Next Generation Resilient Cyber-Physical Systems

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Abstract—A distributed Cyber-Physical Systems (CPS) consists of tightly integrated computing, communication and control technologies. Recent CPS hacking incidents had significant consequences. In such a context, reinforcing their resilience, referring to their capacity to recover from disruptions, is a key challenge. Concretely, it involves the integration of mechanisms to regulate safety, security and recovery from adverse events, including plans deployed before, during and after incidents occur. We envision a paradigm change where an increase of adversarial resources does not translate anymore into higher likelihood of disruptions. Consistently with current system design practices in other areas, employing high safety technologies and protocols, we outline a vision for next generation CPS addressing the resilience challenge leveraging ideas such machine learning and fuzzy systems.

I. INTRODUCTION

Cyber-Physical Systems (CPS) integrate computation, communication and physical processes [25]. The design of a CPS involves several fields including computer science, control theory, automation, networking and distributed systems. Skills from these domains are put together to ensure that a myriad of computing resources and physical elements get orchestrated via networking technologies. In addition, CPS integrate facilities for human-computer interaction. Examples of CPS interacting with humans include industrial control systems (e.g., workers operating industrial machines) and smart cities (involving thousands of nodes and citizens).

CPS are omnipresent in our everyday life. Hacking and failures of such systems have impact on critical services with potentially significant and lasting consequences. Reinforcing their resilience is a key challenge. Resilience refers to the capacity of a system to recover from disruptions. It can be seen as the mechanisms present in a system to regulate its safety and security and to recover from adverse events. Resilience includes actions and plans that are deployed before, during and after adverse events take place. Resilience is a historical term used as a descriptor in complex fields, from psychology and medicine to civil and military engineering. In cybersecurity, it relates to the idea of how a complex system bounces back from a disruption, as well as all the possible post-disruption strategies followed after the events are recognized.

A. Related Work

The state of the art in CPS security has recently been reviewed by Giraldo et al. [13] and Humayed et al. [20]. According to Giraldo et al., past research works have put much emphasis on the problem of preventing perpetration of attacks on CPS, for instance, leveraging cryptographic techniques and building intrusion detection systems. They emphasize the need for more works on techniques for mitigating the consequences of attacks. After they have been detected, the problem of responding to attacks seems to have received little attention. Humayed et al. did a good job at identifying representative CPS and reviewing security issues specific to them. The categories are industrial control systems, medical devices, smart cars and smart grid systems. For every representative CPS, specific threats, vulnerabilities, attacks and controls are examined.

Although the term CPS emerged recently, it builds upon very well-established research fields, i.e., embedded computing, control theory and human-computer interaction. For instance, a CPS can be easily modelled as a Networked-Control System (NCS) [10]. The major difference is that the controller is coupled with the actuators and sensors through a communication network (e.g. an Ethernet-like network). The use of this communication network to connect the components provides flexibility and low implementation costs [16]. NCS classical theoretical problems include (1) stabilization of system processes given delays and packet losses due to the network elements [40], [45]; (2) data rate limiting techniques (e.g., control to systems traffic) [18] and (3) energy efficiency for wireless NCS [3], [37]. It is only until recently that the NCS communities started working on cybersecurity issues of CPS [25], [41]. Obviously, the use of a communication network to transport control and observations, i.e., signals to actuators and from sensors, paves the way to important security vulnerabilities [35]. A NCS can be attacked and needs to be protected.

Attacks exploiting NCS vulnerabilities can be characterized according to three main aspects [36]: (a) adversary’s a priori knowledge about the system and its protective measures, (b) class of disrupted resources (e.g., denial-of-service attacks targeting elements that are crucial to operation) and (c) analysis of control signals during perpetration of an attack (e.g., sensor outputs), that may be used to carry out more sophisticated attacks (e.g., attacks targeting the integrity or availability of the system). The knowledge of adversaries in terms of, e.g., system dynamics, feedback predictability and system countermeasures, can be used to perpetrate attacks with severe security and safety implications, when they target the
operations of, e.g., industrial systems and national infrastructures. They can lead to catastrophic consequences to businesses, governments and society at large. A growing number of attacks on cyber-physical infrastructures are reported in the world, targeting vital activities (e.g., water, energy and transportation) for intelligence or sabotage purposes. Some representative incidents are outlined in Table I.

