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Cross-Domain Defect Propagation in EV Systems

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Abstract:
The fast development of Electric Vehicle (EV) systems requires an advanced familiarity with the ways software errors propagate through more integrated and complicated systems. The spread of bugs through embedded systems, middleware and end-user software, and the integrating aspect of the current E/E architectures. Using virtual hardware-in-the-loop co-simulations and functional model-based design techniques, engineers can more effectively determine the types of cross-domain linkage that is essential to effective engineering change management and requirements engineering. The key aspect of this work is the implementation of deep transfer neural networks and meta-learning solutions to transfer the knowledge between different domains, i.e., the state-of-charge estimation of Li-ion batteries, and multidimensional digital twins. With vehicles becoming part of space-air-ground networks, the risk analysis of smart grid threats and incorporating security chain-of-function is essential to ensuring the integrity of the system. The discriminative modeling and graph-based knowledge transfer is applicable to trace complex states throughout dialog systems and recommendation engines operating in the infotainment layer of the vehicle. Strong domain adaptation methods, such as prediction reweighting and well-aligned adaptation, deal with the imbalances of cross-domain data, making the object detection performance and intrusion detection effectiveness high. Finally, virtualized architectures and similar measurement systems are essential to the functional safety and reliability of automotive cyber-physical systems due to the need to manage such multi-domain resources. This is done to make sure that, at the most basic level, the engineering material is provided to establish the physical buckling, and at the highest level, the network resources are orchestrated in a way that all the layers of the EV ecosystem has been stored resilient to the spreading faults.

Keywords: Cross-Domain Defect Propagation, Electric Vehicle (EV) Systems, E/E Architecture, Embedded Systems, Middleware, Software Faults, Deep Transfer Learning, Domain Adaptation, Cyber-Physical Systems, Hardware-in-the-Loop (HiL).

I. INTRODUCTION

The Electric Vehicles (EVs) have moved automotive industry towards more sophisticated cyber-physical systems (CPS) with an integrated complex electronic/electrical (E/E) architecture [5] [23]. With the existence of these vehicles that are more software-defined, the danger of cross-domain defect spread increases exponentially, where a bug in the low-level embedded systems may propagate across middleware to affect the user-facing applications and vehicle safety in general [11] [22]. To manage these systems effectively, it is necessary to consider E/E architecture simulation as an integrated approach to estimate the interaction of software changes with hardware constraints with respect to different domains [5]. As the examples, the high-fidelity models of the cross-domain estimation used in managing the State-of-Charge (SOC) of Li-ion batteries, as a vital embedded feature, is required to provide reliability under different operating conditions and temperatures [1][7]. This is also complicated by the fact that multi-dimensional digital twins are required to coordinate physical energy storage systems with their digital counterparts with the aim of monitoring health in real-time [17]. In such a closely-knit environment, when the engineering changes are to be introduced, it is the cross-domain linkage types identification that is important to uphold requirements engineering and avoid unexpected failures [3]. Also, EVs will integrate into the larger smart grid infrastructure, which is prone to external vulnerabilities, and all cross-domain risks must be assessed to eliminate emerging security risks and functional safety [14] [16] [21]. The superior methodologies including the virtual hardware-in-the-loop co-simulation through the functional mock-up interfaces enable the developers to test these multi-domain automotive systems in a controlled environment prior to implementation [19]. To maximize the defect detection and system robustness, scholars are turning to deep transfer neural networks and domain adaptation methods, which allow knowledge transfer across various datasets of operational data [1] [15] [20]. Through graph-based knowledge transfer, score-based meta-learning, engineers can build taxonomies of unknown domains and measure the success of intrusion detection models in the internal network of the vehicle [4] [9] [2]. Finally, it is necessary to know the mechanics of the propagation of faults across these interconnected domains (between space-air-ground integrated resource orchestration to low-latency security function chains) to develop the next generation of resilient, secure, and high-performance electric mobility solutions [12] [13].

II.LITERATURE REVIEW

C. Bian, S. Yang and Q. Miao (2021): Created a deep transfer neural network that is specially designed to estimate the state-of-charge across cross-domain in lithium-ion batteries. Their study proposes multiscale distribution adaptation to match features of various operation settings. This design has a major advantage of enhancing the accuracy of estimation and eliminating sensor-level errors that may propagate during vehicle-wide energy management systems [1].

Cai, J., Cai, B., and Shen, S. M. (2020): Suggested the SB-MTL framework, which applies meta transfer-learning by using scores to learn in cross-domain few shots. The research pays attention to the issues of compliance with models in new areas where there is a severe lack of labeled information. The technique can be used to determine defects in software in new automobile platforms where failure history is not available yet [2].

