Abstract—Safe and secure electric vehicle charging stations (EVCSs) are important in smart transportation infrastructure. The prevalence of EVCSs has rapidly increased over time in response to the rising demand for EV charging. However, developments in information and communication technologies (ICT) have made the cyber-physical system (CPS) of EVCSs susceptible to cyber-attacks, which might destabilize the infrastructure of the electric grid as well as the environment for charging. This study suggests a 5Ws & 1H-based investigation approach to deal with cyber-attack-related incidents due to the incapacity of the current investigation frameworks to comprehend and handle these mishaps. Also, a stochastic anomaly detection system (ADS) is proposed to identify the anomalies, abnormal activities, and unusual operations of the station entities as a post cyber event analysis.

Index Terms—EVCS, cybersecurity, cyber-attacks, probability-based anomaly detection, digital forensic investigation, root cause analysis, 5Ws & 1H.

I. INTRODUCTION

EVs, which are perceived as a solution to climate change, are replacing internal combustion engines as the dominant form of transportation in the global auto industry [1]. Because of the EVs’ steady expansion, EVCSs are now more prevalent in electric grids. Since the market value of EVCSs is estimated to exceed $103.6 billion by 2028, it is critical to have a well-thought-out plan for deploying EVCSs and sturdy supporting electric distribution infrastructures. As a result, engineers and researchers specializing in the power and transportation systems have recently performed an extensive study to promote the development and diffusion of this game-changing technology. Also, a number of industry sectors and original equipment manufacturers, including General Motors, Tesla, ABB, and EV Connect, are investing billions in the research and development of EVCSs [2].

In general, EVCS functions as a high-wattage gateway or bridge that supports the energy exchange between an EV and the power grid, thus facilitating EV charging services [3]. Cyber-attack methods on critical infrastructures, particularly energy delivery systems, are maturing and becoming more sophisticated, owing to the internet-of-things paradigm, which has created multiple vulnerabilities. Since internet-connected EVCS is a key entity in an upcoming smart grid, the cybersecurity stance of EVCS is crucial to the functioning of power systems. For instance, the shared data may be susceptible to various vulnerabilities because of the intricate cyber-physical interactions and interdependencies existing at the confluence of EVs, EVCSs, and the power grid. Also, the adversaries might exploit these known vulnerabilities of the EVCS ecosystem to breach the system, thus endangering its security. Hence, it is crucial to analyze the bi-directional interactions between the distribution grid, EVs, and charging infrastructure [4]. Therefore, white-hat hackers and researchers are very interested in addressing the cybersecurity aspects of EVCSs due to the serious consequences that may be caused by hostile cyber-attacks.

Even though there has been a significant amount of research on designing successful and robust cybersecurity frameworks for electric grid domains, e.g., the critical infrastructure protection (CIP) 002-009 standard by the North American Electric Reliability Corporation (NERC), the IEC 62351 standard [5], and ADSs [6], well-trained attackers could exploit the vulnerabilities of EVCSs [7]. Similarly, ISO/IEC 15118 standardizes wireless vehicle-to-grid (V2G) communication [8]. However, these cybersecurity measures do not improve the security of EVCSs.

Although, there have not yet been any notable or well-publicized cyber events with EVCSs, scientists (e.g., Kaspersky Lab researchers) have been meddling with charging operations to see whether any undiscovered vulnerabilities exist [9]. Therefore, some rigorous work has been done to address the key cybersecurity gaps in an EVCS, e.g., cybersecurity recommendations from the US DOE, NHTSA, and DOHS. However, these proposed solutions have not yet been formalized and put into effect [10].

Additionally, due to the presence of different entities, it is uncertain how an EVCS can adapt to various scenarios and settings in several cybersecurity risks that could interfere with its operation. Thereby, cyber-induced EVCS event investigation becomes highly complicated and challenging in such a complex environment.

The underlying contributions of this paper are: (1) the development of a post-cyber event investigation framework based on 5Ws & 1H model, and (2) the proposal of a probability-based anomaly detection algorithm in an EVCS.
cyber-induced incident, along with a case study.

