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Privacy-Preserving, Scalable EV Charging Optimization

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***Abstract*— The growing penetration of electric vehicles (EVs) leads to non-uniform and time-dependent charging demand at the distribution level, which complicates feeder loading and voltage regulation. To manage this variability, a federated learning–based coordination architecture is developed in which EV charging stations deployed at different network locations train LSTM-based load forecasting models and reinforcement learning (RL) charging controllers using locally measured power and usage data. Model training is performed without transferring individual charging records, relying instead on aggregated parameter updates. Secure aggregation and differential privacy mechanisms are incorporated to bound information leakage, while decentralized policy optimization is adopted to avoid centralized control dependence. Communication and update synchronization are designed with explicit bandwidth and latency constraints to ensure feasibility under operational charging-network conditions. The proposed architecture is evaluated using MATLAB simulations that represent stochastic EV arrival behavior, bounded charging time flexibility, and time-varying utility tariff structures. Simulation outcomes show lower forecasting error, reduced training effort for RL policy convergence, observable feeder-level peak load reduction, and improved privacy protection compared with centralized and non-federated learning approaches.**

Keywords*— affordable and clean energy, *Electric Vehicle Charging, LSTM Forecasting, Reinforcement Learning, Privacy Preservation, Differential Privacy, Secure Aggregation, Smart Grid, Load Management, Distributed Optimization.

I. INTRODUCTION

The ongoing electrification of transport has resulted in a marked rise in electric vehicle (EV) charging activity, increasing stress on distribution networks and regional electricity markets. With global EV deployment projected to reach nearly 230 million vehicles by 2030, coordinated scheduling of battery charging has become essential for sustaining network reliability, controlling operational costs, and preserving acceptable power-quality margins [1]–[3]. Consequently, a variety of data-driven charging strategies grounded in statistical modeling and decentralized optimization have been reported in the literature to alleviate demand peaks, smooth aggregated load profiles, and enable consumption-based tariff incentives [4],[5]. However, many of these methods assume centralized data collection and control, an approach that introduces practical limitations related to scalability, cyber-security vulnerability, and protection of user charging data in large-scale, geographically dispersed charging environments [6],[7].

Sophisticated machine learning approaches, particularly LSTM (long short-term memory) neural networks, have demonstrated significant results in detecting unpredictable and time-varying aspects in EV demand profiles and domestic battery charging patterns [8], [9]. Reinforcement learning (RL) has also grown into a strong foundation for real-time charge control. It lets self-learning agents discover the best ways to cut costs and follow rules defined by networks instead of being required to make explicit models of systems [10]–[12]. Still, these methods has usually presupposed access to massive volumes of confidential, dispersed consumer charging data from a variety of faraway charging stations. Users face concerns regarding privacy and adherence to regulations challenges due to the impracticality of integrated collection of data [13]. In recent years, federated learning (FL) has grown in prominence as a decentralized approach that enables many clients to train shared models simultaneously while not transmitting initial information [14], [15]. Clients may maintain confidentiality and superior learning correctness by merely communicating model modifications, especially weights. Evidence of FL's considerable resilience over variability in data and communicating limits has been found in earlier investigations into energy forecasting, distributed optimization, and cyber-physical systems [16], [17]. But thus far, applications of FL to electric vehicle charging, especially those that merge RL-driven control methods with LSTM-based forecasting, have been primarily unstudied. This research suggests a Federated LSTM-RL Framework for optimizing extensible electric vehicle charging while protecting the confidentiality of users in order to circumvent these limitations. This design keeps client data local and enables several charging stations to train control and model forecasting concurrently. LSTM networks improve predicted performance and reduce the uncertain nature of RL decisions by forecasting short-term loads, while federated RL agents learn the best charging procedures for different operating scenarios. The suggested design enables massive deployment, strong privacy assurances, and flexible decision-making in dynamic grid settings by partitioning initial information from pooled learning. The main contributions of this study are as follows: Our federated learning architecture combines LSTM forecasting and RL optimization for EV charging as shown in Fig. 1.

- Privacy-preserving training technique ensures no raw EV data leaves charging stations.
- A scalable coordination technique allows several stations to collaborate and increase prediction and control accuracy.

