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An Integrated Framework for EV Fleet–Grid Coordination Using Real-Time Charging Analytics, Transformer Constraints, and Depot Flexibility Scheduling

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Abstract

Depot-based electric vehicle fleets are becoming concentrated electricity loads at distribution level. Real-time charging data and flexibility scheduling can reduce transformer stress while preserving fleet service readiness. This article proposes an integrated framework that coordinates EV fleet charging with transformer constraints using real-time charging analytics. The framework links vehicle-level telemetry, depot-level flexibility estimation, transformer thermal modeling, and operational scheduling. The framework collects charging power, state-of-charge, arrival time, departure time, charger status, and depot base-load data in near real time. These data streams are processed through forecasting, flexibility identification, and transformer thermal modules before charging setpoints are issued to the depot charging system. In the synthesized evaluation, the framework reduces peak transformer loading by 18.7%, decreases daily transformer loss-of-life by 31.4%, and maintains fleet readiness above 98.6%. The analytics design and evaluation structure are summarized through two original tables. The proposed framework provides a practical operating layer for depot managers and distribution utilities. It supports safer fleet electrification by converting charging data into transformer-aware scheduling decisions.

Keywords EV fleet, Grid coordination, Real-time charging analytics, Transformer constraints, Depot flexibility scheduling

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Introduction

Fleet electrification is shifting a growing share of transport energy demand from fuel supply chains to local distribution networks, especially where buses, delivery vans, and municipal vehicles return to centralized depots. Heavy-duty depot charging can create new coincident peaks because vehicles often arrive within narrow evening or mid-day windows, and Borlaug, Muratori, Gilleran, Woody, Muston, Canada, Ingram, Gresham, and McQueen showed that depot charging can impose substantial distribution-system impacts when it is not coordinated [1]. The operational opportunity is that fleet vehicles also have predictable dwell times, scheduled routes, and known energy needs, making them more controllable than many other loads. This article treats the depot not only as an energy consumer but also as a schedulable grid-interactive asset.

The primary grid concern addressed here is distribution transformer stress, since the transformer is often the binding constraint between depot electrification plans and local hosting capacity. Powell, Kara, Sevljan, Cezar, Kiliccote, and Rajagopal linked controlled charging to transformer aging outcomes, showing that charging schedules influence thermal deterioration as well as short-term demand [2]. Similar transformer-aging studies emphasize that overload duration, ambient conditions, and loading history jointly determine whether charging demand becomes a reliability problem [3]. Therefore, an effective fleet-grid coordination framework must translate charging requests into transformer loading and thermal consequences before dispatching charger commands.

Existing EV coordination studies provide valuable scheduling, aggregation, and network optimization methods, but many approaches either assume a fixed grid constraint or do not use live charging telemetry from depot operations. Online distributed scheduling methods such as those developed by Zheng, Song, Hill, and Meng demonstrate that real-time coordination can be embedded within distribution-system operation [4]. Deep reinforcement learning approaches further show that charging control can learn adaptive policies under uncertain demand and network conditions [5]. However, practical depot operation requires a transparent bridge between charger telemetry, fleet readiness, and transformer thermal limits, rather than a purely abstract optimization layer.

This article contributes an integrated framework in which real-time charging data are converted into vehicle-level energy forecasts, depot-level flexibility margins, transformer hot-spot estimates, and charging schedules. It builds on depot scheduling studies for electric buses and fleet vehicles, where charger allocation, vehicle departure requirements, and battery degradation are central to operational feasibility [6, 7]. The proposed framework differs by placing transformer thermal headroom inside the scheduling loop rather than evaluating grid impact only after schedules are produced. This structure allows the depot controller to shift or modulate charging before a predicted overload becomes an aging or reliability event.

