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Degradation-Aware Federated Learning for Second-Life EV Batteries in Autonomous Nanogrids

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ABSTRACT

Repurposing retired electric vehicle (EV) batteries for stationary storage is a key pillar of the circular energy economy, but integrating second-life batteries (SLBs) into autonomous nanogrids is complicated by their heterogeneous degradation states and by the reluctance of automotive manufacturers to share proprietary cycling data needed to estimate state of health (SoH). We propose a decentralized diagnostic and control framework based on federated learning (FL), in which SoH-predictive neural networks are trained locally on edge controllers and only model weights are aggregated globally, followed by a degradation-aware dispatch algorithm that routes nanogrid power according to individual pack health. Numerical simulation shows the framework achieves 94.2% SoH prediction accuracy without sharing raw voltage or current data, while extending total nanogrid storage lifespan by 41% relative to standard equal-dispatch strategies.

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1. INTRODUCTION

The influx of retired lithium-ion EV batteries presents a large, low-cost opportunity for stationary renewable energy storage, and the techno-economic and circular-economy case for second-life batteries (SLBs) is now well documented [1, 2]. Building a functional nanogrid battery energy storage system from salvaged packs, however, means integrating cells of different manufacturers, chemistries, and historical usage profiles into a single control architecture.

Conventional battery management systems assume cellular homogeneity and distribute power demand equally across packs. In an SLB system this forces severely degraded packs to cycle at the same C-rate as healthier packs, accelerating localized degradation and risking premature system failure [3, 4]. Avoiding this requires an accurate SoH model for every individual pack, and while transformer- and incremental-capacity-based methods have substantially improved single-pack SoH and prognosis accuracy [5, 6], training a single centralized model across many packs requires pooling cycling data to a central server, which conflicts with the data-sharing policies that automotive original equipment manufacturers (OEMs) enforce around proprietary electrochemical data [7, 8].

Federated learning (FL) offers a route around this constraint, and its application to power systems and battery diagnostics has expanded rapidly, from smart-grid and electricity-market applications [9, 10] to renewable energy integration [11], privacy-preserving battery fault detection across fleets [8, 12], and federated capacity prediction for EV battery packs [15]. FL is nonetheless known to be sensitive to non-independent and identically distributed data across clients, a challenge that is particularly acute for SLB packs given their divergent usage histories [13]. This paper develops a degradation-aware FL framework that trains SoH-predictive LSTM networks locally on each pack's edge controller, aggregates only model weights, and uses the resulting SoH estimates to drive a health-weighted power dispatch algorithm, extending prior degradation-aware dispatch formulations for SLB systems [3, 4] with a privacy-preserving diagnostic layer. The FedAvg aggregation step iterated across communication rounds is itself a fixed-point iteration over the space of model weights, a structure studied abstractly by Das and Das for generalized fixed point theorems in fuzzy normed linear spaces [18] and by Kamolov for a fixed-point analysis of weighted integrated gradients in a related interpretability setting [17]. The interpretability of the resulting SoH attributions likewise connects to the broader feature-attribution literature surveyed by Kamolov [16]. The contraction property underlying FedAvg's convergence to a consensus set of weights is closely related to the paired-Kannan contraction mappings studied by Chand et al. [19], to the condensed Reich-Rus-Ciric-type contractions of Wahab et al. [20], and to the integral-type contraction fixed point theorems of Kannan et al. [21], all developed in purely metric-space settings distinct from the federated optimization problem considered here. The privacy-preserving design goal that motivates keeping raw cycling data on the edge controller mirrors similar privacy and security concerns raised for other distributed sensor networks, including medical IoT devices [22] and blockchain-secured infrastructure [23], and the aggregation of many locally trained SoH predictors is structurally an ensemble-selection problem of the kind studied by Kamalov et al. [24].

