Cyber–Physical Security of Powertrain Systems in Modern Electric Vehicles: Vulnerabilities, Challenges, and Future Visions

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***Abstract*— Power electronics systems have become increasingly vulnerable to cyber–physical threats due to their growing penetration in the Internet-of-Things (IoT)-enabled applications, including connected electric vehicles (EVs). In response to this emerging need, a cyber–physical-security initiative was recently launched by the IEEE Power Electronics Society (PELS). With increasing connectivity due to vehicle-to-everything (V2X) and the number of electronic control units, connected EVs are facing greater cyber–physical security challenges. However, existing research extensively focuses on the network security of internal combustion engine vehicles and fails to address the cyber–physical security of EVs specifically. In this article, the challenges and future visions of cyber–physical security are discussed for connected EVs from the perspective of firmware security, vehicle charging safety, and powertrain control security. The vulnerabilities of EVs are investigated under a variety of cyberattacks, ranging from energy-efficiency-motivated attacks to safety-motivated attacks. Simulation results, including hardware-in-the-loop (HIL) results, are provided to further analyze the cyberattack impacts on both converter (device) and vehicle (system) levels. More importantly, an architecture for the next-generation power electronics systems is proposed to address the cyber–physical security challenges of EVs. Finally, potential research opportunities are discussed in detail, including detection and migration for firmware security, model-based, and data-driven detection and mitigation. To the best of our knowledge, this is the first comprehensive study on cyber–physical security of powertrain systems in modern EVs.**

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I. INTRODUCTION

WITH the growing penetration in the Internet-of-Things (IoT)-enabled applications, e.g., electric vehicles (EVs), power electronics systems are becoming more vulnerable to cyber–physical threats ranging from cyberattacks to physical faults. Meanwhile, due to the lack of cyber awareness in the power electronics community, it becomes more urgent to develop monitoring and diagnosis strategies for networked power electronics systems. For many safety-critical applications, if these threats are not detected at the early stage, they can lead to a catastrophic failure and substantial economic loss. In response to this emerging need, a PELS cyber–physical-security initiative was recently launched by the IEEE Power Electronics Society (PELS), and the first IEEE Power Electronics Security Workshop (Cyber PELS) was held in April 2019.

While cyber–physical security of power electronics systems is an emerging area, vehicle security has been actively studied from information/network security aspects over the past few years [1] because of the enormous number of electronics and software that rely on environmental sensors and networks. For example, the traffic, road, and environmental information has been widely used in both academia and industry, which can be obtained from radar, LiDAR, visual sensors, vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), vehicle-to-everything (V2X), and dedicated short-range communication [2], [3]. Some examples of cyberattacks have been demonstrated in the literature and reports [4]. In July 2015, two researchers exploited software vulnerabilities in a Cherokee Jeep to remotely take control of safety-critical systems, leading to severe consequences, such as disabling brakes and losing control [5]. In [6], researchers were able to hack a Tesla via both Wi-Fi and cellular connection, and in [7], the potential cyberattacks specific to automated vehicles and their vulnerabilities were investigated. The automotive industry has made significant efforts to design secure modern cars, and several security standards are established, for instance, the Society

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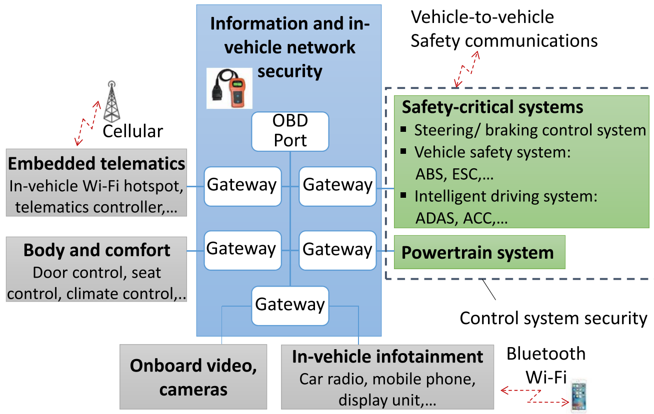

Fig. 1. Typical in-vehicle network architecture of modern cars [12], where ABS means the antilock brake system, ESC means the electronic stability program, ADAS is the advanced driver-assistance system, and ACC is the adaptive cruise control.

of Automotive Engineers (SAE) J3061, the International Organization for Standardization (ISO) 26262, and a committee draft of the "ISO-SAE Approved new Work Item 21434 Road Vehicles—Cybersecurity Engineering" standard. The overview of the recommendations provided by these guidebooks is given in [8]–[10].

Apart from the efforts of the automotive industry, researchers in academia have published studies in the last few years, among which the security of in-vehicle networks, especially for the network in connected vehicles, is a well-researched topic [7], [11]. Typical in-vehicle network architecture of a modern vehicle is shown in Fig. 1, which illustrates multiple electronic subsystems. In this architecture, the safety-critical systems (braking system, engine control unit, and steering control unit), powertrain control, body and comfort control, in-vehicle infotainment, and telematics systems are considered [12]. Based on this architecture, several studies analyzed vehicle cybersecurity and discussed several approaches to defend vehicles against malware attacks. Furthermore, Wise [3], Zhang *et al.* [12], Hodge *et al.* [13], Eiza and Ni [14], and Han *et al.* [15] presented mitigation techniques and solution frameworks to defend modern vehicles against cyberattacks, such as secure onboard diagnostics (OBD-II) port, better firewall, reliable hardware, secure software updates, penetration testing, and code reviews. In addition, some analytics and detection methodologies for in-vehicle network security [16]–[18] and control systems [19], [20] have been studied.

In recent years, the cyber–physical security of vehicles is gaining interest because the information/network security approach alone cannot guarantee the security of the whole system. The core problem is how to assess, detect, identify, and mitigate such attacks and ensure the safe operation of the vehicles. To address this issue, Amoozadeh *et al.* [21] analyzed the impact of security attack (rear-end collision) on the connected adaptive cruise control (ACC) system. In [22], the stability of the vehicle platoon under jamming attacks was investigated. To defend the vehicles against cyberattacks, Mousavinejad *et al.* [20] and Sajjad *et al.* [23] proposed detection and mitigation strategies to reduce collisions for a vehicle platooning system.

A. Work and Contributions

While the aforementioned studies provide surveys and technical foundations, challenges of cyber–physical security in modern EVs remain significant.

1) Most of the existing reviews and studies largely focus on information/network security, and they do not fully address cyber–physical security of vehicle critical control systems.
2) Although several works have been reported concerning automotive control systems (e.g., connected ACC and vehicle platooning), only safety-critical systems are addressed; very few studies focus on cyber–physical security of long-term specifications, such as efficiency performance in powertrain systems, which may result in severe degradation of energy efficiency and battery capacity [24], as well as reducing vehicle's monetary value.
3) The existing security studies of internal combustion engine (ICE) vehicles do not specifically address powertrain systems in EVs, namely, energy management system (EMS), battery, and electric drives.

With increasing connectivity between EVs, charging stations, and smart grids, EVs are exposed to other serious cyberthreats that do not exist for ICE vehicles. In an ICE vehicle, the control systems, e.g., engine control system, steering system, brake system, transmission system, and driver-assistance systems, such as ABS and ESC, are typically distributed. Differently, in an EV, because of the short drive chain and compact drive structure, the control systems in the VCU are more centralized. For example, in four wheel-motor-driven EVs, the torque reference of each motor influence both longitudinal [e.g., regenerative braking system, ABS, and acceleration slip regulation (ASR)] and lateral control performances (e.g., ESC); therefore, controls in an EV are more centralized for coordination between these systems. Then, the more centralized control architecture and higher electrification of EVs will also inevitably expand the attack surfaces and their ultimate impacts, especially on the EMS, battery, and electric drives in powertrain systems.

In this article, challenges and future visions of the cyber–physical security in powertrain systems are discussed, which, to the best of our knowledge, is the first comprehensive study on this area. The main contributions of this article are as follows.

