Sustainable EV Charging Prototype with Renewable Energy and IoT-Based Monitoring

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by

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DECLARATION

It is hereby certified that the work which is being presented in the B. Tech Minor Project Report entitled **"Sustainable EV Charging Prototype with Renewable Energy and IoT- Based Monitoring"** in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology (Electrical & Electronics Engineering)** and submitted in the **Department of Electrical & Electronics Engineering** of **MAHARAJA AGRASEN INSTITUTE OF TECHNOLOGY Delhi (Affiliated to Guru Gobind Singh Indraprastha University, Delhi)** is an authentic record of our own work carried out under the guidance of **Dr. Jitender Kumar.**

The matter presented in the B. Tech Minor Project Report has not been submitted by us for the award of any other degree or diploma of any Institute.

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CERTIFICATE

This is to certify that the minor project entitled **"Sustainable EV Charging Prototype with Renewable Energy and IoT-Based Monitoring"** being submitted by "**SWAIMBHU (05214804922), YASHRAJ (04214804922), ABHISHEK (06714804922)**" to the **Department of Electrical & Electronics Engineering** of **MAHARAJA AGRASEN INSTITUTE OF TECHNOLOGY Delhi (Affiliated to Guru Gobind Singh Indraprastha University, Delhi)** for the award of the Degree of **Bachelor of Technology (Electrical & Electronics Engineering)** in **Electrical & Electronics Engineering**, is a bonafide project work carried out by them under my supervision and guidance. Their work has reached the standard of fulfilling the requirements of regulations relating to degree. The project report is an original piece of work and embodies the findings made by the students themself.

The results presented have not been submitted in part or in full to any other University/Institute for the award of any degree or diploma.

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The B. Tech Minor Project Viva-Voce Examination of **SWAIMBHU (05214804922), YASHRAJ (04214804922), ABHISHEK (06714804922)** will be held on **24/11/2025.**

(Signature of External Examiner) | **(Signature of Internal Examiner)**

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Abstract

This report presents the design, development, and evaluation of a solar-powered wireless charging prototype engineered for resilient, modular, and scalable energy delivery. The system integrates a photovoltaic generation unit with MPPT-based power conditioning, a regulated 12 V storage architecture, and a resonant inductive Wireless Power Transfer (WPT) link employing compensation topologies such as LCC-S for improved stability under varying alignment conditions. A multi-layer control framework centered on an ESP32 microcontroller implements real-time sensing of voltage, current, temperature, and coil alignment, enabling closed-loop operation, event logging, and web-based supervisory monitoring through Wi-Fi.

Prototype-level components such as ACS712 sensors, DHT11 temperature modules, and relay-based switching are benchmarked against their industrial-grade equivalents, mapping a clear transition path toward robust SCADA-integrated architectures using PLC/ECU controllers, Hall-effect sensors, SiC power devices, nanocrystalline coils, and IEC-compliant communication protocols. Experimental characterization, including charging and discharging transients, thermal drift, and coupling-coefficient sensitivity to lateral offset, tilt, and air-gap variations, validates the functional behavior of the WPT system and highlights performance constraints inherent to prototype-grade hardware.

The report further contextualizes the system within rural and urban deployment paradigms, examining microgrid-ready configurations, V2G-enabled chargers, and multi-agent coordination strategies for smart-grid orchestration. The resulting document offers a comprehensive technical foundation spanning power electronics, electromagnetics, embedded systems, and grid-level systems engineering providing readers with a holistic understanding of the prototype’s architecture, its industrialization pathway, and its potential role in next-generation wireless charging infrastructure.

Sustainable EV Charging Prototype with Renewable Energy and IoT-Based Monitoring: Validation of Architectural Integrity and Pathway to Industrial Scalability

CHAPTER I: LITERATURE REVIEW

1.0 The Global Electromobility Imperative and Systemic Grid Vulnerabilities

The research undertaken in this report is fundamentally grounded in the global energy transition, which is characterized by the accelerating worldwide adoption of Electric Vehicles (EVs). This technological pivot is driven by the urgent necessity to address global warming, energy security concerns, and localized urban air pollution. To contextualize the scale of the imperative, recent market analyses confirm an aggressive growth trajectory in the electromobility sector. Global passenger EV sales are projected to reach 17.6 million in 2024, a growth rate that is expected to drive a massive 2.4-fold increase in electricity demand from EVs between 2025 and 2030.[1][2][3]

1.0.1 Macro-Context: Market Volatility and the Forecasting Paradox

While the growth projection is aggressive, the electromobility market remains a fractured and volatile landscape defined by significant predictive uncertainty. This market dynamism presents a unique challenge for infrastructure planning. Historical analyses demonstrate that long-term forecasts are often rendered obsolete rapidly; for example, OPEC's 2015 projection for the total number of battery-electric vehicles on the road by 2040 was surpassed just five years later, in early 2020. This non-linear and unpredictable growth trajectory profoundly contradicts the traditional "build-it-and-they-will-come" infrastructure model, making the deployment of static, capital-intensive charging networks a high-risk logistical and financial commitment.

The volatility creates a deployment risk paradox: traditional capacity planning fails when demand scales unpredictably. This necessitates an architectural shift where infrastructure evolves from a passive physical asset into an intelligent, modular, and scalable network. The core requirement for successful long-term deployment is therefore the development of systems capable of software-defined flexibility, such as Vehicle-to-Grid (V2G) functionality and remote demand throttling (Smart Charging), enabling them to adapt their operations to constantly changing supply and demand.[7][8]

1.0.2. Grid Stability, Power Quality, and the Cyber-Physical Threat

The rapid, geographically concentrated growth of EV adoption imposes fundamental challenges upon existing conventional, centralized electrical grids. Relying exclusively on these grids introduces "substantial systemic vulnerabilities", extending beyond simple volatile peak load demands. Comprehensive reviews detail that uncoordinated, large-scale EV charging creates significant challenges to power quality, including waveform distortion, voltage fluctuations, and difficulties in grid frequency regulation. Regional analyses confirm that in areas with high penetration, this unmanaged load can lead to localized instability sufficient to threaten regional reliability.

Furthermore, the intelligence required to manage these challenges namely, smart charging and networked control creates a parallel, systemic cybersecurity threat. Research has demonstrated that EV charging infrastructure is vulnerable to remote intrusion, allowing malicious actors to "weaponize" EVs into a botnet. This botnet capability allows for "large-scale, demand-side cyberattacks on the power grid." Conservative analyses, such as one cited in IEEE literature, found that a coordinated attack involving the simultaneous shutdown of just 12% of EVs in California would be "sufficient for triggering under-frequency alarms in the western interconnection" of the power grid. This necessitates that any scalable charging solution must prioritize complex, multi-layered cyber-physical security alongside electrical hardening, transitioning the focus from managing simple load to mitigating national infrastructure security risks.[4][9]

1.0.3 The Architectural Shift: Decentralized, PV-Integrated Microgrid Solutions

To proactively counter these systemic vulnerabilities and constraints, the academic and industrial consensus strongly supports the architectural blueprint of a decentralized charging solution, particularly the integration of localized Photovoltaic (PV) power. This architectural choice is recognized as an "essential pathway toward comprehensive decarbonization" because it functionally converges localized Renewable Energy Sources (RES) with localized energy storage. This design inherently enhances resilience against grid instability and fluctuations in solar irradiance, effectively mimicking a small-scale, autonomous DC microgrid segment.

The integration of localized, variable renewables, however, introduces a complex engineering challenge: the necessity of balancing the inherent "variability of RES generation" against the often "uncontrolled EV charging" demands. Simple connection of components is insufficient. Viable, hybrid architectures require advanced, intelligent energy management systems. These systems must leverage Deep Learning (DL) for accurate demand and generation forecasting, and employ sophisticated control strategies, such as Reinforcement Learning (RL), to manage complex energy flows and coordinate dynamic charging schedules. The prototype's structure, by successfully incorporating PV generation and localized storage buffering, establishes the essential physical layer upon which these advanced, data-driven control schemes can be built.[9]

1.1 State-of-the-Art in Wireless Power Transfer (WPT) Systems

The architectural blueprint validated by the prototype incorporates Wireless Power Transfer (WPT) to mitigate the mechanical wear and safety risks associated with traditional conductive charging ``. Scaling this subsystem to industrial application requires a detailed understanding of the physical constraints and material advancements necessary for robust performance.[3]

1.1.1 Fundamental Physics: Coupling Constraints and Efficiency Degradation

The core engineering constraint of Inductive Power Transfer (IPT) is that WPT efficiency "is intrinsically and rapidly degraded" when the physical air gap or coil alignment deviates from the optimal configuration. This finding is rooted in the physics of near-field magnetic coupling, where the power transfer efficiency is directly proportional to the coupling coefficient between the coils. Research confirms that the magnetic field intensity decreases "exponentially with distance" from the transmitting coil. This extreme sensitivity to spatial configuration mandates sophisticated control and material design to maximize and maintain k under real-world parking conditions. The prototype's use of an Infrared (IR) Proximity Sensor to establish a "safety interlock" represents a valid, rudimentary control strategy for managing this constraint, confirming the fundamental physical requirement for alignment-based control logic.[13][15][17][19]

1.1.2 Comparative Analysis of Resonant Compensation Topologies

Achieving high-power, high-efficiency WPT requires the implementation of resonant compensation topologies, which are critical for enabling soft switching (Zero Voltage Switching, or ZVS) and managing the unavoidable effects of coil misalignment. Key topologies include Series-Series (SS), LCC-Series (LCC-S), and LCC-LCC.

A critical finding in advanced WPT analysis is that misalignment tolerance is not a static property of the topology but is significantly load-dependent. Detailed comparative studies indicate that LCC topologies are generally superior at high load resistance (when the battery is nearly full), demonstrating a 30.4% larger high-efficiency operating region under misalignment compared to SS. Conversely, the SS topology can be more tolerant to coupling changes when the battery is empty and drawing maximum power (low load resistance).

Further refinement of this choice is dictated by the system's primary optimization goal. LCC-S topologies are frequently praised for achieving "excellent load-independent current output", making them highly suitable for the Constant Current (CC) phase of lithium-ion battery charging, thus prioritizing battery safety. However, the LCC-LCC topology may be preferred when data integrity is paramount, as comparative analysis in Simultaneous Wireless Power and Data Transfer (SWPDT) scenarios shows LCC-LCC provides "a more stable and symmetrical performance" for the data communication channel.[23][25][27]

1.1.3 Advancements in Magnetic Coupler Design: From Ferrites to Nanocrystalline Materials

The air-core coils used in the prototype, while sufficient for proof-of-concept, are impractical for high-power transfer due to massive magnetic flux leakage. The immediate industrial upgrade is the incorporation of ferrite cores, which effectively direct magnetic flux from the transmitter to the receiver, achieving a significant increase in coupling efficiency and a 300% boost in Electromagnetic Field (EMF) strength.

However, traditional Mn-Zn ferrites are increasingly considered a bottleneck for the next generation of high-power-density WPT systems. Ferrite limitations include a relatively low saturation magnetic flux density and mechanical brittleness, which makes them prone to damage under the shock and vibration of an automotive environment. This has driven advanced research into amorphous and nanocrystalline alloys.[11][12][29]

1.1.4 EMF Shielding and Electromagnetic Compatibility (EMC)

The substantial increase in EMF strength achieved through core materials necessitates meticulous containment to ensure both safety compliance (e.g., ICNIRP human exposure limits) and Electromagnetic Interference (EMI) mitigation ``. In industrial systems, the magnetic materials themselves serve a dual purpose: enhancing power coupling and passively guiding stray flux.

