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RESEARCH ARTICLE

Federated Learning-based Intelligent Energy Management for Distributed Power Electronic Networks in Smart Grids

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Abstract

The increasing integration of Distributed Energy Resources (DERs), renewable generation systems, converter-interfaced loads, battery energy storage systems, and intelligent power electronic controllers has transformed conventional power grids into highly decentralized and data-intensive smart energy networks. However, traditional centralized energy management frameworks face significant challenges including excessive communication overhead, limited scalability, latency constraints, cybersecurity risks, and concerns related to operational data privacy. To address these limitations, this paper proposes a Federated Learning-Based Intelligent Energy Management (FL-IEM) framework for distributed power electronic networks in smart grids. The proposed architecture enables multiple geographically distributed converter controllers to collaboratively train a shared intelligence model without exchanging raw local data, thereby preserving privacy while maintaining coordinated decision-making capabilities. A federated optimization layer based on Federated Averaging (FedAvg) is integrated with a Deep Reinforcement Learning (DRL)-assisted energy dispatch mechanism to enable adaptive control, dynamic power sharing, and real-time energy scheduling under varying renewable generation and load conditions. The proposed framework is validated using an IEEE 33-bus smart distribution system integrated with photovoltaic units, battery energy storage systems, and converter-interfaced loads. Simulation results demonstrate superior performance over conventional centralized learning approaches, achieving reduced operational energy cost, lower communication burden, enhanced voltage regulation, improved renewable utilization, and accelerated model convergence. The proposed FL-IEM framework provides a scalable, privacy-preserving, and intelligent solution for next-generation distributed smart grid energy management.

Keywords: Smart Grid, Federated learning, Intelligent energy management, Distributed power electronic networks, Distributed energy resources, Deep reinforcement learning, Converter-based energy systems.

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1. Introduction

The rapid transformation of conventional electrical power systems into intelligent smart grids has been driven by the increasing deployment of distributed energy resources (DERs), renewable generation systems, battery energy storage systems (BESS), electric vehicle charging infrastructure, and advanced power electronic converters. Unlike traditional centralized power networks, modern smart grids consist of numerous geographically distributed energy nodes capable of bidirectional power exchange, autonomous operation, and real-time coordination [17]- [19]. Power electronic converters play a pivotal role in this transition by facilitating renewable energy integration, voltage regulation, power quality improvement, and dynamic energy sharing among distributed resources [22]- [24]. Consequently, fu-

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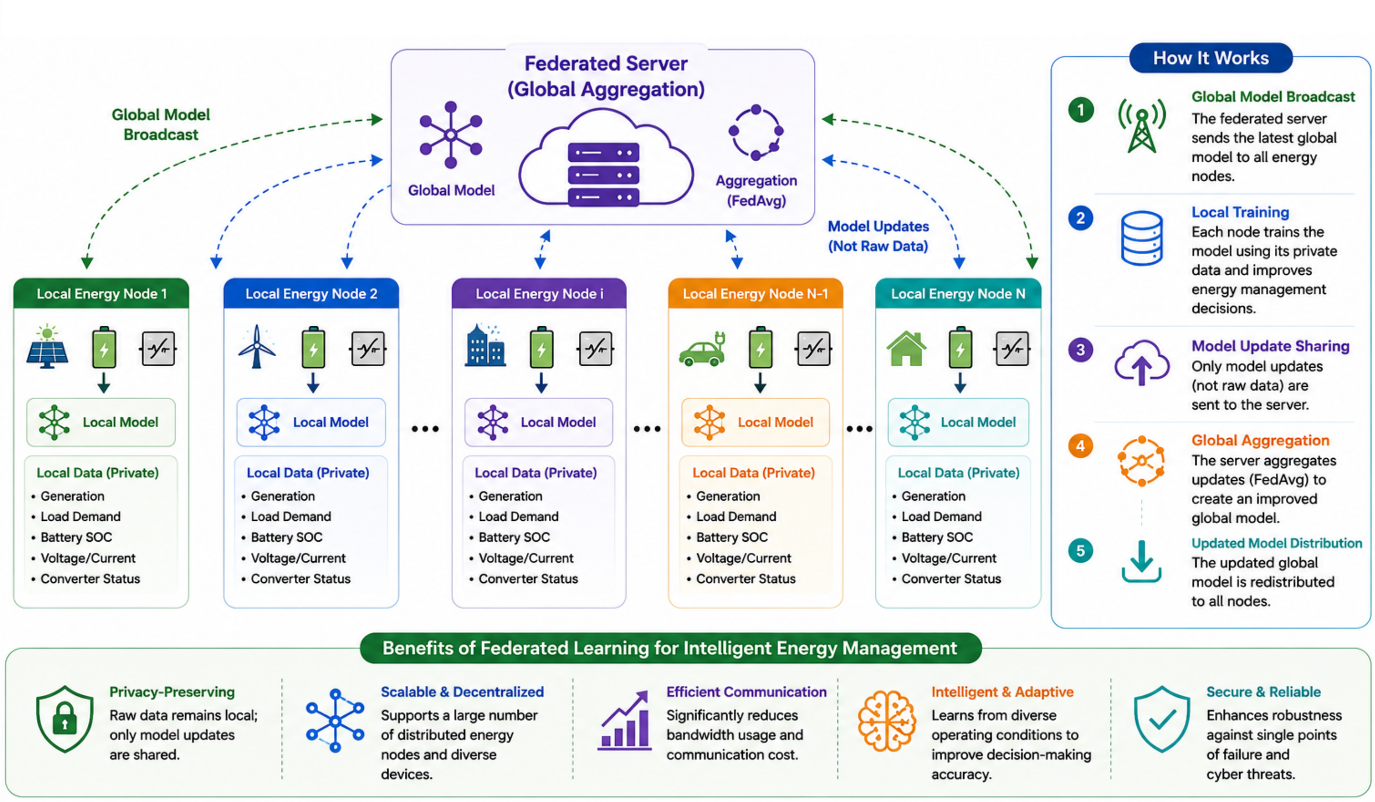
Graphical abstract: FL-IEM framework for distributed power electronic networks in smart grids.



ture distribution networks are expected to operate as highly interconnected cyber-physical systems in which intelligent coordination among converter-interfaced energy resources is essential for ensuring secure, reliable, and efficient grid operation [31], [34].

