08 | 0.09 | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 | 0.14 | 0.25 |
|         |                  | black box | 0.31 | 0.28 | 0.48 | 0.58 | 0.54 | 0.61 | 0.61 | 0.61 | 0.62 | 0.68 | 0.68 |

TABLE IV
WADI DATASET: IMPACT OF FRACTION OF $D$ ON CONCEALING CAPACITY.

| Attack | Original Accuracy | 100% | 75% | 50% | 25% | 10% | 5% |
|--------|------------------|------|-----|-----|-----|-----|-----|
| BATADAL| 0.60             | 0.14 | 0.16 | 0.04 | 0.16 | 0.04 | 0.17 | 0.05 | 0.41 | 0.25 | 0.51 | 0.26 |
| WADI   | 0.68             | 0.31 | 0.35 | 0.08 | 0.31 | 0.01 | 0.29 | 0.04 | 0.28 | 0.09 | 0.30 | 0.13 |

concealment). For WADI, the resulting mean detection accuracy ranges from 0.31 for 100% of $D$ available for AE training to 0.50 for 5% of $D$ available (compared to 0.68 without concealment). In the case of WADI we can Results over BATADAL dataset show, performance of the attacker’s adversarial network is performing almost the same if trained with 100% to 25% of data. Lower than 25% of the data we notice substantial performance degradation. Looking at standard deviation, we notice that less data (10%, 5%) causes high model variance. To perform the black box attack the attacker needs 25% of data to guarantee evasion success.

In the case of WADI dataset performance of the adversarial network remains almost constant across the splits. WADI water distribution network is small and the three stage are repetitive. Information contained in 5% of the data (16 hours of recordings) could be enough to model the system behavior. At the same time, we notice that standard deviation increases in correspondence of 5%, this means that the performance is changing according to the data that are picked in the random split (e.g., some processes occurring through the system are not present in the split). Having access to more data reduces the variance of the models, 25% of the data assures low accuracy with a small standard deviation.

In that case, the attacker can train the network only on the desired class of adversarial manipulations sensors readings.

In Figure 4, we demonstrate how the Availability Attack is performing over 50 time steps of BATADAL dataset. It can be seen that $(\epsilon')$ (after the concealment) is not very far from threshold $\theta$, but the alarm is raised. Checking the physical state of the system directly will result in finding that no physical anomalies seem to be occurring in the system (as it is). The conjunction of these two factors will lead the defender to believe $\theta$ is lower than required, and the detection system is thus unreliable.

H. Real time Evasion Attacks

In order to test the real-time feasibility of our attacks, we deployed the anomaly detector in TestbedX (a real world ICS testbed), and then attacked it in real-time. We collected 15 hours of normal operations occurring over the ICS. We are able to gather 62 sensor readings sampled every 10 seconds.

In this case we tuned the window parameter to 30, that means that the detector is considering the sensor readings occurring in the last 5 minutes. First, we tested the reliability of the system; we left the system running 7 hours without anomalies occurring. We obtained 2 false positives instances occurring for 10 minutes each. We then performed some actuators manipulation over the system. In Table V we report the summary of the tested anomalies. We replicated some of the anomalies reported in WADI dataset that refer with the same identifiers.

While anomalies were occurring, we also launched our integrity attacks in TestbedX to assess their feasibility and efficacy. We tested both the white box and black box approach in real time by simulating the sensors value manipulation done by the attacker, all the instances of the anomalies occurring in the system were successfully misclassified. In Table V the
last two columns summarize the results of white box and black box attacks carried out in real time.

VI. DISCUSSION

In the evaluation section, we showed that replay attacks (while not requiring machine learning algorithms) is only efficient only when all sensor readings replayed. Thus, replay attacks do not represent a viable solution for hiding anomalies when the attacker can act on a limited set of sensor readings. In particular, Replay Attacks introduce contextual anomalies since sensor readings will not be consistent any longer. Even though the physical process is repetitive, replay of set of a subset of sensor values as observed n days earlier cannot be expected to avoid detection. In contrast, we proposed white box and black box integrity attacks overcome this problem by generating examples that are consistent with non-manipulated sensor values. Having access to the detector in white box allows to act only on a very small subset of sensor readings to reach misclassification goal. Black box approach requires the alteration of a larger subset of sensor readings to succeed. That said, the attack scenarios considered in this work require the manipulation of less than half of the total number of variables monitored by SCADA. This fact justifies why an attacker could resort to a sophisticated approach for concealment rather than a replay attacks over all sensor values.