A careful review of incidents as those in Table I reveals that they all have a common element [21], [31]: human adversarial actions forging system feedback measurements for disruption purposes [12]. The underlying issue, hereinafter called the feedback truthfulness problem, refers to intentional situations perpetrated by human adversaries, forging physical observations in a stealthy manner [4], [22]. They are cyber-physical attacks generating anomalies [17], [35]. However, even if detected, the attacks appear as unintentional errors. Hence, they are leading to wrong resilience plans. How to distinguish an intentional attack from an unintentional fault? This a challenge because symptoms may almost be the same, but reactions should be different. Indeed, the correct response to a fault is a repair action that restores the state of the system. In case of an intentional attack, physical resources may not be faulty at all, but the adversary makes them appear faulty. A repair action will not help.

It is crucial to address the aforementioned challenge in a provable manner in order to prioritize appropriate responses and rapidly recover control to assure cyber-physical resilience [11], [21], [24]. That is, to assure the persistence of the system when facing changes, either accidental or intentional [38]. In terms of CPS design, cyber-physical resilience shall also deal with the management of operational functionality that is crucial for a system, and that cannot be stopped. In other words, system functionality that shall be properly accomplished. Regarding the incidents mentioned in Table I, the cooling service of reactor in a nuclear plant, or the safety controls of an autonomous navigation system, are proper examples of critical functionalities. Other system functionalities may be seen as less important; and even be temporarily stopped or partially completed. Such type of functions can be seen as secondary. A printing service for employees in a nuclear plant scenario is a proper example of a secondary function that one might accept to sacrifice, under graceful degradation.

When addressing resilience, two crucial elements to take into consideration are the severity of the actions disrupting the functionalities of a system and properly distinguishing accidental failures from intentional attacks [8], [22], [26], [33], [44]. The objective is to use the proper security stacks and deploy resilience plans, including responses that mitigate the impact of undesirable actions [11]. This includes the use of proactive, often short-term, tactical policies to handle failures; and reactive, usually long-term, strategies for attacks [19], [30], [32]. Security stacks in both areas can include redundancy (e.g., use of additional system replicas), compartmentalization, segmentation, and activation of upgraded modes of protection (e.g., use of cryptography to enable secure handshakes, message signatures, and encryption[13], [20]). The inclusion of resilience plans shall always keep critical processes in a normal operating mode, while the system is confronted with incidents. The challenge of satisfying those requirements on automated CPS designs stresses the importance of determining the root nature of incidents, to drive the appropriate models (e.g., in terms of remediation) that the system must select and enforce in the end.

One may also consider that both accidental failures and intentional attacks can be formally represented as anomalies in the measured data. Recent studies by Iturbe-Urretxa et al. [22], [23] discuss on the feasibility of distinguishing between process disturbances and intrusions in process control systems using multivariate statistical process control. More specifically, the authors define a statistical analysis process for the definition of normal traffic, reporting anomalies (i.e., deviations from the expected profile of a trustworthy entity) as adversarial activities. Authors show the way of dealing with the complexity of data management as a result of monitoring processes collecting and transforming anomalous events in industrial control systems mathematically modeled as NCS. The contributions of the study range from visual analytics to detection and correlation of anomalous events based on statistical management of large datasets.

