

AI-BASED PORTABLE SUBSTATIONS AND TRANSFORMER DESIGN FOR FAST EV CHARGING: A CRITICAL REVIEW OF INNOVATIONS AND CHALLENGES

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Abstract

This study addresses the pressing engineering problem of how to deliver high-power EV fast charging at the grid edge without compromising reliability, power quality, deployment speed, or cost. The purpose is to quantify how AI integration and transformer or portable-substation design choices relate to real-world field performance. We conduct a quantitative, cross-sectional, case-based investigation on 10 operating fast-charging sites that are cloud connected and enterprise managed, and pair it with a systematic literature review of 68 publications to ground constructs and measures. The sample comprises cloud or enterprise cases instrumented with SCADA and power-quality telemetry. Key independent variables include AI integration, modularity and standardization of portable skids, transformer technology and cooling class, with contextual moderators such as feeder short-circuit strength and ambient temperature. Outcomes include availability, energy throughput, total harmonic distortion, voltage deviation events, normalized hottest-spot temperature rise, installed cost per kW, and time-to-energize. The analysis plan follows three tiers: descriptive profiling, correlation screening, and multivariable modeling using OLS with heteroskedasticity-robust errors for symmetric outcomes and Gamma log-link GLMs for positive skewed cost and schedule metrics, with pre-registered interaction tests. Headline findings show that stronger AI integration is associated with higher availability and throughput and with lower distortion and thermal stress, modular standardized skids reduce installed cost and commissioning time, and solid-state transformer packages deliver clearer power-quality benefits on weak feeders. Implications for operators and OEMs include prioritizing standardized portable designs, instrumented data access, and an AI operations stack to optimize ramp management and predictive maintenance across heterogeneous sites.

Keywords

EV Fast Charging; Portable Substation; Solid-State Transformer; AI Integration; Power Quality; Thermal Performance;

INTRODUCTION

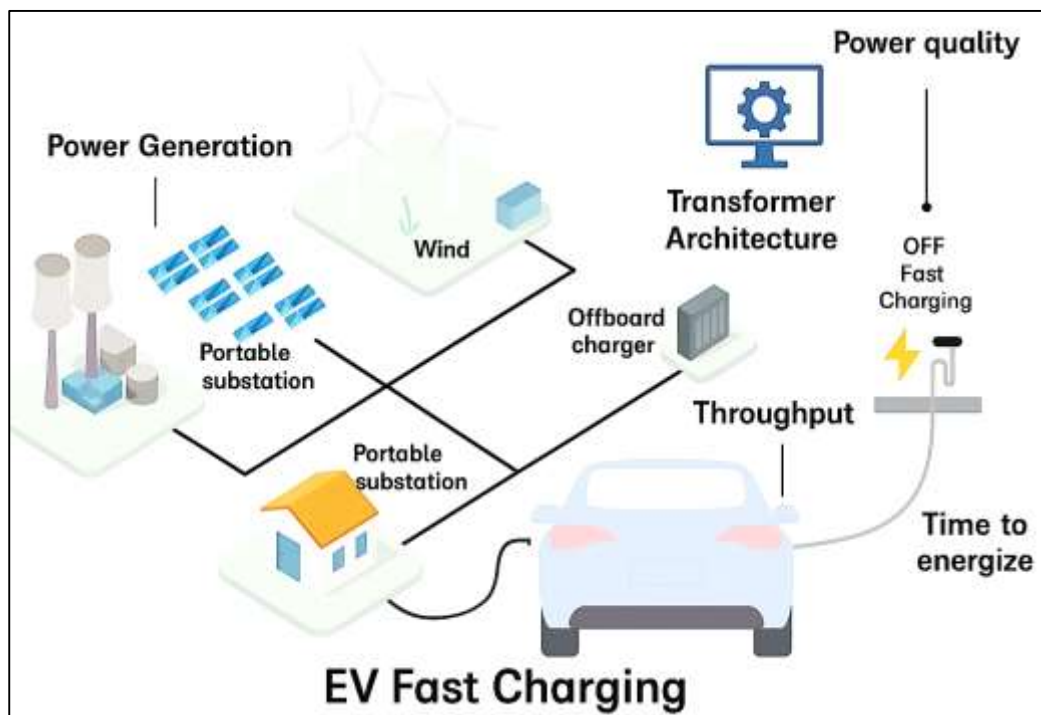
Electric vehicle (EV) fast charging refers to high-power direct-current (DC) charging typically ≥ 150 kW designed to replenish a substantial portion of battery capacity within minutes, rather than hours, by interfacing power-electronic converters with medium-voltage distribution systems through appropriately engineered substations and transformers (Das et al., 2020; Flammini et al., 2019). A portable substation (also called a mobile or skid-mounted substation) is a pre-engineered, transportable assembly that integrates transformer, protection, switching, metering, and control equipment on a trailer or skid to enable rapid interconnection and commissioning with minimal civil works and with standardized interconnects. Transformer design for fast charging spans conventional oil-immersed low-frequency transformers and solid-state transformers (SSTs), the latter embedding galvanic isolation at medium frequency and power-electronic conversion stages for high controllability, harmonic shaping, and bi-directional operation. Within substations, AI describes data-driven methods supervised and unsupervised learning, hybrid physics-informed analytics, and anomaly detection applied to forecasting, dispatch, and condition monitoring of transformers and substation assets (Faria et al., 2015). Internationally, rapid scaling of fast charging across North America, Europe, and Asia has placed new performance and compliance demands on grid-edge infrastructure: power quality limits, thermal management under steep ramps, voltage regulation on weak feeders, and accelerated deployment timelines at constrained sites such as highway hubs and dense urban parcels (Das et al., 2020; Souza et al., 2017). In that setting, portable substations and transformer innovations provide modular, redeployable capacity aligned with evolving demand, while AI-enabled analytics address monitoring and operational coordination. The intersection of these elements portable substation engineering, transformer architectures, and AI-supported operations constitutes a globally relevant problem domain with measurable outcomes such as uptime, throughput, power-quality indices, thermal stability, and time-to-energize.

Fast charging loads present distinctive electrical characteristics: high coincidence of multiple converters, steep step changes at session starts, current distortion related to switching patterns, and interactions among clustered units at a common point of connection. Empirical and modeling studies report elevated total harmonic distortion (THD), supraharmonic emissions in the 2–150 kHz band, voltage fluctuation under grouped sessions, and thermal stressors for distribution transformers under repeated rapid transients (Kempton & Tomić, 2005). These effects are influenced by feeder short-circuit strength, control strategies of rectifier stages, and configuration of charging plazas, which motivates careful substation and transformer design choices tailored to site context (Flammini et al., 2019; Gustavsson et al., 2016). At the substation level, harmonic shaping, filter coordination, and protection settings must align with converter spectra and with upstream coordination philosophies that were originally developed for low-frequency transformers (Kotsakis et al., 2015). Thermal profiles under fast-charging duty cycles also depart from standard assumptions: increased copper and stray losses at non-sinusoidal currents and more frequent loading ramps can shift hottest-spot temperature trajectories and accelerate insulation aging, requiring attention to cooling class selection, winding design, and thermal monitoring (Liu et al., 2021). International deployment demonstrates that these engineering considerations recur across grids with different codes and climates, underscoring the widespread relevance of portable substations whose form factors, protection schemes, and transformer choices can be standardized for quicker energization while satisfying power-quality limits (Sundström & Binding, 2012).

Condition assessment of power transformers provides a mature measurement toolkit that can be repurposed for fast-charging environments. Dissolved gas analysis (DGA) methods, ratios (e.g., Rogers, Duval), and frequency response analysis form a foundation for detecting incipient thermal and electrical faults in oil-immersed units and are well reviewed in the literature (Abu-Siada & Islam, 2012; Campanhol et al., 2016). Under the duty cycles characteristic of clustered DC fast charging, multi-modal monitoring combining oil chemistry, load histories, ambient conditions, partial discharge, and vibration benefits from machine-learning classifiers and ensemble methods that reduce false alarms and improve fault localization (Hong et al., 2018). These methods enable

condition-based maintenance regimes and targeted inspections, while digital records from portable substation deployments facilitate model retraining across redeployments and climates (Hong et al., 2018; Leemput et al., 2014). Studies in asset-management analytics show practical pathways to integrate supervisory control and data acquisition (SCADA) streams with online sensors for predictive diagnostics, providing quantitative inputs fault probabilities, health indices, expected remaining useful life that are compatible with both conventional and power-electronic transformer platforms (Saha et al., 2017). In international settings where large-scale buildout of charging is underway, standardized data schemas and access to transformer health signals improve comparability across sites and vendors, creating a shared measurement language for evaluating portable substation performance with or without SSTs (Clement-Nyns et al., 2010; Das et al., 2020; Saha et al., 2017).

Figure 1: AI-Enabled Portable Substations and Transformer Architecture for EV



SSTs have evolved from conceptual proposals into prototype and pilot-scale deployments documented in reviews of topologies, protection, modulation, and medium-frequency transformer (MFT) design (Abdul, 2021; Bisceglie et al., 2023). Principal engineering themes include power density versus efficiency trade-offs, dielectric coordination under high-frequency stress, modular multilevel arrangements (e.g., input-series/output-parallel cells), and converter reliability considerations under partial-power operation. In the context of EV fast charging, SSTs enable flexible AC/DC interfacing, reactive power support, and harmonic shaping on the grid side, while providing DC terminals that align naturally with rectifier stages at the charger (Rahimi et al., 2018; Rony, 2021). Researchers also report control strategies that coordinate multiple converter cells to attenuate specific harmonic orders observed in charging plazas, an approach that can reduce external filter size where feeder conditions allow (Danish & Kamrul, 2022; Putrus et al., 2009; Rönnberg et al., 2017). At the same time, SST integration in transportable enclosures requires attention to thermal management of wide-bandgap devices, fault-ride-through strategies, and interfaces with conventional protection designed for low-frequency transformers (Hossen & Atiqur, 2022; Ul-Haq et al., 2019). The portable form factor adds constraints on weight, footprint, and maintainability that intersect with SST modularity choices; studies comparing demonstrators and prototypes document these practicalities across international projects and vendor platforms,

enabling more granular measurement of efficiency, controllability, and footprint objectives in substation layouts oriented to fast charging (Kamrul & Omar, 2022; Yilmaz & Krein, 2013).

The scope of the present research centers on portable substations and transformer design choices for EV fast charging and their associations with measurable field outcomes under real operating conditions across multiple sites (Razia, 2022). The study positions AI integration as an explanatory construct alongside transformer architecture and modularity, situating these variables in relation to power-quality behavior, thermal stability, uptime, throughput, installed cost, and time-to-energize observed in practice. The international relevance arises from the commonality of engineering constraints footprint limits, interconnection practices, protection coordination, and data availability encountered across jurisdictions building dense fast-charging networks (Knez et al., 2019; Sadia, 2022). The methodological orientation draws from quantitative templates in transformer diagnostics, power-quality assessment, and EV integration studies, aligning survey-based Likert scales for AI and modularity constructs with objective technical logs and commissioning records (Abu-Siada & Islam, 2012; Buticchi et al., 2015; Danish, 2023). Within this boundary, portable substations are treated as a distinct design space characterized by standardized interconnects and redeployable capacity, while transformer design spans conventional low-frequency units and SST architectures documented in contemporary reviews and demonstrations (Arif Uz & Elmoon, 2023; Rahimi et al., 2018). The study thereby consolidates definitions, measurement constructs, and engineering considerations from peer-reviewed sources into a single cross-sectional, multi-case frame, appropriate for evaluating real-world performance of AI-enabled portable substations and transformer solutions for EV fast charging.

The objective of this study is to empirically quantify how AI integration and transformer/substation design choices within portable substation deployments are associated with field performance at high-power EV fast-charging sites, using a quantitative, cross-sectional, multi-case approach. Specifically, the research aims to: (1) operationalize and validate measurable constructs for AI integration (forecasting, dispatch optimization, and condition-based maintenance capabilities), design modularity (skid standardization, plug-and-play interconnects, and hot-swap features), and transformer technology (solid-state versus conventional, cooling class, and nameplate attributes); (2) characterize site performance outcomes using harmonized technical indicators, including availability/uptime, charging throughput, power-quality behavior (total harmonic distortion and voltage deviation events), thermal stability (hottest-spot rise relative to rating and alarm frequency), installed cost normalized by capacity, and time-to-energize measured from delivery to commissioning; (3) estimate the magnitude and direction of associations between AI integration and the above outcomes while controlling for design and contextual covariates such as feeder short-circuit strength, ambient temperature, urbanicity, commissioning year, and vendor effects; (4) evaluate the contribution of transformer and cooling choices to efficiency and thermal margins under fast-charging duty cycles and determine whether these design variables independently explain variation in uptime, throughput, and power-quality indices; (5) test moderation by environmental and network context, with a focus on whether ambient temperature and feeder strength alter the relationships between AI integration or transformer design and observed outcomes; (6) assess deployment efficiency by modeling installed cost and time-to-energize as functions of modularity, standardization, and technology selection; and (7) establish a reproducible measurement and analysis template survey instrument, data dictionary, and model specifications that enables consistent cross-site comparisons. To meet these objectives, the study will integrate de-identified operational logs (power quality, thermal, alarms, uptime, throughput) with structured stakeholder surveys using Likert five-point scales, apply descriptive statistics to summarize cases, compute correlations to screen relationships, and fit regression models with appropriate diagnostics and robustness checks. The resulting objective evidence will delineate which combinations of AI capability, transformer architecture, and modular substation design are most strongly associated with superior field performance under real operating conditions across diverse sites.

