Visualizing Network Flows and Related Anomalies in Industrial Networks using Chord Diagrams and Whitelisting

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Keywords: Industrial Networks, Security Visualization, Chord Diagrams, Flow Monitoring.

Abstract: Industrial Control Systems are the set of specialized elements that monitor and control physical processes. Those systems are normally interconnected forming environments known as industrial networks. The particularities of these networks disallow the usage of traditional IT security mechanisms, while allowing other security strategies not suitable for IT networks. As industrial network traffic flows follow constant and repetitive patterns, whitelisting has been proved a viable approach for anomaly detection in industrial networks. In this paper, we present a network flow and related alert visualization system based on chord diagrams. The system represents the detected network flows within a time interval, highlighting the ones that do not comply the whitelisting rules. Moreover, it also depicts the network flows that, even if they are registered in the whitelist, have not been detected on the selected time interval (e.g. a host is down). Finally, the visualization system is tested with network data coming from a real industrial network.

1 INTRODUCTION

Industrial Control Systems (ICSs) refer to the group of specialized elements that monitor and control physical processes (Cárdenas et al., 2008). As such, they are responsible for controlling and automating a wide range of processes, both in various industrial sectors and in Critical Infrastructures (CIs) (Stouffer et al., 2011), typically in networked environments known as Industrial Networks. CIs are defined as the assets or systems that are of vital importance for the correct functioning and well-being of modern societies. Examples of CIs include power stations, transportation systems, water supply and critical manufacturing factories.

Traditionally, Industrial Networks have been isolated environments, with proprietary protocols, software and hardware. However, ICSs have evolved into using Commercial off-the-shelf (COTS) software and standard communication systems. Thus, nowadays, industrial networks share a growing number of similarities with regular, computer-based Information Technology (IT) networks, and are getting increasingly connected to enterprise networks.

This means that the traditional isolation and obscurity principles industrial networks have relied on for security do no longer apply. Security incidents regarding industrial networks have shown the impact that a successful attack can cause, ranging from economic loss, environmental damage or even loss of human lives (Miller and Rowe, 2012). The rise of Advanced Persistent Threats (APTs) and targeted attacks like Stuxnet (Falliere et al., 2011), Night Dragon (McAfee, 2011) or Havex (Hentunen and Tikkanen, 2014), specifically targeted to sabotage or steal information from ICSs emphasizes even more the need to protect these assets.

Although industrial networks and IT networks share a common set of technologies, the different nature of the networks require that security solutions have to be tailored to suit each type of network. The differences between both types of networks and its impact on designing security solutions is exposed by Cheminod et al. (Cheminod et al., 2013).

Interestingly, when compared to IT networks, the network topology of industrial networks is static, while the control traffic itself is by nature repetitive and predictable, as most traffic is created by automated processes (Cheminod et al., 2013; Barbosa et al., 2013). Having these traits in mind, we can leverage them to tailor security solutions for industrial networks. Specifically, flow whitelisting[1], has been

[1]Whitelisting refers to the practice of registering the set of network flows that are allowed in a network, raising an alarm or disallowing connections that have not been explicitly allowed.

Iturbe, M., Garitano, I., Zurutuza, U. and Uribeetxeberria, R.
Visualizing Network Flows and Related Anomalies in Industrial Networks using Chord Diagrams and Whitelisting.
DOI: 10.5220/0005670000990106
In *Proceedings of the 11th Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2016) - Volume 2: IVAPP*, pages 101-108
ISBN: 978-989-758-175-5

advocated by industry as an effective method for securing industrial networks (Stouffer et al., 2011; Norwegian Oil and Gas Association, 2009). In this direction, Barbosa et al. (Barbosa et al., 2013) demonstrated that whitelisting is a viable approach to detect network flow-related anomalies.

1.1 Contributions and Paper Organization

In this paper we propose a novel visualization technique for network flows and flow-related anomalies, aiming at industrial networks. Our main contribution consists of a set of chord diagrams that visually render existing flows in a given time interval, visually highlighting the anomalous ones that either have not been whitelisted in the industrial network traffic model or have not been detected even if they should. Consequently, we aim to fill the void of security visualizations designed with ICSs in mind in the scientific literature, as well as representing model violations in an efficient and aesthetically pleasing manner.