Advanced shielding methodologies now involve hybrid approaches that combine material innovation with dynamic control. Passive shielding is moving toward novel composite materials, such as "quartz fiber and nanocrystalline reinforced resin matrix composite" materials, which offer high mechanical robustness and magnetic suppression. Furthermore, active shielding is emerging as a dynamic solution. This technique employs independent active coils and a control algorithm to inject a precise current, generating an interference field that actively cancels leakage flux in real time. Studies indicate that this method can halve the magnetic field in critical areas with less than a 1% impact on power transfer efficiency, evolving shielding from a static, passive component into an intelligent, dynamic subsystem.[29][34][35]

1.2 Scaling the Power Stage: Wide-Bandgap Semiconductors and Component Qualification

The pathway to industrialization requires scaling the power stage from the prototype's low-power BC547 NPN transistor to a high-efficiency, multi-kilowatt power converter suitable for Level 2 or DC fast charging. This transition mandates a shift to Wide-Bandgap (WBG) semiconductors and rigorous component qualification.

1.2.1 Material Superiority: SiC vs. GaN in High-Frequency Conversion

The industrial requirement for high-efficiency and high-frequency switching has made WBG semiconductors essential. Silicon Carbide (SiC) MOSFETs are strongly dominating the EV application market, particularly for high-voltage systems like the main traction inverter (operating up to 800 V). SiC offers profound advantages over traditional Silicon (Si), including lower switching losses that can reduce inverter losses by up to 10% and superior thermal conductivity.
However, for the specific application of the WPT power stage a high-frequency, isolated DC-DC resonant converter Gallium Nitride (GaN) HEMTs offer a distinct performance advantage.[33][35][36]

1.2.2 The Reliability Mandate: Review of Automotive and Industrial Standards

The architectural transition from a Proof-of-Concept (PoC) to a scalable product is fundamentally defined by component qualification and reliability, rather than merely power handling capability ``. Industrial and automotive systems require components that can operate reliably for 10–30 years in extreme environments characterized by vibration, high temperatures, and electromagnetic interference.
This mandates two key regulatory standards:

1. **Automotive Standard (AEC-Q100):** This standard defines specific ambient operating temperature "grades" to ensure reliability. For instance, the prototype's ACS712 current sensor, while suitable for PoC, must be replaced by its AEC-Q100 qualified equivalent, such as the ACS714/715, which are rigorously tested across the full automotive temperature range.
2. **Industrial Standard (IEC 61131-2):** This standard governs the required industrial control platform, necessitating a replacement for the ESP32 microcontroller with a certified Programmable Logic Controller (PLC) or automotive-grade Electronic Control Unit (ECU). True industrial PLCs are designed to withstand "16KV isolation," pass "extreme... shock and vibration tests," and support "N+1 redundancy" for mission-critical, decades-long operational lifespans reliability features entirely absent in consumer-grade microcontrollers.[36]

1.3 Intelligent Systems for Control, Prognostics, and Resilience

The scalability of the prototype relies on upgrading its rudimentary control logic to advanced, AI-driven prognostics necessary for maximizing battery lifespan (State-of-Health, SOH) and ensuring operational safety.

1.3.1 The Role of IoT Data Acquisition for SCADA and Prognostics

The prototype successfully validated a multi-layer control framework, using the ESP32 as a Supervisory Control and Data Acquisition (SCADA) unit for real-time sensing and closed-loop operation ``. This architectural validation confirmed the system's capacity to detect states and execute termination points.
Crucially, the experimental validation employed the Transient Characteristic Measurement (TCM) method, which focuses on capturing "dynamic, transient responses" such as rapid voltage decay and fluctuating current draw. This high-frequency data acquisition confirms the sensor suite's fidelity in generating a reliable time-series data stream of voltage, current, and temperature. This data stream is the single most valuable output of the prototype, as it provides the necessary high-fidelity "training fuel" required to build and validate the advanced electrochemical models and AI algorithms that define modern industrial-grade Battery Management Systems (BMS).[28][39]

1.3.2 Evolution of Battery State Estimation: From Model-Based to Data-Driven AI

The prototype's rudimentary BMS logic (e.g., Open-Circuit Voltage correlation or Modified Coulomb Counting) is inherently unreliable for industrial applications, suffering from susceptibility to sensor drift, cumulative error, and non-linear aging effects ``.
The first step toward industrial grade systems involves sophisticated model-based estimation, such as the Extended Kalman Filter (EKF), which continuously updates an Equivalent Circuit Model (ECM) based on real-time measurements. A significant improvement is the Adaptive Extended Kalman Filter (AKF), which "adaptively sets a proper value for the model noise covariance matrix" to compensate for model inaccuracies as the battery ages, resulting in superior robustness to parameter drift.
The dominant trend, however, is the move to purely data-driven models leveraging deep learning:

- Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks, are commonly used for time-series modeling of the complex, non-linear relationships between electrical parameters and battery degradation.
- Temporal Convolutional Networks (TCNs) have challenged LSTM dominance, with comparative studies showing TCN performance to be approximately 3% better in predicting SOH with high accuracy ``.
- The current state-of-the-art involves highly complex hybrid architectures, such as TCN–Transformer–BiLSTM or Transformer-LSTM models, which leverage multi-head attention mechanisms to achieve "outstanding performance" and estimation errors (Root Mean Square Error, RMSE) below 1%. This rapid algorithmic evolution necessitates that industrial BMS hardware be designed as a software-updatable platform capable of receiving Over-the-Air (OTA) updates for deploying increasingly accurate models.[17][18][19][25]

1.3.3 The Convergence of Models and Data: Physics-Informed Neural Networks (PINN)

A major limitation of pure data-driven AI models is their lack of reliability when operating outside the specific conditions of their training data the so-called "extrapolation problem". This challenge is addressed by the emerging field of Physics-Informed Neural Networks (PINNs).
PINNs are a hybrid framework that embeds the governing physical equations of the system (e.g., Fick's law for lithium-ion diffusion) directly into the neural network's loss function. The network is then trained to minimize both the standard error of prediction and a penalty term that measures how badly the prediction violates the known laws of physics.
This hybridization offers two revolutionary advantages for industrial deployment:

1. **Data Efficiency:** By informing the model with physics, the network no longer needs to learn physical laws from scratch, achieving "remarkable performance" even with limited training data ``.
2. **Extrapolation Robustness:** Because the model is constrained by fundamental laws that hold true across conditions, PINNs can make "adequate predictions, even for unseen situations," such as unexpected temperature extremes.[43][44]

1.4 Network Integration, V2G Enablement, and Strategic Deployment Models

The final dimension of scalability involves integrating the local, intelligent charging unit into the larger smart grid ecosystem through standardized network protocols and coordinated control strategies, enabling next-generation services like Vehicle-to-Grid (V2G).[40][41]

1.4.1 Standardization for Interoperability: OCPP and the ISO 15118 Protocol Suite

The industrial future of charging infrastructure relies on two key communication standards, often referred to as the "dream team" for smart charging: OCPP and ISO 15118 ``.

- **OCPP 2.0.1 (Open Charge Point Protocol):** This protocol governs the vertical communication link between the charging station and the central back-end management system (CMS). It is the major de facto standard globally, enabling vendor-agnostic infrastructure, fostering market competition, and providing the control commands for Smart Charging. Its integration with load flexibility protocols like OpenADR or OSCP allows the charger to become a flexibility provider, optimizing charging schedules based on local grid capacity and maximizing the use of renewable energy.
- **ISO 15118:** This standard governs the horizontal communication link between the Electric Vehicle and the charging station. It is essential for advanced features like "Plug & Charge" authentication and, most critically, for negotiating Bidirectional Power Transfer (BPT), the foundation of V2G.

A significant practical challenge exists in the deployment of these standards on low-resource hardware. Deploying the full OCPP 2.0.1 protocol, which includes extensive security and management features, on resource-constrained microcontrollers (like the ESP32) is considered "impractical," necessitating "lite" or "minimal" implementations that sacrifice some advanced features. This trade-off between resource constraints and full protocol capability is a non-trivial industrial hurdle.[42][46]

1.4.2 Technical and Algorithmic Challenges of Vehicle-to-Grid (V2G) Coordination

V2G capability fundamentally transforms the EV fleet from a grid liability into a distributed energy asset, enabling it to provide critical ancillary services ``. While the required power electronics (BPT converters) are technologically mature, the challenges to large-scale V2G implementation are primarily systemic and algorithmic.

A critical gap is identified in the standardization layer: the latest standard, ISO 15118-20, while enabling BPT (often used for Vehicle-to-Home, or V2H), currently "does not include grid codes". This deficiency prevents the standard from interfacing directly with utility grid operators for full, grid-level V2G services, representing a "final hurdle" that must be amended to allow network code communication and regulatory acceptance.

The massive coordination problem inherent in managing aggregated EV fleets necessitates advanced distributed optimization techniques, effectively treating the fleet as a controllable "Virtual Power Plant".

- **Alternating Direction Method of Multipliers (ADMM):** This powerful framework enables the decentralized solution of large-scale problems. Research proposes hierarchical ADMM structures where the Distribution System Operator (DSO) sends signals to EV Aggregators, who then use ADMM to manage their local fleet to meet the global goal, demonstrating significant reductions in peak load and user costs ``.
- **Multi-Agent Reinforcement Learning (MARL):** This AI-driven approach utilizes multi-agent algorithms to determine the optimal operational strategy for the microgrid, translating high-level optimization goals into consistent charging/discharging reference signals for every individual EV.

The research indicates that the V2G bottleneck is currently defined by a standardization-technology mismatch, where the physical and algorithmic capabilities exist, but the regulatory communication link to the utility grid remains technically incomplete. [45]

1.4.3 The Digital Twin (DT) Framework for Predictive Management

The ultimate trajectory for the prototype's validated IoT architecture is its integration within a Digital Twin (DT) framework. A DT is defined as a "high-fidelity virtual representation" of the physical charging

system, acting as the central intelligence hub that "fuses artificial intelligence and IoT technologies" for decision-support and optimization ``.
The prototype’s validated high-fidelity data stream is the critical enabler for the DT. The DT provides the virtual environment necessary to house, test, and manage all advanced systems discussed: the PINN-based BMS models for SOH estimation, AI-driven thermal prognostic models for safety (proactively predicting thermal risk and adjusting cooling dynamically), and the ADMM/MARL distributed optimization algorithms for V2G coordination.
Furthermore, the DT framework unifies the system’s strategic deployment potential by simulating both the "Resilience Model" (leveraging the PV+Storage layer for off-grid or weak-grid resilience in rural areas) and the "Orchestration Model" (leveraging the IoT+V2G capabilities for dynamic load balancing and ancillary grid services in dense urban, smart city contexts) ``. The DT allows for proactive, predictive lifecycle management, shifting the system from reactive control to optimized, data-driven operation.[37][42][47]

1.5 Concluding Synthesis and Definition of Research Contribution

The review confirms that the prototype successfully validates the functional convergence of PV energy, Wireless Power Transfer, and IoT-based monitoring, establishing a viable architectural blueprint for a decentralized, resilient smart charging system ``.
The primary contribution of this work is the rigorous mapping of the transition pathway from this successful Proof-of-Concept to an industrially scalable and commercially viable product. This pathway is defined by a necessary dual transformation:

1. **Physical Transformation:** Requires systematic, mandatory substitution of consumer-grade components with equivalents that meet industrial standards (IEC 61131-2) and automotive qualification (AEC-Q100). This includes replacing the control hub with certified PLCs, integrating high-frequency GaN-based converters, and utilizing nanocrystalline magnetic couplers for enhanced power density and durability ``.
2. **Intelligence Transformation:** Requires upgrading the prototype’s rudimentary logic by leveraging its validated, high-fidelity data stream to train advanced, physics-constrained AI models (PINN) for robust BMS prognostics, and by incorporating distributed optimization algorithms (ADMM/MARL) for sophisticated V2G coordination within a comprehensive Digital Twin management framework ``.