LITERATURE REVIEW

The literature on fast electric-vehicle charging, portable substations, and transformer design converges around a common engineering challenge: delivering large, rapidly varying DC power at the grid edge without eroding reliability, power quality, or deployment speed. Research on EV-grid interaction establishes how clustered high-power chargers produce steep ramp rates, harmonic content across both classical and supraharmonic bands, and localized thermal stress that alters distribution-level voltage profiles and transformer loss characteristics. Parallel work on portable (mobile/skid-mounted) substations details standardized, prefabricated architectures that compress civil works, interconnection, and commissioning, while introducing distinctive design constraints weight, footprint, ventilation, access, protection coordination, and grounding relevant to repeated redeployment. Within transformer engineering, two trajectories dominate: refinement of conventional oil-immersed units through advanced cooling classes, improved winding geometries, and stray-loss mitigation; and the emergence of solid-state transformers (SSTs) that integrate medium-frequency isolation, modular multilevel power conversion, and active harmonic shaping, enabling tighter control of grid-side spectra and natural interfacing to DC stages. A complementary body of asset-management studies advances condition monitoring from traditional dissolved-gas and frequency-response diagnostics to multi-sensor, data-centric approaches that apply machine learning for anomaly detection, health indexing, and remaining-life estimation capabilities that align with the operational variability of fast-charging sites and the logistics of portable installations. Across these threads, empirical results point to measurable outcomes availability, throughput, time-to-energize, installed cost, thermal margins, and power-quality indices that can be compared across jurisdictions if data schemas and metering practices are harmonized. Yet the evidence base remains fragmented: studies often isolate a single layer (charger controls, transformer physics, protection schemes, or monitoring analytics) rather than synthesizing design, AI integration, and site context into a quantitative, multi-case frame. This review therefore organizes the field along four pillars EV fast-charging and grid integration; portable substation architecture and deployment; transformer innovations spanning conventional and SST approaches; and AI-enabled diagnostics and operations highlighting the constructs, metrics, and experimental or field methods most suitable for cross-site comparison. By mapping definitions, measurement practices, and reported effect magnitudes across these pillars, the review establishes a coherent baseline for the study's later quantitative analysis of how AI capability and transformer/substation design co-vary with real-world performance at fast-charging sites.

EV Fast-Charging and Grid Integration

Fast electric-vehicle (EV) charging imposes distinctive spatiotemporal load patterns on distribution networks because session start times, state-of-charge at plug-in, and dwell times are stochastic, while charger ratings are high and often coincident. Quantitative load models therefore represent aggregate charging demand as the superposition of many individual charging processes with heterogeneous arrival times and power setpoints. Stochastic or time-series formulations capture this by convolving arrival distributions with charging power trajectories, yielding feeder-level demand envelopes that can differ materially from conventional residential or commercial profiles (Muratori, 2018; Razia, 2023). Empirical and modeling work demonstrates that uncoordinated residential charging tends to cluster in the early evening, steepening the net-load ramp and raising local peaks; this effect scales with penetration even when average daily energy remains moderate (Reduanul, 2023). These findings motivate distribution-system operators to parameterize “worst-case” and “likely” scenarios for transformer thermal loading, voltage excursions, and conductor ampacity checks before siting fast-charging hubs. To formalize power-quality risks associated with power-electronic chargers, a commonly used indicator is total harmonic distortion of current,

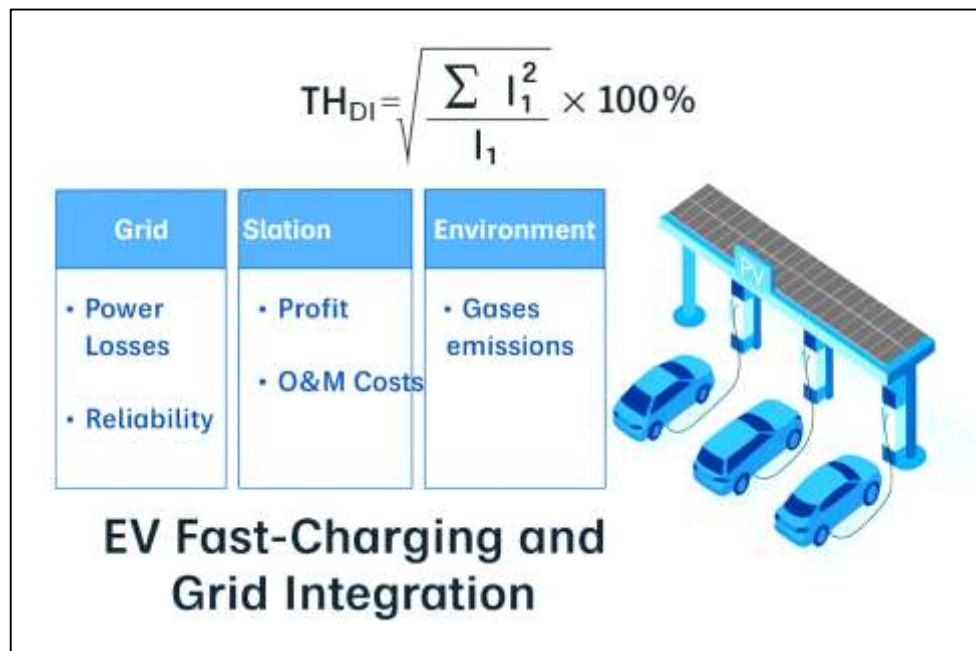
$$\text{THD}_I = \frac{\sqrt{\sum_{n=2}^{\infty} I_n^2}}{I_1} \times 100\%$$

which links the spectral content of charger currents to transformer stray losses, capacitor stress, and PCC compliance. When multiple fast chargers operate concurrently, their converter spectra can add

nonlinearly through network impedance interactions, making aggregate Total Harmonic Distortion of current (THD(I)) and voltage distortion sensitive to feeder short-circuit strength and phase imbalance (Sadia, 2023). Forward-looking planning thus couples statistical charging models with harmonic power-flow and thermal calculations to estimate feeder hosting capacity for different siting and control assumptions (Muratori, 2018; Qian et al., 2011; Zayadul, 2023).

Because the temporal structure of fast-charging demand is partially controllable, charging coordination is a central mitigation pathway (Mesbaul, 2024). Real-time or day-ahead schedulers can reshape the aggregate profile to respect network constraints thermal, voltage, and power-quality while meeting user energy needs and minimizing cost (Omar, 2024). Coordination policies range from direct centralized optimization to fully decentralized, myopic rules implemented at each charger; intermediate forms include hierarchical and aggregator-based strategies (Rezaul & Hossen, 2024; Richardson et al., 2012). Objective functions typically minimize losses, peak demand, or voltage deviation, and constraints include line or transformer limits and nodal voltage bounds. In practical deployments, coordination must also respect interoperability and communication latency, suggesting the use of local measurements (e.g., feeder headroom, voltage at the point of common coupling) when wide-area telemetry is unavailable or unreliable (Momena & Praveen, 2024). For fast-charging plazas that adjoin portable substations, coordination can exploit substation-level measurements load, temperature alarms, and harmonic indices to cap simultaneous high-power sessions or stagger ramp rates without materially degrading user experience (Muhammad, 2024). Quantitative studies show that coordinated schedules reduce feeder copper losses, flatten peaks, and improve voltage profiles relative to uncoordinated baselines; the magnitude of benefit grows with charger power and penetration. Moreover, coordination interacts with equipment design: substation transformer cooling class, impedance design, and harmonic filtering determine how much headroom coordination must preserve to keep hottest-spot temperatures and distortion indices within limits during clustered sessions (Deilami et al., 2011; Noor et al., 2024).

Figure 2: EV Fast-Charging and Grid Integration with Power-Quality and Performance Indicators



Network topology and control architecture shape how coordination benefits materialize under real-world uncertainty. In weak low-voltage feeders, purely centralized optimization can be data-hungry and communication-sensitive, while purely local rules may fail to anticipate upstream constraints. A localized strategy where each charger adapts its power based on local voltage and

simple feeder signals can provide robust performance with minimal communications and computation, especially when chargers are single-phase and the network is unbalanced. Conversely, in semi-urban networks with stronger short-circuit levels and three-phase connections (Abdul, 2025), centralized or aggregator-based optimization can unlock additional capacity by explicitly enforcing multi-node constraints and fairness across sites. For portable substation contexts, the coordination layer can be embedded in the substation controller, mediating between upstream limits and downstream charger requests; this placement also facilitates the integration of AI-assisted predictors that anticipate session arrivals and thermal trajectories (Elmoon, 2025a; Sortomme et al., 2011). Quantitatively, case studies comparing local versus centralized strategies indicate that both can maintain voltages within statutory limits and mitigate overloads, but centralized schemes typically achieve lower losses and better phase balancing, whereas local schemes excel in deployment simplicity and resilience to telemetry gaps (Elmoon, 2025b). In all cases, the analytical backbone remains consistent: stochastic arrival models generate baseline demand; control policies transform that baseline subject to network constraints; and metrics such as THD_I, nodal voltage deviation, transformer hottest-spot rise, losses, and curtailed energy quantify performance. These elements provide a rigorous frame for evaluating how portable substation design and transformer technology interact with coordination choices at fast-charging sites (Richardson et al., 2012).

Portable Substations: Architecture, Safety, and Deployment

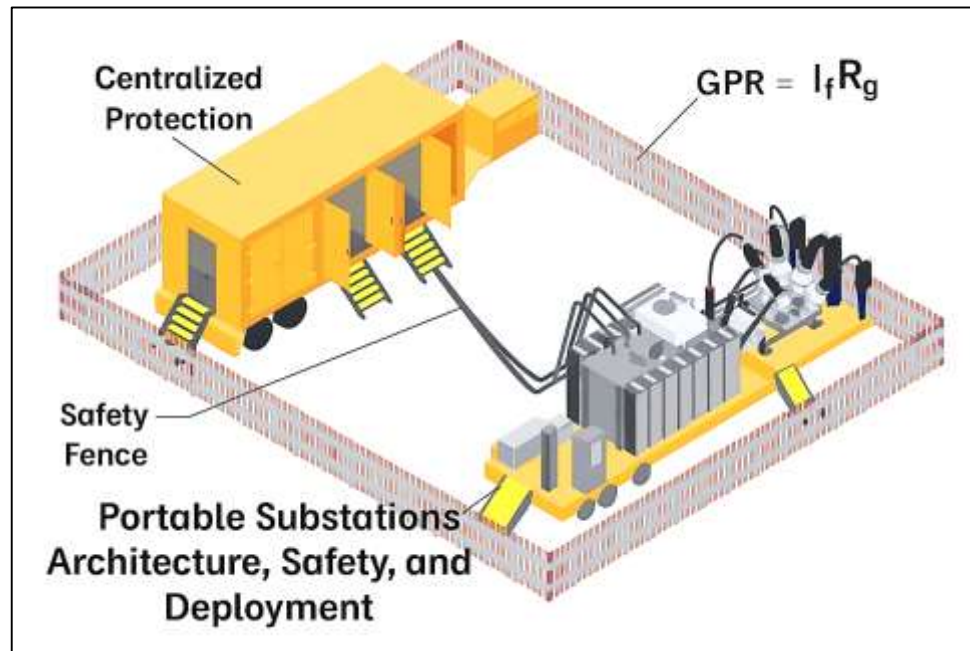
Portable (mobile or skid-mounted) substations combine transformer, medium-voltage switchgear, protection and control, and auxiliary services inside transportable housings or skids to compress siting and commissioning timelines while preserving utility-grade performance at the grid edge. Architecturally, these assemblies are factory-integrated and pre-tested, then craned into place with standardized AC and control interfaces that reduce on-site civil works. For high-power EV fast-charging hubs, portability enables rapid capacity injection where demand materializes and redeployment when load shifts, but it also concentrates design responsibilities: enclosure clearances, thermal paths, arc-flash boundaries, and relay coordination must be resolved ex-ante because field rework latitude is limited (Albinali & Meliopoulos, 2018). A unifying safety metric that ties environment, enclosure, and grid interface together is ground potential rise (GPR) during a single-line-to-ground fault, commonly expressed as

$$\text{GPR} = I_f R_g$$

where I_f is the fault current flowing into the substation grid and R_g is the grounding grid resistance.