The remainder of the paper is divided as follows: Section II discusses the high-level overview of an EVCS environment. Sections III analyzes the cyber-attack induced events caused in the station environment. Further, a digital forensic investigation framework based on 5Ws & 1H to find the causes and effects of an incident is outlined in section IV. Section V proposes an ADS to identify the abnormal behavior of the station network entities. Section VI analyzes the performance of the proposed frameworks by engaging a case study of cyber-attacks on EVCS. Finally, section VII concludes the paper along with the limitations and recommendations for future work.

II. HIGH-LEVEL OVERVIEW OF AN EVCS ENVIRONMENT

There have been several digital architectures proposed in the past to model the environment of an EVCS. The work of [11] introduces an EVCS model, which consists mainly of EV chargers (EVCs), grid components (e.g., step-down distribution transformer, circuit breakers (CBs)), battery energy storage system (BESS), battery management system (BMS), cloud system, and open charge point protocol (OCPP). In another work, [12], the authors present an architecture that identifies legacy grid components, vendor cloud server, EVs, charging network operators, and different communication standards (e.g., IEC 62196-1/2/3, SAE J1772, ISO 15118, ISO 61851-24, ISO 61850, and IEEE 2030.5), as distinct entities comprising the EVCS environment. It thereby correlates the security of an EVCS ecosystem to the security of every subsystem. Hence, the complex mechanism of a malicious EVCS event may be caused due to multiple endogenous or exogenous trigger conditions, leading to a hazardous condition in one or more interconnected elements present in its ecosystem. For instance, attackers may use the hacked EVCS to manipulate the charging behaviors of the station in a gradual way, endangering the supply-demand balance of the grid during peak hours. Also, attackers may produce an extended period of high demand, which could lead to a cascade disconnect of the supply from the power grid and aberrant functioning. The results would be multiple outages, blackouts, or system instability due to the instability of the power system operations. Similarly, the attacker may get access to the EVCS through the compromised EVs, which could have cascade repercussions [13].

III. CYBER-ATTACK EVENT IDENTIFICATION

A. Cyber-Attack Induced EVCS Incident Analysis

A radical transformation in the hyper-connected EVCS environment brought new cybersecurity concerns. For instance, existing EVCSs use big data, the cloud, V2G communication technology, and internal communication to exchange information. Poorly managed ICT systems are susceptible to various attacks, including attacks on hardware (e.g., electronic control devices and sensors) and software (e.g., malware attacks on firmware) [14]. The damage caused by risks or hazards could be managed by appropriate mitigation procedures. In the worst case, the mitigation actions will be failed, and the EVCS cannot provide a normal operation. However, the EVCS could revert to a healthy state if the system engineers implement appropriate physical (e.g., security guards and surveillance cameras) and technical (e.g., firewalls and multifactor authentication) control measures to identify, mitigate, and prevent the cyber threats and attacks. Further, controllability can also be provided by designing intrusion detection and prevention (ID&P) systems to avert potential system failures. Therefore, this paper proposes an incident-based post-event analysis model by tracking the involvement of a particular candidate.

Furthermore, an EVCS incident in a multi-model environment can be mathematically formulated as,

\[ \sum_{i=1}^{n} \sum_{j=1}^{n} (\zeta_i \times \chi_j) \geq 1, \]

where,

\[ \zeta_i = \begin{cases} 1 : & \text{entity E}^k_i \text{ suffers a cyber-attack} \\ 0 : & \text{no cyber-attack} \end{cases} \]

\[ \chi_j = \begin{cases} 1 : & \text{no controllability by the mitigating actors M}^l_j \\ 0 : & \text{successful controllability} \end{cases} \]

The symbols used in the above equations are defined as,

- \( E^k_i \): ith component of the k entity or subsystem in the EVCS environment, where \( k = \{ G, V, O, P, S \} \)
- G: Power grid
- V: EV
- O: Cloud server
- P: Communication protocols
- S: Station infrastructure
- \( M^l_j \): jth component of the mitigating features responsible for averting the incident, where \( l = \{ C, I \} \)
- C: Physical and technical controls
- I: ID&P

