Quantitative System-Level Security Verification of the IoV Infrastructure

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Abstract—The Internet of Vehicles (IoV) equips vehicles with connectivity to the Internet and the Internet of Things (IoT) to support modern applications such as autonomous driving. However, the consolidation of complex computing domains of vehicles, the Internet, and the IoT limits the applicability of tailored security solutions. In this paper, we propose a new methodology to quantitatively verify the security of single or system-level assets of the IoV infrastructure. In detail, our methodology decomposes assets of the IoV infrastructure with the help of reference sub-architectures and the 4+1 view model analysis to map identified assets into data, software, networking, and hardware categories. This analysis includes a custom threat modeling concept to perform parameterization of Common Vulnerability Scoring System (CVSS) scores per view model domain. As a result, our methodology is able to allocate assets from attack paths to view model domains. This equips assets of attack paths with our IoV-driven CVSS scores. Our CVSS scores assess the attack likelihood which we use for Markov Chain transition probabilities. This way, we quantitatively verify system-level security among a set of IoV assets. Our results show that our methodology applies to arbitrary IoV attack paths. Based on our parameterization of CVSS scores and our selection of use cases, remote attacks are less likely to compromise location data compared to attacks from close proximity for authorized and unauthored attackers respectively.

Index Terms—Internet of Vehicles (IoV) Security, Threat Modeling, Risk Assessment, Attack Vector, Markov Chain, IoV Reference Model, Connected Autonomous Vehicles (CAVs).

I. INTRODUCTION

NEW connectivity capabilities in the IoV provide vehicles with access to the infrastructure of the Internet. As a result, upcoming services around connected vehicles access new forms of data for enhanced driving experiences, safety, and automation such as autonomous decision making over maneuvers [1]. Simultaneously, increasing connectivity causes an increase in complexity which, from a security perspective, opens up a larger attack surface. Attackers, who successfully compromise vulnerabilities of the IoV infrastructure, face new opportunities to remotely interfere with vehicles. As a direct consequence, the potential of attacks that affect vehicle safety by accident or on purpose increases [2]–[3].

For the reason that jeopardized safety-critical systems threaten IoV acceptance, the investigation of holistic IoV security concepts represents a common interest of IoV stakeholders [4]. Despite the existence of new and comprehensive security solutions for the IoV, they remain in an early development stage [5], or face difficulties with administrative, legal, or technical development [6]. Thus, the interplay of different technological domains in the IoV demand tailored, automated, dynamic, and adaptive security solutions.

To address this challenge and to evaluate new security concepts for assets of the IoV infrastructure, we propose a new methodology that allows to quantitatively verify system-level security solutions. Our methodology requires the definition...
of attack paths to define assets for the security verification. Additionally, our methodology requires an analysis of the IoV reference architecture to allocate, equip, and assess identified assets.

In order to analyze complex assets in a structured way, reference models, layers, or view models provide ways to categorize the structure of an asset by highlighting different groups of aspects. The 4+1 architectural view model, used in our work, provides the logical, process, developer, and physical views to analyze data, communication, libraries and dependencies, and hardware aspects respectively [7]. We leverage the separated analysis of the IoV assets per view to (1) identify assets of the IoV infrastructure and (2) to accurately map attacks as well as defense mechanisms to assets. As a result, we can label properties of Common Vulnerability Scoring System (CVSS) scores for IoV assets, respecting a result, we can label properties of Common Vulnerability Scoring System (CVSS) scores for IoV assets, respecting a result, we can label properties of Common Vulnerability Scoring System (CVSS) scores for IoV assets, respecting a result, we can label properties of Common Vulnerability Scoring System (CVSS) scores for IoV assets, respecting a result, we can label properties of Common Vulnerability Scoring System (CVSS) scores for IoV assets.

An attack is successful if the attacker exploits vulnerabilities or if the attacker breaches security mechanisms [8]. To reach the goal of an attack path, an attacker is required to perform successful attacks repetitively. In order to model the attacker perspective at different stages as well as quantitatively verify system security, our work leverages state transitions probabilities of Markov Chains. In this context, state transitions represent attacker stages of attack trees. To assess each individual stage of an attack path, we leverage the vulnerability, risk, and security analysis based on CVSS scores. The structure of Markov Models enables our quantitative security verification of IoV assets as well as opportunities to verify system-level security of multiple assets that are part of attack path [9].

To recap the consecutive steps of our methodology, Figure 1 indicates each step that are necessary for the quantitative system-level security verification of the IoV infrastructure. At the same time, Figure 1 refers to the sections of our work which apply the respective analysis. With a general focus on the IoV location service application (see Section III-A), we leverage sub-architectures, defined in the work [10], to model IoV system assets. This measure reduces the complexity and facilitates our security analysis. Section III applies the 4+1 view model analysis of the IoV architecture from a security perspective. Based on our knowledge, our work applies the 4+1 view model in the IoV security context for the first time to the best of our knowledge.