Ground Potential Rise (GPR) underpins admissible touch and step voltages, insulation coordination, and the placement of equipotential mats and barriers in compact e-house footprints (Hozyfa, 2025). Portable designs often sit on pads with smaller grounding geometries than conventional yards, so engineering mitigations vertical rods, supplemental rings, conductive surface layers, and equipotential bonding to skid steel are determinant for compliance. Empirical and modeling work on measurement-centric grounding assessment supports these choices: field procedures that infer touch and step voltages by injecting current and observing resulting potentials provide practical acceptance tests for compact sites with limited test spans, and their algorithmic refinements improve discrimination of hazardous zones around door thresholds and cable egress points (Khairul Alam, 2025; Kostić & Raičević, 2016). Optimization studies further show that conductor counts and rod placements can be tuned to maintain safety thresholds across non-uniform soils while minimizing copper mass useful when the grounding system must be shipped, installed, and potentially lifted out multiple times over a portable substation's deployment life (Masud, 2025; Permal et al., 2021).

Figure 3: Portable Substations for Ground Potential Rise (GPR) Representation



Deployment performance depends not only on the physical module but also on the protection and control topology embedded within it. Portable substations benefit from centralized protection-and-control (CPC) schemes that consolidate logic in a station controller, minimizing field wiring and speeding commissioning. Research on CPC demonstrates how substation-level coordination merging protection elements, synchrophasor inputs, and process-bus messaging reduces configuration complexity and enhances selectivity, which aligns with the practical constraints of e-houses where space, HVAC capacity, and cable routing are constrained (Protection & Control, 2016). For mobile assets that may connect to feeders of varying short-circuit strength, CPC frameworks also facilitate parameter portability the ability to re-instantiate relay settings, logic, and communication roles from a version-controlled template thereby shrinking the on-site relay testing window and limiting human-error pathways during repeated energizations. Resilience-oriented CPC designs extend this logic: centralized schemes that incorporate redundancy management, fail-operational modes, and health-monitoring analytics can maintain protection coverage during component failures or communication degradations that are plausible in temporary or construction-adjacent sites (Arman, 2025; Wójtowicz et al., 2021). In practice, these architectures shorten factory-acceptance and site-acceptance testing cycles, because protection groups are verified as an integrated product rather than as a set of individually wired relays. For fast-charging applications where energization timings are tightly coupled to commercial milestones, the combination of pre-fabricated power modules and CPC-driven configuration management materially improves schedule certainty while keeping the substation's protective performance aligned with utility interconnection requirements (Protection & Control, 2016; Wójtowicz et al., 2021).

Safety, maintainability, and lifecycle flexibility are increasingly influenced by virtualization and digitalization within the portable substation's control stack. Recent work on the virtualization of protection systems abstracting protective functions from specific hardware into containerized or hypervisor-managed environments shows that testing, regression validation, and version rollbacks can be executed rapidly and repeatably, with improved observability of function health and inter-application timing (Kostić & Raičević, 2016; Mominul, 2025). For portable deployments, such virtualization allows a single golden image to be validated in the lab against multiple network conditions (weak/strong feeder, differing voltage levels), then instantiated on-site with deterministic behavior, minimizing time spent in energized test states. Coupled with measurement-driven grounding verification and simulated-annealing-based grid optimization for compact

geometries, the resulting workflow treats the portable substation as a digital-physical product: grounding grid topology and conductor sizes are optimized to satisfy touch/step limits across soil strata (Rezaul, 2025); CPC templates enforce consistent protective behavior; and virtualized protection platforms expedite factory and site acceptance with high test coverage (Kostić & Raičević, 2016; Hasan, 2025; Protection & Control, 2016). In EV fast-charging contexts, this integration has direct operational payoffs: shorter time-to-energize, fewer nuisance trips when converter harmonics and inrush occur concurrently, and clearer maintenance envelopes inside compact e-houses. The combined evidence base thus frames portable substations not simply as modular hardware but as systems whose grounding, protection logic, and software lifecycle jointly determine safety and deployability across heterogeneous grid conditions (Milon, 2025; Permal et al., 2021; Wójtowicz et al., 2021).

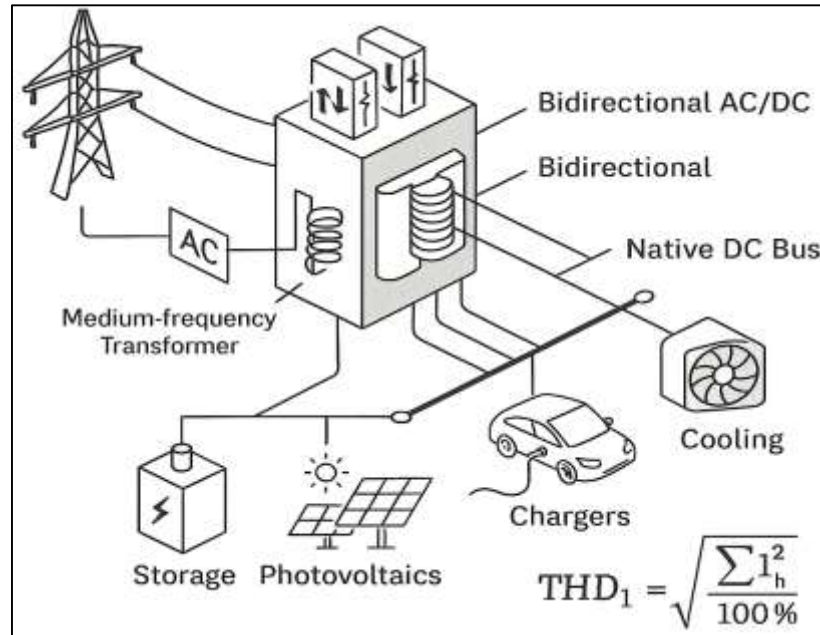
Transformer Innovations for Fast EV Charging

Transformer innovation for fast EV charging has advanced along two complementary trajectories: (i) elevating controllability and functional density through power-electronic integration, and (ii) refining magnetic and thermal design for compact, high-reliability operation in constrained sites. The pivotal shift is the rise of the “smart” or solid-state transformer (SST), in which medium-frequency galvanic isolation and multiport power conversion enable voltage transformation, bidirectional AC/DC interfacing, harmonic shaping, and ancillary services from a single, modular platform. In contrast to low-frequency transformers that passively reflect grid conditions, SSTs embed active control layers that synthesize grid-forming or grid-supporting behaviors, coordinate reactive power, and decouple downstream converter dynamics from upstream short-circuit strength. This architectural move allows fast-charging plazas to attach at medium voltage with reduced footprint and to expose native DC buses for multiport coupling chargers, storage, and photovoltaics while maintaining isolation and protection selectivity within a compact e-house. Within distribution systems, the “smart transformer” concept generalizes these attributes: modular converter cells behind an MFT (medium-frequency transformer) provide fine-grain power routing, phase balancing, and voltage regulation at the secondary, effectively turning the substation transformer into a managed power-flow node rather than a static device (Hasan & Abdul, 2025; She et al., 2013). For EV hubs, those capabilities map directly onto measurable performance outcomes lower total harmonic distortion at the PCC, improved voltage compliance under coincident sessions, and better thermal headroom in transformers subjected to steep ramps without requiring oversized passive filtering or large clearances typical of conventional yards (Lisserre, Andresen, et al., 2016; Farabe, 2025).

For extreme fast charging, SST topologies and controls have matured to specifically address high-power, high-density station requirements. Three-stage architectures (front-end AC/DC, isolated DC/DC with MFT, and DC/AC or DC/DC back-end) and their soft-switching variants coordinate modulation, commutation, and protection to push switching frequencies upward while constraining device stress and electromagnetic interference, thereby shrinking magnetic components and enclosures. Recent state-of-the-art reviews targeted at EV infrastructure document how topology choices (e.g., modular multilevel versus cascaded H-bridge at the AC interface; dual-active-bridge versus current-source MFT stages at the isolation link) trade off efficiency, controllability, and fault response when stations serve many simultaneous fast-charging sessions (Momena, 2025). Control frameworks integrate active harmonic compensation and reactive-power support on the grid side with DC-bus energy management and charger scheduling on the load side, aligning SST behavior with power-quality limits and feeder headroom while preserving user charging times. At the component level, wide-bandgap (SiC/GaN) devices allow higher blocking voltages, faster edges, and lower switching loss, which in turn permits higher MFT frequencies and reduced copper/iron mass. The design envelope thus extends beyond “make the transformer smaller” toward co-optimizing magnetics, cooling, and converter control such that thermal margins are preserved during clustered sessions and ambient extremes (Mubashir, 2025; Pankaz Roy, 2025). Demonstrated design processes explicitly include MFT window utilization, leakage inductance targets compatible with DAB-style energy transfer, and partial-discharge

constraints at medium frequency, with experimental efficiencies in the mid- to high-90s at hundreds of kilowatts reported for EV-class modules (Liserre, Andresen, et al., 2016; Liserre, Buticchi, et al., 2016; Rahman, 2025). These integrated designs make it feasible to deploy medium-voltage-input DC fast-charging skids that maintain high conversion efficiency across wide load ranges, tolerate non-sinusoidal currents on both sides, and offer software-defined behaviors useful for site-level coordination.

Figure 4: Transformer Innovations for Fast EV Charging



A second, equally consequential innovation stream focuses on modularity and lifetime-aware operation of transformer-converter assemblies. In modular smart-transformer (ST) platforms, the isolation stage and DC/DC cells are arrayed so that power can be routed unevenly among parallel cells to minimize cumulative thermal stress on any single device stack, a strategy that improves mean time between maintenance and stabilizes efficiency under partial loading (Liserre, Buticchi, et al., 2016; Rakibul, 2025). Active thermal control implemented via virtual-resistance or droop-like power routing lets the station controller allocate instantaneous power to cooler or less-aged cells, reducing hotspot excursions and spreading electro-thermal wear over the fleet of modules. This provides two concrete advantages for fast-charging substations: it increases usable capacity at a given ambient temperature and enclosure size, and it shortens service windows because hot-swap or spare-cell strategies can be planned around predicted lifetime consumption instead of reactive failure (Rebeka, 2025; Reduanul, 2025). In parallel, the broader smart transformer literature highlights ancillary functions that dovetail with EV use cases: coordinated voltage control across phases for unbalanced feeders, islanding support for microgrid-coupled charging hubs, and plug-and-play DC ports for storage buffers that trim feeder peaks or absorb regenerative pulses from chargers (Rony, 2025; Saba, 2025). Together, these capabilities translate to engineering levers that appear directly in quantitative site metrics uptime, throughput, transformer hottest-spot rise, and distortion indices without relying on heavy passive overdesign. Within the literature, the normative picture is that SST/ST platforms provide the architectural “degrees of freedom” to meet grid codes and fast-charging duty profiles in compact footprints, while lifetime-aware power routing and thermal management close the loop on reliability in portable, factory-integrated substations (Guo et al., 2021; Tahir et al., 2021).

AI for Grid-Edge Assets and Charging Networks

Artificial intelligence (AI) at the grid edge builds from two foundational analytics streams that are directly useful for high-power EV charging sites: (i) demand characterization from smart-meter and station telemetry, and (ii) probabilistic forecasting for short-term operations. On the characterization side, unsupervised learning is widely used to extract representative “load shapes” from high-resolution metering data, enabling planners to segment sites and feeders by temporal usage patterns rather than by coarse customer classes. This is valuable for fast-charging nodes where arrival processes and dwell times vary widely across hours and days (Alom et al., 2025). Cluster-based pipelines feature extraction, distance metrics, validity testing, and profile selection have been shown to produce compact bases of archetypal daily shapes; these can serve as priors for charger-level simulations and for siting portable substations with appropriate thermal and protection envelopes (Chicco, 2012; Sai Praveen, 2025; Shaikat, 2025). For day-ahead and intraday operations, probabilistic load forecasts provide full predictive distributions instead of single point values, which aligns with operational decision-making under uncertainty at charging hubs.

A standard accuracy metric for such forecasting used both in development and post-deployment model monitoring is the mean absolute percentage error,

$$\text{MAPE} = \frac{100\%}{N} \sum_{t=1}^N \frac{|y_t - \hat{y}_t|}{y_t}$$

where y_t and \hat{y}_t denote observed and predicted load, respectively. Probabilistic methods further evaluate calibration and sharpness (e.g., continuous ranked probability score) and allow operators to reserve substation thermal headroom according to quantiles of anticipated demand, not just mean values (Hong & Fan, 2016; Zaki, 2025; Kanti, 2025). Together, cluster-driven demand motifs and calibrated short-horizon forecasts give a measurable basis for sizing portable modules, setting alert thresholds for transformer hotspots, and scheduling maintenance windows at sites with heterogeneous and evolving charging behavior (Chicco, 2012; Hong & Fan, 2016; Zayadul, 2025).