1) For modern EVs, the cyber–physical security of powertrain systems is systematically addressed from aspects of firmware security, vehicle charging safety (vehicle-to-grid (V2G) safety), and powertrain control security.
2) The vulnerabilities of EVs are investigated under a variety of cyberattacks, ranging from energy-efficiency-motivated attacks to safety-motivated attacks. Simulation results, including hardware-in-the-loop (HIL) results, are provided to further analyze the cyberattack impacts on both converter (device) and vehicle (system) levels.
3) An architecture for the next-generation power electronics systems is proposed to address the cyber–physical security challenges of EVs. Potential research

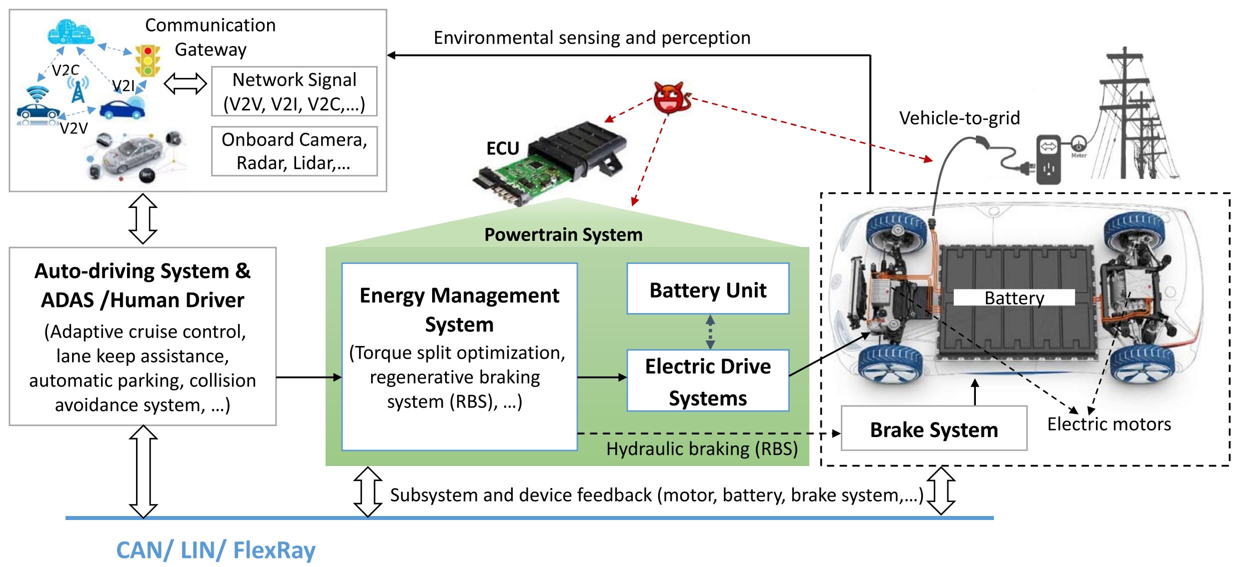

Fig. 2. System diagram of the modern EV.

opportunities for detection, diagnosis, and mitigation of cyberattacks are discussed in detail, which will potentially be used in future research on cyber–physical security for modern EVs.

B. Description of the System Architecture

As illustrated in Fig. 2, a modern EV generally includes one or more motors, a battery pack, and other mechanical and electronic components. Unlike a traditional ICE vehicle, the EV is connected to the charging infrastructure that links with the power grid. The powertrain diagram that characterizes longitudinal driving dynamics can be divided into three parts according to their different functions: environmental sensing and perception, upper driver system, and powertrain system. In the environmental sensing and perception part, the vehicle can be available to the extraneous data reflecting the traffic and road conditions by using V2V, V2I, vehicle-to-cloud (V2C), onboard camera, radar, and LiDAR. Then, the upper driver controller (e.g., autodriving system or a human driver) provides the torque demand to the powertrain system, which generates the desired longitudinal velocity profile under different traffic. All the signals are transmitted by the high-speed control area network (CAN) buses, local interconnect network (LIN), and FlexRay communication. In the powertrain system, given the total desired torque demand, the EMS focuses on optimizing the torque references (positive or negative values) of each electric drive system (EDS) to maximize the energy efficiency. When considering the brake regenerative control, the brake action is derived by optimizing the electrical and hydraulic braking. When a negative torque is required, the motor works as a generator, and the vehicle's kinetic energy charges the battery during deceleration. In the aspect of hardware, all the control systems are embedded in the electronic control unit (ECU). For the cyber–physical security study of the EV, it is assumed that the attacker can illegally access the in-vehicle communication buses, arbitrarily modify the sensor measurements, and hijack the powertrain system. In particular, they may also obtain access to the battery through the connection between the battery management system and the charging infrastructure.

As stated above, the vehicle has two lines of defense against invaders. The first one is information security that aims to prevent malicious attacks, e.g., secure hardware, secure communication techniques, firewall, and secure software update. Among these security applications, reliable hardware is the most critical. For instance, it can offer secure storage, random number generators, and hardware firewalls. Also, secure microcontrollers and drivers can support real-time control systems and online attack detection, diagnosis, and countermeasures. The second line of defense considers the critical issue: once the car has been attacked, what should we do to assess, detect, and mitigate such attacks and ensure the safe operation of the ECUs? Then, effective detection, diagnosis, and mitigation methodologies should be developed. Therefore, in real-world applications, collaborative efforts should be made from both information and control security perspectives. In the following, we first review the access and taxonomy of cyberattacks, including cyberattacks access in terms of firmware security and taxonomy of cyberattacks in the cyber–physical system. Then, vehicle charging safety in V2G and powertrain control security will be discussed.

II. Preliminary Introduction of Cyberattacks

A. Cyberattack Access in Terms of Firmware Security

Perhaps, the most well-known vehicle exploit is the 2015 Jeep hack [5]. In this attack, a myriad of common security issues was identified in the in-vehicle infotainment (IVI) system of a Cherokee Jeep. These issues include low-entropy password generation, improper network isolation, lack of access control, and insecure firmware update. This attack is not the first of its kind. Dating back to 2010, researchers have already successfully comprised the GM Onstar Gen8 and the remote telematics system on GM automobiles [25], [26]. They identified a buffer overflow vulnerability, which can be

TABLE I
FIRMWARE VULNERABILITY AND ITS IMPACTS

	Local attacks	Short-range Wireless Attacks	Remote Attacks
Prerequisites	Physical access	Within wireless signal coverage (less than 100m).	
Example interface	OBD-II port, USB port, etc.	Bluetooth, WiFi, RFID, etc.	3G/Long Term Evolution (LTE)/5G, GPS, etc.
Approach	Malicious hardware dongle, malformed media contents, fault injection, etc.	Malformed media contents, signal spoofing, insecure network configuration, etc.	Insecure network configuration, etc.
Consequence	CAN access, firmware reverse engineering, arbitrary code execution, firmware reprogramming, etc.	CAN access, unauthorized car access, PII leak, arbitrary code execution, etc.	CAN access, firmware reprogramming, arbitrary code execution, etc.

remotely triggered and allows the attackers to penetrate the CAN bus. Nowadays, an average car includes thousands of pieces of hardware on which millions of lines of code run. The greatly enlarged attack surface undoubtedly puts vehicles in danger.

The IVI has been a main target for the attackers. On the one hand, the IVI has direct/indirect access to other ECUs via the CAN bus, which grants the attackers a high return on investment. More specifically, it allows the attackers to directly hijack nonsafety and safety-critical functions, including steering or brake systems. On the other hand, the IVI involves multiple components that implement useful features. They inevitably expose more vulnerabilities to cybercriminals. Note that the IVI firmware is usually powered by a full-fledged OS. It is no different from traditional software, which is subject to vulnerabilities, such as buffer overflow, use-after-free, and return-oriented programming attacks. Several attack vectors to the bloated software stack are discussed based on the attacker's required proximity in delivering a malicious input to a particular access vector in the field. To fix a vulnerability, a complex in-field update has to be implemented, which itself has become a hot attack target. For clear expression, Table I consolidates the access and taxonomy of cyberattacks in terms of firmware security. For each attack category, attack prerequisites, the vulnerable interface being targeted, attack approaches, and the consequences will be discussed.

1) Local Attacks: When the attackers have physical access to the car, they could directly or indirectly access the car's internal networks via physical interfaces. For example, there has been work that exploits the firmware of the aftermarket telematics control unit (TCU), which connects to a car via the standard OBD-II port [27]. Since the OBD-II port is connected to the CAN bus directly, the insecure firmware of TCUs imposes a disconcerting threat to vehicle security. Researchers from Zingbox used a maliciously crafted USB device to infect the IVI [28]. Once the device is plugged into the car's USB port, the injected malware can then put the IVI system into an unusable state. Using similar methodologies, malformed CD-ROM tracks and multimedia files were used to inject Trojan horses into the car [29].

2) Short-Range Wireless Attacks: Short-range wireless channels include Bluetooth, remote keyless entry, radio frequency identification (RFID), tire pressure monitoring systems (TPMSs), and Wi-Fi. Crafting a malformed Bluetooth media, the CarsBlues vulnerability allows attackers to steal personally identifiable information (PII) of users who have synced their phones to cars via Bluetooth [30]. By connecting the car to a malicious Wi-Fi hotspot, the attackers could access the CAN bus via the web browser on a Tesla Model S [31]. Since 2008, the U.S. government has mandated that each newly manufactured vehicle needs a TPMS that provides real-time tire pressure diagnosis. However, the wireless communication used by the ECU of the TPMS and other components has been an attack target [25]. The car's remote keyless system has also been compromised. With code grabbers, which is sold at $32 in the dark web, the attackers can intercept the communication between the key and the car.

3) Remote Attacks: In the first quarter of 2016, connected cars accounted for a third of all new cellular devices [32]. By 2020, virtually, all manufactured vehicles will come with embedded connectivity. The connectivity is enabled by long-range communication channels, including cellular, a global positioning system (GPS), satellite radio, and digital radio. The ability to use the cellular spectrum as an entry point into the car network provides cybercriminals with unprecedented convenience. Once the attackers have penetrated the internal network via the cellular entry point, more attack sources and surfaces can be reached. This consequence has been clearly demonstrated in the 2015 Jeep hack [5]. In this attack, the attackers first remotely broke into the internal network of the IVI via the 3G cellular access point. Then, as insiders, they reprogrammed the firmware of the V850 chip (gateway ECU to the CAN bus) to get access to the CAN bus eventually. In the 2015 Jeep hack, they could even upload a malicious firmware that directly talks to the CAN bus. At the application level, the insider attackers could exploit a bug in the Just-in-Time engine of the browser render process to cause arbitrary code execution on Tesla Model 3's firmware [33].

