Big Data in Critical Infrastructures Security Monitoring: Challenges and Opportunities

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Abstract—Critical Infrastructures (CIs), such as smart power grids, transport systems, and financial infrastructures, are more and more vulnerable to cyber threats, due to the adoption of commodity computing facilities. Despite the use of several monitoring tools, recent attacks have proven that current defensive mechanisms for CIs are not effective enough against most advanced threats. In this paper we explore the idea of a framework leveraging multiple data sources to improve protection capabilities of CIs. Challenges and opportunities are discussed along three main research directions: i) use of distinct and heterogeneous data sources, ii) monitoring with adaptive granularity, and iii) attack modeling and runtime combination of multiple data analysis techniques.

I. INTRODUCTION

Over the past years attackers’ community has developed smarter worms and rootkits to achieve a variety of objectives, which range from credentials compromise to sabotage of physical devices. Cyber threats are targeting extremely diverse and critical application domains including e-commerce systems, corporate networks, datacenter facilities and industrial systems. For example, on July 2010, the well known Stuxnet [1] cyber attack was launched to damage gas centrifuges located at the Natanz fuel enrichment plant in Iran by modifying their speed very quickly and sharply. On August 2012, the Saudi oil giant Aramco was subjected to a large cyber attack [2] that affected about 30000 workstations. On April 2012, the big payment processing provider Global Payments confirmed a massive breach [3] that compromised about 1.5 million cards. On January 2013, the U.S. Department of Energy underwent an intrusion [4] to 14 of its servers and many workstations located at the Department’s headquarters, aimed at exfiltrating personal information about its employees.

For example, Stuxnet was able to fool the supervisory control and data acquisition (SCADA) system by altering the reading of sensors deployed on the centrifuge engines, and it went undetected for months.

Among the possible countermeasures that could be adopted, the idea of leveraging distinct and heterogeneous data sources can help to draw a clearer picture of the system to protect. Indeed, by correlating diverse information flows coming from multiple origins not always collected by current CI monitors, it can be possible to extract additional insights on potentially threatening activities that are being carried out. For instance, the presence of Stuxnet could possibly have been detected by monitoring several other operational and environmental parameters, like the centrifuge energy consumption, and by correlating their readings to infer possible anomalies in the status [2] (e.g., fluctuating power consumption in a centrifuge, correlated with a stable rotational speed can be considered as an anomalous state). In addition, according to a CyberArk’s report [3], several successful attacks including the ones reported above exploited privileged accounts to achieve their objectives, and the same report states that “86% of large enterprises (across North America and EMEA) either do not know, or have grossly underestimated the magnitude of their privileged account security problem”. A possible solution could consist in leveraging the monitoring of the activities of such privileged accounts to pinpoint ongoing suspicious activity.

The use of multiple and diverse sources producing huge amounts of data calls for the research of new solutions for monitoring and analysis, able to timely and efficiently recognize ongoing malicious activities in CIs. This paper introduces the basic notions of a framework for data-driven security monitoring and protection of CIs. Our proposal stems from needs and challenges for effective security monitoring and describes an architectural solution to them, moving along the following research directions: i) the use of large amount of data collected from distinct and heterogeneous data sources; ii) the adoption of monitoring strategies with an adaptable level of granularity, to face the issue of big data volumes; iii) the formalization of attack models and the combination of diverse state-of-art data analysis techniques to improve the capability of detecting threats and triggering protection actions.
II. NEEDS AND CHALLENGES

A. Multiple Data Sources

The idea of using distinct and heterogeneous data sources available in today’s CIs can help to draw a clearer picture of the system to protect and of the threatening activities being carried out. The aim is to improve the protection of future CIs exploiting the (hidden) value of data: they are already available but not fully exploited in today CIs.

However, as the size and complexity of systems increase, the amount of information that can be collected by data sources skyrockets. For example, in the 1300-nodes data center we target as case study (see Section III-D) the monitoring system produces about 16.6 GB of data per day, with observed traffic peaks of about 240000 pkt/s. This is a consequence of multiple factors: (i) the increasing availability of cheap HW probes, (ii) the ubiquitousness of communication infrastructures (either wired or wireless) and the Internet, and (iii) the novel algorithmic approaches that today make handling huge amounts of data practical. A further important aspect is that the heterogeneity of collected data is going to increase as well: new data sources are connected to monitoring systems to collect and analyze different kinds of data as this could potentially provide useful insights on current system statuses.

