Published by :
https://www.ijert.org/
An International Peer-Reviewed Journal

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 10 , October - 2026

Debt-Corrected Voltage-Sensitivity Scheduling for Electric Vehicle Charging: The Trade-Off Between Energy Delivery and Location-Based Equity

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Abstract - Charging more vehicles without violating distribution-feeder limits is an important aim of coordinated electric vehicle (EV) charging. Yet a voltage-aware scheduler may favour customers connected to electrically stronger buses, leaving others with a smaller share of their requested energy. This paper examines that trade-off using debt-corrected sensitivity–urgency (DCSU) scheduling. The controller retains the voltage screening of a sensitivity-based online heuristic but raises the priority of vehicles at high-sensitivity buses when their group has received less charging service. Its correction uses only information available at the dispatch time. On a scaled IEEE 33-bus feeder with 40 synthetic test days and 260 charging requests per day, DCSU reduced the difference in energy-service fractions between low- and high-sensitivity groups from 11.89 to 6.44 percentage points. The improvement cost 1.07 percentage points of overall energy delivery: 91.45%, compared with 92.52% for the original scheduler. Neither controller crossed the modeled 0.950-p.u. voltage floor or the assumed 2.55-MW feeder limit in these tests. However, DCSU reduced the percentage of fully satisfied vehicles from 65.75% to 60.12%. The study therefore shows both the value and the cost of correcting a location-dependent bias in a simple online charging rule. All demand, arrival and photovoltaic profiles are synthetic; the findings should not be interpreted as field-validated operating performance.

Keywords - Coordinated EV charging; distribution voltage; sensitivity-based control; service equity; online scheduling; IEEE 33-bus feeder.

I. INTRODUCTION

The location of a charging station matters as much as the number of vehicles charging. An additional kilowatt at the end of a long distribution feeder can cause a larger voltage drop than the same demand close to the substation. Grid-aware schedulers therefore often give preference to requests that make less use of the available voltage headroom. This can improve total charging service, but it raises a question that aggregate energy figures do not answer: who receives that service?

Coordinated charging has been studied extensively for reducing feeder losses, controlling peak demand and keeping voltages within limits [5]–[12]. More recent work also considers customer costs, fairness and distributed control [14]–[20]. These advances show that a technically feasible schedule is not necessarily an equitable one. In particular, a controller that penalizes electrical distance can systematically defer requests at buses where voltage is more sensitive to load changes.

This study looks at that effect in a deliberately simple setting. Rather than introducing a new global optimizer, it adds a feedback correction to an existing online sensitivity–urgency rule. The correction tracks how much of the requested charging energy has reached two fixed groups of buses. If the electrically weaker group falls behind, its waiting vehicles receive a temporary priority boost. The feasibility checks remain unchanged.

The contribution is specific: an auditable location-service correction; a causal implementation that does not use future arrivals; a separate calibration set for the correction gain; and an evaluation of the price paid in total energy and individual completion. The method is assessed against several heuristic policies and a perfect-foresight linear benchmark. We do not claim that group fairness, debt feedback or voltage-aware scheduling is new in itself.

II. RELATED WORK

Early studies established how EV charging changes feeder loading and voltage, and how coordinated schedules can limit the resulting losses [5]–[9], [29]. Decentralized methods later demonstrated ways to spread decisions across large vehicle populations [10], [11]. Grid-constrained optimization has also been developed to respect voltage and network limits while accommodating charging deadlines [12], [28]. Reviews place these approaches in the wider context of distribution-system planning and operation [13], [21], [22], [27].

The tension between system-level outcomes and customer benefit is already recognized. Proportional-fair charging under voltage limits [14], customer-aware voltage management [15], and hierarchical network/customer coordination [16], [18] address related objectives. Stochastic multiobjective optimization [17], recent reinforcement-learning control [19], and decentralized charging coordination [20] extend the available techniques. Those methods differ in information requirements, objective functions and computational demands, so their published performance figures cannot be compared directly with results from the synthetic feeder used here.

The remaining question for this study is narrower: when a low-complexity online rule rewards electrically favourable locations, can feedback on actual delivered energy reduce the resulting subgroup imbalance without weakening the voltage constraint? The answer also requires reporting what is lost in aggregate throughput and in the number of drivers whose requests are fully met. We use the IEEE 33-bus system [1], [2] and radial branch-flow formulations [3], [4] to make this question reproducible.

