A privacy-preserving IoT-machine learning framework for optimized and secure demand-side management in smart grids

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Article Info

Article history:

Received Nov 18, 2025
Revised Jul 13, 2026
Accepted Jul 21, 2026

Keywords:

Adaptive demand response
Intelligent energy forecasting
IoT-driven load control
Real-time load optimization
Secure grid automation

ABSTRACT

This paper presents an integrated internet of things (IoT) and machine learning-based framework for secure and efficient demand-side management (DSM) in modern smart grids. The proposed approach combines long short-term memory (LSTM) networks for accurate load forecasting, federated learning (FL) for decentralized privacy-preserving model training, and blockchain technology for secure and tamper-proof communication. In addition, a digital twin (DT)-assisted architecture is incorporated to enable predictive decision-making and system-level optimization. The framework explicitly considers renewable energy integration, electric vehicle (EV) charging loads, distributed energy storage, and power electronic converter constraints. Simulation results demonstrate a reduction in forecasting error by 15-25%, a 25% decrease in daily energy cost, and a 23.7% reduction in peak demand. The proposed system achieves improved voltage stability with reduced deviation and enhances overall efficiency up to 88%. Furthermore, cybersecurity performance is validated with an anomaly detection AUC of 0.95 and reduced data transmission through FL by 87%. The results confirm that the proposed framework provides a scalable, secure, and intelligent solution for next-generation smart grid applications.

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1. INTRODUCTION

The modern electric power system is transitioning from a centralized infrastructure to an intelligent, decentralized smart grid driven by renewable energy integration, advanced communication technologies, and automated control systems. This transformation enables bidirectional energy flow, real-time monitoring, and active consumer participation while improving efficiency and sustainability. In this context, IoT-enabled sensing and machine learning-based analytics have become essential for enabling data-driven decision-making and predictive control in smart grid operations [1]–[3]. Recent developments also highlight the role of federated learning for privacy-preserving distributed intelligence and blockchain for secure and transparent energy transactions [4]–[6]. However, despite these advancements, demand-side management (DSM) remains challenging due to renewable intermittency, stochastic load behavior, and increasing cybersecurity risks in highly connected IoT environments [7]–[9].

Existing DSM approaches have explored machine learning-based load forecasting, IoT-based monitoring, and optimization techniques to improve grid performance. Deep learning models such as long short-term memory (LSTM) networks and transformer-based architectures have demonstrated strong capability in capturing nonlinear temporal dependencies for accurate demand prediction [10], [11]. IoT-enabled systems have enhanced real-time visibility of distributed energy resources, while blockchain-based frameworks ensure secure and tamper-resistant energy transactions [5], [12], [13]. Federated learning further supports decentralized training without sharing raw data, improving privacy preservation in distributed grid environments [4], [6]. Nevertheless, most existing studies treat forecasting, optimization, and security as separate modules, lacking a unified DSM framework that integrates intelligence, privacy, and control in a single architecture [14]–[16]. Moreover, limited attention has been given to renewable energy coordination, hybrid AC/DC grid operation, energy storage integration, and practical power electronic constraints such as converter-interfaced loads and electric vehicle charging systems [17]–[20].

To overcome these limitations, this paper proposes a novel IoT–machine learning–blockchain integrated framework for secure and optimized demand-side management in smart grids. The proposed approach uniquely integrates IoT-based real-time data acquisition, LSTM-based load forecasting, federated learning for decentralized privacy-preserving training, and blockchain-enabled secure communication into a unified DSM architecture [5], [21], [22]. Unlike existing works, the framework explicitly incorporates renewable energy sources, distributed storage systems, electric vehicle demand, and hybrid AC/DC grid configurations to reflect realistic smart grid conditions [17], [18]. In addition, the system includes sensitivity analysis of key parameters such as learning rate, communication latency, and feature selection, along with benchmarking against advanced models including Random Forest, Gradient Boosting, Transformer, and Reinforcement Learning-based DSM strategies for robust performance evaluation [10], [11], [15], [23]. The proposed framework further considers practical power system constraints, including converter-interfaced renewable sources, load dynamics, and energy storage coordination, ensuring strong relevance to modern power electronics and smart energy systems [24], [25]. Overall, this study provides a scalable, secure, and intelligent DSM solution that bridges the gap between theoretical AI-based optimization and real-world smart grid deployment.