This mix of factors marks the shift from a mostly human-controlled distributed monitoring model (think, for example, about how railway companies in the past controlled the status of their infrastructures through hundreds of people deployed on the territory along their tracks to locally monitor and then report to their bosses) to fully automated IT infrastructure for monitoring that tries to relieve as much as possible from humans the burden of analyzing data to infer high-level information. Making this new model practical in scenarios where huge amounts of heterogeneous data are available calls for the research of new algorithmic and architectural solutions able to withstand these new challenges.

B. Monitoring with different granularity

An accurate tuning of the amount of variables to be monitored and the frequency of data collected from system probes appears fundamental to study and plan at design time the computational load on the monitoring infrastructure.

First, it is necessary to select what sources are worth monitoring amongst the many available, considering the target system and also the expected workload. For example in sources at the OS level, such as amount of free memory, disk throughput, or network throughput, are selected out of hundreds of possible indicators; their relevance for anomaly detection is further explored and confirmed in [5].

Appropriate selection of data sources is relevant but unfortunately may not be sufficient. In large-scale critical infrastructures, given the number of components, we can reasonably consider that monitoring each parameter using the best possible resolution system is unfeasible. Thus it may be required to define monitoring strategies that minimize the amount of data to analyze and consequently the monitoring resources to be used, still without decreasing the efficacy of the monitor, e.g., adopting different monitoring granularities depending on the current alert level of the system and of its components. This calls for the definition of new solutions able to find the right compromise in terms of the monitoring grain without having a negative impact on the monitoring accuracy as well as without depleting the resources devoted to monitoring.

C. On-Line Big Data Processing

The large number of collected data also implies difficulties in the data processing phase. Several techniques and tools have been proposed to analyze raw data with the objective of detecting on-going attacks. However, the performance of the detection, in terms of coverage and false alarm rate, strictly depends on the adopted technique. Solutions which encompass the (on-line) combination of multiple analysis techniques need to be investigated, in order to improve the capability of detecting potential threats and triggering protection actions on the CI. Recent studies have also proven the usefulness of (temporal and/or typed) graph-based attack models [6]–[12]. If we assume that the input log is a sequence of events having a type and a timestamp, a graph-based attack model has event types as vertices and is defined in such a way that the paths from start to terminal vertices in the model represent a critical event/attack when they correspond to subsequences of the log. Such subsequences are also called instances of the attack model. However, finding correlations among data by comparing analyzed data with attack models and producing alerts in an on-line fashion may become extremely difficult when the number of attack models at hand and the size of the input log increase. It is therefore important to ensure the scalability of the algorithms and data structures used when performing the conformance checking task.

III. A FRAMEWORK FOR DATA-DRIVEN SECURITY OF CIs

Figure 1 proposes an architectural solution to the discussed challenges. The key idea is to combine several data sources and different data analysis techniques to improve the capability of detecting potential threats and triggering protection actions on the CI. The results of the analysis are also useful to assess the current alert level of the CI’s components and to adapt the grain of monitoring through the Monitoring Adapter, e.g., to intensify the monitoring of components deemed of suspicious activity and reduce the monitoring of the other ones. The main blocks of the framework are described in the following.

A. Raw Data Collection

As the name suggests, the Raw Data Collection block is responsible for gathering raw data from the monitored CIs, exploiting available data monitoring technologies and/or logs produced by diverse software layers or hardware controllers.

Many technologies for data monitoring have been developed over the past thirty years, ranging from relatively simple data collection tools (such as Unix syslog) to more sophisticated data analysis systems.

http://www.ietf.org/rfc/rfc3164.txt
Ganglia is a scalable distributed monitoring system. Its hierarchical design is primarily targeted at federation of clusters and grid computing systems. Each monitored node multicasts its monitored metrics to all nodes in its cluster, enabling automatic discovery of nodes. Nagios is one of the most used open source monitoring systems. It offers an advanced notification system and is extensible through plug-ins. Its functioning is based on both active and passive checks of services, hosts and network state. Splunk is a commercial monitoring system that allows search, filtering and analysis of structured and unstructured textual logs through indexing.