B. Cyberattack Modeling in Vehicle Control Systems

Generally speaking, the cyberthreats can be categorized into three types based on their different objectives, namely, cyberattacks on confidentiality, integrity, and availability, which are often denoted as CIA triad for carrying out risk assessments

TABLE II
VULNERABILITY AND IMPACTS OF CYBERATTACKS ON VEHICLES

Attack Setup	Targeting System	Attacker Capabilities	Real-word Examples
DOS attack	Cooperative cruise control (CCC) [19], [21], internal vehicle networks [15], [36].	The attacker has no priori knowledge.	Distributed DOS attacks on Amazon web services in 2020, Six Banks in 2012, and GitHub in 2018 [37].
Replay attack	Linear control system [38], CCC [21], [39], operator-vehicle network [40], internal vehicle networks [41].	The attacker has no priori knowledge but has resources to record and manipulate data in the system.	
Data injection attack	Electric drives in EVs [42], energy management system in EVs [43], linear control system [44].	The attacker has limited system knowledge [45], [46] or full system knowledge [34], [47].	Hackers remotely control a Jeep in July 2015 [5]. Cyber-attacks on Tesla [6].
Stealthy attack	EV battery system [48], supervisory control and data acquisition (SCADA) system [49], smart grid [50].	The attacker has full system knowledge and can access to all sensor and actuator channels.	

on cyber–physical security [34], [35]. In the confidentiality attacks, the malicious attacker attends to obtain the nondisclosure of data, e.g., personal sensitive and private information from unauthorized access. In the second case, the attackers can either physically or remotely gain access to the system or the ECU and generate false signals or modify the system parameters to perform the attack, leading the systems into a dangerous operation region. The cyberattacks on availability mean that timely access to the data or system functionalities is destroyed.

As a cyber–physical control system, the powertrain and power electronic systems in EVs may present similar attack surfaces. Typically, cyberattacks in a cyber–physical control system can be qualitatively categorized into three types: denial-of-service (DOS) attacks, replay attacks, and false data injection attacks [51]. Although the three types of cyberattacks are summarized according to the cybersecurity research in cyber–physical control systems, up to date, they are widely used in vehicle cybersecurity. To clearly express the anomaly of cyberattacks in vehicle control systems, we summarize the related works in Table II, in which attack setup, attackers' capabilities, and real-world examples are presented. For convenient expression, we consider a general control architecture that has three components [52]: the plant (physical phenomena of interest including the actuators), sensors to obtain the system outputs y, and control commands u. Let $\widetilde{y}$ and $\widetilde{u}$ represent the compromised sensor measurement and control signal, respectively. The attack duration is denoted as $\mathcal{T}_a = [t_{\text{start}}, t_{\text{end}}]$, where t_{start} and t_{end} represent the start and end time of attack, respectively. Then, typical mathematical formulas of these three cyberattacks are described as follows [52], [53].

1) DOS Attacks: It means the attacker sends malicious messages or data with a very high frequency to destroy the traffic condition of the whole communications. The sensor cannot reach the controller in the attack duration, and the control signal does not reach an actuator. Then, a conservative response strategy in real applications is to use the last signal received as the current value, as follows:

$$\widetilde{y}(t) = \begin{cases} y(t), & t \notin \mathcal{T}_a \\ y(t_{\text{start}}), & t \in \mathcal{T}_a \end{cases} \text{or } \widetilde{u}(t) = \begin{cases} u(t), & t \notin \mathcal{T}_a \\ u(t_{\text{start}}), & t \in \mathcal{T}_a. \end{cases} \tag{1}$$

2) Replay Attacks: It means the attacker records data from the original normal conditions during the period of disturbance to fool the operator not to take actions. In equations, a replay attack can be expressed as $\widetilde{y}(t) = \mathbf{Y}$ and $\widetilde{u}(t) = \mathbf{U}$, where $\mathbf{Y}$ and $\mathbf{U}$ represent the recorded set of the past sensor and control signal, respectively.

3) Data Injection Attacks: These can directly falsify measurements or inject incorrect instructions to the system, which can be expressed in many forms, e.g., scaling and addictive attacks [53], high-frequency harmonics, and periodic pulse injection [42]. If the attacker has no prior knowledge of the system, the data injection attacks can be designed by mixing the original value with a malicious factor, as

$$\widetilde{y}(t) = \begin{cases} y(t), & t \notin \mathcal{T}_a \\ \nu y(t) + \epsilon, & t \in \mathcal{T}_a \end{cases} \text{ or } \widetilde{u}(t) = \begin{cases} u(t), & t \notin \mathcal{T}_a \\ \nu u(t) + \epsilon, & t \in \mathcal{T}_a \end{cases} \tag{2}$$

where ν and ϵ are the unknown signals due to the malicious modification of the signals, for instance, white noise, periodic function, periodic pulse injection, constant value, and so on. If an attacker is highly skilled and has sufficient knowledge of the system, sophisticated and stealthy data injection attacks can be created. These cyberattacks would constantly affect the system's operation while being undetected. For example, in [38], a stealthy cyberattack was presented, which could remain undetectable to the exploited detector (χ^2-detector based on the Kalman filters). In [50], based on the robust extended Kalman filter, a real-time detection for false data injection attacks was proposed. Miao *et al.* [54] designed an artificial linear control system, generating a sequence of data injection to sensors that pass the state estimator and statistical fault detector. In general, these kinds of stealthy attacks are based on a linear control model. The difference vectors between normal and compromised systems are functions of the attack sequence of the artificial linear control system. The main objective of the attacker is to maximize the estimation error without triggering the alarm while increasing the system states to infinity [54].

Besides the aforementioned cyberattack modeling, there are some potential cyberattacks specific to powertrain and power electronic systems in EVs. These cyberattacks are generated based on their specific attack targets. For example, the battery-drain attacks are studied in [55] and [48], in which the cyberattacks are conducted to deteriorate the power capability of battery packs. On the one hand, to overdischarge the battery cells, cyberattacks are designed by using wake-up functions—let the adversary wake up ECUs. On the other hand, a compromised BMS can modify the upper cutoff voltage to realize overcharge—higher charging voltage. Both the two scenarios would lead to permanent physical damage to the battery packs. For the powertrain system, Fraiji *et al.* [56] demonstrated some potential cyberattacks aiming at misleading the powertrain control system. For example, an attacker may inform the ECU not to charge the battery when it needs to be charged. Also, through GPS deception, the malicious attack may provide the powertrain control system with false information about its location and some other GPS information, which may cause wrong battery consumption prediction and overdischarge of the battery. For the cybersecurity of power electronic systems in EVs, Balda *et al.* [57] demonstrated the cybersecurity challenges related to power electronic systems. In this study, a spoofing attack aims to modify a signal in the system before quantization, and a man-in-the-middle attack can be duplicated by changing the quantized data transmitted by the sensors. In [42] and [58], the impact analysis of various data integrity attacks on power electronics and electric drives is analyzed. Overall, up to date, little research work on power electronics security in EVs has been published. For a more detailed discussion on potential cyberattacks on modern vehicles, please refer to surveys in [13], [34], and [59].

III. Vehicle Charging Security

The impacts of large-scale, light-duty EVs charging demand on distribution networks have been well studied. In general, charging demands of light-duty EVs [60] have been considered as active loads through V2G, grid-to-vehicle (G2V), and vehicle-to-building (V2B) modes [61]. It has been well studied and widely acknowledged that charging EVs in an uncontrolled manner could cause reliability issues and negative effects on power grids [62]–[64]. However, the proliferation of electrified, heavy-duty transit buses [65], [66] brings new challenges to power grids as they are operated with high power and high volatility. A major challenge to accurately investigate the impact of cyberattacks is the lack of real-time, spatial–temporal models to represent the interaction among a large volume of EVs, traffic and driving patterns, and geographically spread charging infrastructures. Furthermore, the size and potential caused by the charging demands of electrified bus fleets are often overlooked. Most major public transportation systems worldwide have announced strategic plans for 100% electric bus fleets in the near future. Moreover, electric buses consume much more power than light-duty EVs due to their size, weight, and loading. For instance, a state-of-the-art Proterra electric bus can be charged at 500 kW. Therefore, the overall charging profile of bus fleets would be high pulsed and volatile [67]. To summarize, the potential impact of both light-duty EVs and electrified bus fleets with vulnerable powertrain systems on power grids can be summarized, as the following two categories.

First, power grids are being operated with inaccurate charging demand models, as almost all state-of-the-art models are based on certain assumptions [68]. For instance, the starting time, initial battery state-of-the-charge, and charging period for EVs in commercial buildings are represented by the normal, log-normal, and truncated normal distributions, respectively [62]. However, it is questionable whether these location-data-driven assumptions can be applied in general to other regions. Therefore, recent efforts have been devoted to identify real-time EV charging profiles [68]–[72]. Furthermore, it is shown that, assuming light-duty EVs are subject to 11-kW charging and tested on the Denmark distribution network data, uncontrolled and altering charging demands [73], [74] could cause local voltage unbalances and also trigger grid component overloading [75]. A proof-of-concept demonstration was provided using public sources from New York City has shown that aggregated EVs could be controlled to launch cyberattacks on the power grid via malicious demand variations [76]. Coordinated attacks on either the cyber or the physical layer could propagate to infect other components and cause cascading effects. The above-discussed literature focuses on coordinated cyberattacks through altering demand caused by vulnerable charging infrastructures, i.e., V2G and G2V applications. It is worth noting that, if instead powertrain systems are malicious, EVs could also cause similar risks to power grid stability under V2G settings. Furthermore, being operated with much higher wattage levels, heavy-duty electrified transportation fleets could significantly amplify the impact of pulsed charging needs and cause unexpected grid stability issues.

