Network Anomaly Detection in Cars: A Case for Time-Sensitive Stream Filtering and Policing

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Abstract

Connected vehicles are threatened by cyber-attacks as in-vehicle networks technologically approach (mobile) LANs with several wireless interconnects to the outside world. Malware that infiltrates a car today faces potential victims of constrained, barely shielded Electronic Control Units (ECUs). Many ECUs perform critical driving functions, which stresses the need for hardening security and resilience of in-vehicle networks in a multifaceted way. Future vehicles will comprise Ethernet backbones that differentiate services via Time-Sensitive Networking (TSN). The well-known vehicular control flows will follow predefined schedules and TSN traffic classifications. In this paper, we exploit this traffic classification to build a network anomaly detection system. We show how filters and policies of TSN can identify misbehaving traffic and thereby serve as distributed guards on the data link layer. On this lowest possible layer, our approach derives a highly efficient network protection directly from TSN. We classify link layer anomalies and micro-benchmark the detection accuracy in each class. Based on a topology derived from a real-world car and its traffic definitions we evaluate the detection system in realistic macro-benchmarks based on recorded attack traces. Our results show that the detection accuracy depends on how exact the specifications of in-vehicle communication are configured. Most notably for a fully specified communication matrix, our anomaly detection remains free of false-positive alarms, which is a significant benefit for implementing automated countermeasures in future vehicles.

Keywords: Time-Sensitive Networking, TSN, in-vehicular networks, automotive security, network simulation, QoS

1. Introduction

Internal networks of current vehicles are based on Controller Area Network (CAN) buses, which are assigned to individual domains and interconnect via a central gateway. New functions of modern vehicles — including advanced driver assistance and autonomous driving (level 3 to 5) — rely on data streams from cameras, LIDARs, etc. These applications demand for significantly higher network capacities and at the same time require massive, time-critical cross-domain communication.

Ethernet is emerging as the core communication technology to serve these needs of future In-Vehicle Networks (IVNs): Ethernet is scalable, of low complexity, and cheap. A new, vehicle-specific physical layer enables transmission speeds of up to 1 Gbit/s via a single twisted pair while also meeting the requirements of electromagnetic compatibility [1, 2]. The IEEE Time-Sensitive Networking (TSN) [3] umbrella standard is a leading classification to build a network anomaly detection system. We leverage to develop a fine granular view on regular packet flows on the link layer. Monitoring the link layer is crucial for implementing automated countermeasures in future vehicles.

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for detecting misbehavior that threatens the safety and security of the vehicle. Protecting link layer communication promises the highest efficiency since performed on the lowest available layer—including the robustness of the network performance (e.g., QoS [19, 20, 21]) and of all upper layers. Early work [22] could already demonstrate how TSN-based anomaly detection can identify bogus traffic without false positives. In this paper, we comprehensively explore the case of a Network Anomaly Detection System (NADS) based on TSN making the following key contributions.

- We leverage the TSN ingress per-stream filtering and policing (PSFP) [3, 23] as the core component of an in-car NADS. PSFP forces all inbound traffic to match regular patterns (e.g., timings, bandwidths, packet sizes) by dropping misbehaving frames. The NADS is established by combining PSFP with a central (TSN or SDN) controller.

- We micro-benchmark the performance of the NADS in simulations. To this end, we classify link layer anomalies caused by attacks and individually analyze each class. Our results confirm that all detection schemes remain free of false positives. We also show how false negatives can be reduced by correlating multiple PSFP indicators.

- We present a realistic macro-benchmark in a simulated zonal IVN topology using attack traces from CIC-IDS 2017 [24] and traffic stimuli from the reference communication of an OEM car. Our NADS shows promising results throughout the comprehensive simulations, while not a single false alarm occurs.

The remainder of this paper is structured as follows. In Section 2, we introduce the concept of per-stream filtering and policing (PSFP) and its potential to detect anomalies. We classify link layer anomalies in Section 3 and assess the effectiveness of detecting them in differentiated micro-benchmarks. In Section 4, we use an OEM car communication model to macro-benchmark the behavior of our NADS in realistic scenarios. Section 5 discusses the problems of cyber protection for cars along with related work. Finally, we conclude in Section 6 with an outlook on future research directions.

2. Time Sensitive Networking in Vehicles and its Potential to Detect Anomalies

In this section, we introduce the initial idea of how real-time flow management in IVNs can simultaneously identify network anomalies. We start from the TSN standard, which enables QoS guarantees in local networks by real-time extensions for IEEE 802.1Q Ethernet [3]. These extensions comprise mechanisms such as traffic shaping [25], ingress control [23] and time synchronization [26]. TSN paves the way for Ethernet IVNs that comply to timing constraints and strictly meet deadlines of safety critical vehicular applications. Time division multiplexing with traffic shaping and prioritization allows synchronous and asynchronous traffic streams of diverging timing constraints to share the same links successfully. Provisioning real-time traffic definitions makes it possible to bound delay and jitter for each critical traffic stream. Synchronous Time Division Multiple Access (TDMA) traffic can limit delays in the range of microseconds and jitter within nanoseconds [27]. For this work, TSN standard IEEE 802.1Q per-stream filtering and policing (PSFP) [23] is of particular interest.

In the following, we explain how (i) PSFP can enforce individual stream behavior in TSN infrastructures, (ii) PSFP can configure a link layer NADS, (iii) general conditions influence the detection quality, and (iv) to implement our concept in a Software-Defined Networking (SDN)-based Ethernet backbone.

2.1. Per-Stream Filtering and Policing

The IEEE 802.1Q per-stream filtering and policing (PSFP) standard [23] controls individual flows and enforces rules on all incoming traffic. Fig. 1 shows how filtering and policing is applied to ingress traffic in PSFP.

A frame needs to pass three stages prior to queueing. The first stage identifies individual streams and maps them to corresponding gates and meters. In the second stage, individual gates are responsible for admission of incoming frames. The state of stream gates can be static or change at runtime depending on a predefined periodic schedule and network-wide synchronized clocks. If a gate is “CLOSED”, incoming frames will be dropped. Once “OPEN”, a flow meter measures the frames in a third stage. Flow meters apply algorithms to determine whether a frame is allowed to pass. For example, a flow meter can limit bandwidth or burst size and would mark or drop a frame that exceeds the bandwidth or burst allowance.

During the IVN design process, traffic relations are predefined in a communication matrix of the vehicle and annotated with behavioral properties such as timings, bandwidths, and bursts. The PSFP meter and gate configurations must match this traffic specification exactly to assure safety and security. Exact configurations avoid unwanted disturbance by traffic of misbehaving streams. Loosely defined configurations could tolerate an over-utilization, which turns harmful for concurrent streams, whereas too strict configurations could lead to dropping frames of valid streams. We focus on the exact PSFP configurations as the basis for in-car network anomaly detection.

