

Intrusion Detection in SCADA Systems via Network Analysis

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Abstract—Given the nature of SCADA systems, we postulate that it is possible to detect intrusions or otherwise malicious activity via network analysis. Utilizing machine learning, we develop software to passively monitor systems and identify possible intrusions and complete a general study of SCADA networks.

Index Terms—scada, network analysis, machine learning, whitelist.

1. Introduction

SCADA (Supervisory Control and Data Acquisition) [1] systems are used to support and monitor the infrastructure that serves as pillars for many industrialized areas. An example SCADA system can be seen in Figure 1. SCADA systems were historically created with an emphasis on availability of data as opposed to implementation of the X.800 security architecture. With the emerging prevalence of IoT security and edge-intrusion testing, the security of these systems has become an increasingly pertinent subject in the security community as networking and remote access becomes more and more desirable. Given that the purpose of SCADA systems is to enable users to manage and perform tasks on a large scale in industrial infrastructures as quickly and easily as possible, security vulnerabilities have the potential to cause serious damage if an attacker gains access to a system. One such example of the consequences can be seen from the Stuxnet worm, controlling and damaging Iranian nuclear reactors in 2010 [2]. The use of open standards for SCADA communication protocols are also increasing, largely due to low cost of implementation, so the risk of future security breaches will likely be applicable to multiple systems rather than limited to single product lines from a particular manufacturer.

2. Theory

It is now obvious that the security of SCADA systems is a pertinent subject for study. As there can be any number of zero-day attacks for these systems, it will likely be more productive to shift focus to detecting these intrusions rather than trying to prevent them. Given the nature of SCADA

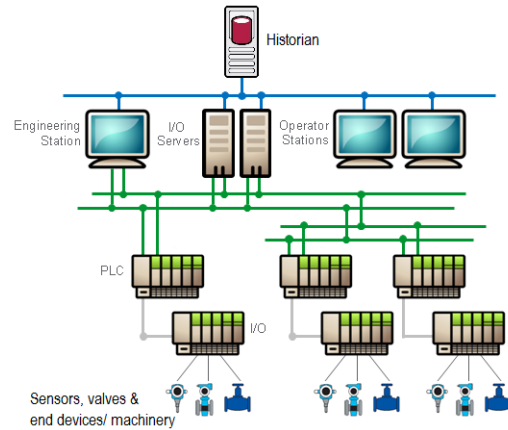


Figure 1. A basic SCADA system

systems, it can be presumed that their network traffic is reasonably predictable. This leads to the proposition that there are detectable network patterns occurring with some regularity for any given system or otherwise some normal level of activity. As stated previously, SCADA traffic patterns are generally stable in comparison to traditional IT networks. Once a certain normalization is established, one may then use that as a baseline to compare future traffic to in order to detect anomalies that may possibly indicate active attacks. Our proposal is that, instead of focusing on systems or network exploits themselves, we write a tool to establish and then passively detect any network anomalies.

2.1. Machine Learning & Network Captures

To implement this tool, we intend to utilize machine learning-based analysis trained on known *regular* traffic levels. We will then introduce network/control anomalies indicative of non-normal system behavior to demonstrate the detection capabilities and to test proper training levels of the algorithm. An obvious source of data to train the algorithm on are just source and destination IP addresses, however were we to go this route it would likely be easier to instead implement a hardware or software firewall with IP filtering at the network gateway level.

Utilizing *Python* along with *Numpy*, *Pandas*, and *Sci-kit Learn*, we focus on the timing and host/source interactions on the network to indicate anomalies. The creation of white-lists attributed to normal traffic coupled with a collection of timing statistics will aid in flagging anomalous traffic.

