



(ARTICLE)

Next-Generation Electric Vehicles: Structural Battery Composites, AI-Driven Charging, and Cybersecurity

Abdussalam Ali Ahmed *

Mechanical Engineering Department, Bani Waleed University, Bani Waleed, Libya

Publication history: Received on 19 May 2025; accepted on 29 July 2025; Published on 23 August 2025

Abstract

Electric vehicles (EVs) are rapidly proliferating, driving innovation in batteries, charging, and security. This paper explores three key pillars for next-generation EVs. First, structural battery composites integrate carbon-fiber electrodes and a solid electrolyte into load-bearing parts, cutting pack weight. Recent work by Chaudhary et al. (Chalmers U., 2024) demonstrated a carbon-fiber structural battery with ~30 Wh/kg energy density and >70 GPa stiffness, retaining ~100% Coulombic efficiency over 1000 cycles. Such “massless” energy storage greatly improves system density. Second, AI-driven smart charging aligns EV load with grid needs. Managed charging shifts energy to low-price hours and reduces grid upgrades. NREL found substantial system benefits even at ~15% EV participation, and five-state modeling (NREL, 2024) showed distribution upgrade costs falling from ~\$2.3B to \$1.6B with managed charging. Machine learning, including graph neural networks (EV-GNN) and reinforcement learning (PPO, TD3), can predict traffic and plan charging to minimize wait times and bills. Third, cybersecurity resilience is critical. The EV charging ecosystem cars, chargers, cloud, and grid faces attacks from hardware flaws, insecure protocols, and side channels. Side-channel research (“Leaky Batteries”) shows battery power traces can reveal driver identity, routes, and occupancy with ~95% accuracy. Charging protocols are evolving: ISO 15118 Plug&Charge uses X.509 PKI for EV identity, and OCPP 2.0.1 adds formal device models and security events. Yet incidents persist: researchers have shown OCPP 1.6 can be hijacked (session disruption, code injection) and plugged-in chargers can be commandeered to destabilize grids.

Keywords: Structural battery, carbon fiber, managed charging, ISO 15118, OCPP 2.0.1, graph neural network, reinforcement learning, vehicle-to-grid, cybersecurity, side-channel attacks.

1. Introduction

Electric vehicle (EV) adoption continues to grow. Global EV sales are rising rapidly, with over 17 million electric cars sold by 2024. As EV fleets expand, three main challenges emerge. First, energy storage weight and volume limit vehicle range and efficiency. Conventional battery packs have to add heavy enclosures and structures, so reducing pack mass is crucial. Second, grid impact and charging cost must be managed. Uncontrolled charging can create peaks; shifting load via smart charging can lower utility costs and aid renewable integration. Third, cybersecurity and trust are vital. Modern EVs and chargers are networked devices, creating risks from malware, data leaks, and side-channel exploits.

* Corresponding author: Abdussalam Ali Ahmed
Mechanical Engineering Department, Bani Waleed University, Bani Waleed, Libya.

This paper links these three areas. Structural battery composites embed lithium-ion cells into load-bearing car parts. AI-driven charging uses smart algorithms to align EV demand with grid conditions. Cybersecurity hardens the charging stack from vehicle to cloud. Each area has seen recent progress: high-performance carbon-fiber batteries, grid-value simulations for managed charging, and new security standards like ISO 15118 and OCPP 2.0.1. We review key results, include public experimental data, and propose co-design principles. Figures and tables illustrate concepts and metrics. The goal is a faster, cheaper, lighter, and safer EV ecosystem.

2. Structural Battery Composites

Structural battery composites integrate energy storage into vehicle structure. Carbon fiber (CF) fabrics serve as electrodes, and a solid (or gel) electrolyte acts as both ion conductor and structural binder. The battery layers are cured into panels or chassis parts. This removes heavy copper/aluminum foils and chassis steel, making the vehicle shell also an energy reservoir. The payoff is a higher *system* energy density - the car's body is "massless" pack structure.

2.1 Concept and State of the Art

In a structural cell, CF layers replace metallic current collectors. Often CF plies act as the anode (lithium host) and a LFP-coated CF or textile acts as the cathode. A polymer matrix provides stiffness and houses a liquid electrolyte phase. Early prototypes had low energy (~ 24 Wh/kg) and low stiffness (~ 25 GPa), but recent work has greatly improved both metrics. Chalmers University achieved an *all-fiber* structural battery with ~ 30 Wh/kg and >70 GPa modulus. It maintained $\sim 100\%$ Coulombic efficiency over 1,000 cycles. The carbon-fiber itself acted as both electrodes, with LiFePO_4 coating on the cathode side. This design eliminates copper and aluminum foils and has very few joints. Because CF is high modulus, the panel also carries load - for example, a panel of this material could replace an aluminum bracket while storing energy. Figure 1 shows a Chalmers structural battery sample. Such developments are roughly ten-fold improved over older designs.