II. BACKGROUND & RELATED WORK

A. View Model Frameworks in the Security Context

There are multiple view angles to analyze an IoV infrastructure [13]. Considering functional, communication, implementation, enterprise, usage, information, physical, stakeholder, and user viewpoints all together is not beneficial regarding security analysis [10]. Categories may introduce either too much complexity and inconsistencies or, in essence, do not contribute to security-related purposes such as attack analysis. Hence, a sufficiently balanced portfolio of viewpoints increases the applicability of appropriate security concepts [14]. It is possible to balance the tradeoff between the applicability of security concepts and the complexity of reference architectures by utilizing the approach of the 4+1 view model which describes the architecture of a scenario using multiple abstract views [7]. Figure 2 shows the 4+1 view model in the IoV context together with common characteristics that apply in each of the views. The abstraction levels of the view model enable the identification of security-relevant system boundaries and information flows.

Fig. 2. The 4+1 View Model in the IoV context.
Threat Analysis and Risk Analysis (TVRA) models analyze threats, risks, and vulnerabilities together.

The work of [20] and [23] address the versatility and applicability of threat modeling approaches where [20] proposes a tailored procedure of threat modeling for the IoV. This procedure adapts the TARA and STRIDE strategy. Based on the work in [20] and due to overlapping threat modeling strategies, the threat modeling of this work follows the strategy of Figure 3. The strategy of the threat model of Figure 3 represents an iterative process of system modeling, threat, vulnerability, and risk analysis, security requirement definition, and tailored security design. This concept aligns with the proposed threat modeling procedures of [16], [20], and [24].

To clarify the statement, [16] relies on the four step framework of system modeling, threat analysis, threat mitigation, and validation. In [20], the adapted TARA model lists threat-agent risk analysis, high-level threat-agent risk evaluation, attack method and exposure analysis, and strategy design to target exposures. The adapted TAL, Methods and Objectives Library (MOL), and Common Exposure Library (CEL) drive this approach.

The work of [24] introduces a risk assessment framework for the automotive domain. The strategy relates to threat modeling approaches and consists of system definition, threat analysis, risk assessment, and definition of security requirements. Their threat analysis identifies assets before the actual threats. Moreover, the risk assessment block comprises threat and impact level estimation and security level determination. Finally, the work of Hamad et al. [25] combines all aspects of threat modeling, attack tree construction, and risk assessment in a comprehensive threat modeling approach tailored to vehicles.

In contrast to general threat modeling approaches, such as fuzzy, probabilistic, tree-based, graphical, and legacy threat modeling, our work follows the agile threat modeling approach. The iterative nature of agile threat modeling provides the necessary flexibility of security analysis for the constantly evolving IoV domain. With this approach, updates of security goals and requirements remain customizable [12]. Software security analysts have the possibility to iteratively decrease abstraction levels, or change the quantification of scenarios.

Moreover, our approach of threat modeling of Figure 3 includes a final block of tailored security design. The reason for this is the work of Xiong et al. [26], which states the design of a tailored security concept as future work, and the requirement definition of a mitigation concept in [27].

Furthermore, the structures of the systematic threat modeling approach of [28] derive from the prominent Road Vehicles Functional Safety (ISO 26262) [29] and Cybersecurity
Guidebook for Cyber-Physical Vehicle Systems (SAE J3061) [30] standards which define a combination of TARA and STRIDE for risk assessment. Our work relates in the way that it analyzes a high-level as well as in-depth details of modules and the implementation of the IoV architecture through the 4+1 view model analysis. Likewise, our work identifies the security requirements of assets and provides a methodology to validate and verify security requirement effectiveness.

C. System Design for Security Verification

The work of Xiong et al. [26] enhances threat modeling with probabilistic attack simulations that are based on networking graphs with attack paths. Their work builds upon the in-vehicle 2014 Jeep Cherokee Controller Area Network (CAN) network model of [31] and utilizes the software tool securiCAD for automated attack modeling and risk assessment. The attack simulations based on the attack path incorporate attack types, vulnerabilities, and countermeasures at every propagation stage to evaluate Time-to-Compromise (TTC) behavior. The findings of this work demand more tailored definitions of meta-models, reference architectures, investigation of countermeasures, security architectures, validation of the approach through case studies, and quantitative input to the quantitative and probabilistic security metric of TTC.

The work of Iqbal et al. [32] describes the transition of the traditional IoV architecture into a data-driven-intelligent framework. Their framework translates the architecture into data collection, preprocessing, data analysis, service, and application layers. Security, privacy, and trust management affect all layers. Last, the approach of Zou et al. [33] proposes an architecture that keeps a security monitoring system, threat intelligence, and networking security modules at the bottom layer. Defense, reinforcement, and response systems complete their so-called 360 connected vehicle safety framework.

To address the outcomes of [26], our work reproduces their threat modeling concept with the following changes. Regarding the reference architecture, our work leverages the outcomes of the IoV reference model architecture analysis of [10]. Based on this model and using a scenario, we apply the 4+1 view model to break down assets to extract detailed vulnerability properties. Our abstraction concept differentiates between hardware, software, networking, and data and enables mappings of attacks and defense mechanisms per system asset.

III. SYSTEM DECOMPOSITION AND AGILE THREAT MODELING BASED ON 4+1 VIEW MODEL ANALYSIS

This section introduces the IoV location service application as the base scenario for aligning assets with reference models. Next, our 4+1 view model analysis in Sections [II-B] to [II-C] identify all sub-architectures as well as security domains of hardware, networking, software, and data. This step marks one of our contributions and allows fine-grained identification and mappings of assets for our security verification method.