The increasing penetration of renewable energy sources has significantly enhanced the sustainability of electrical power systems; however, it has also introduced considerable operational challenges [25]-[27]. Renewable generation is inherently intermittent and uncertain, while electricity demand continuously varies with consumer behavior, weather conditions, and market dynamics. Simultaneously, battery energy storage systems require intelligent charging and discharging strategies to maximize operational lifetime and improve renewable energy utilization. The large number of distributed converters, smart sensors, and edge devices deployed throughout modern distribution networks continuously generates high-dimensional operational data that must be processed for real-time energy scheduling, voltage regulation, and coordinated power management. These characteristics make intelligent energy management one of the most challenging problems in next-generation smart grids [31].

Conventional energy management systems generally employ centralized optimization architectures in which operational measurements collected from geographically distributed controllers are transmitted to a central server for forecasting, scheduling, and supervisory control. Although centralized approaches provide satisfactory performance for relatively small systems, their effectiveness decreases as the number of distributed energy resources increases. Continuous transmission of operational measurements results in high communication overhead, increased computational burden, latency during decision-making, and reduced scalability. Furthermore, centralized learning requires sharing sensitive information such as renewable generation profiles, battery operating conditions, and customer demand characteristics, creating concerns regarding cybersecurity, data ownership, and privacy preservation. These limitations motivate the development of distributed intelligence capable of coordinating multiple energy resources without centralized data collection [22], [26].

Recent advances in artificial intelligence have created new opportunities for addressing these challenges through intelligent and distributed decision-making. Deep learning techniques have demonstrated remarkable capability in renewable energy forecasting, demand prediction, converter control, and fault diagnosis, while DRL has emerged as an effective framework for sequential energy management under uncertain operating conditions. By continuously interacting with the operating environment, DRL agents are capable of learning adaptive control policies for battery scheduling, converter coordination, and energy dispatch without requiring explicit mathematical models of system dynamics [8]- [10], [16]. However, most existing learning-based energy management approaches continue to rely on centralized model training, thereby inheriting the communication, scalability, and privacy limitations of conventional cloud-based architectures [28], [29].

Federated Learning (FL) provides a promising alternative by enabling multiple distributed controllers to collaboratively train a shared intelligence model while keeping operational data locally stored [1], [2]. Instead of exchanging raw measurements, participating energy nodes communicate only model parameters during periodic aggregation, thereby preserving data privacy, reducing communication requirements, and improving scalability [3]- [7]. The decentralized nature of Federated Learning closely matches the architecture of modern smart grids, where geographically distributed energy resources operate autonomously while collectively contributing to global system objectives [11]- [15], [30]. Nevertheless, existing studies have primarily investigated federated learning for individual applications such as forecasting, cybersecurity, demand prediction, or energy optimization, whereas comprehensive frameworks integrating distributed power electronic coordination, adaptive reinforcement learning, renewable energy management, and privacy-preserving collaborative optimization remain limited.

The proposed framework integrates FL with DRL to enable collaborative and privacy-preserving energy management among geographically distributed converter controllers. Local edge controllers independently train intelligent energy management models using locally available operational data, while a FedAvg periodically constructs a global intelligence model without exchanging raw measurements. The proposed approach is validated using an IEEE 33-bus smart distribution network integrated with photovoltaic generation, battery energy storage systems, and converter-interfaced distributed energy resources. Simulation results demonstrate improvements in operational cost, renewable energy utilization, voltage regulation, communication efficiency, and model convergence compared with conventional centralized learning and existing intelligent energy management approaches.

The major contributions of this work are summarized as follows:

1. A privacy-preserving FL-IEM framework is developed for distributed power electronic networks in smart grids.
2. A unified FL–DRL architecture is proposed to perform adaptive battery scheduling, converter coordination, renewable energy management, and real-time power dispatch under dynamic operating conditions.
3. The proposed framework is validated on a modified IEEE 33-bus smart distribution system integrated with photovoltaic generation, battery energy storage systems, and converter-interfaced distributed energy resources.

2. Literature review

2.1. Conventional energy management in smart grids

The evolution of smart grids has significantly increased the complexity of energy management owing to the widespread integration of DERs, renewable generation systems, BESS, and converter-interfaced loads. To maintain secure and reliable operation, conventional Energy Management Systems (EMS) have traditionally employed centralized optimization strategies in which operational measurements from geographically distributed resources are collected by a supervisory controller to perform generation scheduling, power dispatch, voltage regulation, and energy balancing. These approaches have been successfully applied in microgrids with moderate penetration of renewable resources, where centralized coordination enables effective utilization of available generation and storage assets while maintaining network stability [17]- [19].

To improve the operational performance of distributed energy systems, hierarchical and decentralized control architectures have gradually replaced purely centralized supervisory frameworks. Hierarchical control separates primary, secondary, and tertiary control functions to enhance voltage regulation, frequency restoration, and economic energy dispatch, thereby improving the scalability and operational flexibility of microgrids containing multiple distributed generators and storage devices [22], [23]. Furthermore, Model Predictive Control (MPC) has been widely adopted for intelligent energy scheduling because of its capability to optimize converter operation while considering system dynamics and operational constraints over a finite prediction horizon. Such predictive optimization techniques have demonstrated improved renewable energy utilization, battery scheduling, and operating cost reduction compared with conventional rule-based strategies [24].

Battery energy storage has also become an essential component of modern smart grids by mitigating renewable intermittency, supporting peak-load management, and improving power quality. Consequently, several optimization methods have been proposed for battery sizing, coordinated charging and discharging, and multi-period scheduling under varying operating conditions [25]- [27]. In addition, increasing penetration of electric vehicles and vehicle-to-grid technologies has introduced new opportunities for distributed energy coordination, while simultaneously increasing the computational complexity of energy management because of bidirectional power exchange and stochastic charging behaviour [31]. Comprehensive studies on microgrid architectures further emphasize that converter coordination, distributed control, and intelligent energy management constitute the foundation of future resilient and sustainable power systems [34].