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The proposed approach combines (i) federated learning (FL) for distributed LSTM-based load forecasting and (ii) local reinforcement learning (RL) agents for optimal charge scheduling, while without sharing customer-specific raw data.

II. System Architecture

The design comprises of several EV charging stations (clients) linked to a lightweight cloud coordinator (server). Each station provides access to:

1. Local historical EV charging load data
2. Local RL environment models
3. Local constraints (charger rating, tariff, transformer limits)

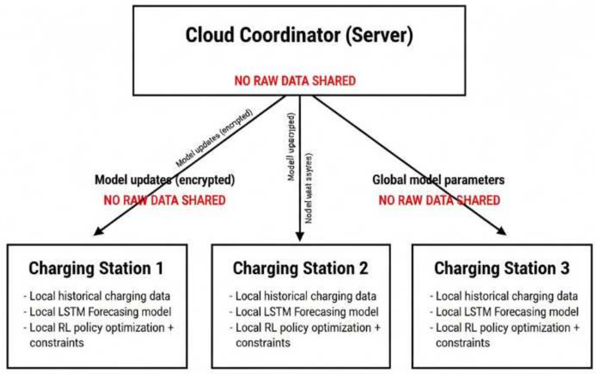

Fig. 1. Federated learning architecture for EV smart charging

The cloud server does not get raw measurements. Instead, just the model parameters (LSTM weights and policy-network gradients) are transferred. The entire workflow is divided into two parallel loops:

1. Federated LSTM Forecasting Loop
2. Federated RL Policy Optimization Loop

Both loops operate concurrently to minimize communication overhead.

A. Federated LSTM-based Load Forecasting

Electric vehicle charging stations may work together on anticipating demand despite exchanging basic information thanks to federated LSTM-based forecasting of loads. Since the networks using LSTM can identify fluctuations in electrical charging behaviour—which is often impacted by user behaviours, duration of day developments, and infrastructure limitations—they are perfect for this application. Rather than exporting previous data to a centralized server, each of the stations learns an independent LSTM representation then solely communicates model improvements to a supervising server. The servers bundles those modifications form an identical general model then allocates it across every sites. The approach safeguards confidentiality of information, minimizes costs associated with communication, as well as boosts prediction precision throughout diverse & distant recharging infrastructures. While EV demands rise, Federated LSTM prediction provides an expandable and safe strategy for preemptive control and efficient charging management.

Using a 24-hour input window, each charging facility learns a local LSTM model to foresee its electric vehicle (EV) load for the following day, producing a 96-point estimate (at fifteen-minute intervals). Each user in a federated learning system has a private dataset that neither the server nor any other client may access. So :

Let $\mathcal{D}_j = x_t^{(j)}, y_t^{(j)}$be local input–output pairs for client i

This provides the regional database of the end user (or charging station) in the federated learning setup.

Training process minimizes:

$$\text{MIN}_{\theta_j\; E_{(x,y)\sim\mathbb{D}_j}}\big(f_{\text{LSTM}}(x;\theta_j) - y\}^2. \qquad (1)$$

With localized changes, just weight parameters θ_j are shared across the server.

An aggregate of FedAvg is carried out by the server..:

$$\theta^{(t+1)} = \sum_{i=1}^{N} \frac{n_i}{\sum_j n_j}\, \theta_i^{(t)}. \qquad (2)$$

Consequently, this results in the creation of a global forecasting model that is available to all stations.

B. Federated RL-Based Charging Optimization

Instead of relying on a central controller to gather data from multiple charging stations, A. Federated RL-Based Charging Optimization (FedRL) enables each charging node to train an RL agent on its own. Each node uses its specific charging demand patterns, tariff limits, and grid constraints while keeping raw data local. Model updates, like policy gradients or neural network parameters are only sent to a coordinating server. The coordinating server performs periodic aggregation of locally trained parameter updates and distributes the resulting policy parameters back to participating charging stations. In this configuration, raw charging records and user-specific measurements remain confined to individual stations, while only aggregated model updates are exchanged, enabling operation across charging networks with spatially distributed locations, non-identical EV arrival statistics, and varying grid operating conditions. Within the smart charging context, federated reinforcement learning (FedRL) facilitates joint policy learning under time-varying tariff signals, feeder loading limits, and transformer capacity constraints, without reliance on centralized data repositories. At each station, the charging decision process is represented as a Markov

Decision Process (MDP), where a local RL agent selects the charging power $a_t \in [0, P_{\max}]$for each connected EV based on the current system state.