The location service application of CAVs represents the main scenario due to the following reasons. Location accuracy contributes to the safety criticality level of a vehicle which, in turn, determines the level of driving automation of CAVs [37]. Autonomous mini-bus shuttles of Original Equipment Manufacturers (OEMs) aim towards running on Society of Automotive Engineers (SAE) driving automation level four [38]. Driving automation level four expects automated steering, acceleration, deceleration, monitoring, handling of dynamic tasking, and driving modes of the vehicle system. To prevent vehicles from stopping due to location inaccuracy, which causes a high safety criticality level, vehicles rely on redundant location services [39].

Several processing services of odometry, Light Detection and Ranging (LIDAR), and Differential Global Positioning System (DGPS) data, as shown in Figure 4, establish necessary localization redundancy. Additionally, the comparison of calculations of local positions of sensor and receiver data with predetermined Simultaneous Localization and Mapping (SLAM) trajectories enhances location estimation. All in all, the services of vehicle DGPS communication, sensor (odometry, LIDAR, camera) data processing and communication, SLAM trajectory comparison, and Vehicle to Cloud (V2C) communication make up the foundation of the following view model analysis.

With the scenario defined, it is necessary to determine the reference model domains of the IoV architecture for the analysis of the attack surface. The work [10] provides a comprehensive IoV reference architecture which considers a physical IoV infrastructure consisting of four sub-architectures of CAVs, devices and peripherals, edge, and cloud. Their reference architecture for attack surface analysis is based on a functional-communication viewpoint which creates feasible complexity and manages incorporation of security relevant details. To further simplify the sub-architecture categorization, we consider the peripherals and the vehicle as one domain. The reasons of (1) dynamic connectivity requirements that apply to vehicles and peripherals in the same way [40] and (2) wired connections of peripherals to the in-vehicle network [41] justify this assumption.
B. Logical View Analysis (Data Management)

1) System Modeling: The works [45] and [46] provide a general overview of the logical software design. Figure 5 combines three detailed logical views where the top part consists of a Global Positioning System (GPS) receiver tracking and vision-based object detection system. The object detection sub-module processes LIDAR front and bird view data as well as video images. Latest Machine Learning (ML) frameworks for visual data processing rely on proposal networks for pre-processing that feed fully connected fusion networks [45]. The GPS receiver tracking system estimates signal traveling times using code and carrier synchronization techniques in order to determine first pseudo ranges. In cases of unreliable GPS signal reception, location services need to rely on predictive DGPS carrier phase corrections [47].

The lower part of the logical view indicates a multi sensor fusion system which processes the results of vision-based tracking, GPS tracking, DGPS correction, and odometry data to determine high precision altitude, position, and velocity values. The combination of LIDAR point cloud and odometry data allows Kalman filter estimation of particle motion between LIDAR scans. To determine a high precision offset of localization, it is possible to match point clouds between the estimated live LIDAR scans and predefined SLAM maps [48].

2) Threat & Vulnerability Analysis: To calculate the CVSS scores of the logical view, it is necessary to gather the threats on identified assets of the logical view. Logical software design, which describes the basic structure of data relationships and, thereby, application logic, belongs to field of system design engineering of software [49]. Hence, the vulnerability taxonomies of [50], the Research in Secured Operating Systems (RISOS) [51], and Protection Analysis (PA) project [52], which describe software Operating System (OS) flaws, apply to any other system design challenges as well. The reason for this is that an OS requires holistic system design modeling.

All possible software data flaws, of the referenced collection, affect the identified assets of Figure 5. For instance, incomplete or inconsistent parameter validation, privileges, identification, authentication, authorization, serialization, or logic errors mark vulnerabilities of the logical view domain. By violating the vulnerabilities of data, an attacker may perform one or multiple Create, Read, Update, and Delete (CRUD) operations. In our use case, data manipulation of applications of location services represents the ultimate goal of an attacker.

3) Risk Analysis & Security Requirements: With the help of the threat and vulnerability analysis of the logical view, we apply risk analysis with the determination of the CVSS metric in Table I where higher vulnerability scores refer to more severe risks. This table indicates our decisions on CVSS parameters that we derive in Section IV-A. Logical security requirements require consideration of best practices of security by design concepts. Another requirement is the incorporation of procedures of incident detection and reaction. Our methodology provides the possibility to cover existing types of such defense concepts in form of backward transition probabilities.

4) Security Considerations: Based on the outcomes of the logical view analysis, a tailored security design from the logical perspective first of all needs to minimize the number of components and functionality requirements which belong to security by design concepts [53]. Other preventive measures such as error handling, consistence of data over time, authentication, validation, modularity, exposure, etc. require consideration and need incorporation into the logical design of the application scenario [50]. For detective and reactive measures, the logical design must detect injections of logic bombs which would intentionally hide, delete, or start processes that affect application logic.

C. Developer View Analysis (Software Management)

1) System Modeling: The software implementation of location services builds upon the software stack of AUTomotive Open System ARCHitecture (AUTOSAR) Classic and AUTOSAR Adaptive which structure libraries, dependencies, and program interactions [54]. The classic version of AUTOSAR applies to deeply embedded systems that focus on safety, real-time capability, and process determinism. By contrast, the adaptive platform targets high-end computing in the form of custom applications.