2.2. Federated learning for smart grid applications

Federated learning was originally proposed to enable communication-efficient distributed optimization by allowing multiple clients to train local models independently and exchange only model parameters with a central aggregation server instead of transmitting raw datasets [1]. Subsequent developments introduced advanced optimization strategies capable of handling statistical heterogeneity, communication constraints, and non-independent and identically distributed (non-IID) data commonly encountered in practical distributed systems. Federated optimization techniques, including federated optimization, Stochastic Controlled Averaging for Federated Learning (SCAFFOLD) [4], and adaptive federated optimization, have significantly improved convergence speed, model robustness, and communication efficiency, thereby establishing FL as a scalable learning framework suitable for large-scale cyber-physical infrastructures [2]- [5]. Comprehensive surveys further demonstrate that federated learning has evolved into a mature distributed artificial intelligence paradigm capable of supporting privacy-preserving optimization across heterogeneous edge computing environments [6], [7].

The characteristics of federated learning closely align with the operational requirements of modern smart grids, where distributed energy resources operate autonomously while collectively contributing to system-wide objectives [18], [20], [21]. Consequently, recent research has increasingly explored FL for distributed energy optimization, renewable energy forecasting, privacy-preserving energy prediction, and secure smart grid operation. Federated learning has been successfully employed to improve distributed energy optimization, enabling geographically dispersed energy nodes to collaboratively enhance scheduling accuracy while reducing communication requirements [11]. Similarly, secure federated frameworks have demonstrated effective energy optimization in smart grids by preserving operational privacy during collaborative learning [12], [13]. Other studies have shown that federated learning can accurately perform energy prediction, detect false data injection attacks, and identify energy theft without exposing sensitive consumer information, thereby simultaneously improving operational intelligence and cybersecurity [14], [15]. More recently, comprehensive surveys have highlighted the growing adoption of federated learning across smart grid applications while also identifying challenges associated with communication efficiency, client heterogeneity, model convergence, and secure deployment in large-scale distributed energy networks [30].

2.3. DRL for energy management

The remarkable success of deep learning in nonlinear function approximation has led to the development of DRL, where deep neural networks are employed to estimate value functions or control policies for complex, high-dimensional decision problems. The pioneering Deep Q-Network (DQN) demonstrated that deep neural networks could effectively learn optimal control policies directly from environmental observations, significantly expanding the applicability of reinforcement learning to practical engineering systems [8]. Subsequent developments have established DRL as a powerful optimization tool for autonomous control, intelligent scheduling, and dynamic resource management, while comprehensive studies have provided robust theoretical foundations and practical implementations for modern reinforcement learning algorithms [10], [28], [29].

In smart grid applications, DRL has been widely investigated for battery energy storage scheduling, renewable energy coordination, demand response, converter control, and intelligent load management. By continuously adapting control decisions according to renewable generation, electricity demand, battery state-of-charge, and network operating conditions, DRL-based controllers can improve operational flexibility while reducing energy cost and enhancing renewable energy utilization. Distributed DRL frameworks have further demonstrated the capability of coordinating intelligent load scheduling among multiple residential energy systems without relying on fixed optimization rules, thereby improving the adaptability of decentralized energy management under stochastic operating conditions [16]. These characteristics make DRL particularly attractive for next-generation smart grids comprising numerous converter-interfaced distributed energy resources.

3. System modelling

3.1. Distributed smart grid architecture

Figure 1 illustrates the overall architecture of the proposed FL-IEM framework. At every sampling interval, the local controller acquires measurements including photovoltaic generation, battery state-of-charge, local load demand, bus voltage, and grid power exchange. These measurements constitute the operating state used by the intelligent controller to determine battery charging or discharging schedules, converter dispatch strategies, and power exchange with the utility grid. Local control decisions are executed through converter interfaces, while only updated learning parameters are periodically transmitted to the federated aggregation server instead of raw operational data [1], [7]. The server combines locally trained models using FedAvg and redistributes the updated global model to all participating controllers, enabling collaborative intelligence across geographically distributed energy nodes without compromising data confidentiality.

3.2. Federated learning model

To enable privacy-preserving collaborative intelligence, the proposed FL-IEM framework employs a FL model in which geographically distributed energy nodes train local energy management models using their own operational data without transferring raw measurements to a centralized server [1], [2]. Figure 2 shows a loop framework of DRL-assisted intelligent energy management. Each edge controller independently utilizes locally acquired information, including photovoltaic generation, battery state-of-charge, load demand, voltage profile, and converter operating conditions, to optimize its local model [6], [7]. After local training, only the updated model parameters are communicated to the federated server, thereby significantly reducing communication overhead while preserving consumer privacy and data ownership [11]- [13].

Assuming that the distributed smart grid consists of K participating energy nodes, the global optimization objective is expressed as (1), where $\mathbf{w}$ denotes the global model parameters, $\mathcal{L}_k(\mathbf{w})$ represents the local loss function of the k^{th} client, n_k is the number of local training samples, and (2) is the total number of samples across all participating clients.

$$\min_{\mathbf{w}} \ \mathcal{L}(\mathbf{w}) = \sum_{k=1}^{K} \frac{n_k}{N} \mathcal{L}_k(\mathbf{w}), \tag{1}$$

$$N = \sum_{k=1}^{K} n_k \tag{2}$$

After completing local optimization, the federated server updates the global model using the FedAvg algorithm is expressed as (3), where $\mathbf{w}_k^{(r+1)}$ denotes the locally trained