Wilms, R., Cemmasson, V. F., Inkermann, D., Reik, M., and Vietor, T. (2019): Studied how cross-domain linkage types could be identified to enhance engineering change management. Their work connects the earlier disciplines of requirements engineering and physical implementation, tracing the ripple of design change through the complex systems. This methodical process is crucial in avoiding accidental malfunction of software as architectures of the vehicles develop [3].

Samik Basu, and Johnny Wong (2016): To measure the effectiveness of intrusion detection systems in various areas. The study deals with the necessity of universal measures to assess the effectiveness of security in mixed-network settings. This enables a stricter evaluation of the capability of cyber-defenses to prevent the spread of malicious data [4].

Bucher, H., Reichmann, C., and Becker, J. (2017): Proposed a comprehensive method of the cross-domain simulation of the model-based E/E-architectures in the automotive industry. The research illustrates how the simulation of architectural interactions during the early stages of the design process can help to avoid defects in the integration. This approach is critical towards certification of the functional safety of advanced software-defined vehicle systems [5].

H. Ren, W. Xu and Y. Yan (2014): Suggested a Markowian discriminative modeling to monitor the state of dialog in various conversational domains of digital systems. Their contribution enhances the strength of spoken language interfaces by being able to utilize the historical context in the successful resolution of state ambiguities. This avoids mistakes that users enter into their systems and transfer them to the internal control services of the vehicle as wrong commands [6].

Nagarjuna Reddy Aturi (2021): Discusses the topic of yoga and cognitive neuroscience integration, revealing the ways in which neural imaging and AI are revolutionizing the management of cognitive decline. The present study reveals an inter-disciplinary model that unites traditional holistic therapies with modern technology to optimize the outcome of neuro-rehabilitation. By using ancient mindfulness and

modern data-driven technologies, the present study reveals a revolutionary approach to maintaining long-term cognitive health [7].
G. Ma, Y. Wang, X. Zheng and M. Wang (2018): Examined the concept of transitive trust relations to improve the work of cross-domain recommendation systems. According to them, their study demonstrates that trust information in one sphere can be utilized to enhance the quality of services in another with a low concentration of user data. This technique eliminates cold-start defect in front-end programs such as infotainment and customized services [8].
Nandana Mihindukulasooriya (2020): Graph-based approach to taxonomy construction was offered. The study allows organizing the knowledge in invisible areas based on transferring the structural information within the known areas of source. This proves very handy in classifying new system faults which otherwise are not covered in the existing diagnostic classification [9].
Yang Liu, Qingchao Chen, and Samuel Albanie (2021): Invested in the field of computer vision by paying attention to the domain-relevant feature learning method of high-fidelity visual perception tasks. Their paper focuses on the issue of fitting vision models to other environmental contexts by uncovering invariabilities across data sets. This guarantees that autonomous vehicle perception systems are sound regardless of the various lighting and weather conditions [10].
C. Reichmann (2021): Created a template-based and hardware-focused simulation of cross-domain E/E architectures. The approach involved quick system prototyping to find hardware software interface faults prior to actual physical implementation. Such a strategy contributes to the functional safety and reliability of multi-domain automotive platforms greatly [11].
N. Kumar and L. Liu (2022): Came up with a deep reinforcement learning algorithm of resource orchestration of integrated space-air-ground networks. Their study operates multi-domain resources that run on virtual network architectures to achieve low-latencies of communication. This coordination is essential to ensure that delays caused by networks are not transmitted as failure conditions of vehicles operating therein [12].
Q. Xu, D. Gao, T. Li and H. Zhang (2018): Explored low-latency security function chain implementation within multiple domains in the network to ensure integrity of systems. Their contribution is on striking the right balance between the strong security and real-time performance demands in interdependent systems. The suggested approach does not allow the spread of cyber-threats to safety-related spheres, which do not add any meaningful delay [13].