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### Table I

**Representative cyber-physical attacks reported in the media.**

| 1. Sabotage of critical facilities, such as a German steel mill in 2015, hospitals, media and financial services in France and the UK in 2017 and 2018. The problem is spanning several countries from the European Union, the US, and beyond. |
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| 2. Remote control of navigation systems, including successful hacking of autonomous cars and avionic systems. Studies and general concern started with a malware that infected over sixty thousand computers of an Iranian nuclear facility, and destroyed more than one thousand nuclear centrifuges. This delayed the Iran’s atomic program by at least two years. |
| 3. Disruptions of large-scale industries have been appointed by the Federal Office for Information Security of Germany as a serious concern to European factory and industrial markets. Similar threats affect drones and smart cities, as well. |
| 1. Human adversarial actions in this scenario, include USB injection of corrupted software binaries, drive-by-download malware installation, spear phishing-based design of websites, and traditional social engineering manipulation of critical infrastructure employees. |
| 2. Human adversarial actions include the use of injection vectors (e.g., USB drives), corrupted updates and patches, radio frequency jamming, radio frequency spoofing, and software binary manipulations. |
| 3. Human adversarial actions include the use of GNSS (Global Navigation Satellite Systems) attacks, such as jamming and spoofing of signals, and hijacking of communications to downgrade communications to insecure modes (e.g., downgrading from encrypted to plain-text communications). |
More relevant related works and reference material are cited throughout the remaining sections of the paper. Section II provides a more thorough introduction to the concept of resilience and the use of security stacks to enable cyber-physical protection. Section III argues the necessity of a paradigm change and discusses our vision of how next generation resilient CPS will be addressing such a change. Section IV closes the paper.

II. Resilience and Security Stacks

Resilience is a term with centuries of use [28]. It encompasses multidisciplinary fields, from psychology and medicine to civil and military engineering. Current application of the term under the scope of cybersecurity is centered upon the idea of bouncing back from failures, while defending forward from attacks. It emphasizes the capacity of a system to recover from disruptions, and is often seen as the underlying technique by which a system regulates its safety and security mechanisms, to recover from adverse events. Resilience includes actions and plans that must be conducted before, during, and after events take place. Resilience is a historical term used as a descriptor in complex fields, from psychology and medicine to civil and military engineering. The modern application of resilience relates to the idea of how a complex system bounces back from a disruption, as well as all the possible post-disruption strategies that may come after the events are identified.

Under the scope of complex systems theory, the concept of resilience may be confused with other traditional concepts such as robustness, fault tolerance and sustainability. However, there exist fundamental differences between such terms. For instance, while robustness stands for the ability to withstand or overcome adverse conditions (e.g., faults and attacks), resilience refers more to the capacity for a system to maintain functionality despite the occurrence of some internal or external disruptions, e.g., adversarial breach [6]. Similarly, fault tolerance refers more to the maintenance of crucial services within a given time-period under the presence of failures and sustainability to similar metaphors in disciplines like environmental and socio-ecological processes [1], [15].

Laprie [27] settled some key definitions when comparing resilience to dependability and fault tolerance. In his work, Laprie related the resilience and dependability terms as follows: Resilience is the persistence of dependability when facing changes. More recently, the relation between resilience and performance targets have been described by Meyer [29] as follows: Resilience is the persistence of Performability when facing changes. This can be accomplished by graceful degradation, i.e., by prioritizing some services over non-essential ones, for as long as possible [14].

The concept of resilience spans across several other disciplines. For instance, when talking about resilience in terms of network theory, resilience refers to the persistence of service delivery when the network faces changes [43]. In terms of quality of service, resilience relates to the degree of stability of the services provided by the system [5]. From a control-theoretic standpoint, resilience refers to the ability to reduce the magnitude and duration of deviations from optimal performance levels [31]. Finally, resilience is also seen in disciplines such as medicine and psychology, as the ability to recover from a crucial trauma or crisis [42]. The common element seen in all the aforementioned definitions relates to adaptation to confront change and significant adversities.

When we move to the specific context of cybersecurity, resilience means accepting that the system is vulnerable to attacks, in addition to faults and failures [19], [4]. It means to accept that there will be breach of security (e.g., by a collusion between insiders and outsiders, attacking and disrupting the system). Handling resilience in the cybersecurity context means holding an adversarial mindset and getting ready to lose some assets [14]. This does not mean sacrificing the system, but deciding which parts of the system we can lose (accepting that we must lose some control over the system) while prioritizing those assets we must give up to assure that the system will remain functional during the disruptions.