Furthermore, existing EV demand models also do not effectively incorporate traffic models and driver behaviors [75]. If powertrain systems are under cyberattacks, power grids could encounter greater vulnerabilities due to coupled transportation-power systems. The intrinsic characteristics of transportation systems, such as traffic nonlinearities, congestion, instabilities, road capacity, and special events, such as extreme weather or sporting events, could dramatically influence EV travel patterns and, in turn, further impact spatial and temporal distributions of the power grid charging demand profiles. As a demonstration example, if a fleet of combined light-duty EVs and electric buses are under cyberattacks and break down during peak hours due to powertrain failures, they could induce designed traffic jams and reshape the forecast load profiles. For instance, a wide area of the residential area could be delayed or cause significant spikes, leading to overloading and voltage stability issues.

A proof-of-concept simulation was conducted by the authors on a 50-km, four-lane highway with a peak density

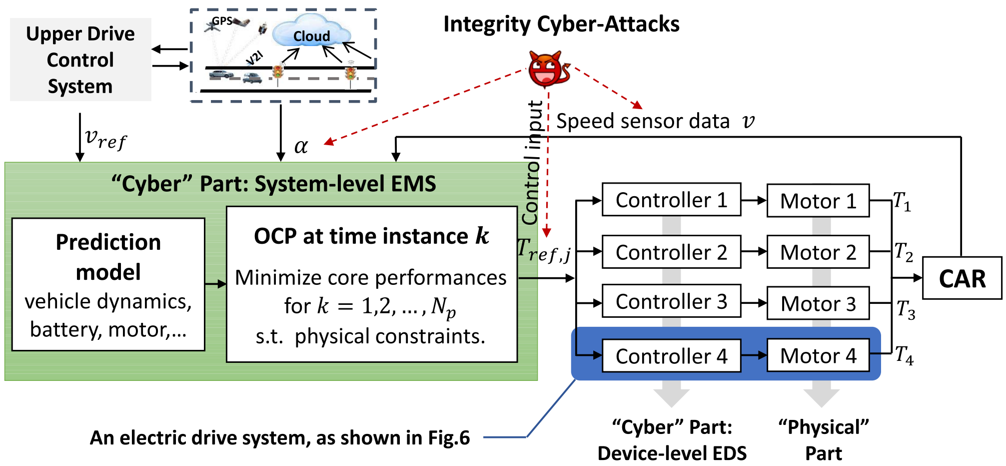

Fig. 3. Diagram of the powertrain control system.

of 533 vehicles per mile in Orange County, California, USA. With 50% of light-duty EV penetration on the highway (which can be equivalent to fewer EVs with some electric buses), the simulation results showed that several EVs under control could induce a significant traffic jam and cause more EVs to reach their lowest battery state-of-the-charge. In turn, those EVs arrive destination late with an immediate need to recharge. A fivefold increase (4–20 MW) in total power demand was observed, and a sevenfold increase (0.19–1.4 MW/km) in local peak demand relative to the baseline profile was also a significant threat to power grid stability.

IV. Powertrain Control Security

As shown in Fig. 3, the powertrain control security involves system- and device-level securities that directly impact the functionality and safety of the vehicles. The system-level EMS is usually denoted as the "Cyber" part, which focuses on the overall performance of the EV, for instance, energy efficiency and battery management. In the device-level EDS, the motor controller and the actuator (plant) are considered as the "Cyber" and "Physical" part, respectively. In general, the control period of the system level is 10–20 ms, and the control period of the device-level EDS is usually 0.1 ms or less.

A. System-Level Cybersecurity of EMS

1) System Description: As shown in Fig. 3, the EMS is developed by optimizing the brake, torque, and battery power to maximize energy efficiency while satisfying the desired dynamic performance, e.g., velocity reference and total wheel torque. To observe the impact of the cyberattacks on EMS, a predictive EMS under the framework of the model predictive control (MPC) is developed. A detailed description of the controller is given in the Appendix.

2) Attack Modeling and Definition: Different from the safety-critical systems, cyberattacks on EMS usually impact energy consumption only. Thus, the driver can hardly notice the attack. In this section, for a better understanding of cyber–physical security, some preliminary results of cyberattacks on the EMS are presented. Based on the MPC-based EMS, Fig. 3 shows the potential cyberattack locations and signals. The cyberattacks may occur in different locations, including sensor measurements (vehicle speed v and road slope α) and control inputs (torque reference of the jth motor, marked as $T_{\mathrm{ref},j}$). As a case study, we first consider the continuous data injection attacks on $T_{\mathrm{ref},j}$. The compromised torque reference that will be used by the motor drive is expressed as

$$T^{\mathrm{atk}}_{\mathrm{ref},j} = \nu T_{\mathrm{ref},j} + \epsilon \tag{3}$$

where ϵ and ν are unknown signals due to the malicious modification; $T_{\mathrm{ref},j}$ denotes the actual signal. Without loss of generality, we set $j = 2$, which means that the second motor is compromised. Four attack scenarios (marked as Cases 1–4) are defined as $\nu = \{-0.5, 0.5, 1.5, 2\}$ ($\epsilon = 0$), respectively; the other four cases (marked as Cases 5–8) are defined as $\epsilon \in \{\pm 0.2T_{\max}, \pm 0.4T_{\max}\}$ ($\nu = 1$), respectively. Here, $T_{\max}$ is set to 400 Nm.

In addition to the effect on energy efficiency, cyberattacks on the powertrain system may also degrade the dynamic performance. Based on the developed EMS in the above, four data injection attacks targeting v (marked as Cases v-1 and v-2) are designed, expressed as $v^{\mathrm{atk}} = \nu_v v$, where v^{atk} denotes the compromised speed, and $\nu_v \in \{0.8, 1.2\}$.

3) Simulation Setup: The simulation is conducted under two typical long-term driving cycles, New European Driving Cycle (NEDC) and Urban Dynamometer Driving Schedule (UDDS), which are widely used in the literature [77]–[81]. In [78], under different driving cycles, trajectories and optimization algorithms of EMSs in EVs (including hybrid EVs and battery EVs) were summarized. Although the real driving scenarios are often more complex, these standardized driving cycles can serve as examples for practical driving tests, as discussed in [79].

4) Results and Impact Analysis: The results of system performance are presented in Fig. 4, including velocity tracking and energy consumption, which illustrates that despite the compromised torque reference of the jth motor, and the

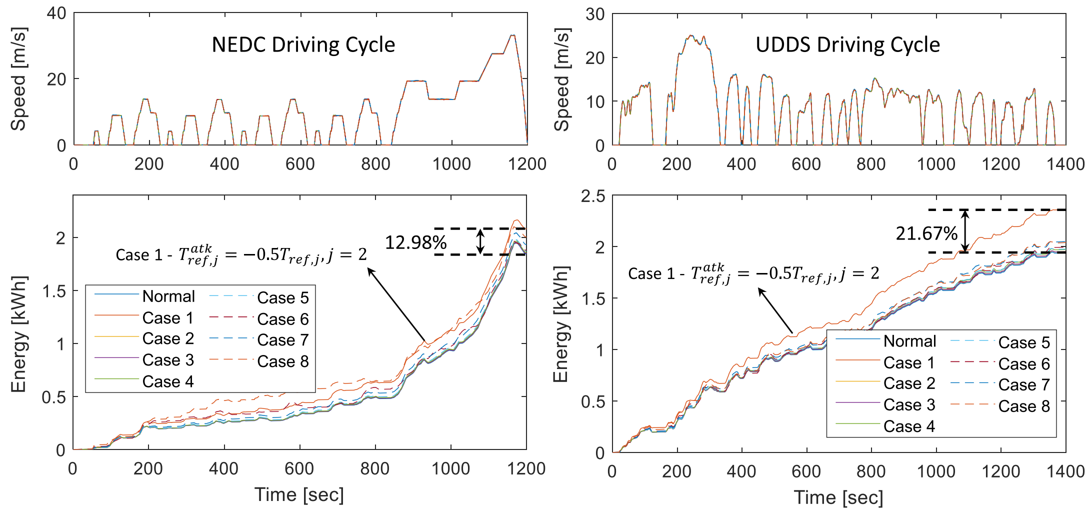

Fig. 4. Impact of cyberattacks on $T_{\mathrm{ref},j}$ under NEDC and UDDS driving cycles.