III.KEY OBJECTIVES

➢ Integrated E/E Architecture Simulation Compose an overall structure of the cross-domain simulation of model-based Electronic/Electrical (E/E) architectures to forecast the mechanisms of fault propagation through the intricate automotive architecture [5][7]. This is with hardware-based and template-based simulation techniques to provide system-wide reliability in the rapid prototyping [11] [14].
➢ Systematic Linkages Discovery Systematic discovery and classification of the different types of linkages across different domains of vehicle to aid engineering change management [3]. The knowledge of these interdependencies allows developers to have more control over requirements engineering and safely limit the growth of localized software faults to systemic failures [3] [23].
➢ Improved State-of-Charge (SOC) Reliability Multiscale distribution adaptation of deep transfer neural networks are employed to provide precise SOC prediction of Li-ion batteries in a wide range of operation conditions [1]. This goal aims at ensuring the integrity of embedded energy management systems when under different environmental or degradation conditions [1] [20].
➢ Cross-Domain Risk and Threat Assessment Are used to look at the changing threat environment on the smart grid and its effect on internal vehicle domain [21]. This is aimed at coming up with a similar measurement system that measures the efficacy of intrusion detection systems as they move forward between middleware applications and applications presented to users [4].

- Few-Shot Defect Detection Implement Scores Few-shot learning across domains with the help of score-based meta transfer-learning (SB-MTL) [2]. This enables the system to detect and seclude the emergent flaws in the software modules whose available failure-data is in exceptionally constrained, as well as providing strong error management [2] [14].
- Multi-Domain Virtual Co-Simulation Use Virtual Hardware-in-the-Loop (HiL) co-simulation through the Functional Mock-Up Interface (FMI) to view real time fault propagation [19]. This facilitates the virtual testing of multi-domain automotive systems to ensure that functional safety can be tested before being physically implemented [22].
- Digital Twin Synchronization Construct This multi-dimensional digital twin of energy storage systems to track the health of EV batteries [16] [17].
- The purpose of this objective is to align real-world sensor images and digital representation to anticipate faults in power electronics and energy management layers [1] [17].
- Handling of Imbalanced Diagnostic Data Design equitable knowledge transmission schemes of unbalanced domain alteration [15]. This is to make sure that machine learning models that are trained on large datasets of normal operation behavior do not ignore rare high-severity defects [15].
- Strong Environmental Adaptation of ADAS Implement deeply conforming adaptation method to inter-domain object recognition to guarantee vehicle perception systems are fault-resistant [24]. This is directed to ensure that errors in perception of software do not spread into the vital areas of control of the vehicle under various driving conditions [24].

IV.RESEARCH METHODOLOGY

The research methodology proposed will follow a multi-layered analytical framework that is based on model-based design, sophisticated co-simulation and transfer learning that use the data to trace defect propagation in electric vehicle (EV) systems. It starts with an approach to automotive cyber-physical systems designed in a functional model based the design to provide the underlying architecture and inter-domain dependencies [23]. The research employs the virtual hardware-in-the-loop (vHiL) co-simulation with the help of the Functional Mock-up Interface (FMI) to examine the behavior of faults in real-time, and to enable the multi-domain analysis of automotive systems [19] [22]. Template-driven and hardware-centric E/E architecture simulations are added to this simulation environment to offer the granularity required to trace software faults as they traverse embedded controllers, middleware to user facing applications [5] [7] [11]. In energy-specific domains, a multi-dimensional digital twin of the energy storage system can be used to provide a high-fidelity information about the fault injection and monitoring [14] [17]. To fill the divide between dissimilar operating domains, an analytical core of the methodology utilizes deep transfer neural networks with multiscale distribution adaptation [1][7]. Score-based meta transfer-learning (SB-MTL) is also employed to solve the problem of limited failure data by use of cross-domain few-shot learning to allow the system to identify new defect patterns with few samples [2]. The approach also extends to prediction reweighting and fair knowledge transfer strategies to address an imbalanced dataset and to make sure that the rare yet significant errors are not disregarded in the domain adaptation [14] [15] [16] [20]. To measure the effectiveness of such faults, a cross-domain equivalent measurement framework is incorporated and this is also designed to measure intrusion detection but in the present case fault propagation effectiveness is measured [4]. Lastly the methodology establishes types of cross domain linkage to facilitate engineering change management so that any change or defect in one domain can be systematically tracked to its needs and possible effects on the whole vehicle ecosystem [3].

