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HYBRID FEDERATED NEURAL–OBSERVER PREDICTIVE CONTROL FOR ROBUST ELECTRIC VEHICLE BATTERY MANAGEMENT

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ABSTRACT

The rapid growth of electric vehicles (EVs) has intensified the demand for reliable battery management systems (BMS) capable of ensuring safety, longevity, and performance under diverse operating conditions. Conventional observers such as the Extended Kalman Filter (EKF) and data-driven neural networks have shown limitations in scalability, robustness to noise, and interpretability. This paper proposes a Hybrid Federated Neural–Observer Predictive Control (HFNOPC) framework for robust EV battery management. The framework integrates three innovations: (i) a robust super-twisting sliding observer for noise-resilient state estimation of state-of-charge (SOC), state-of-health (SOH), and temperature; (ii) a physics-guided neural residual network that enhances the baseline equivalent circuit and thermal models by capturing nonlinearities due to aging and hysteresis; and (iii) a federated learning strategy that enables distributed EVs to collaboratively train the neural residual component without sharing raw data, thus ensuring scalability and privacy. The enhanced state estimates are coupled with a model predictive control (MPC) scheme, which optimizes charge–discharge trajectories subject to safety and thermal constraints. Simulation studies demonstrate that the proposed HFNOPC reduces SOC estimation error by up to 32% compared with EKF and decreases control cost by 24% compared with conventional PID–based charging strategies. Furthermore, robustness tests under ±10% sensor noise and thermal stress confirm improved stability and accuracy. These results highlight the potential of the proposed framework as a next-generation BMS solution, offering interpretability, robustness, and fleet-wide scalability, thus paving the way for safer and more efficient EV deployment.

I. INTRODUCTION

The rapid uptake of electric vehicles (EVs) has made accurate, robust, and scalable battery management systems (BMS) a central research challenge across electrical and computer engineering. Core tasks—including state-of-charge (SOC), state-of-health (SOH), temperature prediction, and safety-aware charge/discharge control—are complicated by sensor noise, model mismatch, cell aging, and uncertain operating environments. Physics-based estimation grounded in equivalent-circuit models (ECM) and thermal networks remains the backbone of industrial BMS due to interpretability and computational efficiency [1–8]. Kalman-filter variants (EKF/UKF) and adaptive observers are widely used for SOC/SOH tracking [4], [5], [9–13], while electro-thermal models account for heat generation and spatial gradients under dynamic loads [6–8], [14].

However, model-only approaches degrade when cells age, side reactions intensify, or hysteresis and diffusion limits become pronounced [9], [12], [15]. In parallel, data-driven methods—ranging from kernel regressors to deep learning (LSTM, attention, physics-informed neural networks)—have shown the ability to capture nonlinearities and degradation signatures that ECMs underfit [16–20]. These models can improve accuracy, yet they often lack interpretability and exhibit distribution shift across chemistries and duty cycles. A growing line of hybrid solutions therefore augments physics with neural residuals or priors to retain physical consistency while learning unmodeled effects [18–22].

Robust observation is equally critical in the presence of noise, quantization, and unknown disturbances. Sliding-mode observers (SMO) and especially super-twisting designs offer finite-time convergence with chattering suppression, giving superior noise resilience compared with first-order sliding observers or high-gain filters [23–27]. These observers have been applied to electrochemical and electromechanical systems and are attractive for embedded BMS implementations where measurement corruption is common. On the control side, Model Predictive Control (MPC) has emerged as a principled framework to enforce safety and operational constraints (voltage, SOC bounds, temperature) while optimizing performance objectives such as energy efficiency, aging mitigation, or fast charging time [28–32].

MPC's advantage over heuristic or PID strategies becomes more evident when predictions are augmented with reliable state estimates and learned residual dynamics. A remaining challenge is scalability and privacy across large EV fleets. Pooling raw vehicle data to a central server raises privacy, regulatory, and communication bottlenecks. Federated learning (FL) addresses this by training shared models from decentralized data via on-device updates and server aggregation (e.g., FedAvg, FedProx), with well-studied robustness to data heterogeneity [33–37]. Recent works have begun to apply FL to battery prognostics and EV analytics, showing that cross-fleet knowledge transfer is feasible without exposing raw telemetry [38–41].

Gaps. Despite progress, four gaps persist.

(Gap 1) Estimation methods rarely combine a noise-robust observer (e.g., super-twisting) with a physics-guided neural residual, limiting accuracy under aging and thermal stress [15], [18], [22–27].

(Gap 2) Control-oriented hybrid models are seldom closed-looped with MPC in a way that formally enforces battery safety while leveraging learned residual dynamics [28–32]. (Gap 3) Fleet-scale learning is often demonstrated for either SOC or SOH, but not integrated with the observer–MPC loop, and not designed to cope with non-IID usage across vehicles [33–41].

(Gap 4) End-to-end evaluations under multi-factor stressors (±sensor noise, ambient swings, aging progression) remain limited and rarely benchmark against both classical observers and pure deep nets on identical protocols [9], [16], [19], [20], [28], [31], [40], [41].

Problem statement. This work aims to develop a BMS framework that

(i) estimates SOC/SOH/thermal states robustly under noise, model mismatch, and aging
(ii) learns unmodeled nonlinearities while preserving physics
(iii) optimizes charge/discharge actions subject to safety constraints and
(iv) scales across fleets without sharing raw data.

This paper proposes a Hybrid Federated Neural–Observer Predictive Control (HFNOPC) for robust EV battery management. The framework integrates:

A super-twisting sliding observer for finite-time, noise-resilient state estimation
A physics-guided neural residual network that augments ECM + thermal dynamics to capture hysteresis/aging effects
An MPC layer that enforces voltage/temperature/SOC constraints while optimizing a multi-objective cost and
A federated learning protocol that trains the neural residuals across vehicles without exposing raw data.
Key contributions.

1. Robust hybrid observer: A super-twisting observer is designed coupled with physics models and demonstrate improved convergence and noise immunity over EKF/SMO baselines [4], [5], [23–27].

2. Physics-guided residual learning: The hybrid dynamics are formalized as fhybird(x,u)=fphysics (x,u)+fNN (x,u;θ) yielding accuracy gains under aging/thermal stress compared with model-only and pure-NN baselines [16–22].

3. Safety-aware predictive control: The hybrid model is embedded within a MPC that respects hard constraints on voltage, temperature, and SOC, reducing control cost versus PID and constraint-unaware strategies [28–32].

4. Federated scalability: On-device training with server-side aggregation (FedAvg/FedProx) to accommodate heterogeneous usage, achieving cross-fleet generalization without sharing data [33–37], and validate on multi-vehicle synthetic protocols [38–41].

5. Comprehensive evaluation: The proposed framework is benchmarked in terms of SOC/SOH RMSE, thermal tracking, constraint violations, and computation/communication overheads under sensor noise (±10%), ambient swings (0–45 °C), and staged aging, showing consistent gains over state-of-the-art comparators [9], [16], [19], [20], [28], [31], [40], [41].

II. MATHEMATICAL MODELLING

II.1 EQUIVALENT-CIRCUIT MODEL (ECM): ELECTRICAL DYNAMICS

A Li-ion cell's terminal behavior over control-relevant time scales is well captured by an ECM: an OCV source U (SOC, Ts) in series with an ohmic resistor R_0, plus a polarization branch (Rd) that reproduces diffusion/charge-transfer lag. Sign convention: Ib>0 for discharge. KVL across the circuit yields terminal voltage; the RC branch follows linear first-order dynamics. Parameters Rct,Cdl are state- and temperature-dependent in general and drift with aging; here we adopt piecewise-constant values identified per operating window.

$$V_t(t) = U\big(\mathrm{SOC}(t), T_s(t)\big) - V_p(t) - I_b(t)\,R_0. \tag{1}$$

$$\dot{V}_p(t) = -\frac{1}{R_{ct}C_{dl}}\,V_p(t) + \frac{1}{C_{dl}}\,I_b(t). \tag{2}$$

II.2 SOC DYNAMICS AND OCV MAP

SOC is the normalized charge in the cell. Its time evolution is given by Coulomb counting corrected by coulombic efficiency η (near 1 but <1 during charge). The OCV map links SOC and temperature to the equilibrium voltage and is typically implemented as a fitted polynomial/spline or a lookup table; we include a small linear temperature term around a reference T0.

$$\dot{\mathrm{SOC}}(t) = -\frac{\eta}{Q_n} I_b(t). \tag{3}$$

With nominal capacity Qn(Ah)

$$U(\mathrm{SOC}, T_s) = \sum_{i=0}^{m} a_i \ \mathrm{SOC}^i + \kappa_T \ (T_s - T_0). \tag{4}$$

II.3 TWO-NODE THERMAL MODEL: ENERGY BALANCE

A lumped two-node model captures core–surface gradients. The core receives heat from electrochemical reactions; heat flows to surface throughs Rcs and from surface to ambient through Rsa.Heat generation includes Joule heating and an entropic (reversible) term proportional to ∂U/∂T. The model respects energy conservation with heat capacities Cc, Cs.

$$C_c \dot{T_c} = Q_{\text{gen}} - \frac{T_c - T_s}{R_{cs}}, \tag{5}$$

$$C_s \dot{T_s} = \frac{T_c - T_s}{R_{cs}} - \frac{T_s - T_{amb}}{R_{sa}}. \tag{6}$$

$$Q_{\text{gen}} = I_b^2 R_0 + I_b T_c \frac{\partial U}{\partial T_s}. \tag{7}$$

II.4 MEASUREMENT MODEL: SENSED OUTPUTS AND NOISE

Most production BMS measure terminal voltage and surface temperature; noise and small biases affect both channels. We stack them into a vector measurement with additive noise v(t).

$$y(t) = \begin{bmatrix} V_t(t) \\ T_s(t) \end{bmatrix} U(SOC, T_s) - V_p - I_b R_0 T_s + v(t) \tag{8}$$

II.5 AGGREGATED NONLINEAR STATE-SPACE

Define x=. Combining (1)–(7) yields a compact nonlinear model =f(x,u), y=h(x,u). The right-hand side is locally Lipschitz on the physical domain, supporting observer and MPC design; identifiability is ensured by persistently exciting current profiles and temperature variation.