The rest of the paper is organized as follows. Section 2 introduces chord diagrams and related works. Section 3 presents the structure of our visualization system. Section 4 tests the aforementioned system in an environment with real industrial traffic. Finally, Section 5 draws some conclusions about the realized work.

2 RELATED WORK

Chord diagrams, also known as Circos diagrams, are circular diagrams that represent relationships between different entities. Though originally conceived for genomics (Krzywinski et al., 2009), the usage of diagrams has expanded into a wide variety of fields.

Typically, the visualized entities are arranged in a circular manner. Each entity occupies a given arc length of the circle mentioned. This length is proportional to the weight the entity has compared to the rest.

Chords are links that match the entities that form the circle between them. Each chord generally links two different entities, and the width of the chord at both ends denotes the nature of the link. The wider chord end belongs to the entity that is dominant in the relationship between both entities linked by the chord. For instance, in the case that the chord represents a trade relationship between two countries, the country with the wider chord end sells more goods to the other country than vice versa.

The main advantage in the usage of chord diagrams to represent network flow data, even under normal network operation conditions, is that diagrams can provide situational awareness to operators in a direct manner, whereas traditional text-based alarm systems can not. This way, network operators can easily check how each host is interacting with the rest of the network.

Moreover, when using chord diagrams, it is not only possible to visualize relationships between different entities, but also their prominence when compared to the rest of the network. When visualizing network flows, it is possible to represent their activity through the size of the chords. For instance, active flows can be depicted using larger chords. Other types of visualizations, such as bi-partite graphs, lack this magnitude feature.

Communication patterns between hosts are fixed in Industrial Networks, as in this type of networks each host usually only communicates with a small subset of the hosts present in the network. Therefore, few chords are necessary to represent all possible flows, and diagrams are kept simple enough to be meaningful, even in large networks.

Chord diagrams are considered to scale well (Mazel et al., 2014; Krzywinski et al., 2009). However, if an industrial network is complex enough to render a unique chord diagram too confusing, simpler chord diagrams can be computed for each of the network segments. Industrial Networks are hierarchical, vertical and segmented by nature(Galloway and Hancke, 2012), so it is possible to use different chord diagrams to represent the traffic in a network segment. Another approach to tackle potential scalability issues might be to use the multi-scale approach proposed by Zeng et al. (Zeng et al., 2013).

In the field of network security, chord diagrams have been used in diverse types of visualization systems, but its usage is not as widespread as other types of diagrams.

Mazel et al. (Mazel et al., 2014) use chord diagrams to perform a visual comparison of different Anomaly Detection Systems and their detection performance.

The work of Layton et al. (Layton et al., 2012) represents the relationships between clusters of phishing websites with chord diagrams.

OCEANS (Chen et al., 2014) uses chord diagrams (dubbed as Ring Graphs) for visualizing network flows between subnets. However, OCEANS is centered in traditional IT networks and lacks the additional information that can be gathered from industrial networks, where whitelisting policies can not be as strict as in industrial networks. Moreover, the color

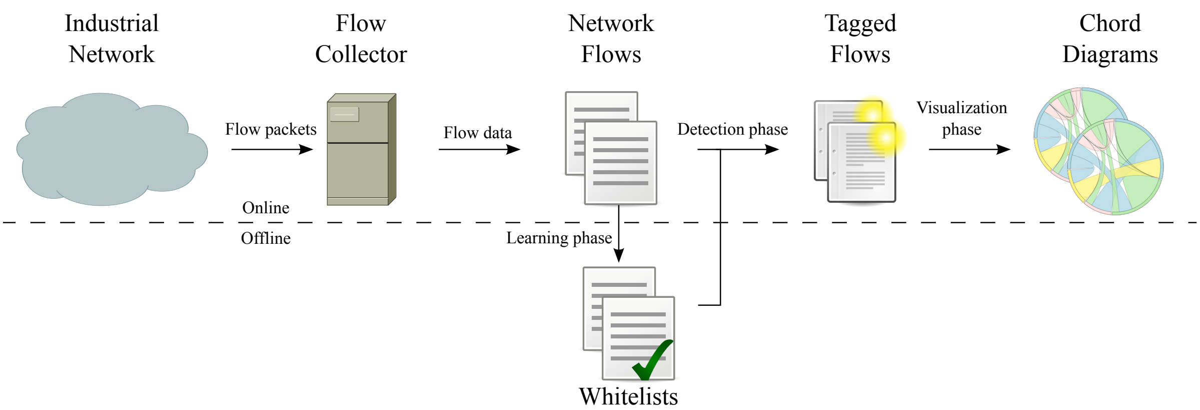


Figure 1: Overview of the flow monitoring system.