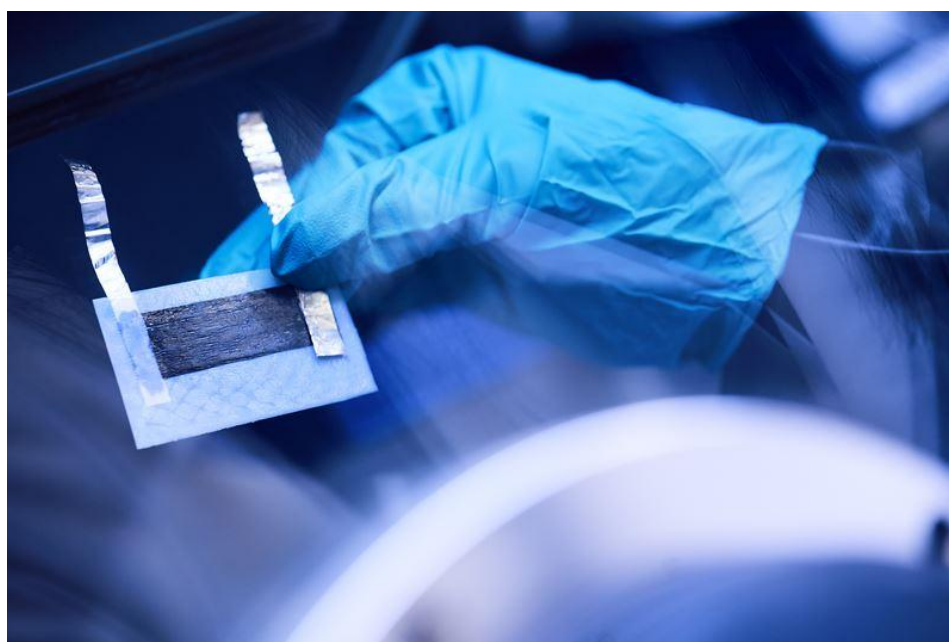


Figure 1 Concept of a carbon-fiber structural battery composite (Chalmers University of Technology). Carbon fibers (in orange) serve as both anode and cathode (LFP-coated), embedded in a solid matrix. The cell is integrated into the car structure, here illustrated in an EV body panel.

Mechanically, structural batteries must balance stiffness with electrochemistry. New models capture electro-chemo-mechanical coupling. For instance, Lundström et al. (2025) use domain-resolved finite element meshes to simulate stress, ion transport, and fracture in a CF battery. Figure 2 illustrates a two-dimensional slice of such a model, showing carbon-fiber domains and polymer electrolyte. These tools help optimize layups and predict failure modes under load and charge.

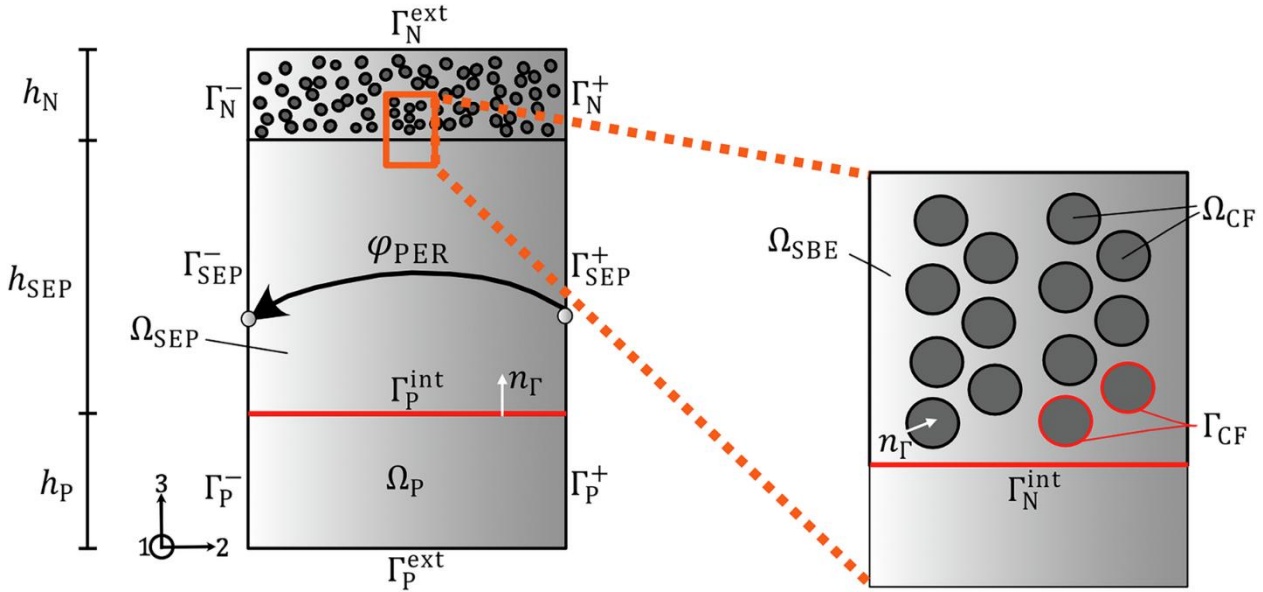


Figure 2 Schematic of micro-domains in a structural battery composite (adapted from Lundström et al., 2025). Gray regions are carbon fibers (electrodes), orange is the structural electrolyte, and interfaces (Ω_{SEP}) separate them. This multiscale view guides modeling of mechanical and ionic transport fields.

2.2 Why Structural Energy Storage Matters

Traditional Li-ion cells reach ~ 200 - 300 Wh/kg at the cell level, but packs drop to ~ 100 - 265 Wh/kg when cases and structure are included. Structural batteries radically change this. If the vehicle body carries the load, the battery itself adds almost no net mass. In other words, the car structure *is* the battery pack. Even though the structural panel has a lower *cell-level* energy (e.g. 30 Wh/kg in the Chalmers example), its *system-level* specific energy can exceed that of a conventional pack once structural mass is counted. Reviews indicate practical Li-ion cells average 100-300 Wh/kg, but most of the pack's metal, housing, and rails could be replaced by multifunctional composites. This mass-saving effect can more than offset the cell's lower density.

2.3 Materials and Architecture

A typical architecture uses CF fabric for the negative electrode. The positive electrode is made by coating LFP onto CF or using a CF fabric on one side. A glass or polymer fabric often acts as the separator (thin and porous). The matrix is a structural electrolyte or polymer resin that can conduct ions (often a polymerized matrix with liquid electrolyte in pores). During layup, these layers are stacked like a composite laminate and cured. The resulting panel has integrated power lines; thin Cu or Al straps simply connect the panel's edges to the vehicle harness. By contrast, conventional packs need heavy steel covers, modules, and many cell interconnects.