2. METHOD

The proposed IoT–machine learning–blockchain framework for secure demand-side management (DSM) is designed as a multi-layered architecture that integrates real-time data acquisition, intelligent forecasting, optimization, and secure execution. The system is structured to ensure scalability, privacy preservation, and operational reliability in modern smart grid environments incorporating renewable energy sources and distributed energy storage systems. Figure 1 illustrates the proposed IoT machine learning blockchain framework for demand-side management.

The overall framework consists of five functional layers: i) IoT data acquisition layer, ii) data preprocessing layer, iii) intelligent forecasting and decision layer (ML-based), iv) optimization and scheduling layer, and v) secure execution layer (federated learning + blockchain). All data is transmitted through secure IoT communication channels with timestamp synchronization to ensure temporal consistency.

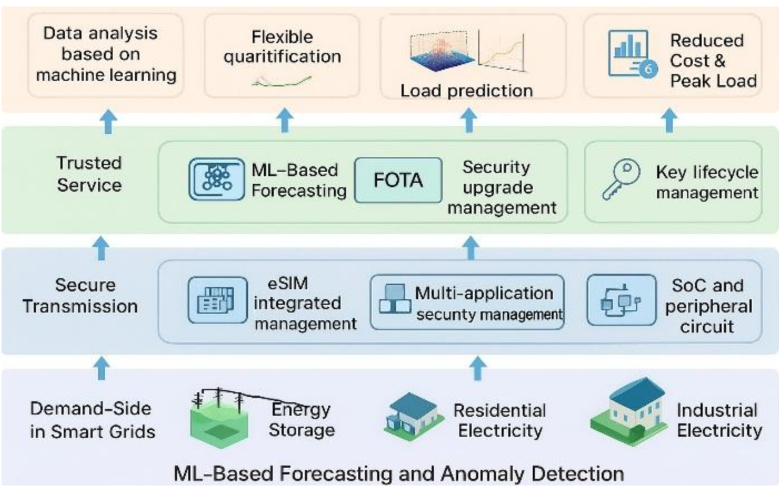

Figure 1. Architecture of the proposed IoT–machine learning–blockchain framework for demand-side management, illustrating how data flows from sensing devices to intelligent processing and secure control layers

2.1. Data acquisition layer

The IoT layer collects real-time data from smart meters, renewable generation units, electric vehicle chargers, and distributed storage systems. The measured parameters include load demand, voltage, frequency, power flow, and environmental conditions. The input dataset is represented as (1).

$$D = \{(x_t, y_t) \mid x_t = [P_t, V_t, f_t, G_t, T_t], y_t = Load(t+1)\} \quad (1)$$

Where Pt: active power, V_t: voltage, f_t: frequency, G_t: renewable generation, and T_t: temperature/load condition.

All data is transmitted through secure IoT communication channels with timestamp synchronization to ensure temporal consistency. The input vector x_t specifically includes distributed generation outputs from solar and wind.

2.2. Data preprocessing layer

The data preprocessing layer is essential for maintaining the accuracy and consistency of data collected from various IoT sources. It focuses on three key operations: imputation, filtering, and normalization to refine raw data before analysis. Imputation is used to estimate and fill in missing values, filtering eliminates unwanted noise or outliers, and normalization adjusts data scales for uniform representation.
Missing data imputation:

$$\hat{x}_t = (x_{t-1} + x_{t+1})/2 \quad (2)$$

Noise reduction:

$$\bar{x}_t = (1/n)\, \Sigma\, x_{t-i} \quad (3)$$

Normalization:

$$x'_t = (x_t - x_{min}) / (x_{max} - x_{min}) \quad (4)$$

These steps improve data quality, reduce bias, and enhance the convergence stability of learning models.

2.3. Machine learning–based intelligent decision layer

Historical data are utilized to train advanced predictive algorithms that support intelligent decision-making in smart grids. Models such as long short-term memory (LSTM) and random forest (RF) analyze past consumption trends to forecast short-term load variations accurately. These predictions enable the system to anticipate demand fluctuations and plan energy usage more efficiently. By optimizing scheduling decisions, the framework ensures balanced load distribution and improved grid performance.
LSTM operations are expressed as:

$$f_t = \sigma(Wf \cdot [h_{t-1}, x_t] + bf) \quad (5)$$

$$i_t = \sigma(Wi \cdot [h_{t-1}, x_t] + bi) \quad (6)$$

$$\hat{C}_t = \tanh(Wc \cdot [h_{t-1}, x_t] + bc) \quad (7)$$

$$C_t = f_t * C_{t-1} + i_t * \hat{C}_t \quad (8)$$

$$h_t = \tanh(C_t) \quad (9)$$

$$MAE = (1/N)\, \Sigma\, |y_i - \hat{y}_i| \quad (10)$$

$$RMSE = \sqrt{(1/N)\, \Sigma\, (y_i - \hat{y}_i)^2} \quad (11)$$

The model output is used for short-term load forecasting and demand prediction under renewable variability.