The classic AUTOSAR software architecture divides into four main layers. On top of the microcontroller layer, which groups Electronic Control Unit (ECU) hardware, the basic software layer as well as the AUTOSAR runtime environment abstract hardware functionality through software modules. The top-level application layer utilizes the runtime environment for software and application module communication [55]. Equal to the classic AUTOSAR architecture, the adaptive AUTOSAR
software architecture builds the adaptive AUTOSAR foundation on top of a virtual machine/hardware layer. The adaptive AUTOSAR foundation consists of Application Programming Interfaces (APIs) and services for the management of the OS, time, execution, communication, configuration, security, and monitoring. This layer enables the AUTOSAR Runtime Environment for Adaptive Applications (ARA) to expose these APIs to applications that run on top of ARA. 

Regarding the software architecture of the cloud, infrastructure, and edge domains of the reference model, the works [56] and [57] introduce recent software networking stacks and cloud software architecture stacks respectively. These software assets mark potential entry points for an attacker and we consider this investigation as future work.

2) Threat & Vulnerability Analysis: Since the developer view is part of the software context, it is possible to consider the traditional software threats of the STRIDE model. Additionally, the software vulnerability taxonomy of [58] lists input validation and representation, states of APIs, timing, errors, code quality, encapsulation, and environment as flaws. These software flaws clearly focus on the implementation and software library modules and do not consider weak spots of data and system design. All the stated flaws apply to the analysis of modules of software architecture which the developer view identifies.

3) Risk Analysis & Security Requirements: Regarding the security requirements of the software context, the security requirements of authenticity, integrity, non-repudiation, confidentiality, availability, and authorization of the STRIDE model apply. With the help of the asset analysis of the developer view and the software vulnerability taxonomy, it is possible to determine the CVSS parameters of the software implementation layer in Table 1. This software CVSS score represents the software risk analysis for the IoV location service scenario.

4) Security Considerations: Tailored security design in the software domain of the developer view concerns safe development, implementation, verification, testing, deployment, and maintenance of services such as interoperability, dynamic and automated risk assessment, attack prediction and attribution, threat predictive analytics, monitoring, and detection intelligence, encrypted traffic analysis, forensic readiness, intrusion detection and prevention, and penetration testing [59], [60]. It is necessary to apply all stated security concepts for location service networking, sensor fusion algorithms, modules, and dependencies of the OS in use.

D. Process View Analysis (Networking Protocols)

1) System Modeling: The process view indicates the interplay of logical components of localization services in a sequential order. Figure 6 represents the order which starts with Assisted GPS (A-GPS) utilization for faster satellite localization. Reception of GPS data from satellites and subsequent merging of DGPS correction data determines the initial position estimation of the vehicle. At the same time, Inertial Measurement Unit (IMU) data of vehicle movement passes the Kalman filter to feed the estimation between vision-based tracking scans. When it comes to the matching of scan and map data, the initial GPS position narrows the area of map matching which optimizes and stabilizes the position estimation [61]. The last part of the process view is the transmission of vehicle location data to the cloud services for vehicle tracking. Services of Advanced Driver Assistance System (ADAS) modules such as maneuver estimation services [62] and lane hypothesis estimation benefit from the SLAM map matching as well [63].

2) Threat & Vulnerability Analysis: All communication protocols of the mentioned services outside of the vehicle make up a direct attack surface for the attacker. Even though communication protocols differ, common attacks such as jamming, spoofing, timing, capturing, modification, removal, payload, etc. apply to all communication protocols independent of the software Open Systems Interconnection (OSI) reference layers [64]. The collection in [50] provides network vulnerability taxonomies which equally apply in the IoV networking domain.

3) Risk Analysis & Security Requirements: The risk analysis of the identified assets, threats, and vulnerabilities of the networking category provides another CVSS score of Table 1. Due to the exposure of communication messages and interfaces, it is necessary to emphasize on the reaction patterns of security requirements for the networking domain. The large scale communication attack mitigation analysis of [65] identifies sixteen reactive defense mechanism and provides pros and cons of each mitigation strategy. Packet dropping, replication, isolation, disconnection, termination, restart, redirect, inspection, filtering, etc. belong to this collection of concepts. The defense mechanisms, thereby, counteract the malicious communicator and attacker types of sensor disruptor of the IoV specific attacker model of [66].

4) Security Considerations: Security considerations for the networking domain affect the safe and reliable connectivity of Vehicle to Infrastructure (V2I) and Peripheral to Infrastructure (P2I). Since man-in-the-middle (MITM) and other networking attacks are difficult to prevent, the focus in this domain lies on detection and, especially, reaction concepts [67]. Another reason for this fact is the necessary exposure of networking interfaces which enable the localization services in the first place. Hence, safe routing, redirect adaptivity, redundant connectivity, etc. point out the direction of tailored communication security for the location services of CAVs.
physical view of the in-vehicle architecture. There exist different architecture designs such as zone, domain, or central gateway based architectures [68]. The reference architecture shown in Figure 7 follows the domain-based architectural design. The reason for it is that the modern anatomy of automotive Ethernet has computationally powerful domain controllers which group ADAS, drive-train, infotainment, Human-Machine Interface (HMI), etc. network segments [41]. The design enables isolation, criticality, and bandwidth measures to unload the gateway component [69].