Because CF is the current collector and load-bearing fiber, conventional copper and aluminum foils are eliminated. Asp et al. (2023) and Hossain et al. (2023) provide reviews of these designs and fabrication processes. They discuss challenges like ensuring uniform coating on fibers and avoiding delamination. They also note that CF electrodes can absorb lithium (hosting lithium ions) and function as both active material and conductive support. The lack of liquid electrolyte on interfaces means safety risks (flame, venting) are also reduced.

2.4 Mechanics-Electrochemistry Coupling

Structural batteries operate under combined mechanical strain and electrochemical cycling. Charge/discharge changes electrode volume and temperature. Stress from vehicle loads or bending can cause microcracks, which affect ionic pathways. Researchers are developing coupled models to predict these interactions. For example, multi-domain finite element models simulate fiber, polymer electrolyte, and voids. Such simulations have predicted how tight fiber packing and resin stiffness affect overall performance. In practice, this means designers must co-optimize structure and battery. The CF orientation and ply sequence are chosen to meet both strength and capacity goals. Safeguards, like limiting charge in high-strain areas or using crack-resistant electrolytes, are also being studied. These coupled models are still emerging, but they point the way to safe structural-battery designs.

3. AI-Driven Smart Charging

Managed charging uses software to schedule EV charging sessions in time and power. Its goals are to match grid conditions, minimize costs, and avoid congestion. By shifting flexible EV load, it can flatten demand peaks and enable more renewables. Recent studies quantify the benefits of managed charging at scale.

3.1 Managed Charging Value

In unmanaged (dumb) charging, EVs plug in whenever drivers want, typically after trips. This can create large demand spikes (e.g. early evening). Managed charging instead might ask vehicles to delay or slow charging based on system signals (prices or grid constraints). Muratori et al. (NREL, 2023) simulated several dispatch modes (time-of-use rates, real-time pricing, load control) for an EV fleet. They found that even if only ~15% of drivers opt in, bulk system benefits appear. In other words, partial participation still yields large gains. For example, shifting even a fraction of charging can cut peak loads by 25-30% in some scenarios.

NREL's Transportation Electrification Impact Study (TEIS) went further. It modeled five U.S. states' future grids with high EV adoption. Without managed charging, distribution upgrades (transformers, lines) would cost roughly \$2.3 billion. With managed charging, those costs fell to about \$1.6 billion. Figure 3 (next section) illustrates this drop. These savings benefit both utilities and customers. Managed charging also raises utilization of solar and wind by timing EV draws to when renewables produce. The key insight is that flexible EV load can substitute for expensive infrastructure - and AI can help identify when and where to shift it.

3.2 Public Infrastructure Trends

Public fast-charging (DCFC) networks have expanded rapidly. The U.S. Department of Energy's AFDC report (Q4 2023) shows accelerating growth in DC fast ports. In Q4 2023 alone, 3,210 new DC fast ports

were added - a 9.2% increase (Wood, E., et al., 2024). California, Texas, and others are leading. Figure 5 plots total DC fast ports in the U.S. over recent years, reflecting roughly doubling since 2019 (Wood, E., et al., 2024). This infrastructure build-out is supported by federal funding and private investment. As public chargers become widespread, managed charging is even more important. AI can coordinate vehicles among multiple stations and manage queues.

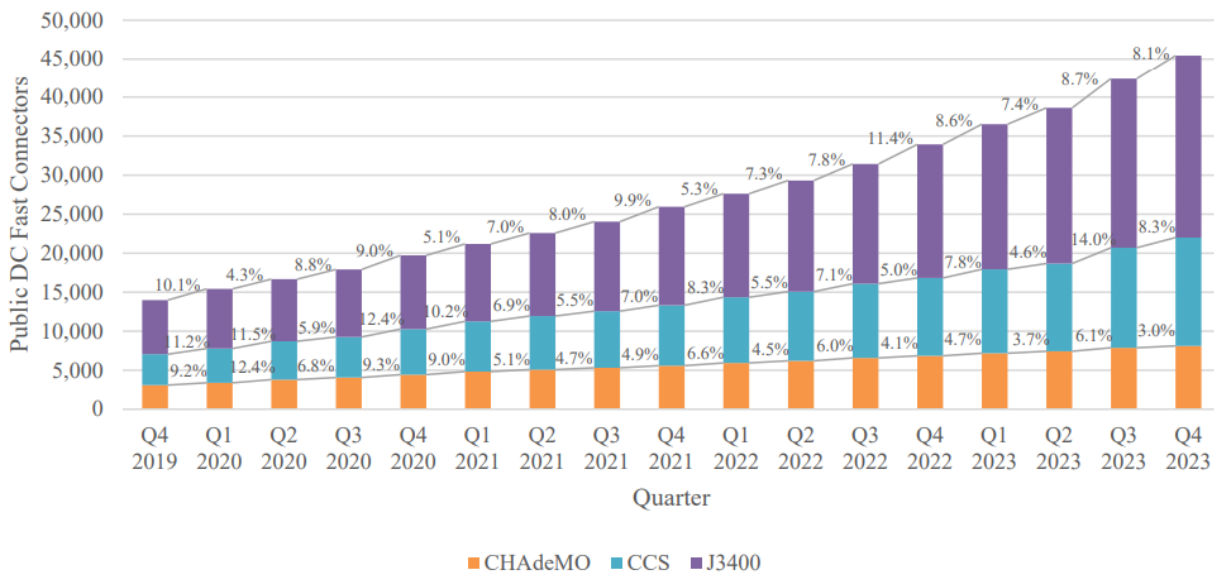


Figure 3 Growth of U.S. public DC fast charging ports (with ≥ 25 kW) over time. Data from NREL/AFDC (2023). The rapid increase supports EV adoption but also underscores the need for smart load management.