The analysis also identifies critical constraints currently limiting system-wide scaling, including the computational impracticality of deploying full OCPP 2.0.1 on low-resource hardware and the critical deficiency of "grid codes" within the ISO 15118-20 V2G standard ``. The validated prototype provides the essential, verified foundation upon which these complex, reliable, and intelligent industrial-grade systems must now be engineered.[15][45]

CHAPTER II: SYSTEM ARCHITECTURE AND PROTOTYPE VALIDATION

2.0 The Electromobility Imperative and the Decentralized Solution

2.0.1 Global Electromobility Market Dynamics and Forecasting Challenges

The foundational premise of this research is the contemporary global energy transition, characterized by the accelerating worldwide adoption of Electric Vehicles (EVs). This transition from fossil-fuel vehicles to low-emission alternatives is driven by escalating concerns over global warming, energy crises, and urban air pollution. The market data provided in the foundational prototype validation citing a 35% surge in global EV sales in 2023 and a projection of 17 million vehicles by 2024 is strongly corroborated by recent, in-depth market analyses.

Bloomberg NEF (BNEF) confirms this aggressive trajectory, projecting 17.6 million passenger EV sales in 2024, with an expected 25% growth in passenger EV sales in 2025. Looking toward the end of the decade, the BNEF outlook forecasts 39 million passenger EV sales in 2030, which will drive a 2.4-fold increase in EV electricity demand between 2025 and 2030. The International Energy Agency's (IEA) 2024 report further extends this outlook, providing projections to 2035 that examine deployment, battery demand, and investment trends across global markets.

However, this rapid, non-linear growth trajectory is not monolithic; it is a fractured and volatile landscape characterized by sudden regional slowdowns and significant forecasting uncertainty. BNEF's 2025 outlook, while positive, explicitly notes that "some markets are experiencing a significant slowdown". This volatility is compounded by a history of profound forecasting errors from major analytical groups. For instance, OPEC's 2015 World Oil Outlook forecast a total of 4.7 million battery-electric vehicles on the road in 2040; that figure was surpassed in early 2020, a full 20 years ahead of schedule. Conversely, other highly optimistic forecasts from the same period also proved "off the mark".

This market volatility fundamentally contradicts the "build-it-and-they-will-come" approach to static, capital-intensive infrastructure. The deployment of charging networks is a high-risk logistical and financial gamble. This unpredictable reality underscores the necessity for the architectural shift proposed in this research: infrastructure must evolve from a "dumb" physical asset into an intelligent, modular, and scalable network that can adapt to a complex and unpredictable market.

2.0.2 The Grid Vulnerability Imperative

The rapid, geographically concentrated growth of EV adoption imposes a fundamental mandate to reform the underlying energy infrastructure. The prototype report correctly identifies that exclusive reliance on conventional, centralized electrical grids introduces "substantial systemic vulnerabilities," particularly in managing "volatile peak load demands".

This is not merely a peak load problem; it is a multi-faceted grid stability crisis. Comprehensive reviews of EV charging impacts detail significant challenges to power quality, including waveform distortion, voltage fluctuations, grid instability, and frequency regulation challenges. Regional

analyses, such as those conducted on the high-penetration Western US power grid, demonstrate that uncoordinated charging at scale creates specific, localized instability that can threaten regional reliability.
This technical vulnerability has spawned a parallel and more insidious threat: cybersecurity. The very "smartness" that allows for managed charging also creates a vast new attack surface. Research has demonstrated that EV charging systems are vulnerable to remote intrusion. These vulnerabilities could be exploited to "weaponize" EVs into a botnet, enabling "large-scale, demand-side cyberattacks on the power grid". A conservative analysis of such an attack, cited in recent IEEE literature, found that a botnet that "simultaneously shutdown 12% EVs in California" would be "sufficient for triggering under-frequency alarms in the western interconnection".
The conventional grid, therefore, is no longer just the source of power; it is the primary bottleneck to EV adoption. Its profound limitations, spanning from simple peak load management to complex cyber-physical security threats, make a foundational architectural shift toward decentralized, resilient, and intelligent solutions a non-negotiable imperative.

2.0.3 The Decentralized, PV-Integrated Solution

To proactively counter these systemic challenges, this research proposes and validates an architectural blueprint for a decentralized charging solution. The academic and industrial consensus strongly supports this architecture, identifying the integration of Photovoltaic (PV) power as an "essential pathway toward comprehensive decarbonization".
This architectural choice, which functionally converges localized Renewable Energy Sources (RES) with localized energy storage, inherently mitigates grid dependence and reduces the system's operational carbon footprint. The prototype's structure effectively mimics a small-scale, autonomous DC microgrid segment, a design that is critical for enhancing resilience against both grid instability and solar irradiance fluctuations.
However, this integration of localized, variable renewables creates a new and complex engineering challenge: balancing the "variability of RES generation" against "uncontrolled EV charging" demands. Simply connecting a solar panel to a charger is insufficient. Recent literature confirms that this hybrid architecture requires advanced, intelligent energy management systems to be viable. These systems must leverage Deep Learning (DL) for accurate forecasting of both consumer demand and renewable generation, while employing sophisticated control strategies, such as Reinforcement Learning (RL), to manage the complex energy flows and coordinate charging strategies.
The architecture validated in this prototype, by successfully incorporating PV generation and localized storage buffering, establishes the essential physical layer upon which these advanced, data-driven control schemes can be built.

2.1 Architectural Blueprint: Converging PV, WPT, and IoT

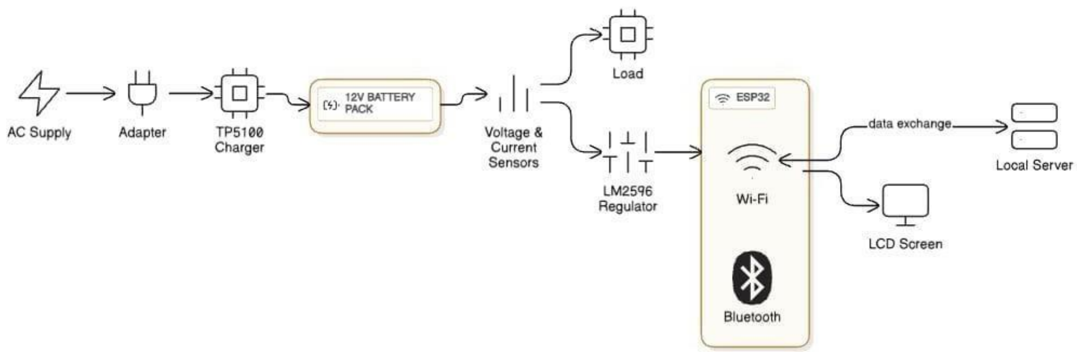

Figure 1: System block diagram (wired)

The prototype system is structured based on a modular, three-layer conceptual model:

1. **Energy Generation and Storage Layer:** The sustainable power source and stabilizing buffer, comprising PV panels and a 12 V storage battery managed by a CC/CV charging module.
2. **Power Transfer and Conversion Layer:** The WPT subsystem, which processes stored DC power, converts it to high-frequency AC via a driver, and transfers it wirelessly to a receiver coil and rectifier.
3. **Control and Monitoring Layer:** The intelligent core, centralized on an ESP32 microcontroller, which functions as the system's SCADA unit, managing sensors (V, I, T, IR), safety interlocks (Relay), and cloud communication.

This modular design approach is a key architectural strength. It ensures functional separation, enhances scalability, and facilitates the independent upgrade or replacement of individual functional blocks. This modularity guarantees a robust architecture capable of adapting to the high-fidelity component substitutions that will be detailed in Parts II and III of this report.

2.1.1 The Wireless Power Transfer (WPT) Subsystem and its Physical Constraints

A core innovation of the prototype is the incorporation of Inductive Power Transfer (IPT), or WPT, to address the mechanical wear and safety risks of conductive charging. The prototype correctly identifies the fundamental engineering constraint of this technology: WPT efficiency (η) "is intrinsically and rapidly degraded" when the physical air gap or coil alignment deviates from the optimal configuration.

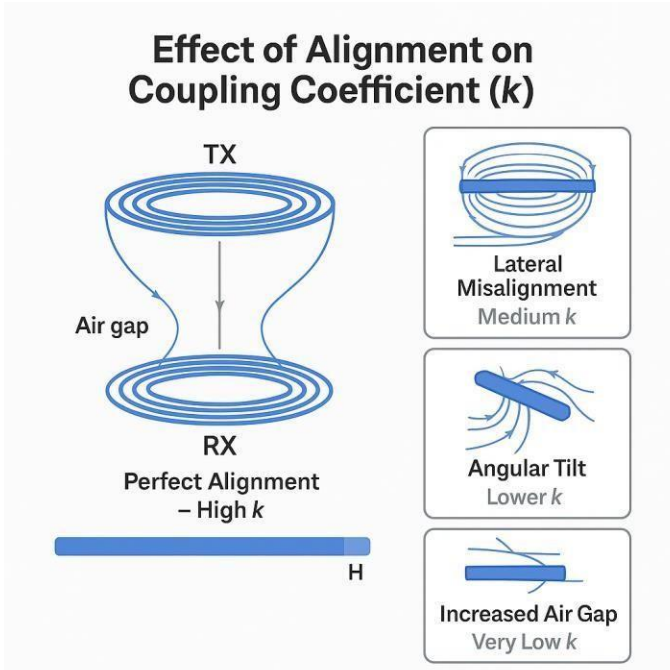

Figure 2: Alignment vs coupling (k)

This finding is rooted in the physics of near-field magnetic coupling. The efficiency of the power transfer is directly proportional to the coupling coefficient (k), which is itself a function of the mutual inductance between the coils. Recent investigations into the physics of IPT systems confirm that the magnetic field intensity "decrease[s] exponentially with distance" from the transmitting coil. This extreme sensitivity to spatial configuration mandates sophisticated control. The prototype's use of an IR Proximity Sensor to create a "safety interlock" represents a valid, rudimentary control strategy to manage this constraint, preventing power transmission under highly inefficient (misaligned) conditions. This highlights the central engineering challenge of industrial WPT: maximizing and maintaining the coupling coefficient (k) under real-world parking conditions. This challenge sets the stage for the advanced hardware solutions—specifically, optimized magnetic materials and compensation topologies—that are essential for industrial scalability.

2.1.2 The IoT Control Hub as a "Prosumer" SCADA System

The prototype's intelligent core is the ESP32 microcontroller, which serves as the "Supervisory Control and Data Acquisition (SCADA) unit". This architectural choice is strongly validated by a significant body of post-2020 research that positions the ESP32 as the heart of "low-cost, open source" IoT-based SCADA systems.