The automotive Electrical/Electronic-Architecture attaches sensors and actuators to ECUs which in turn connect to domain controllers or directly connect to the central gateway component depending on safety critical functionality [69]. With the transmission of location data to the cloud, the gateway enables cloud services to publish vehicle information to smartphone applications [33]. Our physical analysis neglects the focus on infrastructure for SLAM map construction as it happens before CAV deployment [70].

2) Threat & Vulnerability Analysis: It is unlikely for an attacker to gain physical access to infrastructure units in the cloud, networking, or satellite domain due to their remote location. For this reason, we focus on the threats and vulnerabilities of the physical vehicle architecture. The general attack taxonomy of physical attack on Internet of Things (IoT) devices of [71] counts twelve types of hardware threats. Here, threats and attacks map to affected security requirements and countermeasures. Object tampering, outage, object replication, camouflage, side-channel, hardware trojans, physical damage etc. attacks are among the threats of the work in [71].

Highlighting in-vehicle attacks specifically, the work in [41] provides a detailed attack surface. Here, non-CAN attacks, in the form of Tire Pressure Monitoring System (TPMS) and KeeLoq Cipher, and CAN attacks, in the form of media player, On-Board Diagnostics (OBD), Bluetooth module, and Telematics Control Module (TCM) attacks, exploit physical vulnerabilities of the listed devices. The vulnerability assessment of [72] further identifies boot memory, debug interfaces, inter-chip communication channels, and side-channel attacks as susceptible hardware units.

3) Risk Analysis & Security Requirements: With the attack surface, threat modeling, and vulnerability analysis, it is possible to calculate the CVSS scores of physical assets in Table I. Regarding physical security requirements, the taxonomies in [41] mention monitoring for intrusion detection as well as authentication as the main requirements. To further protect hardware vulnerabilities, [72] and [11] emphasize on stack canaries, no execute bit, address space layout randomization, protection units, management units, privilege separation, and Hardware Security Module (HSM) mitigation concepts.

4) Security Considerations: Opposed to networking components, access to physical components remains a challenging task due to location and speed dynamics of vehicles and the distance to cloud or infrastructure assets. Thus, tailored security for physical components of the IoV location service focuses on insider attacks [73]. This means physical attack surfaces such as OBD assets require misbehavior detection frameworks and secure aggregation mechanisms.

IV. VULNERABILITY SCORES AND MARKOV CHAIN-BASED SECURITY VERIFICATION

This section walks through each CVSS vulnerability metric and defines each metric per view model perspective. All abbreviations used throughout this section refer to CVSS parameters and can be found in Table I. Our scores mark the first input to probability calculations for state transition of our Markov Chain model. Section IV-B describes our quantitative system-level security verification concept. The second input for our Markov Chain model are attack vectors that contain assets for the system-level security verification. Possible attack vectors are presented in the evaluation Section V-A.

A. Labeling of CVSS Parameters

The connectivity of the IoV architecture components enables the label "remote" (R) for the Access Vector (AV) in every category. The Access Complexity (AC) has a similar distribution where every category except networking fulfills the label "high" (H). The reason for this choice is the safety-critical application of CAV which requires the highest access control standards at every stage. Networking AC remains "low" (L) in the location service scenario due to the fact that attackers face direct access to networking applications of redundant location services.

Regarding authentication (A), software provides data access and authentication privileges per default. To access the IoV cloud and vehicle environment "requires" (R) authentication but infrastructure services such as GPS data reception does "not require" (N) authentication. Every category requires authentication concepts except the data domain. Regular GPS receivers do not necessarily authenticate satellites. However, software behind signal reception interfaces authenticates correct signals.

Compromising software has the potential to cause "complete" (C) confidentiality, integrity, and availability loss in the system. Equally, successful data and networking integrity manipulation could allow data or network participants to propagate through the system, if not correctly detected in initial checks. Otherwise, the impact on the confidentiality, integrity, and availability requirements remains "partial" (P).

For the Impact Bias (IB) and with regard to the location service scenario, data and networking components weight
TABLE I

| Parameters                  | Data | Software | Networking | Hardware |
|-----------------------------|------|----------|------------|----------|
| Access Vector               | R    | R        | R          | R        |
| Access Complexity           | H    | H        | L          | H        |
| Authentication              | N    | R        | R          | R        |
| Confidentiality Impact      | P    | C        | P          | P        |
| Integrity Impact            | C    | C        | C          | P        |
| Availability Impact         | P    | C        | P          | P        |
| Impact Bias                 | I    | A        | I          | N        |
| Base Score                  | 6.8  | 4.8      | 5.1        | 3.4      |
| Exploitation                | PoC  | U        | F          | PoC      |
| Remediation Level           | TF   | OF       | TF         | OF       |
| Report Confidence           | UCB  | UCF      | UCB        | UCF      |
| Temporal Score              | 5.2  | 3.2      | 4.1        | 2.4      |
| Collateral Damage Potential | H    | H        | M          | M        |
| Target Distribution         | M    | L        | H          | L        |
| Environmental Score         | 5.7  | 1.6      | 5.3        | 1.2      |
| Total                       | 17.7 | 9.6      | 14.5       | 7        |

"integrity" (I) over other requirements, as incorrect location data or communication entities potentially destroy the service. Since there is a centralized sensor fusion software module, the IB of software applies greater weighting to "availability" (A). With respect to the hardware category, exploiting any of the listed security requirements leads to comparable "normal" (N) impact of the attack on the system. Regarding data attacks, existing research on GPS spoofing provide a "proof of concept" (PoC) to manipulate location data [74]. This fact can be used to assume the existence of additional "unconfirmed" (UCF) sources for the report confidence (RC). At the same time and concerning the Remediation Level (RL), "temporal fix" (TF) solutions exist for the detection and prevention of such attacks.

