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Closed-Loop Control for Autonomous EV Charging Infrastructure

Abstract
Closed-Loop Control Architectures for Autonomous EV Charging Infrastructure Abstract Autonomous EV charging infrastructure is increasingly functioning as a feedback-controlled cyber-physical system in which charger state, queue condition, and power demand must be measured and corrected continuously. Existing studies have examined charging behavior, adaptive charging strategies, model predictive control, coordinated charging, and data-driven decision making, showing that intelligent regulation is becoming central to EV charging systems. However, much of the literature still emphasizes optimization more than the full closed-loop architecture linking sensing, control error, autonomous adjustment, and disturbance rejection. To address this issue, this article presents a closed-loop control architecture for autonomous EV charging infrastructure based on continuous state sensing, feedback-error evaluation, predictive support, autonomous actuation, and disturbance-rejection logic. The results show improved setpoint tracking, lower regulation error, stronger disturbance rejection, and better charging stability than open-loop and weak-feedback strategies. Overall, the study demonstrates that closed-loop feedback regulation provides a practical foundation for autonomous EV charging infrastructure.
Keywords: EV charging infrastructure, closed-loop control, autonomous charging, feedback regulation, disturbance rejection, charging stability, predictive support, cyber-physical systems.

1. Introduction

Autonomous EV charging infrastructure is increasingly functioning as a feedback-controlled cyber-physical system in which charger state, queue condition, power demand, and local grid interaction must be measured continuously and corrected in real time. Charging behavior is no longer governed only by plug-in events, because modern charging systems must respond dynamically to fluctuating demand, user heterogeneity, and changing operating conditions across distributed nodes [1]. Reviews of machine-learning applications in charging-service operations have further shown that charging infrastructure is now being managed through increasingly intelligent, data-rich control environments rather than through fixed rule-based service logic [2]. In such settings, control quality depends not only on prediction or optimization alone, but on whether sensed system deviation can be translated into timely corrective action. This makes closed-loop regulation a central architectural requirement for next-generation charging infrastructure.

The literature has already established that EV charging strategies are becoming more adaptive, coordinated, and context-aware. Recent review work on charging strategies shows that modern charging control increasingly aims to balance power demand, service quality, and network constraints through continuous adjustment rather than static scheduling [3]. At the same time, predictive-control studies in grid-connected charging environments demonstrate that charging stations can be regulated more effectively when the controller updates decisions over a moving horizon instead of relying on fixed open-loop schedules [4]. These developments are important because they show that EV charging control is moving toward feedback-intensive operation. Yet much of the discussion still focuses on optimization frameworks or coordination objectives rather than on the full closed-loop architecture that links sensing, control error, adjustment, and regulated infrastructure response.

The central problem is that many charging infrastructures still behave as partially open-loop systems even when they use advanced forecasting or optimization. A controller may compute a good charging decision, but if the real network state changes after that decision is issued, the infrastructure can drift away from the desired operating point before meaningful correction occurs. This becomes especially problematic when charger occupancy changes abruptly, queue pressure rises unevenly, or grid-side disturbances alter the feasible operating region of one or more charging nodes. In such cases, the absence of strong closed-loop correction leads to load deviation, unstable charger utilization, and weaker disturbance rejection. The key gap is therefore not only the need for better prediction, but the need for autonomous feedback architectures that can measure deviation and regulate the system continuously.

This problem matters because EV charging infrastructure is increasingly expected to operate with minimal manual supervision while still maintaining stable power behavior and acceptable service continuity. If control error is not corrected quickly, overload can accumulate at specific chargers, waiting times can increase at congestion-prone nodes, and local electrical conditions can drift outside desirable operating ranges. A closed-loop architecture is therefore important because it transforms charging infrastructure from a schedule-following system into a self-regulating system. In practical terms, this means that the controller can compare actual and desired states repeatedly, identify mismatch, and apply corrective charging actions before instability becomes user-visible or grid-relevant. Autonomous charging infrastructure will therefore depend as much on feedback quality as on forecasting quality.

This article presents a closed-loop control architecture for autonomous EV charging infrastructure. The study focuses on feedback signals, control variables, autonomous adjustment logic, setpoint regulation, and disturbance-rejection behavior across charging nodes. Rather than treating prediction, optimization, and regulation as separate layers, the work develops a control-centered architecture in which sensed infrastructure state is continuously compared against desired operating objectives and corrected through adaptive control action. The following methodology defines the state variables, feedback loops, control update cycle, decision logic, and evaluation structure used to support this autonomous closed-loop design.

