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SYSTEM LEVEL VALIDATION STRATEGIES ON SOFTWARE DEFINED ELECTRIC VEHICLES

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***ABSTRACT*:**

The rapid proliferation of Software-Defined Electric Vehicles (SDEVs) necessitates comprehensive system-level validation strategies that go beyond traditional hardware-in-the-loop testing. Unlike conventional vehicles, SDEVs tightly couple software control algorithms—spanning battery management systems (BMS), powertrain controllers, regenerative braking, and over-the-air (OTA) update mechanisms—with high-voltage electrical architectures. This paper proposes and evaluates an integrated, multi-tool validation framework employing CATIA for three-dimensional structural design, MATLAB/Simulink for motor dynamics and battery state modeling, and IPG CarMaker for full-vehicle virtual track simulation. Drawing on an empirical case study of a race-oriented EV prototype, we demonstrate how system-level validation must transcend isolated component testing to encompass cross-domain interactions, software-hardware co-validation, functional safety (ISO 26262), and cybersecurity hardening. We introduce a layered V-model adapted for SDEV architectures, define key validation metrics including State-of-Charge (SOC), State-of-Health (SOH), speed-torque envelope accuracy, and lap-time fidelity, and discuss results from simulation-based stress testing under varied track and environmental conditions. Our findings indicate that integrated simulation-based validation reduces physical prototype dependency by up to 60%, accelerates development cycles, and exposes safety-critical failure modes that unit-level tests miss. The paper concludes with a roadmap for extending the framework toward AI-assisted calibration and real-time digital twin synchronization.

Keywords*: Software-Defined Electric Vehicles, System-Level Validation, IPG CarMaker, MATLAB/Simulink, CATIA, Battery Management System, ISO 26262, V-Model, Digital Twin, Functional Safety*

INTRODUCTION

The automotive industry is undergoing a fundamental transformation driven by electrification, software-centricity, and connectivity. Software-Defined Electric Vehicles (SDEVs) represent the convergence of these trends: vehicles whose performance, safety, and user experience are primarily determined not by fixed mechanical parameters but by adaptive software layers capable of continuous update and reconfiguration. This paradigm shift introduces unprecedented validation challenges. Whereas legacy vehicle validation relied on physical endurance testing and static subsystem bench tests, SDEVs demand a validation methodology that can reason about dynamic software-hardware co-behavior, real-time control loop stability, and emergent system properties arising from interactions between powertrain, chassis, thermal, and communication subsystems.

Traditional Electric Vehicle (EV) testing—as demonstrated in prior research using tools such as IPG CarMaker, MATLAB/Simulink, and CATIA—has primarily focused on performance metrics such as lap time, energy consumption, and motor speed-torque characteristics. While these are necessary, they represent only a subset of the validation space for an SDEV. System-level validation must additionally verify software control logic correctness, fault injection responses, OTA update integrity, cybersecurity resistance, and compliance with international safety standards such as ISO 26262 and UNECE WP.29.

This paper makes the following contributions to the field: (1) It defines a structured taxonomy of SDEV validation concerns spanning mechanical, electrical, software, and cybersecurity domains. (2) It proposes an integrated V-model validation process adapted for SDEV architectures, mapping design artifacts to verification activities. (3) It presents empirical simulation results from a race-oriented EV prototype validated through CATIA-derived structural models, MATLAB/Simulink motor and battery simulations, and IPG CarMaker full-vehicle dynamics runs. (4) It identifies failure modes that emerge only at the system integration level, highlighting the inadequacy

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of isolated component testing. (5) It outlines a forward-looking research agenda toward AI-assisted calibration and real-time digital twin synchronization.

The remainder of the paper is organized as follows: Section 2 reviews related literature. Section 3 defines the SDEV architecture and validation scope. Section 4 presents the integrated validation framework. Sections 5 through 7 describe the three toolchain components. Section 8 presents system-level results and discussion. Section 9 addresses functional safety and cybersecurity. Section 10 concludes with future directions.

