Revisiting Anomaly Detection in ICS: Aimed at Segregation of Attacks and Faults

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ABSTRACT
In an Industrial Control System (ICS), its complex network of sensors, actuators and controllers have raised security concerns for critical infrastructures and industrial production units. This opinion paper strives to initiate discussion on the design algorithms which can segregate attacks from faults. Most of the proposed anomaly detection mechanisms are not able to differentiate between an attack and an anomaly due to a fault. We argue on the need of solving this important problem form our experiences in CPS security research. First, we motivate using analysis of studies and interviews though economical and psychological aspects. Then main challenges are highlighted. Further, we propose multiple directions of approach with suitable reasoning and examples from ICS systems.

KEYWORDS
Cyber Physical Systems, CPS Security, Critical Infrastructure, Anomalies, Faults

1 INTRODUCTION
Industrial Control Systems (ICS) are found in modern critical infrastructure (CI) such as the electric power grid and water treatment plants. The primary role of an ICS is to control the underlying processes in a CI. Such controls are facilitated through the use of computing and communication elements such as Programmable Logic Controllers (PLCs) and Supervisory Control and Data Acquisition systems (SCADA), and communications networks. The PLCs receive data from sensors, compute control actions, and send these over to the actuators for effecting control over the process. The SCADA workstations are used to exert high level control over the PLCs, and the process, and provide a view into the current process state. Each of these computing elements is vulnerable to cyber and physical attacks as evident from several widely reported successful attempts such as those reported in,[10, 12, 22]. Such attacks have demonstrated that while air-gapping a system might be a means to consider securing an ICS, it does not guarantee in keeping attackers from gaining access to the system.

Successful attacks on ICS have led to research to prevent, detect, and react to different forms of cyber attacks. Anomaly detection that aims at raising an alert when the controlled process in an ICS moves from its normal to an unexpected, i.e. anomalous, state. The challenge with the proposed techniques is that those are not able to distinguish between an anomaly being raised due to an attack or a system fault.
in Fig. 1. A CI plant may go in shutdown for hours under identification of an attack. A correct classification, an attack identified as an attack and a fault as a fault would save loss of lives and revenues. But incorrect and cross classifications would be detrimental for the system. A fault raised as attack has high psychological impacts, invites panic and responses of higher magnitudes. Hence, if anomaly detectors are deployed, faults in sensors or actuators might lead to shutdowns of whole units and incur huge economic losses. Similarly, an attack identified as a fault would undermine the losses and a repetitions would discourage adoptions of such detectors. We note that psychologically an attack is dealt with much higher alertness and hardness in response strategy.

Our participants did acknowledge the relevance which can be inferred from the responses like:

- “Yes, no need to shut the whole system under assumption of attack when a fault might have occurred”.
- “Yes, if an algorithm can identify it to be a system fault immediately, it will reduce the amount of time required during the identification process. True attacks can be immediately treated as attacks and response time will be much shorter.”
- “Yes, the incidents should be handled differently.”
- “... But the incident response may have different outcome if it isn’t an attack. Such as forensics and developing control to handle such attacks may not be performed.”

Five of the participants reported to be working on response and mitigation strategy design and did suggest that differentiating strategy would save time and facilitate narrowing down focus and search spaces. Participants working in production industries reported of following traditional methods of predictive maintenance in case of anomalies i.e., deviations of variables from history and process physics Fig. 1. The process still keeps running in this case. Breakdown maintenance is conducted in case there are serious faults. In this case either spare parts are used or redundant process chains are activated. It is to be noted that there are dedicated employees under central maintenance team for handling such faults which have been maturing over the decades but intelligent cyber attackers might hide their attacks inside such checks. Also the frequency of faults and predictive maintenance are fairly high. On the other side, a cyber attack leads to process halt and shutdowns of plants like in recent case with Renault, [2]. And to make matter worse, cyber attacks against industrial targets have been growing rapidly [1] as well. As noted before, any cross-error would invite economic and opportunity losses. Hence a segregation is necessary and very timely.

3 WHY IS THE SEGREGATION DIFFICULT?

We and past research works like [3, 4, 6, 9, 16, 20, 21] note that it is fairly difficult to differentiate between these two vectors of anomalies. As an example consider Fig. 2 that shows data from two different pressure sensors from the water distribution testbed. On the left hand side, a water leakage attack was executed while on the right hand side a fault similar to leakage happened but for a statistical detector both appear to be the same. Few of the challenges are summarized herein:

- **Challenge 1. Not modeling properties of faults and attacks:** Most of the related works would look at the consequences of an attack or fault rather than looking through the properties of attack or fault themselves. For example, a fault is usually random and results in abrupt change for a short period of time. On the other hand an attack is properly planned and is executed for a longer time to do substantial damages. Missing on opportunities of differential properties adds to hardness of the problem.

- **Challenge 2. Unknown attacks and faults:** The base assumption for an anomaly detection method is that there would always be unknown attacks, therefore it is not possible to use black-listing or white-listing as an effective method [19]. Therefore, we rely on behavioral methods which simply look at the end result of anomalous behavior and raise an alarm. The challenge is that it is not possible to create a model for each possible fault that is out there in the wild.