Artemis is a monitoring system primarily designed for analyzing large-scale distributed logs. It has a modular design, separating data collection from data analysis. The log collection module supports heterogeneous data sources and types (e.g. text, binary, XML). Collection and analysis modules are extensible through plugins and application-specific functions. Chukwa is a MapReduce-based log collection and monitoring system. It uses the Hadoop distributed file system (HDFS) as a store and analyzes collected logs through MapReduce jobs. It is designed to collect data from hundreds of sources reducing the number of required HDFS files. Logbus is a framework for the collection and analysis of rule-based logs, i.e., logs produced according to formal rules in the source code and designed to improve the detection of runtime problems in terms of detection rate and false alarms.

Data collectable through these monitoring systems can be classified in three broad categories: performance, environment, and operational data. Performance data are among the most monitored, and are related to the use of system resources. Main examples are the usage of CPU or memory. Other sources are about the use of the network, such as inbound and outbound traffic. Environment data are rarely exploited, even if they could be very useful to detect ongoing cyber physical attacks. They describe the status of the environment in which the system is placed and nodes’ parameters not related to performed activities. In this category fall temperature, humidity, the status of cooling systems, if any, etc. The monitoring of the energy consumption is also in this category. Finally, Operational data encompass all the information achieved by collecting, and presumably parsing and filtering, logs from the various software layers of the system, including event logs produced by applications, the OS and IDSes, if present.

B. Adaptive Monitoring

As shown in Figure 1, the main idea is to adapt the monitoring by dynamically changing what raw data to collect and analyze, thus shaping at run time the resource utilization of the monitoring framework.

All the monitoring systems described in the previous Section II-A have been designed so as to allow users to plug-in custom modules, in order to extend their functionalities such to fit application-specific needs. The plug-in modules can be implemented so as to receive external commands that dynamically adapt their monitoring capabilities. An initial proposal to reduce the complexity (i.e. the quantity of collected data, hence required storage space and processing resources) is to define two different monitoring layers. By default, the monitoring system operates in a coarse-grained layer collecting a limited number of variables, causing a high False Alarm Rate, but also a low Missed Detection Rate. In this configuration, the system acts as a very suspicious monitor which observes a reduced set of indicators and that easily raises alarms. When the coarse-grained layer detects an alarm in a specific area of the system, it triggers a fine-grained layer for monitoring that specific area through an enlarged set of indicators, a finer granularity of data, possibly reducing the False Alarm Rate.

The two-layers approach may lead to two different design solutions to be explored:

- The monitoring infrastructure is created with sufficient spare resources that are used to activate the fine-grained layer (we call this overprovisioning approach).
- The monitored system is created such that it does not have spare resources, or with a very limited number of spare resource. The activation of the fine-grained layer in a certain area of the critical infrastructure requires to reduce the monitoring activity in some other areas (we call this the downgrade approach).

The first approach leads to unused resources and the number of possible concurrent activations of the fine-grained layers is limited by the amount of spare resources. The second approach has no spare resources, but the downgrade of the monitoring activity risks to expose the system, leading to a not sufficient level of protection and/or to an unacceptable rate of False Alarm Rate. Also, the two approaches could be merged trying to take advantage of both of them.

Clearly, the selection of the right approach and its tuning require to understand the distribution and temporal persistence

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[1] http://ganglia.sourceforge.net/
[2] http://www.nagios.org/
[3] http://www.splunk.com/
[4] https://chukwa.apache.org/
[5] http://httpd.apache.org/monitoring.html
of anomalies in the system. This is relevant to understand the expected frequency of fine-grained layer activations, and the extent to which it is possible to reduce the monitoring resolution without significantly affecting the detection of threats.

On the other side of the spectrum, general purpose data analysis systems, which include a large family of tools like rule engines (e.g. Drools\(^1\)), map reduce frameworks (e.g. Hadoop\(^2\)) and complex event processing systems (e.g. Esper\(^3\) and Storm\(^4\)) can be integrated with data gathering and diffusion platforms (e.g. multicast and publish/subscribe middleware) to create ad-hoc monitoring solutions. Nevertheless, the flexibility of this approach comes at a cost: most of these solutions must be designed and developed from scratch since often strictly tied to their initial target environment.