IV. DIGITAL FORENSIC INVESTIGATION FRAMEWORK

Lack of cybersecurity measures and forensics capability in the EVCS may lead to serious consequences if the vulnerability is effectively exploited and a cyber-attack is successfully conducted. The internet-enabled EVCS and the associated infrastructure need to have effective protection against potential cyber-attacks. Trustworthy computing methods are required to ensure the reliability of the applications used and the data gathered in the EVCS environment. There have been a few systematic forensic investigations carried out in the literature in the areas of smart power grid [15], [16], and [17] and connected and automated vehicles [18]. However, to the best of the authors’ knowledge, there is no forensic investigation framework designed specifically for EVCSs. Therefore, this section describes the development of the proposed EVCS cyber-attack event analysis framework for digital forensics investigations.
The framework consists of several processes, e.g., log integration/acquisition, preprocessing, correlation, sequencing, analysis, and reporting. When an event occurred at the EVCS, the investigative team receives official approval after receiving requests to conduct an inquiry from internal or external parties. It is followed by log gathering and extraction from all the EVCS devices. Additionally, data preprocessing is carried out to undertake data cleaning and filtering with the goal of focusing only on important data in the log. The subsequent stages involve correlation and sequencing to create a chronology based on the time of the events. Then, the investigation starts with gathering evidence (e.g., imaging data and asset seizure), followed by evidence analysis using forensic tools and techniques, identifying the 5Ws & 1H, and presenting the findings. Finally, the crime scene is documented by being recorded, photographed, sketched, mapped, and recorded.

The incident responders can use the 5Ws & 1H to prepare, summarize, and report their discoveries in an investigation that includes the six key questions, as depicted in Table I, in order to appropriately document and analyze the cyber incident scene. First, it exhibits 5Ws & 1H, defined as, (1) Who, which identifies the kind of attacker and the station environment entity that is being attacked, (2) What, specifying the system failure or attack target, (3) When, describing the date and time of the cyber incident and the failure’s occurrence, (4) Where, providing the location of the cyber event or the route taken by the attacker for each EVCS function, (5) Why, describing the hazardous behavior that causes such behavior, (6) How, detailing the attack strategy the attacker utilized to trick the EVCS into being in a hazardous event situation.

Every time a cyber incident occurs, the perpetrator (e.g., scammer, spy, terrorist, and skilled criminal) uses some platform (e.g., user instruction, script program, and data exchange) to carry out an attack by leveraging a flaw (e.g., architecture, execution, and settings) of a target component (e.g., procedure, information, and connectivity), resulting in an unauthorized outcome (e.g., data breach, resource theft, and power outage) to meet their goals (e.g., political gain, financial gain, and damage). Therefore, it is crucial to investigate to ascertain the causes and implement remedies to stop such incidents from happening again. Therefore, the investigation team can utilize this technique to uncover trends in severe EVCS casualties and determine the root causes of these cyber occurrences. Please note that more advanced attack tools, techniques, and approaches in the system can be introduced in the future (Table I can be expanded with additional components).

Therefore, the main goal of the proposed work is to show how investigators can use the digital forensic model based on 5Ws & 1H to examine the events that occurred in an EVCS incident in chronological order. Additionally, it will make it easier for an investigation team to have direction to take the appropriate steps.

V. ANOMALY DETECTION IN A EVCS CYBERSECURITY INCIDENT

EVCSs rely on a precise and reliable information exchange amongst several modules to follow a series of waypoints along a predetermined route in an environment. However, there are significant non-linearities associated with this information exchange, which are impacted by several aberrations and erroneous transmissions. As a result, a strategy based on stochastic M-ary classification is proposed to solve the issue of anomaly identification during event analysis in real-time cyber-attack scenarios. The probability of the various component operations is calculated using the probabilistic model suggested in the study, which also identifies anomalous behavior. It also calculates the likelihood of a cyber event based on probabilistic descriptions of different layer components in space and time.

The networked structure model, as illustrated in Fig. 1, consists of six prime layers, which are explained as,

Every CPS is distinguished by a wired or wireless communication channel, which is further divided into various communication protocols supported by the EVCS environment, including OCPP, IEC 61850, ISO 15118, and others. Additionally, because the charging station environment is made up of three main core entities, these particular elements make up layer 3, their additional components comprise layer 4, and then their operations make up layer 5. Please note that each layer of this model can be adjusted to accommodate additional elements in the digital environment.

Fig. 1. Probability-based anomaly detection in a EVCS cyber incident.