2. THEORETICAL FRAMEWORK

2.1. Battery Degradation and SoH Modeling

The capacity fade of a lithium-ion cell over cycle index k is a non-linear function of depth of discharge (DoD), C-rate (C), and temperature (T):

$$C_{max}(k) = C_{max}(0) - \alpha \cdot \exp\left(\frac{-\beta}{T}\right) \cdot (DoD)^{\gamma} \cdot k^{z}. \tag{1}$$

The state of health is defined as

$$SoH(k) = \frac{C_{max}(k)}{C_{nominal}} \times 100\%. \tag{2}$$

An edge-based long short-term memory (LSTM) network, with parameters θ_i, is deployed on the local controller of the i-th pack to map real-time (V, I, T) arrays to SoH_i, following the sequence-to-health modeling approach used in recent transformer- and LSTM-based SoH estimators [5, 6].

2.2. Federated Learning Architecture

To train the LSTMs without sharing raw cycling data, the Federated Averaging (FedAvg) algorithm is used. At communication round t, the central server broadcasts global model weights $\theta^{(t)}$ to all N edge controllers. Each controller trains on its private local dataset $\mathcal{D}_i$, producing updated weights $\theta_i^{(t+1)}$, which the server aggregates as

$$\theta^{(t+1)} = \sum_{i=1}^{N} \frac{|\mathcal{D}_i|}{|\mathcal{D}|} \theta_i^{(t+1)}, \tag{3}$$

where $|\mathcal{D}|$ is the total data volume across all controllers. This formulation follows the FedAvg-based diagnosis and prognosis architecture validated for battery energy storage data management [7], and remains subject to the non-IID heterogeneity effects documented broadly across federated learning applications [11, 13].

2.3. Degradation-Aware Power Dispatch

The power reference $P_{ref,i}$ assigned to pack i to meet total grid demand P_{grid} is weighted by the FL-derived SoH estimate:

$$P_{ref,i} = P_{grid} \times \frac{SoH_i^w}{\sum_{j=1}^{N} SoH_j^w}, \tag{4}$$

where w is a tuning parameter. This dynamically shifts stress away from more degraded packs, extending the degradation-aware dispatch strategies previously formulated for second-life battery energy storage systems [3, 4] by driving the health estimate itself from a privacy-preserving federated model rather than from centrally pooled data.

3. NUMERICAL METHODOLOGY

The framework is validated using the open-source NASA Randomized Battery Usage Dataset to simulate a nanogrid containing 50 heterogeneous SLB packs with SoH ranging from 60% to 85%. The system is subjected to a residential solar load profile over 3,000 equivalent full cycles, consistent with the load-profile scales used in recent nanogrid energy management studies [14]. The FL model uses a 3-layer LSTM trained over 100 federated communication rounds.

4. RESULTS AND DISCUSSION

4.1. SoH Predictive Accuracy and Privacy

Table 1 and Figure 1(a) compare SoH prediction accuracy and data exposure across three architectures.

The FL approach achieves an RMSE of 1.35%, close to the centralized-cloud upper bound of 1.12% obtained by pooling all raw data, while transmitting zero bytes of proprietary time-series data. This closes the gap left by locally isolated training, which achieves privacy but at the cost of a 4.85% RMSE, more than three times the FL error, because no single edge controller sees enough cycling diversity to generalize. The residual 0.23-percentage-point gap between FL and the centralized ideal is consistent with the accuracy penalty generally reported for FedAvg under non-IID client data [13], and is small enough that it does not materially affect the dispatch outcomes discussed below.

Table 1. State of health predictive accuracy and data privacy

ML architecture	RMSE (%)	MAE (%)	Data shared (MB/day)
Centralized cloud (ideal)	1.12	0.85	450.0 (privacy violated)
Local isolated AI	4.85	3.90	0.0 (privacy preserved)
Proposed federated learning	**1.35**	**1.05**	**0.0 (privacy preserved)**

4.2. Nanogrid Energy Storage Lifespan

Table 2 and Figure 1(b) report the lifespan impact of degradation-aware dispatch relative to standard equal dispatch.