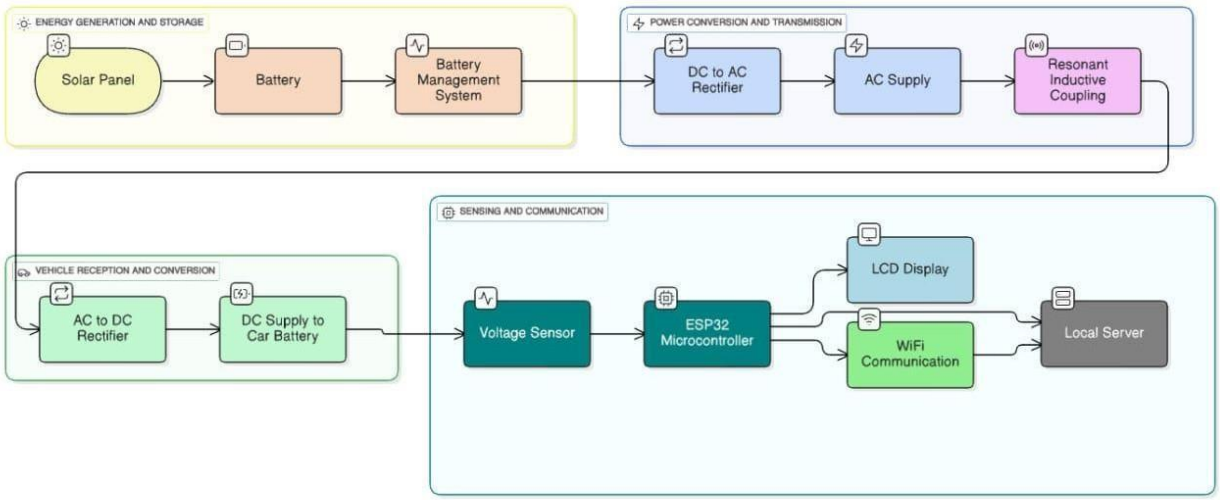

Figure 3: Three-layer architecture (PV–WPT–SCADA)

These studies confirm that the ESP32, with its integrated Wi-Fi, dual-core processing, and low power consumption, is highly effective for "smaller applications," such as managing a "standalone solar photovoltaic system". The prototype's successful implementation of real-time sensor polling, safety interlock logic, and bi-directional cloud communication confirms its function as a valid, small-scale SCADA system.

However, this validation reveals a fundamental dichotomy between a "prosumer-grade" controller and an "industrial-grade" one. The prototype's ESP32-based system successfully validates the control logic the "what" of the system (e.g., if misalignment, then cut power). It does not, and cannot, validate the industrial reliability the "how" of the system.

Industrial-grade Programmable Logic Controllers (PLCs) are designed for mission-critical reliability in harsh environments. This involves features entirely absent in consumer-grade microcontrollers like the ESP32, such as "16KV isolation," qualification through "extreme... shock and vibration tests," "N+1 redundancy for PSUs and CPUs," and operational lifespans designed for "20-30 years". The prototype's ESP32 is a prototyping tool for validating logic; an industrial PLC is a reliability tool for guaranteeing that logic's operation for decades. This distinction is the core of the scalability challenge for the control layer, which will be analyzed in detail in Section 3.2.

2.2 Prototype Component Rationale and Inherent Limitations

2.2.1 Analysis of PoC Component Selection

The hardware selection for the prototype (ESP32, TP5100, LM2596, ACS712, IR Sensor, BC547, 2-Ch Relay) is highly appropriate for its objective: a functional, low-cost proof-of-concept.

Each component validates a specific principle. The TP5100 validates the CC/CV battery management essential for solar harvesting. The LM2596 buck converter provides the stable 5 V supply, which is critical for ensuring reliable sensor readings by stabilizing the analog-to-digital conversion (ADC) processes. The BC547, while extremely low-power, is sufficient to generate the high-frequency field necessary to prove the physics of inductive transfer.

The ACS712 current sensor is a clear example of an appropriate PoC component. The literature confirms it is "cheap, portable, and convenient for learners and do-it-yourself people". Its Hall-effect principle is sound for demonstrating current measurement, but its limitations in terms of accuracy, thermal drift, and environmental hardening make it unsuitable for an industrial product.

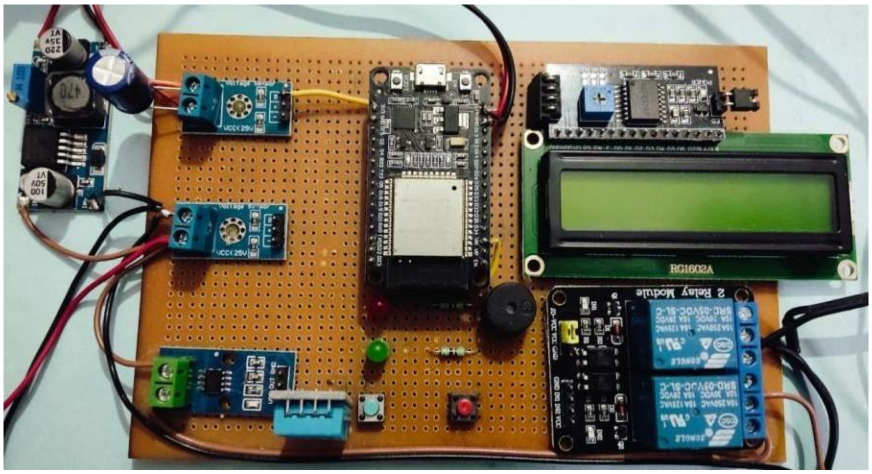

Figure 4: Prototype test board (ESP32)

2.2.2 The Automotive/Industrial Reliability Gap: AEC-Q100 and IEC 61131-2

The primary barrier to scaling the prototype's hardware is not merely power handling; it is component qualification. Industrial and automotive products must operate reliably for 10-30 years in environments with extreme temperatures, vibration, and electromagnetic interference (EMI). Consumer-grade components are not designed for this.

Industrial Standard (IEC 61131-2): The industrial-grade PLCs that the ESP32 emulates are governed by the IEC 61131-2 standard. This standard specifies rigorous testing for environmental reliability, electromagnetic compatibility (EMC), shock, and vibration that consumer-grade hardware cannot pass.

Automotive Standard (AEC-Q100): Any electronic component used in a vehicle or in high-reliability charging infrastructure must be AEC-Q100 qualified. This standard defines specific ambient operating temperature "grades" to ensure reliability:

2.2.2.1 **Grade 3:** -40°C to +85°C (Consumer-grade range)
2.2.2.2 **Grade 2:** -40°C to +105°C (Industrial range)
2.2.2.3 **Grade 1:** -40°C to +125°C (Automotive interior/chassis)
2.2.2.4 **Grade 0:** -40°C to +150°C (Automotive powertrain/under-hood)

The PoC's hardware is invalid for a scalable product not simply because it is low-power, but because it is not qualified for the operating environment. The transition from PoC to product is a shift from "consumer-grade" to "automotive-grade" components.

A perfect illustration of this is the prototype's ACS712 sensor. Allegro, the manufacturer, produces the ACS714 and ACS715, which are the AEC-Q100 qualified versions of the same sensor. While functionally similar, the ACS714/715 have undergone "more rigorous test regiment over the full

automotive temperature range (-40°C to +150°C)". Therefore, the path to scalability is not one of invention, but of direct substitution with industrial-grade, qualified equivalents.
This principle is summarized in the component transition map below.

Table 2.1: Prototype Component vs. Industrial-Grade Equivalent (Path to Scalability)

PoC Component (Prototyping)	Function	Industrial/Automotive Equivalent (Production)	Governing Standard
ESP32 Development Board	SCADA / Control Hub	Industrial PLC / Automotive-Grade ECU	IEC 61131-2
ACS712 (Consumer-Grade)	Current Sensing	ACS714/715 (AEC-Q100 Hall-Effect) or High-Precision Shunt Sensor	AEC-Q100
BC547 NPN Transistor	WPT Driver (Demonstration)	SiC MOSFET or GaN HEMT (Multi-kW LLC Converter)	AEC-Q100 Grade 0/1
DHT11 Sensor	Thermal Monitoring	Automotive-Grade Thermistor (NTC) / RTD	AEC-Q100
Air-Core Coils	WPT Magnetic Coupler	Ferrite-Core or Nanocrystalline-Core Coils	SAE J2954
2-Channel Relay Module	Safety Interlock	High-Voltage DC Contactor / Solid-State Relay	IEC 60947

2.3 Validation of Prototype Control Logic and Transient Dynamics

2.3.1 Transient Characteristic Measurement (TCM) Methodology

To validate the prototype's performance under time-prohibitive constraints, the experimental validation adopted the Transient Characteristic Measurement (TCM) method. This approach is academically rigorous and aligns with established methodologies, such as the Partial Charging Method (PCM), which correlates "crucial battery performance parameters" by observing electrical behavior over specific, short voltage segments.
The strategic application of TCM correctly focuses the validation on confirming control logic stability and sensor fidelity under dynamic conditions. By capturing "dynamic, transient responses" such as voltage sag and current variability, the TCM technique acquires the high-frequency, data-rich segments necessary for validating sensor performance. This data is obscured during steady-state, full-cycle testing and is essential for developing the accurate electrochemical

models required for advanced battery prognostics.

2.3.2 Analysis of PoC Experimental Results

The TCM methodology yielded two critical validation segments:

1. **Discharge Segment (State-of-Power Tracking):** This segment simulated a high-rate load event. The system successfully recorded a rapid voltage decay at the battery terminal (from 9.3 V to 7.0 V) while simultaneously tracking a high, fluctuating current draw (12.1 A to 12.6 A). The ability of the ACS712 and 0-25 V sensor package to capture this rapid, high-current transient confirms the high-fidelity performance of the data acquisition system for real-time State-of-Power (SoP) monitoring.
2. **Wireless Charging Segment (WPT Efficacy):** This segment tested the complete functional chain of the WPT system. The system successfully observed a steady voltage recovery at the load (11.42 V to 12.00 V). The corresponding charging current was confirmed to be a stable, low-rate charge fluctuating in a narrow 0.10 A to 0.13 A band. This stability validates the functional efficacy of the entire WPT chain, from the BC547 driver to the rectifier, and proves that the IR alignment interlock and control logic are effectively managing the power transfer.

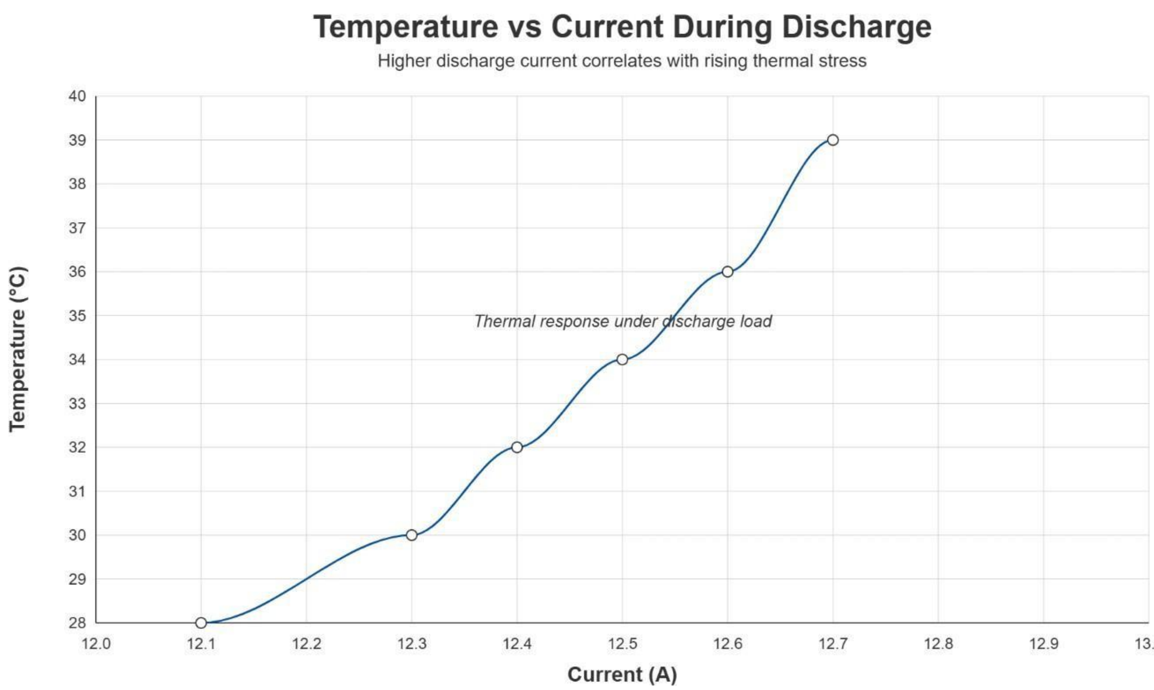

Figure 5: Temperature vs Current (discharge)