We now discuss the quality of results coming from the proposed approaches. Figure 7 represents the comparison between trend of $\varepsilon(\hat{e})$ wrt. the threshold $\theta$ during the whole actuators’ manipulation done in one attack from WADI dataset. Comparing the white and black box $AE$ $\varepsilon(\hat{e})$ results, we notice that the solution provided by the white box algorithm is closer to $\theta$ than the black box solution. This is because the white box algorithm is looking at $\theta$ value to decide whether to stop the computation. Black box is not performing any optimization wrt. the attacked detector, so it is providing a solution that is matching the learned physical behavior, and what the detector expects from a non-anomalous sample. After second 200, the magenta line shows that the $\varepsilon(\hat{e})$ is around 0, meaning that we are sending inputs that are in line with the detector expected behavior. A comparison of $AE$ and $CNN$ black box solutions shows that the detector’s reconstruction error based on the concealment by the $CNN$ is closer to $\theta$. This means that the learned physical behavior by the CNN is not error free, but sufficient to classify the data as ‘safe’.

VII. RELATED WORK

We now discuss important related work in the area of anomaly detection in CPS, and evasion attacks on classifiers. 

Anomaly Detection in CPS. Detecting stealthy attacks in CPS through the identification of process-based anomalies, without requiring a detailed physical model, is an active research topic. Hadžiosmanović et al. [31] use an autoregressive model on time series extracted from modbus PLC traffic, evaluating their approach on data from two water treatment plants; Krotofil et al. [32] use an information theoretical approach to detect sensor spoofing attacks; Aoudi et al. [8] use model-free techniques rooted on singular spectrum analysis to detect structural changes in the process behavior.

More recently, various proposals in this space use deep learning techniques, usually by training a learning-based model on data gathered during the normal operation of the process, and statistically comparing the sensor readings with the model’s prediction at runtime. Wickramasinghe et al. [33] provide an overview on how Deep Learning techniques can be used in the context of CPS security. Goh et al. [7] propose an architecture to detect anomalies over a water treatment testbed with a Recurrent neural network (LSTM-RNN) used to predict sensor readings, and CUSUM to compute the difference between the predicted outputs and the actual sensor readings; building on this approach, and using the same dataset for evaluation, Kravchik et al. [10] suggest the use of a convolutional neural network to perform one-step prediction, while Taormina et al. [11] propose the autoencoder-based detector that we use as a target to evaluate our attacks.

Adversarial Learning for Classifier Evasion. The effectiveness of Adversarial Machine Learning to evade ML-based classifiers has been demonstrated in a wide range of applications, ranging from face recognition [37] to voice recognition [40] and malware detection [22]. Table VI classifies recent techniques in this domain according to the adversary’s knowledge on the classifier’s algorithm and training dataset. In the white box scenario (i.e., the adversary knows the internals of the trained model and the training set completely), Rndić and Laskov [34] present a case study on the evasion of PDFRate,
a malicious PDF detector based on random forests, using a white box gradient-based evasion method [41], comparing it to a black box mimicking attack, and discussing the attack effectiveness according to different attacker models. After the seminal paper that demonstrated the existence of adversarial examples for neural networks [19], work has shifted to Deep Learning. Goodfellow et al. [36] study the cause of adversarial examples and devise a fast gradient method to perform adversarial perturbations, demonstrating their results in the image classification context under a perfect-knowledge white box scenario. More recently, Carlini and Wagner [35] defeat a defensive technique known as defensive distillation [42]. White box techniques have also been applied to defeat face recognition, also through physical perturbations (e.g., wearing specially crafted accessories) [37].

In more restrictive scenarios, the adversary is only aware of the general structure of the model and how features are extracted. Papernot et al. [38] use this imperfect knowledge to build a surrogate model and demonstrate the effectiveness in source-target misclassification (image recognition). Grosse et al. [20] generalize the adversarial example crafting algorithm presented in [38] to malware detection systems. In other cases, the adversary attacks a classifier while querying the system under attack as an oracle. This is the case of attacks against proprietary online learning systems: to evade an online malware classifier, Xu et al. [22] leverage the fact that the target systems outputs the classification score to build a genetic algorithm that morph the adversarial examples into being undetected. More recently, Dang et al. [24] lifted the assumption of knowing the classification score, attacking oracle-like black-box classifiers that only output a binary label; Papernot et al. [29] work similarly in the context of multi-class classifiers for image classification.

With respect to the state of the art, in our black box attack the adversary does not rely on querying the classifier as an oracle, neither on building a surrogate learner; instead, we exploit the characteristics of the CPS domain to lift this requirement.