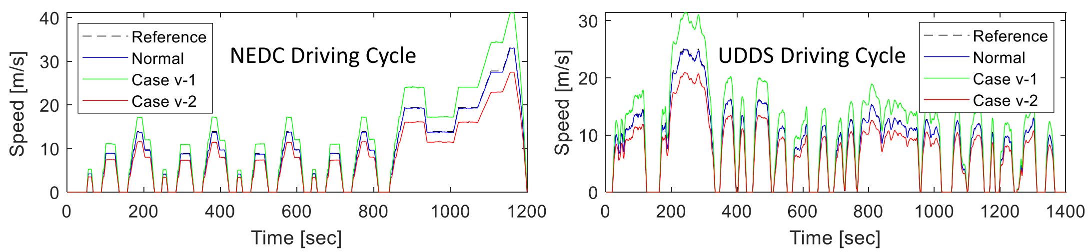

Fig. 5. Impact of cyberattacks on υ under NEDC and UDDS driving cycles.

system presents a similar dynamic performance in terms of speed tracking. This implies that those efficient-goal-oriented attacks (e.g., cyberattacks in $T_{\mathrm{ref},j}$) can cause significant efficiency degradation while not affecting driving tasks. Based on the comparison between the energy consumption profiles, the cyberattacks exhibit different effects on energy efficiency. When a reverse command ($\nu < 0$) is input to the objecting motor, e.g., attack case 1, the energy efficiency would be reduced over 20%. This significant reduction of energy efficiency is likely to occur in practical applications. For example, when the initial command of the targeted motor is to drive the car by providing positive torque, and a compromised torque reference makes it constantly work as a generator, then the other motors need to output more power to fulfill the required wheel torque. In such a case, compared with the normal conditions, the extra power will be wasted. Although the negative power from the jth motor can recharge the battery, the energy loss due to the internal resistance and other losses in the motor cannot be ignored. Besides the negative-ν-attack, other false data injection attacks with various definitions of ϵ and positive ν may also lead to higher energy consumption (up to 10%), causing a considerable energy loss in the long term. Therefore, unlike the cyberattacks on life-critical systems, such as driver-assistance systems (e.g., ESC), cyberattacks that deteriorate system efficiency also require attention and further investigation. From the results in Fig. 5, it can be seen that cyberattacks on υ may significantly affect the tracking accuracy. In real-world applications, the larger tracking error will lead to poor dynamic performance.

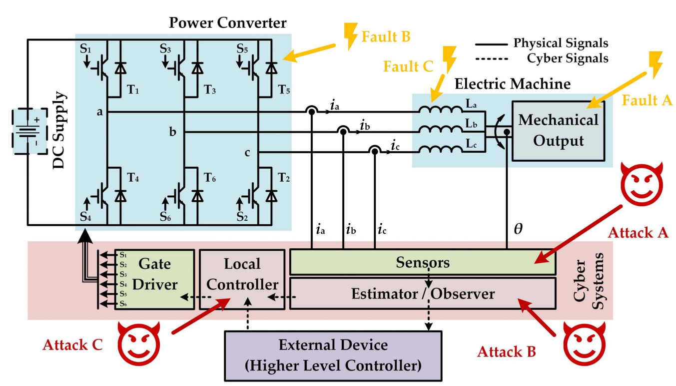

Fig. 6. Diagram of a general EDS.

B. Device-Level Cybersecurity of EDSs

1) System Description: As mentioned earlier, at the device level, the function of an EDS is to track the torque commands given by the system-level controller. Fig. 6 shows the cyber–physical diagram of a typical EDS, wherein the physical systems (dc supply, power converter, and electric machine) are denoted in blue, and the cyber systems are denoted in red. According to the feedback signals gathered from sensors and torque command from the system-level controller, the local controller calculates the duty cycles needed for pulsewidth modulation (PWM) signals, which then drives the power converter through a gate driver.

2) Attack Modeling and Definition: In the traditional EDS, the communication to the external systems is limited;

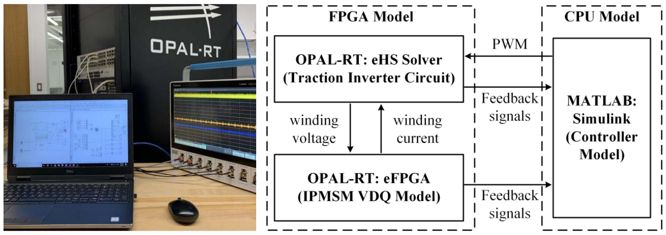

Fig. 7. OPAL-RT HIL real-time simulation testbed.

thus, the traditional EDS is hardly targeted by the cyberattacks, and the physical faults are the primary concerns. For example, as shown in Fig. 6, three types of common physical faults are denoted in yellow: mechanical faults (fault A), open-circuit faults in power electronics (fault B), and machine winding interturn short-circuit faults (fault C). In the past decades, the physical faults of the EDS and related components and devices are widely studied. In [82] and [83], some of the research outcomes and progress of EDS condition monitoring and fault diagnosis were reviewed, such as interturn short-circuit fault detection in the electric machines and open-circuit fault diagnosis in power electronics modules.

However, with the increasing computational capability of the digital signal processors (DSPs) and microcontroller units (MCUs), and the development of the communication network techniques, local controllers can achieve advanced functionalities, such as online optimization, fault diagnosis, and multimode operations. Such functions require the modern EDS to communicate more frequently with the onboard networks than ever, making the EDS much more vulnerable to malicious attacks from the cyber systems. In Fig. 6, some common attacks are denoted by red attack vectors. Attack A represents the sensor attacks, in which the attacker could fabricate false sensor signals or block the communication between sensors and estimators. Attack B represents the estimator attacks or observer attacks, in which the attacker could use false signals or parameters to modify the estimator. Attack C denotes the local controller attacks, in which the attacker could manipulate the controller parameters or directly modify the control commands to the gate drivers. Besides, data injection attacks targeting the EDS controller parameters could also lead to system instability. Meanwhile, a series of false current reference injected to the current controller could make the EDS operate at deteriorated efficiency without being detected, which will largely reduce the vehicle cruising capability. Also, introducing random delay to the feedback signals could cause a large ripple in the output torque and current, which eventually could shorten the battery and machine life.

As a case study, several replay and false data injection attacks on i_a (see Attack A in Fig. 6) in an interior permanent magnet synchronous machine (IPMSM) are conducted. The false data injection attacks are expressed as $i_a^{\text{atk}} = \nu_i i_a$, where $\nu \in \{1.2, -0.75\}$. Then, three replay attacks are defined with different attack start timings, denoted as $t^{\text{atk}} \in \{72, 103, 181\}$ s, wherein the recording time horizon is set to 5 s.

3) Simulation Setup: The simulation is conducted under a high-fidelity EV powertrain model in a real-time HIL testbed (OPAL-RT OP5700), as shown in Fig. 7. In this testbed, a detailed model of the motor (IPMSM) and vehicle dynamics is included. The sampling time is set to 25 μs.

4) Results and Impact Analysis: The results in Fig. 8 demonstrate that the compromised i_a may cause a larger tracking error of the motor. Notably, in replay attack scenarios, the torque increases dramatically once the cyberattacks are activated. From the perspective of the longitudinal performance in the powertrain, despite the short attack period, this transient degradation in performance of torque tracking may further cause unexpected jerk of the vehicle body, significantly reducing the driving comfortability. From the lateral performance aspect, if the attack occurs on a curve road segment, the higher tracking error may also lead to lateral instability.

From the attacker's perspective, once the EDS is compromised, the attacker's benefits could be summarized in three categories: safety, economy, and information.

1) *Safety:* A malicious attacker could simply aim at causing some damages to the systems. For example, it could increase the current reference in the current control loop or modify the duty cycle from the controller output so that the power converter will be overcharged and eventually damaged.
2) *Economic:* A profit-driven attacker could anticipate gaining economic benefits from the attacks. For example, a charging station operator could intrude into the EDSs through the charging station and inject some false data into the sensors or estimators. This kind of cyberattacks will cause higher current harmonics and eventually lead to higher energy loss in the traction inverters. In such a case, the vehicle's cruise range will be reduced, and the customers will have to recharge their vehicles more frequently. Then, the operator will gain more money.
3) *Information:* Some attackers also intend to steal the system information so that they could either intercept the technological property or invade customers' privacy. For example, the attack could be deployed to the estimators, where system operation data will be calculated and sent to external devices.

5) Preliminary Discussion on Distinguishing Between Malicious Cyberattacks and Physical Faults: When it comes to cybersecurity, a broad concern is how to distinguish between malicious cyberattacks and physical faults. One of the possible fault situations in the powertrain system is motor failures, leading to misbehavior during driving. To observe the difference between malicious cyberattacks and physical faults, several fault scenarios are presented in Fig. 9. Results of a cyberattack are also given for comparison. In this figure, physical faults 1–3 represent winding grounded short-circuit fault on phase A, phases A & B, and phases A & B & C, respectively. Physical fault 4 represents an open-circuit fault in the upper switch of phase A. Overall speaking, the *D*-axis current profiles have severe distortion and oscillation for both cyberattacks and physical faults, but the frequency of the oscillation is different. While the oscillation and distortion patterns due to cyberattacks are considerably random, the ones due to physical faults show specific regular variation because faults often have a fixed physical model, such as short-circuit faults. In particular, we can see that, despite the physical faults,

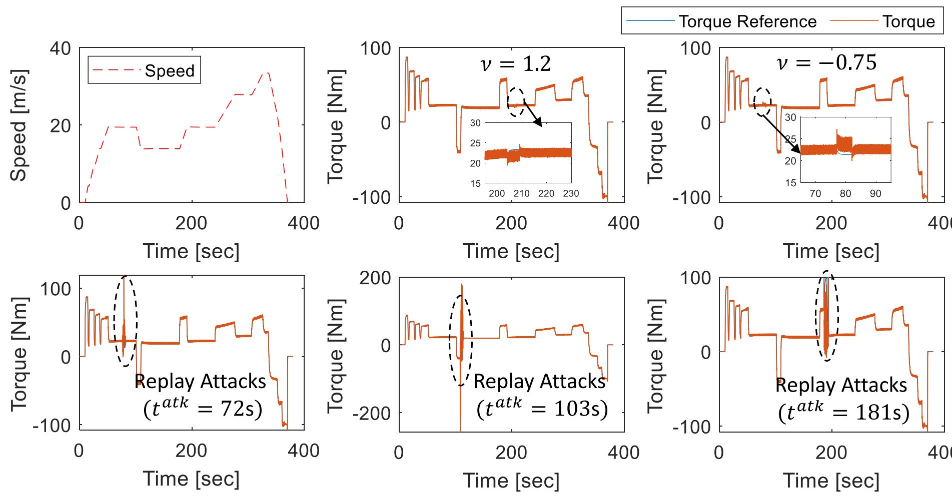

Fig. 8. Impact of cyberattacks on i_a in an IPMSM under the OPAL-RT HIL testbed.