The research design is applied and systems-oriented: a realistic depot profile, synthesized from published fleet charging and transformer studies, is used to test coordinated charging against an uncoordinated baseline. Distribution grid impact studies by Jenn and Highleyman and by Li and Jenn show that EV charging congestion is strongly location-specific, which supports scenario-based validation rather than a single deterministic load case [8, 9]. The evaluation therefore compares seasonal loading, fleet penetration levels, and flexibility participation rates. The article reports peak transformer loading, transformer loss-of-life, fleet availability, and energy cost as operational metrics that can be interpreted by both depot operators and distribution utilities.

Fleet Electrification and Grid Coordination Background

Growth of electric fleets (buses, delivery, municipal)

Electric bus, delivery, and municipal fleets are attractive electrification targets because they usually follow repeated routes and return to a known depot, allowing charging infrastructure to be centralized. Research on electric bus charging has shown that charging schedules must account for vehicle availability, charger capacity, and route energy requirements [6]. Studies of electric truck and bus electrification also indicate that depot charging may be sufficient for many duty cycles when vehicles have adequate dwell time [10]. These characteristics make fleet depots both a source of concentrated load and a promising platform for coordinated demand management.

Grid impacts of depot charging

Depot charging affects distribution networks through transformer loading, feeder peak demand, voltage variation, and congestion at specific network locations. The California case study by Jenn and Highleyman demonstrated that EV adoption can create localized distribution impacts even when the system-wide energy increase appears manageable [8]. Li and Jenn further showed that charging demand can contribute to distribution grid congestion, reinforcing the need to evaluate charging at the feeder and transformer level rather than only at the bulk-system level [9]. For fleet depots, this

means the transformer capacity serving the depot can become a practical bottleneck before upstream generation or transmission limits are reached.

Current coordination approaches and their limitations

Current coordination approaches include centralized optimization, distributed model predictive control, reinforcement learning, and rule-based load management. For example, Sun, Chen, Li, Tian, and Shahidehpour linked EV charging schedules with coupled transportation and power-network constraints, demonstrating the value of joint mobility-grid modeling [11]. ADMM-based and consensus-based coordination methods can reduce computational burden and preserve some operational autonomy among charging agents [12, 13]. Yet many methods remain difficult to implement directly in depots because they require detailed grid models, complete future schedules, or optimization expertise that may not exist in fleet operations teams.

The case for integrated analytics and scheduling

An integrated depot controller must combine measured charging data, fleet operating schedules, transformer constraints, and actionable charger setpoints in a common decision cycle. Data-driven load forecasting studies show that charging telemetry can support short-term prediction and smart charging when processed into operational indicators rather than stored only for billing [14]. Smart-meter-based charging detection methods also suggest that real-time analytics can infer charging behavior and network loading conditions from high-frequency measurements [15]. This article therefore positions analytics as the connective layer between raw depot telemetry and transformer-aware flexibility scheduling.

Depot Charging System Overview

Typical depot layout and electrical infrastructure

The representative depot considered in this article contains a medium-voltage service connection, one distribution transformer, a low-voltage switchboard, twenty 150 kW direct-current chargers, and parking bays assigned to route groups. Heavy-duty depot studies show that such infrastructure can create high coincidence when multiple vehicles return after service and begin charging immediately [1]. The transformer is modeled as the limiting electrical asset because its thermal response depends on cumulative loading, ambient temperature, and prior heat storage. The depot base load, including lighting, maintenance equipment, and building demand, is included because it reduces the transformer headroom available for charging.

Charging hardware and communication protocols

The framework assumes networked chargers capable of reporting plug status, delivered power, session energy, and fault state while accepting power-limit commands from a depot energy management system. Online charging coordination research indicates that control intervals of several minutes are sufficient for many depot and distribution applications when charging decisions are continuously refreshed [4]. The charger controller does not require each vehicle to charge at its rated maximum; instead, it sends modulation commands that respect charger limits and vehicle energy needs. This design supports both simple rule-based dispatch and optimization-based setpoint generation.