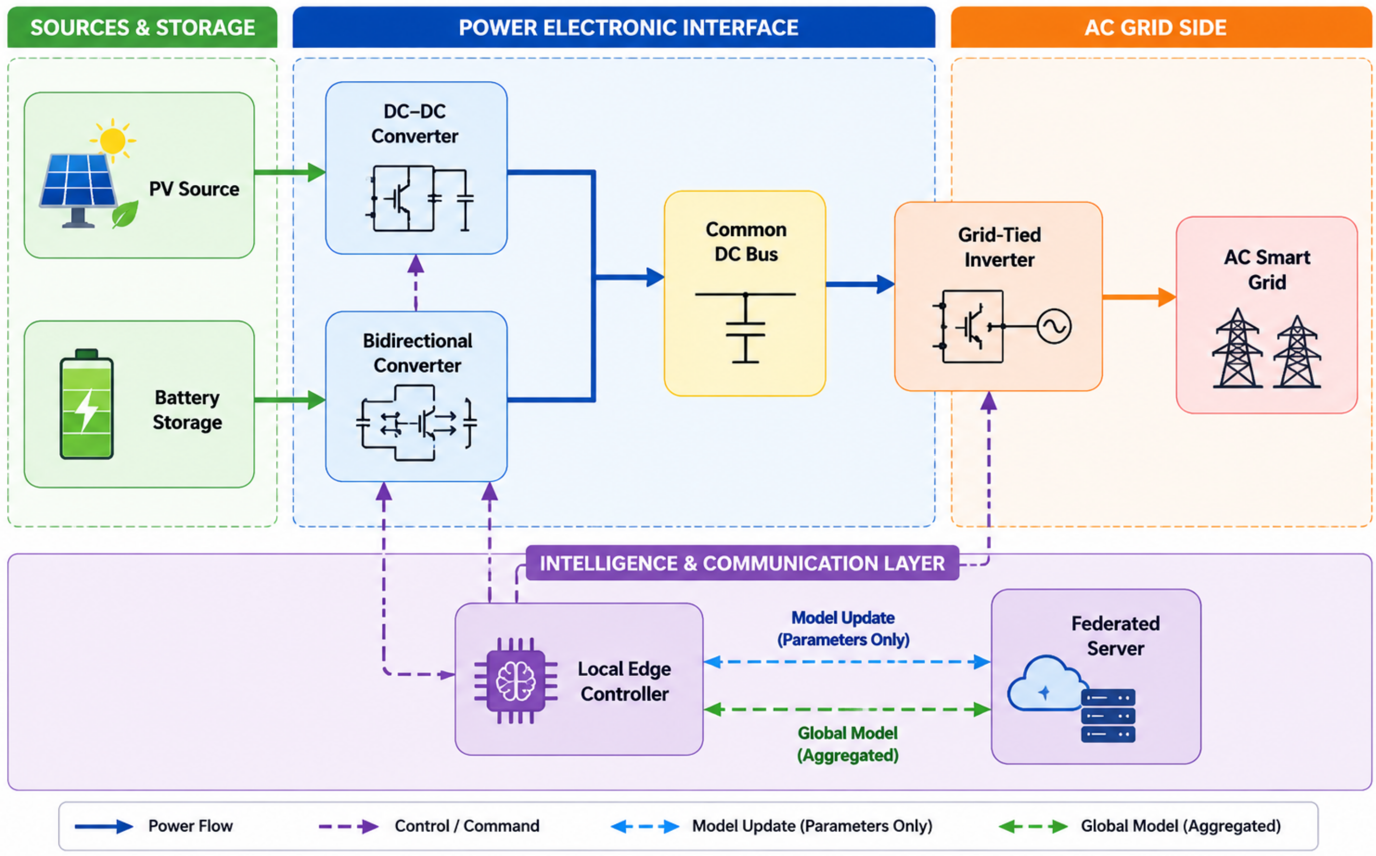


Figure 1: Architecture of the proposed FL-IEM framework for distributed power electronic networks in smart grids.

model parameters after communication round r. The aggregated global model is subsequently redistributed to all distributed controllers for the next learning iteration. This collaborative learning strategy enables geographically distributed converter controllers to continuously improve their intelligence while maintaining communication efficiency, scalability, and operational privacy across the distributed smart grid [1], [5], [30].

$$\mathbf{w}^{(r+1)} = \sum_{k=1}^{K} \frac{n_k}{N} \mathbf{w}_k^{(r+1)} \tag{3}$$

3.3. DRL-based energy management

To achieve adaptive and real-time energy scheduling under dynamic operating conditions, the proposed FL-IEM framework incorporates a DRL-based decision-making model at each distributed energy node. Unlike conventional rule-based or deterministic optimization techniques, the DRL agent continuously interacts with the local smart grid environment and learns an optimal energy management policy through trial-and-error without requiring an explicit mathematical model of system uncertainties [8], [9]. The local controller observes the operating state of the distributed energy system, determines an appropriate control action, receives a reward based on operational performance, and iteratively improves its policy to maximize long-term system efficiency [10], [16].

The energy management problem is formulated as a Markov Decision Process (MDP) is given by (4), where $\mathcal{S}$ denotes the state space, $\mathcal{A}$ represents the action space, $\mathcal{P}$ is the state transition probability, $\mathcal{R}$ denotes the reward function, and γ is the discount factor. At every control interval, the local controller observes the operating state is expressed by (5), where P_t^{PV} is the photovoltaic power generation, P_t^{L} represents the local load demand, SOC_t denotes the battery state-of-charge, V_t is the bus voltage magnitude, and P_t^{grid} is the exchanged utility grid power.

$$\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma), \tag{4}$$

$$s_t = \left[P_t^{PV}, P_t^{L}, SOC_t, V_t, P_t^{grid}\right], \tag{5}$$

Based on the observed operating condition, the DRL agent determines the optimal control action is written as (6), where P_t^{ch} and P_t^{dis} denote the battery charging and discharging powers, respectively, while P_t^{grid} represents the imported or exported grid power. These actions collectively regulate renewable energy utilization, battery scheduling, and converter power dispatch while maintaining system operational constraints.

$$a_t = \left[P_t^{ch}, P_t^{dis}, P_t^{grid}\right] \tag{6}$$

To encourage economically efficient and technically secure operation, the reward function is formulated as (7),