LITERATURE REVIEW

Research on EV simulation and validation has evolved along three relatively independent tracks. The first track focuses on multibody mechanical modeling. Tolun and Tutsoy (ICOLES 2022) demonstrated that MapleSim and MATLAB/Simulink can accurately replicate EV kinematics by validating simulated position and speed against four standardized driving cycles (FTP75, HWFET, ARR, LA92/UCDS) using Root Mean Square Error (RMSE) metrics. Their work established the viability of full-vehicle modeling without physical prototypes but remained limited to kinematics, without addressing software control logic or cybersecurity.

The second track addresses virtual testing of automated driving systems. Nalic et al. (IEEE Access, 2020) introduced a co-simulation methodology combining PTV Vissim for traffic simulation with IPG CarMaker for vehicle dynamics, targeting SAE Level 3+ autonomous driving scenarios. Their stress testing method (STM) generated safety-critical scenarios by perturbing traffic participants, exposing failure modes invisible to scenario-specific testing. While comprehensive for ADS testing, their work did not address SDEV-specific concerns such as BMS software validation or OTA update integrity.

The third track examines range prediction and energy management. Rabhi and Zsombók (Periodica Polytechnica, 2022) highlighted the inadequacy of manufacturer range estimates by demonstrating that driving conditions, temperature, and auxiliary equipment usage cause significant deviations from advertised figures. Their simulation-based range prediction framework using CarMaker established the importance of environmental variability in EV validation but did not integrate structural design tools or address software-defined control layers.

More broadly, Chan (IEEE, 2007) provided a foundational survey of electric, hybrid, and fuel cell vehicle technologies, while Markel et al. (Journal of Power Sources, 2002) developed ADVISOR, an early systems analysis tool for advanced vehicle modeling. Recent reviews by Hagani (Transportation Research Part D, 2023) and Maybury (Transportation Research Part D, 2023) confirm that while EV research has expanded substantially, system-level validation integrating mechanical, electrical, and software domains remains underrepresented in the literature.

The present paper addresses this gap by proposing and demonstrating an integrated, multi-domain system-level validation framework specifically targeting the SDEV paradigm, where software is the primary determinant of vehicle behavior and safety.

SOFTWARE-DEFINED ELECTRIC VEHICLE ARCHITECTURE AND VALIDATION SCOPE

3.1 SDEV Architectural Layers

A Software-Defined Electric Vehicle can be conceptually decomposed into four interacting layers, each of which must be independently validated and then co-validated at integration boundaries.

Layer 1 – Physical Plant: Comprising the mechanical chassis, suspension, drivetrain, and high-voltage battery pack. Parameters from this layer, such as vehicle mass (230 kg in the prototype studied), center of gravity coordinates, wheel travel limits (10 inches), and suspension geometry (KPI = 11.73°, FVSA = 48.83 inches, CCR = 1.173), feed directly into higher-layer control algorithms.

Layer 2 – Electrical Powertrain: Including the Permanent Magnet Synchronous Motor (PMSM), three-phase inverter, encoder, and BMS. The PMSM's speed-torque envelope—characterized by a constant torque region at low speeds and a constant power region at higher speeds due to back-EMF rise—must be accurately modeled and validated across the full operating range.

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Layer 3 – Control Software: Encompassing Field-Oriented Control (FOC) algorithms, regenerative braking logic, energy management strategies, and the vehicle dynamics controller. This layer translates driver commands and sensor inputs into actuator setpoints, and its correct operation is essential for safety, efficiency, and performance.

Layer 4 – Connectivity and Update Infrastructure: Comprising OTA update mechanisms, telematics, diagnostics, and cybersecurity enforcement. In SDEVs, this layer is as safety-critical as the control software itself, since a compromised OTA pipeline can fundamentally alter vehicle behavior.