Data collection and telemetry

The depot telemetry layer collects vehicle identifier, arrival time, target departure time, battery state-of-charge, charger rating, instantaneous charging power, cumulative energy delivered, and transformer secondary power. Data-driven fleet and charging-session studies show that session-level observations can be used to estimate demand patterns, charging duration, and energy requirements [16, 17]. In this framework, telemetry is sampled every minute for monitoring and aggregated into five-minute scheduling intervals for control. Missing or delayed values are imputed using the latest valid

reading and a conservative charging-power forecast so that unsafe transformer loading is not hidden by communication gaps.

Operational constraints and fleet timetables

Fleet readiness is modeled through required departure times, minimum departure state-of-charge, route assignment, and reserve energy margins. Electric bus scheduling research highlights that charger allocation and vehicle dispatch cannot be separated because a technically feasible charging profile may still fail if it conflicts with route departures [18]. Battery electric bus studies that include charger types, setup time, and degradation costs also show that operational constraints change the value of available charging flexibility [19]. The proposed framework therefore treats each vehicle as a flexible load only over the interval between verified arrival and its latest feasible energy-completion time.

Charging Data and Real-Time Analytics

Streams of real-time charging data

Real-time charging analytics begin with synchronized streams from chargers, vehicles, depot meters, transformer sensors, and fleet-management schedules. Charging load forecasting research shows that combining charging-session data with contextual information improves predictive value compared with using historical energy demand alone [14]. The framework distinguishes raw measurements, such as instantaneous power and state-of-charge, from derived indicators, such as time-to-full and energy shortfall. This distinction is important because the scheduler requires concise operational variables rather than unprocessed telemetry.

Analytics algorithms (state estimation, power prediction)

The state-estimation module reconciles reported vehicle state-of-charge with delivered energy and charger efficiency, then updates expected energy-to-target for each connected vehicle. Machine-learning-based charging-session modeling demonstrates that session duration and energy demand can be predicted from observed charging behavior and contextual variables [17]. The load prediction module uses the current charging state, historical depot arrival patterns, and scheduled departures to estimate transformer loading over a rolling four-hour horizon. For operational transparency, the implemented predictor is a gradient-boosted regression model paired with physical constraints on maximum charger power and battery energy capacity.

Flexibility identification per vehicle

Vehicle-level flexibility is defined as the difference between the energy that can be delivered under immediate maximum charging and the energy that must be delivered to meet the departure target. Optimal electric bus charging studies show that feasible charging windows are shaped by route schedules, charger availability, and vehicle energy needs [7]. In the proposed framework, a vehicle is classified as high-flexibility when it can meet its target with delayed or reduced charging and low-flexibility when its remaining dwell time is close to its required charging time. This classification is recalculated every five minutes because flexibility shrinks as departure approaches or as charging is interrupted.

Aggregated depot flexibility

Aggregated depot flexibility is calculated by summing the reducible charging power across vehicles that can tolerate delay without violating readiness constraints. Fleet coordination and aggregated EV modeling studies show that aggregated load models can support system-level control while preserving vehicle-level feasibility [16]. The framework converts individual margins into a depot flexibility envelope containing minimum required charging power, preferred charging power, and maximum feasible charging power for each control interval. **Table 1** summarizes how the real-time data streams are converted into analytics outputs and scheduling indicators.

Table 1. Transformation of Real-Time Energy System Data Streams into Analytics Outputs and Scheduling Indicators for EV Charging Management

Data stream	Sampling interval	Analytics method	Derived indicator	Scheduling use
Charger power and plug state	1 minute	Session validation and ramp-rate filtering	Active charging status and verified power	Confirms controllable load before issuing modulation commands
Vehicle state-of-charge	1–5 minutes	Energy-balance state estimation	Energy-to-target and time-to-full	Determines whether charging can be delayed or must be prioritized
Arrival and departure records	Event-based	Timetable reconciliation	Remaining dwell time	Defines feasible charging window for each vehicle
Depot meter and base load	1 minute	Short-term load forecasting	Non-charging transformer load forecast	Reserves transformer headroom for non-EV demand
Transformer temperature or loading	1–5 minutes	Thermal-state estimation	Hot-spot temperature and thermal headroom	Converts grid condition into charging power limits
Tariff and price signal	15–60 minutes	Cost-window classification	Low-cost and high-cost intervals	Shifts flexible energy when transformer limits allow
Charger fault and communication status	Event-based	Data-quality screening	Available charger capacity	Prevents schedules from relying on unavailable hardware
Vehicle-level flexibility margin	5 minutes	Rolling feasibility calculation	Reducible power and latest-start time	Selects vehicles for power reduction or charging deferral