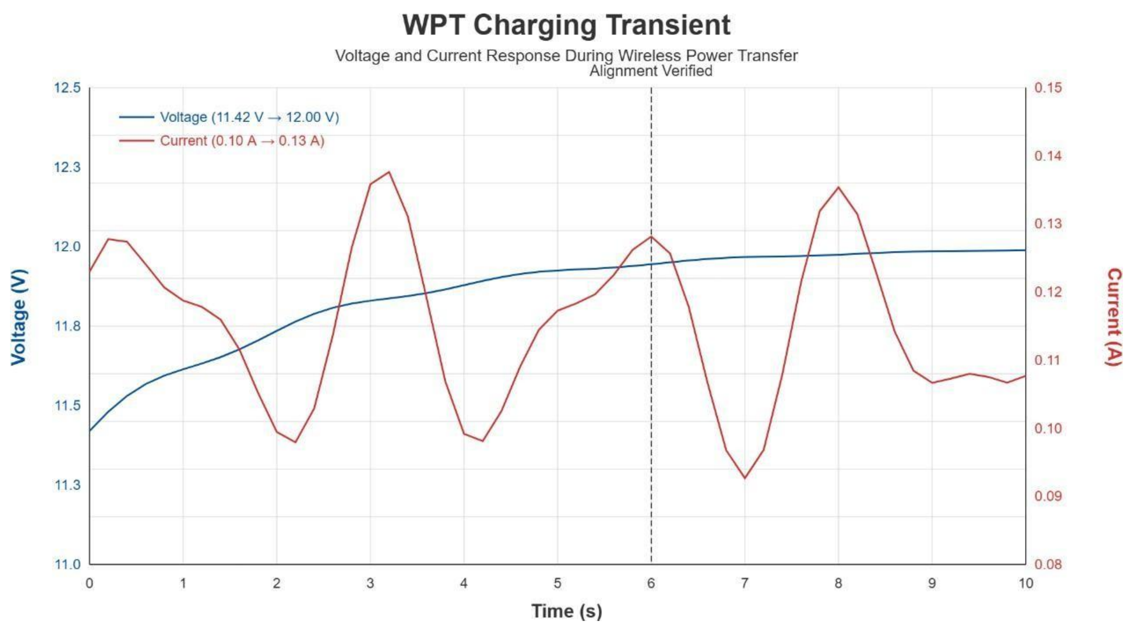

Figure 6: Discharge: V & I

The most valuable output of this prototype is not the hardware itself, but the validated, high-fidelity time-series data stream (V, I, T). The PoC report itself notes that this captured transient data is "necessary for developing accurate electrochemical models" and is the data "required to train and execute these advanced algorithms".

This connects directly to the body of research on industrial-grade Battery Management Systems. Modern, data-driven prognostics are built entirely on "real-world datasets", "time series battery degradation data", and "real-world assessment[s]". The PoC's primary success, therefore, was not simply charging a battery at 0.1 A; it was validating an entire data acquisition system capable of generating the high-fidelity training fuel required to build and validate the industrial-grade, AI-driven BMS algorithms that will ultimately replace the prototype's rudimentary logic.

CHAPTER III: INDUSTRIAL SCALABILITY: POWER ELECTRONICS AND WPT PHYSICS

3.0 Scaling the Power Stage: From Transistors to Wide-Bandgap Semiconductors

3.0.1 The Multi-Kilowatt Requirement

The prototype's use of a BC547 NPN transistor was sufficient to demonstrate the principle of generating a high-frequency magnetic field. The transition to an industrial, multi-kilowatt system suitable for EV charging (e.g., Level 2 at 7.2 kW or DC fast charging >50 kW) necessitates a complete redesign of the power stage. This requires a move from simple transistors to high-efficiency, high-voltage power-switching architectures, dominated by wide-bandgap (WBG) semiconductors.

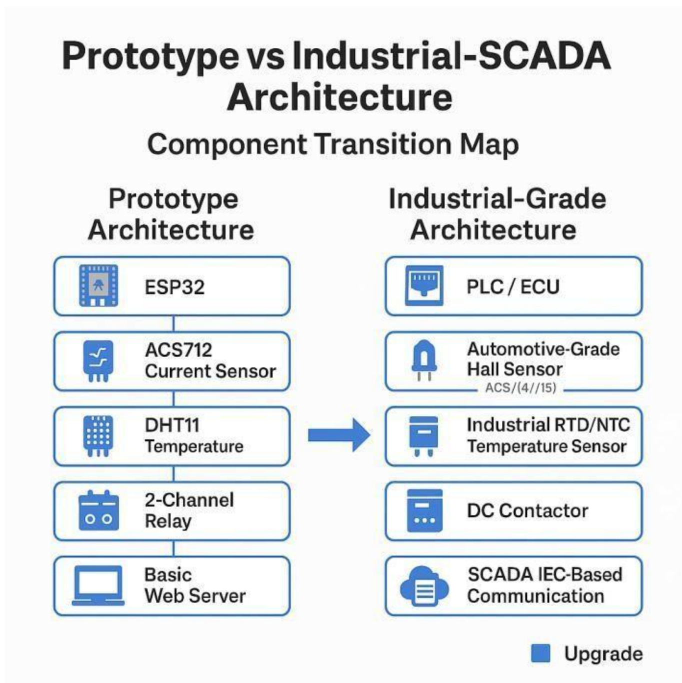

Figure 7: Prototype → Industrial

3.0.2 The Rise of Silicon Carbide (SiC) MOSFETs

The prototype's literature survey correctly identifies Silicon Carbide (SiC) MOSFETs as the preferred replacement for traditional Silicon (Si) IGBTs. Recent (post-2020) analysis confirms that SiC is "strongly dominating" the EV application market, particularly for high-voltage components like the main traction inverter (operating up to 800 V) and on-board chargers (OBCs).

The key advantages of SiC over Si are profound:

3.0.2.1 **Superior Efficiency:** SiC's lower switching losses are a primary driver. This can reduce inverter losses by up to 10%, an efficiency gain that translates directly into an increased driving range for the EV.

3.0.2.2 **Superior Thermal Performance:** SiC possesses a significantly higher thermal conductivity than silicon. This allows SiC MOSFETs to operate reliably at junction temperatures up to 200°C, which in turn simplifies the vehicle's complex and heavy thermal management (cooling) systems.

3.0.2.3 **Higher Power Density:** The high switching frequency capabilities of SiC, combined with its thermal stability, enable the use of smaller, lighter magnetic components and heat sinks, thus increasing the overall power density of the charging system.

3.0.3 Gallium Nitride (GaN) for High-Frequency Converters

While SiC dominates the high-voltage traction inverter, the WPT power stage is a different application. It is a high-frequency, isolated DC-DC converter, typically an LLC resonant converter topology. For this specific application, a different WBG material, Gallium Nitride (GaN), offers superior performance.

A direct comparison of 650 V commercial devices reveals GaN's critical advantages for this topology:

3.0.3.1 **Drastically Lower Gate Charge:** A representative GaN HEMT has a 0 g of 6.1 nC. This is nearly an order of magnitude lower than its SiC (48 nC) and Si (61 nC) counterparts. Since gate-driver losses are a primary component of switching losses, this enables efficient operation at much higher frequencies.

3.0.3.2 **Lower On-Resistance:** The GaN device exhibits the lowest (63 m) compared to SiC (104m) and Si (99 m), resulting in lower conduction losses.

These superior material properties mean that GaN-based LLC converters can achieve peak efficiencies above 98% while operating at switching frequencies up to and beyond 1 MHz. This ultra-high-frequency operation allows for a 2-3x improvement in power density over Si-based designs, as the magnetic components (transformers, inductors) can be drastically miniaturized.

The choice between SiC and GaN is therefore not mutually exclusive; it is application-specific. A fully optimized industrial EV system would likely be a hybrid, leveraging SiC MOSFETs for the vehicle's "hot and high-voltage" main traction inverter, while using GaN HEMTs for the "fast and efficient" WPT system's LLC resonant converter.

Table 3.1: Comparative Analysis of Wide-Bandgap Semiconductors (Si vs. SiC vs. GaN)

Parameter	Si (MOSFET)	SiC (MOSFET)	GaN (HEMT)	Significance
Bandgap	1.12 eV	3.2 eV	3.4 eV	Higher voltage, higher temp operation.
Critical Field	0.3 MV/cm	2.2 MV/cm	3.3 MV/cm	Higher blocking voltage in smaller space.
Thermal	1.5 W/cm K	3.8 W/cm K	1.3 W/cm K	SiC has superior heat dissipation.
R (650V)	99 m	104 m	63 m	GaN has lowest conduction losses.
Gate Charge	61 nC	48 nC	6.1 nC	GaN has drastically lower switching losses.
Ideal Application	Low-Power / Legacy	EV Traction Inverter (800V+)	WPT LLC Converter (>1MHz)	

3.1 Magnetic Coupler Design: From Air-Core to Optimized Magnetic Materials

3.1.1 The Ferrite Core Standard

The prototype's air-core coils are a valid tool for demonstrating physics principles but are unsuitable for high-power transfer due to massive magnetic flux leakage. The first-level industrial upgrade, correctly identified in the prototype's literature survey, is the incorporation of ferrite cores.
Recent (post-2020) research details this as a "breakthrough" in WPT design. By integrating optimized "ferrite boxes" into circular coil designs, the magnetic flux is effectively directed from the transmitter to the receiver. This design achieves a remarkable 50% increase in coupling efficiency and a 300% boost in Electromagnetic Field (EMF) strength. Further studies on ferrite structure optimization confirm these gains, with one novel design improving power transfer by 119.9% simply by providing a low-reluctance closed path for the magnetic field.

3.1.2 Beyond Ferrite: The Nanocrystalline and Amorphous Frontier

While ferrite is the current industrial standard (e.g., in SAE J2954) , it is now widely considered a "bottleneck" that restricts system power density. The limitations of traditional Mn-Zn ferrites are twofold:

1. **Low Saturation Magnetic Flux Density (B_s):** Ferrites saturate at relatively low magnetic field strengths, limiting the amount of power that can be pushed through a given core size.
2. **Mechanical Brittleness:** Ferrite is a ceramic material that is heavy, brittle, and prone to cracking under the shock and vibration of an automotive environment.

This has driven cutting-edge research into advanced amorphous and nanocrystalline alloys as a replacement. The advantages are clear and directly address ferrite's weaknesses:

- **Higher Saturation:** Fe-based nanocrystalline materials exhibit a 1.25 T, more than double the 0.53 T of standard Mn-Zn ferrite. This allows for significantly higher power transfer through the same-sized magnetic coupler.
- **Mechanical Flexibility:** These advanced materials are fabricated as "flexible nanocrystalline laminated ribbons". This flexibility overcomes the brittleness of ferrite, enabling lightweight, conformable designs that can be integrated into curved vehicle underbodies.

Performance studies confirm that nanocrystalline cores have lower core loss, higher saturation, and better temperature stability than ferrites. This enables the design of high-efficiency (92%) systems with extremely high-power density (29.9 W/cm^3), paving the way for the next generation of WPT. This establishes a clear technology ladder for magnetic couplers:

1. **Air-Core (PoC):** For principal demonstration.
2. **Ferrite (Industrial Standard):** For cost-effective efficiency and EMF direction.
3. **Nanocrystalline (Cutting Edge):** For high-power-density, lightweight, and mechanically flexible applications where performance is paramount.