2.2. Anomaly Detection with Filters and Policies

Anomaly detection is a function of an Intrusion Detection System (IDS), which can monitor from the perspective of a
host (H) or a network (N). There are two flavors of IDSs [28].

(i) Signature detection systems that identify patterns by predefined signatures. These systems work reliably but are limited to known misbehavior. (ii) Anomaly Detection Systems (ADSs) follow a behavioral approach by using predefined descriptions of regular patterns. Deviating patterns are then marked as misbehavior, which allows to also detect zero-day attacks in safety critical systems. The finer the regular patterns are described, the more accurate can the anomaly detection operate.

Safety-critical communication flows of in-car networks are pre-defined in the network design. In PSFP, each unique traffic flow is represented as a link layer stream. Hence, the pre-defined link layer behavior of safety-critical communication is already part of the PSFP configuration. From this perspective, the PSFP configuration can be read as an implicit description of the behavioral horizon between normal and abnormal link utilization. To this end, a frame drop by a PSFP rule indicates unintended behavior and acts as a detector of an anomaly—a valuable input for an anomaly detector.

False positives in the anomaly detection hinder automated counter measures. They occur whenever traffic classifications need not be rigorously met. As in-vehicle control traffic is pre-defined by design, we can focus in the following on traffic characteristics which cars in regular and error-free operations never violate. Corresponding indicators then operate reliably in the sense that they remain free of false positives, provided the PSFP configuration is correct.

Managed switches collect statistics of network events for administrative inspection. A TSN switch also records TSN-specific statistics. The number of individual frame drops of PSFP flow meters and stream gates are such values of a TSN switch. Traditional network management can use SNMP [29] or NETCONF [30] to control and monitor local switches. SDN-based networks can also collect data from forwarding devices via OpenFlow [31, 32]. Network managers or SDN controllers can aggregate statistics of all switches in the network and hence enable an anomaly detection function by applying appropriate algorithms to analyze PSFP data.

The central collection of statistics from switches introduces a delay, which adds to the time at which anomalies are first discovered. In our setting, this delay remains uncritical for the link layer availability since PSFP is a self-protecting system that drops frames which violate regular patterns. This local guarding prevents compromised streams from spreading and negatively impacting concurrent streams. Since network resource consumption is controlled by PSFP, individual streams cannot exceed predefined resources. This in particular prevents volumetric DoS attacks from spreading in the car network.

Overall, combining PSFP with event monitoring in switches provides a toolbox that can detect anomalies in the network reliably and prevent resource exhaustion. It is noteworthy that the underlying base technologies are already in discussion for an IVN deployment [5, 33]. The proposed Network Anomaly Detection System (NADS) is based on the configuration patterns in PSFP for regulating network traffic.

2.3. Quality of Anomaly Detection

The strict safety requirements for vehicles on the road challenge the quality of an onboard anomaly detection system. A NADS in the vehicle must achieve high precision while minimizing false alarms. At the same time, there is no technology that detects all known and unknown attacks. Hence, a NADS must be considered as only one component of a comprehensive security solution.

PSFP based network anomaly detection offers the potential to detect a wide range of misbehavior. Those are not limited to attacks. Failures, bugs, and configuration errors are also possible sources of deviations from standard behavior.

The PSFP configuration quality, i.e., correctness and completeness of traffic rules, is the key factor for detection quality. This configuration, which includes e.g., timings, bandwidth, and maximum transmission unit (MTU) is already required for guaranteed real-time communication and vehicle safety. During testing phases, a NADS can help to expose configuration errors. After a complete fix of configuration errors, operational network traffic never violates the configured constraints under normal condition—including worst case scenarios and bursts, e.g., in case of edge scenarios like a crash. A correct and exact PSFP configuration that also considers worst case scenarios consequently enables a detection with zero false alarms.

Nevertheless, such an NADS is not able to detect every kind of misbehavior. Bogus traffic, for example, which matches exactly with the specifications of a stream remains undetectable. We investigate the detection performance and its limits in a micro benchmark for all possible misuses on the link layer, as well as in a macro benchmark based on a realistic in-vehicle network (see Section 3 and 4).

2.4. Implementation in an SDN Backbone

SDN enables a programmable control plane and shifts the control logic to a central controller. In contrast to traditional switches and routers, the central SDN controller populates flow tables in forwarding devices using open standards such as OpenFlow [32]. This drastically increases flexibility and controllability of the network [34]. Central knowledge and dynamic forwarding decisions also enable the implementation of countermeasures by reconfiguring the networking in response to alarms. In recent years, use cases of SDN extended to areas such as vehicular networks [35, 33, 34] and industrial plants [36].

Figure 2: Example of a PSFP based NADS by combination with SDN
In an SDN-based in-car backbone, events from PSFP instances in individual switches reach the central SDN Controller. For example, an advanced NADS application can be deployed at the SDN controller without putting additional stress onto the switches or adding additional devices to the network. Such a NADS controller application can use individual events and inspect these in combination with other reports.

Fig. 2 visualizes the operation of a NADS with PSFP and SDN infrastructure. Each port (0 to n) of the TSN switches 0 to i has an instance of PSFP containing its individual configuration. All switches monitor events per port of their running PSFP instances (e.g., frame drops). The PSFP in port 0 of switch 0 receives a frame that violates a meter configuration and gets dropped. This event is monitored and recorded in switch 0. Switch 0 forwards these event statistics upstream to the SDN controller. The NADS application of the controller inspects whether the data of the switches indicate a traffic anomaly. Every increase in the absolute number of dropped frames since network initialization is considered an anomaly. No additional resources are needed in switches and limited data processing is required in the SDN controller to interpret the counters. Whenever an anomaly is detected, the NADS controller application could send combined reports to a higher instance (e.g., a cloud defense center [15]), or initiate countermeasures by reconfiguring the network flow tables or the TSN settings.

3. Micro-Benchmarking Anomaly Detection

We now proceed to a systematic exploration of the performance for our network anomaly detectors. We evaluate how reliably PSFP statistics can serve as link layer monitors in the presence of attacks. Root causes of attacks could be malicious Electronic Control Units (ECUs) or external attackers. We first characterize the anomaly classes, the assessment metrics, and the simulation environment. Then we present the results of all dedicated benchmarks.

3.1. Classification of Link Layer Anomalies

Misbehaving traffic traversing a network influences links and becomes visible at ingress points. We classify these interactions based on common link layer operations. All possible operations on Ethernet frames are: Elimination, injection, inspection, manipulation, redirection, reordering, and rescheduling. The impact of any attack traversing the Ethernet layer falls into at least one of these classes.

Fig. 3 shows a stream and its frames traversing the network in a baseline scenario without impairment. Our focus is on an intermediate, “current” node, at which a TSN PSFP inspects all incoming frames.