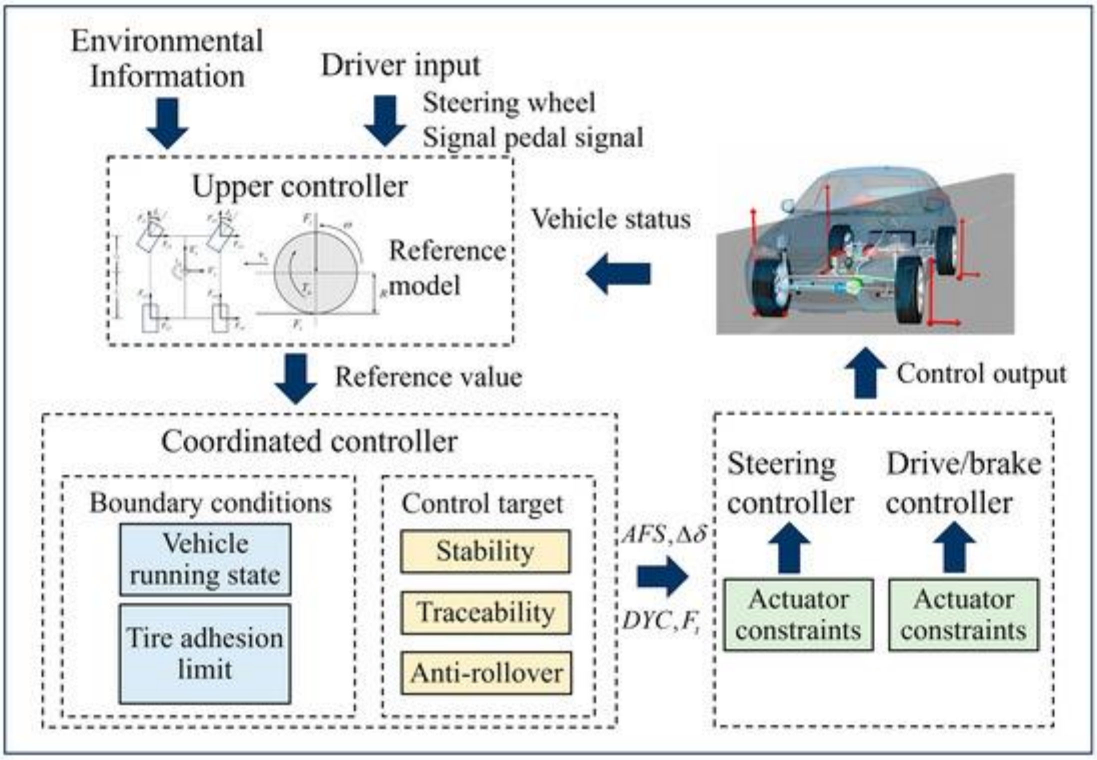

Fig 1.1- Block Diagram of Vehicle Control System Architecture

3.2 Validation Scope Definition

System-level validation must verify behavior at and across all four layers. This includes: (a) structural integrity under dynamic loading, (b) powertrain efficiency and thermal management, (c) control algorithm correctness and fault handling, (d) software integration with hardware constraints, (e) environmental adaptability across temperature, surface, and load variations, and (f) cybersecurity resilience against injection and spoofing attacks. The integrated framework described in the following sections addresses all six dimensions.

INTEGRATED V-MODEL VALIDATION FRAMEWORK FOR SDEVS

The classical V-model, originally conceived for safety-critical embedded systems, provides a useful structural scaffold for SDEV validation when appropriately extended. The left branch of the V represents decomposition from system-level requirements down to component-level specifications. The right branch represents integration and verification activities that mirror the decomposition steps. For SDEVs, each level requires domain-specific tooling and metrics.