3.2 Compensation Topologies: A Comparative Analysis for Real-World Misalignment

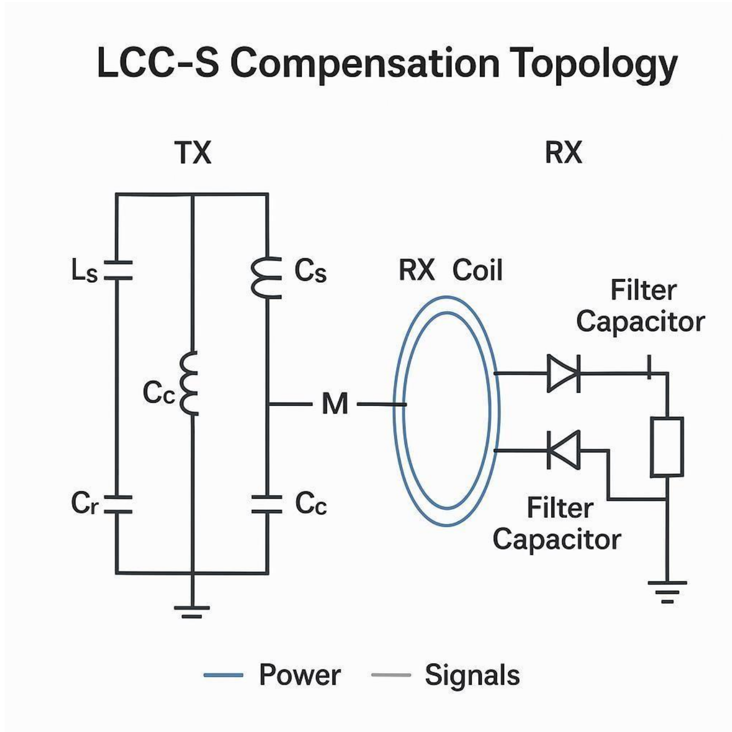

Figure 8: LCC-S topology

3.2.1 The Role of Compensation Networks

Scaling from the prototype's simple full-bridge rectifier to a multi-kilowatt, bidirectional system requires the implementation of advanced resonant compensation topologies. These networks are crucial for achieving high efficiency, enabling soft switching (Zero Voltage Switching, or ZVS) for the power electronics, and—most critically—managing the inevitable coil misalignment. The prototype's literature survey correctly identifies the main contenders: Series-Series (SS), LCC-S, and LCC-LCC.

3.2.2 The SS vs. LCC Misalignment Debate

The prototype's literature review (citing refs,) makes the claim that LCC topologies are "safer" during misalignment because their output current is "less dependent on... magnetic coupling changes".

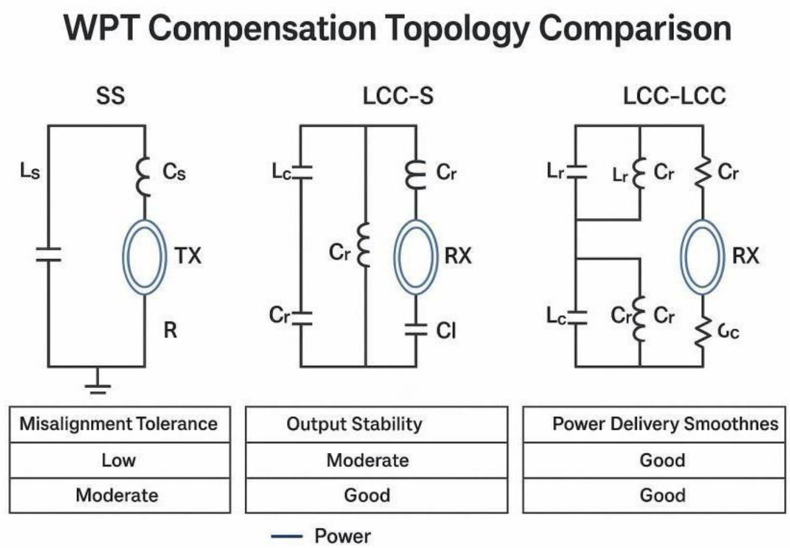

Figure 9: Compensation comparison

Recent, more detailed analyses show the reality is far more complex and nuanced. Misalignment tolerance is not an absolute property of the topology; it is load-dependent. A deep comparative analysis reveals the following critical relationship:

3.2.2.1 **At High Load Resistance** (i.e., when the battery is nearly full or charging at a low rate): The LCC topology is indeed superior. It is less sensitive to misalignment, and one study demonstrated a 30.4% larger high-efficiency (>90%) operating region compared to SS under these conditions.

3.2.2.2 **At Low Load Resistance** (i.e., when the battery is empty and drawing maximum power): The SS topology is actually more tolerant to misalignment and less sensitive to coupling changes.

This finding complicates the design choice, suggesting that the "best" topology may depend on the battery's typical charging state.

3.2.3 LCC-S vs. LCC-LCC: Optimizing for Different Goals

Furthermore, the "LCC" family is not uniform. The choice between an LCC-S (LCC-Series) and an LCC-LCC (LCC-LCC) topology depends on the system's primary optimization goal. This creates a "compensation trilemma" where engineers must tradeoff between power stability, current stability, and data stability.

1. **LCC-S (Optimization for Constant Current):** Research focusing on LCC-S topologies praises them for their "excellent load-independent current output". This is a highly desirable feature for battery charging, which relies on a Constant Current (CC) phase. This topology provides a "robust power characteristic against wide misalignment," making it ideal for prioritizing battery safety and stable charging.
2. **LCC-LCC (Optimization for Data Integrity):** A critical function of a "smart" charger is

communication via ISO 15118, which often happens simultaneously with power transfer (SWPDT). A recent comparative analysis of SS and LCC-LCC for SWPDT found that the **LCC-LCC** topology provides a "more stable and symmetrical performance" for the data channel during misalignment.

This reveals a complex trade-off: an LCC-S topology may be superior for stable current delivery , but an LCC-LCC topology appears to be more robust for stable data delivery. An industrial system that must guarantee ISO 15118 communication for V2G and Plug & Charge, even under partial misalignment, may be forced to choose LCC-LCC, even if LCC-S offers a more stable charging current.

Table 3.2: Comparative Analysis of WPT Compensation Topologies

Topology	Misalignment Tolerance (Power)	Output Characteristic	Data Channel (SWPDT) Stability	Key Finding
SS (Series-Series)	Superior at low loads	Load-dependent	Less stable	Simple, but load-dependent.
LCC-S	Superior at high loads	Load-independent current	Not specified	Ideal for battery safety (CC charging).
LCC-LCC	Superior at high loads	Load-independent voltage	Most stable & symmetrical	Ideal for systems needing robust ISO 15118 data transfer.

3.3 EMF Shielding and Electromagnetic Compatibility (EMC

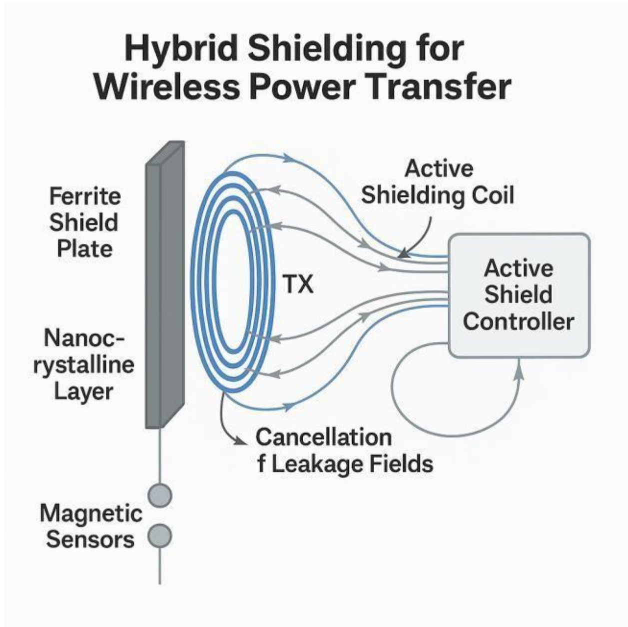

Figure 10: Hybrid shielding

3.3.1 The Dual Role of Magnetic Materials

The "300% boost in EMF strength" created by the ferrite cores described in Section 2.1 is a double-edged sword. While it enhances power transfer, this powerful magnetic field must be meticulously contained to meet human exposure safety standards (e.g., ICNIRP) and prevent Electromagnetic Interference (EMI) with other vehicle systems. The magnetic materials (ferrite, nanocrystalline) serve a dual purpose: enhancing the coupling factor (k) and acting as a passive shield to guide stray flux.

3.3.2 Advanced Shielding Methodologies

The prototype, being a low-power PoC, did not require shielding. An industrial system, however, requires an advanced shielding architecture. Post-2020 research has moved far beyond simple passive plates.

3.3.2.1 **Advanced Passive Shielding:** This involves the development of novel materials and geometries. Instead of brittle ferrite, new shields are being proposed using "quartz fiber and nanocrystalline reinforced resin matrix composite" materials. These composites are mechanically robust, lightweight, and effective at suppressing magnetic leakage. This is often combined with optimized geometries, such as "reactive shields" or structures designed to provide a "low reluctance closed path" for stray magnetic fields, thereby shielding the environment and improving coupling simultaneously.

3.3.2.2 **Active Shielding:** This is a cutting-edge technique that treats shielding as a dynamic control problem. An "active" shield consists of "multiple active coils" powered independently. A control algorithm (e.g., Gradient Descent) is used to calculate and inject the precise current into these coils needed to generate a destructive-interference field. This field actively cancels the leakage flux. Studies have shown this method can halve the magnetic field in critical areas with less than a 1% impact on power transfer efficiency.

EMF shielding is thus evolving from a static, passive component (a "dumb" plate) into a dynamic, intelligent subsystem. The most advanced industrial systems will likely use a hybrid approach: optimized passive shields made of nanocrystalline composites combined with AI-controlled active shielding coils to dynamically manage EMF exposure in real-time, ensuring safety without sacrificing efficiency.

CHAPTER IV: INDUSTRIAL SCALABILITY: INTELLIGENT SYSTEMS AND NETWORK INTEGRATION

4.0 From Prototype Sensing to Industrial-Grade BMS

4.0.1 The Limits of Rudimentary Estimation

The prototype's "rudimentary BMS approach”, based on fundamental methods like Open-Circuit Voltage (OCV) correlation or Modified Coulomb Counting, is a valid starting point for a PoC. It confirms the system's capacity to detect basic states and termination points. However, these methods are grossly insufficient for an industrial application. They are highly susceptible to sensor drift, cumulative error (in Coulomb counting), temperature variations, and non-linear aging effects, making their State-of-Charge (SOC) and State-of-Health (SOH) estimations unreliable and potentially unsafe.

4.0.2 Model-Based Estimation (The Kalman Filter Family)

The first step toward an industrial BMS, as cited in the prototype's literature, is the use of model-based adaptive filters.

4.0.2.1 **Extended Kalman Filter (EKF):** The EKF is a well-established standard, commonly used in conjunction with an Equivalent Circuit Model (ECM) of the battery. The EKF continuously updates the ECM's state variables based on real-time sensor measurements. Its primary weakness, however, is that its accuracy is fundamentally dependent on the pre- defined ECM. If the model is inaccurate, or as the battery ages and its parameters drift, the EKF's estimation accuracy degrades.

4.0.2.2 **Adaptive Extended Kalman Filter (AKF):** A significant improvement over the EKF, the AKF is designed to compensate for model inaccuracies. The AKF "adaptively sets a proper value for the model noise covariance matrix based on online innovation analysis". In essence, it "learns" the model's error in real-time and adjusts its own parameters, resulting in a lower estimation error and superior robustness to battery aging and parameter drift.