3.1.1. Elimination

An anomaly that impairs a stream by removing frames. In Fig. 4, frame number 2 is eliminated by one of the previous nodes and detected as missing at the current node. This observation corresponds to blackholing scenarios in wide area networks.

3.1.2. Injection

A stream modification by inserting frames at a previous node. In Fig. 5, new frames are injected between frame 1, 2, and 3 as observable by the current node. Common examples for this class are Denial of Service (DoS) and Distributed DoS (DDoS) attacks, but also replay attacks.

3.1.3. Inspection

An unauthorized observation of frames. The traditional example for this class is eavesdropping. The actual inspection introduces no changes to the observed stream (see Fig. 6) but compromises its confidentiality. The current node is not able to observe this impairment.

3.1.4. Manipulation

A modification of frame payloads. In Fig. 7, a stream is impaired by manipulating frame 2 at a previous node. This class includes attacks such as spoofing or application data corruption. If corresponding header values (e.g., checksum and length) remain unadjusted, or manipulated packets violate the constraints of the stream class, manipulation of frames can be observed at the current node. Manipulations that change the stream affiliation will either appear as a combination of stream elimination and injection, or result in unknown streams.

3.1.5. Redirection

A rerouting of frames to a differing path on the network. In Fig. 8, frame number 2 is redirected to another next hop by a previous node. Hence, frame 2 is missing in the stream reaching the current node, which can be observed but remains indistinguishable from frame elimination. On the counter side, redirection appears as an injection. A wide area network correspondence for this attack is route poisoning or hijacking. In a local SDN topology a compromised controller can also manipulate the flow tables in the forwarding devices.
3.1.6. Reordering

A change in sequence of frames. In Fig. 9, the frame order is changed from $1 \rightarrow 2 \rightarrow 3$ to $2 \rightarrow 3 \rightarrow 1$. An attack example for reordering is message sequence violation of communication protocols. If not executed at the source, a frame is taken and inserted after any number of other frames passed. Reordering of frames is observable at the current node in particular as it changes the timing of frames.

3.1.7. Rescheduling

A change of the forwarding time for individual frames in a stream. In Fig. 10, frames 1 and 2 are slightly delayed. This also could be an impact of a malicious manipulation of drift clocks via the time synchronization protocol. Changes in timing are observable at the current node.

3.2. Metrics

To evaluate and compare our classification results we apply common metrics, which are also known from the assessment for automotive IDS performance authored by the U.S. National Highway Traffic Safety Administration [37]. Table 1 summarizes these metrics.

Precision represents the accuracy of identified alarms. Without False Positives (FP) the precision equals 1, but decreases with increasing FPs:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall represents the fraction of detected attacks from all attacks. Without False Negatives (FN) the Recall equals 1, but decreases with increasing FNs:

$$\text{Recall} = \frac{TP}{TP + FN}$$

**In-Vehicle Security Implications.** In driving operations, FPs in combination with automated countermeasures can cause damage. Even a very small FP rate like 0.001% for a message with a viable cycle of 100 ms leads to an average false positive every 2.8 operating hours. This may quickly degrade confidence in the Anomaly Detection (AD) mechanism.

Due to the strict safety requirements for vehicles, it is important to establish a highly trustworthy anomaly detection system.

| Metric                  | Description                                      |
|-------------------------|--------------------------------------------------|
| False Negatives (FN)    | No. of unidentified misbehavior                  |
| False Positives (FP)    | No. of false alarms                              |
| True Positives (TP)     | No. of identified misbehavior                    |
| Precision               | Fraction of alarms that identified misbehavior   |
| Recall                  | Fraction of identified out of all misbehavior    |

In particular, a NADS in the vehicle must achieve high precision. As of today, there is no technology that can detect all known and unknown misbehavior in a system, which – outside of test environments – always leads to realistic recall values $< 1$. From this follows that it is impossible to operate with zero FNs. Anomaly detection systems try to maximize detection rates by their ability to detect zero-day attacks.

Every NADS is limited, and FNs could allow a malicious attacker or device malfunction to cause harm without detecting it. It is therefore even more important to measure the limits of these systems to be able to determine the risk of unidentified misbehavior. To protect future cars, a NADS is only one component in a comprehensive security solution consisting of various systems and methods.

3.3. Simulation Environment and its Configuration

We use the discrete event simulator OMNeT++ for the execution of all benchmarks. Fig. 11 shows the frameworks in use for the simulations. We use this environment as the base for all simulations in this paper.

![Figure 11: Simulation environment for micro- and macro-benchmarks](https://github.com/CoRE-RG)

Basis of the environment is the OMNeT++ discrete event simulator. The combination with the INET framework [38] enables the simulation of Ethernet networks. In the past years, we have built and published a comprehensive open-source environment for simulating IVNs in OMNeT++ [39]. The frameworks marked in red (CoRE4INET, FiCo4OMNeT, SignalsAndGateways, and SDN4CoRE) are parts of this past work. They enable the concurrent simulation of real-time

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1[https://github.com/CoRE-RG]
Ethernet (e.g., TSN), field busses (e.g., CAN), gateways (e.g., CAN/Ethernet Gateways), and SDN.

In a first step, our goal is to keep the topology as simple as possible for executing micro-benchmarks. Later in Section 4, we assess performance values in macro-benchmarks using a real-world IVN topology. Fig. 12 depicts the topology for all micro-benchmark simulations.

![Topology of the simulated network for the micro-benchmark](image)

The initial topology consists of three nodes linked via 100 Mbit/s Ethernet. Since different Ethernet speeds just rescale, the findings will remain applicable for lower and higher maximum Ethernet throughput. All traffic is generated at the source host and directed through a switch to the sink host. To assess how the traffic type affects detection performance, three different traffic patterns and background cross-traffic are transmitted from the source host:

- **Timed control traffic:** Maximal Ethernet frames forwarded with the highest 802.1Q priority (7) in a synchronized TDMA schedule that reserves time slots on the links in a static period of 0.5 ms. All other traffic shares the remaining time slots according to their priorities.

- **Shaped data stream:** A data stream with a bandwidth of ~17 Mbit/s. 802.1Q priority is set to 6 and the traffic is shaped by Credit Based Shaping (CBS). The CBS maintains a credit value that ensures a stream does not exceed its reserved bandwidth, while still allowing bursts to make up for time slots where the bandwidth was not reached due to concurrent traffic. The remaining bandwidth is available to lower priorities.

- **Prioritized CAN tunnel:** Legacy CAN messages encapsulated in Ethernet frames with an 802.1Q priority set to 5. Messages are generated in a period of 0.5 ms.

- **Background cross traffic:** Cross traffic generates network load and concurrently increases the mix of traffic. It is generated without 802.1Q tag from uniformly distributed packet sizes and intervals (125 µs–500 µs).