A possible solution we foresee for the Monitoring Adapter block is represented by an hybrid approach, where existing monitoring systems and general purpose data analysis tools are mixed and deployed in such a way to maximize their effectiveness in reaching the desired adaptability goals. Monitoring systems could locally analyze and observe specific subsystems to provide more high level information to data analysis tools for correlation with information provided by other different sources. The complexity involved in mixing these approaches together, however, remains to be studied.

C. Data Analysis

This component analyzes the data and provides as outputs information about (i) how to adapt the grain of the monitoring, (ii) what protection actions should be performed on the CI. Starting from our past experiences on attack modeling and data analysis, we consider the following functional blocks.

Data Processing. Collected raw data typically contain useless or redundant information that can undermine the goodness of performed analysis \(^5\). The first analysis step to be performed is thus to polish raw data, adopting filtering or event coalescence techniques, such as the ones analyzed in \(^6\).

Attack Modeling. This functional block provides tools to define and statically analyze attack models. The attack model used in this block must be capable of: (i) providing a high degree of flexibility in representing many different security scenarios in a compact way; (ii) allowing the specification of various kinds of constraints (e.g., temporal) on possible attacks; (iii) representing attack scenarios at different abstraction levels, allowing to “focus” the conformance checking task in various ways. Typed temporal graph-based attack models \(^7\) appear to be good options for the above requirements. They are rich in terms of temporal constraints that can be expressed. In addition, it is relatively easy to handle the definition of generalization/specialization hierarchies among event types.

By way of temporal graph-based model example, consider the hypergraph shown in Fig. 2. Here it is assumed that the log is a sequence of tuples that represent high-level actions corresponding to types of possible security exploits – such logs can be built on-line from operational data. Actions are depicted with plain circles ($v_i$), while (hyper-)edges are depicted with dotted circles ($h_i$). As an instance, according to the semantics given in \(^9\), $h_1$ is a start hyperedge (indicated with a white arrow) so an attack can begin with it. The vertex labeled Local Access requires the presence of a group of log tuples with one more tuples of type Local Access (cardinality constraint “$\geq 4$”); the same applies to the Directory Traversal vertex. The hyperedge itself represents an association between the two vertices, with a temporal constraint of $(3,10)$ time points for the log segment. Hyperedge $h_3$ requires, in any order: (i) one or more Directory Traversal tuples; (ii) between 2 and 5 SQL Injection tuples; (iii) one or more Buffer Overflow tuples. The same applies to other hyperedges, such as $h_4$ and $h_7$. In particular, since $h_7$ is a terminal hyperedge (indicated with a black arrow), an attack can end with it.

Conformance Checking. The main purpose of this functional block is that of detecting attack instances in sequences of logged events by checking the conformance of logged behavior with the given set of attack models. The main requirement of this block is obviously scalability. In real-world critical infrastructure protection scenarios, in fact, logged events are streamed into the system on-line and, ideally, we would like to raise an alert as soon as an event with a “criticality” above the threshold is logged. It is therefore important to define appropriate data structures that ensure fast access to the relevant information, as well as suitable algorithms that are tightly coupled with such structures in order to ensure the fast detection of an attack \(^6\), \(^10\). Moreover, it is important to identify conditions that make the problem tractable from a theoretical point of view. One possibility is that of imposing specific limitations to the structure of the allowed models. In fact, recent work on the detection instances of temporal automaton-like models in sequences of logged events \(^7\), \(^8\), \(^10\) has shown that acceptable detection times in real-world cases can be obtained by limiting the number of partial solutions through a form of early filtering based on temporal constraints. Finally, the parallelization of both the data structures and the conformance checking algorithms (see, e.g., \(^11\)) appears mandatory when we target big data for security protection.

Fig. 2: Example graph-based attack model
Logs to be analysed by the maintainers.

### 5.1.2.2 Detected Violations

The detection capabilities of the identified invariants have been tested, as in Section 3.4.1, which takes into account the two time series are very similar, but the order of magnitude differences, with a large risk of false positives.