### VIII. Conclusions

So far, deliberate manipulation of ICS attack detectors has not been discussed in literature. In this work, we investigated two kinds of real-time evasion attacks on Deep Learning-based anomaly detectors in the context of Industrial Control Systems. The goal of the attacks is to conceal an ongoing manipulation of the process by manipulating the sensor values reported to the detector. We argue that in contrast to evasion attacks in other settings, such attacks on ICS require both manipulations that comply to inherent physical constraints between the features (that were learned by the detector), and need to be performed in real-time (as the dynamic state of the system cannot easily be predicted by the attacker). In particular, we also show that replay attacks (while being fast) are only effective if the attacker can manipulate all features, otherwise the replaying of recorded data will lead to violations of physical constraints that are detected. To mitigate those issues for the attacker, we proposed white box and black box attacks. Our white box attacker uses an optimization approach with a detection oracle, while the black box attacker uses an autoencoder (or CNN) to translate anomalous data to normal data in real time. The evaluation of our implementation of both approaches using data from two water distribution systems demonstrates that attacks are feasible in general, and perform better than replay attacks in cases where not all features can be manipulated. In particular, we show that for the BATADAL dataset our novel black box attack using autoencoder was able to reduce detection accuracy as efficiently as the white box attack (accuracy dropped from 0.60 to 0.14 in both cases). Our results demonstrate that the required autoencoder can be trained without knowledge of the detector (only using normal operational data) and is computationally cheap (after training). In addition to constraining the number of features to be manipulated, we also investigated constraints on the attacker knowledge of normal system operations (in the black box). In general, the attacker required a dataset that was roughly a quarter of the training dataset size to launch effective attacks. We implemented our attacks in a real testbed, and showed that malicious data could be generated on-the-fly, i.e., in between each sampling step (every 10s, actual example generation took around 0.6s). That demonstrates that the proposed attacks are allowing attackers to perform evasion detection on

### TABLE V

| Attack Identifier | Starting Time | Ending Time | Duration (minutes) | Detected | First instance detected | Detected concealment |
|------------------|---------------|-------------|--------------------|----------|------------------------|---------------------|
| WADI 1           | 14:09         | 14:31       | 22                 | ✓        | 14:24                  | ✗                  |
| WADI 7           | 15:07         | 15:11       | 4                  | ✓        | 15:08                  | ✗                  |
| WADI 8           | 15:30         | 15:40       | 10                 | ✗        | 15:40                  | ✗                  |
| WADI 9           | 10:57         | 10:58       | 1                  | ✓        | 10:58                  | ✗                  |
| WADI 14          | 11:59         | 12:01       | 2                  | ✓        | 12:00                  | ✗                  |

### TABLE VI

| Malware | White Box | Grey Box | Black Box |
|---------|-----------|----------|-----------|
| Image   | 34        | 20       | 13        |
| ICS     | 13        | 20       | 13        |

**Recent adversarial learning techniques for evasion, according to the attacker’s knowledge and the domain of application. The setting for our attacks is marked with ⋆.**
dynamic systems in real-time. In prior work, manipulations are usually performed offline against a dataset, or assume that data to be manipulated can be precisely predicted.

In addition to the Integrity attacks, we considered Availability Attacks. In those attacks, the goal is to trigger detection events with minimal changes of the reported data, in order to reduce confidence in the detector. We show that we were always able to introduce false alarms with minimal manipulations. As consequence of our finding, we believe that future ML-based attack detectors for complex feature sources such as Cyber-Physical Systems need to be designed not only for accurate detection of uncontrolled attacks, but only to be more robust against Evasion attacks. We plan to release our code as open source, complementing the publicly available datasets.

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Appendix

A. Effect of constraints over Black box approach

Table VII shows the effect of constraining black box over a different set of sensor readings. Specifically, we constrained black box approach to manipulate the features that we extracted from white box approach. Black box performance can be improved by the set of sensor readings that are available to the attacker. BATADAL dataset case performance of black and white box approach are similar. In the WADI case the performance of black box is almost the same across all the different experiments, the best performance is found when it is constrained to manipulate 3 sensor readings.
| Dataset | Original Accuracy | Experiment | 43/82 | 20 | 15 | 10 | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 |
|---------|-------------------|------------|-------|----|----|----|---|---|---|---|---|---|---|---|
| BATADAL | 0.60              | replay     | 0.00  | 0.93| 0.90| 0.78| 0.69| 0.79| 0.77| 0.77| 0.71| 0.68| 0.78| 0.73|
|         |                   | white box  | 0.14  | 0.22| 0.22| 0.22| 0.22| 0.25| 0.25| 0.25| 0.27| 0.35| 0.51| 0.52|
|         |                   | black box  | 0.14  | 0.20| 0.20| 0.20| 0.20| 0.23| 0.29| 0.30| 0.33| 0.39| 0.52| 0.55|
| WADI    | 0.68              | replay     | 0.07  | 0.87| 0.85| 0.65| 0.64| 0.62| 0.62| 0.60| 0.44| 0.40| 0.40| 0.49|
|         |                   | white box  | 0.07  | 0.07| 0.07| 0.08| 0.09| 0.12| 0.12| 0.12| 0.12| 0.14| 0.14| 0.25|
|         |                   | black box  | 0.31  | 0.30| 0.30| 0.27| 0.27| 0.27| 0.27| 0.27| 0.27| 0.27| 0.21| 0.30|

**TABLE VII**

**Black Box performance when constrained to work on the set of features extracted from white box attack.**