The switch operates with pre-configured PSFP at the port that connects the source host. The following single configurations per traffic type enforce key properties of a valid behavior:

- **Timed control traffic:** The states of all PSFP stream gates depend on a synchronized gate control list. Every frame that arrives at the switch port during a closed gate period gets dropped. Regular TDMA traffic always reaches the respective stream gate in open state.

- **Shaped data stream:** As for the CBS, a Credit Based Metering (CBM) [40] is applied to meter a PSFP flow and enforce bandwidth reservation. Frames that exceed the reserved bandwidth for a stream get dropped.

- **Prioritized CAN tunnel:** An encapsulated CAN message (maximum 16 B) always results in a minimum Ethernet frame. Therefore, PSFP is configured to drop all frames with a size that exceeds 64 B.

- **Background cross traffic:** Stream filters match to known cross traffic streams and grant passage through PSFP without additional metering rules.

- **Undefined stream:** PSFP drops all traffic that does not match any stream filter.

Table 2: Overview of Anomalies in our Benchmarks

| Anomaly            | Details                  | Benchmark |
|--------------------|--------------------------|-----------|
| 3.1.1 Elimination  | Deletion of frames       | Yes       |
| 3.1.2 Injection    | Creation of extra frames | Yes       |
| 3.1.3 Inspection   | Observing frames and contents: Not observable in stream behavior | No        |
| 3.1.4 Manipulation | Alteration of frames     | Yes       |
| 3.1.5 Redirection  | Adjusting route of frames | No        |
| 3.1.6 Reordering   | Changing frame sequences | Yes       |
| 3.1.7 Rescheduling | Delay frames             | Yes       |

Table 2 gives an overview of anomalies that will be analyzed in our benchmarks. Five of the seven mechanisms are implemented in simulation. We exclude inspection (cf., Section 3.1.3) and redirection (cf., Section 3.1.5). Inspection has no effect on the behavior of traffic streams and hence remains unobservable. Redirection is excluded because it cannot be distinguished from elimination, injection, or manipulation.

![Placement of the corruption layers for simulation in source host](image)

Fig. 13 shows stream corruptions implemented on two different layers within the stack of the source host. The frames for each stream are generated at the application layer and forwarded onto the link layer before leaving the device. To cover all elements of compromise, modifications of a stream can be
### Table 3: Drop detection micro-benchmark results with True Positives (TP), False Negatives (FN), and Recall (R)

| Traffic pattern                  | Elimination | Injection | Manipulation | Reordering | Rescheduling |
|----------------------------------|-------------|-----------|--------------|------------|--------------|
|                                  | TP  | FN  | R    | TP  | FN  | R    | TP  | FN  | R    | TP  | FN  | R    |       |       |       |
| Application Layer Corruption     |     |     |      |     |     |      |     |     |      |     |     |      |       |       |       |
| Timed control traffic            | 0   | 6646| 0.0  | 6814| 2602| 0.72 | 5356| 1254| 0.81 | 0   | 6635| 0.0  | 3    | 6622| 0.0  |
| Shaped data stream               | 0   | 8918| 0.0  | 0   | 9412| 0.0  | 0   | 8880| 0.0  | 0   | 8875| 0.0  | 0    | 8882| 0.0  |
| Prioritized CAN tunnel           | 0   | 6664| 0.0  | 9145| 263 | 0.97 | 6489| 173 | 0.97 | 0   | 6659| 0.0  | 0    | 6657| 0.0  |
| Link Layer Corruption            |     |     |      |     |     |      |     |     |      |     |     |      |       |       |       |
| Timed control traffic            | 0   | 5656| 0.0  | 8701| 706 | 0.92 | 4606| 1073| 0.81 | 5616| 1   | 1.0  | 4382| 1253| 0.78 |
| Shaped data stream               | 0   | 8367| 0.0  | 8931| 483 | 0.95 | 5862| 2513| 0.7  | 2   | 8389| 0.0  | 1    | 8378| 0.0  |
| Prioritized CAN tunnel           | 0   | 5616| 0.0  | 9204| 207 | 0.98 | 5584| 165 | 0.97 | 0   | 5696| 0.0  | 0    | 5692| 0.0  |

The results of the micro-benchmarks are presented first from a baseline scenario without modifications and from five scenarios with corruptions thereafter.

The baseline scenario contains only regular traffic, i.e., all streams behave as designated. For this reference benchmark, ten simulation runs (10 s length) with randomly varying conditions are executed to maximize state coverage. The results show zero frame drops in all simulations by any module including PSFP (cf., Table 4), which implies that the configuration rule set of PSFP is consistent with the regular in-car traffic. Accordingly, FP=0 for all micro-benchmarks, which implies a perfect precision value of 1:

\[
\text{Precision} = \frac{TP}{TP + FP} = \frac{TP}{TP + 0} = 1
\]

It should be noted, though, that legitimate frames may still be dropped in the presence of malicious streams—an incident of misbehavior, which is not a false-positive.

If the NADS detects misbehavior, a precision value of 1 indicates a highly trustworthy system. To evaluate the overall NADS performance, however, the number of false negatives and the recall must also be considered.

In each simulation (10 s length) with corruption exactly one of the three traffic patterns (timed control traffic, shaped data stream, prioritized CAN tunnel) is modified on one layer. For five different attacks, this results in thirty different simulation runs. All stream modifications and frame drops are counted and recorded during the simulations. The corrupted events are randomized to maximize state coverage. They take a minimum interval of 1 ms to make them distinguishable for analysis.

The numbers of randomly corrupted events range from 5000 to 10000 per simulation. Only events from PSFP are used as anomaly indicators. In a first step, only frame drop events are considered. Table 3 summarizes the results.

### Table 4: No. of PSFP frame drops (FPs) in the baseline benchmark

| Simulation run | No. of frames in PSFP |        |        |        |
|----------------|------------------------|--------|--------|--------|
|                | Arrived                | Forwarded | Dropped (FP) |
| #0 — #9        | 1,199,688              | 1,199,688 | 0     |

3.4. Results

The results of the micro-benchmarks are configured to occur between application layer and link layer (application layer corruption), or between link layer and physical port (link layer corruption). As the major difference, application layer corruptions need to pass TSN traffic shaping, while link layer corruptions are conducted thereafter. In our benchmarks, each case will be executed on both layers.

**Elimination.** Elimination is configured to delete frames of the observed stream with a measure of coincidence (probability: 50%). Since only frames are missing from the stream, it is expected that this type of corruption is not detectable using drops inside PSFP as anomaly indicators. The results in Table 3 confirm the expectation. The recall value is zero for all traffic patterns.