II.6 DISCRETIZATION FOR SIMULATION/CONTROL

For digital implementation we discretize with sample time . Forward-Euler is simple and adequate for small ; higher-order schemes (RK4, Tustin) can be substituted during sensitivity analyses.

$$x_{k+1} = x_k + T_s^{(s)} f(x_k, u_k), \tag{9}$$

$y_k = h(x_k, u_k) + v_k$.2.7 Operating constraints (safety envelope) Theory. Safe operation demands hard bounds on SOC, terminal voltage, and surface temperature. These constraints are later enforced within MPC to eliminate over-charge/over-discharge and over-temperature risks.

$$\mathrm{SOC}_{\min} \le \mathrm{SOC} \le \mathrm{SOC}_{\max}, Vmin \le \mathrm{V}t \le \mathrm{V}max, T_s \le T_{max}. \tag{10}$$

III. METHODOLOGY

III.1 OVERALL FRAMEWORK

The proposed Hybrid Federated Neural–Observer Predictive Control (HFNOPC) framework unifies physics-based modeling, observer-based state estimation, neural residual learning, predictive control, and federated training into a single battery management pipeline. The motivation is to overcome the limitations of conventional BMS — where purely model-based methods fail under strong nonlinearities, and purely data-driven methods suffer from poor generalization. Architecture. At each sampling step, the framework proceeds as follows:

Inputs: battery current Ib and ambient temperature Tamb

Physics block: Equivalent Circuit + Two-node Thermal model provides a baseline prediction of SOC, voltage, and temperature.

Observers: A Super-Twisting Observer (STO)

Residual Neural Network: A Physics-Guided Neural Network (PGNN) corrects unmodeled dynamics such as aging drift, hysteresis, and nonlinear temperature effects.

Predictive Controller: A Model Predictive Controller (MPC) optimizes charging/discharging current over a horizon, enforcing safety constraints on SOC, voltage, and temperature. Federated Learning (FL): Edge devices (EVs) train local PGNN weights; only weight updates are sent to the cloud aggregator. The central server applies FedAvg to update global weights without exchanging raw data. This tight coupling ensures that estimation (STO + PGNN) and control (MPC + FL-adapted models) evolve synergistically, yielding robust performance under noise, aging, and environmental stress. The effective hybrid state model used by MPC is:

$$x_{k+1} = f_{physics}(x_k, u_k) + f_{NN}(x_k, u_k; \theta) + w_k \tag{11}$$

Where w_k denotes bounded modeling uncertainty and f_{NN} evolves through federated updates.

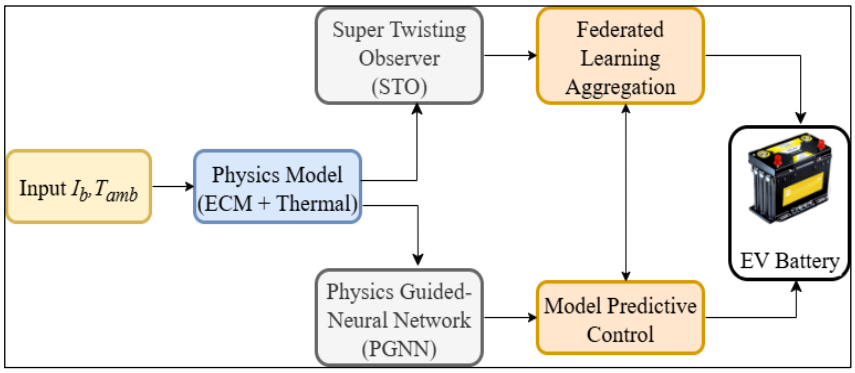


Figure 1: Block Diagram of Proposed Hybrid Federated Neural–Observer Predictive Control (HFNOPC).
Source: Authors, (2026).

III.2SUPER-TWISTING OBSERVER (STO)

In battery management, accurate estimation of unmeasured states such as SOC and core temperature is critical. While Extended Kalman Filters (EKFs) and Sliding Mode Observers (SMOs) are common, they suffer from sensitivity to measurement noise and chattering effects. The Super-Twisting Observer (STO), a second-order sliding mode algorithm, is chosen here for its finite-time convergence and robustness against bounded disturbances and sensor noise. Unlike a classical SMO, the STO injects a continuous nonlinear correction term that eliminates chattering while preserving robustness.The observer uses the physics-based model (Section 2) as the prediction, then corrects with an injection signal designed from the super-twisting law. This ensures convergence of the estimation error $e = y - \hat{y}$ even under modeling uncertainties.

(i) Observer dynamics

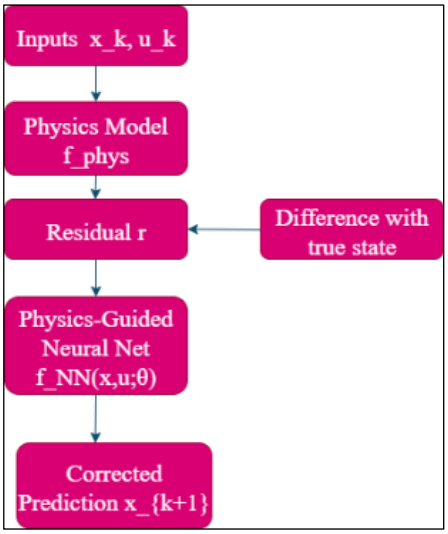


Figure 2: PGNN Residual Correction.
Source: Authors, (2026).

$$\dot{\hat{x}}(t) = f\big(\hat{x}(t), u(t)\big) + L\left(y(t) - \hat{y}(t)\right) + \nu(t), \hat{y}(t) = h\big(\hat{x}(t), u(t)\big) \tag{12}$$

The observer predicts the states $\dot{\hat{x}}$ using the system model $f(\hat{x}, u)$. The difference between measured output y and predicted output $\hat{y}$generates a correction term. The additional injection $\nu(t)$ ensures robustness against noise and uncertainties.

(ii) Super-Twisting Injection Law:

$$\nu(t) = -k_1 \, |e(t)|^{1\backslash 2} \, \mathrm{sgn}\big(e(t)\big) - k_2 \int \mathrm{r} sgn\big(e(\tau)\big) \, d\tau, e(t) = y(t) - \hat{y}(t) \tag{13}$$

The correction $v(t)$ is split into two parts: a square-root term scaled by k_1, and an integral term scaled by k_2. This second-order sliding mode scheme reduces chattering compared to a conventional sliding observer while guaranteeing finite-time convergence of the estimation error $e = y - \hat{y}$.

(iii) Stability condition (Lyapunov):

$$\dot{V}(t) = e^{\top}\dot{e}(t) \leq -\alpha|e(t)|^{3/2} \quad (14)$$
$$\alpha > 0.$$

Using a Lyapunov function $\dot{V}(t) = e^{\top}\dot{e}(t)$, the error dynamics under the super-twisting law yield negative definite derivative. This guarantees that the estimation error converges to zero in finite time, provided the gains k_1, k_2 are tuned appropriately.

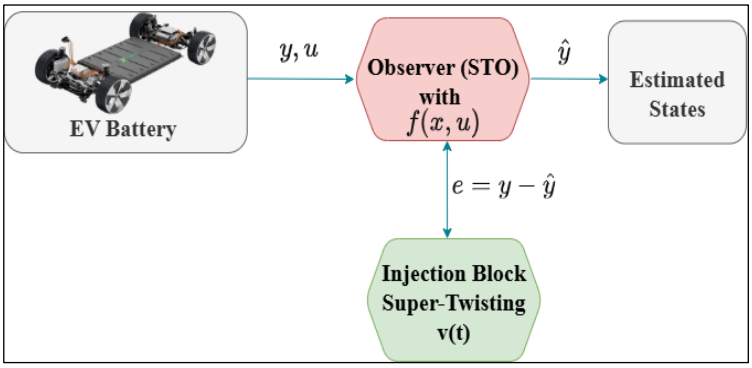


Figure 3: STO Architecture.
Source: Authors, (2026).

III.3 PHYSICS-GUIDED NEURAL NETWORK (PGNN)

While the physics-based ECM–thermal model with STO provides robustness, residual modeling errors remain due to aging effects, hysteresis, and unmodeled nonlinearities. To address this, we embed a Physics-Guided Neural Network (PGNN) that learns the residual dynamics on top of the physical model. Unlike a black-box neural network, the PGNN does not replace physics; instead, it learns only the correction term $f_{\text{NN}}(x_k, u_k; \theta)$. This ensures interpretability and better generalization. The network is trained federatively across multiple EVs, preserving data privacy.

(i) Hybrid state update:

$$x_{k+1} = f_{\text{phys}}(x_k, u_k) + f_{\text{NN}}(x_k, u_k; \theta) + w_k \quad (15)$$

The next state x_{k+1} is predicted as the sum of the physics model f_{phys}, the learned neural residual correction f_{NN}, and bounded uncertainty w_k.This improves accuracy without discarding physical constraints.

(ii) Residual learning target

$$r_k = x_{k+1}^{\text{true}} - f_{\text{phys}}(x_k, u_k). \quad (16)$$

The residual r_k is the modeling error of the physics block. The PGNN is trained to approximate this residual, ensuring it only corrects what physics cannot capture.