code used in OCEANS' chord diagrams is by the logical location of the host or subnet (internal or external IP), not by the nature of the connection (normal or anomalous).

To the best of our knowledge, no flow and security-oriented visualization system has been developed for industrial networks, let alone using chord diagrams. Nevertheless, some advances have been made to ease process monitoring visualization (Tack et al., 2014).

3 PROPOSED VISUALIZATION SYSTEM

Figure 1 shows the workflow of the flow monitoring and visualization system.

First, flow-enabled networking devices inside an industrial network send network flow packets to a flow collector.

Once flow collection has started, the flow collector is queried to generate offline, a model of detected flows. The model contains a whitelist of allowed network traffic flows. We call this phase the learning phase. Once a model has been created, the system queries the collector for new flow records and compares them to the model online, detecting flows that do not comply with the policies and tagging each individual detected flow as valid or anomalous. This corresponds to the detection phase. Finally, once the tagged dataset is available, the system builds a set of chord diagrams to represent the results. This is the visualization phase. While the learning phase happens once per network, the detection and the visualization phases occur periodically.

3.1 Learning phase

In this phase, a model is automatically created from the flows that have been detected in the network in a given time frame. The length of this time frame to build the model depends on the nature of the controlled process. For instance, a process that consists in small batches will require shorter learning time than longer, continuous processes, as the cyclical network patterns will be shorter. The collected network flows in this time window are considered legitimate and are used to build the model.

The whitelist that models the network flow behavior is stored in a human-readable Comma-Separated Values (CSV) file. This way, it is possible for an operator to add missing flows to the modeled whitelist, or, on the contrary, to delete flows that should be considered anomalous.

In our approach, we store the following data on the whitelist per flow: source IP address, destination IP address, server port, IP protocol and registered number of packets in the flow in the given time. For whitelisting purposes, the client port is not registered as it is assigned randomly and taking it into account would yield false positives. Barbosa et al. (Barbosa et al., 2013) do not take the number of packets in the flow into account. However, we consider packet number an important aspect to be recorded for two main reasons: (1) on the one hand, it is a good metric to be used with chords in the visualization (e.g. to depict the more active flows as wider chords), allowing the operator the identification of the main network flows. (2) On the other hand, this approach allows the system to detect flow anomalies that relate to its size (e.g. Denial of Service attacks or a downed host).

3.1.1 Whitelisting with Time-dependent Flow Data

As useful as might be, taking into account the number of packets complicates the usage of whitelists. As the number of packets in a flow is time-dependent (the longer the time, the higher the number of registered packets), it is necessary to establish the time frame in which the whitelist is valid when comparing this value. In other words, a whitelist is only relevant if the capture time that has been used to build it is the same as the time length of the incoming flow data. For instance, if a whitelist records the first ten minutes of the flow data from an industrial network, it is necessary to poll the network in intervals of ten minutes in order to be able to correctly compare packet numbers.

There are two approaches that can be followed:

1. A single whitelist is created, with recorded flow data from a specific time frame. All incoming flow data is collected and later, when querying it, it is divided in chunks where the capture duration of each chunk is the same as the time the whitelist has used upon creation. The latest chunk of flow data and the whitelist are compared and a single visualization is created.
2. Various whitelists are created, each containing data belonging to different time frames. Flow data is collected, and when querying it, the chunk size varies to the duration of the specific whitelist it is being compared to. Latest chunks of flow data are compared with each correspondent whitelist and different visualizations are created, each showing the information of the last time frame belonging to the chunk and whitelist.