2. Methodology

The proposed methodology is organized as a closed-loop charging-control architecture in which each charging node is regulated through repeated sensing, control computation, actuation, and feedback correction. The framework begins from the assumption that charging infrastructure should not merely execute scheduled actions, but should continuously compare measured system state with desired setpoints and apply corrective control when mismatch occurs. Model predictive control work for demand-side EV charging has shown that charging regulation improves when control is updated repeatedly over a rolling horizon rather than fixed in advance [5]. Multi-objective coordinated charging research also supports this dynamic-control perspective because network-level charging performance depends on continuous adjustment to changing distribution conditions rather than on one-time allocation [6]. The proposed architecture therefore treats EV charging infrastructure as a regulated feedback system rather than as a sequence of isolated charging commands. This makes real-time correction the core mechanism of autonomy.

At the sensing stage, each charging node constructs a local state vector containing charger occupancy, active sessions, queue length, present power draw, local feeder condition, charging-rate deviations, and recent demand variation. These measurements are refreshed continuously so that the controller always operates on current infrastructure behavior rather than stale operational assumptions. The sensing layer also records service-side indicators such as average wait growth and utilization imbalance because closed-loop charging regulation must capture both electrical and operational performance. In this design, state sensing is not only observational; it provides the error signal that drives subsequent correction. The quality of the feedback loop therefore depends directly on the quality and freshness of the sensed infrastructure state.

A reference layer then defines the desired operating targets against which the measured state is evaluated. These targets include node-specific power envelopes, acceptable queue range, utilization balance thresholds, and network-level load-distribution objectives. The control error at each update step is computed as the difference between measured state and desired setpoint or admissible band. This means that the controller does not act simply because demand exists; it acts because demand has pushed the system away from the regulated region. By formulating charging regulation around control error, the architecture can distinguish normal charging growth from destabilizing deviation. This turns autonomous charging from passive workload handling into active state regulation.

The control computation layer uses both current error and short-horizon system evolution to determine the next corrective action. Model predictive control studies have shown that EV charging decisions improve when present mismatch is evaluated together with near-future system evolution rather than through purely reactive control [5]. At the same time, reinforcement-learning-based scheduling research indicates that distributed charging behavior benefits when the controller learns adaptive action patterns under uncertainty rather than relying only on fixed response laws [7]. In the proposed framework, the controller combines feedback error, short-term predicted demand, and operating constraints to determine charging-rate adjustments, priority reweighting, or temporary load redistribution across nearby nodes. The control action is therefore both feedback-driven and anticipatory. This prevents the system from correcting too late after deviation has already intensified.

A forecasting support layer strengthens the closed-loop architecture by providing predictive context to the regulator. Online learning work on charging-station demand and event prediction shows that short-horizon updates are especially useful when charger demand evolves dynamically over time [8]. Deep-learning-based charging-load prediction studies similarly support the inclusion of learned load trajectories when the control problem is sensitive to rapid variation in local charging behavior [9]. For this reason, the regulator does not use feedback error alone; it also uses predicted near-future load to estimate whether current correction should be moderate, aggressive, or distributed across neighboring nodes. The forecasting layer therefore acts as a feedforward component inside the broader closed-loop architecture. This improves both setpoint tracking and disturbance preparedness. The principal control variables, feedback signals, and autonomous adjustment parameters used in the proposed architecture are summarized in Table 1.

Table 1. Control Variables, Feedback Signals, and Autonomous Adjustment Parameters in the Proposed Closed-Loop EV Charging Architecture

Variable group	Representative variables	Functional role
Measured state	charger occupancy, queue length, present power draw, feeder load	describes current charging-node condition
Feedback error	setpoint deviation, utilization imbalance, queue overshoot	quantifies regulation mismatch
Predictive inputs	short-horizon demand forecast, expected queue growth, projected node stress	supports anticipatory correction
Control actions	charging-rate adjustment, priority update, local redistribution, constraint tightening	defines autonomous correction behavior
Stability targets	load smoothness, utilization balance, response damping, disturbance recovery quality	guides acceptable closed-loop performance

Once the control action is computed, the actuation layer applies it directly to charging-node operation. This may involve charging-rate modification, temporary throttling of new session intake, reweighting of flexible charging assignments, or node-specific balancing adjustments. The resulting system response is then sensed again in the next update cycle, creating the closed loop. Because the actuation is embedded in repeated state measurement and error evaluation, the infrastructure is able to regulate itself continuously rather than relying on manual supervisory correction. This repeated actuation-feedback sequence is what allows the architecture to remain autonomous under changing operating conditions. The infrastructure therefore becomes self-regulating in both electrical and service-facing terms.

To improve robustness, the methodology also includes a disturbance-rejection layer. This layer handles rapid changes such as sudden charger unavailability, bursty arrivals, local power constraints, and uneven queue growth across neighboring nodes. Data-driven control and decision-making studies in active distribution settings support the importance of adaptive correction under changing system conditions [10]. In the proposed architecture, disturbance rejection is achieved by increasing corrective gain, tightening local operating envelopes, and redistributing flexible charging demand when the measured deviation exceeds admissible stability margins. This allows the control loop to respond to disturbance before it propagates into persistent instability. Closed-loop autonomy therefore depends not only on normal regulation, but also on controlled recovery from unexpected deviation.