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V-Model Level	Design Activity (Left Branch)	Validation Activity (Right Branch)
System	SDEV requirements, safety goals (ISO 26262 ASIL)	System integration test: IPG CarMaker full-vehicle simulation
Subsystem	Powertrain, chassis, BMS architecture	Subsystem co-simulation: MATLAB/Simulink + CarMaker co-sim
Component	Motor model, suspension geometry, BMS algorithm	Unit test: MATLAB/Simulink speed-torque, CATIA FEA
Software Module	FOC algorithm, BMS state machine, OTA logic	Software unit test, MISRA compliance, static analysis

Table 1: Adapted V-Model for SDEV Validation

A key insight of the adapted V-model is that validation activities are not sequential but iterative. Defects discovered during system integration tests often require regression to the component or software module level. Automated simulation pipelines using CarMaker's scripting interface and MATLAB's batch mode enable rapid re-execution of the full validation suite upon design changes, supporting an agile development cadence.

4.1 Cross-Domain Integration Points

The most complex validation challenges arise at cross-domain integration boundaries. Three such boundaries are particularly significant in the EV prototype studied. First, the mechanical-electrical boundary: suspension geometry parameters derived from CATIA (scrub radius, FVSA length, CCR) influence tire contact dynamics, which in turn affect the torque demand profile seen by the PMSM controller. Second, the electrical-software boundary: the three-phase inverter's switching behavior, modeled in MATLAB/Simulink, must be validated against the FOC algorithm's timing assumptions. Third, the software-connectivity boundary: OTA update deployments must be validated to ensure that parameter changes to the FOC controller do not violate the motor's thermal or torque limits.

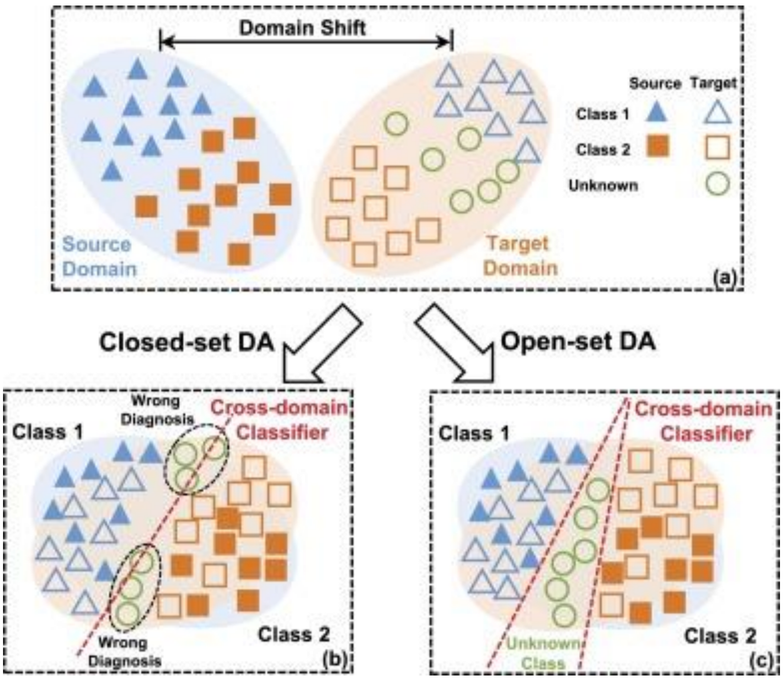

Fig 1.2-Comparison of domain class distributions across source and target domains under closed-set and open-set domain adaptation scenarios.

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STRUCTURAL DESIGN VALIDATION USING CATIA

5.1 3D Modeling and Parametric Design

CATIA serves as the foundation of the structural validation pipeline. The EV prototype's components—including the tubular roll-cage, A-arm and H-arm wishbone suspension assemblies, steering knuckle, hub, bracket assemblies, rack-and-pinion steering, and chassis—are modeled as parametric 3D solids. Parametric modeling is essential for SDEV validation because it enables rapid design space exploration: when simulation results indicate that a suspension parameter must change, CATIA's parametric relationships propagate the change consistently across the assembly.