**Injection.** Frames are injected into each stream in a uniformly distributed interval. The distribution length corresponds to the maximum transmission unit of Ethernet (≈125 µs on 100 Mbit/s links). This is done to increase the number of distinct network states represented in the simulation runs. Therefore, the size of each frame is also determined by a uniformly distributed payload size ranging between the allowed minimum (0 B) and maximum (1500 B). The results in Table 3 show that for traffic shaped by TSN on link layer (shaped data stream, timed control traffic) the detection of application layer corruptions is worse than of link layer corruptions. The reason is that the scheduling and shaping of TSN enforces a determined configured to occur between application layer and link layer (application layer corruption), or between link layer and physical port (link layer corruption). As the major difference, application layer corruptions need to pass TSN traffic shaping, while link layer corruptions are conducted thereafter. In our benchmarks, each case will be executed on both layers.
stream behavior and thus the influence of application layer corruptions on stream behavior is less powerful. Scheduling and shaping generate a defined stream behavior and PSFP ensures that aspects of the behavior are adhered to. Timed control traffic is forwarded on pre-defined time windows. PSFP also only allows reception in those time windows shifted by the transmission delay. All frames injected in application layer will accumulate together with valid frames in the queues of the corruption source. Injected frames that do not influence transmission delay through differing size will not be dropped in PSFP. In case of the shaped data stream the CBS is shaping the traffic exactly on specification. The CBM in PSFP is not dropping any frames and the NADS has a recall value of 0. For a stream with strict priority shaping and a fixed frame size (prioritized CAN tunnel) the detection performance is independent of the injection layer. All frames with a size not matching the PSFP configuration are dropped.

Manipulation. A frame manipulation in the respective stream takes place with a factor of randomness (probability: 50%). The manipulation modifies the payload. The new Ethernet payload has a uniformly distributed size ranging between the minimum (0 B) and maximum (1500 B). In some cases, this is the same length as the valid frame, but in most cases the new frame length differs. Again, no application layer corruptions are detected for the shaped data stream. CBS shapes the frames correctly according to their size. Differing frame sizes do not change the forwarded bandwidth of the stream in their respective measurement intervals. Manipulations on timed control traffic and prioritized CAN tunnel frames were detected with a high recall value (cf., Table 3).

Reordering. With coincidence (probability: 50%) a frame is taken from a stream and then delayed to be inserted after the next frame of the same stream. Since reordering has no effect on frame size or bandwidth consumption, it is not detectable in most cases without further inspection of, for example, sequence numbers. For reordering of timed control traffic on application layer, the TDMA timing is enforced by the source host on link layer. In this case, only the loss of the taken frame is an observable misbehavior. On the other hand, the timing of frames for link layer reordering is not dependent on the configured shaping. Therefore, those frames miss the period where the respective gate is open in PSFP of the switch. This causes almost all reordered frames of timed control traffic to be dropped.

Rescheduling. Frames of the corrupted stream get delayed randomly (probability: 50%) by a uniformly distributed time. Again, distribution length corresponds to the maximum transmission unit of Ethernet (=125 μs). Timed control traffic is the only one with a PSFP configuration dependent on timing. Once again, the source host gates enforce the designed timing for send windows. Therefore, the wrong timing is not detected for application layer but for link layer corruptions.

Enhancement using TDMA loss detection. In addition to frame drops, other statistics can also be used as anomaly indicators. These can be selected in such a way that further modifications become recognizable and the recall increases. Further indicators shall be selected such that 100% precision is preserved and no false alarm occur. In the following example, a loss recognition is implemented using a counter for frames that pass through an opened gate. This counter exactly increases by one for each opened window with timed control traffic. If the counter is not increased during an open gate window, an expected packet has not arrived. 10 simulations without corruption confirm that this anomaly indicator also attains an FP value of 0 for the static timed control traffic. Table 5 shows the simulation results for all modifications on timed control traffic with a NADS using frame drops and the TDMA loss detection in combination.

With the addition of loss detection all 5 link layer corruptions are detectable for critical TDMA-based traffic. The recall minimum is 0.78 and goes up to the maximum of 1. At the same time, a precision value of 1 highlights a strong and reliable performance for link layer network anomaly detection. Corruptions with a high recall value indicate a strong deviation from the specified stream behavior and thus can have a strong impact on network performance and competing real-time streams. The detection performance increases analogous to those higher risk modifications.

Tailored indicators and strict PSFP configurations lead to further improvements in the recall. In this way, a TSN traffic configuration not only minimizes latency and jitter but can also im-
prove security for data streams on the link layer by improving detectability of and resilience against misbehavior.

3.5. Discussion

The results show that anomaly detection without false positives is possible for all five application and link layer corruptions. On the other hand, our approach is not geared towards minimizing false negatives. The measured recall values resulting from the number of false negatives show which scenarios could be detected. The detection performance is influenced by the traffic shaping and the configuration of the PSFP. Application layer corruptions suffer higher false negatives because the traffic shaping is counteracting the misbehavior. In general, injection and manipulation scenarios are detected with a higher recall value than elimination, reordering, and rescheduling. Elimination is impossible to detect with a packet drop statistic. With strict PSFP configurations, further statistics can be used as false positive free anomaly detectors and reduce the number of false negatives to expand detectable scenarios.

4. Macro-Benchmarking a Realistic Vehicle

We now proceed to evaluating our approach in a realistic environment. We use the simulation techniques presented in Section 3.3 with a zonal IVN topology based on a real car communication matrix. First, we simulate regular traffic with a strict PSFP schedule to confirm the absence of false positives. Next, we replace legitimate streams from the car network by selected attacks derived from the CIC-ID$S$ 2017 [24] dataset to investigate the impact on PSFP drops. CIC-ID$S$-2017 contains traces from common Internet attacks. From these, we select attacks which are likely to be seen at connected cars. Datasets with attacks specific to TSN link layers have not been recorded, yet, and thus could not be fed into our vehicular environment. All macro-benchmarking simulations with complete configurations and the used datasets are available online\footnote{https://github.com/CoRE-RG/SignalsAndGateways/tree/paper/network_anomaly_detection_in_cars} for further research.

4.1. In-Vehicle Network Topology

The communication systems of future cars are expected to transition to zonal topologies that still contain legacy devices, before converging to a flat Ethernet backbone [5]. Therefore, the network topology of our sample car is split into nine zones (3x Front, 3x Center, 3x Rear) and contains four types of devices (CAN hosts, Ethernet hosts, switches, zonal controllers) as visualized in Fig. 14. Each zonal controller represents a zone of the topology. CAN hosts are connected via buses to the closest zonal controller depending on physical placement. The CAN traffic is derived from a communication matrix of a production car. CAN messages sent between zones traverse the Ethernet backbone (100 Mbit/s links), which consists of three linked switches. In addition to the zonal controllers, cameras, LIDARs, a radar, infotainment, collision avoidance, and sensor fusion are also using this backbone for communication.