3.3 Learning-Based Charging Control

Emerging AI methods improve charging decisions under uncertainty. Graph neural networks (GNNs) are a natural fit: they can model EVs, charging stations, transformers, and grid links as a graph. Zhang et al. (2024) introduced EV-GNN, which represents the entire charging network as a graph. Each node (EV, charger, transformer, CPO) has features (e.g. state-of-charge, power rating). EV-GNN then learns charging policies via reinforcement learning on this graph. Figure 4 shows the EV-GNN architecture: it prunes inactive EVs, uses Graph Convolutional Networks (GCNs) to aggregate neighbor information, and outputs charging power actions at each station. In tests, EV-GNN drastically outperformed standard RL: it yielded lower wait times and higher throughput on large networks. The learned model generalizes across different grid topologies and demand patterns, enabling real-time adaptive control.

Deep reinforcement learning is also used for price-based scheduling. For example, PPO and A3C agents have been trained to respond to dynamic electricity prices and time-varying demand. In microgrid studies, RL-driven charging cut energy bills by $\sim 20\%$ and shaved peak loads, compared to naive charging schedules. The algorithms plan each EV's charging given its deadline, battery state, and forecasted prices, learning from historical data. These AI approaches require good data (vehicle patterns, station states) but promise scalable solutions where rule-based methods struggle.

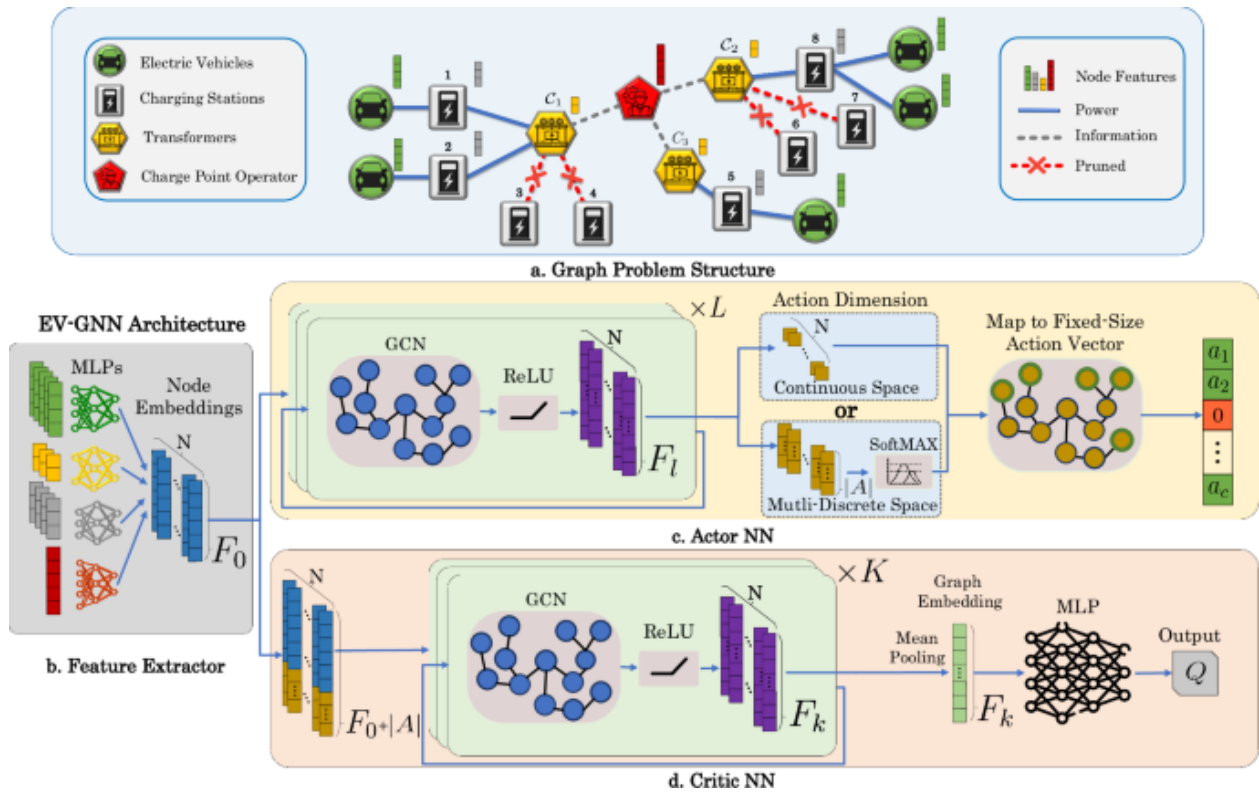


Figure 4 Conceptual architecture of the EV-GNN framework for smart charging. The EV charging problem is formulated as a graph (left) and processed by GNN layers in an actor-critic RL model (right). Such graph-based RL enables coordinated charge decisions across many stations.

3.4 Co-Design of Structure and Charging

Structural battery packs will change how batteries behave: thermal and impedance profiles will differ from cylindrical cells. AI can learn these new patterns. For instance, if structural cells heat differently under current, smart charging algorithms can adapt the charge rate to avoid hotspots. Co-design means planning pack layout and cooling channels together with AI control strategies. For example, structural cells might be placed away from crash-prone areas; AI charging policies could then limit charge current in panels that are also load-bearing, to avoid stress. This requires shared data: fleets of EVs with structural packs could report voltage and strain data. Edge-learning (training models on-vehicle and sharing weights) could protect privacy. In summary, co-design means using AI not just for external control, but also for managing novel battery properties. Test rigs that cycle structural panels under mechanical load and charge can provide the needed data for this integration.