The second option is a better option, as it offers more granularity and increases the ability to detect flow anomalies that might not be easy to detect with a single, fixed-length whitelist. For instance, let us assume a host that sends a large number of packets in short bursts but within the packet number limits of the whitelist with short time frames. If this bursts should decline after a short time, but for whatever reason they do not, the unique whitelist system will not be able to detect the anomaly, as it is not able to check the system in the long run and the packet number is correct in each of the short time frames.

If the opposite case, where the whitelisting time frame is too long, we might not be able to detect short bursts of a high number packets that might not change much the whole number of packets in the long run.

Therefore, in our approach we propose a system where whitelists of different time length are considered. Nonetheless, the optimal number of whitelists and the time length of each of them is process-dependent and should be studied for each network. However, it is important to note that with longer learning periods, the probability of whitelisting malicious traffic gets higher.

3.2 Detection Phase

In this phase, the different created whitelists are used to evaluate new flow data. This flow data is queried from the flow collector with different time lengths in order to match each of the time lengths registered with the whitelists. Later, this new flow data is compared to the whitelist corresponding to the same time frame. This way, the packet number of each flow is kept consistent, as comparing data collected in different time lengths would raise a high number of false positives. This process is repeated constantly in a batch manner.

The mechanisms checks if the flow data matches the one in the whitelist. In the case of source and destination addresses, server port and protocol, the flow information must match exactly. In the case of the registered number of packets in the time frame there is an exception: both numbers do not have to match exactly, but do not have to differ vastly either. The detector gives the possibility of setting a user-defined threshold for packet number tolerance in terms of percentage. Flows that are above or below this percentage threshold are considered anomalous, while the ones that are within the limits are considered valid.

If the flow is whitelisted, no alarm is raised and the flow is tagged as legitimate. Still, if a non-whitelisted flow is detected, the system raises an alarm and the flow is tagged as anomalous. In addition, the system also checks if all the flows registered in the whitelist also happen during the given time frame. If a flow registered in the whitelist has not been detected in the given time frame the flow is tagged as missing and an alarm is raised. This gives the opportunity of detecting a downed host or connection.

We have created the following tags in the detector, based on the comparisons the system does between whitelists and new flow data:

Whitelisted Flow. The flow is considered legitimate according to the whitelist.

Anomalous Network Flow. Two hosts communicate between them but according to the whitelist, these two hosts are not allowed to do so. All flows regarding a previously unknown host are marked as such.

Incorrect Port. A host tries to access a different port than the usual on a host it is allowed to communicate with.

Incorrect Protocol. A network flow is detected using a different IP protocol to the whitelisted one.

Missing Flow. A flow contemplated on the whitelist has not been detected on the collected flow data.

Anomalous Flow Size. The packet number on the designated flow is either higher or lower than the defined threshold when compared to the whitelist.

Each of this tags is used to give information about the cause of the anomaly both in the raised alarm and in the rendered chord diagram.

Once the data has been tagged, the system translates known IP addresses into host names in the tagged dataset in order to make flow data easier to understand to the user.

Finally, after the detection phase, we have a fully tagged flow dataset. This tagged information is later used in the visualization phase to build the chord diagram that depicts the network flows and related anomalies in the industrial network.

3.3 Visualization Phase

In this phase, each of the tagged flow datasets is rendered visually in the form of a chord diagram.

First, each of the active hosts in the network is given an arc section of the circle of the chord diagram. The arc length is given by the number of packets the host has sent on the measured time frame; more active senders have wider arcs than more silent hosts. The nature of the host determines its color; each type of host has an identifying color (e.g. PLCs are blue) while individual hosts are differentiated by having a different shade of the same color.

In our case, Programmable Logic Controllers (PLCs) are depicted with blue colors, control servers are green, Human Machine Interfaces (HMIs) are purple and, finally, different network devices (gateways, switches etc.) are colored in orange.

Once the hosts have been located, it is necessary to represent network flows between them. This is achieved by using chords: each bidirectional network flow is rendered as a single chord that links two distinct hosts. If two hosts have different network flows (for instance, a host communicates with two different services offered by another host), only a single chord is created in the diagram. The width of each chord end is given by the number of packets the related host sends. For example, if in a given flow Host A sends more packets to Host B than vice versa, the chord will be wider at the Host A's end. Similarly, more busy flows are depicted as wider chords than the almost-inactive counterparts. Later, each of the legitimate flow chords is filled with the color of the more active host in the communication.