Future Ethernet backbones contain traffic with heterogeneous QoS demands. Synchronous and asynchronous traffic shaping with priorities will be used to meet these demands [41]. Therefore, there are three archetypal traffic types in this network:

- **Timed control traffic**: Synchronous frames with a size of 64 B and 802.1Q priority 7 are sent with a period of 1 ms from “Radar” and “Sensor Fusion” to “Collision Avoidance”. A gate control list with the same period implements a TDMA schedule in each switch to enable exclusive time slots for this synchronous traffic where the gates of all other priorities are closed.

- **Shaped data streams**: Cameras (burst of 27,000 B every 0.033 s per device) and LIDARs (burst of 10,500 B every 0.04 s per device) stream data with 802.1Q priority 5 to the “Sensor Fusion” ECU. For this traffic, class A bandwidth is reserved (14.144 Mbit/s for each camera stream and 4.544 Mbit/s for each LIDAR stream) on each device along its paths, and a CBS shapes the egress.

- **Prioritized CAN tunnel**: CAN messages that are exchanged between devices located in different zones are tunneled via Ethernet. There is a total of 416 different CAN IDs generated by the CAN hosts of which 201 traverse the backbone. Their periodicity (0.01 s to 2 s) and
payload size (4 B to 8 B) is derived from the real car communication matrix. Each CAN message traversing the backbone is encapsulated in a single Ethernet frame which is padded to a minimum sized frame of 64 B. The frames are mapped to four different 802.1Q priorities (0,1,3,6) depending on their criticality.

Each port is PSFP-configured according to the incoming traffic types. This results in a total of 21 PSFP instances in the three switches. All configurations use parameters of the network design to check for valid behavior. Matching the traffic, we use four different types of ingress control:

- **Timing:** This configuration uses the static TDMA schedule of the time control traffic to accordingly set the gate control list that drives the state of the stream gates.
- **Bandwidth:** For the shaped data streams a metering is configured to enforce a max. incoming bandwidth [40].
- **Frame size:** Because a prioritized CAN tunneling frame contains only one CAN message the size of these Ethernet frames is always 64 B. For the ingress control of this traffic a meter drops all frames larger than 64 B.
- **Undefined traffic:** Ingress control drops traffic without a matching stream filter.

### 4.2. In-Vehicle Network Scenarios

In the following, we simulate four scenarios. All simulations share an identical TSN configuration and cover a period of 10 s, which corresponds to the length of the attack sequences.

The first baseline scenario runs with only regular IVN traffic to verify the absence of false positives. Ten simulations with different pseudo random number generator seeds are executed to cover different cases. In all simulations without corruption, not a single frame is dropped by any PSFP instances (cf., Table 6). This consistently indicates zero FP and full precision.

| Simulation run | Sum of frames in all PSFP instances | Arrived | Forwarded | Dropped (FP) |
|----------------|-------------------------------------|---------|-----------|--------------|
|               |                                     | 3,166,150 | 3,166,150 | 0            |

Table 6: Sum of PSFP frame drops (FPs) in the baseline scenario

The next three scenarios use attack samples exported from CIC-IDS 2017 [24] (SSH-Patator, Web Attack Brute Force, DoS Slowloris). All attacks included in CIC-IDS 2017 are application layer corruptions from the PSFP perspective. Trace excerpts of these attacks contain frames targeting the same destination. This enables the matching into IVN streams by replacing MAC addresses and adding a Q-Tag (VLAN and priority). The three attack traces contain 8 to 26 frames. In each simulation, one of the three participant (Radar, Camera Front, Zonal Controller FrontLeft) gets corrupted and performs an attack. Each scenario contains three simulation runs, in which one network participant is the source of a modified traffic type (timed control traffic, shaped data stream, prioritized CAN tunnel).

#### 4.2.1. Attacks using SSH-Patator

Patator is a tool for brute force attacks using a multitude of protocols (e.g., FTP, SSH, DNS). The CIC-IDS 2017 trace excerpt used in this scenario contains traffic of a SSH login brute force attack.

The sources of corrupted streams during three different simulations are Radar, Camera Front and Zonal Controller FrontLeft. Switch Front is the first hop for all corrupted streams and thus the first point where PSFP is applied. The first column of Fig. 15 shows the SSH-Patator attack trace content and the respective PSFP drops in Switch Front that were collected during the three different simulations.

Radar → Collision Avoidance (Control traffic). The regularly timed control traffic from Radar to Collision Avoidance is replaced by SSH-Patator traffic. The send timing in the source Radar is ensured through the TSN scheduling and shaping configuration. Nevertheless, all frames miss their arrival time window on Switch Front because their size is larger than the regular 64 B. Therefore, the gates in the responsible PSFP instance are closed when the frames arrive, and they get dropped. The NADS detects the stream corruption.

Camera Front → Sensor Fusion (Data stream). SSH-Patator traffic replaces the regularly shaped data stream. Not a single frame is dropped in Switch Front, so a detection is not possible. The reason is the same as in the application layer corruption micro-benchmarks (s. Section 3): The CBS at Camera Front shapes the attack traffic exactly according to the specification.

In this case, however, one frame of this stream gets dropped in PSFP of Switch Center, which is highlighted in green. Interference with other traffic between Switch Front and Switch Center causes the CBS in Switch Front to transmit a burst that is not allowed by the PSFP configuration in Switch Center. Since PSFP operates on individual streams, it is still possible to infer the misbehaving stream. Following this direction can improve the detection of bogus shaped data streams.

Gateway FrontLeft → Gateway *(CAN tunnel). One CAN tunnel stream is replaced by the SSH-Patator traffic. Here the regular traffic again consists of minimal Ethernet frames (64 B) each containing only one CAN message at a time. The PSFP instance drops larger frames because the flow meter is configured to enforce the minimum Ethernet frame size. All attack frames are larger and get dropped in Switch Front. The stream corruption is detected.

#### 4.2.2. Brute Force Web Attacks

This trace excerpt contains an attempt to login via HTTP using a password list. Again, the second column in Fig. 15 shows the Web Brute Force attack trace and the respective PSFP drops in Switch Front that were collected during three simulations.
**Radar → Collision Avoidance (Control traffic).** The timed control traffic of Radar is replaced by traffic from a Web Brute Force attack trace. The larger frames are dropped again because they miss the time window for allowed reception in Switch Front. The frames at 0.2 s and 5.2 s simulation time, however, are not dropped. They are small enough (74 B) to meet the configured timing requirement and arrive just before the responsible PSFP gate closes. Despite of this, the corruption is detectable because some attack frames are dropped.

**Camera Front → Sensor Fusion (Data stream).** The shaped data stream of Camera Front is corrupted by Web Attack Brute Force traffic. As before, the Camera Front CBS shapes the attack traffic exactly according to the specification. Hence, Switch Front PSFP drops, and no severe misbehavior occurs via concurrency with other streams after Switch Front. Therefore, no frame is deleted at any location and detection remains unsuccessful.