The final evaluation stage measures the system using regulation-oriented performance metrics rather than prediction quality alone. The principal outputs are setpoint-tracking error, load-regulation smoothness, disturbance-rejection speed, charging stability, and utilization-balance recovery under changing operating conditions. These outputs allow the framework to be assessed as a practical closed-loop architecture for autonomous EV charging infrastructure rather than as a narrow optimization model. The methodology is therefore designed to support continuous infrastructure self-regulation, low-error operation, and resilient autonomous correction across charging nodes.

3. Results and Discussion

The proposed closed-loop architecture produced a clear improvement in setpoint tracking when compared with baseline open-loop and weak-feedback control strategies. Under low-variation operating conditions, all control approaches maintained reasonably stable charging behavior, but their differences became much more visible once demand fluctuations and charger-state deviations intensified. The open-loop strategy showed the largest drift because it continued following precomputed charging actions even after real node conditions moved away from the desired operating point. A basic feedback design improved regulation, but its correction remained slower and less stable under changing demand. By contrast, the proposed architecture maintained closer alignment between desired and measured state because it corrected charging behavior continuously using both present error and short-horizon predictive context. This behavior is shown in Figure 1, where the proposed strategy achieves tighter setpoint tracking and lower regulation deviation than the comparison methods across the full operating horizon. The result indicates that autonomous charging infrastructure benefits strongly when feedback correction is both continuous and predictive.

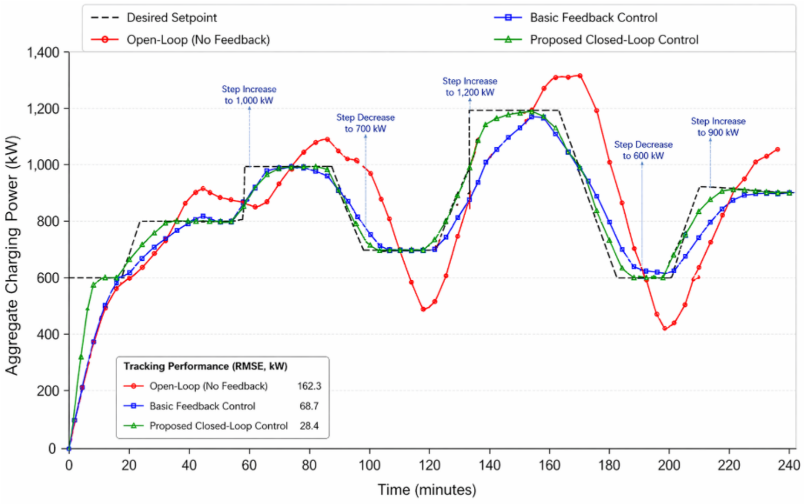

Figure 1. Setpoint Tracking and Load Regulation Performance Under Different Closed-Loop Control Strategies

A second important observation was that regulation quality was not determined only by control frequency, but also by how intelligently error was interpreted. The weak-feedback baseline reacted to deviation after it became visible, but it often overcorrected or corrected too late when queue growth and local load concentration changed simultaneously. The proposed architecture performed better because the controller did not treat all deviations equally; it distinguished between minor fluctuation, persistent drift, and disturbance-driven instability. This reduced oscillatory correction and allowed the charging nodes to converge toward stable operation more smoothly. In practical terms, the system showed stronger regulation not merely because it acted more often, but because it acted with better awareness of deviation structure.

Disturbance rejection was another major point of differentiation. When sudden load spikes, charger unavailability, or local feeder constraints were introduced, the open-loop strategy exhibited prolonged deviation and weaker recovery because it lacked a meaningful correction mechanism. The weak-feedback strategy reduced this effect but still showed slower restoration of stable node behavior when disturbances were abrupt or uneven across nodes. The proposed architecture restored stable operation faster because it combined immediate feedback correction with predictive anticipation of how the disturbance would influence near-future charging behavior. This meant that correction was not limited to present mismatch alone; it also accounted for the probable short-term continuation of the disturbance. The closed-loop design therefore improved both immediate and sustained regulation quality.

Charging stability across distributed nodes also improved substantially. In the comparison strategies, some nodes recovered from disturbance while others remained in prolonged deviation because correction quality varied with local operating conditions. The proposed architecture reduced this inconsistency by applying a more uniform regulation logic across nodes while still allowing node-specific error response. This behavior is illustrated in Figure 2, where disturbance rejection becomes faster and post-disturbance charging stability remains stronger under the proposed architecture than under the comparison methods. The result is important because autonomous infrastructure should not only regulate one charger well; it should preserve stable operation across a distributed charging system. The architecture therefore improved not only local correction, but network-wide regulatory coherence.