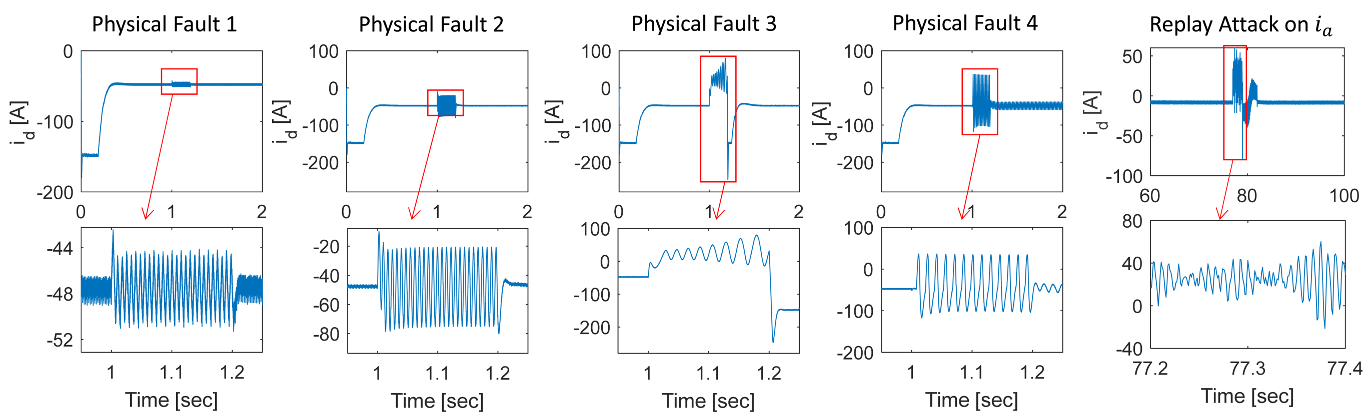

Fig. 9. Comparison between malicious cyberattacks and physical faults.

i_d still presents a fixed frequency characteristic. For one type of physical faults, the amplitude is related to the physical parameters of that fault. This feature may provide a guideline to distinguish the cyberattacks and physical faults. Moreover, for those physical faults causing gradual performance degradation, such as increasing internal resistance, specific physical characteristics should be utilized to address the long-term abnormal behavior. This kind of persistent rule of performance degradation may also be used to distinguish faults from cyberattacks.

V. Detection and Mitigation Opportunities and Future Visions

To design secure power electronics systems and overcome the issues related to cyber–physical security, this section presents a cybersecure architecture of next-generation power electronics systems for EVs, considering both hardware and software aspects. The proposed architecture, as shown in Fig. 10, will provide a cybersecure solution to the next generation of power electronics systems at the design and operation stages. More importantly, this architecture will focus on both device and system levels, aiming to monitor the vehicle system real time. Corresponding detection, diagnosis, and mitigation algorithms will be designed and then discussed in Sections V-B and V-C in order to improve the security and resilience of connected EVs.

At both the device and system levels, each controller module includes a primary microcontroller (MC) and a secondary MC. In the recent article [84], the authors presented a comprehensive review of the state-of-the-art traction inverter designs from several leading automotive manufacturers. In most autonomous applications, only one MC, such as DSP, is included on a dedicated control board within the inverter [85], for instance, traction inverters in Audi MY2016 A3 e-Tron [86] and Nissan MY2012 LEAF [87]. Although, in certain vehicles, such as BMW MY2016 i3 [84], two DSPs are used in the control board within the traction inverter, the secondary DSP is not used for security purpose. Unlike the current design methodologies, the proposed cybersecure architecture introduces and encrypts a secondary MC through a firmware security module to provide extra security. In normal cases, the converter is controlled by the primary controller, while the monitoring systems, including cyberattack detection and diagnosis algorithms, are integrated into the secondary MC. Once a cyberattack is identified and the compromised signal is diagnosed, a resilient control algorithm in the secondary MC would be used to replace the primary MC and recover the system from cyberattacks at the early stage.

At the device level, both primary and secondary MCs can receive sensor feedback signals from the converters, such as phase current and position/speed of the electric machines,

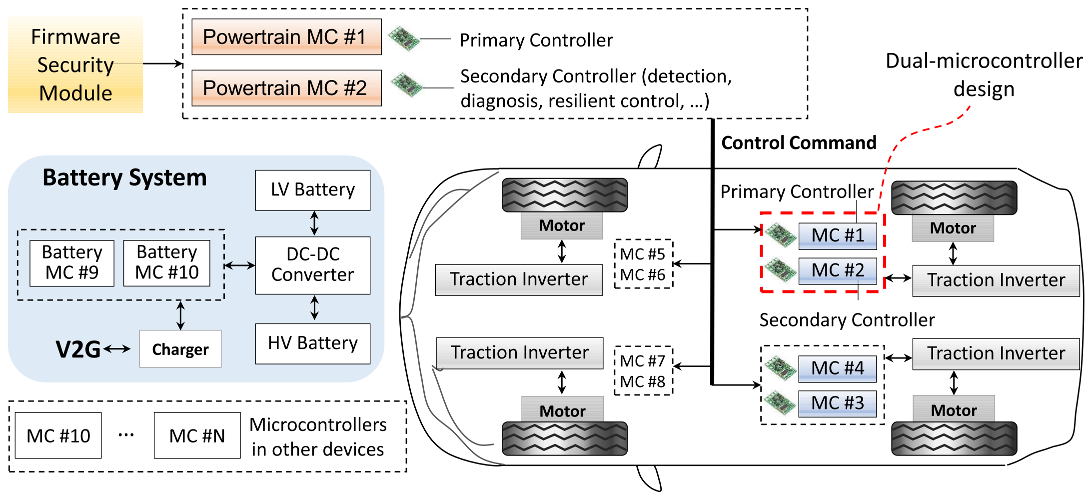

Fig. 10. Diagram of the cybersecure architecture of next-generation power electronics systems for EVs.

and provide a control command to the converter when necessary. At the system level, besides the critical signals in the powertrain system, the secondary MC also collects the sensor measurements and monitoring states of each device (denoted as MC #1, MC #2, . . ., MC #N) to identify the presence of the cyberattacks. It should be noted that Fig. 10 only shows the diagram of the cybersecure architecture. In real-time applications, this cybersecure architecture is more complicated. Besides the two MCs, some other devices need to be used. For a detailed discussion on the validation of this dual-MC design methodology, please refer to the literature [88], which provided a cybersecure power router prototype and results of switching between the primary and secondary MCs.

Cyberattack detection methods, including data- and physics-based that will be discussed in Sections V-B and V-C, can be used to detect and diagnose cyberattacks in connected EVs. Through dual-MC systems, mitigation algorithms can be applied to improve the resilience and recovery of the powertrain system in an EV once the cyberattack occurs.

A. Detection and Mitigation for Firmware Security

The software bug is a major source of vehicle hacking. As more vehicles are connected to the Internet, we should expect to see more software attacks. To prevent, detect, and mitigate attacks targeting connected vehicles, multilayered, autonomous defense systems should be designed.

First, in-house software testing should be extensively applied to mission-critical firmware. Combined with memory checker [89], taint analysis [90], and symbolic execution [91], [92], traditional software bugs, such as buffer overflow, use-after-free, double-free, and integer error, could be eliminated in the first place.

Second, the state-of-the-art advances in a programming language should be incorporated in software development. In the short term, using more secure programming languages, such as RUST [93], is a tangible way of improving code quality. In the long term, OEMs should employ formal verification to prove the security of the released firmware [94] theoretically.