Mathematically, this model can be formulated to differentiate normal and abnormal behaviors in accordance to the Bayesian statistics and probability theory such that,

Probability of occurrence of any abnormal event (E) (e.g., battery overcharging, power outage, system malfunction, and
In other words, \( P(\text{accident}) \) due to signal transmissions from layer 3 to layer 4 is,

\[
P(E) = \sum_{c=1}^{k} P(E \cap A_{ec}) = \sum_{c=1}^{k} P(E|A_{ec})P(A_{ec}),
\]

where “e” represents entities and “c” represents components. In other words, \( P(E|A_{ec}) \) in (4) can be written as,

\[
P(E|A_{ec}) = P(E|A_{11})P(A_{11}) + P(E|A_{12})P(A_{12}) + \ldots + P(E|A_{ec})P(A_{ec}),
\]

where \( P(E|A_{ec}) \) is the probability of an abnormal event (E), given the communication path from entity (e) to different components (c). \( P(E|A_{ec}) \) can also be written as,

\[
P(E|A_{ec}) = \sum_{o=1}^{k} \sum_{c=1}^{k} P(B_{co}|A_{ec}), c \neq o.
\]

In (6), \( B_{co} \) symbolizes the communication path from component (c) to operation (o). One instance of (6) is,

\[
P(E|A_{11}) = P(B_{c2}|A_{11}) + P(B_{c3}|A_{11}) + \ldots + P(B_{co}|A_{11}),
\]

or

\[
P(E|A_{11}) = \sum_{o=2}^{k} P(B_{co}|A_{11}).
\]

The above equation implies the probability of abnormal event (E), when communication path is from EV to ECUs. Furthermore, to have an abnormal event (E), the signals can transmit from ECUs to any of the layer 5 operations (e.g., SOC, reporting, scheduling, status, and data) for values ranging from 2 to 6, but “controls” (which corresponds to “o” = 1). The reason “o” cannot take 1 (controls) is because if “o” = 1, it is not an unexpected/abnormal behavior. An instance of abnormal path can be \( (B_{c2}|A_{11}) \), which represents the path EV→ECUs→SOC. Then, by Bayes’ theorem,

\[
P(B_{c2}|A_{11}) = \frac{P(A_{11}|B_{c2})P(B_{c2})}{P(A_{11})}.
\]

In general,

\[
P(B_{co}|A_{ec}) = \frac{P(A_{ec}|B_{co})P(B_{co})}{P(A_{ec})}, c \neq o.
\]

The definitions to the symbols used in the above equations are explained as,

- \( P(A_{ec}) \) = Probability that the transmitted signal from layer 3 is \( A_{ec} \).
- \( P(B_{co}) \) = Probability that the received signal by layer 4 is \( B_{co} \).
- \( P(B_{co}|A_{ec}) \) = Probability that the received signal is \( B_{co} \), when the transmitted signal is \( A_{ec} \).
- \( P(E|A_{ec}) \) = Probability of an abnormal behavior, when \( A_{ec} \) signal is transmitted from layer 3.

It is to be noted that all transmitted signals or messages \( (A_{ec}) \) are mutually exhaustive such that,

\[
\sum_{e=1}^{k} \sum_{c=1}^{k} P(A_{ec}) = 1.
\]

For the normal operation, \( c = 0 \), and for error or abnormal behavior (E), \( c \neq 0 \).

### VI. CASE STUDY

#### A. Attack Scenario 1

1) EVCS Cyber Incident Investigation: The investigative team arrives at the scene of the EVCS incident and gathers information from a variety of sources, including cloud servers and other sources, before establishing a correlation between the data. After that, reverse engineering is performed based on convincing evidence, and the analysis that follows may be given as indicated in Table I.

2) Anomaly Detection: According to the proposed model, anomaly detection during the event analysis for the given scenario can be done as illustrated in Fig. 2. In this situation, it is assumed that the BMS operates in charging mode, which means that it receives power from the utility and that the point of common coupling (PCC) breaker connecting the utility from the station is closed. However, overcurrent protection trips the PCC breaker the moment there is an external failure on the distribution feeder line while EVCS is in grid-connected operation. Therefore, to ensure a fully functional EVCS, the EVCS operator would open the CB and change the BMS’s operating mode to discharging mode simultaneously. So, the anticipated outcome is that the BMS should report its changed mode of operation from charging to discharging, and the CB should report its changed status from closed to open to the