The networking category behaves similar except that it is possible to access "functional" (F) exploit code for networking attacks by using specific OSs for hacking. With software, it is possible to assume non-disclosed algorithms which implement sensor fusion and localization. This fact sets the exploitability (E) of location service ECU software to "unproven" (U). Due to the criticality of location service correctness, one must expect "official fixes" (OF) of newly confirmed vulnerabilities. However, if software bugs remain undiscovered, they remain "unconfirmed" (UCF) from the report confidence perspective.

The collateral damage potential (CDP) of data and software is "high" (H), as it directly affects system safety. Redundancy and robustness of location services enables temporal autonomy of a vehicle and reduces the damage potential of networking and hardware attacks to "medium" (M) [75]. Regarding target distribution, the multi sensor fusion software as well as the physically reachable hardware deserve a "low" (L) target distribution (TD) value. Communication and location data propagate from infrastructure nodes through the vehicle to the cloud and require a "high" (H) distribution value. However, compromised location data of cloud services does not affect the location service functionality of the vehicle itself. Only the redistribution of malicious location data from cloud services to other vehicles causes problems. For this reason, the evaluation labels the distribution of highly critical location data as "medium" (M).

With all parameters specified, it is possible to calculate the overall CVSS scores Base Score (BS), Temporal Score (TS), and Environmental Score (ES). The equations [1][2] and [3][4] calculate the main CVSS scores and can be found in [76], where the values of Confidentiality Impact Bias (CIB), Integrity Impact Bias (IIB), and Availability Impact Bias (AIB) depend on the setting of the IB.

\[
BS = 10 \cdot AV \cdot AC \cdot A \cdot ((CI \cdot CIB) + (II \cdot IIB) + (AI \cdot AIB)) \tag{1}
\]

\[
TS = BS \cdot E \cdot RL \cdot RC \tag{2}
\]

\[
ES = (TS + (10 - TS) \cdot CDP) \cdot TD \tag{3}
\]

B. Quantitative Security Verification Model

It is possible to choose a slightly simplified version of the attack realization metric and algorithm in [9] to demonstrate the applicability of extended Markov Chain models on attack propagation graphs that follow the categorization structures of the 4+1 view model analysis. The reason not to rely on non-homogenous continuous-time Markov models, as in [77], is the fact that the extended Markov Chain suffices in modeling the high-level attack stages of our IoV use cases.

The discrete-time finite state Markov Chain represents a time and state discrete stochastic process where future states at time \( t_{i+1} \) depend on current states at time \( t_i \) only, without relying on past states at time \( t_{i-1} \). Per definition, the Markov Chain \( MC(I, P, A) \) is a 3-tuple consisting of system state space \( I \), transition probability matrix \( P \), and a set of possible atomic actions \( A \). We assume no empty action that affects the realization metric \( E \), hence, setting it to \( E = 1 \). To further simplify, it is possible to remove both sums of the state to target probability. The reason for this is the interest in the worst-case attack with maximum significance. This fact maintains state transitions that connect starting and target states without detours. As a result, the following characteristics count for (1) state, (2) transition, (3) action, and (4) total state to target probability of attack realization respectively:

1) \( S_i \in I \), where the state \( S_i \) has one of the labels of \( HW, SW, Net, \) or \( Data \) of the view model perspectives.
2) \( \sum_{j=1}^{\infty} p_{ij} = 1, \forall p \in P \).
3) \( a_i, d_i \in A \) are probabilities of successful attacks and defense mechanisms.
4) \( W^n(S_i=1) = \sum_{S_j \in \text{SUBSEQ}(S_i)} p_{ij} \cdot W^{n-1}(S_j) \), where \( \text{SUBSEQ} \) returns the set of remaining states \( S_j \).

The state transition probabilities, shown in Figure 8 include attack \( a \) and defense \( d \) actions. Only the initial state starts with either a successful attack or remains in the set of initial states. Similarly, the last state changes through an effective response action against the attacker only. For all intermediate steps, there is no state transition if a successful attack faces
an immediate countermeasure (ad), or neither an attack nor a
defense action happens \([(1-a)(1-d)]\). If an attack action
succeeds and no defense reaction occurs \(a(1-d)\), the attacker
moves to the next state. Vice versa, failing attacks and success-
ful reactions \(d(1-a)\) may transition the attacker backwards.
Section V-B provides sample calculations of the probabilities
which enable the quantitative security verification. As a last
rule, outgoing weights of each state sum up to the value of
one.