Third, after the firmware has been deployed, mitigation techniques could serve as another line of defense. Currently, code diversity techniques (e.g., address space layout randomization, stack protections (e.g., stack canaries [95]), control-flow integrity [96], and data execution prevention (DEP) have been the standard security features on PCs. However, how to apply them to vehicle firmware, especially those written for less powerful ECUs, remains an open problem. As an illustrative example, DEP, the fundamental technique to defeat code injection, is achieved on PCs using the memory management unit, which is unfortunately not present on most ECUs. Although there has been a significant effort on system-level mitigation techniques for MC systems, existing work either requires radical hardware retrofit [97]–[99] or relies on heavy instrumentation to the binaries [100], [101], which imposes considerable runtime overhead and, thus, compromises the real-time constraint of many ECU tasks. Toward this direction, we should creatively utilize existing hardware features available on MCUs, such as performance monitoring units or TrustZone, to minimize the runtime overhead. Clean-slate hardware–software codesign is also a direction that pursues to meet both the security and performance requirements.

Fourth, when the system is suspicious of attacks, logging provides analysts from OEMs with valuable data for quick causality analysis. As such, trusted logging should be implemented to collect and store security-related events from each module. Note that the logging subsystem should be properly isolated from others since a sophisticated attacker could overwrite the logging data once the ECU firmware is compromised.

With hardware support, trusted computing is the ultimate goal. In trusted computing, a dedicated chip is integrated into the system to provide fundamental security features, such as memory isolation, platform integrity, and remote attestation. In embedded systems, SMART [102] has been a highly influential proposal that follows the sprite of trusted computing. It can establish a dynamic root of trust for MC devices. SMART requires no additional hardware—only a few small changes to the MCs. The follow-up work, called TrustLite [103], augments SMART with support for running arbitrary code (trustlets), isolated from the rest of the system. An execution-aware memory protection unit (EA-MPU) ensures that the data of a trustlet can be accessed only by

TABLE III
CYBERATTACK DETECTION AND MITIGATION FOR CYBER–PHYSICAL SYSTEM

Attack Setup	Model-based (attack location; prediction model; detection method)	Data-driven (application; model)
DOS attack	Sensors; LDS [19]; observer-based [19], [105].	Smart grids, industrial control systems, electric vehicles; dynamic state estimation [106], support vector machine (SVM) [107], multi-layer machine learning models [108], etc.
Replay attack	Sensors and actuators; LDS [38], [44], [109], auto-regressive model [110]; state estimation in the presence of sensor noise [111], χ^2-detector based on Kalman filters [112], etc.	Power systems, wide-area measurement systems; self-correlation coefficient [113], singular value decomposition [114], stochastic coding [115], frequency-based signature [116], etc.
Data injection attack	Sensors and controllers; LDS [117], [118], SLS [119]; state estimation [117], MPC [118], statistical anomaly detection technique [120], etc.	Smart grids, CAN bus; support vector machine (SVM) [121], Gaussian mixture model (GMM) [122], neural networks [123], etc.
Stealthy attack	Sensors and controllers; LDS [124]–[127]; water marking method [124]–[127], robust extended Kalman filter [128], moving target defense approach [129], [130], etc.	Networked control systems, smart grid, automatic voltage controls (AVCs); closed-loop recursive identification [69], low-rank and sparse matrix approximation [131], reinforcement learning [132], etc.

the code of the trustlet itself. These proposals form the fundamental hardware environment for mission-critical firmware to run in. OEMs should closely collaborate with academia to quickly apply these results to the most critical ECU modules.

Apart from software bugs, we should also pay attention to “logic bugs” that are directly associated with the design logic of the vehicles. For example, limit what kinds of communications that a particular device can engage in (e.g., disabling ODB-II dongles from sending CAN message via CAN firewalls). It is necessary to enforce isolation so that compromised IVI could not easily communicate with other critical ECUs. When the firmware is found vulnerable, software patches should be prepared, and OTA updates should kick in immediately [104]. However, the OTA updates should be immune from the attack itself. Otherwise, the attacker could misuse this mechanism to flash malicious firmware. To safeguard OTA updates, end-to-end security should be guaranteed between the update server and the vehicle. This implies that static keys should never be used, and strong encryption should be employed.

B. Model-Based Cyberattack Detection and Mitigation

As the final protection line, cyber–physical security detection and identification are gaining increasing attention, which is broadly divided into two groups: model-based and data-driven methods. To clearly express the cyberattacks, vulnerabilities, and potential mitigation techniques, Table III summarizes the related works on cybersecurity of cyber–physical systems, including both model-based and data-driven approaches. Due to the little literature on cyberattack detection and mitigation for EVs, most of the reviewed methodologies are from cyber–physical control systems. Although they are not developed aiming at cybersecurity of EVs and power electronic systems, they can provide a reference for further research in vehicle cyber–physical security. Meanwhile, considering the different features of vehicle powertrain and power electronic systems, unique cyber–physical security challenges of powertrain systems are discussed later.

Model-based methods show promise in cyberthreat detection and diagnosis based on the known physical models, while data-driven approaches work more effectively in applications that do not have explicit physical models. The key idea of model-based detection is to compare the predicted measurements based on previous signals and models with real sensor measurements [52]. The prediction model that gives the relationship between the sensor measurements, control commands, and the predicted measurement can be developed from physical equations, such as Newton’s laws, fluid dynamics, electromagnetic laws, autoregressive model, and a technique called system identification. For example, in [38], [44], [109], and [111], in response to the sensor attacks in the presence of noise, the detection methods were designed based on a linear dynamic system (LDS) with sensor and perturbation noise. In [110], an autoregressive model-based approach was developed to detect cyberattacks on process control, wherein the autoregressive model was used to capture the behavior of the system. Overall speaking, almost all the existing works are based on LDS, static linear state space (SLS), or simply near-linear control systems such that well-known prediction or estimation approaches can be used, e.g., the Kalman filter, state observers, parameter estimation techniques, and weighted least-square observers. Typically, research works on the trigger condition of anomaly detection focus on scoring the anomaly and the conditions for raising an alert. In most publications, the residual at the kth time instance is defined as $r(k) = |y(k) - \hat{y}(k)| \geq \tau$, where τ is a threshold, and y and $\hat{y}$ represent the measured output the system and its estimated value, respectively. Then, this residual is considered as a proxy for the presence of attacks, such as [54] and [133]. Apart from the deterministic objective, some statistical [120], [134], payload-based [135], and classification-based [136] algorithms are often used for designing an anomaly detector. One of the representative residual-based detection strategies is χ^2-detector based on Kalman filters, which has the capability against both bad data and false data [112].

To protect the system against stealthy cyberattacks, some studies inserted an additional signal (also named watermark) to the system inputs for cyberattack detection. Mo and Sinopoli [38] added an authentication signal (Gaussian distribution with zero means) to the control input, with which the stealthy replay attacks were detected. However, the introduced watermark may cause degradation of the system performance in normal conditions. To address this issue, within the context of replay attacks, several publications aimed to design watermarks with consideration of tradeoffs between security and control performance [124]–[127]. For example, in [137], based on the game-theoretic paradigm, a suboptimal switching control policy that balances control performance with the intrusion detection rate was proposed. Specifically, considering the problem of tracking a constant reference at the output, Romagnoli *et al.* [124] presented a deterministic watermark based on model inversion, which, to a certain extent, allows a defender to achieve control performance during normal operation and detect malicious behavior while under replay attack. Alternatively, some other active defense techniques, e.g., authentication changes to the parameters, sensing, and communication, can also help detect these stealthy attacks [138]. Extensions of watermarking-based methods can be found in [139] and [140]. Besides the watermarking-based methods, some other approaches have also been proposed in recent years [54], [129], [130]. In [129] and [130], a moving target defense approach was used for identifying sensor attacks in control systems, wherein deterministic and stochastic scenarios were discussed.

Besides cyberattack detection, attack–resilient controls are applied to guarantee the ability of recovery from cyber–physical attacks [141], and up to date, two representative resilient control strategies have been proposed in the published literature. One is to develop a state estimation algorithm that is resilient to various attacks and modeling errors, provided that the controller can obtain a reasonable estimate of states and actuator commands [141]–[143]. On the basis of state estimation, an appropriate controller can be designed by using a switching strategy, for instance, observer-based resilient control [144], [145]. Besides the accurate state estimation, the second attack–resilient control strategy designs a high-assurance control system to mitigate the threat from cyber–physical attacks via various control theories [112], which can be further categorized into two schemes. The first scheme designs a resilient controller that focuses on a certain type of attack, such as denial-of-service, various deception attacks (false data injection attacks, zero-dynamic attacks, and so on), and replay attacks. The second scheme uses adaptive control to assure the security and reliability of closed-loop systems, considering the presence of unknown attacks. For example, in [146]–[148], adaptive resilient control strategies against unknown sensor and actuator attacks are presented, which guarantees the closed-loop stability for LDSs. It should be noted that the first scheme assumes that the attack type or schedule are open to the resilient controllers. For instance, Zhu and Martinez [149] assumed that the replay attacks can always be detected, and on this basis, the attack–resilient receding horizon control law is developed. However, for real applications, accurate detection is hard to achieve. In the second scheme, although no prior knowledge of attacks is utilized, the attack values in the dynamic system are often supposed to be state-dependent and bounded; hence, in most cases, to guarantee robustness and stability, the designed resilient controllers expose some considerable conservatism.