To improve resilience from the cybersecurity standpoint relies on enforcing a traditional security stack, in terms of identifying the system weaknesses (e.g., in their software and infrastructure themselves) that could potentially be controlled by a skilled adversary with the purpose of disrupting the system. Management in terms of identifying vulnerabilities must be followed as well by assessment of incidents, service continuity and, in general, any risks affecting the system. These aforementioned management perspectives must be driven by resilience thinking in the form of bouncing back (or defending back) from disruptive or adverse events. In other words, attacks against the availability of a given service, as well as any incident leading to security breaches must be quickly solved (e.g., incidents must properly be absorbed).

III. Moving Forward

In the previous section, we argued that modern CPS must change today’s adversarial paradigm where an increase in the resources of the adversaries always translates into higher likelihood of disruption. In this section, we survey some promising techniques that could potentially help the dynamics of the game. All computer based systems can take advantage of these techniques to improve their safety and security. In the context of CPS, we discuss how each of these techniques can improve security.

Machine Learning — Artificial Intelligence (AI) by means of the subfields of Machine Learning (ML) and search provides a large set of techniques appropriate for resilient cyber-physical systems. There are three main ML paradigms, namely, supervised, unsupervised and reinforcement. In supervised machine learning, there are old and new data points. Old data points are labelled. A label represents a classification of data points. Comparing their similarity with old data points, supervised machine learning assigns classes or labels to new data points. With unsupervised ML, the data points are unlabelled (i.e., learning is about extracting information from data). Data points are grouped together into classes according to similarity. The classes need to be labelled by a human expert. In contrast, reinforcement learning rewards or penalizes the learner following the validity of inferred classifications, i.e.,
there is no need for labelled data. Learning is inferred from the successes and failures.

Supervised and reinforcement ML is used for system identification and model fitting. Different alternative learning methods exist, based on different considerations on the type of the model (e.g., rule-based, support-vector machines, deep learning models) and its properties (e.g., explainable models/decisions, efficiency).

Resilience plans build upon rational responses. Their performance often requires rapid completion of search tasks. Their efficiency can be greatly improved when the search are informed, i.e., when it applies heuristics. The AI subfield of search provides us with algorithms and methods for complex decision making problems. For example, systems based on Monte Carlo tree search have been proven successful in difficult games (e.g., AlphaGo and AlphaZero). Connection between Monte Carlo tree search and reinforcement learning exists in the AI literature [34], [39].

How does CPS security can take advantage of ML? The start of an answer can be found in a book authored by Chio and Freeman [7]. It is worth mentioning that the applicability of ML to computer security has been demonstrated in the past. The most successful story is the use of the approach to control spam emails. Meta-data, source reputation, user feedback and pattern recognition have combined to filter out junk emails. Furthermore, there is an evolution ability. The filter gets better over time. ML is about data and, together with clever algorithms, building experience such that next time the system does better. This way of thinking is relevant to CPS security because its defense can learn from attacks and make the countermeasures evolve. Focussing on CPS-specific threats, as an example pattern recognition can be used to extract in data the characteristics of attacks and prevent them in the future. Because of its ability to generalize, ML can deal with adversaries hiding by varying the exact form taken by their attack. Note that perpetrators can also adopt the ML paradigm to learn defense strategies and evolve attack methods. The full potential of ML for CPS security has not been fully explored. The way is open for the application of ML in several scenarios.

**Fuzzy Decisional Systems** — Fuzzy sets can be used to model imprecision and vagueness. A concept is said imprecise when several values satisfy it (e.g., the temperature is below zero). A concept is vague when it represents partial truth. For example, the fact that a temperature is near zero can be a matter of degree and there is no value under which temperatures are near zero and over which it is completely false that the temperatures are near zero. Fuzzy systems are typically rule based systems in which concepts are represented by means of fuzzy sets. This permits that in particular situations, terms are partially fulfilled and, as a consequence, rules are partially fired.