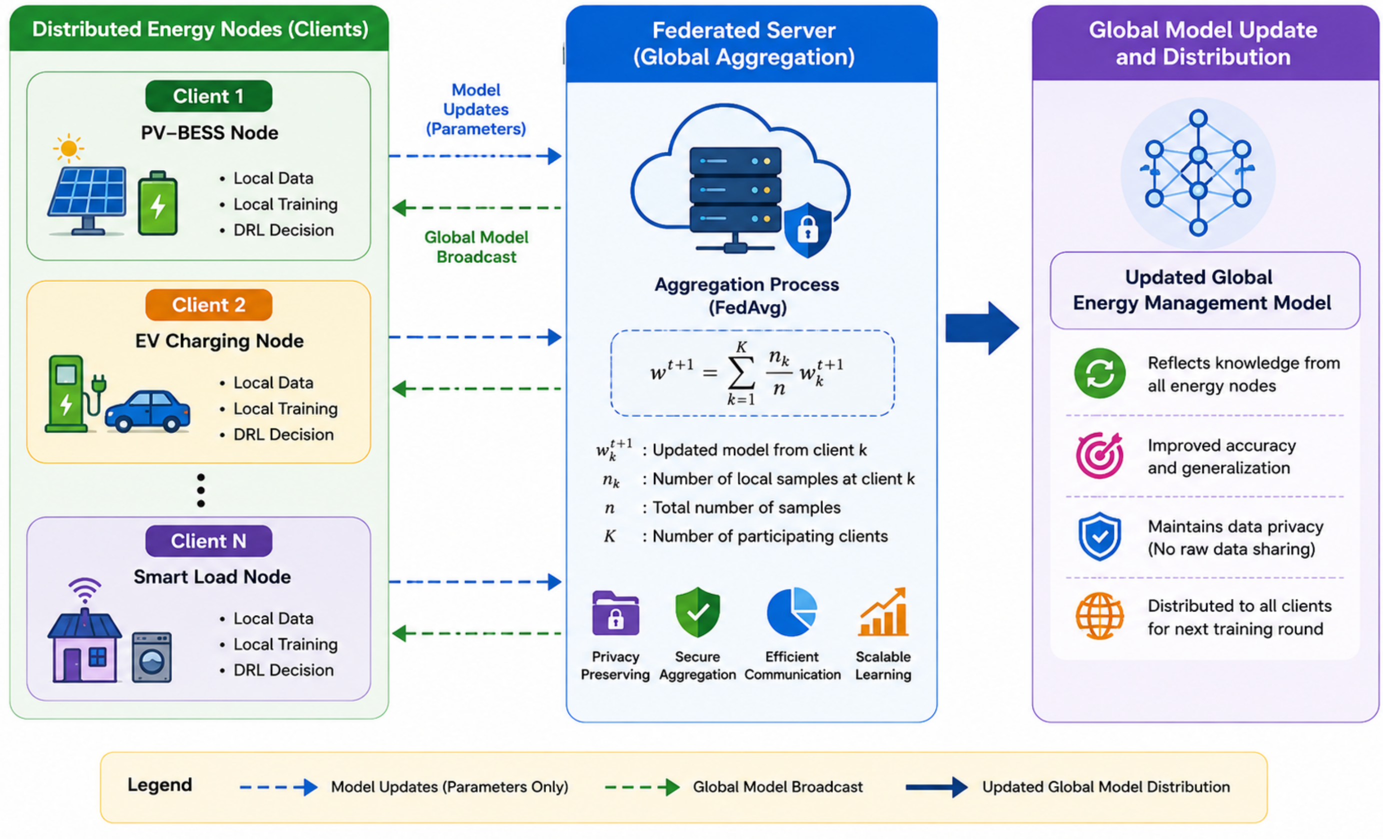


Figure 2: Federated learning process for distributed energy management.

where C_t is the operational energy cost, P_t^{loss} represents feeder and converter losses, V_{ref} denotes the reference bus voltage, D_t^B is the battery degradation penalty, and α, β, λ, and μ are weighting coefficients. This reward formulation simultaneously minimizes operating cost, network losses, voltage deviation, and unnecessary battery cycling. The optimal energy management policy is obtained by maximizing the cumulative discounted reward can be framed as (8).

$$R_t = -\left(\alpha C_t + \beta P_t^{loss} + \lambda |V_t - V_{ref}| + \mu D_t^B\right) \tag{7}$$

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t R_t\right] \tag{8}$$

Within the proposed FL-IEM framework, each distributed controller independently updates its DRL model using locally available operational data. The learned model parameters are then periodically shared with the federated aggregation server, where collaborative knowledge is constructed without exposing raw measurements. Consequently, the proposed framework combines the adaptive decision-making capability of DRL with the privacy-preserving collaborative intelligence of Federated Learning, enabling scalable, communication-efficient, and real-time energy management for distributed power electronic networks [11], [16], [30].

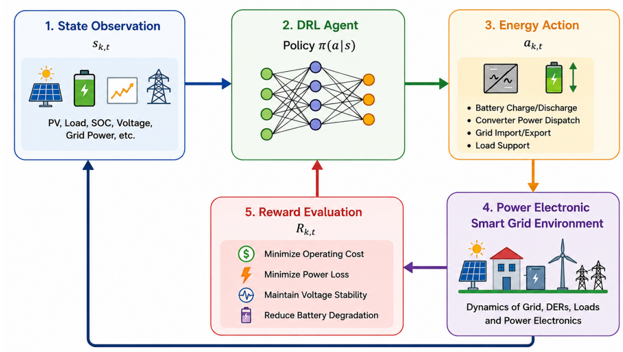


Figure 3: DRL-assisted intelligent energy management loop.