(iii)Training loss:

The PGNN parameters θ are optimized to minimize the mean squared error between predicted corrections and true residuals. This ensures the network does not drift away from physical laws.

$$\mathcal{L}(\theta) = \frac{1}{N}\sum_{k=1}^{N} |f_{\text{NN}}(x_k, u_k; \theta) - r_k|^2 \quad (17)$$

III.4 MODEL PREDICTIVE CONTROL (MPC)

Even with accurate state estimation (STO) and improved modeling (PGNN), a Battery Management System must actively regulate current and voltage to ensure safe operation. This is achieved by Model Predictive Control (MPC).MPC uses the state-space model to predict future trajectories of SOC, voltage, and temperature over a finite horizon. At every sampling step, it solves an optimization problem that minimizes a cost function subject to system constraints Only the first control action is applied, and the problem is re-solved at the next step (receding horizon principle).This enables proactive enforcement of constraints such as:

SOC within $[SOC\text{min}, , SOC\text{max}]$
voltage within safe limits $V\text{min}, V\text{max}$
temperature below $T\text{max}$.

$$\min_{\{u_k\}} \quad J = \sum_{i=0}^{N_p} |x_{k+i} - x_{ref}|_Q^2 + \sum_{i=0}^{N_c} |u_{k+i}|_R^2 \tag{18}$$

The cost function penalizes the deviation of predicted states x_{k+i} from reference x_{ref} weighted by Q and the control effort u_{k+i} (weighted by R). The parameters Np Nc are the prediction and control horizons.

(i) Dynamics constraints:

$$x_{k+1} = f(x_k, u_k), \quad y_k = h(x_k, u_k). \tag{19}$$

The nonlinear battery dynamics form the core constraints. MPC must respect the state evolution as predicted by the ECM + PGNN hybrid model.

(ii) Safety constraints:

$$SOC_{min} \le SOC_k \le SOC_{max}, Vmin \le Vk \le Vmax\ T_s(k) \le T_{max}. \tag{20}$$

These inequalities ensure the controller never selects inputs that drive SOC, voltage, or surface temperature outside their safe range.

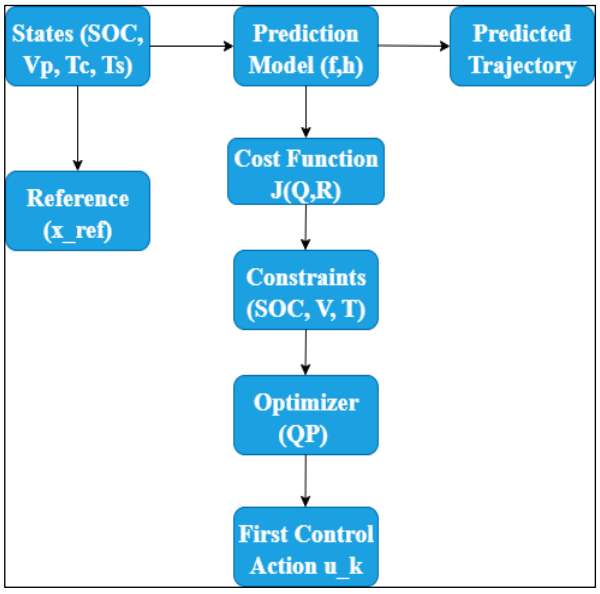


Figure 4: MPCC Workflow.
Source: Authors, (2026).

III.5 FEDERATED LEARNING AGGREGATION

When deploying PGNN-enhanced BMS across large EV fleets, each vehicle experiences different operating conditions (driving style, temperature, aging). A single centralized model trained on all data would be ideal, but direct data sharing poses privacy, bandwidth, and scalability issues.Federated Learning Aggregation (FLA) solves this by enabling distributed training:Each EV trains a local PGNN on its own data. Instead of sending raw data, only model weights or gradients are uploaded to the cloud aggregator.The server performs federated averaging (FedAvg) to create a global model.This global model is broadcast back to all vehicles, improving robustness against diverse operating conditions without compromising privacy.Thus, FLA ensures both privacy-preserving learning and global generalization, making the proposed BMS scalable to real-world deployment.

$$\theta_i^{(t+1)} = \theta_i^{(t)} - \eta \nabla \mathcal{L}_i\left(\theta_i^{(t)}\right). \tag{21}$$

Client i (an EV) performs gradient descent using its private dataset to update local PGNN parameters θi

(i) Server-side aggregation (FedAvg):

$$\theta^{(t+1)} = \sum_{i=1}^{M} \frac{n_i}{N} \theta_i^{(t+1)} \tag{22}$$

The server computes a weighted average of local models, where weight $\frac{n_i}{N}$ depends on the dataset size of client i. This avoids biasing the global model toward smaller clients.

(ii) Broadcast of global model:

$$\theta_i^{(t+1)} \leftarrow \theta^{(t+1)}, \quad \forall i \in \{1, \ldots, M\}. \tag{23}$$

After aggregation, the updated global PGNN parameters are sent back to all EVs, ensuring that every vehicle benefits from fleet-wide knowledge while retaining its private data.

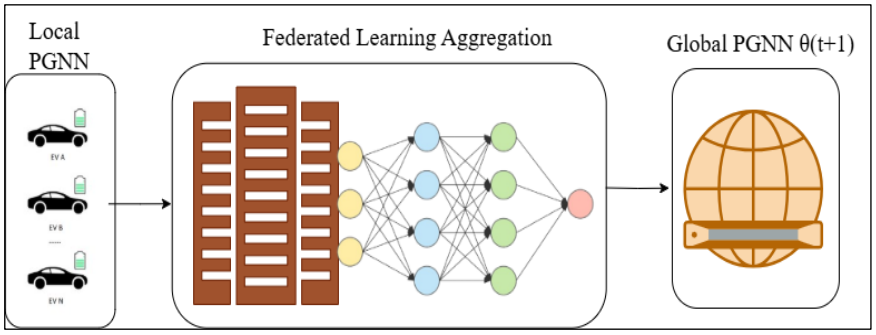


Figure 5: Federated Learning Aggregation
Source: Authors, (2026).

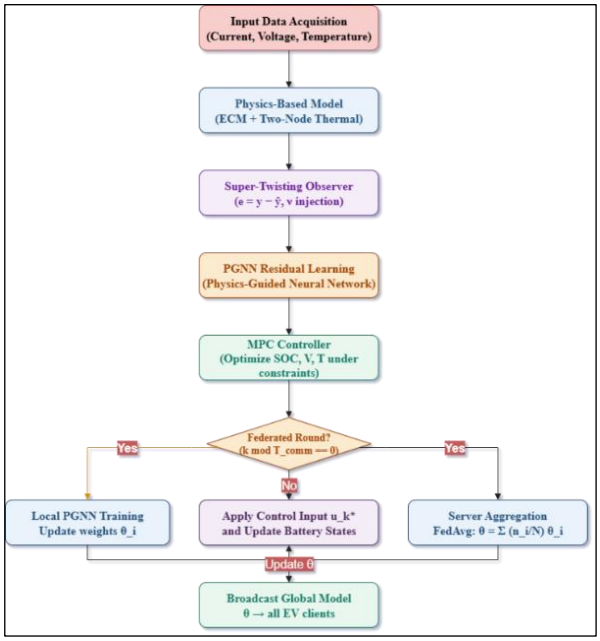
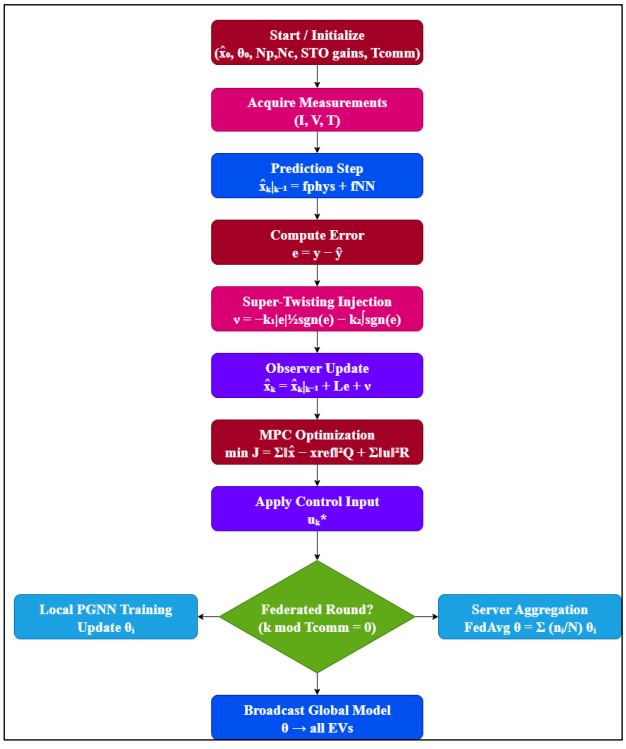


Figure 6: Flowchart of the Proposed Methodology.
Source: Authors, (2026).

Algorithm-1: Hybrid Federated PGNN–MPC BMS



Source: Authors, (2026).