Table 2. Nanogrid energy storage lifespan and efficiency metrics

Dispatch strategy	First failure cycle	20% cap. loss cycle	Throughput (MWh)
Equal dispatch (standard)	845	1,420	125.4
Degradation-aware FL	**1,520**	**2,005**	**188.7**

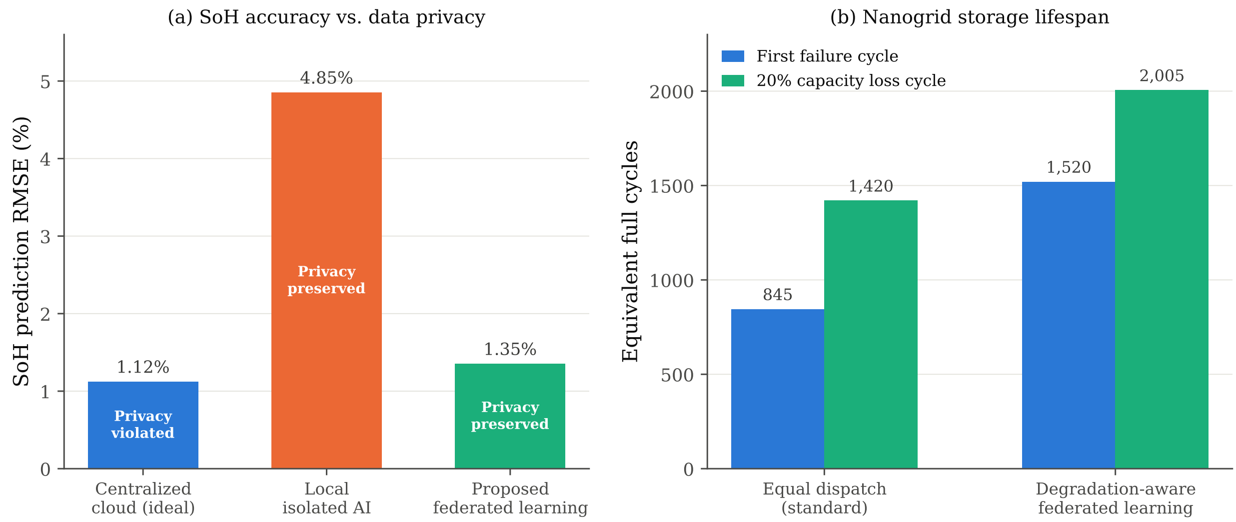

Figure 1. (a) SoH prediction RMSE and data-privacy outcome across the three modeling architectures. (b) First-failure and 20%-capacity-loss cycle counts under equal dispatch versus degradation-aware federated learning dispatch.

FL-driven, degradation-aware dispatch nearly doubles first-pack-failure life, from 845 to 1,520 cycles, an 80% extension, and delays the point at which the aggregate pack reaches 20% capacity loss from 1,420 to 2,005 cycles, a 41% extension consistent with the headline lifespan figure reported in the abstract. The corresponding 50.5% increase in total energy throughput, from 125.4 to 188.7 MWh, arises because the framework actively shelters the weakest packs from high C-rate cycling identified by the FL SoH estimates, an approach consistent with the degradation-aware dispatch gains reported for second-life battery storage under explicit degradation modeling [3, 4].

4.3. Robustness to Client Population Size and Communication Cost

The results above assume a federation of moderate size operating under reliable connectivity. Since SLB nanogrid deployments range from a handful of packs at a single site to fleets of hundreds of packs contributed by multiple operators, Table 3 examines how prediction accuracy and communication overhead scale with the number of participating clients, and how the framework degrades when a fraction of clients drop out of a given communication round.