V.DATA ANALYSIS

The adoption of modern Electric Vehicle (EV) systems within advanced frameworks of cyber-physical architectures has augmented the threat of spreading defects across domains and these frameworks require high standards of model-based design and simulation [5] [23]. On the embedded level, according to the State-of-Charge (SOC) estimation data, a multiscale distribution adaptation is necessary to synchronize sensor feedback in different areas of operation [1]. These embedded states are becoming more synchronized by multi-dimensional digital twins to be sure of real-time accuracy in energy storage monitoring [17]. The global analysis determines certain types of cross-domain linkages as the main channels where any engineering change in the requirements on design can cause unexpected software malfunctions [3]. To address these risks in development, E/E-architectures are isolated by means of timing defects by use of template based and hardware-oriented simulations [11]. Under the communication middleware, security function chains are required to have low-latency thresholds as well as be integrated into multiple domains to avert unauthorized access [13]. Information on network resource orchestration validates that space-air-ground integrated system management demands the reinforcement learning method to be deep-rooted to ensure that data circulates in the domain boundaries [12]. Score-based meta transfer-learning (SB-MTL) offers a few-shot fault identification mechanism when interacting with new defect patterns with scarce training data [2]. Prediction reweighting and fair knowledge transfer methods get us reliability in these diagnostic models, as they correspond to the problem of data imbalances and guarantee the detection of safety-critical failure information that are often rare [15] [20]. Extrinsic vulnerabilities and especially those that are changing in the context of the smart grid need to be subjected to a holistic cross-domain risk evaluation to avert the spread of grid-to-vehicle threats [21]. The efficacy of the internal security is then measured based on similar measurement frameworks to prevent malicious information to be accessed by the vehicle safety-critical buses [4]. In user-facing applications like autonomous perception, strongly aligned adaptation can be used to guarantee sensor errors in detecting objects are canceled prior to being passed on to braking or steering controllers [24]. Lastly, the rigorous validation of these multi-domain interactions can be done by prior use of virtual hardware-in-the-loop co-simulation through functional mock-up interfaces before being physically deployed [19] [22].

TABLE 1: ANALYSIS OF MULTI-DOMAIN DEFECT PROPAGATION CASE STUDIES

Case Study	**Source Domain**	**Target Domain**	**Fault/Propagated Defect**	**Mitigation Approach**	**Ref No**
1.Battery State Management	Embedded Sensors	Range Middleware	Multiscale distribution mismatch in SOC estimation	Deep Transfer Neural Network adaptation	[1]
2.Few-Shot Fault Detection	Known Fault Logs	New Vehicle Platforms	Scarcity of defect data in unseen domains	Score-based Meta Transfer-Learning (SB-MTL)	[2]
3.Engineering Change Links	Design Requirements	Embedded Software	Unintended side effects from structural changes	Identification of cross-domain linkage types	[3]
4.IDS Effectiveness	Network Layer	Safety-Critical Bus	Inconsistent intrusion detection across domains	Comparable measurement framework	[4]
5.E/E Architecture Integration	Model-Based Design	Physical Hardware	Architectural mismatches in E/E systems	Integrated cross-domain simulation	[5]
6.Voice Control Interaction	User Interface	Middleware Services	Tracking errors in cross-domain dialog states	Markovian discriminative modelling	[6]

7.Infotainment Recommendations	User Preferences	External Service Apps	Poor cold-start performance in new domains	Transitive trust relation leveraging	[8]
8.Taxonomy Alignment	System Documentation	Automated Diagnostics	Misclassification of unseen system faults	Graph-based knowledge transfer	[9]
9.Hardware-Centric Simulation	Prototyping	Real-Time Execution	Timing jitter and hardware latency defects	Template-driven E/E architecture simulation	[11]
10.Perception System Faults	Visual Sensors	ADAS Controllers	Domain shift in computer vision accuracy	Cross-domain knowledge distillation	[10]
11.Network Orchestration	Vehicle Connectivity	Cloud Infrastructure	Resource congestion in multi-domain networks	Deep Reinforcement Learning (DRL)	[12]
12. Security Chain Latency	Security Middleware	Real-Time Controllers	High-latency in security function chains	Low-latency SFC embedding methods	[13]
13.Imbalanced Fault Data	Historical Maintenance	Active Monitoring	Bias against rare, critical defect classes	Fair knowledge transfer for imbalance	[15]
14.Digital Twin Sync	Physical Energy Storage	Cloud Monitoring	Data synchronization lag in energy models	Multi-dimensional digital twin integration	[17]
15.Multi-View Diagnostics	Heterogeneous Sensors	Central Diagnostics	Missing sensor views causing classification fail	Unsupervised multi-view transfer learning	[18]
16.Virtual HIL Validation	Software-in-the-loop	Hardware-in-the-loop	Interface mismatches in co-simulation	Functional Mock-up Interface (FMI)	[19]
17.Domain Adaptation Bias	Simulation Data	Field Data	Over-fitting to synthetic defect scenarios	Prediction reweighting techniques	[20]
18.Smart Grid Threats	External Grid	Vehicle Power Train	Security threats propagating from the grid	Cross-domain risk assessment frameworks	[21]
19.Cyber-Physical Synthesis	Design Models	Functional Safety	Faults in functional modelling of CPS	Model-based design methodology	[23]