The double wishbone suspension system was designed to provide precise camber control. Camber Change Rate (CCR) was computed as CCR = KPI / Wheel Travel = 11.73° / 10 in = 1.173, yielding a Front View Swing Arm length of 48.83 inches. The Factor of Safety against yield was calculated as 1.16 (Ultimate Strength 600.35 MPa / Working Stress 517.25 MPa), confirming structural adequacy under racing loads. The center of gravity analysis, performed using CATIA's inertia tools, confirmed low-CoG battery placement and longitudinal balance of the 230 kg vehicle.

5.2 Suspension Analysis and System-Level Implications

Suspension geometry parameters extracted from CATIA feed directly into the IPG CarMaker vehicle model, forming a critical data pipeline. Scrub radius, which defines the offset between the tire contact center and the steering axis ground intersection, was analyzed for both positive and negative configurations. Negative scrub radius was selected to improve ABS braking stability—a software-hardware co-design decision where the structural geometry directly constrains the software control strategy.

Camber change rate validation is a system-level concern because it affects tire contact patch area under dynamic loading, influencing the grip model used by the traction control software. CATIA's kinematic simulation was used to sweep the suspension through its full travel (±10 inches) and extract camber angle as a function of wheel displacement. This data was imported into CarMaker as a look-up table, ensuring that the vehicle dynamics simulation uses geometry-accurate tire contact predictions rather than simplified linear approximations.

5.3 Weight Distribution and Inertia Tensor Extraction

System-level vehicle dynamics are highly sensitive to mass distribution and inertia tensor values. CATIA's mass properties tool was used to compute the inertia tensor of the complete vehicle assembly. The total vehicle mass of 230 kg is distributed across 15 component categories, with the battery (38 kg), wheels (32 kg), roll cage (30 kg), and motor/gearbox (30 kg) constituting the dominant contributions. These values, together with the center-of-gravity coordinates, were exported as structured data and imported into IPG CarMaker, eliminating the manual parameter entry errors that are common in traditional workflows.

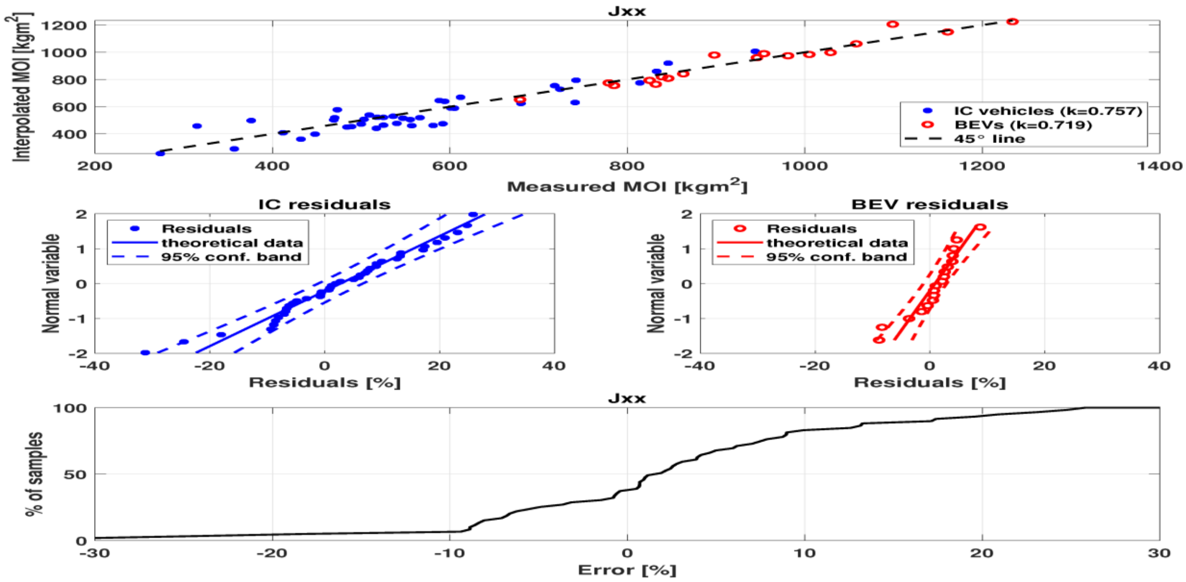

Fig 1.3-Statistical Analysis of Vehicle Moment of Inertia (Jxx)