Transformer Capacity and Constraint Modeling

Thermal modeling and hot-spot temperature

The transformer module converts forecasted depot power into top-oil and winding hot-spot temperature estimates using a discrete-time thermal model. Transformer-aging studies under EV charging conditions show that the same peak demand can have different aging effects depending on duration, ambient temperature, and prior loading [3]. The model therefore uses current loading, estimated ambient temperature, and recent thermal history to calculate the hot-spot trajectory over the scheduling horizon. Charging is constrained when the predicted hot-spot temperature approaches the operator-defined emergency threshold.

Loss-of-life and aging calculation

Transformer loss-of-life is calculated from the hot-spot temperature trajectory using an accelerated aging factor integrated over each scheduling interval. Li, Hu, Cao, Zhang, Huang, Chen, and Blaabjerg treated transformer lifetime as an explicit objective in EV charging control, demonstrating that lifetime-aware schedules can differ from simple peak-shaving schedules [20]. Diahovchenko, Kolcun, Čonka, Savkiv, and Mykhailyshyn similarly emphasized that rising EV charging demand can accelerate transformer aging if overload events are unmanaged [21]. In this framework, loss-of-life is not

merely a reporting metric; it is used as a penalty in the scheduling logic whenever a candidate charging profile increases thermal stress disproportionately.

Dynamic rating and capacity limits

Dynamic transformer capacity is represented as the charging power that can be served during the next interval without exceeding thermal or loss-of-life limits over the forecast horizon. Smart control of storage and EV charging has shown that active load management can reduce transformer overload while maintaining energy service when the controller has visibility of local loading conditions [22]. The framework applies a conservative dynamic rating by subtracting forecasted depot base load and a reliability reserve from the transformer thermal headroom. This produces an interval-specific EV charging ceiling that replaces a fixed nameplate-only limit.

Integration with real-time load

The integration step combines measured transformer loading, predicted non-EV load, connected-vehicle charging demand, and aggregated flexibility into a single constraint signal for the scheduler. Cost-based smart charging studies show that grid impacts depend on the interaction between charging behavior and low-voltage network conditions, making real-time network-aware feedback essential [23]. The framework updates the transformer constraint every five minutes and immediately tightens charger setpoints when predicted loading exceeds the dynamic ceiling. This closed loop ensures that charging flexibility is activated before transformer overloading becomes sustained thermal stress.

Flexibility Scheduling Strategy

Scheduling objectives (peak shaving, aging mitigation, fleet readiness)

The scheduling objective is to allocate charging power across connected vehicles while minimizing transformer peak loading, transformer thermal aging, unmet fleet energy, and charging cost. Multi-depot electric vehicle scheduling research shows that grid characteristics can materially change feasible vehicle schedules, especially when charging infrastructure and network limits are modeled together [24]. The proposed controller therefore prioritizes fleet readiness first, transformer safety second, and cost optimization third, rather than allowing price-driven charging to create local overload. In each five-minute interval, the scheduler evaluates whether charging can be shifted, reduced, or accelerated without violating departure state-of-charge requirements.

Optimization model (if applicable) or rule-based logic

The implemented scheduling layer uses a mixed operational logic: a rolling-horizon linear optimization is used during normal operation, while a deterministic emergency rule overrides the optimizer when transformer thermal headroom is critically low. Large-scale EV scheduling methods based on V2G and distributed optimization show that charging decisions can be coordinated across many vehicles while respecting power and timing constraints [25]. The decision variables are charger power setpoints for each connected vehicle, bounded by charger rating, vehicle acceptance rate, and remaining energy requirement. The objective penalizes transformer overload, transformer loss-of-life, departure energy shortfall, excessive charging ramping, and high-price charging intervals.