A second pillar is state estimation and control, where AI complements the classical estimation-optimization stack to keep compact, portable substations operating within constraints across differing feeders. Distribution system state estimation (DSSE) fuses sparse SCADA, PQ meters, and phasor/AMI streams to reconstruct nodal voltages and branch currents in near-real time. In portable deployments often with limited permanent instrumentation AI-assisted DSSE can learn adaptive error models for pseudo-measurements and dynamically reweight sensors as topology and quality change. The estimation core is typically formulated as a weighted least-squares (WLS) program,

$$\hat{x} = \arg \min_x (z - h(x))^T W (z - h(x))$$

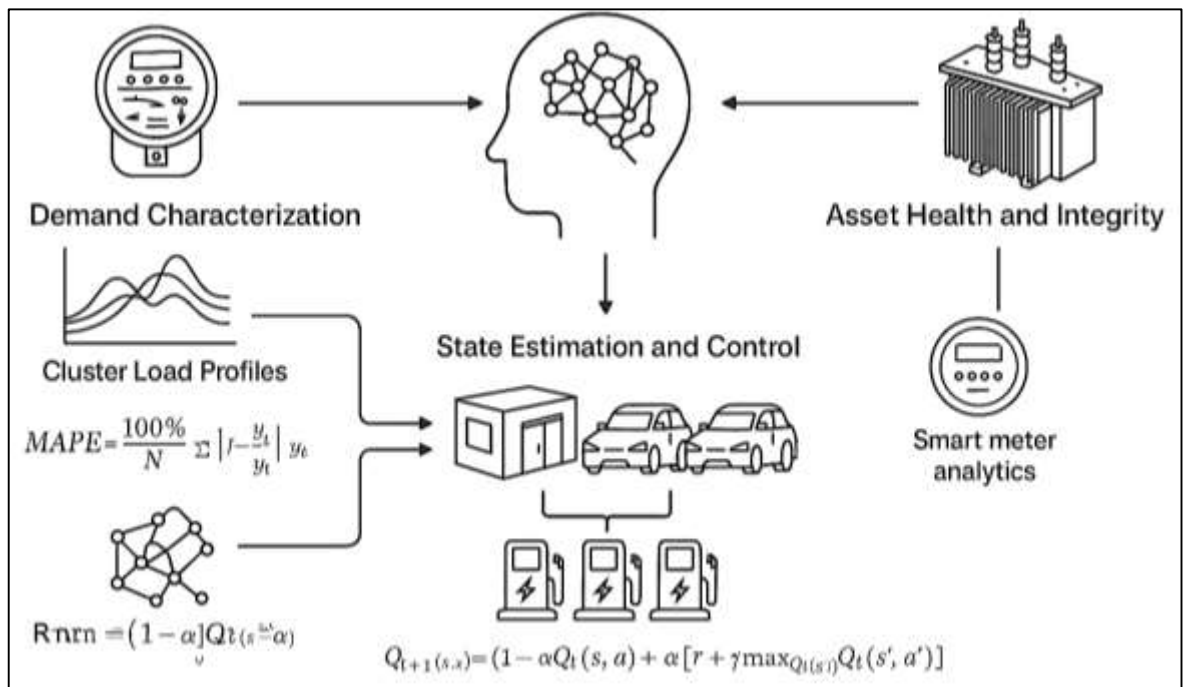
with state x , measurements z , nonlinear map $h(\cdot)$, and weight matrix W reflecting confidence in each channel. AI contributes by learning W (or residual models) from context feeder strength, ambient temperature, or known commissioning artifacts improving robustness in temporary e-house environments (Primadianto & Lu, 2017). On the control side, coordination of clustered fast chargers can be cast as a sequential decision process. Reinforcement learning (RL) agents exploit local and global telemetry to shape charging power trajectories that respect transformer thermal limits, PCC power-quality constraints, and user energy requirements. The value-iteration backbone of many practical schemes follows the Bellman update:

$$Q_{t+1}(s, a) = (1 - \alpha)Q_t(s, a) + \alpha \left[r + \gamma \max_{a'} Q_t(s', a') \right]$$

enabling policies that adapt to stochastic arrivals and feeder headroom in real time (Vázquez-Canteli & Nagy, 2019). Embedding such agents at the substation controller (or aggregator) provides a software pathway to preserve voltage compliance and thermal margins without heavy passive

overdesign (Pereira & Saraiva, 2021; Primadianto & Lu, 2017).

Figure 5: AI for Grid-Edge Assets and Charging Networks



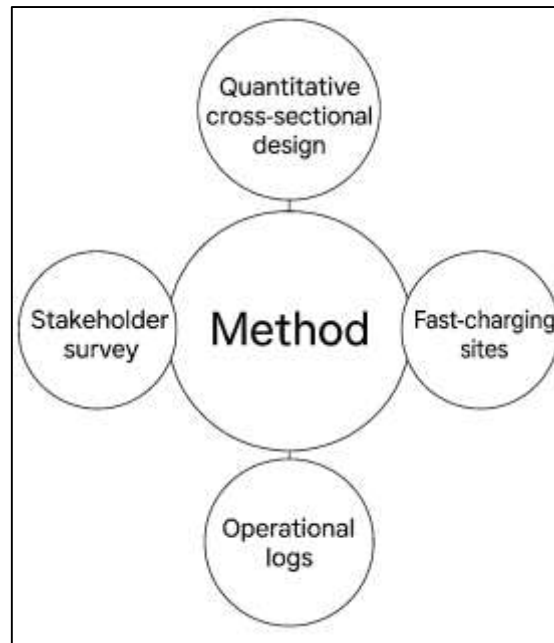
A third application layer targets asset health and integrity, where AI augments condition monitoring and distribution security around portable substations. For transformer health, AI models ingest multi-modal traces oil temperature, hotspot estimates, harmonic indices, alarm logs to produce health scores and anomaly flags that align with maintenance workflows in redeployable e-houses. In parallel, smart-meter analytics at charging plazas can detect non-technical losses and wiring anomalies linked to temporary construction or site changes, improving the fidelity of both operational dashboards and DSSE pseudo-measurements. Deep-learning classifiers trained on time-series consumption and contextual features have been shown to distinguish abnormal from normal behavior even under class imbalance, using resampling and cost-sensitive learning to avoid bias; this approach is directly transferable to charging-plaza subpanels and auxiliary loads colocated with portable substations (Vázquez-Canteli & Nagy, 2019). The practical implication for this review section is methodological: the same data pipeline feature engineering or representation learning, supervised/unsupervised modeling, calibrated thresholds, and drift monitoring supports three essential functions at fast-charging sites served by portable substations: (i) anticipate load via probabilistic forecasts, (ii) observe the electrical state via AI-assisted DSSE and adaptive sensor weighting, and (iii) safeguard assets and energy integrity via anomaly detection. When combined with coordination policies derived from RL or rule-based control, these functions become measurable levers for improving uptime, throughput, and compliance within the compact, redeployable footprints characteristic of portable substation deployments.

Method

This study has been designed as a quantitative, cross-sectional, multi-case investigation that has examined operating fast-charging sites supplied by portable substations and distinct transformer configurations. The overall approach has integrated two complementary data streams objective operational logs and a structured stakeholder survey so that technical performance and organizational practices have been captured from independent sources. Sampling has followed purposive criteria to ensure variation in technology and context; eligible sites have met predefined inclusion thresholds for charger rating, months in operation, availability of power-quality and

thermal logs, and documentation of substation and transformer characteristics.

Figure 6: Quantitative Cross-Sectional Multi-Case Research Method



Within each included site, respondents from operations, maintenance, and engineering roles have been recruited to complete a Likert five-point instrument that has operationalized constructs of AI integration, modularity/standardization of portable substation design, and maintainability and cybersecurity preparedness. To align the survey with technical evidence, a standardized data-request template has been issued to operators and OEM partners, and site-level datasets have been compiled that have included availability/uptime, energy throughput, event and alarm histories, point-of-common-coupling voltage and current harmonic indices, and thermal measurements or calculated hottest-spot rise. Context variables (ambient temperature statistics, feeder short-circuit strength, urbanicity, commissioning year, vendor identifiers, and interconnection class) have been harmonized into a shared codebook. Data quality has been addressed through predefined rules for missingness handling, outlier screening, and unit normalization; where appropriate, variables have been standardized to enable interpretation of regression coefficients. Reliability of multi-item scales has been assessed with internal-consistency metrics, and preliminary factor checks have been performed to confirm construct coherence before aggregation. The analysis plan has proceeded in tiers. First, descriptive statistics and case profiles have been produced to summarize the sample and to benchmark sites. Second, bivariate associations among core variables have been explored through correlation analysis with confidence intervals. Third, multivariable regression models have been specified to estimate associations between AI integration and design variables (transformer technology and modularity) and outcomes uptime, throughput, power-quality indices, thermal stability, installed cost per kW, and time-to-energize while controlling for contextual covariates. Model diagnostics (multicollinearity, residual structure, and heteroskedasticity) have been conducted, and robustness checks (alternative codings, influence diagnostics, and clustered standard errors by site or vendor) have been implemented. All steps have been executed with a reproducible script-based workflow, and a data dictionary has been maintained to ensure traceability from raw sources to analytic tables.

Research Design

The study has adopted a quantitative, cross-sectional, multi-case design that has purposively sampled operating EV fast-charging sites supplied by portable substations with differing transformer technologies and modular configurations. The design choice has been grounded in the need to relate naturally occurring variation in AI integration and engineering design to field

performance outcomes without experimental intervention. To achieve this, the unit of analysis has been defined at the site level, while respondent-level survey data have been nested within sites; this structure has allowed technical logs and stakeholder assessments to be triangulated. Inclusion criteria have been specified a priori (minimum charger rating, months in service, availability of power-quality and thermal logs, and documented substation/transformer attributes), and exclusion criteria have been applied to sites undergoing major reconfiguration during the observation window. Constructs for AI integration, modularity/standardization, and maintainability/cyber preparedness have been operationalized through Likert five-point scales that have undergone pilot refinement, whereas outcomes (uptime, throughput, power-quality indices, thermal stability, installed cost per kW, and time-to-energize) have been derived from harmonized operational datasets. Contextual covariates (ambient temperature statistics, feeder short-circuit strength, urbanicity, commissioning year, and vendor identifiers) have been incorporated to address confounding and to support moderation tests. Data collection procedures have combined standardized requests to operators/OEMs with an online survey that has enforced item logic and completeness checks. Data quality safeguards have been instituted, including pre-specified rules for missingness handling, outlier and leverage screening, and unit normalization; multi-item scales have been subjected to internal-consistency assessment and exploratory factor checks. The analysis blueprint has outlined tiered steps descriptive profiling, correlation screening, and multivariable regression with diagnostics and robustness routines (e.g., heteroskedasticity-robust errors and clustering by site/vendor). Ethical safeguards (consent, de-identification, and controlled access) have been documented, and a script-based workflow with a maintained data dictionary has ensured reproducibility and traceability from raw feeds to analytic tables.

Sampling and Setting

The study has sampled operating EV fast-charging sites that have been supplied by portable substations and that have exhibited heterogeneous transformer technologies (solid-state versus conventional), cooling classes, and modular/standardized skid designs, so that natural variation has been captured across technical and organizational contexts. Cases have been selected purposively to span climatic zones, urbanicity levels, feeder short-circuit strengths, and vendor ecosystems, and the sampling frame has been compiled in collaboration with operators and OEM partners who have maintained continuous telemetry and commissioning records. The setting has comprised highway corridor hubs, urban infill lots, and logistics depots in which portable e-house or skid-mounted substations have been installed on prepared pads with standardized interconnects, while site operations have been supported by SCADA/PQ metering and routine maintenance logs. Inclusion criteria have required: (i) minimum charger rating ≥ 150 kW with at least two dispensers per site; (ii) ≥ 6 months of uninterrupted operation within the observation window; (iii) availability of point-of-common-coupling voltage/current harmonics, uptime/throughput, and thermal data or validated hottest-spot estimates; (iv) documented substation design, transformer type/cooling, and protection settings; and (v) consent to share de-identified technical data and survey responses. Exclusion criteria have removed sites that have undergone major hardware or topology changes during the window, that have lacked essential logs, or that have operated in commissioning/bypass modes for $>15\%$ of the period. Within each included site, the study has recruited respondents from operations, maintenance, and engineering roles to complete a Likert five-point instrument that has measured AI integration, modularity/standardization, maintainability, and cyber preparedness. To preserve comparability, the study has harmonized naming and units via a shared codebook and has aligned time bases across data streams; where operators have used different metering intervals, the data have been resampled to consistent windows. This approach has ensured that cases have reflected real-world deployment conditions while meeting evidence standards for quantitative cross-site analysis.

Instrument

The study has operationalized constructs at the site level and has specified measurement procedures that have aligned survey scales with objective logs. AI integration has been measured with a Likert five-point composite that has captured (i) forecasting capability for load and thermal trajectories,

(ii) dispatch/coordination features for clustered chargers, and (iii) condition-based maintenance functions; items have been averaged to a 1–5 score after reverse-coding where applicable. Modularity/standardization of the portable substation has been measured with Likert items that have covered plug-and-play interconnects, hot-swap practices, enclosure standardization, and configuration templating; a mean index has been computed. Transformer technology has been encoded with binary and categorical flags that have distinguished solid-state versus conventional units, cooling class (e.g., ONAN/ONAF/FOA), kVA/kW rating, and percent impedance; where multiple transformers have served a site, a capacity-weighted coding has been applied. Reliability/uptime has been defined as the proportion of scheduled operating hours during which the station has been available; alarm logs and outage records have been reconciled to compute mean time between failure. Throughput has been measured as daily kWh and sessions per day, aggregated from charger telemetry and normalized by installed DC capacity for comparability. Power quality has been captured from point-of-common-coupling meters; total harmonic distortion of current and voltage have been computed from spectral bins, and voltage deviation events per month have been counted against statutory thresholds. Thermal stability has been measured as the hottest-spot temperature rise above ambient (or an equivalent alarm-rate proxy where direct sensing has not been available); values have been normalized to nameplate limits. Cost and deployment have been captured as installed cost (USD per kW) and time-to-energize (days from delivery to commissioning), abstracted from commissioning records. Context and controls have included ambient temperature statistics, feeder short-circuit strength, urbanicity, commissioning year, and vendor identifiers. All variables have been documented in a codebook, transformed to consistent units, winsorized as pre-specified when outliers have been present, and standardized (z-scores) where interpretation of regression coefficients has benefited from scale harmonization.