Figure 2 shows a completed chord diagram where all the registered flows have been tagged as legitimate. Note that hosts of the same type share similar colors. In chord diagrams where network flow data is shown, all chords will link distinct hosts, as when a host accesses a local service, the network communication is carried out through the loopback interface and the data does not travel over the network. When the user hovers over an specific flow, the visualization shows basic information about the flow, such as the name of the involved hosts and the number of packets that take part in each direction of the network flow.

Since under normal operation conditions legitimate traffic flows represent most of the traffic of an industrial network, the reproduction of each traffic flow by a selection of a color-range makes easier to distinguish between different flows. Thus, the network operator can determine if the traffic tagged as legitimate is behaving as expected.

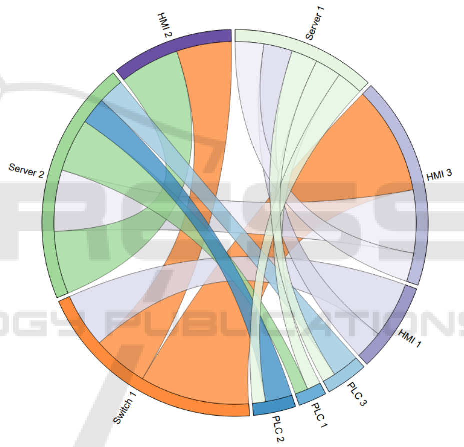
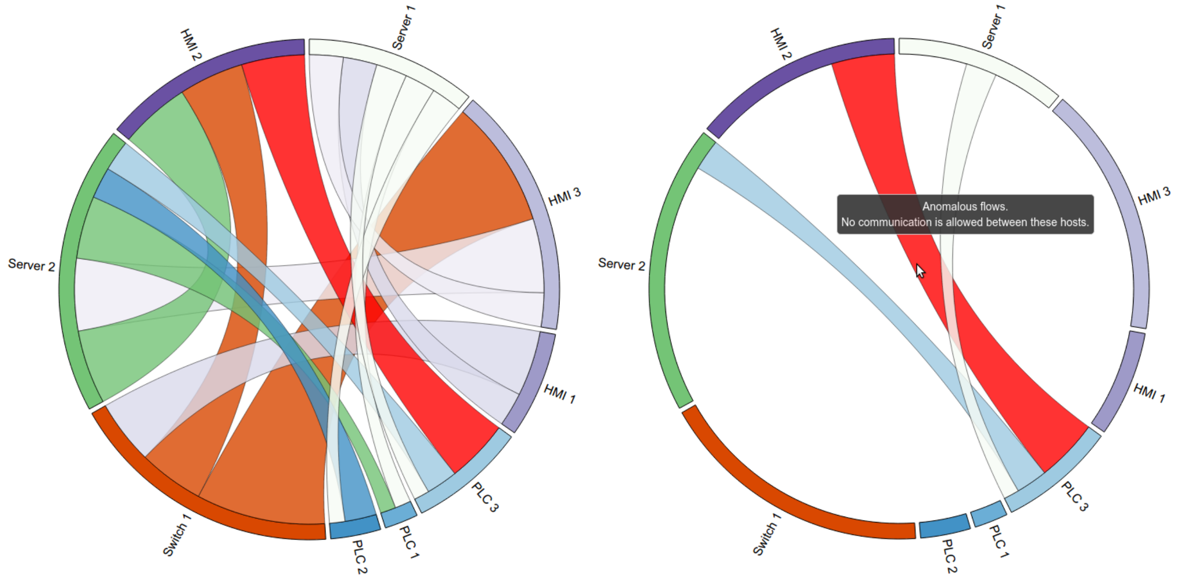


Figure 2: Chord diagram depicting a set of legitimate network flows.

In case of non-legitimate flows, the chord is filled with red color, as it can be seen in Figure 3. On the one hand, Figure 3a represents how the red color stands out over the rest of chords when the diagram is rendered. On the other hand, Figure 3b shows how the diagram filters the information concerning a single host when hovering the mouse over it, to highlight related information and ease visualization. As it is also shown, when hovering over the anomalous flow, the diagram shows additional information about the flow, regarding the reason why it has been flagged as such. As stated before, this information is contained in the tag assigned in the detection phase. In this case, no traffic between the PLC 3 and HMI 2 is allowed according to the whitelist.