3.4. Multi-objective optimization

The objective of the proposed FL-IEM framework is to determine an optimal energy management policy that simultaneously minimizes operational cost, feeder power losses, voltage deviation, and battery degradation while maximizing renewable energy utilization. Accordingly, the multi-objective optimization problem is formulated as (9), where J_{cost} denotes the grid operating cost, J_{loss} represents feeder and converter power losses, J_{volt} corresponds to voltage deviation from the nominal operating value, and J_{deg} denotes the battery degradation cost. The weighting coefficients α, β, λ, and μ regulate the relative importance of each objective according to the desired operational requirements. The optimization is performed subject to the physical and operational constraints of the distributed smart grid, including power balance is given by (10). The following constraints from (11)-(13) ensure secure system operation while enabling the proposed FL-IEM framework to achieve economically efficient, privacy-preserving, and adaptive energy management under dynamic smart grid operating conditions [17], [32], [33].

$$\min J = \alpha J_{\text{cost}} + \beta J_{\text{loss}} + \lambda J_{\text{volt}} + \mu J_{\text{deg}}, \tag{9}$$

$$P_t^{PV} + P_t^{grid} + P_t^{dis} = P_t^{L} + P_t^{ch} + P_t^{loss}, \tag{10}$$

battery operating limits

$$SOC^{min} \leq SOC_t \leq SOC^{max}, \tag{11}$$

converter power ratings

$$0 \leq P_t^{ch}, P_t^{dis} \leq P^{max}, \tag{12}$$

and permissible bus voltage limits

$$V^{min} \leq V_t \leq V^{max}. \tag{13}$$

3.5. Federated DRL-based intelligent energy management algorithm

The proposed FL-IEM framework operates through iterative communication rounds between distributed edge controllers and the federated aggregation server. Initially, the global model is initialized at the server and distributed to all participating energy nodes. Each local controller observes its operating state, applies DRL-based energy management to determine converter and battery control actions, trains the local model using locally available measurements, and transmits only updated model parameters to the federated server. The server aggregates the received parameters using FedAvg and redistributes the updated global model for the next round. Training continues until the global loss converges or the maximum number of communication rounds is reached. Algorithm 1 ensures that adaptive energy scheduling is performed locally while global intelligence is improved collaboratively through federated aggregation. Since raw operational measurements are not transmitted to the server, the proposed algorithm preserves data privacy, reduces communication burden, and supports scalable implementation in distributed power electronic smart grids [3], [6]- [8], [30].

4. Experimental setup and results

4.1. Experimental setup

The proposed FL-IEM framework was evaluated using a modified IEEE 33-bus radial distribution system. Figure 4 represents diagrammatic structure of Modified IEEE 33-bus distribution system with PV and BESS integration. The test network was selected because it is widely used for analyzing voltage regulation, distributed generation placement, network losses, and energy management in smart distribution grids. The original IEEE 33-bus system was modified by integrating PV generation units, BESS, converter-interfaced loads, and local edge controllers at selected buses Table 1 provides the test system parameters

Algorithm 1 Federated DRL-based intelligent energy management.

Input: Number of clients K, communication rounds R, local datasets $\mathcal{D}_k$, learning rate η, tolerance ϵ
Initialize: Global model parameters $\mathbf{w}^0$ at the federated server
for each communication round $r = 0, 1, \ldots, R-1$ **do**
  Server broadcasts global model $\mathbf{w}^r$ to all participating clients
  for each client $k = 1, 2, \ldots, K$ in parallel **do**
    Collect local measurements $\mathbf{x}_{k,t}$ from PV, BESS, converter, load, and grid sensors
    Construct local state $s_{k,t}$ and select DRL action $a_{k,t}$ using policy $\pi(a|s)$
    Apply selected action for battery charging/discharging, converter dispatch, and grid exchange
    Compute reward $R_{k,t}$ from cost, loss, voltage deviation, and battery degradation terms
    Train local model using $\mathcal{D}_k$ and update parameters $\mathbf{w}_k^{r+1}$
    Upload only $\mathbf{w}_k^{r+1}$ to the federated server
  end for
  Server updates global model using FedAvg:

$$\mathbf{w}^{r+1} = \sum_{k=1}^{K} \frac{n_k}{N} \mathbf{w}_k^{r+1}$$

  Redistribute updated global model $\mathbf{w}^{r+1}$ to all clients
  if $\left|\mathcal{L}^{r+1} - \mathcal{L}^r\right| \leq \epsilon$ **then**
    Stop training
  end if
end for
Output: Final global FL-IEM model $\mathbf{w}^R$

and training parameters are given in Table 2. The main objective of the experimental study was to evaluate the capability of the proposed FL-IEM framework in reducing operational cost, improving voltage stability, lowering power losses, and minimizing communication overhead while preserving local data privacy.

PV generation units were connected at buses 6, 14, 24, and 30, while BESS units were placed at buses 10, 18, and 25. These locations were selected to represent distributed renewable penetration across different sections of the radial feeder. Each renewable-storage unit was interfaced with the grid through a bidirectional power electronic converter and a local edge controller. The local controller collected measurements such as PV output power, load demand, bus voltage, battery state of charge, converter power, and grid exchange power. Each local node acted as a federated client, while the global aggregation unit acted as the federated server.

The simulation was carried out over a 24-hour scheduling horizon with a 15-minute sampling interval, resulting in 96 time steps per day. The load profile was modeled using a normalized residential and commercial demand pattern, while PV generation was represented using a time-varying solar irradiance profile. The battery state of charge was constrained between 20% and 90% to avoid deep discharge and overcharging. The proposed FL-IEM framework was compared with three benchmark approaches: conventional rule-based energy management, centralized deep learning-based energy management, and standalone deep reinforcement learning-based energy management.

Table 1: Modified IEEE 33-bus system configuration.

Parameter	Value
Test system	IEEE 33-bus radial distribution network
Base voltage	12.66 kV
Base power	100 MVA
Number of buses	33
Number of branches	32
PV installation buses	6, 14, 24, 30
BESS installation buses	10, 18, 25
Scheduling horizon	24 h
Time resolution	15 min
Total time steps	96
SOC limits	20–90%
Converter efficiency	96%

Table 2: Federated learning and DRL training parameters.