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III. FEEDER MODEL AND TEST SCENARIOS

A. Network and charging assumptions

The simulated distribution network follows the standard 12.66-kV, 33-bus radial feeder with 32 branches [1]. Its published base demand of 3.715 MW and 2.300 Mvar is scaled by 0.60 and varied over an assumed two-peak daily load profile. Five buses have a total of 80 kW of synthetic photovoltaic generation. The modeled operating limits are a 0.950-p.u. voltage floor and a 2.55-MW ceiling on total feeder demand. These values define the test case; they are not ratings obtained from utility equipment.

For each simulated day, 260 EV requests are assigned to 25 possible buses. Time is divided into 48 half-hour slots. Arrival times follow a normal distribution centred at 08:36 with a standard deviation of 1.3 h. Dwell times are centred at 7.3 h (standard deviation 1.5 h) and limited to 3–11 h. Battery-energy requests follow a truncated Gamma distribution with shape 3.2 and scale 4.8 kWh, bounded to 5–40 kWh and adjusted to respect charger-feasible durations. Charging power is limited to 7.2 kW per vehicle with 92% assumed efficiency. These distributions were selected for an illustrative workplace-like setting; they were not estimated from measured charging records.

Setting	Value
Feeder	IEEE 33-bus; 12.66 kV
Time step	0.5 h; 48 slots/day
Vehicles	260 per day; 25 eligible buses
Charger limit	7.2 kW; efficiency 0.92
Grid limits	$V \geq 0.950$ p.u.; $P \leq 2.55$ MW
Dispatch reserve	0.002 p.u.
Calibration / test	8 days / 40 days

TABLE I. Simulation parameters; limits and demand profiles are assumptions.

B. Voltage screening and power-flow check

Feasibility is evaluated using a balanced, loss-inclusive radial branch-flow calculation [3]. The active- and reactive-power balances include downstream flows and line losses, while bus voltages are updated from branch resistance and reactance. Before allocating charging power, the controller estimates the voltage effect of an incremental load from the resistance shared by the paths to the source. If H(k,j) denotes that sensitivity at monitored bus k for a load at bus j, the location footprint of vehicle i is defined as $h_i = \max_k H(k,b_i)$, where b_i is its connection bus.

At every dispatch interval, new charging increments must satisfy both remaining feeder capacity and the sensitivity-based voltage limit, with a 0.002-p.u. scheduling reserve. After dispatch, the nonlinear radial power-flow calculation is repeated to evaluate bus voltages. This screening is an engineering approximation, not a proof of feasibility for an unbalanced three-phase network. Line ampacity, tap-changing equipment and phase asymmetry are outside the model.

IV. ONLINE CHARGING CONTROLLER

A. Sensitivity–urgency baseline

The baseline ranks connected vehicles using time remaining before departure, unmet energy and the location footprint. For a vehicle with deadline d_i, remaining energy $D_i - E_i(t)$, and charging efficiency η, laxity is the time left beyond the minimum time needed to finish charging:

$$L_i(t) = (d_i - t)\Delta t - [D_i - E_i(t)]/(\eta\, P_{max}).$$

With $\Delta t = 0.5$ h and $P_{max} = 7.2$ kW, the scheduling score is

$$U_i(t) = \{2/[0.6 + \max(L_i, 0)] + 0.8[1 - E_i(t)/D_i]\}/(1 + 25{,}000\, h_i).$$

A larger score gives a request earlier access to the available headroom. Power is assigned greedily in score order and is checked against both feeder and voltage limits. The numerical weights are fixed baseline settings taken from the preceding benchmark experiment; they are not optimized in this paper.

B. Correcting unequal location-based service

The 25 eligible charging buses are divided into high- and low-sensitivity groups using the median location footprint of the eligible buses. This threshold depends only on the feeder topology and is held fixed for all simulated days. The two groups are therefore defined before any vehicle arrives.

At time t, the service fraction Rg(t) is the total energy already delivered to vehicles in group g divided by their total requested energy, counting only vehicles that have arrived. Departed vehicles remain in this accounting, so unfinished requests do not disappear from the group balance. The observed shortfall of the high-sensitivity group is

$$\delta(t) = \min\{0.30, \max[0, R_{low}(t) - R_{high}(t)]\}.$$

Debt-corrected sensitivity–urgency (DCSU) scheduling multiplies the original score of a high-sensitivity vehicle by $\exp[\gamma\delta(t)]$, where γ controls the correction strength. Scores at low-sensitivity buses are unchanged. At $\gamma = 0$, the algorithm is identical to the baseline. Because the correction uses only arrived requests and energy already served, it does not require knowledge of future vehicles, charging demands or solar production. The physical feasibility screen is the same for both policies.