With the exception of the "Missing flow" tag, all detected non-legitimate network flows are dyed in red



(a) Anomalous flow between PLC 3 and HMI 2. (b) Detail of the flow when hovering the mouse over it.

Figure 3: Representation of an anomalous network flow.

to visually highlight it from the rest of the flows. However, due to the different nature of the "Missing flow" tag, these flows are rendered in black (see Figure 7). These flows are as well the only flows that are rendered with the data from the whitelist instead of the collected flows, as no data regarding them has been retrieved from the network.

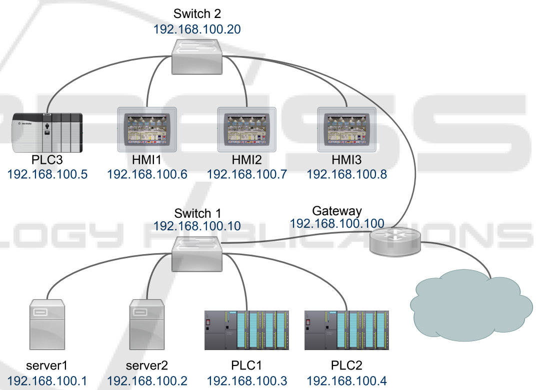


Figure 4: Network topology of the test industrial network.

4 APPLICATION IN AN INDUSTRIAL NETWORK MONITORING DASHBOARD

This section tests the previously described system within an industrial network.

4.1 Test Network

As security testing on a live network can have unexpected consequences, such as malfunctioning or safety issues (Duggan et al., 2005), and currently, to the best of our knowledge, there is no network flow data for industrial networks, we have duplicated the network of a real industrial installation in our laboratory. The original network is the control network of a car painting line in a manufacturing facility.

Figure 4 shows the topology of our test network. Both network switches are the network agents that send flow packets to the collector. In our case, we use Cisco's NetFlow, version 5. Moreover, Switch 1 is also the DNS Server of the network.

There are three Programmable Logic Controllers (PLCs) in the network that are responsible for controlling the industrial process. Two supervisory control servers poll process data from all the PLCs. Communication between servers and PLCs is done through the Modbus/TCP protocol.

There are also three Human Machine Interfaces (HMIs) present in the network, that enable operators to overview the process through the representation of process data in a visual, accessible manner. HMI 1 gathers data from Server 1, HMI 2 renders data from Server 2 and finally, HMI 3 visualizes data from both servers. Communication between HMIs and the servers is done using the OPC protocol.

A gateway gives the industrial network access to external hosts, such as the network flow collector.

4.2 System Implementation

For our tests, we use Cisco's Netflow (version 5) as network flow system to send data to the flow collector. The switches from the network send flow data to a Logstash[2] agent that receives it, parses it and later indexes it in an ElasticSearch[3] cluster. This approach allows potential large-scale usage of the monitoring system and fast querying of the flow data to render visualization. The visualization system that builds these chord diagrams has been developed using the D3 (Bostock et al., 2011) library.

4.3 Cases

In this section we show rendered chord diagrams in three different anomalous cases: a Denial of Service (DoS) attack, a network scan that aims to enumerate hosts in the network, and a network outage where a host goes down. For test purposes, all the next chord diagrams have been created with data taken at ten minute intervals, using their equivalent whitelist and with a threshold of 20% variation tolerance in the number of packets in the flow.

4.3.1 Denial of Service

Denial of Service (DoS) attacks occur when an attacker tries to obstruct the normal functioning of a host or service by making it unavailable to legitimate users. In industrial networks, where availability is the primary security concern and latency issues can create significant network problems, DoS attacks are a real problem. In our case we mimic a DoS attack from the HMI 3 to Server 1 by making a great number of illegitimate network requests.

Figure 5 shows the rendered result. The flow with the attack is painted in red, as it has surpassed the established threshold for network packages. As the sent number of packets gets higher, HMI 3 also gets a wider arc in the chord diagram circle, as well as the chord's end in its side.