Parameter	Value
Number of federated clients	7
Communication rounds	100
Local epochs	10
Batch size	64
Optimizer	Adam
Learning rate	0.001
Aggregation method	FedAvg
DRL agent	PPO
Discount factor	0.99
Reward weights $(\alpha, \beta, \lambda, \mu)$	(0.40, 0.25, 0.25, 0.10)

4.2. Performance evaluation metrics

The performance of the proposed FL-IEM framework was evaluated using energy cost, active power loss, voltage deviation, renewable utilization, communication overhead, and convergence performance. The daily energy cost was computed based on grid import power and time-varying electricity price. The total operating cost is expressed as (14), where C_t^{grid} is the grid electricity price, P_t^{grid} is the grid import power, and Δt is the sampling interval.

$$C_{total} = \sum_{t=1}^{T} C_t^{grid} P_t^{grid} \Delta t \tag{14}$$

The total active power loss of the distribution feeder is calculated as (15), where I_l and R_l represent the current and resistance of the l^{th} feeder branch, respectively. Voltage deviation is used to evaluate the voltage regulation capability of the energy management strategy and which is given by (16), where N is the number of buses and V_{ref} is the nominal voltage.

$$P_{loss} = \sum_{l=1}^{N_l} I_l^2 R_l \tag{15}$$

$$VD = \frac{1}{NT} \sum_{t=1}^{T} \sum_{i=1}^{N} |V_{i,t} - V_{ref}| \tag{16}$$

Communication overhead was estimated by calculating the total information exchanged between edge controllers and the central server. In centralized learning, raw operational data from all nodes are transmitted to the cloud server, whereas in FL-IEM only model parameters are exchanged. Therefore, the communication reduction is expressed as (17), where $D_{centralized}$ and D_{FL} represent data transfer requirements under centralized and federated learning schemes, respectively.

$$CR(\%) = \frac{D_{centralized} - D_{FL}}{D_{centralized}} \times 100 \tag{17}$$

4.3. Results and comparative analysis

The obtained simulation results demonstrate that the proposed FL-IEM framework outperforms conventional energy management approaches in terms of cost reduction, voltage improvement, loss minimization, and communication efficiency. The rule-based controller provides limited adaptability because it follows predefined operating thresholds and does not learn from dynamic operating conditions. Centralized deep learning improves scheduling performance but requires high data transfer and exposes local operational information. Standalone DRL achieves adaptive decision-making but lacks collaborative learning among geographically distributed converter nodes. In contrast, FL-IEM combines distributed learning and adaptive decision-making, resulting in improved overall system performance.

Table 3 shows the comparative performance of the proposed method against other approaches. The proposed FL-IEM method achieved the lowest daily operating cost of 1284.6 monetary units compared with 1627.4 for rule-based EMS, 1453.2 for centralized DL, and 1376.8 for standalone DRL. The reduction in cost is mainly attributed to improved renewable utilization, optimal battery scheduling, and reduced grid import during peak price intervals. Moreover, the proposed method reduced active power loss to 132.5 kW, indicating better distributed power sharing and voltage support.

Table 3: Performance comparison of energy management strategies.

Method	Cost (units/day)	Loss (kW)	VD (p.u.)	REU (%)
Rule-based EMS	1627.4	186.3	0.048	71.2
Centralized DL	1453.2	159.8	0.039	78.5
Standalone DRL	1376.8	148.6	0.035	82.7
Proposed FL-IEM	1284.6	132.5	0.029	88.9

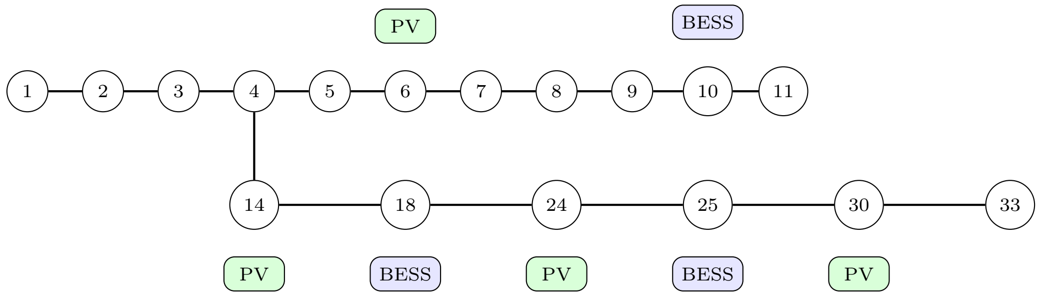


Figure 4: Modified IEEE 33-bus distribution system with PV and BESS integration.

Table 4 shows a comparison of voltage profile improvement. Further, Figure 5 shows a comparison of rule-based EMS versus proposed FL-IEM. The voltage profile of the IEEE 33-bus system was significantly improved after applying the proposed energy management framework. The minimum bus voltage under rule-based control was 0.913 p.u., whereas the proposed FL-IEM maintained the minimum voltage at 0.951 p.u. This improvement was achieved through coordinated dispatch of distributed batteries and converter-interfaced PV systems near weak buses. The results confirm that federated intelligence can enhance local decision-making while supporting global voltage regulation.

Table 4: Voltage profile improvement.

Method	$V_{\min}$ **(p.u.)**	$V_{\max}$ **(p.u.)**	**Avg. VD (p.u.)**
Rule-based EMS	0.913	1.021	0.048
Centralized DL	0.936	1.018	0.039
Standalone DRL	0.944	1.016	0.035
Proposed FL-IEM	0.951	1.013	0.029

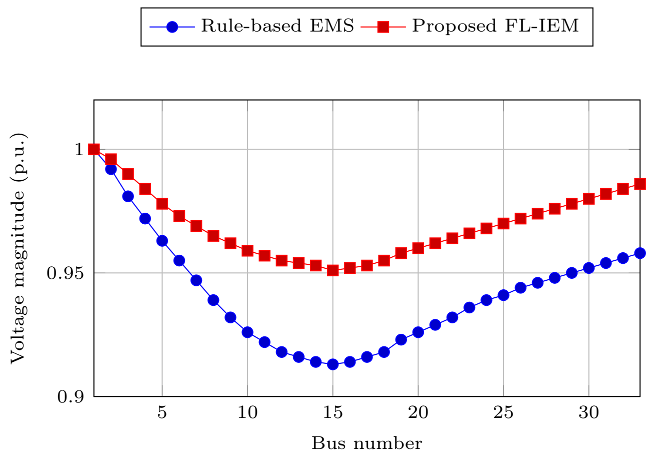


Figure 5: Voltage profile comparison for IEEE 33-bus system.