**Gateway FrontLeft → Gateway * (CAN tunnel).** Web Brute Force attack traffic is injected into a CAN tunnel stream. All attack frames, even small ones (at 0.2 s and 5.2 s), are dropped because they are larger (74 B) than Switch Front PSFP allows (64 B). The system fully detects the stream corruption.

### 4.2.3. Attacks using DoS Slowloris

This trace contains an attack that tries to stress a server with multiple simultaneous HTTP connections. The third column in Fig. 15 shows the DoS Slowloris attack trace and the respective PSFP drops in Switch Front that were collected during three simulations.

**Radar → Collision Avoidance (Control traffic).** DoS Slowloris traffic replaces the regularly timed control traffic from Radar. All larger frames are dropped. The trace contains minimal Ethernet frames (64 B), which are not dropped by PSFP. An exception in this case are two minimal frames at 5.17 s sent by the source app with a gap of 229 µs. Both frames arrive in the outgoing queue of Radar before the send interval starts. After the gate for the outgoing queue opens, both frames are transmitted consecutively. The first frame passes through the Switch Front PSFP. The second frame gets dropped on arrival because it no longer fits into the Switch Front PSFP time window. Corruption detection is successful.

**Camera Front → Sensor Fusion (Data stream).** The shaped data stream corrupted by DoS Slowloris shows the same results as for SSH-Patator and Web Attack Brute Force. No detection is possible because no frames are dropped.

**Gateway FrontLeft → Gateway * (CAN tunnel).** One prioritized CAN tunnel stream is replaced by DoS Slowloris. All frames that are not minimal (64 B) get dropped. Both minimum frames at 5.17 s can pass the Switch Front PSFP, because in this case only the frame size is enforced. Nevertheless, the attack is detected.

### 4.3. Findings

The macro-benchmarks confirm the results previously found in the application layer micro-benchmarks (s. Section 3) for all
evaluated scenarios. We find zero false positives in a realistic automotive setup with a strict, consistent PSFP configuration based on a real car communication matrix. Real attacks are reliably detected in all scenarios, except for shaped data stream corruptions. Most importantly, traffic exceeding specification limits such as volumetric DoS attacks is fully identified. The data stream corruptions are not detectable on the link layer because the CBS traffic shaping at the attack source nodes enforce valid bandwidth usage. Undetected corruptions, however, are not breaking with configured specifications and should have lower risk in damaging QoS of concurrent streams. Additionally, one scenario showed a successful detection of a corrupted shaped data stream through interference with concurrent traffic on the path to the second switch. This opens directions for further improving the detection in the future.

5. Security for Cars and Related Work

The seminal work by Checkoway et al. [6] examines interfaces that are part of the attack surface of a car. These interfaces are classified into three categories: Physical access (ODB-II, CD, USB), short distance wireless access (Bluetooth, Wi-Fi, Remote-Keyless-Entry) and long-distance wireless access (GPS, digital radio, mobile services). The authors could gain access to the on-board network in each category using reverse engineering and debugging. Hence, it is safe to expect that unauthorized access is possible to all in-car components. Each communication source within the vehicle could become that unauthorized access is possible to all in-car components.

5.1. Security in Future Cars

In addition to TSN and SDN technologies, several network technologies entered the design discussion for enabling safe and secure communication with high performance for IVNs in recent years. The industry standard Scalable service-Oriented Middleware over IP (SOME/IP) [44] introduces Service-Oriented Architecture (SOA) for IVNs. Even containerized services are discussed for deploying dynamic functionalities in high performance ECUs [45].

Multi-sided measures are needed to protect future cars against attacks [11]. Furthermore, new regulations like the European Cybersecurity Act [18] and guidelines like ISO/SAE 21434 demand extensive security features such as updates, monitoring, and incident management/response for the entire lifecycle of future vehicles [46, 17]. To protect the security of future IVNs, the appropriate tools from the toolbox of established network security mechanisms, such as encryption, authentication, firewalling, and intrusion detection, must be adapted and implemented. [47].

One of the first steps for securing information systems is the risk assessment [48]. Monteuuis et al. [49] propose a systematic thread analysis and risk assessment framework for autonomous cars. They build upon traditional methods to support consideration of the safety implications through automotive attacks. To compute risk values, they use severity, observation, controllability and the attack likelihood. Further, they clarify the importance of countermeasures for risk assessment: “[... ] risk analysis is an iterative process that ends once countermeasures have been applied to critical threats until the risk value converges to an acceptable level.” Countermeasures are dependent on the detection of threats. Thus, anomaly detection and comprehensive information on observability of corruptions are important for precise risk assessment and vehicle safety and security. Therefore, we classify link layer effects of anomalies and benchmark the detection performance.

The work of Bernardini et al. [50] inspects the main security and privacy issues of vehicular communication and explores related research. Authors found that effective network monitoring is one of the open problems for the security of modern cars. Our work tries to fill this gap by targeting link layer anomaly detection and detailed measurements.

Rumez, Grimm et al. [12] discuss the security implications of SOAs. They show that, in general, the protection of IVNs must be achieved by integrating different layers of protection. The review presents approaches on automotive firewalls, IDSs and Identity- and Access Management (IAM). The target of all reviewed IDSs is the CAN bus protocol. In contrast, we investigate a real-time Ethernet backbone.

Pesé et al. [13] present a hardware/software co-design for an automotive firewall. They demonstrated how an embedded design can fulfill automotive requirements in a cost-efficient way. The investigations on the performance of our NADS are simulation-based and do not address specific implementation aspects related to hardware or software resources deployable in a production vehicle. Nevertheless, the design we propose is efficient on in-car resources because no specialized NADS devices are needed for operation. Instead, we utilize TSN mechanisms, already discussed for on-board networks, to additionally detect anomalies.

Firewalls are often a part of gateways between domain- and system borders. Those gateways also fulfill roles such as proxy, access control [51], and intrusion detection [16]. Gateways are also introduced as pure security nodes [14]. They can enforce static specified communication streams between their in- and outputs. Thus, those gateways are able to prohibit unknown communication. This inline flow-control can be fulfilled by switches in SDN-based Ethernet networks. In past work, we analyzed the security implications of control flow embedding strategies [34]. Now, we show how valid flows can be monitored and misbehaving flows can be detected in IVNs using TSN and SDN principles.

Langer et al. [15] show how security of complete vehicle fleets could be managed over lifetime. The proposed Automotive Cyber Defense Center (ACDC) adapts established IT in-
frastructure technologies to the nomadic nature of vehicle fleets. Such cloud services can be used to collect reports of severe incidents detected by an IDS. This enables large-scale countermeasures. Data from our NADS approach is a substantial source of information for global security infrastructures such as this ACDC.