Each half-hour dispatch proceeds as follows. Newly arrived vehicles are added to the active set; the two group service fractions are updated; active vehicles are ranked by the corrected score; and power increments are allocated in order subject to the electrical limits. Delivered energy and bus voltages are then updated. This is a heuristic priority rule, not an optimization algorithm with a fairness or optimality guarantee.

C. Choice of the correction gain

The candidate gains $\gamma = \{0, 2, 4, 8, 12, 20\}$ are evaluated on eight development days (seeds 1704–1711). The selection rule chooses the smallest location-service gap among gains that reduce total delivery by no more than 2.5 percentage points relative to $\gamma = 0$ on this development set. It selects $\gamma = 4$. The selected gain, feeder threshold and scheduling weights are then kept fixed for the 40-day comparison (seeds 1904–1943). These 40 seeds were previously used to study the original heuristic; they are held out from the new gain-selection exercise, not from all earlier analysis.

V. SIMULATION RESULTS

A. Location-service gap and total delivery

Across the 40 test days, the original sensitivity–urgency policy delivered an average of 92.52% of requested charging energy. DCSU delivered 91.45%. The small reduction in aggregate service accompanied a larger reduction in the difference between the two electrical-location groups: from 11.89 to 6.44 percentage points. The paired mean difference in group disparity was 5.44 points, with a 95% bootstrap interval of 4.25–6.66 points. Under these simulated conditions, the correction therefore recovered part of the service lost at higher-sensitivity buses rather than simply increasing total energy delivery.

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 10 , October - 2026

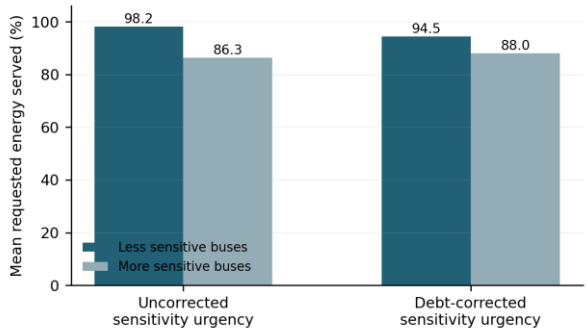

Fig. 1. Average charging service by electrical-sensitivity group for the baseline and DCSU policies (40 simulated days).

B. The cost in customer completion

Improved group balance did not mean that more drivers left fully charged. Under the original rule, 65.75% of requests were completed; with DCSU, the value declined to 60.12%. The mean fraction delivered to the least-served quarter of requests also decreased from 69.15% to 67.21%. Jain's fairness index [24] changed only slightly (0.9611 to 0.9604). These measures answer different questions: group-level energy shares can become more equal even while the number of individually satisfied customers falls. It would therefore be misleading to describe DCSU as uniformly fairer.

Policy	Energy (%)	Full EVs (%)	Group gap (pp)
Voltage-aware EDF	86.36	77.90	−0.20
Sensitivity–urgency	92.52	65.75	11.89
DCSU (γ = 4)	91.45	60.12	6.44
Offline LP	95.88	—	—

TABLE II. Means across 40 matched simulated days. The offline linear program has future information and a different electrical approximation.

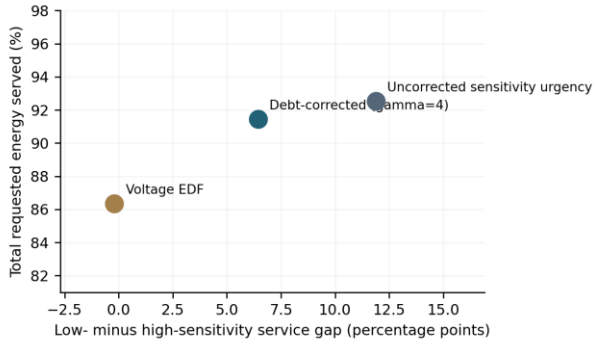

Fig. 2. Aggregate energy delivered and fixed-group location disparity in the synthetic test set.

C. Gain sweep and comparison with reference policies

On the eight calibration days, increasing γ reduced the mean location gap from 14.22 points at γ = 0 to 1.07 points at γ = 20. Over the same range, energy delivery declined from 91.49% to 87.61%. At the selected γ = 4, calibration-set delivery was 89.71% and the gap was 6.79 points. A stronger correction (γ = 8) lowered the gap further to 3.79 points but exceeded the predefined throughput-loss allowance. The observed trend is therefore a trade-off, not evidence of a universally best gain.