\[
a = \frac{f_{CVSS}(v_{domain})}{42.5}; \quad i \in \mathbb{N}. \tag{4}
\]
\[
a_i = 1 - e^{-\frac{\log_{10}(v_{domain})}{22.5}}; \quad i \in \mathbb{N}. \tag{5}
\]

It is possible to model parameters of the attack and defense
probabilities with the CVSS vulnerability assessment. Addition-
ally, the stage of the Markov Chain depends on the view
model perspectives of type hardware, networking, software,
and data of the asset under attack. Since the CVSS score has
a maximum possible value of 42.5 (choose largest possible
value for every CVSS parameter), it is possible to normalize
each vulnerability score with respect to this value. Equation
4 shows the resulting attack probability, where \(i\) refers to the
attacking stage of the attack vector. The attack stage
determines what view model perspective type to choose. It
is possible to improve the model of the attack probability \(a
\) per stage \(i\) by introducing Equation 5 (adapted from the work
in [73]). Equation 5 describes an increase of the attacking
likelihood for increasing stages \(i\). The underlying assumption
of Equation 5 is the fact that a single successful attack
opens up opportunities to compromise more vulnerabilities or
combinations of vulnerabilities. More chances for the attacker
to find vulnerabilities increases the likelihood of a successful
attack.

The defense mechanism probabilities \(d\) depend on actual
attack actions. It is possible to model probabilities of suc-
cessful countermeasures independent of the attack due to
missing attack attribution formulas which would enable attack
identification, assessment, and reaction actions for all attacking
stages. This measure simplifies the quantitative calculations in
the Markov Chain model, but requires further investigation in
the future.

V. EVALUATION OF QUANTITATIVE SYSTEM-LEVEL
SECURITY VERIFICATION

This section performs and evaluates our quantitative system-
level security verification on a selection of attack paths that
contain assets of the location service scenario. To do so,
Section V-A introduces chosen attack vectors. The assets of
these attack paths are allocated to 4+1 view perspectives.
Section V-B utilizes the assets of the attack vectors and applies
them together with our CVSS scores to the Markov Chain
verification model. The last section lists the results of the
security verification and evaluates its features and trends.

A. Selection of IoV Attack Paths

Attack vectors define the points of an infrastructure where
an attacker enters the system unauthorized. The sum of an
attack vector represents the attack surface which is what an
attacker faces when attacking a system [82]. There are differ-
ent methods for an attacker to enumerate, analyze, exploit, and
enter the attack surface [83]. Afterwards, an attacker follows
an arbitrary path until she reaches the target. Regarding attack
propagation characteristics, attacking capability and scope of
the attacker model remain the dominating properties for the
determination of the depth of the attack [84].

For the scope of our work, we consider unauthorized as
well as authorized attackers with equal skill level to specify
different initial starting points for attacks. Table II shows our
selection of IoV attacks that contain assets identified during
the 4+1 view model analysis in Section III. The attack path
of attack with ID 1 start in the cloud domain to eventually
compromise the vehicle location service by provoking a lane
departure. With the help of our analysis, the affected assets at
different stages of the attack can be mapped to a networking
attack in the cloud (C-Net), software compromise in the cloud
(C-SW), in-vehicle network attack (V-Net), and vehicle data
attack (V-Data). The reason for grouping the propagation
stages with regard to hardware, networking, software, and data
attacks serves for asset to view category mapping to facilitate
the application of our Markov Model for security verification.

The infrastructure attack with ID 2 initially targets road
signs to cause distortions in camera images that are processed
by the 3D proposal network and thus, the multi sensor fusion
unit. The attack with ID 3 directly targets the vehicle TPMS
with the intention to either stop or compromise vehicle privacy
(signing location data) by indicating wrong tire pressure
values. Analysing this variety of attacks with different length
of attack paths allows to investigate the behavior of our security
methodology as well as if our methodology can be applied to
any attacks in the IoV infrastructure. The assumption for the
authorized attack with ID 5 is a malicious but trusted develop-
er with OBD and ECU authentication credentials. For this type
of attacker, performing CAN replay attacks to eventually
affect vehicle trajectories of the ADAS system should not be
delete.
TABLE II

| ID  | Attacker Type  | Model Type       | Sample Attack Path Propagation                                                                                                                                 |
|-----|----------------|------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 1   | Unauthorized   | Cloud            | Browser redirect attack & Shell access (C-Net) ⇒ Privilege escalation (C-SW) ⇒ Access to ECU (V-Net) ⇒ CAN bus attack (V-Data) [10] |
| 2   | Unauthorized   | Infra & Edge     | Road sign attack (I-HW (a) or I-Net (b)) ⇒ Road sign distortion (I-Data) ⇒ Camera image data modification (V-Data) [25]                                         |
| 3   | Unauthorized   | Vehicle & Peripherals | Eavesdropping wireless TPMS (V-Net) ⇒ Reverse engineering attack (V-SW) ⇒ Packet injection attack (V-Data) [79]                             |
| 4   | Authorized     | Cloud or Infra & Edge | Malicious software update (V-SW) & Driver assistance attack (V-Data) [80]                                                                                      |
| 5   | Authorized     | Vehicle & Peripherals | Disabled ECU hardening & CAN replay attack (V-Data) [25] (based on [81])                                                                                     |

B. Evaluation of our Methodology (Perform Security Verification of Attack Paths)

In order to evaluate the 4+1 view model analysis in the security context, we apply our methodology to our selection of attacks (see Table II). With the 4+1 view model analysis, it becomes feasible to allocate every asset of IoV attack paths to one of the domains. At the same time, each view model domain marks a stage of our Markov Chain transition model to verify security quantitatively. The following paragraphs demonstrate the process of applying one of the attack paths to our results gained from the 4+1 view model analysis. Afterwards, we contrast the results of different attack paths to determine the behavior, features, and possibilities of our concept. For showcasing the application of the view model security verification concept, we consider the attack path with ID 1, consisting of a cloud network (C-Net) and software (C-SW) attack as well as vehicle networking (V-Net) and data (V-Data) attack.