### 5.2.2.2 Detected Violations

With the threshold $\text{value of } 0.99$, proportion to the expected output of the model $R^2$, the system that is not able to provide useful results to reduce the number of false alarms. With these parameters, all the invariants are broken for almost each sample.

### 5.3.3.3 Detected Violations

The Large Hadron Collider computing grid, \texttt{http://wlcg.web.cern.ch}.

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**Carlo Corso**, 
**Laurea Magistrale in Ingegneria Informatica**

**Mining Invariant Relationships for Failure Analysis of Batch Software Systems**

**Scuola Politecnica e delle Scienze di Base**

**D. Case Studies**

In the framework of the Research Project of National Interest (PRIN) “TENACE - Protecting National Critical Infrastructures from Cyber Threats”, we plan to experiment the framework on data extracted from two real-world systems.

The first is the data center of the Italian Ministry of Economic and Finance (MEF), which represents an important CI because it manages a wide range of software, spanning from very large applications with millions of end-users, such as those for the consumer credit support, to very mission critical applications, such as those for managing the auctions of Italian Government Bonds and Treasury bills, and those for monitoring the government securities market (MTS). In its architecture each rack is organized in up to five sub-racks. Each sub-rack can include up to sixteen blade servers and is connected to the datacenter network through four switches. A probe is connected to each switch in order to monitor flowing network traffic. Two smart PDUs are connected to each sub-rack to gather information about energy consumption. This configuration allows to enforce non-intrusive monitoring and to consider the system as a blackbox.

The second is the S.Co.P.E. supercomputer, a scientific data center at the University of Naples Federico II and Italian Institute of Nuclear Physics (INFN). It is equipped with a monitoring system that collects data similar - for type and amount - to those collected by data centers of real CIs. S.Co.P.E. mainly runs scientific batch jobs and also acts as a Tier-2 resource of the Worldwide LHC Computing Grid (WLCG). It is composed of 512 servers, each equipped with 2 quad core CPUs and 32 GB of memory. For jobs queuing and scheduling and resource management, S.Co.P.E. uses Maui/TORQUE. The monitoring system collects performance and environment data (adopting Ganglia extended with created additional scripts), and logs, producing about 0.7 GB of data per day. Logs from Torque Resource Manager are used for collecting jobs’ related data. Logs from the operating systems can be used for collecting anomaly related data.

### IV. CLOSING REMARKS AND OPEN ISSUES

Field data represent a rich source of information for improving the security monitoring and protection of future critical infrastructures. Existing monitoring technologies already offer the possibility of collecting different types of data, such as performance, environmental and operational data. The idea of collecting these types of heterogenous data, and analyze them trough a combination of state-of-art attack modeling and data

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14The Large Hadron Collider computing grid, \texttt{http://wlcg.web.cern.ch}
analysis techniques, is promising to improve the accuracy of detection and drive the adaptation of the monitoring itself. In addition, the availability of existing analysis approaches and open, configurable monitoring tools represents a good start for the viability of the proposed framework. However, the achievement of envisioned research objectives requires to face many open issues, such as:

- lack of publicly available data sets and ground truth. Such data sets are vital for the validation of approaches like the one proposed in this paper. Some datasets are outdated (such as DARPA[1]) or unlabeled (such as, iCTF[2]), while others target standard IT systems (such as UNB iSCX[3]). To date, there are no datasets available for CIs.
- difficulty of performing long-running tests on real-world systems (or representative reproductions). These tests are very useful to improve the understanding of phenomena and to produce realistic datasets. However, honeypot-like approaches cannot be adopted in the case of CIs, due to the possibility of physical damages as a consequence of an attack. Innovative controlled environments are to be created, involving the expertise and equipment of CIs stakeholders.
- need of strategies for changing the monitoring configuration at runtime on the basis of some predefined logic, without being forced to stop and restart the services in charge of gathering and analyzing data. This is important because it provides large freedom in adapting the monitoring without interrupting related services.
- urgency of scalable solutions to combine the outputs generated by the different data analysis techniques, as the ones envisaged in the framework. Further research is in order, involving the different views and know-how of the researchers active in these fields.

Hence, the path towards industry-ready solutions calls for further joint industry-academia efforts, involving major players and stakeholders, to take real advantage of big data for the security monitoring of future critical infrastructures.

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