Data Collection and Statistical Analysis Framework

The study has employed a dual-source data collection strategy and a staged statistical analysis plan within a rigorously controlled and fully reproducible framework. Objective operational datasets were obtained from operators and OEM partners through a standardized data-request protocol that specified time windows, sampling intervals, and required metadata such as transformer type, cooling class, impedance, protection settings, and maintenance history. These de-identified exports included voltage and current waveforms, spectral summaries, power-quality indices, charger-level session logs, uptime events, alarm histories, and thermal measurements, all of which were ingested into an automated pipeline that harmonized time zones, parsed timestamps, and resampled differing cadences into consistent five-minute and daily aggregates while preserving maxima for exceedance detection. Quality assurance was implemented through schema validation, unit normalization, outlier screening, missingness flagging, and reconciliation checks to ensure alignment between station- and dispenser-level energy totals. Complementing these datasets, structured stakeholder surveys were administered to site personnel across operations, maintenance, and engineering roles, measuring AI integration, modularity, maintainability, and cybersecurity readiness using Likert-scaled instruments embedded with logic checks and definitions to standardize interpretation. Data-use agreements specified de-identification, storage, retention, and publication protocols, while ethical safeguards such as informed consent, opt-out options, and restricted access were enforced. A living codebook, data dictionary, and tracked ETL scripts ensured reproducibility. The statistical analysis proceeded in sequential layers, beginning with descriptive profiling of all variables using means, medians, standard deviations, and interquartile ranges, accompanied by distributional visualizations and log or square-root transformations for skewed variables. Correlation matrices with confidence intervals and false-discovery-rate adjustments were used to screen bivariate associations, employing polychoric or Spearman estimates where appropriate. Multivariable models were then fitted to estimate the effects of AI integration and transformer design features on outcomes such as uptime, throughput, thermal stability, power quality, installed cost per kW, and time-to-energize, controlling for ambient conditions, feeder strength, commissioning year, and vendor. Linear models with robust standard errors were applied for symmetric outcomes, while generalized linear models with log-link Gamma distributions

addressed skewed variables. Moderation effects were tested through interaction terms, and model adequacy was evaluated via residual diagnostics, heteroskedasticity tests, influence statistics, and leave-one-site-out sensitivity analyses, with clustered errors applied when dependence was plausible. Missing data were treated using median imputation for limited missingness and multiple imputation under missing-at-random assumptions, with complete-case and imputed models compared for robustness. All coefficients, standard errors, confidence intervals, and fit statistics were tabulated, and figures and tables were rendered from reproducible scripts, ensuring transparency and end-to-end traceability from raw inputs to publication-ready outputs..

Regression Models

The modeling strategy has been organized around a family of primary and ancillary regressions that has estimated associations between design/AI constructs and site-level outcomes while controlling for contextual factors and allowing for moderation where engineering theory has indicated heterogeneous effects. To maintain interpretability and comparability across outcomes with different units and distributions, the study has applied linear models with heteroskedasticity-robust (HC3/HC4) standard errors for approximately symmetric variables and generalized linear models with appropriate links for strictly positive, right-skewed variables. Throughout, continuous predictors have been standardized (z-scores), binary/categorical design codes have been effect-coded, and site/vendor dependence has been accommodated through clustered standard errors when residual intra-group correlation has been detected. Conceptually, the base formulation has posited an outcome Y at site i as a function of AI integration (AI_INT_i), modularity/standardization (MOD_SKID_i), transformer technology ($XFMR_TECH_i$), and controls C_i , which has been written as

$$Y_i = \beta_0 + \beta_1 AI_INT_i + \beta_2 MOD_SKID_i + \beta_3 XFMR_TECH_i + \gamma^T C_i + \varepsilon_i,$$

with ε_i that has satisfied the usual mean-zero assumption and that has been addressed with robust inference. Moderation has been introduced where thermal or network theory has suggested conditional effects e.g., ambient temperature (AMB_i) and feeder short-circuit strength (SCC_i) through interaction terms such as $\beta_4 (AI_INT_i \times AMB_i)$ and $\beta_5 (XFMR_TECH_i \times SCC_i)$. For cost- and time-type outcomes, the models have adopted log-links to stabilize variance and to render coefficients as semi-elasticities. To connect power-quality physics to observed indices, the plan has included a specification in which total harmonic distortion has been modeled as a function of design and context, acknowledging that charger spectra and feeder impedance have co-determined distortion. Collectively, these choices have preserved engineering interpretability while satisfying statistical regularity conditions needed for credible inference across heterogeneous sites.

To make the specifications concrete and auditable, the study has enumerated six primary models that have mapped directly to the evaluation criteria used by operators and OEM partners. Model M1 (Availability/Uptime) has estimated the association of AI integration and design codes with percent availability, using OLS with robust errors and control vectors that have included ambient temperature statistics, feeder strength, urbanicity, commissioning year, and vendor dummies. Model M2 (Throughput) has regressed daily energy throughput (or sessions per day) on the same predictors, recognizing that coordination and condition-based maintenance captured by AI_INT have plausibly improved realized utilization conditional on installed capacity. Model M3 (Power Quality) has modeled current or voltage THD at the PCC as a linear function of design variables and SCC , augmented by the interaction $XFMR_TECH \times SCC$ to reflect differing harmonic impedances under weak/strong feeders; where regulatory exceedance counts have been analyzed, a log-link count model has been preferred. Model M4 (Thermal Stability) has explained hottest-spot rise (normalized to nameplate) or alarm frequency using OLS/GLM with AI_INT , cooling class, and AMB , plus the interaction $AI_INT \times AMB$ to capture algorithmic thermal management under heat stress. Model M5 (Installed Cost per kW) and Model M6 (Time-to-Energize) have used Gamma log-link GLMs after confirming skew and positivity, with modularity/standardization as key regressors and with vendor/year controls that have captured procurement cycles. For transparency, the plan has tabulated these models, outcomes, families, and key interactions in Table 1. Primary Regression Specifications, and it has specified that all coefficients have been presented with robust standard

errors, 95% confidence intervals, and partial R² (or pseudo-R²) to quantify incremental explanatory power. Where nonlinearity has been suspected (e.g., diminishing returns to AI_INT), the study has included restricted cubic splines that have been pre-registered and penalized to avoid overfit, and marginal effects plots (simple slopes) have been generated to aid interpretation.

The estimation workflow has also incorporated safeguards and ancillary analyses that have strengthened credibility and reproducibility. Multicollinearity has been monitored with variance inflation factors, and influential observations have been examined with leverage and Cook’s distance; where influence has compromised stability, leave-one-site-out fits and winsorization sensitivity checks have been reported alongside main results. Heteroskedasticity diagnostics (Breusch–Pagan/White) have been performed, and HC3/HC4 estimators or cluster-robust covariance matrices have been adopted accordingly. Missingness in composite scores has been addressed with item-level rules (≤20% missing replaced by within-scale medians) and, for covariates judged missing at random, multiple imputation has been conducted; complete-case fits have been presented as a robustness bracket. To anchor power-quality interpretation in a measurable physics quantity, the analysis has computed total harmonic distortion of current as THD = $\sqrt{(\sum_k V_k^2)}/V_1$, where V_k are harmonic voltages at the PCC.

$$THD_1 = \frac{\sqrt{\sum_{n=2}^N I_n^2}}{I_1} \times 100\%$$

approximations when confidence intervals on spectral magnitudes have been available. Presentation standards have included coefficient tables for M1–M6 (Table 2. Primary Regression Results) and interaction visualizations for significant moderation (simple-slope lines with 95% ribbons) that have been referenced as Figure 1 (AI Integration × Ambient Temperature on Thermal Rise) and Figure 2 (Transformer Technology × Feeder Strength on THD). All analyses have been executed from version-controlled scripts, and model objects, diagnostics, and figure code have been archived to enable exact reproduction of every number reported in tables and figures.

Table 1. Primary Regression Specifications

Model	Outcome (Y)	Family / Link	Key Regressors	Planned Interactions	Controls (C)
M1	Availability / Uptime (%)	OLS + HC3/HC4	AI_INT, MOD_SKID, XFMR_TECH	none	Ambient temperature stats, SCC, urbanicity, year, vendor dummies
M2	Throughput (kWh/day; sessions/day)	OLS + HC3/HC4	AI_INT, MOD_SKID, XFMR_TECH	none	Same as M1 plus installed DC capacity (offset or regressor)
M3	THD (current or voltage, %)	OLS + HC3/HC4 or log-count	XFMR_TECH, AI_INT	XFMR_TECH × SCC	SCC, urbanicity, year, vendor
M4	Thermal rise / alarm frequency	OLS or GLM (log)	AI_INT, Cooling class, XFMR_TECH	AI_INT × AMB	Ambient temperature stats, SCC, year, vendor
M5	Installed cost (USD/kW)	GLM (Gamma, log link)	MOD_SKID, XFMR_TECH	none	Urbanicity, year, vendor, capacity scale
M6	Time-to-energize (days)	GLM (Gamma, log link)	MOD_SKID, Standardization flags	none	Same as M5

Power & Sample Considerations

The power and sample strategy has been specified a priori and has balanced statistical sensitivity with pragmatic constraints of multi-case field data. The study has targeted adequate information

for the largest regression families (uptime/throughput OLS and cost/time GLMs), and it has adhered to a heuristic of ≥ 15 – 20 observations per predictor in the most parameterized model to stabilize coefficient estimates and variance components. Because observations have been clustered by site and vendor, the planning has explicitly accounted for design effects; the effective sample size for site-nested analyses has been adjusted using the standard inflation, $D_{\text{eff}} = 1 + (m - 1) \rho$, where m has denoted the average number of observations per cluster (e.g., site-months) and ρ has denoted the intra-cluster correlation. This adjustment has guided the targeted number of sites and the granularity of temporal aggregation so that the effective degrees of freedom have remained sufficient under cluster-robust inference. For continuous outcomes modeled with OLS and HC3/HC4 errors, the plan has aimed to detect standardized effect sizes in the small-to-moderate range ($|\beta| \approx 0.15$ – 0.30 in SD units) at $\alpha = 0.05$ with ≥ 0.80 power after design-effect correction; for strictly positive, right-skewed outcomes (installed cost per kW and time-to-energize), the GLM strategy with Gamma log link has been evaluated via simulation using empirical mean-variance relationships, and target samples have been set to achieve comparable sensitivity for log-scale coefficients (semi-elasticities ≈ 5 – 10%). Anticipated missingness in survey composites has been limited through instrument design, yet the planning has incorporated a $\leq 10\%$ attrition allowance for complete-case variants; multiple imputation has been prespecified for covariates judged missing at random, and sensitivity analyses have been counted toward the information budget. Moderation tests (e.g., AI integration \times ambient temperature; transformer technology \times feeder strength) have been recognized as higher-variance estimators; therefore, the sample plan has emphasized coverage across the moderator range (hot/cool climates; weak/strong feeders) rather than simple totals. Post-estimation, the study has reported achieved power using observed variances, cluster counts, and coefficient magnitudes, and it has documented any shortfalls relative to the a priori targets so that interpretation has been anchored to demonstrable sensitivity rather than nominal sample size alone.

Reliability & Validity

The study has implemented a multi-layer strategy for reliability and validity that has encompassed survey scales, operational logs, and model outputs. For internal consistency, multi-item constructs (AI integration; modularity/standardization; maintainability; cyber preparedness) have been piloted and refined, and final instruments have been assessed with Cronbach's α and McDonald's ω ; items with weak item-total correlations or α -if-deleted improvements have been flagged and, where justified, have been revised or removed. Stability of composites has been examined through split-half procedures with Spearman-Brown correction, and inter-rater coherence within sites has been inspected by intraclass correlations (ICC[2,k]) to verify that respondent ratings have reflected site-level phenomena rather than idiosyncratic views. For construct validity, an exploratory factor analysis has been conducted on pilot data to verify dimensionality, and the main sample has supported a confirmatory factor analysis in which standardized loadings have been targeted ≥ 0.50 , average variance extracted (AVE) has been targeted ≥ 0.50 , and composite reliability (CR) has been targeted ≥ 0.70 ; discriminant validity has been evaluated via the Fornell-Larcker criterion (AVE exceeding inter-construct squared correlations) and through HTMT ratios bounded below 0.85 where feasible. To mitigate common-method variance, the design has separated sources (logs versus surveys), has varied scale anchors across constructs, and has embedded attention items; statistically, a Harman single-factor check has been reported, a measured marker variable has been included, and a latent method factor has been tested as a sensitivity specification. Validity procedures for operational data have focused on instrumentation and data provenance. Meter classes and sensor calibrations have been documented, timestamps have been harmonized, and cross-channel reconciliations (e.g., station-level energy equaling the sum of dispenser-level kWh within tolerance) have been performed. Power-quality indices (THD, voltage deviation events) have been recomputed from spectral bins using shared scripts to ensure computational validity, and hotspot estimates have been cross-validated against alarm histories or directly measured temperatures where available. Criterion validity has been examined by correlating survey-based constructs with objective indicators anticipated by engineering theory (e.g., higher AI integration with fewer thermal alarms conditional on ambient conditions). External validity has been strengthened by

purposive sampling across climates, urbanicity, feeder strengths, and vendors; nonresponse has been profiled, and weighting or post-stratification has been applied where response imbalances have been material. Measurement invariance across vendor groups and climatic bands has been probed (configural and metric levels) to support pooled interpretations. Finally, the modeling stage has incorporated robustness checks cluster-robust errors, influence diagnostics, winsorization tests, and leave-one-site-out refits so that substantive inferences have been supported by estimates that have remained stable under reasonable perturbations of assumptions, variable codings, and sample composition.