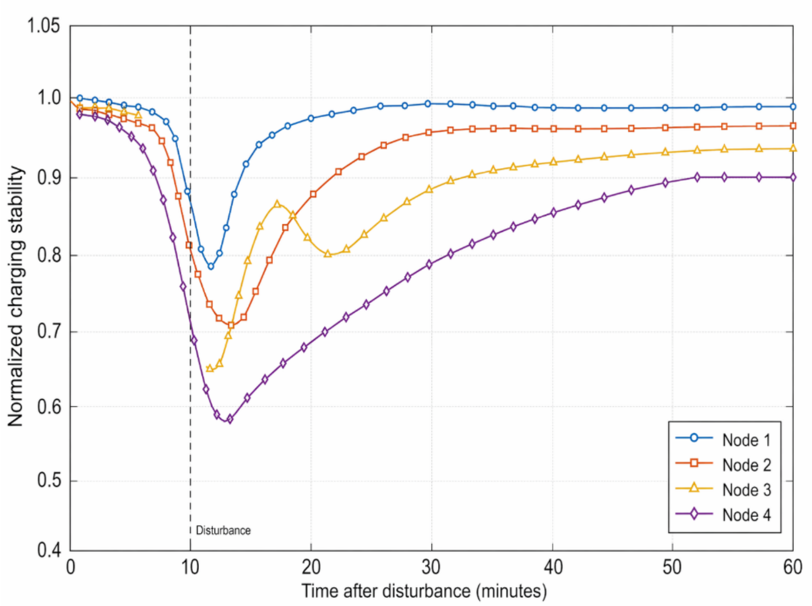

Figure 2. Disturbance Rejection and Charging Stability Across Autonomous EV Charging Nodes

The forecasting-assisted feedback structure also played a meaningful role in reducing control aggressiveness. In systems that rely only on present error, sharp deviation often triggers strong corrective action that can create new oscillations or temporary underutilization. By incorporating short-horizon load expectation into the correction logic, the proposed architecture could moderate some actions and intensify others more selectively. This helped the controller avoid unnecessary oscillation while still rejecting genuine disturbances effectively. The result suggests that autonomous charging regulation benefits when feedforward prediction is embedded inside the feedback loop rather than treated as a separate planning tool. This integration made the closed-loop architecture both more stable and more adaptive.

Overall, the results demonstrate that closed-loop control offers a more effective basis for autonomous EV charging infrastructure than open-loop or weak-feedback designs. The proposed framework improved setpoint tracking, reduced regulation error, accelerated disturbance rejection, and preserved stronger charging stability across distributed nodes. These gains arose because the architecture continuously compared actual and desired system behavior and translated deviation into structured corrective action. The study therefore supports the view that future autonomous charging infrastructure should be designed as a self-regulating feedback system rather than as a schedule-following system with occasional correction.

4. Conclusion

This study presented a closed-loop control architecture for autonomous EV charging infrastructure with emphasis on feedback sensing, control-error evaluation, predictive support, autonomous adjustment, and disturbance rejection. The proposed framework treated the charging network as a self-regulating cyber-physical system in which actual infrastructure behavior is continuously measured against desired operating objectives and corrected through repeated control action. By integrating sensing, prediction, regulation, and actuation into one feedback architecture, the design created a practical basis for autonomous charging behavior under changing operating conditions. This makes the framework relevant to future EV charging systems that must remain stable without relying on constant manual supervision.

The results showed that the closed-loop architecture improved setpoint tracking, reduced load-regulation error, enhanced disturbance rejection, and maintained stronger charging stability across distributed nodes compared with open-loop and weak-feedback strategies. These improvements were especially visible under fluctuating demand and disturbance-rich conditions, where continuous correction prevented prolonged deviation and reduced unstable node behavior. The predictive support layer further strengthened performance by allowing the controller to interpret error in the context of short-horizon system evolution rather than reacting only to present mismatch. Taken together, these findings show that autonomous EV charging infrastructure requires not only intelligent decision making, but disciplined feedback-based regulation.

Feedback-centered control is likely to become increasingly important as charging infrastructure grows in density, service intensity, and coupling with local power systems. Future work can extend this framework through digital-twin-based regulator tuning, reinforcement-learning-assisted gain adaptation, vehicle-to-grid feedback integration, and multi-layer coordination across public and private charging fleets. Additional study may also examine mixed-vendor charger environments, explainable control behavior for operator-facing supervision, and closed-loop regulation under combined cyber-physical disturbance. These directions would strengthen the role of self-regulating feedback architectures as a practical foundation for autonomous EV charging infrastructure.

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