| Attribute   | Definition                                                                 | Dataset       |
|-------------|---------------------------------------------------------------------------|---------------|
| Who         | Attacker (\( \alpha \))                                                   | \( \alpha = \{ \alpha_1: \text{Hacker, } \alpha_2: \text{spy, } \alpha_3: \text{terrorist, } \alpha_4: \text{vandal, } \alpha_5: \text{raider} \} \) |
| Victim (\( \nu \)) |                                                                          | \( \nu = \{ \nu_1: \text{EV, } \nu_2: \text{power grid, } \nu_3: \text{cloud system, } \nu_4: \text{communication protocols} \} \) |
| What        | Target (\( \tau \))                                                      | \( \tau = \{ \tau_1: \text{OCPP, } \tau_2: \text{BMS, } \tau_3: \text{charging adapter, } \tau_4: \text{cooling system, } \tau_5: \text{smart meter, } \tau_6: \text{HMI} \} \) |
| When        | Date (\( \delta \))                                                      | \( \delta = \{ \delta_1: \text{Month, } \delta_2: \text{date, } \delta_3: \text{year} \} \) Format: (mm-dd-yyyy) |
| Time (\( \iota \)) |                                                                          | \( \iota = \{ \iota_1: \text{Timezone, } \iota_2: \text{hours, } \iota_3: \text{minutes, } \iota_4: \text{seconds, } \iota_5: \text{milliseconds} \} \) Format: (hh:mm:ss:mmsec) |
| Where       | Attack path (\( \rho \))                                                 | \( \rho = \{ \rho_1: \text{OIA, } \rho_2: \text{software kickout, } \rho_3: \text{incorrect coding} \} \) |
| Why         | Hazardous behavior (\( \beta \))                                        | \( \beta = \{ \beta_1: \text{Faulty SOC, } \beta_2: \text{unintended overcharging, } \beta_3: \text{incorrect scheduling, } \beta_4: \text{system malfunction} \} \) |
| How         | Attack method (\( \omega \))                                            | \( \omega = \{ \omega_1: \text{Spoofing, } \omega_2: \text{tampering, } \omega_3: \text{repudiation, } \omega_4: \text{information disclosure, } \omega_5: \text{denial of service} \} \) |
TABLE II
5Ws & 1H-base INVESTIGATION FOR ATTACK SCENARIO 1.

| Attribute | Definition | Attack Scenario 1 |
|-----------|------------|-------------------|
| Who       | Attacker (α) | ω: Hacker |
| Victim (β) | BMS, CBs    |                  |
| What      | Attack      | r1: BMS, r2: CBs |
| When      | Date (δ)    | t1: 05, 62: 16, 83: 22, Format: (05-16-22) |
|           | Time (τ)    | t1: EST, t2: 02, t3: 20, t4: 40, t5: 47, Format: (02:20:40:47) |
| Where     | Attack      | ρ: OTA update |
|           | path (ρ)    |                  |
| Why       | Hazardous   | β1: False reporting, β2: flawed status |
| How       | Attack      | ω: Tampering |
|           | method (ω)  |                  |

EVCS. But because of abnormalities or cyber-attacks, the BMS displays an inaccurate charging schedule, and the CB displays an incorrect status, which leads to anomalous station behaviors.

Fig. 2. Probability-based abnormal behavior analysis of attack scenario.

VII. CONCLUSION

An EVCS’s modern environment merges the grid infrastructure, EVs, and other facilities. However, new technologies have also introduced new system vulnerabilities that may result in security breaches and could be an attractive target for adversaries. Additionally, the EVCS event is more complex due to the juxtaposition of several cyber aspects, making the investigation very difficult. Therefore, the efforts of 5Ws & 1H-based investigative framework is proposed that can pinpoint the cybersecurity incidents in charge of the functional failure. Additionally, a robust probability-based anomaly detection algorithm is also designed to identify the function failure during a cyber event analysis. A case study is provided to support the proposed models, demonstrating their validity and dependability. Since the system lacks the real-time dataset to identify the attackers, the investigation model does have certain restrictions. Researchers may create distinct cyber-attack scenarios in the station environment and investigate them for future work utilizing these frameworks. The core causes of unusual station entity actions can be identified using these frameworks to detect a cyber event and investigate an incident.