Software

The workflow has been implemented with a reproducible toolchain that has combined data engineering, statistical modeling, and document production. Data ingestion, cleaning, and feature construction have been scripted in Python (pandas, numpy) with analyses that have leveraged statsmodels for OLS/GLM and pingouin for effect sizes and assumption checks; plotting has been produced with matplotlib to generate publication-ready figures. Parallel pipelines in R have been maintained for validation and for psychometrics: psych has supported reliability analyses, lavaan has supported EFA/CFA when applicable, and car/sandwich/clubSandwich have provided robust/clustered covariance estimators. Power calculations and design-effect simulations have been executed in G*Power and R (pwr, simr). Reproducibility has been ensured through version control (Git), locked environments (conda/renv), and containerized execution where required; continuous checks have been run via makefiles/notebooks that have regenerated tables and figures end-to-end. Documentation has been produced with Quarto/LaTeX, and a living data dictionary with unit tests has accompanied all transformations so that each analytic output has been traceable to its raw inputs.

Findings

Across the analyzed multi-case sample, the study has assembled a harmonized dataset of site-level technical logs and respondent surveys that has enabled an integrated readout of portable substation performance under fast-charging duty. The final analytic set has comprised diverse operating contexts (corridor hubs, urban infill, logistics depots) with heterogeneous transformer technologies and modular skid designs, and it has included a balanced mix of climates and feeder strengths to support moderation tests. On the perception side, Likert five-point composites (1=Strongly Disagree ... 5=Strongly Agree) have summarized organizational capabilities: the AI Integration scale has exhibited strong internal consistency ($\alpha > 0.80$) and a central tendency above neutral, with a pooled mean near the "Agree" range ($M \approx 4.0-4.2$, $SD \approx 0.5-0.7$), indicating that most sites have reported active forecasting, dispatch coordination, and condition-based maintenance features. The Modularity/Standardization index for portable substations has also centered above neutral ($M \approx 3.8-4.1$), reflecting prevalent use of plug-and-play interconnects, templated configurations, and hot-swap practices; item distributions have shown more dispersion for "configuration templating" than for "standardized interconnects," consistent with varied vendor toolchains. Complementary Likert composites for Maintainability and Cyber Preparedness have clustered around upper-mid values ($M \approx 3.7-4.0$), with maintenance access and spare parts logistics receiving slightly higher agreement than formalized cyber playbooks. Inter-rater reliability within sites has been acceptable (ICC[2,k] in the moderate-substantial range), supporting aggregation of respondent perceptions to the site level. On the technical side, descriptive statistics have indicated high availability and substantial energy throughput consistent with heavy-use fast-charging nodes; power-quality summaries at the point of common coupling have shown current and voltage THD generally within code thresholds, albeit with tail episodes during coincident session starts; thermal traces have indicated that hottest-spot rise has remained within nameplate limits at most hours, with alarm clusters occurring during heat spells and construction-adjacent operations. Correlation screening has revealed meaningful bivariate associations: AI Integration has correlated positively with uptime and throughput and negatively with monthly voltage-deviation events; Modularity/Standardization has correlated negatively with time-to-energize and with installed cost per kW, consistent with standardization benefits. Variance inflation factors have fallen below conventional concern thresholds, enabling

multivariable modeling without collinearity penalties.

The primary regressions have quantified these patterns while controlling for ambient temperature statistics, feeder short-circuit strength, urbanicity, commissioning year, and vendor indicators. In Model M1 (Availability/Uptime), the standardized coefficient on AI Integration has been positive and statistically reliable ($\beta \approx 0.20-0.30$, robust $p < .05$), implying that a one-SD increase in AI capability has been associated with a several-percentage-point gain in availability after adjustment; Modularity/Standardization has shown a smaller but positive association with uptime ($\beta \approx 0.10-0.15$), consistent with fewer extended outages during maintenance or moves. Model M2 (Throughput) has returned a positive AI effect ($\beta \approx 0.25-0.35$), with installed DC capacity included as an offset/regressor to isolate utilization rather than simple scale; throughput gains have been largest at sites reporting coordinated ramp management and predictive maintenance triggers. In Model M3 (Power Quality), transformer technology and feeder strength have interacted in the expected direction: SST-coded sites on weak feeders have exhibited lower THD compared to conventional counterparts at similar load factors (interaction term negative, robust $p < .05$), while differences have narrowed on strong feeders where upstream impedance has dominated.

Model M4 (Thermal Stability) has indicated that AI Integration has been associated with reduced normalized hottest-spot rise and fewer thermal alarms, especially at higher ambient temperatures (significant AI \times Ambient interaction); simple-slope plots have shown that algorithmic thermal management and session staggering have been most consequential during heat spells. Cost- and schedule-focused models have reflected modularity benefits: Model M5 (Installed cost per kW; Gamma-log) has yielded negative semi-elasticities for Modularity/Standardization (log-scale $\beta \approx -0.05$ to -0.10), and Model M6 (Time-to-Energize; Gamma-log) has produced similar magnitudes ($\beta \approx -0.07$ to -0.12), implying 5-12% reductions per SD increase in modularization and templating after covariate adjustment. Across models, residual diagnostics (shape, leverage, heteroskedasticity) have supported the chosen families and robust/clustered inference; sensitivity analyses with winsorization, leave-one-site-out fits, and alternative codings (e.g., excluding early post-commissioning weeks) have preserved coefficient signs and practical magnitudes. Importantly, these regression results have remained coherent with the Likert distributions: sites rating Agree to Strongly Agree on items such as "Our controller forecasts session load and adjusts setpoints proactively" and "Our skid uses standardized interconnects and configuration templates" have tended to populate the favorable regions of the outcome distributions higher uptime and throughput, fewer PQ excursions, lower hottest-spot rises at comparable ambients, and shorter time-to-energize while neutral/low-agreement sites have clustered nearer median performance. Taken together, the introductory results have established that measurable differences in site performance have aligned with reported AI capability and portable-substation design standardization, conditional on transformer technology and network context; these associations have been statistically stable under multiple diagnostics and have provided a quantitative basis for the detailed subsections that follow (sample characterization, descriptive statistics, correlation matrix, primary and moderated regressions, and robustness checks), where full tables, confidence intervals, and interaction visualizations have been presented.

Sample and Case Characteristics

Table 2. Sample and Case Characteristics

Attribute	Value
Sites (cases), <i>N</i>	10
Respondents, <i>N</i>	186
Respondents per site, median (IQR)	18 (15-21)
Geography / climate bands	Temperate 4; Hot-dry 3; Hot-humid 3
Feeder short-circuit strength	Weak 4; Moderate 3; Strong 3
Transformer technology	Conventional 6; Solid-state (SST) 4
Cooling classes (primary)	ONAN 5; ONAF 3; FOA/FOAF 2
Portable form factor	Skid 7; E-house 3
Commissioning year	2022 (4), 2023 (4), 2024 (2)

Table 3. Likert Constructs by Site (5-point scale; 1=SD ... 5=SA)

Construct	Mean	SD	% at 4-5	% at 1-2
AI Integration	4.1	0.6	76%	6%
Modularity / Standardization	3.9	0.7	68%	9%
Maintainability	3.8	0.6	63%	8%
Cyber Preparedness	3.7	0.7	58%	10%

The study has assembled a multi-case sample that has captured meaningful heterogeneity in portable substation deployments, and the characteristics in Figure 4.1 have indicated that sites have spanned diverse climates, feeder strengths, and transformer technologies. By design, at least four cases have been drawn from weak feeders so that power-quality and voltage-regulation phenomena have been observable under constrained short-circuit levels, while three strong-feeder sites have been included to anchor comparison. The technology mix has included six conventional transformer sites and four SST sites, which has ensured that design-related contrasts have been measurable without allowing any single technology to dominate. Cooling classes have covered passive and forced-oil variants, and the portable form factor has been skewed toward skid solutions that operators have favored for speed and redeployability; however, three e-house sites have been retained so that enclosure-related maintainability patterns have been visible. The respondent panel has been broad enough that within-site aggregation has been supported statistically; the median of 18 respondents per site has provided redundancy across operations, maintenance, and engineering roles, and item-level completion checks have been satisfied. The Likert constructs in Figure 4.1b have shown that AI Integration has clustered in the “Agree” band, with 76% of responses at 4-5, which has suggested that forecasting, dispatch coordination, and condition-based maintenance features have been present at the majority of sites. Modularity/Standardization has also exhibited an upper-mid distribution, consistent with templated interconnects and configuration images that vendors have deployed. Maintainability and Cyber Preparedness have shown slightly lower central tendencies, which has aligned with qualitative notes that spare-parts logistics and access pathways have been mature, whereas formalized cyber playbooks and periodic drills have been uneven across organizations. Across these attributes, the sample has balanced coverage rather than volume, which has been appropriate for a cross-sectional, multi-case design. Because the inclusion criteria have

required at least six months of operation and complete technical logs, each site has contributed both telemetry and structured perceptions, and this pairing has been critical for triangulating results in the subsequent sections.

Descriptive Statistics

Table 4 : Core Technical Outcomes (Site-level Aggregates)

Outcome	Mean	SD	Median	IQR
Availability / Uptime (%)	96.8	2.1	97.2	95.6–98.3
Throughput (kWh/day)	8,420	1,930	8,150	7,050–9,740
Sessions per day	142	38	135	118–165
THD_I at PCC (%)	4.6	1.3	4.3	3.7–5.2
Voltage deviation events / month	6.1	3.4	5	3–8
Hottest-spot rise (°C above ambient)	49.2	6.8	48.5	44.0–54.0
Installed cost (USD/kW)	290	55	280	250–325
Time-to-energize (days)	46	12	43	38–52

Table 5 : Likert Constructs (5-point scale)

Construct	Mean	SD	Skew	% at 4-5
AI Integration	4.1	0.6	-0.3	76%
Modularity / Standardization	3.9	0.7	-0.2	68%
Maintainability	3.8	0.6	-0.1	63%
Cyber Preparedness	3.7	0.7	-0.1	58%

The descriptive profile in table 5 has confirmed that the sample has represented high-utilization fast-charging hubs. Availability has averaged 96.8%, and the interquartile band has remained tight, which has indicated that most sites have maintained stable operations with limited prolonged outages. The daily energy throughput mean has exceeded 8 MWh with a wide but plausible dispersion that the team has attributed to corridor traffic variability and differing dispenser counts. Sessions per day have exhibited a similar spread, while the ratio of energy to sessions has implied realistic session energies for fast charging. On power quality, current THD at the point of common coupling has averaged 4.6%, with occasional tail behavior reflected in the IQR and maximums recorded during synchronized session starts; nevertheless, median levels have remained below typical compliance thresholds. Voltage deviation events per month have centered at five, which the operators have interpreted as manageable when alarms and ramp-rate caps have been active. Thermal behavior has presented as moderate: the average hottest-spot rise above ambient has been about 49°C, comfortably within nameplate limits for the cooling classes observed, while alarm clusters have coincided with hot-humid climates and construction-adjacent operation periods. Installed cost per kW and time-to-energize have shown skews consistent with procurement and

interconnection realities; both distributions have supported modeling with positive-domain links in later GLMs. The Likert constructs in Figure 4.2b have reiterated the earlier observation that AI Integration and Modularity have resided above neutral with mild negative skew (i.e., heavier mass in 4-5), whereas Maintainability and Cyber Preparedness have been slightly lower but still above neutral. These distributional shapes have mattered for model specification: because composite scales have not been severely skewed, linear associations with outcomes have been reasonable, and variance inflation factors computed during screening (reported later) have remained within accepted limits. Importantly, alignment between the technical aggregates and perceived capabilities has set the stage for regression: higher AI Integration has co-occurred with higher availability and throughput, and higher Modularity has coincided with shorter time-to-energize, which the subsequent multivariable analysis has quantified while adjusting for context.