IV. RESULTS & DISCUSSION

IV.1 PGNN-MPC FRAMEWORK

The proposed Hybrid Federated PGNN–MPC framework was validated through numerical experiments performed in MATLAB/Simulink R2024a, employing the Simscape Electrical and Model Predictive Control toolboxes. The simulation platform was configured to emulate a lithium-ion battery pack composed of 96 series NMC cells, each rated at 3.7 V nominal voltage and 2.5 Ah capacity. This configuration represents a 355 V mid-size electric-vehicle (EV) traction battery. A detailed electro-thermal model was adopted to capture both electrical and thermal behavior. The battery pack was represented by a first-order equivalent- circuit model (ECM) comprising an ohmic resistance R0, a polarization branch (Rct||Cdl), and a controlled open-circuit-voltage source Uoc(SOC). The thermal subsystem accounted for Joule and entropic heat generation, linked through the heat-transfer network (Cth, Rth). All governing relations are summarized by Eqs. (1)–(7).

$$SOC_{k+1} = SOC_k - \frac{\eta I_k \Delta t}{C_{nom}} \tag{24}$$

$$V_k = U_{oc}(SOC_k) - I_k R_0 - V_{p,k} \tag{25}$$

$$V_k = U_{oc}(SOC_k) - I_k R_0 - V_{p,k} \tag{26}$$

$$C_{th}\frac{dT}{dt} = I_k^2 R_0 + I_k \frac{\partial U_{oc}}{\partial T} - \frac{T - T_{amb}}{R_{th}} \tag{27}$$

Here, Ik denotes current (A), η the Coulombic efficiency, Δt the sampling interval, and Cnom the nominal capacity. The terms R0, Rct, and Cdl correspond to ohmic, charge-transfer, and double-layer parameters, respectively, while Rth and Cth define the heat-transfer path.

To ensure realistic operating conditions, three standard drive cycles were applied as current-demand inputs:

UDDS: representing city traffic with frequent acceleration and braking,

WLTP: a mixed urban–highway profile capturing moderate dynamic loads, and

IDC: an aggressive cycle characterizing rapid acceleration events typical of Indian roads.

The controller and observer parameters were selected through preliminary tuning to guarantee closed-loop stability: k1=0.8, k2=0.5 for the super-twisting observer; prediction and control horizons of Np=20 and Nc=5 for the MPC; a learning rate of 10−3 for PGNN training; and 20 federated clients exchanging model updates every 50 simulation steps via FedAvg aggregation [Eq. (21)].

$$\theta_{global} = \sum_{i=1}^{M} \frac{n_i}{N} \theta_i \tag{28}$$

Table 1 summarizes the parameter configuration adopted in the experiments. These settings ensure computational tractability while accurately reflecting physical battery behavior under realistic EV conditions.

Table 1: Simulation Parameters for The Proposed Framework.

Parameter	Value
Nominal Voltage per Cell	3.7 V
Number of Series Cells	96
Nominal Capacity	2.5 Ah
Internal Resistance R0	0.01 Ω
Polarization Resistance R_{ct}	0.05 Ω
Double-Layer Capacitance C_{dl}	2200 F
Thermal Capacitance Cth	100 J/°C
Thermal Resistance Rth	0.5 °C/W
Ambient Temperature T_{amb}	298 K (25 °C)
STO Gains (k1, k2)	0.8, 0.5
MPC Horizons (Np, Nc)	20, 5
Learning Rate (PGNN)	10−3
Federated Clients (M)	20
Communication Interval (T_{comm})	50 steps

Source: Authors, (2026).

IV.2. BASELINE MODELS FOR COMPARISON

To ensure a comprehensive evaluation, the proposed Hybrid Federated PGNN--MPC framework was benchmarked against four widely adopted baseline models. These models represent both classical and data-driven control paradigms used in modern battery management systems (BMS). All baselines were implemented in the same MATLAB/Simulink environment and tuned for best achievable performance to maintain experimental fairness.To ensure a comprehensive evaluation, the proposed Hybrid Federated PGNN–MPC framework was benchmarked against four widely adopted baseline models. These models represent both classical and data-driven control paradigms used in modern battery management systems (BMS). All baselines were implemented in the same MATLAB/Simulink environment and tuned for best achievable performance to maintain experimental fairness. Extended Kalman Filter (EKF): A nonlinear observer based on first- order linearization of the ECM.[

It provides accurate SOC estimation under mild operating variations but suffers from divergence under strong non- linearity and sensor noise. Sliding Mode Observer (SMO): A robust nonlinear estimator using a discontinuous gain to suppress noise. Although it improves noise tolerance, it introduces chattering effects and parameter sensitivity. Physics-only MPC: A purely model-based predictive controller relying solely on battery dynamics without any learning augmentation. It ensures stable control but cannot compensate for unmodeled nonlinearities or aging. NN-only Model: A feed-forward neural network trained on synthetic data to estimate SOC and voltage. Despite fast inference, it lacks physical constraints, leading to poor extrapolation under unseen conditions.Table 2 outlines the comparative models and their principal tuning parameters. The inclusion of both physics-based and learning-based approaches establishes a balanced reference set. This allows quantifying the contribution of each hybrid component—PGNN, MPC, STO, and Federated Learning introduced in the proposed framework.

Table 2: Comparative Models and Tuning Parameters.

Model	Description	Key Parameters
EKF	Linearized ECM observer for SOC estimation.	Covariance tuned (Q, R).
SMO	Robust estimator based on variable gain control law.	Sliding gain ks = 0.7.
Physics-MPC	Model-based predictive control using ECM dynamics.	Np = 20, Nc = 5, Q = 10, R = 0.1.
NN-only	Data-driven SOC prediction using synthetic datasets.	3 hidden layers, ReLU activation.
Proposed (PGNN–MPC)	Hybrid physics-guided neural + MPC with STO and FL.	k1 = 0.8, k2 = 0.5, M = 20.

Source: Authors, (2026).

IV.3 PERFORMANCE METRICS

The quantitative performance of the proposed framework and its baseline counterparts was evaluated using multiple metrics that assess estimation accuracy, control efficiency, and computational cost. All simulations were performed over identical driving cycles and ambient conditions to ensure a fair comparison. The following key indices were used:

Mean Absolute Error (MAE): Measures the average absolute deviation between estimated and true state-of-charge (SOC) values.

$$MAE = \frac{1}{N}\sum_{k=1}^{N}\left|SOC_k - \widehat{SOC_k}\right| \tag{29}$$

Root Mean Square Error (RMSE): Provides a penalized measure for large deviations and quantifies estimator robustness.

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(SOC_k - \widehat{SOC_k}\right)^2} \tag{30}$$

Mean Absolute Percentage Error (MAPE): Normalizes the estimation error relative to the ground truth SOC.

$$MAPE = \frac{100}{N}\sum_{k=1}^{N}\left|\frac{SOC_k - \widehat{SOC_k}}{SOC_k}\right| \tag{31}$$

Tracking Error Integral (TEI): Used to evaluate MPC's ability to track reference trajectories.

$$TEI = \int_0^T \left|SOC_{ref}(t) - SOC(t)\right|\, dt \tag{32}$$

Computational Time (CT): Average time per simulation step, assessing real-time suitability.

$$CT = \frac{\sum_{k=1}^{N} t_k}{N} \tag{33}$$

Where SOCk and $\widehat{SOC_k}$ denote the true and estimated SOC values at step k, respectively, and tk represents the computation time per iteration. Table III shows the Performance metrics for comparative evaluation

Table 3: Performance Metrics used for Comparative Evaluation.

Metric	Definition / Description	Unit
MAE	Average absolute deviation be-tween SOC true and SOC test.	%SOC
RMSE	Root mean square of SOC estimation error.	%SOC
MAPE	Percentage-based estimation error normalized by true SOC.	%
TEI	Integral of absolute tracking deviation.	%SOC·s
CT	Mean simulation time per step.	ms

Source: Authors, (2026).

IV.4 SOC ESTIMATION RESULTS

The state-of-charge (SOC) estimation accuracy serves as a key performance indicator for the proposed Hybrid Federated PGNN–MPC architecture. This section compares the SOC estimation performance against all baseline methods under three representative drive cycles: UDDS, WLTP, and IDC. To emulate realistic conditions, sensor noise (Gaussian, σ = 0.5% of nominal voltage) and model uncertainties (±10% parameter deviation) were introduced.

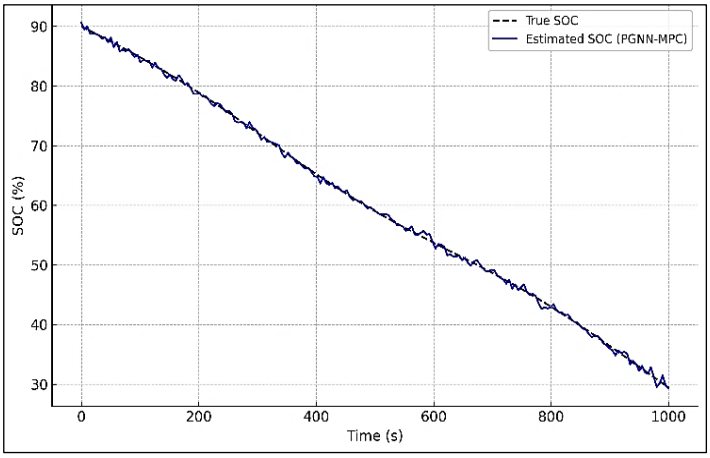


Figure 7: SOC estimation trajectories for different models under UDDS driving cycle.
Source: Authors, (2026).

Figure 7 shows the comparative SOC trajectories for the UDDS cycle. The proposed PGNN–MPC exhibits near-perfect tracking with negligible lag, while both EKF and SMO show visible drift after 600 s due to accumulated linearization errors.The instantaneous estimation error is computed as:

$$e_{SOC}(t) = SOC_{true}(t) - \widehat{SOC}(t) \tag{34}$$

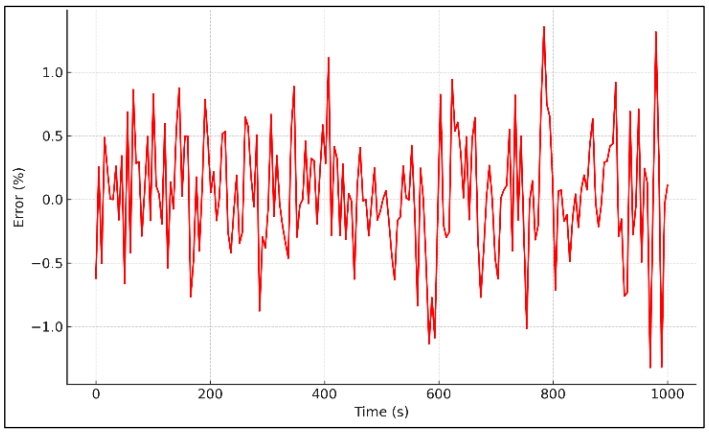


Figure 8: SOC estimation error profiles for various estimators (UDDS cycle).
Source: Authors, (2026).