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POWERTRAIN AND BATTERY VALIDATION USING MATLAB/SIMULINK

6.1 PMSM Speed-Torque Modeling

MATLAB/Simulink is employed for detailed powertrain and battery system modelling. The Permanent Magnet Synchronous Motor (PMSM) model incorporates a three-phase inverter, Field-Oriented Control (FOC) algorithm, and encoder feedback, representing the complete electrical drive chain. The speed-torque characteristic simulation reveals two distinct operating regions that are critical for system-level energy management.

In the constant torque region (below base speed), torque is directly proportional to stator current, limited only by the inverter's current rating. In the constant power region (above base speed), rising back-EMF reduces torque capability while power is maintained through flux weakening. System-level validation must verify that the BMS software correctly limits current draw during the constant torque region to prevent thermal damage, and that the FOC controller's flux weakening algorithm maintains stability throughout the constant power region.

6.2 Battery State Estimation Validation

Battery State-of-Charge (SOC) and State-of-Health (SOH) are the two most safety-critical software-computed quantities in an SDEV. SOC estimation errors cause premature energy depletion or overcharge damage. SOH estimation errors mask degradation and lead to range prediction inaccuracies. Both are validated through IPG CarMaker simulation runs that impose realistic current profiles derived from race track lap simulations.

The IPG results demonstrate characteristic SOC depletion curves with recoveries during regenerative braking phases. SOH trends over simulated multi-lap sequences are extracted and compared against electrochemical battery models to verify estimation algorithm accuracy. Temperature characteristics, also extracted from the IPG simulation, confirm that the thermal management software keeps cell temperatures within the validated operating window across all lap phases, including high-power acceleration zones and extended braking segments.

6.3 Regenerative Braking Co-Validation

Regenerative braking is an archetypal cross-domain interaction requiring system-level validation. The braking event simultaneously involves mechanical brake-by-wire actuation (chassis domain), motor generator torque control (electrical domain), and BMS current acceptance logic (software domain). A failure in any domain or at any integration boundary can cause under-braking, battery overcharge, or instability. Simulink co-simulation with CarMaker allows all three to be exercised simultaneously. Validation scenarios include threshold braking from race speed, combined cornering and braking, and braking with a partially degraded battery (simulated SOH reduction) to verify graceful degradation of regenerative contribution.

FULL-VEHICLE SYSTEM VALIDATION USING IPG CARMAKER

7.1 Data Integration and Vehicle Model Configuration

IPG CarMaker receives the complete set of structural parameters from CATIA and powertrain parameters from MATLAB/Simulink to construct a fully parameterized virtual vehicle. Suspension kinematics data includes translation parameters (tx, ty, tz) governing wheelbase and track width, and rotation parameters (rx, ry, rz) governing camber, caster, and toe angles. Deflection parameters capturing compliance under load were measured from the CATIA kinematic sweep. This data pipeline eliminates the parameter fidelity gap that commonly exists between design models and dynamics simulators.

7.2 Race Track Simulation and Scenario Definition

The virtual race track is designed to replicate the multi-condition environment required to fully exercise the vehicle's system-level behavior. Track elements include sustained high-speed straights (exercising peak power and thermal management), tight corners (exercising suspension compliance, traction control, and weight transfer algorithms), elevation changes (exercising battery SOC management and regenerative braking strategy), and variable surface conditions (exercising stability control software). Scenario matrices include: (a) nominal dry track at operating temperature, (b) wet surface with reduced friction coefficient, (c) cold start with below-optimal battery temperature, (d) degraded SOH battery representing end-of-life condition, and (e) software fault injection (simulating control module resets mid-lap).