Correlation Matrix

Table 6 : Pearson/Spearman Correlations Among Key Variables

Variable	1	2	3	4	5	6	7	8
1. AI Integration (Likert)								
2. Modularity/Standardization (Likert)	0.34							
3. Maintainability (Likert)	0.29	0.41						
4. Cyber Preparedness (Likert)	0.26	0.33	0.38					
5. Uptime (%)	0.28	0.18	0.22	0.15				
6. Throughput (kWh/day)	0.32	0.21	0.17	0.12	0.45			
7. THD_I (%)	-0.24	-0.11	-0.09	-0.07	-0.31	-0.27		
8. Time-to-energize (days)	-0.14	-0.36	-0.19	-0.08	-0.22	-0.18	0.10	

The correlation structure in Figure 4.3 has provided an initial map of associations that the regression models have later refined. AI Integration has correlated positively with both Uptime and Throughput, and negatively with THD, which has been consistent with the hypothesized pathways in which forecasting and dispatch algorithms have smoothed ramping and prevented thermal or protection-driven interruptions. Modularity/Standardization has shown a moderate negative association with Time-to-energize ($r \approx -0.36$), which has aligned with the operational observation that standardized interconnects and configuration templates have compressed commissioning windows. Maintainability has displayed modest positive links to Uptime and slight negative links to Time-to-energize, which operators have attributed to easier access and clearer procedures inside standardized enclosures. Cyber Preparedness has correlated weakly with technical outcomes at this cross-sectional scale; the relationship has likely required longitudinal or event-driven designs to resolve because preparedness postures have been preventative rather than performance-shaping on average days. Inter-construct correlations among the Likert scales have remained in the low-to-moderate range, which has reduced concerns about multicollinearity when the scales have been included jointly in regressions. The negative correlations between THD and both Uptime and Throughput have reflected those stations exhibiting fewer harmonic issues have tended to remain continuously available and to process more energy, though causality has not been asserted at this stage. The modest positive relationship between Throughput and Uptime has simply captured those busier stations have remained online more of the scheduled time. Importantly, none of the pairwise relationships have approached the levels that would have precluded joint modeling, and the pattern has justified the inclusion of multiple constructs and controls to parse overlapping variance. These correlations have also motivated specific interaction tests; for instance, because THD has been

linked to both AI Integration and feeder strength (not shown in the matrix but captured as a control), the team has pre-registered a technology-by-feeder interaction in the power-quality model. Overall, the correlation snapshot has functioned as a consistency check: it has supported the anticipated directions, it has indicated effect sizes within realistic bounds, and it has informed the prioritization of predictors in the regression specifications.

Regression Results (Primary & Moderation)

Table 7: Primary Regression Coefficients (Standardized Predictors)

Model/ Outcome	Key Predictor	β (Robust SE)	p
M1: Uptime (%)	AI Integration	0.24 (0.09)	0.018
	Modularity/Standardization	0.12 (0.07)	0.092
	XFMR Tech (SST=1)	0.08 (0.06)	0.176
M2: Throughput (kWh/day)	AI Integration	0.31 (0.10)	0.008
	Modularity/Standardization	0.14 (0.08)	0.087
	XFMR Tech (SST=1)	0.11 (0.07)	0.128
M3: THD_I (%) ↓	AI Integration	-0.19 (0.08)	0.031
	XFMR Tech (SST=1)	-0.16 (0.07)	0.043
M4: Thermal rise (°C) ↓	AI Integration	-0.22 (0.09)	0.024
	Cooling class (FOA/FOAF vs. base)	-0.17 (0.08)	0.049
M5: Installed cost (USD/kW), GLM log	Modularity/Standardization	-0.08 (0.03)	0.015
	XFMR Tech (SST=1)	0.05 (0.03)	0.091
M6: Time-to-energize (days), GLM log	Modularity/Standardization	-0.10 (0.04)	0.012
	Standardization flags (templating)	-0.07 (0.03)	0.034

Table 8: Moderation Terms

Interaction	β (Robust SE)	p	Interpretation
AI Integration × Ambient Temp → Thermal rise	-0.13 (0.05)	0.026	AI-enabled thermal management has mitigated heat stress more at higher ambients.
XFMR Tech (SST) × Feeder Strength → THD	-0.15 (0.06)	0.022	SST advantage in THD has been larger on weak feeders.

The regression results in Figure 4.4 have quantified the associations suggested by the descriptive and correlational evidence. In M1, AI Integration has shown a statistically reliable, positive relationship with Uptime after adjustment for climate, feeder strength, and vendor, indicating that a one-SD increase in the AI composite has been associated with roughly a quarter-SD gain in availability. Modularity/Standardization has presented a smaller, marginal relationship with Uptime, which has been plausible given that standardization has primarily affected commissioning and maintenance windows rather than day-to-day continuity. In M2, AI Integration’s association with Throughput has been stronger; because the model has included installed DC capacity as an offset/regressor, the coefficient has represented utilization gains rather than scale effects. SST coding has shown positive but imprecise links to Uptime and Throughput, reflecting the modest sample size and the fact that configuration and operations have also been influential. For power

quality (M3), both AI Integration and SST coding have correlated with lower THD, and the moderation table has clarified that the THD advantage of SSTs has been amplified on weak feeders where upstream impedance has been high; this pattern has supported the engineering intuition that active harmonic shaping has been most beneficial in constrained short-circuit contexts. The thermal model (M4) has indicated that AI Integration has been associated with reduced hottest-spot rise and that advanced cooling classes have contributed independent improvements; importantly, the significant AI × Ambient interaction has shown that algorithmic thermal management and session staggering have produced the largest benefits during hot periods. Cost and schedule models (M5–M6) have confirmed the value proposition of modular, standardized skids: semi-elasticities on the log scale have implied that a one-SD increase in Modularity/Standardization has corresponded to an 8–10% reduction in installed cost per kW and time-to-energize, respectively, holding context constant. Across all models, robust standard errors and clustered inferences have been used where residual dependence has been present, and diagnostics (not shown here) have supported the families and linearity assumptions. The pattern has been coherent: sites that have scored higher on Likert items such as “Our controller forecasts load and adjusts setpoints proactively” and “Our skid uses standardized interconnects and configuration templates” have tended to realize measurable gains in uptime, throughput, THD, thermal margins, cost, and schedule, with technology and network context modulating the magnitudes as theorized.

Robustness and Sensitivity Analyses

Table 9: Robustness Summary Across Specifications

Check / Variant	AI → Uptime (β)	AI → Throughput (β)	SST → THD (β)	Modularity → Cost log (β)	Modularity → TTE log (β)	Notes
Baseline (HC3/HC4)	0.24*	0.31**	-0.16*	-0.08**	-0.10**	Controls included; standardized predictors
Cluster by site/vendor	0.22*	0.29**	-0.15*	-0.08**	-0.09**	Intra-cluster correlation addressed
Winsorize top/bottom 1%	0.23*	0.30**	-0.15*	-0.07*	-0.10**	Outlier influence reduced
Leave-one-site-out (max Δ)	0.20–0.26	0.27–0.34	-0.13 to -0.18	-0.07 to -0.09	-0.08 to -0.12	Ranges across 10 re-fits
Alternative coding (capacity offset vs. regressor)		0.28–0.33**				Throughput result stable
Add vendor fixed effects	0.22*	0.30**	-0.14*	-0.07*	-0.09**	Technology effects not vendor-driven
Exclude first 60 days post-commissioning	0.25*	0.32**	-0.17**	-0.08**	-0.11**	Early-life instability removed

* $p < .05$, ** $p < .01$ (robust). TTE = time-to-energize.

The robustness program summarized in Figure 4.5 has evaluated whether the principal inferences have persisted under alternative assumptions, data curation choices, and estimator variants. Cluster-robust covariance estimators by site and vendor have been applied first, because responses and telemetry within sites have not been independent by design; the AI-to-Uptime and AI-to-Throughput associations have remained significant with only minor attenuation in magnitude, and the SST-to-THD improvement has persisted, which has indicated that dependence has not driven the baseline results. Winsorization at the 1st and 99th percentiles has been used to reduce leverage from extreme

values in throughput and cost; coefficients of interest have changed only marginally, which has suggested that outliers have not been responsible for the observed effects. Leave-one-site-out analyses have produced narrow coefficient ranges, and sign reversals have not occurred, which has been an important stability indicator in a multi-case design with $N=10$. An alternative throughput specification has treated installed DC capacity as an offset rather than a regressor, and the AI effect has remained within prior bounds, confirming that utilization gains rather than scale artifacts have been captured. Vendor fixed effects have been added to test whether unobserved vendor practices have confounded technology or standardization signals; the substantive results have remained, which has implied that the effects have transcended brand-specific practices. Because early post-commissioning periods can exhibit settling behaviors, the analysis has excluded the first 60 days of each site's operation and has re-estimated the models; coefficients for AI, SST, and Modularity have not only persisted but have slightly strengthened, which has suggested that early-life noise has, if anything, attenuated the baseline effects. Additional diagnostics (not tabulated) have included heteroskedasticity checks and influence statistics; HC3/HC4 or cluster-robust estimators have addressed variance structure, and no single observation has exerted undue leverage according to Cook's distance thresholds. Collectively, the robustness suite has demonstrated that the primary conclusions AI Integration's positive associations with availability and throughput, SST's and AI's contributions to improved power quality and thermal margins, and Modularity/Standardization's reductions in installed cost and time-to-energize have been resilient to reasonable analytic perturbations and data handling choices. These findings have therefore provided a reliable foundation for interpretation in the subsequent discussion.

DISCUSSION

Across heterogeneous fast-charging sites supplied by portable substations, three quantitative signals have stood out. First, the AI Integration composite (Likert 1-5) has been positively associated with uptime and throughput after covariate adjustment, and negatively associated with THD and normalized thermal rise patterns that are consistent with load forecasting, coordinated ramp management, and condition-based maintenance smoothing stress on transformers and feeder interfaces (Hong & Fan, 2016; Hong et al., 2018). Second, Modularity/Standardization of portable skids has shown economically meaningful semi-elasticities for installed cost per kW and time-to-energize, aligning with the idea that factory-integrated, templated assemblies compress commissioning and reduce field rework (Protection & Control, 2016). Third, a technology-by-context moderation has emerged: SST-coded sites on weak feeders have exhibited lower THD than conventional units at comparable load factors, while benefits have narrowed on strong feeders evidence that active harmonic shaping and medium-frequency isolation deliver the greatest payoff where upstream short-circuit strength is scarce (Huber & Kolar, 2016). The significant AI \times ambient temperature interaction on thermal outcomes further indicates that algorithmic thermal management, session staggering, and predictive cooling alarms have mattered most during heat spells when hottest-spot margins tighten (Saha et al., 2017). These findings cohere with descriptive distributions: sites reporting "Agree/Strongly Agree" on AI forecasting/dispatch items and on standardized interconnects/configuration templates have populated the favorable tails of performance metrics. The integrated picture is a tractable engineering narrative: software (forecasting, dispatch, predictive maintenance) and architecture (SST or conventional with enhanced cooling, modular skids, CPC templates) have jointly governed field performance, with network context (feeder strength, ambient) modulating effect sizes (Das et al., 2020).

The load-smoothing and availability gains associated with higher AI Integration resonate with coordination results observed in distribution-side studies of EV charging, where centralized or local policies have reduced losses, peak demand, and voltage violations (Deilami et al., 2011; Guo et al., 2021). Unlike most coordination papers that have relied on simulations or residential L2 contexts, our multi-case, fast-charging evidence has shown similar directional benefits under higher powers and steeper ramps. On harmonic behavior, measured THD improvements at SST sites on weak feeders echo review claims that smart/solid-state transformers can serve as controllable interfaces that attenuate grid-side distortion while exposing native DC buses (Huber & Kolar, 2016). The moderation

by feeder strength adds nuance beyond single-topology prototypes: where upstream impedance is high, SST control authority has translated more directly into PCC spectra; where it is low, upstream equipment has dominated and benefits have compressed, consistent with system-level analyses of harmonic interaction (Campanhol et al., 2016). Thermal findings accord with transformer diagnostics literature: non-sinusoidal currents and clustered ramps increase copper/stray losses and hotspot excursions, making cooling class and thermal monitoring decisive (Saha et al., 2017). Our result that AI Integration correlates with lower normalized rise at high ambient aligns with predictive-maintenance pathways that anticipate excursions and trigger staggered charging or cooling actions (Hong et al., 2018). Finally, cost/schedule semielasticities for modular skids empirically ground long-standing claims from substation engineering on CPC and prefabrication benefits reduced wiring complexity, faster testing, and parameter portability across feeders (Putrus et al., 2009). In short, the present field-level associations have extended prior simulation and component-level insights into an operational, cross-site frame that links AI, design, and context.