The values for the calculation of the Markov Chain state transition matrix P depend on the probabilities of successful attacks and patches. Table II shows the vulnerability scores per asset for each domain of the view model perspectives. Higher values determine a higher likelihood of attacking an asset successfully. The domain specific CVSS score over the maximum possible CVSS score determines the attacking probability a (see Formula 4). Considering the initial cloud networking attack of attack path with ID 1, the attacking probability a depends on the networking stage CVSS score \( f_{cvss}(Net) = 14.5 \) and calculates as shown in Equation 6. To simplify the evaluation, we leverage a constant value for a successful countermeasure probability d, which can be seen in Equation 7.

\[
a = \frac{14.5}{28} = 0.34; \quad (1 - a) = \frac{28}{42.5} = 0.65 \quad (6)
\]

\[
d = \frac{1}{10} = 0.1; \quad (1 - d) = \frac{9}{10} = 0.9 \quad (7)
\]

With the attack path with ID 1, the attack stages one to four consist of type C-NET, C-SW, V-Net, and V-Data. Furthermore, considering the attack forward transition probabilities \( a_1 = a \) at stage \( i = 1 \), \( a_i = a(1 - d) \), and \( a_{i=n} = 0 \) of Figure 8 the attack probabilities calculate as follows: At stage \( i = 1 \), the first attack transition probability calculates as \( a_1 = 1 - e^{-2(\frac{14.5}{42.5})} = 0.4946 \), assessing a cloud networking attack. Subsequent stages calculate as \( a_2 = (1 - e^{-4(\frac{14.5}{42.5})}) \cdot (1-0.1) = 0.53541 \), \( a_3 = (1-e^{-6(\frac{14.5}{42.5})}) \cdot (1-0.1) = 0.78381 \), and \( a_4 = (1-e^{-8(\frac{14.5}{42.5})}) \cdot (1-0.1) = 0.9643 \), assessing a cloud software, vehicle network and data attack respectively. Figure 9 indicates these numbers with the blue line of the attack path with ID 1. For a total attack probability (includes all forward transition probabilities), the product of these values result in \( a_1 \cdot a_2 \cdot a_3 \cdot a_4 = 0.2001 = 20\% \) as indicated in Table III. Other values of Table III correspond to all other attack paths of Table I where Figure 9 shows intermediate probability values.

Our results show that with the 4+1 view model analysis, arbitrary IoV attack paths can be mapped to view model domains. This enables comparative and quantitative system-level security verification of system assets. The attack realization probabilities of the initial states align with the expected behavior of lower probable attacks for longer attack paths. The lower percentages for paths that originate from the cloud and infrastructure locations confirm this claim.
Furthermore, authorized attackers have higher probabilities to successfully attack localization services which aligns with expectations. This fact can be seen when inspecting authorized versus unauthorized attack probability results. This outcome makes sense due to the possible size of an in-vehicle attack propagation compared to the Internet attack propagation path. Similarly, the results of direct vehicle or close proximity attacks are more likely to affect location data. An explanation could be that the set of attacks of the local attacker contains the attacks of the remote attacker as subset.

It is important to emphasize that changing our assumptions and with that the CVSS parameterization changes the outcomes of the security verification. Hence, the variance in the security verification results depends on our IoV driven parameterization. Additionally, the decomposition of multiple views into more fine-grained categories lowers the attack probabilities drastically (longer paths) due to the multiplicative aggregation. Here, additional calculation are required to stabilize the multiplications of numbers lower than one. In general, it is possible to state that the level of detail should remain similar for security designs with comparable complexity.

### VI. Conclusion

This paper applies the well-established 4+1 view model in the security context of the IoV and utilizes agile threat modeling and risk assessment for a structured identification and security assessment of IoV assets. The view model analysis separates data, software, networking, and hardware categories and enables the allocation of attack path assets to these respective domains.

With the mapping of attack path assets to respective 4+1 view model domains, our Markov Chain model uses state transition probabilities to assess attack and defense probability results. The results show the applicability of our methodology to arbitrary IoV assets included in attack paths. Our CVSS parameterization is driven by the IoV infrastructure analysis and indicates security critical parts of IoV architecture.

#### A. Future Work

- To support the quantitative security verification results based on the 4+1 view model analysis, hacker teams need to conduct comprehensive and multidisciplinary methodologies such as QuERIES [59].
- No research has been conducted with regard to automation of the security analysis approach. To cope with complex systems of the IoV, automation of analysis concepts is mandatory for system wide security coverage.

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