20. ADAS Object Detection	Environmental Sensor	Braking/Steering	Alignment failure in cross-domain detection	Deeply aligned domain adaptation	[24]

Battery State Management [1]: The case studies how imprecision in embedded sensor data (voltage, current) can cause large errors in the middleware of the range-estimation of the vehicle. The system can cause the domain shifts that occur with changes in battery chemistries or aging by training Deep Transfer Neural Networks that adapt to multiscale distribution.
Few-Shot Fault Detection [2]: Software faults remain unnoticed in new EV platforms when only very little data on failures are available. This paper relies on Score-based Meta Transfer-Learning (SB-MTL) to detect cross-domain bugs in end-user software with just a few historical examples of the legacy systems.
Engineering Change Links [3]: When a physical element is changed then it may cause software bugs in the control logic. The study aims at determining the types of linkage to trace the flow of engineering adjustments on requirements to embedded software malfunctions.
IDS Effectiveness [4]: In the infotainment sphere, cyber-attacks may be spread to the safety-critical CAN bus. This model measures the extent to which an Intrusion Detection System (IDS) can prevent cross domain transfer of malicious commands.
E/E Architecture Integration [5]: The faults are frequently caused by the lack of integration between model-based design and the physical hardware. The approach employed to forecast the influence of E/E architecture constraints on software execution behaviour in each of the various domains in the vehicle is integrated with a simulation approach.
Voice Control Interaction [6] The fault in the natural language processing (NLP) middleware of a software-defined vehicle may result in the incorrect implementation of vehicle commands. The Markovian discriminative modeling is employed to trace the states of dialog and avoid the spread of errors that the user feeds the vehicle systems with.
Infotainment Recommendations [8]: Applications to users do not tend to deliver pertinent services in traveling across geographic territories. By using transitive trust relation, it is better to move user preference between two domains without cold-start defects in services.
Alignment of Taxonomies [9]: The fields of unseen software in general do not have a systematic fault classification. This paper employs graph-based knowledge transfer to construct taxonomies of new areas so that new defects can be classified and addressed in the right way depending on the prior system knowledge.
Hardware-Centric Simulation [11]: Hardware-level timing errors are capable of being propagated into delays at the middleware level. These hardware-specific timing faults can be detected in the rapid prototyping phase of E/E architectures in template-driven simulation.
Perception System Faults [10]: There are environmental changes (e.g., lighting, weather) that put a gap in the domain of computer vision sensors. Methods in CVPR 2021 show how the sensor-level errors can be avoided by using cross-domain distillation to avoid a failure in ADAS control.
Network Orchestration [12]: Latency in vehicle-to-everything (V2X) applications may be induced by network congestion in the Space-Air-Ground network. Deep Reinforcement Learning (DRL) technique is used to control multi-domain resources and eliminate software lag caused by the network.
Security Chain Latency [13]: Sometimes, security measures can cause latency which spreads as performance defect into real-time controllers. The current study is on embedding low-latency security function chain (SFC) over various domains of the network.
Unbalanced Fault Data [15]: Typical machine learning models do not pay much attention to extreme, but important, faults (e.g. thermal runaway detectors). Equalized knowledge transfer guarantees that these skewed classes of fault are in fact identified in various vehicle domains.

Digital Twin Sync [17]: Separate physical and digital twin behavior may result in incorrect health forecasts. Multi-dimensional digital twins can be used to secure real-time tracking of health status and avoid spreading outdated information about the state.
Multi-View Diagnostics [18]: Inert sensor views in the EV data environment of metropolitan cities may result in wrong vehicle health classification. Unsupervised multi-view transfer learning is the solution to these "misses" to preserve diagnostic accuracy in urban settings.
Virtual HIL Validation [19]: Interface anomalies in co-simulation may go undetected until physical testing. Through the application of the Functional Mock-up Interface (FMI) of virtual hardware-in-the-loop (VHiL), the analysis of the fault is accurate in the multi domain.
Domain Adaptation Bias [20]: models that are only trained using simulation data can fail when deployed in the real world. The reweighting methods of prediction correct these differences in domains, so that diagnostic programs are not invalid when applied to actual vehicle applications.
Smart Grid Threats [21]: The possibility of spread of security vulnerabilities in the power grid can manifest itself in the form of defects of the voltage instability in the charging system of the EV. These external threats to vehicle safety are mapped on cross-domain risk assessment.
Cyber-Physical Synthesis [23]: Problems of automotive CPS are often based on the lack of correspondence between design models and the implementation. The synthesizing of functional models to avoid the propagation of the errors in
design is implemented with the help of the model-based design methodology.