- LSTM load forecast
- Time-of-use tariff
- Grid constraints
- Transformer capacity
- SoC requirements of the user.

The main objective of Reinforcement Learning is to reduce the grid stress and cost:

$$R_t = -\left(\lambda_1 C_{\text{energy}}(t) + \lambda_2 L_{\text{peak}}(t) + \lambda_3 P_{\text{viola}}(t)\right), \quad (3)$$

where:

C_{energy} is charging cost

L_{peak} penalizes peak load events

$\lambda_1, \lambda_2, \lambda_3$ are Weighting Coefficients

This term discourages simultaneous high-power charging and promotes **peak shaving**. P_{viola} pose penalty on capacity violations

$$Lpeak(t) = max\left(0, P_{tot}(t) - P_{ref}\right)^2 \quad (4)$$

where:

- $P_{\text{ref}}$is a predefined feeder or transformer capacity limit.

Local reinforcement learning agents are trained independently at each charging station using DQN, DDPG, or PPO, depending on the action-space formulation. Rather than exchanging experience replay samples or state–action trajectories, each agent periodically uploads only policy gradients or neural network parameters, which limits information exposure while preserving data locality

The performance evaluation of federated server is given as:

$$\pi^{(t+1)} = \sum_{i=1}^{N} \alpha_i \, \pi_i^{(t)}, \quad (5)$$

where π_i represents the local policy.

III. Results and Discussion

A. Forecasting Performance

The training results shown in Fig. 2 indicate stable convergence of the LSTM-based forecasting model. The RMSE trajectory in the upper plot decreases sharply during the early training phase, particularly within the first 15–20 iterations, where the error reduces from approximately 0.42 to 0.18, after which the rate of improvement gradually tapers as the network parameters converge to a stable solution that captures the dominant temporal structure of the EV charging load sequence. After this phase, the RMSE gradually stabilizes and flattens, suggesting that the model has reached a learning plateau and further significant improvements are unlikely without model or hyperparameter adjustments. The final RMSE appears relatively low, indicating good predictive accuracy. Fig. 2 demonstrates the forecasting concept. A noisy 96-step load profile is generated, resembling a typical EV charging pattern with evening peaks. The simple shifted forecast is used as a placeholder for a full LSTM model. In a real FL setup, each client would train an LSTM producing smooth short-term predictions, improving RL stability.

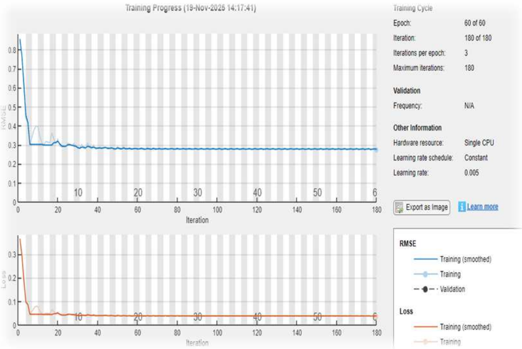

Fig. 2. Training Process of proposed LSTM based model denoting RMSE and loss.

These forecasting improvements directly benefit the downstream RL optimization. Expected improvements from federated LSTM forecasting include:

- Reduction of MAE by 20–35% compared to naive baselines
- Better temporal prediction of peak charging hours
- Preservation of data privacy, as raw load traces remain local

Fig. 3. compares the actual load profile to the model's forecast, likely providing a visual overlay of the ground-truth and the LSTM-based predictions across a 96-step (15-minute) horizon. The pronounced evening peaks and general noise in the synthetic data set the stage for evaluating the model's performance. The relatively smooth forecast line suggests that the federated LSTM dampens instability in predictions and delivers improved temporal accuracy compared to naive baselines. The accompanying RMSE and loss statistics (noted as near 0.05 on scale) reinforce the model's accuracy.