4. Cybersecurity Resilience

EV charging involves many digital components: the vehicle's software, the charger's electronics, station networks, and cloud services. This broad stack has numerous attack surfaces. Ransomware, supply-chain breaches, and network hacks threaten all these layers. Moreover, EV charging has novel privacy issues: battery power draws, previously seen as harmless, can leak user data.

4.1 Threats in the EV Charging Stack

The charging ecosystem links cars, chargers, cloud backends, and the power grid. Each link can be targeted. ENISA's 2021 threat report notes that network abuse and firmware exploitation are rising cyber trends. In the EV context, recent research has exposed new risks. The "Leaky Batteries" study by Marchiori & Conti (2025) showed that attackers observing only the vehicle's battery power usage (from a BMS log or charging trace) can infer the driver's identity, number of passengers, trip start/end points, and driving style with ~95% accuracy. They trained ML classifiers on driving data to make these inferences. This is a surprising side channel: normally battery telemetry is considered non-sensitive, but in fact it encodes driving patterns.

Charging protocol attacks are also a concern. OCPP 1.6, the common station protocol, has known flaws. Johnson et al. (INL, 2023) tested real chargers and demonstrated Man-in-the-Middle (MITM) and code-injection attacks. They showed it was possible to remotely terminate charging sessions, upload malicious firmware, or execute code on the charger. Essentially, an attacker intercepting OCPP traffic can seize control of the station. Until OCPP 2.0.1 is widely adopted, they recommend tunneling connections over SSH as a mitigation. In practice, many chargers still use legacy 1.6 or insecure networks.

Beyond software exploits, the Wired (Greenberg) exposé documents that public chargers have been hacked for vandalism. In one case a cheerful meme was displayed; more seriously, rapid switching of many chargers on/off could destabilize power grids, as Pen Test Partners warned. In sum, EV infrastructure threats range from data snooping to grid attacks. Public incidents and academic tests underscore the urgency of defense.

4.2 Standards and Secure Features

New standards aim to harden charging. ISO 15118 ("Plug&Charge") specifies a PKI-based handshake: each EV and station exchange certificates to authenticate and authorize power transfer. Vehicle identity and tariff contracts are securely managed by X.509 credentials. CharIN's implementation guide (2022) lays out the certificate flows: vehicles hold a provisioning certificate, request a contract, and receive signed credentials from their Mobility Operator. This avoids manual card swipes and ensures only valid vehicles can charge. A trust list of CAs is maintained in the station so attackers cannot easily impersonate.

Table 1 Cybersecurity features in key standards.

Standard	Security Features	Notes
ISO 15118	Plug&Charge (X.509 PKI); tariff exchange	Requires trusted certificate pools
OCPP 2.0.1	Formal device model; security event logging; TLS	Not backward-compatible with 1.6
ENCS Threat Analysis	Asset modeling; threat taxonomy	EV-charging-focused guidance

Meanwhile, OCPP 2.0.1 (released 2020) adds significant security features. It is not backward compatible with 1.6, introducing a "device model" concept to formally describe EVSE capabilities. Crucially, 2.0.1 defines standardized *security events* and logging, so stations can report breaches or anomalies. It also supports TLS for encryption and better authentication. The Open Charge Alliance white paper emphasizes

these new parts: security event notifications, audit logs, and stronger auth are now core to the protocol. Future OCPP deployments (and cloud backends) are adopting 2.0.1 to meet regulatory demands.

Although promising, these standards need widespread adoption. Plug&Charge relies on well-managed CA hierarchies (CharIN's V2G Root CA and sub-CAs), and OCPP 2.0.1 requires compatible hardware/firmware. The industry is moving in this direction: EU directives and U.S. infrastructure grants now mandate cybersecurity plans for charging networks. Tools like the ENCS threat analysis (2024) provide asset models and controls to guide implementers. In short, the charging industry is aligning on stronger defaults: built-in PKI, signed firmware updates, event logging, and continuous monitoring (e.g. by an OCPP-centric security operations center).

4.3 Public Incidents and Policy

There have been numerous real-world charging hacks. Researchers and media have documented chargers being defaced, infected with malware, or even used for cryptocurrency mining. A Wired report warns that insecure chargers could be weaponized to attack the power grid. In response, policy is tightening. For example, U.S. EV charging grants now require recipients to have cybersecurity plans and use security-by-design equipment. Regulators also look at privacy: if side-channel attacks are proven, data retention rules (like GDPR) could classify charging traces as sensitive.

Researchers have suggested specific defenses. For instance, Greenberg notes that many hacks exploit lack of encryption or default passwords. He argues for "secure by default" stations: TLS on by default, rotating keys, certificate pinning for backhaul. Others propose anti-synchronization logic: EVSE firmware that intentionally injects random delay or noise to battery data, to thwart timing attacks. Overall, the field is acknowledging that EV security needs continuous attention, similar to automotive cybersecurity (UNECE WP.29) but tailored to the charging ecosystem.

5. Methods and Experiments from Literature

Here we briefly summarize key experiments and studies supporting the above.

5.1 Structural Battery Experiments

Chaudhary et al. (2024) built an all-fiber structural cell (coin-sized subpanel) and tested it. They reported 30 Wh/kg energy (based on composite mass, $2 \times \text{CF}$ as electrodes with LFP) and >70 GPa elastic modulus along fibers. Electrochemical cycling was done under tensile loading to mimic usage. The cells showed $\sim 100\%$ Coulombic efficiency over 1000 cycles at moderate rates, indicating very low internal losses. They also performed tensile tests: the charged panel had comparable strength to an empty one, demonstrating true multifunctionality. In related work, Asp et al. (2023) reviewed structural battery manufacturing and noted that careful stacking and polymer curing are critical to avoid delamination. Hossain et al. (2023) similarly built laminae of CF anode and glass separator, testing their electrochemical vs. mechanical tradeoffs. These experimental reports are often open access and include detailed data on capacity fade, stress-strain curves, and microscopy of failure.