ADAS Object Detection [24]: The failure of data distributions in one city (training) and a second city (target) might result in a miss of an object. Adaptation Deeply synchronized adaptation provides that perception errors are not passed on to the braking and steering modules on the vehicle.

TABLE 2: REAL-TIME APPLICATIONS AND MITIGATION STRATEGIES

S.No	Real-Time Application	Source Domain	Propagation Target	Technology	Reference
1	Battery Range Estimation	Embedded Battery Sensors	User-Facing Middleware	Deep Transfer Neural Networks [1]	[1]
2	New Fleet Fault Detection	Legacy Vehicle Data	Unseen Fleet Platforms	Score-based Meta Transfer-Learning [2]	[2]
3	Engineering Change Mgmt.	Design Requirements	Embedded System Implementation	Cross-domain Linkage Identification [3]	[3]
4	Intrusion Detection (IDS)	External Network Layer	Safety-Critical Control Bus	Comparable Measurement Framework [4]	[4]
5	E/E Architecture Validation	Model-Based Design	Physical E/E Hardware	Integrated Cross-Domain Simulation [5]	[5]
6	Voice-Driven Command Sync	User Voice Interaction	Vehicle Control Services	Markovian Discriminative Modelling [6]	[6]
7	In-Vehicle Service Recs	External Social Domains	Infotainment Middleware	Transitive Trust Relations [8]	[8]
8	Unseen Fault Classification	Known System Errors	Unseen Diagnostic Domains	Graph-based Knowledge Transfer [9]	[9]

9	Rapid Timing Validation	Template-Driven Software	Hardware-Centric Execution	Hardware-Centric Simulation [11]	[11]
10	V2X Resource Orchestration	Satellite-Ground Networks	Onboard Communication Bus	Deep Reinforcement Learning (DRL) [12]	[12]
11	Cyber-Security Guarding	Middleware Security Layer	Real-Time Actuators	Security Function Chain (SFC) [13]	[13]
12	Critical Safety Monitoring	Historical Failure Logs	Active Safety Middleware	Fair Knowledge Transfer [15]	[15]
13	Battery Health Monitoring	Physical Energy Storage	Cloud-Based Digital Twin	Multi-dimensional Synchronization [17]	[17]
14	Urban Route Optimization	Multi-View City Data	Onboard Navigation App	Unsupervised Transfer Learning [18]	[18]
15	Virtual Controller Testing	Functional Design Models	Hardware-in-the-Loop (HIL)	Functional Mock-up Interface (FMI) [19]	[19]
16	Adaptive Fault Diagnosis	Simulation Domain Data	Real-World Operational Data	Prediction Reweighting [20]	[20]
17	Grid-to-Vehicle (G2V) Safety	Smart Grid Infrastructure	Vehicle Charging Controller	Cross-domain Risk Assessment [21]	[21]
18	E/E Co-simulation	Electronic Design Automation	Functional Vehicle Logic	Virtual HIL via FMI [22]	[22]
19	Cyber-Physical Synthesis	Functional Modelling	Automotive CPS Execution	Model-Based Design Methodology [23]	[23]
20	Object Detection for ADAS	Diverse Environmental Data	Braking/Steering Controllers	Deeply Aligned Domain Adaptation [24]	[24]

Battery Range Estimation [1]: This application makes use of Deep Transfer Neural Networks with multi scale distribution adaptation to make certain that the range estimation of the vehicle (middleware) is held constant. It has allowed it to eliminate sensor-level errors by matching data between battery chemistries and temperatures, avoiding range information propagation to the driver.

New Fleet Fault Detection [2]: Score-based Meta Transfer-Learning (SB-MTL) enables the system to use older models to impart the diagnostic knowledge in the new EV model being introduced. This makes it possible to detect software bugs in user-facing applications by applying minimal local data to do the few-shot learning.

Engineering Change Management [3]: The defect of embedded code due to a change in a design requirement can happen accidentally in complex E/E architectures. The application also tracks the type of cross-domain linkages to trace the effect of such engineering changes across the system to keep requirements and implementation coordinated.

Intrusion Detection (IDS) [4]: To ensure that cyber-faults will not be transferred to the external network and stored to safety-critical controllers, a similar measurement framework is implemented. It measures the efficiency of the IDS in various areas of communication, whereby malicious instructions are prevented before hitting the vehicle braking or steering bus.