Fuzzy sets have been proven to be effective in modelling safety and control. Fuzzy control being one of the most successful application areas of fuzzy sets. In these applications, a control system is defined by a set of fuzzy rules that will be fired all at once. The set of consequents of all rules are then combined taking into account the partial fulfillment of each rule. Combination results into a fuzzy set that needs to be defuzzified to result into an actual value. When the number of variables in a system become large, the construction of fuzzy sets systems need to deal with the course of dimensionality, as the number of rules are typically exponential on the number of variables. Hierarchical fuzzy systems have been developed to deal with this problem. Adaptive systems exist that modify the rules according to changes in the environment. Fuzzy rules can be learned from data and, thus, used for adversarial identification. Fuzzy rule based systems can be efficiently deployed in real-time systems. This is so because rules can be fired in parallel and inference can be also implemented in an efficient way. Fuzzy systems can also be used to model high-level decision making processes, as e.g., reason about identification of adversarial actions, and the remediation to be taken. These decisions need to take into account high doses of uncertainty.

The potential of fuzzy decision making in computer system security has been demonstrated. Its ability to deal with uncertainty is particularly useful for risk assessment [2], [9]. Normal operation conditions of a CPS are a vague concept and detection of abnormal conditions and unstable states can be modelled and inferred using fuzzy systems where partial truth is accommodated. Fuzzy systems are also useful for adaptive control environments, in which the underlying models (e.g., system dynamics and related parameters) vary frequently, due to the high degree of uncertainty in the system. All this needs to be combined with probabilistic approaches as attacks are either present or absent and thus better represented with probabilistic approaches (i.e., attacks being related to intentionality while failures and faults associated to uncertainty).

**IV. Conclusion**

A CPS is a physical process observed and controlled through a computer network. Signals to actuators and feedback from sensors are exchanged with a controller using a network. The advantages of such an architecture are flexibility and relatively low deployment cost. A CPS will always be prone to failures and malicious attacks. The networking aspect of CPS opens the door to cyber-physical attacks. Analysis of past incidents highlights the advanced knowledge degree of the adversaries perpetrating the attacks. Adversaries are smart and they can learn. Their sophistication is such that they can fool the controllers forging false feedback. Hence, a fundamental CPS security problem is the feedback truthfulness.

The first burning question is the need to distinguish an unintentional failure from a malicious attack. The signs resulting for these undesirable situations may be the same, but the responses should be different. A fault can be repaired. Against, an attack a CPS has to defend itself. Acknowledging that the operation of a CPS may be disrupted by a malicious attack, the second burning question is building a CPS with resilience. That is, it must be able to recognize the presence of an attack, recover and maintain operation. Several stories of attacks and disruption told in the media (see Table I) are evidence of the relevance of the problem and the increasing risks of major catastrophes in sectors such as industry, manufacturing,
transport or power generation. Currently, CPS are in principle secure by design, in the sense that they implement state of the art cryptography and protection techniques. In the future, they need to be resilient by construction. We introduced the defense learning paradigm where knowledge is built about adversaries, their techniques are identified, weaknesses are discovered, actions are anticipated and transformed into regular actions.

We have presented our vision on how next generation resilient CPS will be. The same way that nobody can think about current CPS without perfect safety to argue resilience: we have claimed that in some years, nobody would think about a CPS without perfect cyber-physical protection, in which the adversarial paradigm would have to change and make sure that an increase in the adversarial resources does not translate into higher likelihood of CPS disruption. We have also listed some promising techniques promoted by artificial intelligence (AI) and machine learning (ML) communities, that may materialize the new security stack addressing security beyond breach. We believe AI/ML, heuristic search and fuzzy decisional systems will play roles in the design of CPS resilience.

The essence of the war between adversaries and defenders is knowledge. On the one hand, supervised and reinforcement learning can be used by an adversary for the purpose of system identification, an enabler for covert attacks. On the other hand, the design of resilience plans can leverage AI heuristic search to speedup decision taking during the execution of a resilience plan. The adaptive control that resilience requires may be obtained using the fuzzy decisional approach. Quantum techniques could eventually perform searches with time complexity that is data size independent.

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