4.0.3 Data-Driven Estimation (The AI "Arms Race")

The dominant trend in post-2020 BMS research is the move to purely data-driven models. These models leverage the exact type of high-fidelity, transient (V, I, T) data stream that the prototype successfully validated (as discussed in Section 1.3.2). This field is in a state of rapid evolution, an "arms race" of competing AI architectures.

4.0.3.1 **Long Short-Term Memory (LSTM):** LSTMs, a type of Recurrent Neural Network (RNN), are heavily cited. They are purpose-built to model time-series data, allowing them to learn the complex, non-linear relationships between current, voltage, temperature, and battery degradation over time.

4.0.3.2 **Temporal Convolutional Networks (TCN):** While LSTMs are effective, newer research is already challenging their dominance. A 2022 study directly comparing TCNs and LSTMs for SOH estimation found that "the performance of the TCN was 3% better than that of the LSTM" in predicting SOH with high accuracy.

4.0.3.3 **Transformers and Hybrids:** The current state-of-the-art in sequence modeling is the Transformer architecture. Recent studies are demonstrating the power of hybrid models that combine these architectures. A TCN–Transformer–BiLSTM hybrid model and a Transformer-LSTM model have shown "outstanding performance" and "superior results," achieving Root Mean Square Error (RMSE) values below 1%.

This rapid architectural evolution—from LSTM to TCN to Transformers in just a few years—means that any industrial BMS hardware must be designed as a software-updatable platform. The "best" algorithm will be a moving target, and the system must be capable of receiving over-the-air (OTA) updates to deploy new, more accurate models as they are developed.

4.1 Advanced Battery Prognostics: Physics-Informed Neural Networks (PINN)

4.1.1 A Third Path: Hybridizing Physics and AI

A critical weakness of the data-driven models in Section 3.0.3 is that they are "data-hungry" and can be unreliable when operating outside the specific conditions of their training data. This has given rise to an emerging "third path" that hybridizes the model-based (EKF) and data-driven (LSTM) approaches: the Physics-Informed Neural Network (PINN).

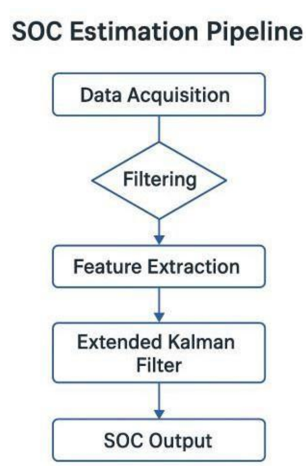

Figure 11: SOC estimation pipeline (EKF)

A PINN is a deep learning framework that embeds the governing physical equations of the system such as Fick's law of diffusion for lithium-ion movement—directly into the neural network's loss function. The total loss function that the network minimizes becomes a weighted sum of two terms: Here, Loss is the standard error between the network's prediction and the sensor's measurement, while loss is a penalty term that measures how badly the network's prediction violates the laws of physics.

4.1.2 The Advantage of "Physics-Constrained" AI

This hybrid approach provides two revolutionary advantages that solve the primary weaknesses of pure data-driven AI:

1. **It Solves the "Data-Hungry" Problem:** By "informing" the model with the laws of physics, the network no longer needs to learn these laws from scratch. As a result, PINN can achieve "remarkable performance" and high accuracy (e.g., RMSE of 0.014% for SOC) even with limited training data.
2. **It Solves the "Extrapolation" Problem:** A pure AI model trained on data from 20°C to 40°C has no reliable way to predict behavior at 50°C. A PINN, because it is constrained by physical laws that hold true at all temperatures, can make "adequate predictions, even for unseen situations".

PINN represents a paradigm shift in intelligent prognostics. By baking the physics of the battery into the AI, it creates a robust, scalable, and data-efficient model. This approach is the most promising path toward an industrial-grade, universally applicable AI-BMS that can be deployed without requiring massive, unique, and dangerous test datasets for every new battery chemistry or operating environment.

Table 4.1: Advanced BMS Algorithm Comparison

Category	Algorithm	Core Principle	Pros	Cons
Rudimentary	OCV / Coulomb Count	Lookup Table / Integration	Simple, low-compute.	Highly inaccurate; sensor drift.
Model-Based	EKF / AKF	Uses ECM + Kalman Filter.	Low compute, reliable.	Accuracy depends entirely on model. AKF is better.
Data-Driven	LSTM / TCN / Transformer	Learns from data patterns.	High accuracy. TCN/Transformers > LSTM.	"Data-hungry"; poor extrapolation to "unseen" conditions.
Hybrid	PINN	Data-driven, but constrained by physics equations.	High accuracy with limited data. Robust in "unseen" situations.	Computationally complex to train.

4.2 The Control Hub: From ESP32 to Industrial-Grade SCADA

4.2.1 Re-evaluating the ESP32 as an Industrial RTU

This section expands on the "prosumer vs. industrial" dichotomy introduced in Section 1.1.3. The prototype's use of the ESP32 as a SCADA unit is validated by a large body of research for "low-cost, open source" IoT applications. There are even commercial "ESP32 PLCs" available that emulate PLC functionalities for automation and monitoring.

However, these devices are not substitutes for true industrial controllers in mission-critical, harsh-environment applications. Literature reviews on the ESP32's industrial reliability are cautious, noting it is "reliable if you keep them in a friendly temperature range" and "wouldn't use them for anything truly mission critical". A consumer-grade microcontroller, even a powerful one, lacks the input/output (I/O) protection, galvanic isolation, and environmental hardening for a 20-year service life.

4.2.2 The Industrial PLC: A Mandate for Reliability

The industrial alternative is the Programmable Logic Controller (PLC) or an automotive-grade Electronic Control Unit (ECU). The difference between an ESP32 and a true PLC is not performance, but certified reliability.

A true industrial PLC is designed, tested, and certified for:

- 4.2.2.1 **Harsh Environments:** They are built to withstand "16KV isolation, extreme contact/air discharge, shock and vibration tests".
- 4.2.2.2 **Mission-Critical Redundancy:** They support "N+1 redundancy for PSUs and CPUs," where multiple processors "vote" on the correct action, allowing for "hot-swapping" of a failed CPU while the system is running.
- 4.2.2.3 **Long-Term Operation:** They are not disposable; they are designed for "an installation that lasts 20-30 years".

This class of industrial-process control device is governed by the IEC 61131-2 standard, which specifies the rigorous "Equipment requirements and tests" they must pass.

The transition from the prototype's ESP32 to a scalable, industrial product is therefore not an "upgrade"—it is a category change. A commercial charging station must use a controller certified to IEC 61131-2 and built with power-stage components qualified to AEC-Q100. This is a non-negotiable regulatory, safety, and reliability hurdle that defines the boundary between a prototype and a product.

4.3 Network Standardization: Implementing OCPP 2.0.1 and ISO 15118

4.3.1 Defining the "Dream Team" of Protocols

The prototype report correctly validates the premise that its physical control layer (ESP32 controlling a relay) is the foundation upon which "supervisory software layers" like OCPP and ISO 15118 can be built. These two protocols are often called the "dream team" for smart charging. It is critical to understand their separate, non-overlapping domains:

- 4.3.1.1 **OCPP (Open Charge Point Protocol):** Governs the vertical communication link, from the Charging Station Back-End Management System. It is used by the network operator for remote control, operations, data analytics, and dispatching "Smart Charging" commands.

4.3.1.2 **ISO 15118:** Governs the horizontal communication link, from the Electric Vehicle Charging Station. It is used by the vehicle to automate authentication (for "Plug & Charge") and, most importantly, to negotiate Bidirectional Power Transfer (BPT), the core technology of V2G.

4.3.2 Practical Deployment Challenge 1: OCPP and Constrained Hardware

The prototype's plan to run these protocols on its existing ESP32 controller faces a significant, practical hardware bottleneck.
Recent (post-2020) analyses on deploying the full OCPP 2.0.1 protocol, with all its features (smart charging, security, firmware management), on resource-constrained microcontrollers have found it to be "impractical". The full protocol's RAM and ROM footprint is too large. This has forced the development of "lite" or "minimal" implementations, such as MicroOCPP, which strip out optional features to implement only the "Core" profile. While functional, this streamlined version, which can operate within 50 kB of RAM, represents a significant compromise and a loss of the advanced features that OCPP 2.0.1 promises.

4.3.3 Practical Deployment Challenge 2: The ISO 15118 "V2G Gap"

A more fundamental barrier exists for V2G. The prototype, and indeed much of the industry, operates on the assumption that ISO 15118 is the V2G-enabling standard. This is only partially true.
A critical finding from recent (2024) technical analyses is that the latest standard, ISO 15118-20, does not include grid codes. This means that while the protocol can successfully negotiate bidirectional power flow between the car and the charger (enabling Vehicle-to-Home, or V2H), it lacks the network communication standards to interface with the utility grid operator for full, grid-level Vehicle-to-Grid (V2G) services.
This is identified as one of the "final hurdles" to V2G implementation and a significant gap in the standard that must be amended to allow network code communication. Therefore, the prototype's validated "pathway to industrial network integration" is currently blocked by both its chosen low-resource hardware and the technical immaturity of the V2G standard itself.

Table 4.2: Network Protocol Functions and Deployment Challenges

Protocol	Governs Communication	Key Functions	Deployment Challenge (Post-2020)
OCPP 2.0.1	Charging Station Back-End Mgmt.	Remote Control, Smart Charging, Analytics	Impractical for low-resource MCUs (e.g., ESP32); requires "lite" versions.
ISO 15118-20	EV Charging Station	Plug & Charge, Bidirectional Power (V2G)	Does not include grid codes. Currently enables V2H, but not full utility V2G.

CHAPTER V: FUTURE TRAJECTORIES AND STRATEGIC DEPLOYMENT

5.0 Enabling Bidirectional Power: The Vehicle-to-Grid (V2G) Ecosystem

5.0.1 The V2G Value Proposition and Technical Hurdles

The prototype's future scope correctly identifies Vehicle-to-Grid (V2G) enablement as a primary research trajectory. V2G capability, facilitated by Bidirectional Power Transfer (BPT), fundamentally transforms the EV fleet from a massive, destabilizing grid liability into a distributed, flexible grid asset. By functioning as mobile energy storage, the EV fleet can provide critical ancillary services, support power balance during peak demand, and store excess renewable energy. The technical prerequisites for this are bidirectional power converter topologies (as reviewed in) and advanced control strategies capable of managing both active (P) and reactive (Q) power.
However, the most significant challenges to V2G deployment are not hardware; they are systemic. A 2024 review highlights a "lack of a transparent business model," an "absence of stakeholder involvement," and, most critically, the immense grid risk of "unethical and unscheduled V2G practices" causing new forms of instability. A coordinated, intelligent system is mandatory.

5.0.2 The Fleet Coordination Problem: Distributed Optimization

Coordinating the charging and discharging of thousands or millions of privately-owned EVs is computationally impossible for a single, centralized entity. The solution, now a major focus of post-2020 research, is distributed optimization, where each charging node possesses the intelligence to make local decisions that serve a global goal.

5.0.2.1 **Alternating Direction Method of Multipliers (ADMM):** ADMM is a "powerful framework for solving large-scale problems in a decentralized manner". Research has proposed a hierarchical ADMM framework where the Distribution System Operator (DSO) sends high-level price/need signals to "EV Aggregators" (EVAs). The EVAs then use ADMM to manage their local fleet of EVs to meet that goal. A simulation of this model, managing both active and reactive power, demonstrated a 300% decrease in peak EV load for the DSO and a 28% reduction in electricity costs for users.

5.0.2.2 **Multi-Agent Reinforcement Learning (MARL):** An alternative, AI-driven approach utilizes a "dual-layer" system.

5.0.2.2.1 **Upper Layer (Optimization):** A Multi-Agent Reinforcement Learning algorithm (specifically, a two-stage MAPPO) determines the optimal operational strategy for the microgrid as a whole.