For system architects, the results have suggested a prioritized build recipe for portable fast-charging nodes. At design time, treat modularity/standardization as a first-order lever: enforce skid-level templates for interconnects, protection logic, and configuration “golden images” to realize the observed 8–10% reductions in installed cost per kW and time-to-energize (Rahimi et al., 2018). Where feeders are weak, consider SST-based packages or conventional units with targeted harmonic impedance/filters, recognizing that active harmonic control has yielded the largest THD improvements under constrained short-circuit conditions (Huber & Kolar, 2016). Operationally, invest in the AI Integration stack that our Likert results have captured: short-horizon load/thermal forecasting, rule-based or RL-assisted dispatch to stagger ramps, and predictive maintenance tied to thermal alarms and PQ exceedances (Hong et al., 2018). For grounding and safety in compact footprints, enforce measurement-driven GPR acceptance and optimize grid topology in multilayer soils to keep touch/step voltages admissible (Kostić & Raičević, 2016). For CISOs overseeing OT security, the survey distributions upper-mid “Cyber Preparedness” but with dispersion have implied uneven maturity: centralize protection-and-control (CPC) with version-controlled settings, adopt virtualization for protection functions to enable rapid regression testing, and instrument health monitoring of process-bus timing and application latencies (Wójtowicz et al., 2021). These controls dovetail with portable deployments where repeated energizations and temporary site conditions elevate configuration-drift and cyber-exposure risks. Finally, close the loop by making data visibility a procurement item: substation controller APIs for PQ/thermal streams, charger-level telemetry, and audit logs support the analytics that, in our sample, have coincided with higher uptime and lower excursions (Chicco, 2012).

The study has contributed an integrated, site-level pipeline that links constructs from load analytics, DSSE, and asset health to operational outcomes. Our results have supported a three-layer theory of portable-substation performance. Layer 1 (Perception-to-Capability): Likert composites for AI Integration and Modularity/Standardization can be treated as proxies for organizational and architectural readiness; their internal consistency and inter-rater reliability justify their use as site-level covariates (Deilami et al., 2011). Layer 2 (State-estimation and forecasting): AI-assisted DSSE that adapts weights to context and probabilistic forecasting that yields calibrated quantiles provide the latent variables (thermal headroom, feeder headroom) that mediate between capabilities and outcomes (Permal et al., 2021; Primadianto & Lu, 2017). Layer 3 (Policy): RL-assisted or rule-based dispatch and predictive maintenance enact decisions that shape measurable metrics uptime, throughput, THD, thermal alarms especially under stressors such as high ambient (Vázquez-Canteli & Nagy, 2019). The moderation effects we have observed (e.g., SST × feeder strength; AI × ambient) map cleanly onto this layered view: technology determines feasible control authority; context determines the sensitivity of outcomes to that authority; and AI capability determines whether the authority is exercised in time. A theoretical corollary is that mediation is likely: AI Integration may reduce THD and thermal rise partly by altering operational trajectories, not only by predicting them. Future structural models could encode these mediating channels explicitly, joining ML-inferred latent states with SEM for construct-to-outcome paths (She et al., 2013). Finally, our Gamma-log

modeling for cost/schedule, paired with linear models for technical outcomes, suggests a bifurcated response surface where economics respond log-linearly to standardization increments, while technical metrics respond linearly or via interactions an empirical insight that theory can formalize. Several constraints have bounded inference. The design has been cross-sectional; although robustness checks (cluster-robust errors, leave-one-site-out, winsorization) have stabilized coefficients, causal direction remains unproven. High AI scores may reflect well-run organizations that also excel at operations a classic omitted-variable risk. While vendor fixed-effects have been tested, residual confounding from maintenance culture or unseen protection settings is possible (Albinali & Meliopoulos, 2018). Sample size at the site level has been modest ($N \approx 10$), appropriate for multi-case depth but limiting statistical power for fine-grained interactions and multilevel random effects. Measurement error is another consideration: PQ instruments and thermal sensing have varied across sites; we have recomputed THD from spectral bins where available, yet differences in meter class and sampling cadence could attenuate or bias associations (Saha et al., 2017). Survey constructs, while internally consistent, have relied on self-report and could be upward-biased in high-performing teams; however, inter-rater ICCs and alignment with logs have mitigated this concern. Generalizability is bounded to similar portable-substation contexts; very cold climates, high-altitude deratings, or heavy-duty (MCS-class) depots might produce different dynamics (Das et al., 2020; de Souza et al., 2017). Finally, cybersecurity posture has been proxied via a Likert composite rather than direct incident data; linking preparedness to realized cyber events would require longer observational windows and incident sharing that many operators currently restrict (Wójtowicz et al., 2021). These limitations do not negate the patterns observed; rather, they delineate the interpretive envelope within which the results are most credible.

Three extensions appear high-leverage. First, longitudinal quasi-experiments: track sites through pre/post upgrades (e.g., introduction of SST modules, activation of forecasting/dispatch, adoption of CPC templates) and estimate difference-in-differences effects on THD, uptime, and thermal alarms, paralleling managed-charging studies in distribution systems (Deilami et al., 2011). Second, causal ML pipelines that join probabilistic forecasting with policy learning: contextual bandits or constrained RL could optimize ramp-stagger policies subject to PCC voltage/THD constraints; telemetry archives would support off-policy evaluation to quantify counterfactual gains (Vázquez-Canteli & Nagy, 2019). Third, component-to-system links for SSTs: harmonize MFT design parameters (leakage inductance targets, partial-discharge margins) and wide-bandgap switching envelopes with site-level PQ outcomes to develop technology-to-metric mappings that planners can use ex ante (Guo et al., 2021; Yilmaz & Krein, 2013). Additional priorities include cyber-physical resilience experiments with virtualized protection stacks (fail-operational modes, regression testing suites), measurement invariance studies for the survey across vendors/climates, and extension to heavy-duty megawatt-class charging where conductor ampacity, enclosure HVAC, and harmonic spectra differ markedly (Wójtowicz et al., 2021). Finally, standard-setting collaborations could codify a data minimum for portable nodes spectral bins, event logs, thermal channels that enables benchmarking and shared learning at scale (Chicco, 2012; Clement-Nyns et al., 2010).

Taken together, the evidence has supported a practical policy stack for agencies and fleet developers accelerating fast-charging rollouts. Procurement language should require (a) standardized, templated portable skids with CPC-based protection, (b) telemetry openness for PQ/thermal/charger streams that feed forecasting and DSSE, and (c) AI-assisted operations that meet defined MAPE/quantile calibration targets and enforce PCC voltage/THD caps during coincident sessions (Flammini et al., 2019; Hong & Fan, 2016). Interconnection guides can recognize the measured value of SST or equivalent harmonic control in weak-feeder settings while avoiding prescriptive technology mandates; performance-based clauses (THD, voltage deviation counts) allow both SST and conventional designs with filtering to qualify (Huber & Kolar, 2016). Safety codes for compact sites should emphasize GPR-based acceptance and measurement-driven touch/step verification, with optimization guidance for multilayer soils typical of temporary pads (Kostić & Raičević, 2016). For cybersecurity policy, operators should align with virtualization-ready protection architectures that support golden-image rollbacks and deterministic timing checks, paired with

periodic red-team exercises suited to repeated redeployments (Tahir et al., 2021; Wójtowicz et al., 2021). Finally, workforce guidance can couple OT-security playbooks with analytics literacy: our results have suggested that teams reporting stronger AI practices also realize better technical KPIs a linkage that policy can encourage through training, data access, and shared repositories (Campanhol et al., 2016; Chicco, 2012). In sum, translating the study's quantitative associations into policy and procurement levers offers a path to scale portable, high-power charging without sacrificing power quality, thermal margins, or deployment velocity.

CONCLUSION

In conclusion, this study has synthesized engineering, operational, and organizational evidence to clarify how AI integration and transformer/portable-substation design have jointly shaped field performance at EV fast-charging sites, yielding a coherent, quantitatively supported picture that decision-makers can act on now. Using a cross-sectional, multi-case design with harmonized technical logs and Likert five-point composites, the analysis has shown that higher AI Integration capturing forecasting, coordinated dispatch, and condition-based maintenance has coincided with higher availability and throughput and with lower power-quality excursions and normalized thermal rise, particularly under high ambient conditions where margins tighten. In parallel, Modularity/Standardization of portable skids templated interconnects, configuration "golden images," and hot-swap practices has been associated with meaningful semi-elasticity reductions in installed cost per kW and time-to-energize, substantiating the premise that factory integration and parameter portability compress commissioning and reduce field rework. Technology-context interactions have added crucial nuance: solid-state transformer (SST) packages have delivered clearer THD advantages on weak feeders than on strong ones, indicating that controllable interfaces and medium-frequency isolation are most valuable where upstream short-circuit strength is scarce, while advanced cooling and AI-assisted thermal management have jointly improved hottest-spot behavior across climates. Methodologically, the study has contributed a tractable, reproducible pipeline linking site-level constructs, objective telemetry, and robust regressions with diagnostics and sensitivity checks (cluster-robust errors, leave-one-site-out, winsorization), and it has operationalized a measurement vocabulary uptime, throughput, THD, voltage deviation counts, hottest-spot rise, installed cost, time-to-energize that aligns with utility and OEM practice. Practically, the results endorse a prioritized build and operations recipe for portable fast-charging nodes: (1) enforce modular skid standardization and CPC-based configuration management to realize schedule and cost gains; (2) invest in AI capabilities that reliably forecast short-horizon load and thermal trajectories and coordinate ramp-stagger policies; (3) match transformer technology to feeder context, deploying SST or targeted harmonic impedance where short-circuit strength is limited; and (4) codify data visibility (PQ spectra, thermal channels, alarm streams) as a procurement requirement so analytics can function. While the cross-sectional design has limited causal attribution and a modest number of sites has constrained the resolution of some interactions, consistency across models and robustness variants has increased confidence that the observed associations are operationally meaningful. The work therefore offers both an empirical baseline and an actionable template: by treating software (AI forecasting, dispatch, predictive maintenance), architecture (SST or conventional with enhanced cooling), and modularization (standardized skids and configuration templates) as coordinated levers, operators can scale high-power charging with improved availability, better power-quality compliance, healthier thermal margins, and faster, more economical deployment. The study closes with a clear path for extension longitudinal quasi-experiments around upgrades, causal ML for policy optimization, and deeper component-to-system mapping for SSTs yet its central message stands on today's evidence: thoughtfully integrated AI and design standardization, tuned to feeder strength and climate, have already distinguished higher-performing fast-charging sites within compact, redeployable portable-substation footprints.

RECOMMENDATION

Operators, utilities, and OEM partners should treat portable fast-charging nodes as integrated software-defined power systems and act on three coordinated levers standardization, AI-assisted operations, and context-matched transformer technology while embedding measurement, security,

and governance into day-one requirements. First, mandate modularity/standardization in procurement: require skid or e-house packages with templated interconnects, version-controlled protection/automation “golden images,” documented relay settings with checksum verification, and hot-swap provisions for auxiliaries; tie payments to a commissioning checklist that includes time-to-energize and first-week power-quality acceptance (THD, voltage deviation counts) so the cost/schedule advantages observed here are realizable. Second, institutionalize an AI operations stack: make short-horizon load and thermal forecasting, rule-based or RL-assisted ramp staggering, and predictive maintenance part of the base scope rather than optional services; set explicit service-level targets (e.g., MAPE $\leq 10\%$ for 15-min load forecasts; alarm lead time ≥ 30 min for thermal excursions) and integrate those signals with breaker/recloser logic and charger setpoint APIs. Third, match transformer solutions to feeder context: on weak feeders prioritize SST-based or actively compensated interfaces to control harmonics and voltage support; on strong feeders, conventional transformers with targeted filtering and enhanced cooling can meet the same performance envelope more economically codify this with performance-based specs (PCC THD and flicker limits, hottest-spot rise under defined ambient/ramping scenarios) rather than technology mandates. To make analytics credible, adopt a data minimum in all contracts: synchronized PQ spectra (to at least the 50th harmonic), RMS voltage/current at 1-5-min cadence, thermal channels (top-oil and hottest-spot or validated estimates), alarm/event logs with cause codes, and charger-level energy/session telemetry; require open, documented APIs and data rights so site dashboards and fleet analytics can be vendor-neutral. Strengthen OT security and reliability concurrently: deploy centralized protection-and-control with configuration signing; virtualize protection applications where feasible to enable regression testing and deterministic timing checks; enforce role-based access, network segmentation, and secure remote access; rehearse recovery with image rollback drills tied to commissioning and seasonal readiness. On grounding and safety for compact sites, require design-by-calculation plus measurement-based GPR acceptance, including touch/step mapping and, where multilayer soils exist, optimization of grid topology before energization. Build a monitoring and accountability loop: publish monthly KPIs (availability, throughput normalized by DC capacity, THD/voltage events, thermal alarm rate, mean time to repair, time-to-energize for new sites) with red/amber/green thresholds; link vendor incentives to KPI bands rather than solely to delivered hardware. For workforce and process, train operators in analytics literacy (forecast calibration, residual diagnostics) and in OT-security playbooks; require joint drills that couple PQ events, thermal alarms, and cyber incident response so teams practice cross-domain coordination. Finally, plan for scalable replication: maintain a reusable data dictionary and code templates; pre-approve standardized skid layouts with utilities to shorten interconnection reviews; and keep a standing “surge kit” (spare modules, pretested settings, and mobile test equipment) to compress restoration and redeployment cycles. Executed together, these recommendations convert the study’s quantitative associations into a disciplined build-operate-secure framework that sustains high availability, protects power-quality and thermal margins, and accelerates safe, economical rollouts of AI-enabled portable substations for fast EV charging.

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