2.1.1. Timing Analysis. In analyzing typical pcap files acquired from various SCADA networks, it can be seen that the timing of host interactions can be used as an indicator for anomalous activity. Consider Figure 2 below:

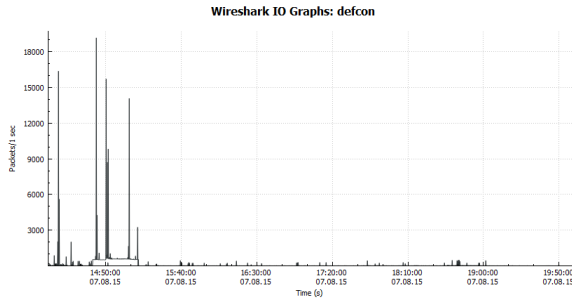


Figure 2. Anomalous Traffic in a SCADA System

This data has been retrieved from a publicly available pcap file from DEFCON SCADA 23 ICS Village via Ntetresec. [4] The data exhibits timing anomalies, displayed as packets per second. A more localized view of the graph follows in Figure 3, focusing on the anomalies seen in the overview above.

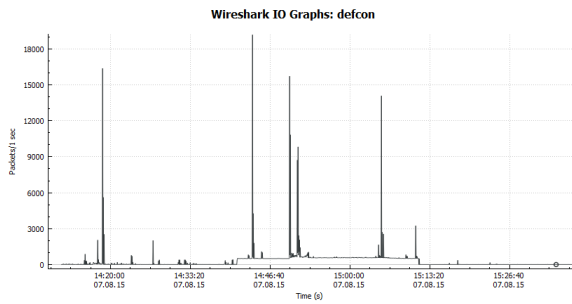


Figure 3. A more detailed overview of anomalous traffic

Given that each increment represents one second, we see spikes of more than 18,000 packets in just milliseconds of traffic. Our algorithm would flag the data based on rate of communication, and report the source and destination addresses. A clearer version of the traffic is shown in logarithmic view, which is similar to how a machine learning algorithm would visualize things. An example of this is provided in Figure 4.

2.1.2. Whitelist Automation. Our usage of ML will initially undergo a *learning phase* over a certain period of time to create a type of whitelist. The rationale for this is that SCADA systems commonly have frequent and consistent interactions amongst the same hosts. They act in such a way

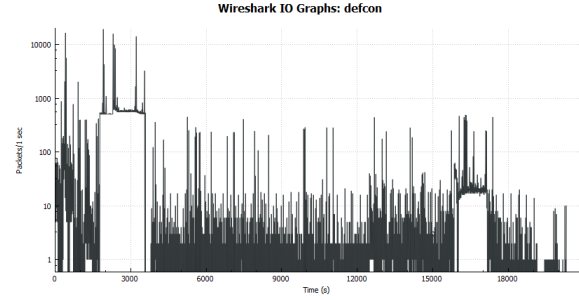


Figure 4. A logarithmic view

because all network traffic (incoming and outgoing) should interact and be handled by one "SCADA server" [5]. These common communications will serve in identifying several MAC and IP address pairs. It is safe for us to assume that the common pairs identified during the learning phase are authenticated devices.

To create the whitelist, a few items are taken into consideration. These list entries are *client IP address*, *server IP address*, *port*, and *IP protocol*. These packet items were chosen to be consistent with research previously performed, specifically involving flow whitelisting in SCADA Networks. [7] Systems themselves that have been identified as authenticated devices are whitelisted in conjunction to their MAC and IP addresses. IP protocol is important because traditionally, industry control systems work off of a *Modbus* communication protocol. Modbus is modeled in a master-slave dynamic. That is, a Modbus will connect a supervisory computer (master) with a subordinate *remote terminal unit* (RTU). [8] The core attributes of the Modbus protocol we are interested in is the function code and data components. Function codes have the capability of telling us what instructions are being carried out to the system. Using WireShark, analysis of our pcap file from DEFCON SCADA 23 ICS, it was noted that 71% were of the TCP/Modbus protocol. Since control systems act in a behavior that is fairly predictable, analysis during the learning phase of what commands constitute as normal will aid us in detecting anomalies. [6] A visual representation of our whitelisting components is shown in Figure 5 below.