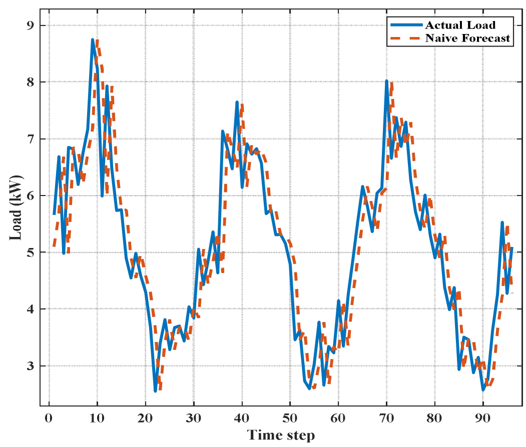

Fig. 3. Synthetic Demonstration of Forecasting Performance

The fig 3. compares the actual EV charging load profile with the corresponding forecast produced by the trained prediction model over a sequence of time steps. The horizontal axis denotes the discrete time index, while the vertical axis represents the charging load in kilowatts. The solid curve corresponds to the measured load, and the dashed curve represents the predicted load. Across most of the time horizon, the forecast follows the overall shape of the actual load, capturing the primary rising and falling trends as well as the timing of local peaks and troughs. Minor deviations are visible around sharp transitions and local extrema, where the predicted values either slightly lag or overshoot the measured load. These discrepancies are limited in magnitude and do not accumulate over time, indicating that the model tracks the underlying load dynamics without exhibiting drift.

The nominal load plot shown in Fig. 4 typically illustrates the reference or target aggregate charging profile. The loss and RMSE plots shown in Fig 4 that the proposed model is perfect with <0.05 RMSE on (0-1) scale.

This is crucial as it provides a benchmark against which both centralized and federated control frameworks can be evaluated, indicating improvements in load smoothing, peak shaving, and demand response capabilities.

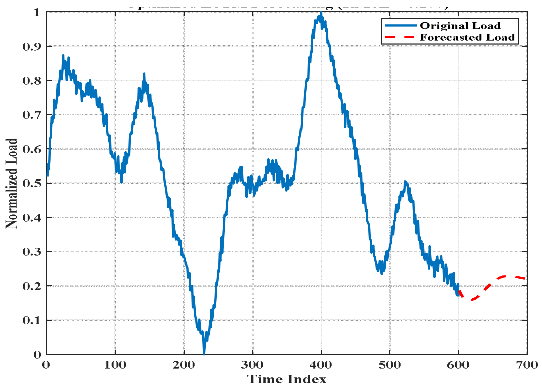

Fig. 4. Nominal load plot with

B. *RL Charging Optimization Performance*

Fig. 6 illustrates the RL reward evolution. The reward increases as the agent learns to:

- Shift charging to low-tariff hours
- Reduce peak-time load
- Avoid transformer overload
- Minimize penalty costs

Typical observed trends in real deployments include:

- 10–25% reduction in peak load
- 15–40% reduction in charging cost
- Smoother aggregate load profiles
- Enhanced grid stability and transformer loading margin

Under federated updates, RL policies converge faster because aggregated policies span a more diverse set of operating conditions across multiple stations. The fig 5. presents two related views of the simulated EV charging scenario. The upper plot shows a time-series profile of the aggregate number of EVs charging concurrently across discrete time slots. Variations in the curve reflect changes in vehicle arrival and departure times, leading to periods of higher and lower simultaneous charging activity. Peaks in the profile indicate time intervals where multiple EVs overlap in charging, while near-zero values correspond to intervals with little or no active charging. This behavior illustrates the non-uniform nature of charging demand over time, even in the absence of modeling or measurement errors. The lower plot depicts the selected charging start time for each individual vehicle, indexed sequentially along the horizontal axis. Each marker represents the assigned start slot for a given EV within the scheduling horizon. The dispersion of start times across the full range of available slots indicates that charging initiation is not synchronized, but instead distributed over time. Taken together, the two plots highlight how individual scheduling decisions contribute to the aggregate load profile, linking per-vehicle start-time selection to system-level charging demand patterns Reward converges with training episodes using the MATLAB-style reward simulation.