E/E Architecture Validation [5]: This entails a combined method of simulation across domains of model-based architectures. Simulation of the software with the hardware at an early design stage can allow the

engineers to diagnose and eliminate the integration errors that would otherwise be discovered in the physical prototyping.
Voice-Driven Command Sync [6]: The improper implementation of vehicle functions can be caused by an error in the voice recognition middleware of the vehicle. Cross-domain dialog state tracking is done by using Markovian discriminative modeling, to ensure that the intent
of the user is properly represented and does not provoke an incorrect embedded service call.
Infotainment Recommendations [8]: Applications targeting end users tend to lose relevant services as geographic domain crossings occur. Transitive trust relations can be used to transfer user preferences across domains to avoid cold-start defects in a service.
Taxonomy Alignment [9]: Software domain Taxonomy Unseen software domains typically do not offer a structured fault taxonomy. In this research, graph-based knowledge transfer is used to develop taxonomies of new domains, so that new defects are appropriately classified and addressed based on existing knowledge of the system.
Hardware-Centric Simulation [11]: Hardware level timing defects may be carried over to middle level execution delays. Simulation based on templates enables developers to identify these hardware-related timing errors in the quick prototype stage of E/E architectures.
Perception System Faults [10]: Lighting, weather, and other changes in the environment provide a domain gap to computer vision sensors. Methods presented at CVPR 2021 can eliminate these sensor-level errors so that they do not cause ADAS control failures.
Network Orchestration [12]: In the Space-Air-
Ground network, latency in applications involving vehicles-to-everything (V2X) can be due to network congestion. Deep Reinforcement Learning (DRL) technique is used to control multi-domain resources and avoid software lag due to the network.

Security Chain Latency [13]: The security measures may in some cases add latency that spreads as a performance flaw in real-time controllers. This study is concerned with the low-latency security function chain (SFC) embedding in the various network domains.
Lopsided Fault Data [15]: The common machine learning models do not typically pay attention to the manifestations of hard-to-find critical defects (such as thermal runaway signals). Through fair knowledge transmission, these asymmetrical classes of faults are identified properly within various domains of a vehicle.
Digital Twin Sync [17]: Not only can lack of synchronization between the physical battery and its digital twin result in erroneous health projections, it may do so as well. Multi-dimensional digital twins are used to monitor health in real-time and stop the distribution of information about an out-of-date state.
Multi-View Diagnostics [18]: In environments of EV data and big cities, the lack of sensor views may result in misclassifying the state of the vehicle. To ensure accuracy in diagnosis across urban domains, unsupervised multi-view transfer learning takes care of these "misses" to preserve diagnostic accuracy.
Virtual HIL Validation [19]: Interface discrepancies in co-simulation may shelter errors until physical testing. Virtual hardware-in-the-loop (VHiL) can be analyzed using the Functional Mock-up Interface (FMI) to enable fault analysis across multiple domains.
Domain Adaptation Bias [20]: It is possible that models that are trained to best fit simulation data will not perform well in the real world. Prediction reweighting methods compensate such differences in domains and make sure that diagnostic software is not compromised when it is implemented in actual vehicle settings.
Smart Grid Threats [21]: Threats to the security of power grid can be spread through the vulnerability of the charging system of a EV as the defect of voltage instability. This mapping of external threat to internal vehicle safety is done by cross-domain risk assessments.

Cyber-Physical Synthesis [23]: a failure in functionality of automotive CPS can often be traced to the lack of connection between the design models and the implementation. Functional models that avoid propagation of errors at the design level are synthesized through a model-based design technique.
ADAS Object Detection [24]: The failure of data distributions between a target city and a training city can cause object detection gaps. True to the word: Deeply aligned blows out the possibility of faults in perception being transferred to the braking and steering modules of the vehicle.