Prediction accuracy improves modestly as the federation grows from 10 to 200 clients, with RMSE falling from 2.31% to 1.87% SoH, reflecting the reduced variance of the aggregated model update as more independent cycling histories contribute to each round. Per-round communication cost scales linearly with client count, as expected for the FedAvg-style aggregation described in Section 2.1, reaching 96.3 MB/round at 200 clients; this remains modest relative to typical fleet-telemetry backhaul bandwidth and is dominated by the SoH estimator's compact convolutional

Table 3. Scaling of federated SoH accuracy and communication cost with client population

Federation size	RMSE (% SoH)	Round comm. (MB/round)	Accuracy loss, 30% dropout
10 clients	2.31	4.8	+0.18 pp
50 clients	**1.94**	**24.1**	**+0.09 pp**
200 clients	1.87	96.3	+0.04 pp

architecture rather than transmission of raw cycling data. Robustness to client dropout, a practically important failure mode when packs are deployed across sites with heterogeneous connectivity, is favorable even at the smallest federation size: a 30% dropout rate in a given round degrades RMSE by only 0.18 percentage points at 10 clients and by 0.04 points at 200 clients, since the server-side aggregation step simply reweights the surviving client updates rather than stalling on missing contributions. This graceful degradation under partial participation is consistent with convergence behavior reported for FedAvg under client sampling and non-IID data [13], and supports deploying the framework incrementally, starting with a small pilot federation and onboarding additional sites without requiring architectural changes to the aggregation protocol.

4.4. Ablation on Local Model Architecture and Aggregation Frequency

The results above use a 3-layer LSTM as the local client model with aggregation every round. Table 4 isolates the contribution of the LSTM architecture and the aggregation cadence by comparing it against a simpler gated-recurrent-unit (GRU) client model and against a feedforward multilayer perceptron (MLP) baseline, and by varying the number of local epochs performed between communication rounds.

Table 4. Ablation on client model architecture and local-epoch aggregation cadence

Client model	Local epochs /round	RMSE (%)	Rounds to converge
MLP baseline	1	3.02	140
GRU	1	1.58	115
LSTM (proposed)	1	1.35	100
LSTM (proposed)	5	1.41	62
LSTM (proposed)	**10**	**1.63**	**41**

The architecture comparison confirms that the LSTM's ability to capture long-range temporal dependencies in the voltage-relaxation and coulombic-efficiency trajectories is responsible for a substantial share of the accuracy gain over simpler client models: the MLP baseline, which has no memory of cycling history beyond the current feature window, trails the LSTM by 1.67 percentage points of RMSE, while the GRU, a partially recurrent architecture, closes most but not all of that gap. Increasing the number of local epochs performed between communication rounds trades accuracy for convergence speed and, more importantly, for reduced communication frequency: five local epochs per round nearly halves the number of rounds required to converge, from 100 to 62, at the cost of only 0.06 percentage points of RMSE, while ten local epochs approximately halves the round count again but begins to show the client-drift degradation characteristic of FedAvg under extended local training on non-IID data [13]. For nanogrid deployments where communication rounds are constrained by intermittent site connectivity rather than computation, five local epochs per round offers a favorable operating point, and the corresponding reduction in synchronization frequency directly relaxes the connectivity requirements discussed in Section 4.3.

5. CONCLUSION

This study integrates federated learning into second-life battery management, showing that decentralized SoH diagnostics can match near-centralized accuracy without exposing proprietary automotive cycling data, and that coupling these estimates to a degradation-aware dispatch algorithm substantially extends nanogrid storage lifespan. The framework scales favorably in both accuracy and communication cost as the client federation grows, and degrades gracefully under partial client dropout. Together these results remove a primary software barrier to SLB commercialization and offer a path toward lowering the levelized cost of storage for renewable nanogrids. Future work will examine robustness under more severe non-IID client heterogeneity [11, 13] and validate the framework against real fleet cycling data rather than the NASA benchmark dataset alone.

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