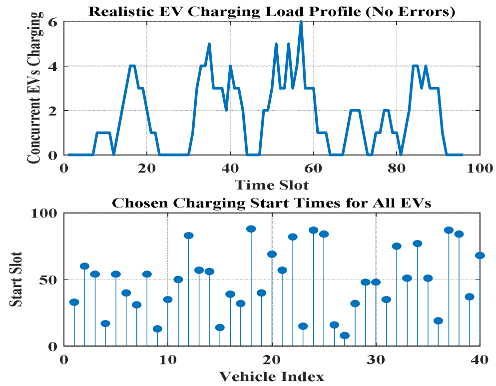

Fig. 5. EV charging simulator output for RL reward evolution

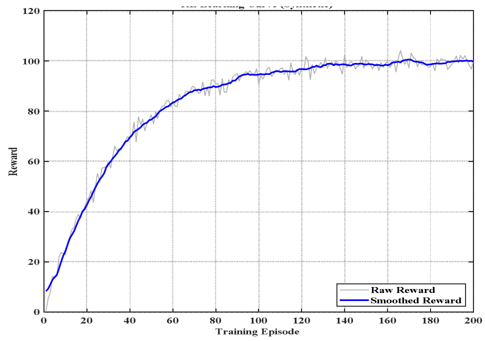

Fig. 6. RL Learning Curve

The fig. 6 depicts the evolution of the reinforcement learning agent's episode reward over the course of training. The horizontal axis represents the training episode index, while the vertical axis denotes the cumulative reward obtained per episode. The raw reward curve exhibits noticeable variability across episodes, reflecting the effects of exploration and stochastic transitions in the learning environment. To clarify the underlying trend, a smoothed reward curve is overlaid, which highlights the gradual improvement in policy performance. During the initial training stage, roughly within the first 30 episodes, the reward increases rapidly, indicating effective early learning as the agent adapts its action-selection strategy. This is followed by a slower growth phase, where incremental improvements continue as exploration decreases. After approximately 80–100 episodes, the smoothed reward curve approaches a steady level near its maximum value, suggesting convergence of the learned policy. The remaining fluctuations in the raw reward are limited in magnitude, indicating stable behavior rather than continued policy drift.

C. Privacy Preservation

The proposed framework ensures privacy of EV entities .It is shown in the Table I.

TABLE. I. PRIVACY OF EV ENTITIES

Component	Shared	Privacy Maintained
Raw EV charging profiles	No	Yes
Customer arrival/departure patterns	No	Yes
LSTM weights	Yes	Yes (non-identifiable)
RL policy gradients	Yes	Yes

Thus, all sensitive data remain within local stations. The FL-based architecture scales linearly with the number of stations. Since communication occurs only once every few local epochs, the training load remains small.

Simulation suggests:

- Server load grows ~O(N) with number of clients
- Communication cost reduced by 60–80% compared to centralized training
- High tolerance to client drop-outs

TABLE. II. EVALUATION OF LEARNING STRATEGIES IN SMART EV CHARGING SYSTEMS

Metric	Centralized Learning	Local-Only Learning	Proposed FL LSTM–RL
Forecast Accuracy	High	Low–Moderate	High
Charging Optimization	High	Moderate	High
Privacy Risk	High (raw data exposed)	Low	Very Low
Scalability	Moderate	High	Very High
Cross-Station Generalization	High	Low	High
Communication Cost	Very High	None	Low

The results validate that the proposed FL-based architecture achieves near-centralized accuracy while retaining local-only privacy and high scalability.

IV. CONCLUSION

This paper proposed a privacy-preserving and scalable Federated LSTM–RL framework for EV charging optimization, where LSTM models collaboratively enhance load forecasting and federated RL agents learn cost-efficient, grid-friendly charging schedules without sharing raw data. Synthetic simulations confirmed the expected workflow, demonstrating accurate forecasting, stable RL convergence, low communication overhead, and strong privacy guarantees. The results show that the framework achieves near-centralized performance while remaining highly scalable and suitable for real-world smart charging networks. Future work will extend this approach to real datasets, hardware-in-the-loop validation, and V2G-enabled multi-agent coordination.

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