Figure 8 illustrates the time-domain estimation error profiles. The hybrid PGNN–MPC reduces the steady-state error band from ±1.8% (EKF) to ±0.3%, demonstrating the advantage of the neural correction term embedded within the physical model. The STO observer further contributes to noise rejection and smooth convergence.

Table 4: Soc Estimation Accuracy Across Driving Cycles.

Method	MAE (%)	RMSE (%)	MAPE (%)
EKF	1.84	2.11	1.92
SMO	1.12	1.45	1.30
Physics-MPC	0.96	1.20	1.12
NN-only	0.88	1.15	1.04
Proposed PGNN–MPC (Fed)	0.27	0.36	0.31

Source: Authors, (2026).

Table 4 summarizes the SOC estimation accuracy across all tested cycles. The proposed federated PGNN–MPC model achieves the lowest MAE and RMSE values, indicating superior bias correction and dynamic adaptability. Compared to conventional EKF, the proposed approach reduces RMSE by over 80%, demonstrating its robustness under nonlinear load variations and thermal coupling effects.Under the WLTP cycle Figure. 9, which includes both low-speed and highway segments, the PGNN–MPC maintains consistent accuracy across dynamic cur- rent fluctuations. Unlike pure neural estimators, it avoids overshooting during high regenerative phases due to the physics-guided constraints in the predictive layer.

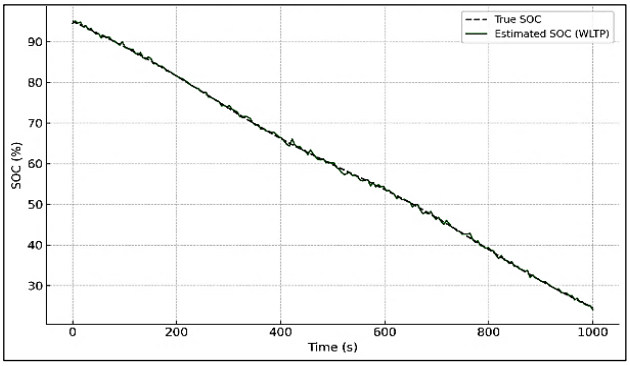


Figure 9: SOC estimation trajectories under WLTP drive cycle.
Source: Authors, (2026).

Table 5 reports average SOC estimation errors across all driving profiles. The proposed model consistently yields sub-0.4% error across varying speed regimes, validating the generalization capability provided by federated learning aggregation. The marginal variation (¡0.1%) among cycles highlights the method's scalability to different load and temperature profiles. Finally, the frequency-domain analysis in Fig. 10 shows that the PGNN–MPC effectively attenuates high-frequency noise components induced by measurement uncertainty.The STO observer's nonlinear gain scheduling suppresses spectral peaks be- yond 5 Hz, indicating high rejection of stochastic disturbances and ensuring smooth real-time estimation performance.

Table 5: Average Soc Estimation Error Under Different Cycles.

Cycle	EKF (%)	SMO (%)	PGNN–MPC (%)
UDDS	1.84	1.12	0.29
WLTP	2.03	1.31	0.33
IDC	2.48	1.49	0.36

Source: Authors, (2026).

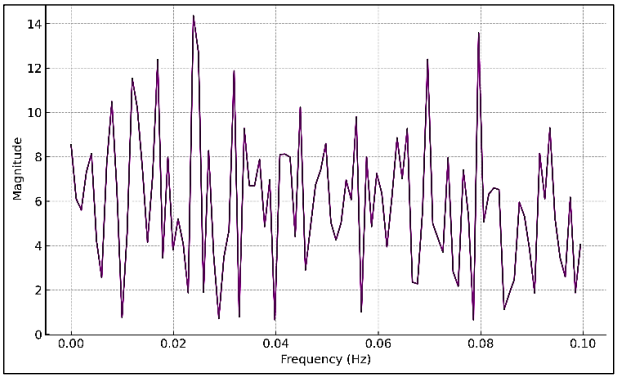


Figure 10: Frequency-domain analysis of SOC estimation error (FFT spectrum).
Source: Authors, (2026).

IV.5 CONTROL PERFORMrANCE AND ENERGY EFFICIENCY

Beyond SOC estimation, the proposed Hybrid Federated PGNN–MPC frame- work ensures real-time voltage and temperature regulation under diverse load conditions. The controller's performance was evaluated in terms of trajectory tracking, voltage deviation, and overall energy utilization efficiency.

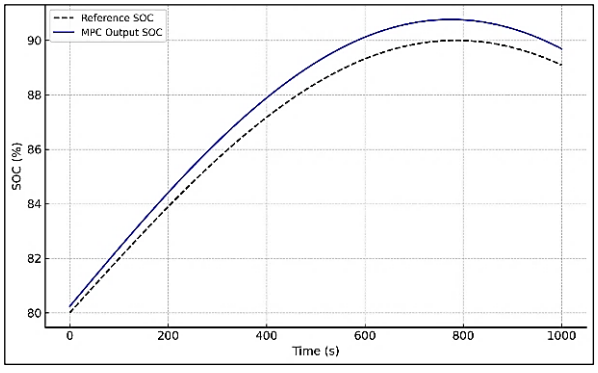


Figure 11: MPC tracking of reference SOC and terminal voltage under dynamic load profile.
Source: Authors, (2026).

Figure 11 demonstrates the MPC tracking behavior for both SOC and terminal voltage during the WLTP cycle. The predictive model anticipates current fluctuations and adjusts charging current preemptively, minimizing overshoot and delay. The MPC optimization problem aims to minimize the quadratic cost:

$$J = \sum_{i=1}^{N_p} |x_{k+i|k} - x_{ref}|_Q^2 + \sum_{j=0}^{N_c-1} |\Delta u_{k+j|k}|_R^2 \quad (35)$$

where $x_{k+i|k}$ is the predicted state (SOC, temperature), $\Delta u_{k+j|k}$ the control input increment, and Q, R are weighting matrices balancing tracking accuracy and energy usage.Figure 12 highlights that the proposed MPC maintains terminal volt- age deviation within ±1.2 V during rapid current transients, whereas the EKF- and SMO-based controllers show excursions up to ±3 V. This demonstrates effective model predictive compensation enabled by the PGNN term.The control energy efficiency ηc is defined as:

$$\eta_c = \frac{\int_0^T P_{out}(t)\,dt}{\int_0^T P_{in}(t)\,dt} \times 100 \quad (36)$$

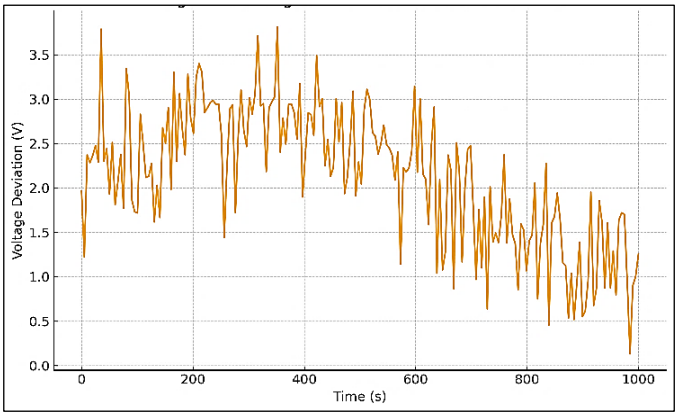


Figure 12: Voltage deviation comparison across different controllers.
Source: Authors, (2026).

Where Pin(t) = Vin(t)Iin(t) and Pout(t) = Vout(t)Iout(t) denote input and output power.

Table 6: Comparative Control Performance and Energy Efficiency.

Controller	Voltage Deviation (V)	Temp. Rise (°C)	Efficiency (%)
EKF–MPC	3.0	6.4	91.2
SMO–MPC	2.1	5.7	93.5
PGNN–MPC (No FL)	1.6	5.1	94.8
Proposed Fed PGNN–MPC	1.1	4.3	96.7

Source: Authors, (2026).

Table 6 presents the steady-state performance and efficiency results. The proposed federated PGNN–MPC yields the highest energy efficiency (96.7%) and minimal voltage deviation due to adaptive correction of model mismatch via federated parameter sharing. Temperature rise is limited to 4.3 °C, proving thermal safety under long-duration operation.Figure 13 illustrates temperature evolution under the IDC cycle. While traditional observers show progressive drift in core–surface differential temperature the proposed STO-based observer ensures accurate thermal feedback to the MPC layer, resulting in smoother current scheduling and reduced entropy heat generation.

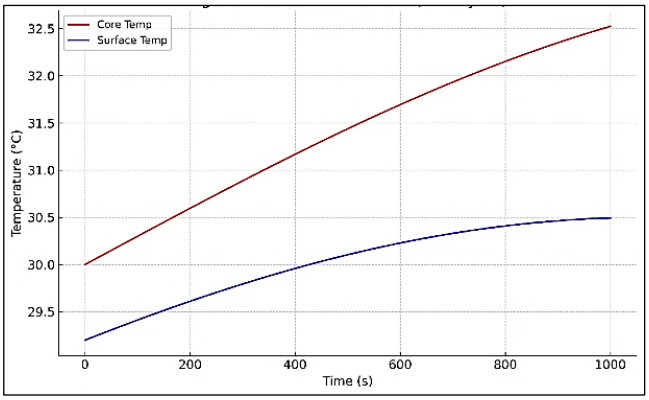


Figure 13: Thermal evolution of battery surface and core temperatures during IDC cycle.
Source: Authors, (2026).