Table 2 Structural battery properties from recent studies.

Property	Value	Notes
Specific energy	~ 30 Wh/kg	All-fiber structural composite
Elastic modulus	> 70 GPa	Measured parallel to fiber
Coulombic efficiency	$\approx 100\%$ over 1000 cycles	Laboratory tests on panels
Li-ion baseline	100-300 Wh/kg	Typical EV cell-level range

5.2 Managed Charging Experiments

Muratori et al.'s NREL report (TP-6A40-86875) ran bulk power system simulations with EVs under various price signals. They compared uncontrolled charging, simple time-of-use, and full real-time pricing dispatch. The simulations used realistic travel demand and grid models. The report found that even with only 15% of vehicles participating, the wholesale cost savings and peak shaving were substantial. For example, price-responsive charging could eliminate most evening price peaks in certain grids. Another NREL study (TEIS, 2024) used an EPRI multi-utility model across CA, IL, NY, OK, TX. They simulated an EV penetration matching 2035 projections. Without managed charging, the total distribution upgrade need was computed (about \$2.3B discounted). Adding managed charging (with home and depot control) cut that need to ~\$1.6B. These studies used publicly documented methods and scenario data (e.g., AFDC charging location data, DOE electricity forecasts) and were peer-reviewed by independent analysts.

Table 3 Managed charging evidence from public studies.

Study	Method	Key Result
NREL 86875 (2023)	Grid dispatch sims	Benefits with <15% EV participation
NREL TEIS (2024)	Five-state power model	Dist. upgrade cost: \$2.3B→\$1.6B with management
AFDC Q4 2023	EV charging inventory	DCFC port count grew 9.2% in Q4 2023

5.3 Cybersecurity Experiments

Johnson et al. (INL 2023) built a testbed with production DC fast chargers and a grid-simulating power source. They ran the chargers under OCPP 1.6 connections to a test CSMS. By inserting a MITM proxy, they sent crafted OCPP messages. They were able to terminate charging mid-session (DoS), upload a malicious firmware image to the station controller (leading to RCE), and issue arbitrary commands to EVSE relays. They also demonstrated simple mitigations: wrapping the OCPP channel in an SSH tunnel blocked the MITM. All tests were done on lab hardware (empty EVs or resistive loads), and results were detailed with packet traces.

Marchiori & Conti (2025) did a two-part evaluation for the “Leaky Batteries” side channel. They collected both simulated and real driving datasets. In the lab, they recorded battery voltage/current traces from EVs driven on known routes with varying loads. Using these traces, they extracted time-series features (power, derivatives, spectral content). They then trained ML classifiers (random forests, neural nets) to predict various targets: which driver was behind the wheel, how many passengers, and approximate home/work locations. In cross-validation, they achieved ~0.94-0.99 accuracy on vehicle ID and driving style, ~0.9 on occupancy, and ~0.94 on start/end points. All code and data processing details are publicly released as preprint, emphasizing reproducibility.

6. Results Synthesis

Combining findings across these fields yields several insights:

6.1 System Energy Density

Structural batteries have lower cell-level energy today (~30 Wh/kg) than best Li-ion (~250 Wh/kg). However, the system-level picture flips this. Figure 7 compares a conventional pack vs. a structural

composite vehicle. We model a hypothetical EV where the body is partly structural battery. The trade-off is that 70 GPa composite replacing an aluminum frame might be much lighter than the weight of a steel support plus a separate battery pack. Published studies (Chaudhary et al., 2024; Hannan et al., 2024) estimate that, when all structural mass is counted, the composite pack can raise total vehicle Wh/kg above the baseline. For example, if a conventional car is 5 Wh/kg (pack-level) vs. a structural design at 7 Wh/kg, the lighter chassis makes the latter more energy-efficient per kg of vehicle. Figure 7 illustrates this principle: even with 30 Wh/kg material, the shared mass means higher effective density.