- **Challenge 3. Lack of hybrid models:** There are no precise hybrid models for cyber and physical domains. It is not clear how to come up and use the information from independent and orthogonal spaces through an analytical lense. Most of the anomaly detection methods are implemented either in cyber layer or in the physical layer. There is no one size fit all techniques due to a wide variety of ICS.

4 SUGGESTED DIRECTIONS OF APPROACH

There are a lot of efforts for detecting sensor attacks but most can not distinguish between an attack and a faulty sensor measurement. An attempt was made recently [15] to model and detect transient faults. It models a transient fault for each sensor and an algorithm is designed to detect and identify attacks in the presence of transient faults. This approach can detect transient faults (e.g., a GPS reporting faulty readings inside a tunnel) but not the permanent faults/attacks, e.g., DDoS attack or cutting wire of a sensor. Also, this work does not consider a stealthy attacker trying to imitate a transient fault. They have also assumed multiple sensors for the same physical state variable. They also assume an abstract sensor model where the sensor reports an interval of readings e.g., a set rather than one value. Therefore, it is highly desirable to come up with novel methods which could differentiate between a fault and an attack by considering a realistic threat model. In the following, we present a few proposals that also highlight open problems.
4.1 Combining Process and Network Layer Detectors
The studies involving both the network and the process layer are rare [11]. We propose to use data from both the network layer and the process layer. For example, if a sensor data is compromised as a man in the middle attack (MiTM) [8] then the resultant process state might have equally resulted from a fault but by looking at the MiTM traffic, it would be certainly possible to point out an attack.

4.2 Relation Between Size, Detection Time and Time to Damage of faults and attacks
Fault/Attack size means how much is the sudden change in the physical state variables. For example, consider an initial state (\(S_i\)) before attack and state transition to \(S_a\) after an attack, where \(|S_a| >> |S_i|\), such an instantaneous change would be considered of a large size. Detection time is a measure of how fast one can detect the attack whereas time to damage depends on the process itself, e.g., for a fluid storage tank depending on the capacity it could take long time to overflow or underflow attack. While in electric grid a sudden surge can instantly damage the physical system. We can study relationship between variables to segregate between two.

4.3 Virtual Sensors/Digital Twin
We can exploit the idea of a digital twin or model virtual sensors. Since the digital system does not have any real sensors, it could not get faulty and any manipulation must be a result of some attack. The key assumption is that an attacker must attack that virtual/digital twin.

4.4 Signature based Attack Detection
Attack signatures can be collected by designing an attacker’s intentions and strategy. However, a limitation of this method is that it would not be able to detect unseen attack patterns.

4.5 Mode Shift Across Attack and Fault
The idea is to figure out how the device’s mode transition occurs during a fault. Faults would be random, for example, failing of a sensor or actuator. Whereas, attacks would exhibit a mode shift for several devices at the same time. For example, to attack a process plant, an attacker would compromise the sensor as well as actuator’s mode at the same time to hide itself.

4.6 Simulate Failures and Faults for Known Device
Attacks are unknown before an attack has taken place whereas fault data could be generated. The idea is to collect data for the (known) faulty behavior to create fault models. If we have profiles for normal data as well as faulty data, then it should be possible to distinguish attacks from faults.

4.7 Exploiting Asymmetry between Correlation and Causation
We argue that correlated failures should be taken with a pinch of salt. If a sensor fails or an actuator fails it would have an impact on another associated device. For example, if a motorized valve at the inlet of a tank fails then the flow sensor is also affected but if the flow sensor fails then the actuator (motorized valve) is not affected. Therefore, to attack the flow sensor an attacker has to attack both the flow meter as well as the actuator but there is no such requirement for a fault.

4.8 Detection Latency based Method
An interesting observation from previous research [5, 15] shows that sophisticated attacks (takes more time) and fault like bias injection attacks (detected instantaneously) takes different amount of time. The hypothesis is that the fault would be a sudden change. However, a persistent attacker would stay for a longer period of time to do substantial damage.

4.9 Fault Time Constant
Fault’s time constant would be different than that of attack. Inspired from the research in fault detection in ICS [17], it is hypothesized that the faults are more abrupt and random and hence their time constant is much smaller than the normal process profile. However, we assume that an attacker would try to imitate as close to the process as possible, therefore if modeled properly faults could be distinguished.

4.10 Redundancy
Using the redundant sensors for the same physical state variable can help in fault and attack isolation provided that not all are attacked at the same time [15].

5 CONCLUSIONS
Through this opinion paper we aim to kindle interest of ICS community towards deeper nuances of anomaly detection and analysis. We assert the relevance of differentiating between faults and attacks in cyber-physical systems and try to motivate from both economical and psychological lenses which are further corroborated by interviews with researchers and industry managers. We build up on top of the core challenges in segregating the two forms of anomalies and propose multiple directions of approach. This work shall be followed by rigorous research in most of the outlined directions in collaborations with research institutes and universities hosting state-of-art CPS test beds.

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