5.0.2.2.2 **Lower Layer (Control):** A "consensus control method" translates that global strategy into uniform, consistent charging/discharging reference signals for every individual EV in the network.

V2G is therefore not a simple power electronics problem. It is a large-scale distributed computing and algorithmic control problem. The most promising solutions (ADMM, MARL) treat the aggregated EV fleet as a controllable "Virtual Power Plant", using advanced optimization algorithms to achieve global grid stability from millions of local, decentralized decisions.

5.1 Predictive Lifecycle Management: AI-Driven Thermal Prognostics and Digital Twins

5.1.1 AI-Driven Thermal Prognostics

The prototype's future scope includes moving beyond its reactive thermal protection (a DHT11 sensor triggering a relay) to proactive prognostics. This is a critical field for ensuring the safety and longevity of EV batteries.

By leveraging the high-frequency (V, I, T) data stream validated in the PoC, advanced AI models (LSTMs, TCNs) can be trained to "predict temperature distribution, thermal gradients, and fire risk in real time". This predictive capability allows the BMS to move from simple shutdowns to "dynamic cooling adjustments" or real-time optimization of charging parameters (like current) to prevent thermal excursions before they happen. This proactive thermal management is essential for maximizing both battery lifespan (SOH) and operational safety.

5.1.2 The Digital Twin (DT) Integrating Framework

This leads to the ultimate evolution of the prototype's IoT architecture: the Digital Twin (DT). A Digital Twin is a "high-fidelity virtual representation" of the physical charging system. It is a framework that "fuses artificial intelligence and IoT technologies," where real-time sensor data from the physical asset is fed into its virtual counterpart.

The prototype's validated IoT data stream (Section 1.3.2) is the essential enabler for this DT. The user's own cited reference explicitly proposes a "Digital Twin Framework for Decision-Support and Optimization", which uses techniques like Agent-Based Modeling (ABM) to simulate driver behavior and optimize infrastructure planning.

The Digital Twin is the master framework that unifies every other advanced topic discussed in this report. It is the virtual environment that will house, test, and manage the AI-driven systems:

- 5.1.2.1 The **PINN-based BMS models** (Section 3.1) for SOC/SOH estimation.
- 5.1.2.2 The **AI-driven thermal prognostic models** (Section 4.1.1) for safety.
- 5.1.2.3 The **ADMM or MARL distributed optimization algorithms** (Section 4.0.2) for V2G coordination.

The prototype's ESP32 is a single data-collection nerve ending; the Digital Twin is the intelligent, adaptive brain that receives all sensor data and manages the entire network.

5.2 Grid Stability and Cybersecurity in a V2G-Enabled Network

5.2.1 The Smart Grid's Attack Surface

The transition to a "smart" grid, while solving the peak load problem, creates an entirely new vulnerability. This is the paradox of the smart grid: the very features that enable V2G and demand response (remote, networked, high-power IoT control) are the same features that create an attack surface of unprecedented scale.

Research into the cybersecurity of smart charging warns that the primary threat is "weaponizing" the EV fleet into a botnet to launch "large-scale, demand-side cyberattacks on the power grid". This is not a theoretical threat. A simulation cited in IEEE literature demonstrated that a botnet that "simultaneously shutdown 12% EVs in California" would be "sufficient for triggering under-frequency alarms in the western interconnection of the US power grid".

5.2.2 Identifying Attack Vectors

These vulnerabilities exist at every layer of the smart architecture validated by the prototype :

5.2.2.1 **User Layer:** Vulnerable smartphone applications used to manage charging.

5.2.2.2 **Vehicle Layer:** The unencrypted, insecure nature of the in-vehicle Controller Area Network (CAN) bus.

5.2.2.3 **Protocol Layer:** Most critically, the ISO 15118 standard itself. This "smart" protocol "lacks security measures such as message certification and end-to-end encryption in a trusted transport layer security". This allows a remote attacker to "eavesdrop, modify, and spoof the EV charging message".

In a scalable smart-charging network, cybersecurity is not an "add-on" feature. It is the single most critical component for ensuring grid stability, and it must be designed into the hardware, software, and protocols from the very beginning.

5.3 Strategic Deployment Models: From Resilient Rural Hubs to Smart City Integration

The single, validated architecture of the prototype serves two entirely different strategic deployment models, each leveraging a different part of its converged design.

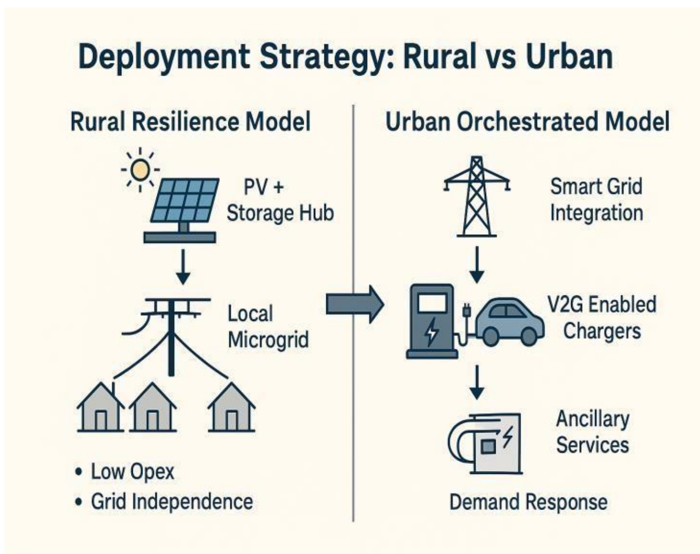

Figure 12: "Rural vs Urban deployment"

5.3.1 The "Resilience Model": Rural and Weak-Grid Deployment

This model validates the prototype's application for "rural or weak-grid deployment". This is a critical, underserved market. Rural residents in the US, for example, "drive more than their urban counterparts, spend more on vehicle fuel and maintenance, and often have fewer alternatives".

For this market, the PV + Storage layer of the prototype is the key value proposition. The architecture creates a resilient, off-grid or grid-supplementing charging hub that promotes equitable and sustainable transportation access where grid expansion is prohibitively expensive or

technically complex.
The strategic framework for this model is well-defined. The U.S. Department of Transportation's "Charging Forward" toolkit provides a clear path for both planning (e.g., utility coordination, equitable planning processes) and funding (e.g., Department of Energy VTO grants, DOC EDA programs, and VW Settlement Funds). This model sells grid-independence, access, and resilience.

5.3.2 The "Orchestration Model": Smart City Integration

This second model leverages the prototype's "smart city networks" potential. In a dense urban context, the charger is not an autonomous hub but a fully grid-integrated asset.
For this market, the IoT + V2G capabilities of the prototype are the key value proposition. This model relies entirely on the successful implementation of the OCPP and ISO 15118 protocols. Its purpose is to achieve "sectoral coupling"—the deep integration of the transportation and energy sectors —and to use the aggregated EV fleet for dynamic load balancing, frequency regulation, and other ancillary grid services. This model sells grid-services, demand-response, and optimization.

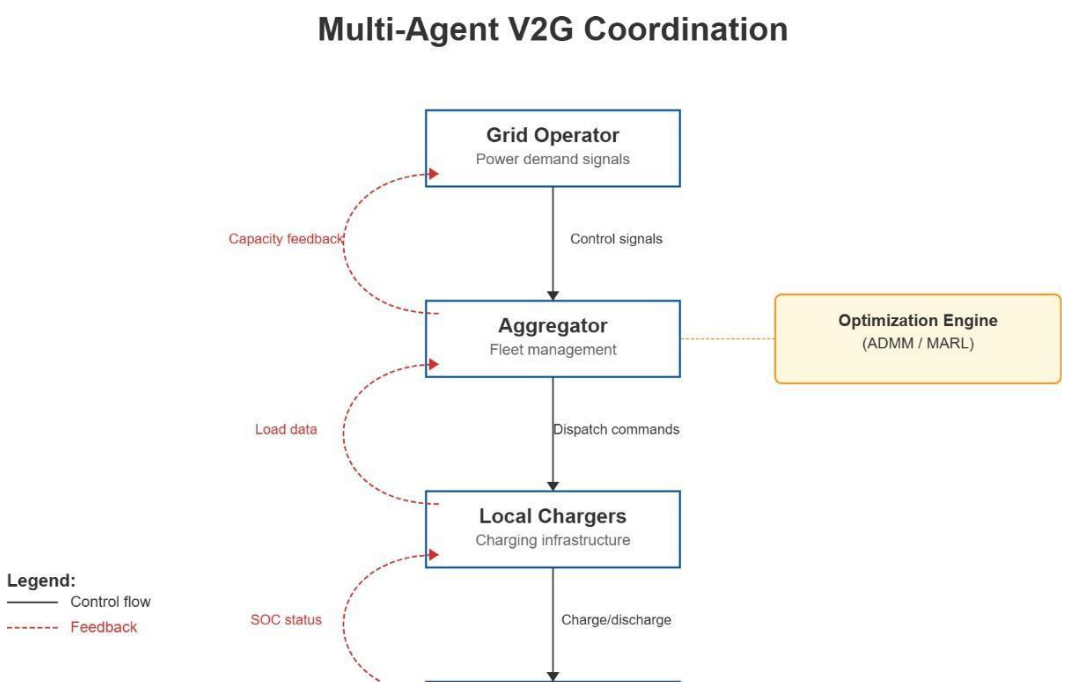

Figure 13: V2G coordination

The prototype's single architecture is thus a powerful blueprint for two distinct business models: one that solves a grid problem by decoupling from it (Rural), and one that solves a grid problem by deeply integrating with it (Urban).

5.4 Concluding Synthesis

This project successfully achieved its primary objective: the functional convergence and architectural validation of a sustainable, IoT-enabled EV smart charging system Proof-of-Concept.

The system cohesively integrated four distinct technological domains: PV energy harvesting with CC/CV management, Inductive Power Transfer with alignment-based safety interlocking, real-time sensor data acquisition (V, I, T), and cloud-based Supervisory Control (SCADA).
The use of Transient Characteristic Measurement (TCM) provided rigorous experimental validation of the control logic's stability and the sensor suite's high-fidelity performance in tracking dynamic transient conditions. The most significant output of this validation is the confirmation of a reliable, high-frequency data stream, which serves as the essential training data required for the advanced, AI-driven prognostics that define modern industrial-grade systems.
The path from this successful prototype to an industrially scalable and commercially viable product is a dual transformation:

1. A **Physical Transformation:** This involves a systematic, one-for-one substitution of the prototype's consumer-grade components with their industrial and automotive-qualified equivalents. This means replacing the ESP32 with an IEC 61131-2 certified PLC; replacing the BC547 and air-core coils with a GaN-based LLC converter and nanocrystalline-core magnetic couplers; and replacing all sensors and relays with AEC-Q100 qualified components. This transformation scales the system's reliability, power, and environmental robustness.
2. An Intelligence Transformation: This involves upgrading the prototype's rudimentary logic with a sophisticated, multi-layered intelligent system. This means replacing simple OCV estimation with a Physics-Informed Neural Network (PINN) for BMS prognostics; evolving the simple relay logic into a Digital Twin framework capable of running AI-driven thermal prognostics; and expanding the simple IoT data push into a full V2G-capable network coordinated by distributed optimization algorithms (e.g., ADMM).

This analysis has also identified critical, unresolved gaps in the current industrial landscape, namely the resource limitations of microcontrollers for full OCPP 2.0.1 deployment and the "grid code" deficiency in the ISO 15118-20 standard, which remains a primary hurdle to full V2G.
The validated prototype, therefore, is not an end-point. It is the essential, verified, and open-platform foundation upon which this complex, reliable, and intelligent industrial-grade system can be confidently engineered.

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