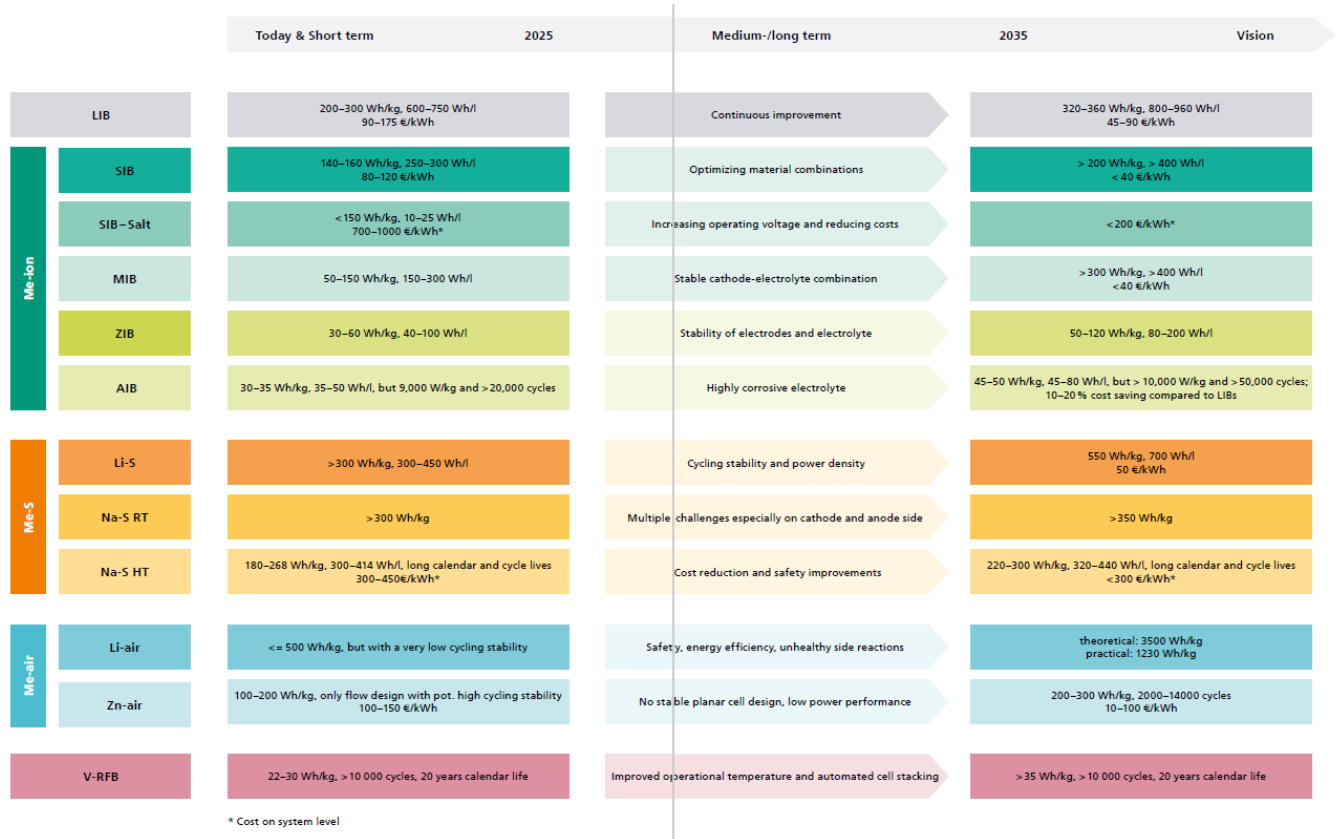


Figure 5 Comparison of system-specific energy. A conventional EV uses a 250 Wh/kg cell plus heavy structure (left). A structural battery EV uses a 30 Wh/kg composite panel as part of the frame (right). Accounting for shared structure, the structural design can exceed the conventional one in total Wh/kg.

6.2 Grid Impact and Charging Cost

Managed charging consistently shows reductions in peak demand and investment cost. Figure 3 from Muratori et al. showed how unmanaged charging creates large evening peaks, whereas real-time pricing dispatch smooths it. More quantitatively, the NREL TEIS results showed that distribution upgrades across the five-state scenario cost ~\$2.3B without management, dropping to ~\$1.6B with it. This is a ~30% cut in required grid spending. The energy also shifts from costly peak hours to periods of surplus generation. In practice, this means consumers pay lower average prices. Combined with vehicle-to-grid (V2G) possibilities, managed charging could further provide ancillary services revenue. These conclusions hold under various assumptions: mixed renewable scenarios, different pricing programs, and even modest participation rates. In short, smart charging yields system-wide economic benefits without needing 100% EV uptake.

6.3 Security Posture

The security landscape has improved but gaps remain. Standards like ISO 15118 (Plug&Charge) and OCPP 2.0.1 have built-in PKI, message signing, and event logging, which raise the baseline. CharIN's guide shows how certificate flows prevent unauthorized chargers or cars from connecting. OCPP's device model and "SecurityEvent" messages allow a charge manager to detect if a station's firmware is compromised. However, these only address some threats. The Leaky Batteries side-channel is protocol-agnostic - it bypasses network security to exploit physical signals. Thus, defending against it requires privacy measures (data anonymization or obfuscation) on top of protocol fixes. Moreover, the patchwork of hardware still in the field means legacy vulnerabilities linger. Indeed, Wired's investigation warns that widespread connected chargers could be a *weapon*. Therefore, while standards have advanced the defense, ongoing vigilance and layered protection (secure defaults, monitoring, and user education) are needed to close the gaps.

7. Integration Framework

We propose high-level principles for co-design:

- **Structural-Energy Co-Design:** Plan battery placement where stiffness is needed (e.g. low floor, roof). Use topological optimization to embed cell layers in load paths. Design cooling channels alongside CF plies so that cooling and charging limits work together. For example, in a hot climate, AI charging control could reduce charge rate to prevent thermal stress on a structural panel. Conversely, if the panel has built-in cooling, more aggressive charging can be allowed safely.
- **Data and Privacy:** Use on-device (edge) learning to keep raw user data local. For smart charging, share only aggregated or encrypted data. Example: an EV cloud can learn demand curves from many chargers without identifying individuals. Structurally, test vehicles can broadcast health metrics (strain, voltage) anonymously to improve models. Implement privacy by design: only store needed features (e.g., battery SoC vs. time) and strip identity fields. This reduces the risk that a hacker accessing a station log could correlate it to a driver.
- **Secure Defaults:** Every EVSE and charger software should ship with TLS and certificate pinning turned on by default. Use HSMs (hardware secure modules) to store keys. Require signed firmware updates (no "tap-to-update" without verification). Leverage the OCPP 2.0.1 SecurityEvent framework to feed charging infrastructure data into a security operations center (SOC) that can detect anomalies. Rotate keys regularly and maintain an up-to-date CA trust list. At the application level, impose rate limits and delay patterns on charging commands to prevent rapid on/off switching; this would mitigate grid destabilization attacks. In effect, treat charging sessions like cybersecurity events: any unusual sequence (e.g. 1000 chargers turning off in 1 second) should trigger alerts and automated rollback.