For cybersecurity of powertrain and power electronic systems in EVs, the above model-based literature provides fundamental methodologies, for instance, observer-based cyberattack detection during charging for battery packs [150], in which a linear battery dynamics model is used. To improve the cyber–physical security of EVs with four motor drives, Guo and Ye [151] proposed a coordinated detection methodology that combines state observer and performance-based evaluation metrics. Currently, the research of cybersecurity of EVs is still at an early stage, and most of the literature focus on driving-level control systems, such as detection and recovery mechanism design for vehicle platooning [19], [20]. Cyber–physical security issues of vehicle powertrain and power electronic systems are not well addressed in both academia and the industries, and few studies have been devoted to this area. In the previous work [42], [58], vulnerabilities of EDSs due to sensor false data injection attacks were analyzed, wherein some innovative metrics were developed. These performance-based metrics can help identify the cyberattacks.

C. Data-Driven Cyberattack Detection and Mitigation

Unlike model-based solutions, data-driven-based algorithms are model-free; thus, neither system parameters nor models are needed in the attack detection and diagnosis. Data-driven methods have diverse branches, such as statistical models, machine learning (ML) techniques, and data-mining techniques. As data-driven methods do not require explicit physical models, they can cope with complex, complicated, and heterogeneous phenomena. There are many data-driven methods for the security issues, such as the geometrically designed residual filter [46], signal analytics-based [152], generalized likelihood ratio [153], the cumulative sum (CUSUM) [154], leverage score [155], influential point selection [156], support vector machine (SVM) [121], the Gaussian mixture model (GMM) [122], neural networks [123], ML [121], and deep learning [157].

More specifically, targeting the three possible attack types in the powertrain systems in modern EVs, DOS, replay attack, and false data injection attacks, the related data-driven solutions will be introduced. In general, data-driven methods can be viewed as using trained models to detect abnormal system behavior based on the observation data collected from the system, which are usually based on the idea that under normal conditions, the observation data would be constant with minor variations due to measurement inaccuracies and system noises. The main motivation is that the normal data and the tampered data tend to be separated in a certain feature space [121], [158] or using given quantitative metrics [107], [159]. Commonly, labeling information is needed for supervised learning, and one can train a classifier to identify attacks according to the class labels, while, if labels are not given, unsupervised learning-based methods cluster unlabeled data into classes according to the hidden features.

In terms of theoretical methods, the linear regression (LR) detects the cyberattack if the measured data does not fit the linear model fit from the training data set. Signal temporal logic proposed in [160] compared the dc voltages and currents with the predefined upper and lower boundaries. SVM is another linear discriminative classifier formally defined by a separating hyperplane, which has been widely used to detect attacks [161]. The artificial neural network (ANN) model is a computational model based on the structure and functions of networked neurons, used for classification and regression. Depending on activation functions and neurons, ANN can model complicated relationships between inputs and outputs [123]. A recurrent neural network (RNN) is a type of deep neural network (DNN). With the internal memory unit, RNN can better capture the signal dynamics, which is important for the time-series data analytics [162]–[164]. A convolutional neural network (CNN) is another type of DNN, which is widely used for image processing. CNN utilizes the convolutional kernels to extract texture features of the measurement matrices [165]. Need to mention, DNNs with a higher number of hidden layers are expected to yield more precise detection results. However, the computation cost will be higher.

For the cybersecurity of vehicles, although there have been a series of research works on data-driven cyberattack detection for vehicles, most of them are developed for in-vehicle-network security and less for powertrain control systems. For example, Kavousi-Fard *et al.* [166] proposed a deep learning-based approach for cyberattack detection in vehicles. In this work, a generative adversarial network classification is used to assess the message frames transferring between the ECU and other hardware in the vehicle. In [167], for cybersecurity of in-vehicle network communication, a cloud-based intrusion detection approach is presented. By using deep learning, distributed DOS, command injection, and network malware can be identified.

D. Challenge and Future Versions

Although these detection and mitigation approaches provide technical foundations against malicious attacks, several challenges remain to be solved for cybersecurity of powertrain and power electronic systems in EVs.

1) Notice that, in real-world applications, the powertrain system in an EV is nonlinear and complicated, and most of the controllers in ECUs include a large number of engineering-experience-based rules and lookup tables. Under these circumstances, the traditional theory-based methods would be ineffective to analyze the stability, security, robustness, and resilience of the system because most of them are based on LDS modeling. One of the potential solutions is to develop index-based attack impact analysis, detection, and diagnosis to fully utilize the physical features and performance of the powertrain system, such as the discussions in the previous work [42], [43], [58], [151].
2) Although data-driven methods for cyber–physical control systems provide an alternative way to cyberattack detection and mitigation, there are still limitations and challenges, especially for EV cybersecurity. On the one hand, unlike the cybersecurity in power grids and other cyber–physical systems with fixed normal conditions, real-time driving cycles of vehicles demonstrate high uncertainty, and a broader range of variation (even in normal scenarios). Therefore, it is difficult to distinguish abnormal conditions and varying driving conditions, such as frequent start–stop driving in urban traffic. On the other hand, data scarcity is generally the most critical issue that needs to be solved. However, real EV data can be hard to obtain and are often confidential by the carmakers. Besides, the training data may not be available for every attack scenario in a particular EV. Therefore, more novel solutions to reduce data dependence, improve computation efficiency, and increase the model fidelity need to be explored.
3) Most of the current research in cyber–physical control systems does not consider computational requirements. However, power electronic systems, e.g., EDSs, are operating faster than other processing control systems. A fast detection methodology needs to be developed such that the cyberattack could be detected at an early stage. Therefore, besides the detection accuracy, the sampling rate, computational burden, and time to detection need to be considered. From this perspective, model-based approaches that do not require online optimization, such as an observer-based cyberattack detector with fixed observer gain [19], [105], are available for power electronic systems. In addition, computational-efficient data-driven methods can be used. It is worth noting that, compared with root-cause diagnosis, the purpose of cyberattack detection is to distinguish between normal and cyberattack scenarios, thus requiring less computational time in real applications. Once a potential cyberattack or a physical fault is detected during driving, the human driver can stop the car and request car maintenance for further cyberattack diagnosis.
4) Besides, advanced root diagnosis methods must be developed to distinguish cyberattacks and physical failures, as the existing literature is mostly focused either on physical fault detection or cyberattack detection. For power electronic systems in the EV, this article has presented a preliminary discussion on this topic (see Section IV-B). However, it is difficult to distinguish physical faults from various cyberattacks, especially considering the time-varying and uncertain driving conditions of the powertrain system. Therefore, a comprehensive study on this topic is still an emerging topic in the future.

VI. Conclusion

This article has presented a comprehensive study of cyber–physical security of modern EVs, with a particular focus on three representative components relevant to the powertrain system: 1) firmware of ECUs; 2) V2G in-vehicle charging system; 3) powertrain control system that includes system-level EMSs and device-level EDSs. For practical guidance, some preliminary results of security assessment on the powertrain control system are also presented, which are further divided into two major parts: the powertrain control system and the EDS. Finally, the state-of-the-artwork firmware, model-based, and data-driven detection, diagnosis, and mitigation opportunities are discussed comprehensively. Unique cyber–physical security challenges of powertrain systems and future versions are also discussed.

Appendix

Suppose that the prediction horizon is discretized into N_p steps on Δt-axis. Then, the EMS is designed by solving an optimization that find the optimal $u = [T_{\mathrm{ref},i}(1), T_{\mathrm{ref},i}(2), \ldots, T_{\mathrm{ref},i}(N_p - 1)] (i = 1, 2, 3, 4)$, such that

$$\min_{u \in \mathcal{U}} \mathcal{J} = \sum_{k=1}^{N_p} [(v(k) - v_{\mathrm{ref}}(k))^2 + \kappa V_{\mathrm{oc}}(k) I_{\mathrm{bat}}(k)] \tag{4}$$

where $T_{\mathrm{ref},i}$ represents the torque reference of the ith motor; v is the vehicle speed; v_{ref} is the desired vehicle speed of the upper drive controller; κ is the weighting factor; V_{oc} is the battery open-circuit voltage; I_{bat} is the battery current; and $\mathcal{U}$ is the closed set of admissible controls. In the above cost function, the first term illustrates the dynamic performance of the vehicle, which reflects the capability to track the velocity profile of the upper drive controller. The second cost denotes the power consumption of the battery. The nonlinear and time-varying system dynamics are summarized in [168]–[170] as follows:

$$v(k+1) = v(k) + \left[\sum_{i=1}^{4} T_{\mathrm{ref},i}(k)/r_w - \mathcal{G}(k)\right] \Delta t / M \tag{5a}$$

$$I_{\mathrm{bat}}(k) = [V_{\mathrm{oc}}(k) - \sqrt{V_{\mathrm{oc}}^2(k) - 4 P_{\mathrm{bat}}(k) R_b}]/2R_b \tag{5b}$$

where r_w is the tire radius; M is the total mass of the vehicle; $\mathcal{G}$ represents the total resistance during driving, including the rolling resistance, air resistance, and gravity resistance caused by road slope; P_{bat} is the power consumption of the battery; and R_b is the battery internal resistance. Finally, the first control command is applied to the lower system, and at the next time instance $k+1$, a receding horizon control is realized.

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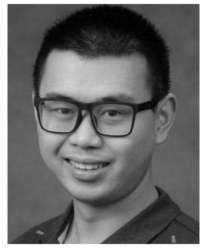

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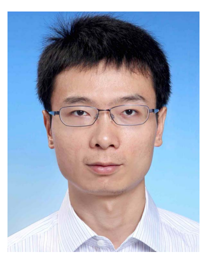

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