4.4. *Federated learning convergence and communication analysis.*

The convergence behavior of the proposed FL-IEM framework was analyzed over 100 communication rounds and Figure 6 shows convergence performance of the proposed FL-IEM framework. The global training loss decreased steadily during the initial rounds and reached a stable value after approximately 82 communication rounds. Compared with centralized deep learning, the federated framework exhibited competitive convergence while significantly reducing the need for raw data transmission. The convergence behavior confirms that distributed converter controllers can collaboratively learn a generalized energy management policy even when operating under heterogeneous local conditions.

Communication efficiency is a major advantage of the proposed framework. In centralized learning, all local measurements from PV units, BESS systems, loads, and converter controllers are transmitted to a cloud-based server. This increases bandwidth usage and introduces privacy vulnerabilities. In the proposed FL-IEM framework, only model weights are exchanged between local controllers and the federated server. As shown in Table 5, the proposed method reduced daily communication burden from 4.85 GB to 2.06 GB, corresponding to a 57.5% reduction.

Table 5: Comparision of communication burden.

Method	**Data transfer (GB/day)**	**Reduction (%)**
Centralized DL	4.85	–
Standalone DRL	3.92	19.2
Proposed FL-IEM	2.06	57.5

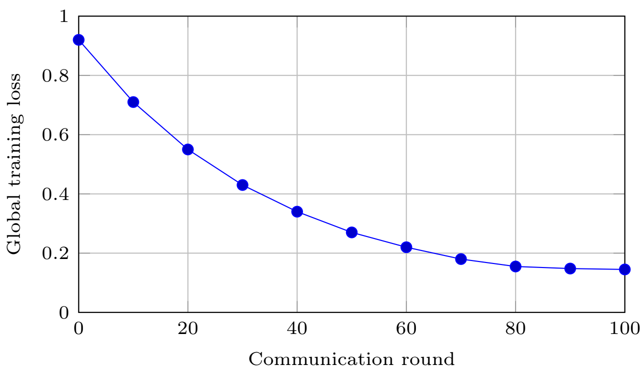


Figure 6: Convergence performance of the proposed FL-IEM framework.

4.5. *Energy scheduling and battery operation*

As shown in Figure 7, the proposed FL-IEM framework effectively scheduled battery charging and discharging based on renewable availability, load demand, and grid price variation. During high PV generation periods, excess renewable energy was used to charge the battery units. During peak load and high tariff periods, the BESS discharged energy to support local demand and reduce grid import.

The battery state-of-charge remained within the allowable operating range throughout the simulation period. Table 6 shows the parameters performance of battery operation. The intelligent controller avoided unnecessary charge-discharge cycling, thereby reducing battery degradation penalty. Compared with standalone DRL, federated learning improved generalization across different buses by allowing controllers to learn from distributed operating patterns without sharing raw local measurements.

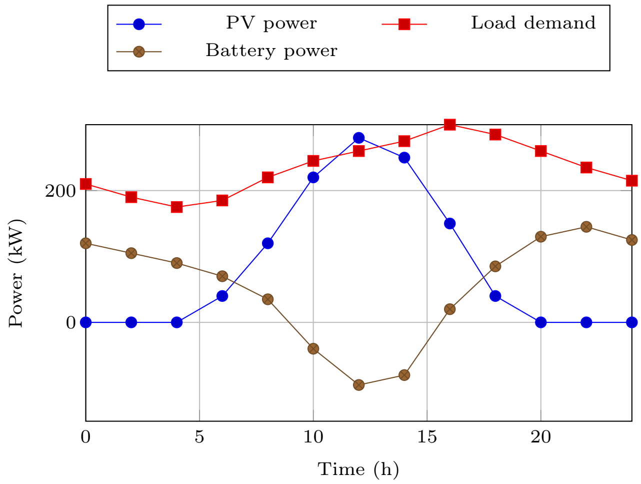


Figure 7: Daily energy scheduling under the proposed FL-IEM framework.

Table 6: Performance of battery operation.

Parameter	Proposed FL-IEM
Initial SOC	50%
Minimum SOC	28.6%
Maximum SOC	86.4%
Average SOC	57.8%
Daily charge energy	426.3 kWh
Daily discharge energy	391.7 kWh
Battery violation count	0

The integration of federated learning enables distributed controllers to collaboratively improve energy management performance without centralizing raw data. Meanwhile, the DRL-assisted scheduling layer improves adaptability under time-varying renewable generation, load demand, and electricity pricing conditions.

5. Conclusion

This paper presented FL-IEM framework for distributed power electronic networks in smart grids. The proposed approach integrates privacy-preserving federated learning with DRL-assisted energy scheduling to enable coordinated converter operation without sharing raw local data. Validation on the modified IEEE 33-bus distribution system demonstrated that the proposed FL-IEM framework effectively reduces operational cost, minimizes feeder losses, improves voltage regulation, enhances renewable energy utilization, and lowers communication burden compared with conventional centralized and standalone learning-based methods. The results confirm that distributed intelligence can provide scalable, secure, and adaptive energy management for renewable-rich smart grids. Hence, the proposed framework offers a practical pathway for next-generation converter-dominated power systems involving distributed energy resources, battery storage, electric vehicle charging infrastructure, and edge-enabled smart grid applications.

Declarations and ethical statements

Conflict of interest: The authors declare that there is no conflict of interest.
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Artificial Intelligence usage statement: During the preparation of this manuscript, the authors utilized ChatGPT solely for grammatical corrections and visualizations. The author carefully reviewed and revised the generated content and take full responsibility for the accuracy, integrity, and originality of the final manuscript.
Availability of data and materials: The data and/or materials that support the findings of this study are available from the corresponding author(s) upon reasonable request.

CRediT authorship contribution statement

Ashok Yadav: Data collection, Editing & Visualization. **Bomma Siddhartha**: Conceptualization, Editing & Formal analysis. **Balwant Singh Kuldeep**: Data collection & Formal analysis. **Deigratia Sutnga**: Formal analysis & Visualization. **Aashish Samota**: Conceptualization, Investigation, Writing – review & editing.

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