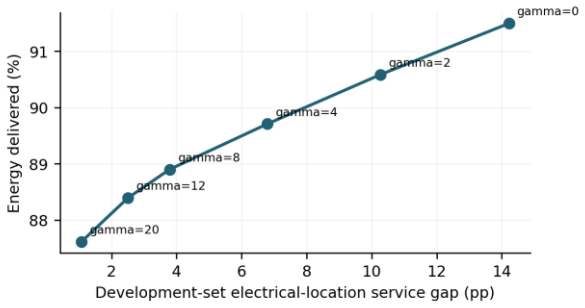

Fig. 3. Development-set sweep of the service-debt gain, using eight simulated days per setting.

The original six-policy comparison provides context. Voltage-aware earliest-deadline-first (EDF) delivered 86.36% of requested energy, compared with 92.52% for sensitivity–urgency. A clairvoyant full-horizon linear program, which knows all future sessions and uses linearized voltage constraints, delivered 95.88%. This is a useful reference for attainable performance under its own assumptions, but not a rigorous upper bound for the nonlinear network model. The near-zero location gap of voltage EDF should also be read alongside its different individual-completion outcome.

D. Electrical checks and guard-band sensitivity

Neither DCSU nor the original sensitivity heuristic violated the 0.950-p.u. floor or the 2.55-MW ceiling in the 40-day comparison. A separate 20-day safety-reserve experiment on the original heuristic showed how sensitive this result is to the assumed margin. At a 0.001-p.u. reserve, delivery increased to 98.47% but six intervals fell below the voltage threshold. Reserves of 0.002, 0.004 and 0.008 p.u. produced 92.89%, 72.77% and 33.84% delivery, respectively, with no threshold breaches in those subsets. These results are evidence about the test model, not a guarantee of safe grid operation.

An independently coded in-house current-injection check agreed with the branch-power calculation to within 2.28×10^{-4} p.u. at the tested points. That is a useful numerical consistency result, but it is not independent validation in OpenDSS, pandapower or a field network [25], [26].

VI. DISCUSSION AND LIMITATIONS

The main lesson is that a controller can be efficient at the feeder level while allocating that benefit unevenly across its buses. Penalizing voltage sensitivity is attractive because it preserves scarce voltage headroom. The same penalty, however, makes some connections consistently less competitive for charging service. DCSU partly compensates for this effect with one bounded, directly observable feedback term. It does so without changing the underlying electrical limits or asking for future trip information.

The correction is not costless. Assigning additional energy to electrically demanding locations reduces the energy available elsewhere and can leave more individual sessions incomplete. Moreover, the two groups capture a property of the network topology, not income, accessibility, disability or other measures of social equity. A lower group gap is therefore best described as greater electrical-location balance, not a general social-fairness result.

The study also has important limits. Requests, daily load and PV production are simulated rather than measured. The feeder is balanced and radially operated, with scaled baseline loading; line thermal limits, phase imbalance, control-device actions, communication failures, battery degradation and forecast uncertainty are absent. The 40 comparison seeds were not untouched across the full research history. No full head-to-head reimplementation of the recent fairness-

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International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 10 , October - 2026

constrained controllers in [14]–[20] was undertaken. A stronger test would use recorded sessions such as ACN-Data [23], a three-phase simulator, independently defined new test scenarios and optimization baselines that explicitly include individual and group service objectives. These are necessary steps before claiming deployment relevance or superiority over modern alternatives.

VII. CONCLUSION

On the scaled IEEE 33-bus test feeder, debt-corrected sensitivity–urgency scheduling narrowed the high/low-sensitivity service gap from 11.89 to 6.44 percentage points, at a cost of 1.07 points in total energy delivered. The voltage and feeder-capacity constraints were met in the 40 synthetic test days, but the share of fully completed charging requests declined. Taken together, the results support a limited and practical conclusion: online feedback can soften a location bias created by voltage-aware prioritization, but group balance, aggregate throughput and individual completion must be reported separately. Validation on real charging records and more detailed feeder models remains necessary.

DATA AND CODE AVAILABILITY

The source code, feeder data, seeded synthetic-session generator, controller implementations, numerical result tables and figure data are available from the corresponding author on request. No measured EV charging sessions were used in this study.

DECLARATION OF AI ASSISTANCE

ChatGPT (OpenAI) assisted with study framing, simulation-code development, numerical analysis, figure production, literature organization and manuscript drafting and editing. The author is responsible for verifying the code, results, references and scientific interpretation.

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