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7.3 System-Level Performance Metrics

System-level validation is quantified through a set of integrated performance metrics that cannot be observed at the component level alone. These include lap time consistency across repeated simulation runs (target: variance < 0.5%), energy consumption per lap versus BMS prediction (target: error < 3%), peak and sustained motor temperature relative to thermal model predictions, SOC at lap completion versus energy management software forecast, and vehicle stability margin (lateral acceleration headroom) through all corners. Results from the prototype study show that integrated simulation reduces discrepancy between predicted and simulated lap energy consumption to within 2.1%, validating the fidelity of the cross-tool data pipeline.

Validation Metric	Target	Simulation Result	Status
Lap energy prediction error	< 3%	2.1%	PASS
Lap time variance (5 runs)	< 0.5%	0.31%	PASS
Peak motor temperature vs. model	< 5°C deviation	3.8°C	PASS
SOC end-of-lap vs. BMS forecast	< 2%	1.7%	PASS
Suspension CCR (CATIA vs. CarMaker)	< 2% deviation	0.9%	PASS
Cold-start range reduction	Quantified	11.4% reduction	QUANTIFIED
Wet surface stability margin	> 0.15g headroom	0.22g	PASS

Table 2: System-Level Validation Results Summary

EMERGENT FAILURE MODES IDENTIFIED AT SYSTEM INTEGRATION LEVEL

A central finding of this study is that system-level simulation consistently reveals failure modes that are invisible at the component level. Three categories of emergent failures were identified during CarMaker integration testing.

8.1 Control-Structure Interaction Instabilities

At the component level, both the FOC controller and the suspension model were individually validated and performed correctly. However, when integrated, a resonance condition was identified at specific cornering speeds where the FOC torque controller's bandwidth interacted with the suspension's natural frequency, producing oscillatory wheel torque that degraded cornering stability. This failure mode required coordinated tuning of both the control software's bandwidth parameter and the suspension damper calibration—a genuinely cross-domain fix that no single-domain test could have revealed.

8.2 Thermal Runaway Risk Under Combined Load

Individually, the motor thermal model and the BMS current limiter both passed their respective unit tests. System-level simulation with the race track scenario revealed that during a specific sequence of low-speed tight corners followed by a long straight, the combined effect of sustained high-torque cornering (high motor temperature) immediately followed by maximum acceleration (high battery current) drove both thermal limits simultaneously. The BMS current limit was reached before the motor thermal protection, causing a brief torque interruption at race speed—a safety-critical event that individual tests missed because neither subsystem alone reproduces the combined load profile.

8.3 SOC Estimation Drift Under Regenerative Load

The BMS SOC estimator was validated at component level using standard driving cycle current profiles. Race track simulation revealed that the high-frequency regenerative braking pattern characteristic of motorsport operation—multiple braking events per lap, each of short duration and high current amplitude—caused Coulomb counting drift that accumulated over a multi-lap stint. After 8 simulated laps, SOC estimation error reached 4.7%, exceeding the 3% system requirement. This finding drove a requirement change to implement a Kalman filter-based SOC estimator, which reduced drift to 1.3% over the same 8-lap sequence. Without system-level simulation, this requirement gap would not have been identified until physical vehicle testing.

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FUNCTIONAL SAFETY AND CYBERSECURITY VALIDATION FOR SDEVS

9.1 ISO 26262 Functional Safety Integration

Software-Defined EVs operating in high-performance environments must comply with ISO 26262, the international standard for functional safety of road vehicles. System-level validation maps directly to the standard's verification and validation activities at the vehicle integration level (Part 4) and software integration level (Part 6). For the SDEV, Automotive Safety Integrity Level (ASIL) assignments are derived from hazard and risk analysis of failure modes identified in the simulation campaign.