In previous works, we explored how SDN can be integrated in a real-time Ethernet IVN and how SDN can enhance its resilience [52, 34]. Furthermore, we demonstrated a prototype of an IVN that enables protection, monitoring, detection, incidence management, and countermeasures in a real production car [53]. The implementation uses SDN, AD, secure gateways, hypervisors, dynamic orchestration of applications and cloud services to enable protection and countermeasures. This prototype uses a machine learning based NADS which is prone to frequent false positive alarms. In this work, we show a NADS that is robust against false positive alarms.

5.2. Anomaly Detection in Future Cars

Dibaei et al. [28] survey attacks and defenses on intelligent connected vehicles. They categorize security-related attacks into cryptography, network security, software vulnerability detection, and malware detection. Authors further stress that IDSs are the most effective countermeasure for network security. They discuss the advantages and shortcomings of signature-based and anomaly-based IDS approaches, in particular a high false negative rate for signature-based IDS and a high false positive rate for anomaly-based IDS. In our anomaly-based approach, we use the accurate per-stream filtering and policing (PSFP) configuration as the baseline. Our concept enables link layer anomaly detection without false positives.

There are many anomaly detection algorithms at hand to describe and evaluate a regular state [54]. They can be classified in statistical (e.g., Signal Processing), classification based (e.g., Support Vector Machine), clustering-based (e.g., k-Means), soft computing (e.g., Neural Network), knowledge-based (e.g., Rule and expert-system), or combination learners (e.g., Hybrid). All ADs algorithms try to fingerprint normal behavior. They are trained or configured to distinguish between normal and abnormal behavior. One key challenge for anomaly detection is to keep the false-positive rate as low as possible. Any unclear or ill-defined distinction or rare event may lead to false positive anomaly reports and degrade detection quality. By using TSN mechanisms which are designed to also configure the behavior of the traffic our approach operates at an intersection of anomaly detection and traffic shaping. This enables a clear definition of normal real-time traffic behavior and thus zero false positives. On the other hand, the rate of false negatives is not guaranteed to be leading. It is no inherent property of our approach to maximize the number of abnormal behavior that is detectable. Also, in contrast to other detection algorithms, our approach is naturally limited to TSN networks.

Rajbahadur et al. [55] dedicate a survey to anomaly detection for connected vehicles. They discuss a large body of work in the spectrum of anomaly detection for current cars. Most of the work addressing the use of anomaly detection systems in IVNs aim at traditional CAN bus infrastructures. Ethernet IVNs, though, have very different communication patterns leading to different requirements on a NADS. Our approach aims at Ethernet using PSFP—an integral part of TSN.

Waszecki et al. [56] present a distributed IVN traffic monitoring via behavioral analysis on CAN buses. Their decentralized approach enhances reliability of attack detection and reduces implementation costs. Our approach is also decentralized and cost-effective by using every port on every switch in the network as an anomaly sensor. No additional network nodes are required to implement the anomaly sensors into an IVN.

The work that exploit CAN protocol properties for anomaly detection in IVNs are based on CAN ID sequences [57] or remote frames [58]. This achieves high detection accuracy for message injection attacks. Our micro benchmarks evaluate the performance also for the orthogonal link layer anomaly classes including elimination, injection, manipulation, reordering, and rescheduling.

Paul et al. [59] use an artificial neural network for CAN anomaly detection with high detection performance for DoS and Fuzzy attacks. Islam et al. [60] present a graph-based intrusion detection system that show high detection performance for DoS, fuzzy, replay, and spoofing attacks. Technically parts of those approaches are transferable to Ethernet based IVNs, but they do not operate without false alarms. Our focus is on exploiting TSN properties that enable zero FP anomaly detection.

Khraisat et al. [61] discuss the increasing sophistication of cyber-attacks and urge the need for accurate intrusion detection. Authors present a taxonomy of contemporary IDS, including signature-based and anomaly-based intrusion detection system, and provide a comprehensive review of recent work, commonly used datasets for evaluation, evasion techniques used by attackers, and future research challenges. Our work deviates strongly from classical network environments in the application area. The behavior of attackers on IVNs with TSN is still unspecified and datasets must additionally represent the regular real-time Ethernet behavior.

Ring et al. [62] give an overview of network-based data sets for testing and evaluating IDSs. They analyze which properties the individual data sets fulfill. To the best of our knowledge, there are no datasets that contain attacks specific to real-time Ethernet and its link layer QoS, which is a major attack surface in cyber physical systems such as cars. In our macro-benchmarks, we integrate traffic of the CIC-IDS 2017 [24] dataset, which includes the most common attacks according to the 2016 McAfee report.

6. Conclusions and Outlook

Communication flows for vehicle control are pre-defined to a large extend, and TSN per-stream filtering and policing (PSFP) builds its traffic control rules for all incoming traffic streams on this knowledge. In this paper, we showed how the PSFP control rules can serve as the basis for a Network Anomaly Detection System (NADS). The PSFP configuration serves as an implicit distinction between normal and malicious network behavior on the data link layer.
Conceptually and by simulation experiments we could show that this anomaly detection remains free of false positives, provided the PSFP indicators are defined concisely and correctly. In all baseline simulations, not a single valid frame was dropped by any PSFP instance.

The efficiency to detect misbehavior depends on the origin of frame corruption, its link layer anomaly type, and its traffic type. Overall, corruptions on the link layer are more reliably detected than application-specific misbehavior. Most of the critical impairments in real-time networks impact the link layer, since it accumulates the risk of breaking QoS guarantees for concurrent streams. In particular, this holds for any kind of volumetric DoS attacks. In addition, there are TSN traffic shaping mechanisms that enable a detection of application layer corruptions by frame drop indicators. We showed by example that such indicators, which also remain free of false positives, can be successfully deployed and improve the detection rate.

We also presented macro-benchmarks, in which real attack traces were played back in a simulated zonal IVN topology based on a real-world in-car communication matrix. Our results indicate that the NADS works well in realistic IVN environments and consistently avoids false positives. Our simulations also revealed the limits of our approach and characterized the bogus traffic classes which remain undetectable.

Our work opens three directions for future research.

1. Options for improving detection performance should be explored. Additional PSFP anomaly indicators are promising candidates to improve the accuracy without introducing false positives. This includes the investigation of further TSN forwarding procedures such as Asynchronous Traffic Shaping and the effects of chained PSFP instances in switches on stream paths.

2. Evaluation in more complex, realistic scenarios is likewise desirable. We will investigate how complete IDS datasets can be used for comprehensive evaluations on detection performance in the context of TSN-based IVNs. This may include the creation of a special attack dataset for IVNs [63]. In addition, the proposed NADS mechanism should be examined in a TSN testbed to validate its effectiveness and measure resource consumption.

3. An integration with orthogonal NADS concepts external to the core network, which use extrinsic mechanisms such as machine learning to define regular pattern, should be evaluated for extending the intrusion detection system to application layer characteristics.

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