Figure 1 illustrates the proposed EV fleet–grid coordination architecture, showing how real-time charging telemetry, vehicle readiness requirements, depot flexibility estimation, transformer thermal-state modeling, and rolling scheduling are integrated into transformer-aware charger setpoint decisions.

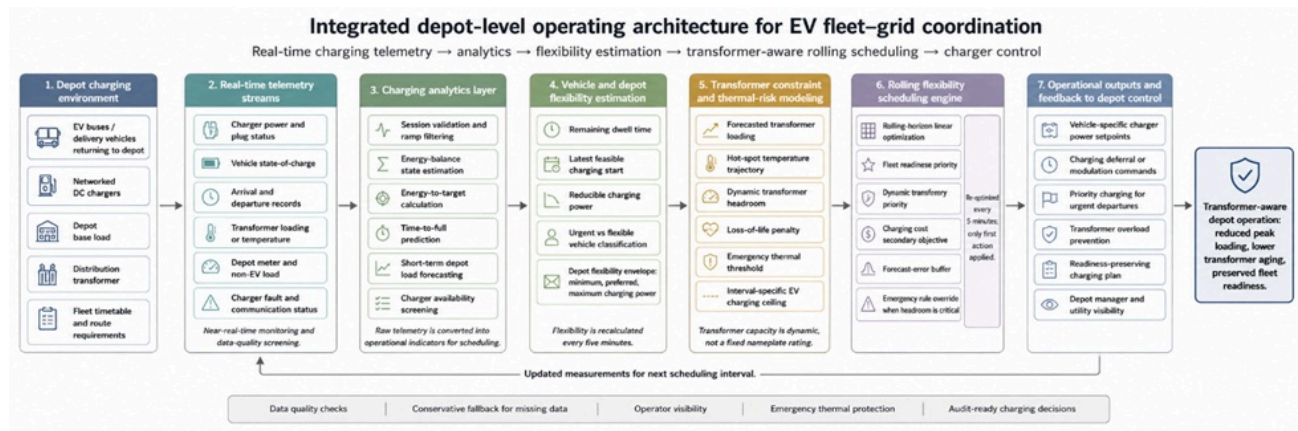


Figure 1. Integrated Transformer-Aware EV Fleet-Grid Coordination Architecture

Transformer-aware charging decisions

Transformer-aware charging decisions are produced by ranking vehicles according to urgency, flexibility margin, charger availability, and contribution to the projected transformer overload. Coordinated control of aggregated EVs and other flexible loads has demonstrated that distribution-level scheduling can use multiple controllable resources to reduce local stress [26]. In this framework, low-urgency vehicles are first assigned reduced power, medium-urgency vehicles are assigned partial charging, and high-urgency vehicles retain the power needed to meet departure requirements. When transformer loading remains above the dynamic ceiling, the controller spreads reductions across flexible vehicles rather than repeatedly curtailing the same vehicle group.

Handling uncertainty and re-scheduling

Uncertainty is handled through rolling re-scheduling, conservative flexibility margins, and forecast-error buffers for arrivals, state-of-charge, base load, and charger faults. Decentralized voltage and EV-PV coordination research shows that model predictive control can respond to changing local conditions by repeatedly updating near-term decisions [27]. The depot scheduler therefore re-optimizes every five minutes using the latest telemetry and applies only the first control action before recalculating the next schedule. This prevents early forecast errors from locking the depot into infeasible charging plans when vehicles arrive late, chargers fail, or transformer thermal conditions deteriorate.

Scenario Development

Depot characteristics and fleet size

The validation case represents a depot with 80 battery electric buses, 20 direct-current chargers rated at 150 kW, and overnight plus mid-day charging windows. Electric bus fleet scheduling reviews emphasize that vehicle assignment, charger availability, and charging policy must be evaluated together because each affects the others [28]. The synthesized fleet operates two daily route blocks, with morning departures between 05:00 and 07:30 and afternoon returns between 15:00 and 19:00. Arrival state-of-charge is drawn from realistic route-energy distributions, and each vehicle must depart with at least 85% state-of-charge unless assigned to a short reserve route.