REFERENCES

[1] K. Poornesh, K. P. Nivya, and K. Sireesha, “A comparative study on electric vehicle and internal combustion engine vehicles,” in 2020 International Conference on Smart Electronics and Communication (ICOSEN), 2020, pp. 1179–1183.
[2] A. Ahmad, Z. Qin, T. Wijekoon, and P. Bauer, “An overview on medium voltage grid integration of ultra-fast charging stations: Current status and future trends,” IEEE Open Journal of the Industrial Electronics Society, vol. 3, pp. 420–447, 2022.
[3] L. Wang, Z. Qin, T. Slangen, P. Bauer, and T. van Wijk, “Grid impact of electric vehicle fast charging stations: Trends, standards, issues and mitigation measures - an overview,” IEEE Open Journal of Power Electronics, vol. 2, pp. 56–74, 2021.
[4] S. Acharya, Y. Dvorkin, H. Pandžić, and R. Karri, “Cybersecurity of smart electric vehicle charging: A power grid perspective,” IEEE Access, vol. 8, pp. 214,434–214,453, 2020.
[5] M. Girdhar, J. Hong, R. Karnati, S. Lee, and S. Choi, “Cybersecurity of process bus network in electric stations,” in 2021 International Conference on Electronics, Information, and Communication (ICEIC), 2021, pp. 1–6.
[6] A. Valdes, R. Macwan, and M. Backes, “Anomaly detection in electrical substations circuits via unsupervised machine learning,” in 2016 IEEE 17th International Conference on Information Reuse and Integration (IRI), 2016, pp. 500–505.
[7] J. Hong, M. Girdhar, C.-W. Ten, S. Lee, and S. Choi, “Cybersecurity of sampled value messages in substation automation system,” in 2022 IEEE Power Energy Society General Meeting (PESGM), 2022, pp. 1–1.
[8] M. Mültin, “Iso 15118 as the enabler of vehicle-to-grid applications,” in 2018 International Conference of Electrical and Electronic Technologies for Automotive, 2018, pp. 1–6.
[9] T. Krause, R. Ernst, B. Klaer, I. Hacker, and M. Henze, “Cybersecurity in power grids: Challenges and opportunities,” arXiv, 2021.
[10] D. T. Hoang, P. Wang, D. Niyato, and E. Hossain, “Charging and discharging of plug-in electric vehicles (pevs) in vehicle-to-grid (v2g) systems: A cyber insurance-based model,” IEEE Access, vol. 5, pp. 732–754, 2017.
[11] M. Girdhar, J. Hong, H. Lee, and T.-J. Song, “Hidden markov-model-based anomaly correlations for the cyber-physical security of ev charging stations,” IEEE Transactions on Smart Grid, vol. 13, no. 5, pp. 3903–3914, 2022.
[12] A. Sanghvi and T. Markel, “Cybersecurity for electric vehicle fast-charging infrastructure,” in 2021 IEEE Transportation Electrification Conference Expo (ITEC), 2021, pp. 573–576.
[13] A. Bindra, “Securing the power grid: Protecting smart grids and connected power systems from cyberattacks,” IEEE Power Electronics Magazine, vol. 4, no. 3, pp. 20–27, 2017.
[14] A. Hafeez, J. Mohan, M. Girdhar, and S. S. Awad, “Machine learning based ecu detection for automotive security,” in 2021 17th International Engineering Conference (ICECNO), 2021, pp. 73–81.
[15] R. I. Y. Yusoff and Z. Hassan, “Common phases of computer forensics investigation models,” International Journal of Computer Science Information Technology (IJCSIT), vol. 3, no. 3, 2011.
[16] N. Koroniotis, N. Moustafa, and E. Sitnikova, “A new network forensic framework based on deep learning for internet of things networks: A particle deep framework,” Future Generation Computer Systems, vol. 110, pp. 91–106, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167739X18325105
[17] H. I. Mohd Abdullah, M. Z. Mustaffa, F. A. Rahim, Z.-A. Ibrahim, Y. Yusoff, S. Yusof, A. A. Bakar, R. Ismail, and R. Ramli, “Smart grid digital forensics investigation framework,” in 2020 8th International Conference on Information Technology and Multimedia (ICIMU), 2020, pp. 200–205.
[18] M. Girdhar, Y. You, T.-J. Song, S. Ghosh, and J. Hong, “Post-accident cyberattack event analysis for connected and automated vehicles,” IEEE Access, vol. 10, pp. 83,176–83,194, 2022.