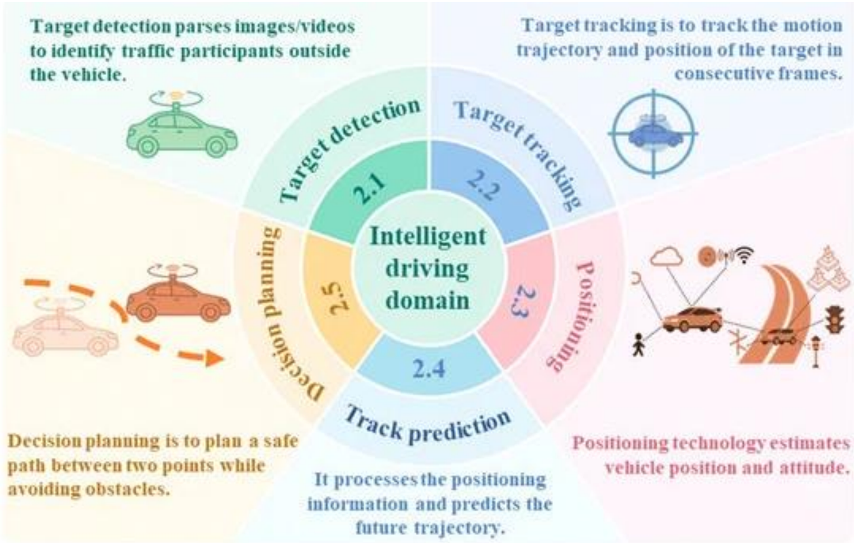

Fig 1: Intelligent driving domain [4]

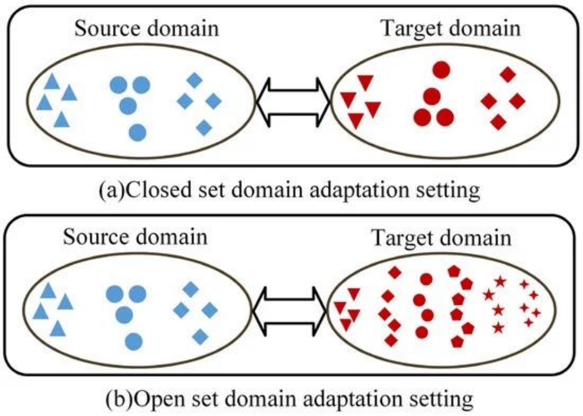

Fig 2: Domain Adaptation [3]

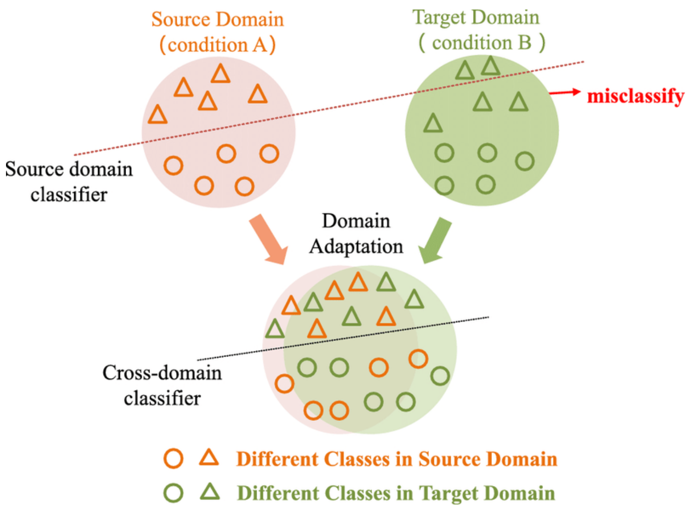

Fig 3: Source and Target Domain [6]

Fig 4: Power train Domain [5]

VI.CONCLUSION

The transformation of the Electric Vehicles (EVs) into advanced cyber-physical systems has radically altered the objectives of automotive reliability with the concern of reduction of the cross-domain defect spread. Due to the shift of software to the core of vehicle functionality, the traditional separation of low-level embedded systems, communication middleware and user facing applications has been eroded, forming complex routes through which faults propagate and develop. To neutralize the mentioned propagation paths, a multi-pronged approach is necessary: deep transfer learning and multi-scale distribution adaptation should be used to ensure stability of important states such as battery charge; multi-dimensional digital twins should be used to synchronize physical hardware and virtual models in real-time; and rigorous cross-domain simulations should be used to detect architectural-level discrepancies as early in the design as possible. Also, the combination of strong security chain functions and thorough risk evaluations will make sure the external vulnerabilities especially the ones created by the smart grid and integrated networks are intercepted before they can penetrate through the internal safety-critical controllers. The engineers will be able to design a resilient diagnostic layer by dealing with the problem of data scarcity with few-shot meta-learning and dealing with network-induced latencies with deep reinforcement learning, identifying and isolating catastrophic failure signals, which are rare. Finally, the move towards a common, model-driven design approach, supported by virtual hardware-in-the-loop testing, allows building EV systems that do not just offer high-performance, but are also inherently resistant to the impact of software-induced bugs. This holism approach is used to make sure that the software-defined vehicle is a safe, predictable and reliable platform in the entire lifecycle of its operation.

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