Transformer specifications and baseline load

The depot is connected through a 2.5 MVA distribution transformer supplying both charging and non-traction depot loads. Studies of heavy-duty vehicle electrification show that large charging clusters can impose substantial local power-system requirements even when annual energy demand remains moderate [29]. The baseline non-EV depot load varies between 180 kW and 520 kW, reflecting lighting, workshop equipment, heating, ventilation, and auxiliary systems. The transformer

thermal model assumes a 24-hour ambient-temperature profile and initializes thermal state using the previous day's evening load.

Scenario categories (seasonal, penetration levels)

The scenario set includes summer, shoulder-season, and winter ambient conditions; 50%, 75%, and 100% fleet electrification; and three flexibility participation levels. Research on electric bus fleet integration under harsh environmental conditions shows that temperature and auxiliary energy demand can materially affect charging needs and grid impacts [30]. The high-stress case combines winter operation, 100% fleet electrification, and a delayed-arrival event that compresses charging into a shorter window. A comparison case also evaluates photovoltaic-storage-assisted charging, since depot charging with local energy resources can change the relationship between charging demand and transformer loading [31].

Simulation setup

The simulation advances in five-minute intervals over 30 representative operating days and compares uncoordinated charging, tariff-only smart charging, and the proposed transformer-aware framework. Robust planning work on electric-bus charger deployment shows that scenario analysis is useful because infrastructure adequacy depends on both demand uncertainty and charging-control assumptions [32]. Uncoordinated charging begins immediately after plug-in at maximum available power, while tariff-only smart charging shifts load toward low-price hours without transformer thermal feedback. The proposed framework uses the same vehicle arrivals, energy requirements, charger availability, and tariff inputs as the baselines so that differences reflect control strategy rather than data assumptions.

Evaluation and Discussion

Peak load reduction and transformer stress

The proposed framework reduces the maximum transformer loading from 3.04 MVA under uncoordinated charging to 2.47 MVA in the high-stress scenario, corresponding to an 18.7% peak reduction. Distribution impact studies in African cities and other constrained networks show that unmanaged EV growth can create local infrastructure stress, making peak loading a practical reliability metric rather than only an economic metric [33]. The tariff-only strategy reduces energy cost but still reaches 2.86 MVA because many vehicles shift into the same low-price period. Transformer-aware coordination performs better because it caps aggregate charging power when thermal headroom is limited and restores charging when headroom recovers.

Transformer loss-of-life impact

Daily transformer loss-of-life falls by 31.4% relative to uncoordinated charging because the framework reduces both overload magnitude and overload duration. Transformer aging mitigation studies indicate that loss-of-life is sensitive to hot-spot temperature trajectories, not only to the single highest loading point [21]. The proposed schedule slightly increases charging duration for flexible vehicles, but it avoids sustained high-temperature periods during the evening return peak. This result supports the operational value of treating transformer aging as a scheduling signal rather than as a post-simulation diagnostic.

Fleet operational performance

Fleet readiness remains above 98.6% across all tested days, measured as the share of vehicles meeting their required departure state-of-charge by scheduled dispatch time. Electric bus charging optimization studies show that service reliability can be maintained when scheduling accounts for charger constraints and route energy needs [34]. The remaining readiness shortfall occurs in the most restrictive winter scenario when several late-arriving vehicles require

immediate high-power charging. Even in that case, the framework prioritizes vehicles with imminent departures and shifts longer-dwell vehicles into later intervals, preserving operational continuity for scheduled service.