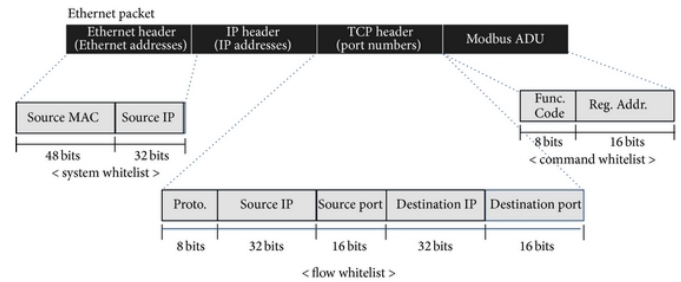


Figure 5. Representation of whitelist components

Once network traffic has been processed through the

learning phase, it is our expectation that any non white-listed connections and instructions will raise alarm. Therefore, we ensure that only known hosts are participating on the network as well as expected system interactions. By automating this process through ML, the need for human involvement is mitigated during pcap analysis.

For the act of whitelisting to be effective, we will have to assume that our list is a 1) reasonable, manageable size and 2) relatively stable in its nature. The ratio of "acceptable" entries versus the overall size of the capture should be smaller by comparison. Similarly, we would like to have this list structured and stable. A highly dynamic, changing list would likely correlate to an influx of false positives. As with all Intrusion Detection Systems, this is not a desirable trait.

Apart from common IT infrastructure, it would not be wise to automatically quarantine suspected malicious content in SCADA systems. In the event of a false positive, "legitimate" traffic communications not being able to be made have a possibility of causing large-scale implications such as black-outs or extreme water levels.

2.2. Common Attacks

Considering the preceding explanations on timing analysis and whitelist automation, we explore common attacks in SCADA systems that our software may have the capability of detecting.

The injection of requests to a network can indicate an attempt of discovering available hosts and services. An attacker would then use the revealed information in to maliciously impact the system. It is our theory that our software be able to flag these forms of information gathering attacks, as it violates system as well as flow whitelisting.

Modbus/TCP protocol holds a vulnerability making a system susceptible to *Denial of Service*(DOS) attacks. This is due to an implementation error when a system is processing *Read Discrete Inputs* during request/response messages. Remote, unauthenticated attackers can exploit this in a way that allows them to alter the request or response parameters. [6] Attackers can replace these otherwise harmless parameters with malicious values in the "data field" option, then sending it to a system Modbus/TCP implementation. This processing of messages has the possibility of triggering a Denial of Service attack to a vulnerable system.

3. Implementation

The implementation software is divided into two basic sections - the analysis module and the capture module. The implementation module controls the retrieval and subsequent conversion of the *pcap* data into *csv* files and calls routine analysis on the data via the capture module.

In order to run machine learning analysis on input data, the file must first be converted to numerical values via enumerations. This is done with a *Python* script that is run on a *CSV* export of the network traffic captures. The

data is then accessed by the frameworks to split, train and verify model results. Parameters may then be changed to achieve an optimally trained model. Pseudo-code can be seen below in Algorithm 2 for the data interpretation, and Algorithm 3 demonstrates analysis. Algorithm 1 details the basic collection scheme.

Data: Target Network
Result: PCAP file
for *Specified time period* **do**
 | *output_file* \leftarrow *packet data*
end

Algorithm 1: Data Collection



Data: Input PCAP
Result: Numerically translated data
for *row* \in *input* **do**
 for *data entry* \in *row* **do**
 if *literal* \in *enumeration* **then**
 | *assign enumeration value*
 else
 | *add value to enumeration*
 | *assign enumeration value*
 end
 end
 | *write to new file*
end

Algorithm 2: Data Translation



Data: Interpreted Data
Result: Trained Model
split data
for *row* \in *input* **do**
 | *trained model* \leftarrow (SRCIP, DESTIP, TIME, PROTOCOL)
end
for *row* \in *test* **do**
 | *verify results*
end
if *confidence acceptable* **then**
 | *save model*
else
 | *retrain model*
end

Algorithm 3: Model Training and Verification

4. Conclusion

We believe we have collected sufficient data to conclude that our implementation plan will be successful as described, so we will now move on to code implementation and machine learning analysis and control/response.

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