4.3.2 Host Discovery

Host discovery is one of the first steps an attacker performs when obtains access to an unknown network in order to gather insight about it. Port scanning is one of the most used techniques for host discovery. For our test, conducted a TCP Connect scan with Nmap from the host HMI 3.

[2]https://github.com/elastic/logstash

[3]smallhttps://github.com/elastic/elasticsearch

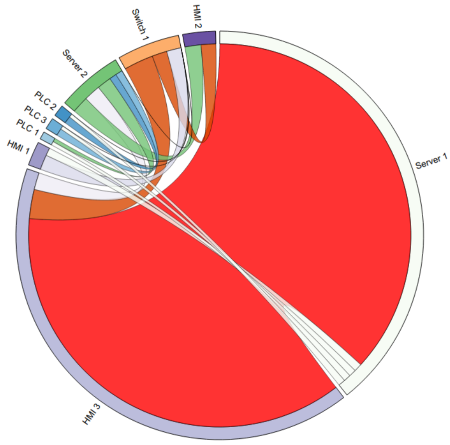


Figure 5: Visualization of a Denial of Service attack.

Figure 6 shows the chord diagram depicting the attack. All flows regarding HMI 3 are flagged as malicious, either because it is communicating with non whitelisted hosts (e.g. PLCs) or because it uses different protocols and/or ports with hosts that it is actually allowed to communicate with.

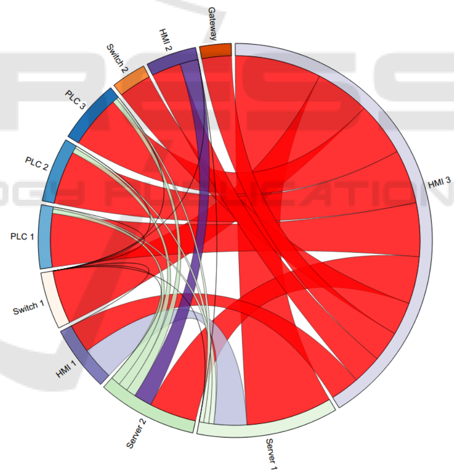


Figure 6: Visualization of a port scan.

4.3.3 Host Down

Finally, we consider the case when a host goes down from the network and it is not able to receive or send packets. In this case, we have physically disconnected Server 1 from the network.

Figure 7 shows how the system shows the downed host, with black chords representing that we are dealing with missing flows. In order to be able to render the diagram, data is taken from the whitelist, as no real data has been collected from the network regarding these flows.

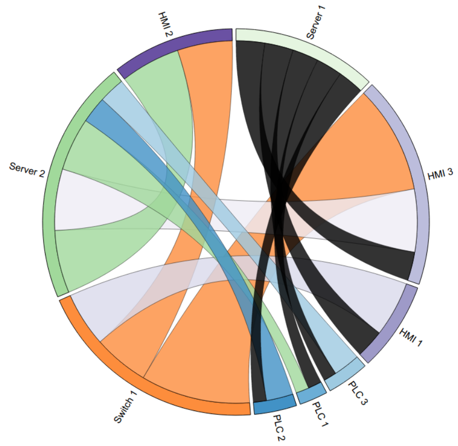


Figure 7: Visualization of a downed host.

5 CONCLUSIONS

We have presented a novel pipeline to network data analysis that enables to visually monitor industrial networks by using whitelists and chord diagrams. To do so, first we build a time-based industrial traffic model which whitelists allowed network flows. Moreover, the model considers packet throughput, in addition to host addresses, server ports and IP protocols that makes possible to detect additional flow-related anomalies (DoS attacks and downed hosts). Each entry of the model whitelists an specific duration of gathered flow data. In the same way, every new flow data is compared against the traffic model to see if it fits an entry. All flows are tagged according to its nature (legitimate, anomalous, incorrect port or protocol, missing and anomalous flow size).

This tagged data is used to build chord diagrams that represent network flow relationships between different hosts. The size of the chords represents the amount of network packets in the flow, used as the main metric to build the diagram. The tagging system provides a color code to highlight anomalous flows (in red and black) and also provides feedback about its nature.

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