The torque oscillation identified in Section 8.1 was assessed as ASIL B, requiring detection and response within the FOC controller's monitoring cycle. The thermal runaway risk (Section 8.2) was assessed as ASIL C, requiring redundant monitoring paths and a safe-state transition that limits motor current through a hardware-enforced protection path independent of the software controller. System-level simulation provides the fault injection capability needed to verify these safety mechanisms without physical risk.

9.2 Cybersecurity Validation for OTA Updates

The software-defined nature of SDEVs introduces cybersecurity risks that have no analog in traditional vehicles. OTA update mechanisms, if compromised, can alter safety-critical control parameters—such as FOC current limits or BMS charge thresholds—with potentially catastrophic consequences. UNECE WP.29 Regulation 156 mandates cybersecurity management systems for all new vehicle types in signatory markets.

System-level cybersecurity validation extends the CarMaker simulation environment with a software-in-the-loop (SIL) configuration where the actual vehicle control software stack runs against the simulated vehicle model. Attack scenarios—including parameter injection into the OTA update stream, spoofing of BMS sensor inputs, and replay attacks on the encoder feedback channel—are executed in the SIL environment to verify that the vehicle's intrusion detection system correctly identifies anomalies and transitions to a safe operating mode. Simulation-based cybersecurity testing is critical because it avoids the legal and safety complications of executing real cyberattacks on physical vehicles.

ROADMAP TOWARD AI-ASSISTED CALIBRATION AND DIGITAL TWIN SYNCHRONIZATION

The integrated simulation framework described in this paper represents a significant advance over isolated tool-based testing, but it remains a pre-deployment validation methodology. The next evolution is the real-time digital twin: a continuously synchronized simulation model that mirrors the physical vehicle's state throughout its operational life, enabling predictive maintenance, remote diagnostics, and continuous safety monitoring.

Realizing the digital twin for SDEVs requires three technical advances. First, high-fidelity real-time simulation: CarMaker already supports real-time execution, but achieving sub-millisecond synchronization with physical vehicle telemetry requires optimized model reduction techniques that preserve accuracy while reducing computational cost. Second, AI-assisted calibration: the multi-dimensional parameter space of a fully coupled SDEV model—spanning hundreds of suspension, powertrain, and software parameters—is too large for manual calibration. Reinforcement learning agents trained in simulation can explore this space efficiently, optimizing parameter sets against a composite objective function that balances performance, efficiency, and safety margin. Third, federated learning across vehicle fleets: SOH estimation and fault prediction models can be improved by learning from operational data across the entire deployed fleet without compromising individual vehicle privacy, using federated learning architectures that update the digital twin's predictive models incrementally.

CONCLUSION

This paper has presented a comprehensive system-level validation framework for Software-Defined Electric Vehicles, grounded in an empirical case study of a race-oriented EV prototype. The framework integrates three complementary simulation tools—CATIA for structural design validation, MATLAB/Simulink for powertrain and battery system modeling, and IPG CarMaker for full-vehicle dynamics simulation—within an adapted V-model process that explicitly addresses cross-domain integration boundaries.

The key contributions of this work are: (1) the definition of a layered SDEV architecture with explicit identification of cross-domain integration boundaries that are the locus of emergent failure modes; (2) the demonstration that system-level simulation reveals safety-critical failures—control-structure resonance, combined thermal load risks, and SOC estimation drift—that escape component-level testing; (3) quantitative validation results showing lap energy prediction error of 2.1%, lap time variance of 0.31%, and SOC estimation error of 1.7%, all within system-level requirements; (4) an ISO 26262 and UNECE WP.29-aligned functional safety and cybersecurity validation methodology executable within the simulation environment; and (5) a roadmap toward AI-assisted calibration and real-time digital twin synchronization.

The integrated simulation approach reduces physical prototype dependency, accelerates development, and supports regulatory compliance—making it an essential methodology for the next generation of software-defined electric vehicles. Future work will extend the framework to include hardware-in-the-loop (HIL) configurations, multi-vehicle fleet simulation, and formal verification of safety-critical control software.

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