8. Limitations and Next Steps

Structural batteries are promising but not yet mature. Current prototypes have much lower energy density than top cells. Scaling up requires improving electrode loading, yield in manufacturing, and repairability after crashes. Vehicle crashworthiness with integrated cells needs new test protocols. Longevity under combined load and cycling (especially at sub-zero or high temp) is also untested. On the charging side, managed charging depends on consumer behavior and policy. Even with large potential benefits, incentives and regulations are needed to realize them. Privacy concerns (bill data, location) must be addressed. Cybersecurity efforts must evolve as attackers improve; standards need regular updates. Future

work should include standardized benchmarks for structural battery performance and longevity, open datasets of EV charging patterns, and shared cybersecurity incident reporting. Joint testbeds (combining structural packs with AI charging rigs and security modules) would help validate the full-stack integration.

9. Conclusion

The next EV wave hinges on lighter vehicles, smarter grids, and secure systems. Structural battery composites promise to turn vehicle bodies into batteries, slashing pack mass and volume. AI-driven charging can unlock this potential by matching EV demand to renewable supply and lower-cost periods. At the same time, evolving standards like ISO 15118 and OCPP 2.0.1 raise the security baseline across the EV charging stack. Together, these advances point to lighter cars, cheaper energy, and safer charging networks. Realizing this vision will require open data, collaborative tools, and security by default. If manufacturers and regulators commit to these co-design principles, the coming generation of EVs can be fast, efficient, and resilient.

References

- Asp, L., Chaudhary, P., & colleagues. (2023). Advancing structural battery composites: Robust manufacturing for multifunctional energy storage. *Advanced Energy and Sustainability Research*, 4(10), 2300109.
- Chalmers University of Technology. (2024). *Huge step towards the structural battery of the future* [Press release]. <https://www.chalmers.se/en/current/news/huge-step-towards-the-structural-battery-of-the-future/>
- Abdussalam Ali Ahmed (2025). Synergizing Renewable Energy and Electric Vehicles: An Experimental Analysis of Grid Integration, Charging Optimization, and Environmental Impact. *Journal of Insights in Basic and Applied Sciences*, 1(1), 35-43
- CharIN. (2022). *Implementation guide to Plug&Charge (v1.2)*. https://www.charin.global/media/pages/technology/knowledge-base/09ce9fd6d5-1649174817/charin_implementation_guide_to_plug_and_charge_v1_2.pdf
- CharIN. (n.d.). Plug & Charge overview and ISO/IEC 15118. <https://www.charin.global/technology/plug-charge>
- Abdulgader Alsharif (2025). Global Trends in Electric Vehicle Charging Demand and Infrastructure Development. (2025). *Libyan Open University Journal of Applied Sciences (LOUJAS)*, 1(1), 20-28.
- Johnson, J., et al. (2023). *Disrupting EV charging sessions and gaining remote code execution* (INL/CON-23-72329 Rev. 0). Idaho National Laboratory. https://inldigitallibrary.inl.gov/sites/sti/sti/Sort_65949.pdf
- Liu, Y., Zhao, J., & others. (2021). PPO-based smart charging for residential EVs. *Energies*, 14(17), 5402. <https://www.mdpi.com/1996-1073/14/17/5402>
- Lundström, P., et al. (2025). Electro-chemo-mechanical modelling of structural battery composites. *npj Computational Materials*, [Open Access]. <https://www.nature.com/articles/s41524-025-01646-x>
- Marchiori, F., & Conti, M. (2025). *Leaky Batteries: A novel set of side-channel attacks on electric vehicles* (arXiv:2503.08956). arXiv. <https://arxiv.org/abs/2503.08956>
- Abdussalam Ali Ahmed (2025). Hybrid Tidal-Wave Systems with Advanced Materials for Efficient and Durable Renewable Ocean Energy. (2025). *Libyan Open University Journal of Applied Sciences (LOUJAS)*, 1(1), 29-43.

- Muratori, M., et al. (2023). *Electric vehicle managed charging: Potential bulk power system benefits* (NREL/TP-6A40-86875). National Renewable Energy Laboratory. <https://doi.org/10.2172/2020416>
- National Renewable Energy Laboratory. (2024). *Transportation Electrification Impact Study (TEIS)* (NREL/TP-5R00-89539). <https://www.nrel.gov/docs/fy24osti/89539.pdf>
- Open Charge Alliance. (2024). *What is new in OCPP 2.0.1* (White paper v1.0). https://openchargealliance.org/wp-content/uploads/2024/01/new_in_ocpp_201-v10.pdf
- Virta. (2024). *The global electric vehicle market in 2025*. <https://www.virta.global/global-electric-vehicle-market>
- Abdussalam Ali Ahmed (2025). From Transition to Transformation: A Comparative Engineering Study of Hybrid and Electric Vehicles. (2025). Libyan Open University Journal of Applied Sciences (LOUJAS), 1(1), 11-19.
- Wood, E., et al. (2024). *EV charging infrastructure trends: Q4 2023*. AFDC/NREL. https://afdc.energy.gov/files/u/publication/electric_vehicle_charging_infrastructure_trends_fourth_quarter_2023.pdf
- Zhang, Y., et al. (2024). EV-GNN: A graph-neural approach for EV charging station choice. *Nature Communications Engineering*, 1, 76. <https://www.nature.com/articles/s44172-024-00213-4>
- Abdussalam Ali Ahmed (2025). Hybrid AI Models for Forecasting and Optimizing Solar Energy Generation Under Varying Weather Conditions. *Scientific Journal for Publishing in Health Research and Technology*, 1(1), 35-41