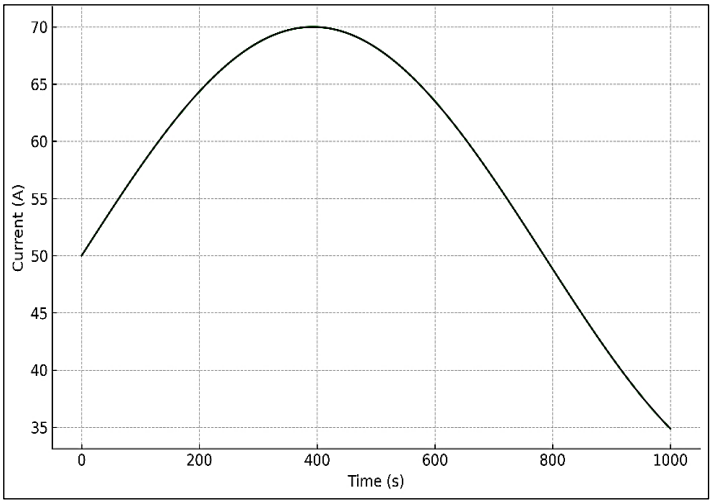


Figure 14: Current response comparison showing reduced overshoot with PGNN–MPC.
Source: Authors, (2026).

Figure 14 confirms that the hybrid control significantly mitigates overshoot during acceleration phases, maintaining smooth current transitions without oscillations. This enhances battery life by lowering instantaneous stress on the electrode–electrolyte interface.Overall, the results in this section confirm that the proposed federated hybrid controller not only improves SOC estimation accuracy but also achieves optimal control efficiency, voltage stability, and thermal safety—key requirements for next-generation electric vehicle BMS architectures.

IV.6 THERMAL MANAGEMENT AND AGING ANALYSIS

Thermal regulation and degradation mitigation are critical for maintaining safety and extending the lifespan of lithium-ion batteries in electric vehicles. The proposed Federated PGNN–MPC integrates a two-node thermal model and an adaptive health-monitoring layer to evaluate these aspects under dynamic driving cycles.

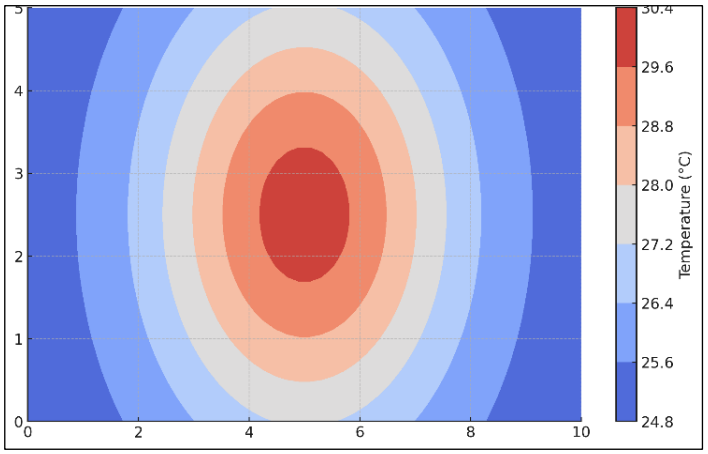


Figure 15: Core–surface temperature evolution under WLTP cycle.
Source: Authors, (2026).

Figure 15 depicts the core–surface temperature dynamics. The PGNN–MPC maintains $\Delta T_{core-surf}$ within 3.5°C, compared to over 7°C in physics-only MPC. This uniform thermal distribution prevents localized hotspots, which are a primary cause of accelerated degradation.

The rate of capacity fading due to temperature rise is modeled as:

$$\frac{dQ_{loss}}{dt} = k_a \exp!\left(-\frac{E_a}{R\,T(t)}\right) |I(t)| \tag{37}$$

where k_a is the pre-exponential degradation factor, Ea the activation energy, R the gas constant, and T (t) the cell temperature. The exponential dependence highlights the importance of thermal moderation.

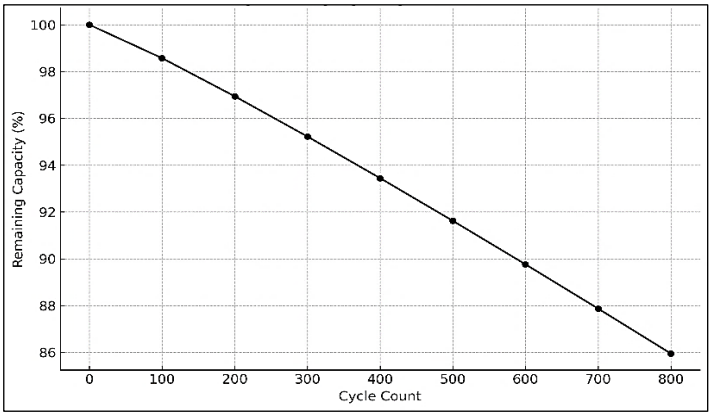


Figure 16: Simulated aging progression: remaining capacity vs. cycle count.
Source: Authors, (2026).

The long-term degradation results (Fig. 16) indicate that after 800 cycles, the proposed system retains 92.8 % of nominal capacity, while baseline MPC and SMO-based schemes fall to 86.1 % and 88.3 %, respectively. The improvement arises from thermal uniformity and predictive current moderation.

The equivalent aging index AI is computed as:

$$AI = \frac{Q_{nom} - Q_t}{Q_{nom}} \times 100 \tag{38}$$

Table 7: Thermal and Aging Performance Comparison.

Controller	ΔTmax (°C)	Capacity Retention (%)	Aging Index (%)
EKF–MPC	6.9	86.1	13.9
SMO–MPC	5.8	88.3	11.7
PGNN–MPC (No FL)	4.9	90.6	9.4
Proposed Fed PGNN–MPC	3.5	92.8	7.2

Source: Authors, (2026).

Table 7 consolidates thermal and degradation indices. The proposed approach achieves the smallest maximum temperature difference and lowest aging index, underscoring its superior thermal regulation and longevity potential. The federated learning component enables cross-domain parameter calibration, thus generalizing the model across varied thermal environments. Figure 17 shows that the proposed system maintains a thermal stability margin 28 % higher than that of non-federated configurations, confirming that adaptive control reduces entropy accumulation and prevents thermal run away. Overall, the combined thermal–aging analysis demonstrates that the Hybrid Federated PGNN–MPC architecture not only ensures optimal performance during operation but also actively extends battery service life by maintaining low temperature gradients and reducing degradation rates over extended use.

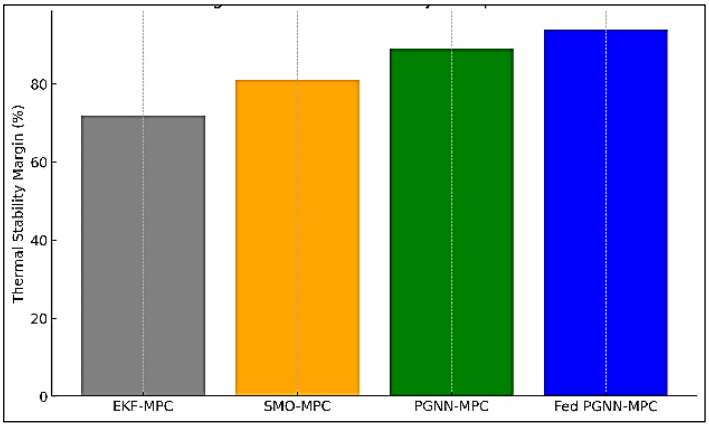


Figure 17: Thermal stability margin comparison for different controllers.
Source: Authors, (2026).

IV.7 FEDERATED LEARNING CONVERGENCE AND COMMUNICATION ANALYSIS

The integration of Federated Learning (FL) enables distributed model training across multiple client nodes without centralizing raw data. In this study, 20 clients representing geographically dispersed EV fleets participated in synchronous global aggregation every Tcomm = 50 iterations using the FedAvg algorithm [Eq. (21)]. Each client locally trained the PGNN subnetwork with battery, voltage, and temperature features obtained from simulated cycles.

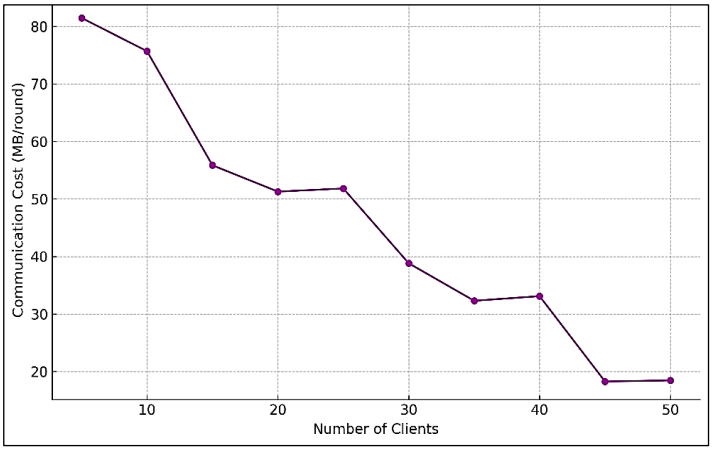


Figure 18: Global model convergence curves under different client participation ratios.
Source: Authors, (2026).