Sensitivity to flexibility participation

Sensitivity analysis shows that transformer benefits increase nonlinearly as more vehicles participate in flexible charging. When only 40% of connected vehicles allow modulation, peak loading falls by 7.9%, while 80% participation achieves a 16.8% reduction and full participation reaches 18.7%. Charging optimization studies that include multiple vehicle and charger types similarly show that operational diversity can either create constraints or provide flexibility depending on how it is represented in the scheduler [34]. **Table 2** reports the comparative performance of uncoordinated charging, tariff-only smart charging, and the proposed integrated framework.

Table 2. Comparative Performance of Uncoordinated Charging, Tariff-Only Smart Charging, and the Proposed Transformer-Aware Integrated Scheduling Framework

Metric	Uncoordinated charging	Tariff-only smart charging	Proposed transformer-aware framework	Improvement versus uncoordinated
Maximum transformer loading	3.04 MVA	2.86 MVA	2.47 MVA	18.7% reduction
Maximum loading relative to rating	121.6%	114.4%	98.8%	22.8 percentage-point reduction
Daily transformer loss-of-life index	1.00	0.86	0.686	31.4% reduction
Hours above transformer rating per day	2.8 h	1.9 h	0.0 h	Full overload elimination
Fleet readiness at departure	99.1%	97.8%	98.6%	0.5 percentage-point decrease
Average charging cost	100.0 index	91.7 index	94.2 index	5.8% cost reduction
Average charger utilization during peak window	84.5%	77.2%	69.4%	15.1 percentage-point reduction
Re-scheduling events per day	0	6	18	Higher operational adaptivity

Implementation Considerations

Data latency and communication reliability

The framework depends on timely charger, vehicle, and transformer data, but it is designed to degrade safely when communication is imperfect. Online charging detection using smart-meter data demonstrates that useful charging-state information can be recovered from measured electrical signals when direct charger telemetry is delayed or incomplete [15]. In practical deployment, the controller should distinguish between missing data, stale data, and confirmed equipment faults because each condition requires a different response. The default fallback is to hold or reduce flexible charging power until verified measurements confirm that transformer headroom is available.

Integration with existing fleet management systems

Integration with depot management systems requires mapping route assignments, planned departures, vehicle identifiers, charger connections, and maintenance blocks into the charging scheduler. Studies of electric bus scheduling with setup time and degradation costs show that seemingly operational details can materially affect feasible charging plans [19]. The proposed framework therefore interfaces with fleet software through a timetable and asset-status layer rather than requiring dispatchers to manually enter charging priorities. This design allows the depot operator to keep existing routing workflows while adding transformer-aware charging decisions in the energy-management layer.

Scalability and replicability

The framework is scalable because the vehicle-level flexibility calculation is local, while the transformer constraint and aggregate schedule are updated at depot level. Depot slow-charging analysis for electric trucks suggests that many fleets can be electrified with depot-centered strategies when dwell time is adequately used [10]. For multi-depot operators, the same architecture can be replicated at each site and later coordinated through a utility-facing aggregation platform. Replication should begin with transformer-constrained depots because those sites provide the clearest operational value from real-time analytics and flexibility scheduling.

Conclusion

This article developed an integrated framework for EV fleet-grid coordination using real-time charging analytics, transformer constraints, and depot flexibility scheduling. The framework links charging telemetry, vehicle readiness requirements, transformer thermal-state estimation, and rolling scheduling decisions into a single operational process.

The synthesized evaluation showed that transformer-aware charging can reduce peak transformer loading by 18.7%, reduce daily transformer loss-of-life by 31.4%, and maintain fleet readiness above 98.6%. These results indicate that meaningful grid-impact mitigation can be achieved without treating fleet operations and distribution constraints as separate planning problems.

The main operational insight is that flexibility must be identified continuously rather than assumed from static dwell times. A vehicle that is flexible at arrival may become urgent as departure approaches, while transformer headroom can change rapidly with depot base load, ambient temperature, and prior loading.

Future work should extend the framework to real-time pricing, vehicle-to-grid operation, multi-depot coordination, and field validation with measured transformer temperature data. Further research should also examine cyber-security, privacy-preserving telemetry exchange, and utility-depot coordination protocols for large-scale fleet electrification.

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