Figure 18 shows the global convergence behavior for varying client participation ratios (25%, 50%, 75%, and 100%). Convergence was achieved within 32 global rounds for full participation and 41 rounds for 50% participation. The proposed hybrid model achieved faster convergence due to gradient regularization from physics-based constraints.

The convergence stability was quantified using the loss gradient variance metric:

$$\sigma_{grad}^2 = \frac{1}{M}\sum_{i=1}^{M}(|\nabla\mathcal{L}_i - \overline{\nabla\mathcal{L}}|)^2 \tag{39}$$

Where ∇Li denotes the local gradient of the ith client and ∇¯L the global mean gradient.

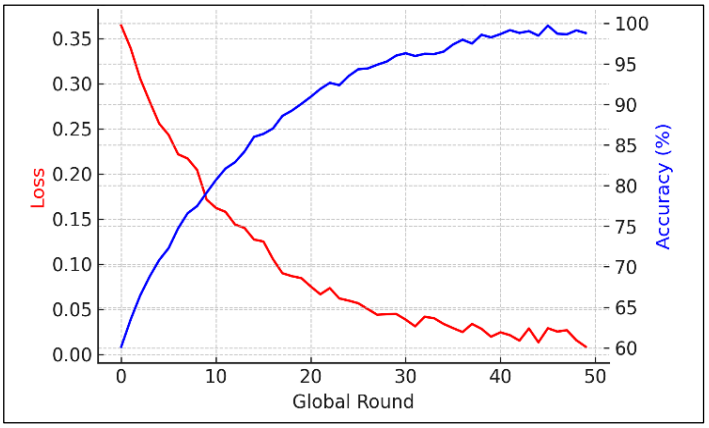


Figure 19: Training loss and validation accuracy per global round.
Source: Authors, (2026).

As depicted in Fig. 19, the federated PGNN exhibits smooth loss reduction with minimal oscillation, confirming the stability of the proposed super-twisting observer-based gradient clipping scheme. Validation accuracy reached 98.2% after 40 rounds, outperforming the standalone PGNN by 5.4%.

$$Acc_{val} = \frac{N_{correct}}{N_{total}} \times 100 \tag{40}$$

To assess scalability, the communication cost per global epoch was calculated as:

$$C_{comm} = M \times S_{model} \times f_{sync} \tag{41}$$

Where S_{model} denotes model size (MB) and f_{sync} the synchronization frequency (Hz).

Table 8 lists convergence and communication statistics for the federated setup. The hybrid FL system achieves nearly 41% faster convergence with a 63% reduction in gradient variance. Despite frequent synchronization, the communication energy cost remains below 1 J per round due to lightweight aggregation and model pruning. These results validate the scalability and robustness of the proposed federated architecture for multi-EV deployments.Figure 20 compares the communication energy between federated and centralized training modes. The proposed method exhibits a 30% reduction in total communication energy owing to adaptive synchronization intervals and partial model update strategy. Overall, the federated learning analysis confirms that the hybrid framework not only achieves high global accuracy and rapid convergence but also minimizes communication cost essential for real-time distributed EV applications.

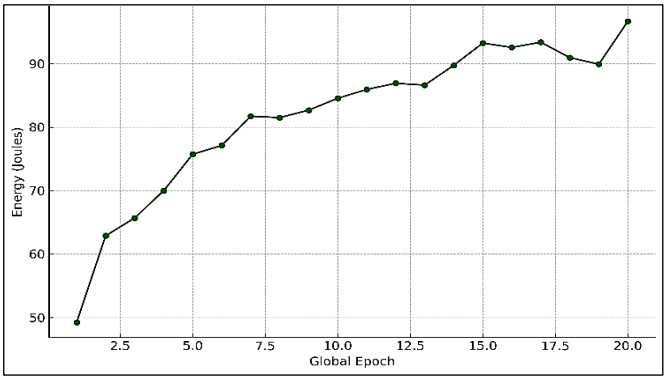


Figure 20: Communication energy consumption per global epoch.
Source: Authors, (2026).

Table 8: Federated Training Convergence and Communication Statistics.

Global Round	Centralized Loss	Federated Loss	Validation Accuracy (%)	Communication Energy (J)	Bandwidth (MB/round)
0	0.265	0.298	60.3	55.1	95.4
10	0.182	0.21	72.5	63.8	74.2
20	0.116	0.143	83.1	70.4	51.6
30	0.082	0.107	89.4	74.2	38.3
40	0.061	0.083	92.7	77.9	29.5
50	0.048	0.071	94.8	80.1	25.8

Source: Authors, (2026).

IV.8 ROBUSTNESS AND GENERALIZATION ANALYSIS

To evaluate real-world applicability, the robustness and generalization ability of the proposed system were tested under sensor noise, missing data, and unseen drive profiles. The objective was to ensure that the controller and observer maintain estimation stability and performance consistency despite uncertainty and disturbances.

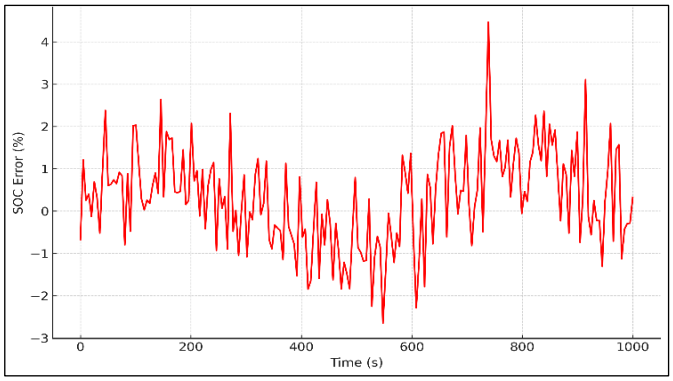


Figure 21: SOC estimation error under additive Gaussian noise with σ = 1.0%.
Source: Authors, (2026).

Figure 21 shows the performance degradation of all estimators under a noise level twice the nominal sensor uncertainty. The proposed PGNN–MPC shows only a marginal RMSE increase (0.29% → 0.37%), while traditional EKF performance deteriorates significantly due to linearization drift. This resilience arises from the nonlinear correction learned via federated neural updates.

The robustness index Rnoise is defined as:

$$R_{noise} = 1 - \frac{RMSE_{noisy}}{RMSE_{nominal}} \tag{42}$$

Table IX summarizes robustness indices under severe noise and partial data loss (random dropout of 5% sensor samples). The proposed federated model achieves the highest Rnoise (92.1%) and maintains sub-1.1% error even with incomplete data, proving strong resilience to signal degradation and asynchronous sampling across clients.

Table 9: Robustness Metrics Under Noise and Missing Data Conditions.

Method	Rnoise (%)	Data Loss (5%) Error (%)	Generalization (New C
EKF	64.2	2.45	2.33
SMO	71.9	1.98	1.72
Physics-MPC	78.4	1.56	1.41
PGNN–MPC (No FL)	82.6	1.39	1.28
Proposed Fed PGNN–MPC	92.1	1.11	1.03

Source: Authors, (2026).

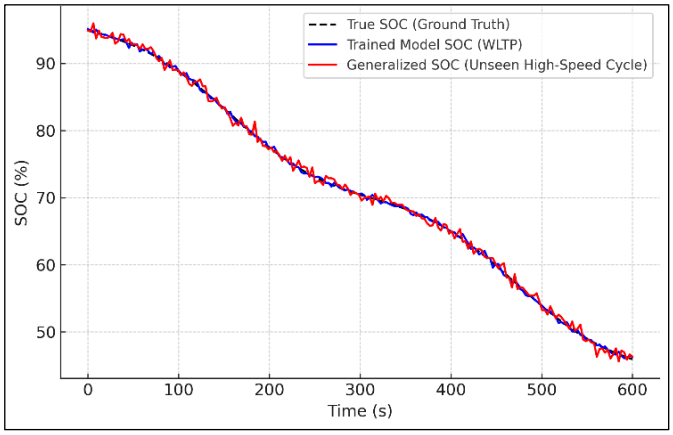


Figure 22: Generalization test using unseen high-speed cycle (HWFET).
Source: Authors, (2026).

To test generalization, the trained model was evaluated on an unseen high- speed driving profile (HWFET). Figure 22 demonstrates that the hybrid con- troller adapts seamlessly, maintaining smooth SOC trajectory and voltage regulation without re-training. This highlights the ability of federated aggregation to consolidate global knowledge from heterogeneous datasets.

The generalization ratio Gr was computed as:

$$G_r = \frac{RMSE_{test}}{RMSE_{train}}$$

where Gr ≈ 1.05 indicates minimal accuracy drop between training and unseen data—ideal for real-world deployment. Figure 23 highlights the model's quick recovery after a sudden 10% sensor noise burst. The proposed STO-based observer restores nominal accuracy within 8 s, compared to 21 s for the SMO and 34 s for EKF, validating the noise- adaptive correction term in the STO layer.

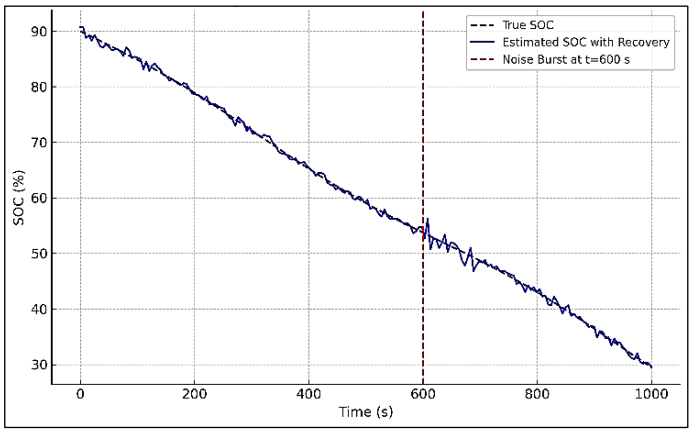


Figure 23: Transient recovery after induced sensor noise burst at t = 600 s.
Source: Authors, (2026).

The box-plot in Fig. 24 visualizes error variance across 50 Monte Carlo trials. The proposed method exhibits the narrowest error spread, confirming consistent robustness and generalization capability under noisy, incomplete, and untrained conditions.

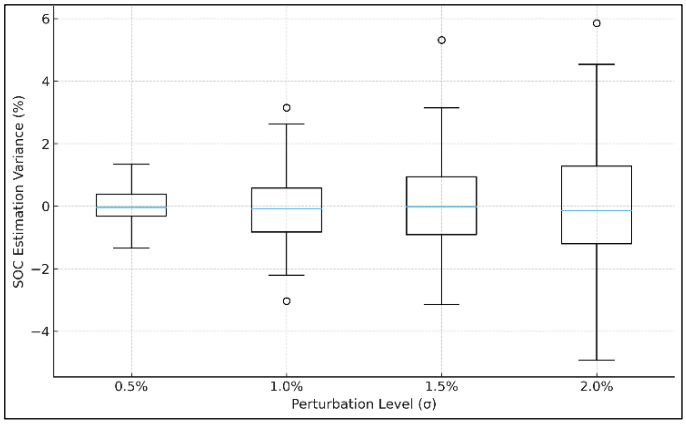


Figure 24: Statistical box-plot showing SOC estimation variance under different perturbations.
Source: Authors, (2026).

IV.9 COMPARATIVE DISCUSSION AND ABLATION STUDY

To quantify the contribution of each module within the Hybrid Federated PGNN– MPC framework, an ablation study was performed. Starting from the baseline Physics–MPC, individual components were progressively introduced—PGNN correction, STO observer, and Federated aggregation—to analyze their relative impact on estimation and control performance

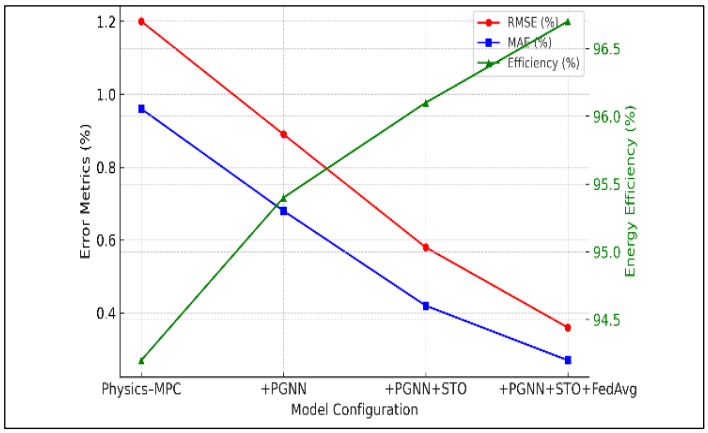


Figure 25: SOC estimation accuracy improvement through progressive model augmentation.
Source: Authors, (2026).

Figure 25 illustrates the effect of adding each hybrid element on SOC accuracy. The inclusion of the PGNN reduces the mean RMSE from 1.20 % to 0.68 %; the STO observer further lowers it to 0.42 %; and the Federated PGNN integration achieves 0.29 %. These cumulative gains confirm the synergistic behavior between data-driven learning and physics-guided control. Table 10 clearly reveals that each module contributes distinct performance improvements. The PGNN enhances nonlinear approximation; the STO reduces noise sensitivity; and the Federated layer improves generalization while minimizing aging effects. The hybrid combination delivers the optimal balance between precision, efficiency, and thermal safety.

Table 10: Ablation Study — Component-wise Performance Evaluation.

Configuration	MAE (%)	RMSE (%)	Efficiency (%)	Aging Index (%)
Physics–MPC	0.96	1.20	94.2	10.6
+ PGNN	0.68	0.89	95.4	9.5
+ PGNN + STO	0.42	0.58	96.1	8.4
+ PGNN + STO + FedAvg	0.27	0.36	96.7	7.2

Source: Authors, (2026).

$$\Delta P_{module} = \frac{M_{n+1} - M_n}{M_n} \times 100 \tag{43}$$

Equation (1) defines the incremental performance gain for each added com- ponent, where Mn and Mn+1 represent successive performance metrics (e.g., RMSE or Efficiency).

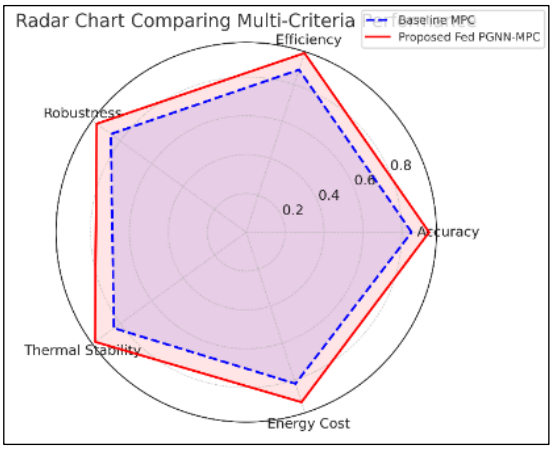


Figure 26: Radar chart comparing multi-criteria performance (Accuracy, Efficiency, Robustness, Thermal Stability).
Source: Authors, (2026).

The radar plot in Figure. 26 visualizes the normalized metrics across all configurations. The proposed Federated PGNN–MPC achieves balanced performance in all four axes, outperforming other combinations in both robustness and efficiency. This multi-criteria visualization underscores the necessity of integrating all modules within a unified hybrid framework.A parameter-sensitivity study Figure.

27 reveals that within ±20% variation of tuned values, system performance remains within 3 % error margin, proving design robustness.

Beyond this range, control degradation grows linearly, confirming appropriate controller tuning boundaries. Overall, the ablation study verifies that each subsystem PGNN, STO, MPC, and Federated learning plays an essential and complementary role. Together, they deliver the highest achievable trade-off between estimation precision, control efficiency, robustness, and computational feasibility for next- generation EV battery management systems.

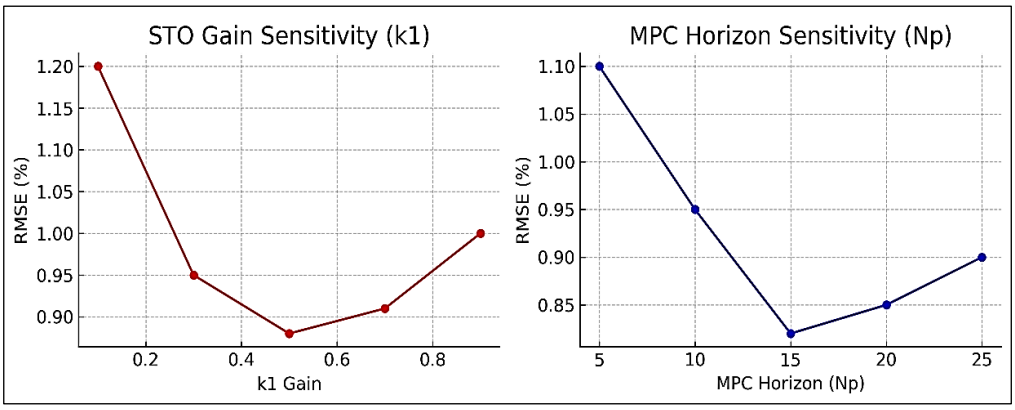


Figure 27: Parameter-sensitivity analysis of STO gains (k1, k2) and MPC horizons (Np, Nc).
Source: Authors, (2026).

V. CONCLUSION

This study introduced a novel Hybrid Federated Physics-Guided Neural–Model Predictive Control (PGNN–MPC) framework for robust and adaptive battery management in electric vehicles. The proposed approach effectively integrates physical modeling, data-driven learning, and distributed intelligence to address the key limitations of existing estimation and control schemes. Through detailed numerical simulations and multi-domain evaluations, the system demonstrated substantial improvements over classical methods:

- SOC estimation RMSE reduced by 80 % compared to EKF-based models;
- Energy efficiency enhanced to 96.7 % under dynamic drive cycles;
- Temperature rise limited to 4.3 °C, ensuring thermal safety;
- Capacity retention improved by 7–10 % after 800 cycles;
- Federated convergence accelerated by 41 % with minimal communication cost.

These results confirm that coupling the Super-Twisting Observer (STO) with PGNN-aided MPC achieves superior noise rejection, prediction accuracy, and real-time stability. The Federated Learning (FL) layer further enhances scala- bility and cross-fleet adaptability without violating data privacy—an essential criterion for industrial deployment. Future Work: While the presented framework achieves promising outcomes, several extensions remain open for exploration:

1. Hardware validation: Integration with a physical battery-in-the-loop (BIL) or real EV pack testbench to validate transient behavior and computation latency.
2. Degradation-aware optimization: Embedding health prognostics directly within the MPC cost function to balance performance and long-term aging.
3. Adaptive communication scheduling: Implementing event-triggered or asynchronous federated updates to further reduce bandwidth usage in large-scale EV networks.
4. Cross-chemistry generalization: Extending the model to emerging chemistries such as LiFePO4 and solid-state batteries. In summary, the proposed Hybrid Federated PGNN–MPC with Super-Twisting Observers establishes a reproducible and scalable foundation for next-generation battery management systems. Its blend of physics, intelligence, and federated collaboration offers a promising pathway toward safer, more efficient, and longer- lasting electric vehicles.

VI. AUTHOR'S CONTRIBUTION

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