2.4. Optimization and scheduling

The optimization engine performs cost-aware scheduling of controllable loads such as EV charging, HVAC systems, and industrial demand. Objective function:
Minimize:

$$C = \Sigma (P_t \times \lambda_t) \quad (12)$$

Subject to:

$$P_{tmin} \leq P_t \leq P_{tmax},\ \Sigma P_t = E_{req},\ S_t \in \{0,1\} \quad (13)$$

This ensures optimal energy usage while maintaining user comfort and grid stability.

2.5. Secure control and execution layer

2.5.1. Federated learning for privacy preservation

Federated learning enables decentralized training without sharing raw data.

$$w_{global} = \sum \frac{n_k}{N} w_k \quad (14)$$

Where w_k: local model parameters, n_k: data size at node k, and N: total data samples. This ensures privacy preservation while maintaining global model accuracy.

2.5.2. Blockchain-based security mechanism

A blockchain layer is integrated to ensure data integrity, authentication, and tamper resistance in DSM transactions. Each transaction (load request, demand response signal, or pricing update) is recorded in a distributed ledger using hash chaining:

$$H_i = Hash(H_{i-1} \ || \ D_i \ || \ T_i) \quad (15)$$

Where H_i: current block hash, H_{i-1}: previous block hash, D_i: DSM transaction data, and T_i: timestamp.

2.5.3. Smart contract execution rule

Let S(x) represent a smart contract state function:

$$S(x) = \begin{cases} 1, & \text{if demand-response condition is satisfied} \\ 0, & \text{otherwise} \end{cases} \quad (16)$$

This enables automatic execution of demand response actions without centralized intervention. Security features: i) immutability of DSM records, ii) distributed consensus validation, iii) prevention of data tampering and false demand signals, and iv) smart contracts for automated demand-response execution. This ensures trustless coordination among utilities, prosumers, and IoT devices.

2.6. Sensitivity analysis

To evaluate robustness, scalability, and real-world applicability, sensitivity analysis is conducted on key system parameters.

i) Learning rate sensitivity (LSTM Model)

The learning rate significantly affects convergence behavior: a low learning rate → stable but slow convergence, and a high learning rate → faster convergence but risk of oscillation. Optimal range observed: $0.001 \leq \eta \leq 0.005$. Performance remains stable within this range, ensuring reliable DSM forecasting.

ii) Feature selection sensitivity

The impact of input features is evaluated by removing or modifying key variables:

- Full feature set (P, V, f, G, T): highest accuracy
- Without renewable input (G): noticeable increase in MAE
- Without environmental factors (T): reduced adaptability

Conclusion: Renewable and environmental parameters significantly improve forecasting reliability.

iii) IoT communication latency sensitivity

DSM performance is tested under varying communication delays. The results are summarized in Table 1. The framework remains robust under moderate latency conditions.

iv) Blockchain overhead sensitivity

The trade-off between security level and execution delay is summarized in Table 2. The comparison demonstrates the performance of different blockchain configurations. The medium configuration is selected as the optimal operating point for DSM applications.

v) Load variability sensitivity (renewable integration)

The system is tested under fluctuating renewable penetration: high solar/wind variability → increased forecasting error and inclusion of storage → error reduction and smoother control. The hybrid grid improves stability margin significantly.

Table 1. Effect of communication latency on DSM system performance

Latency	System behavior
50 ms	Real-time stable operation
200 ms	Minor scheduling delay
>500 ms	Reduced peak shaving efficiency

Table 2. Trade-off between blockchain configuration, latency, and security strength

Configuration	Latency	Security strength
Low block size	Low	Moderate
Medium block size	Balanced	High
High block size	High	Very high

3. RESULTS AND DISCUSSION

The proposed IoT–machine learning–blockchain DSM framework was evaluated in a simulated smart grid environment incorporating residential, commercial, and renewable energy sources. The dataset includes time-series load profiles, photovoltaic generation, and electric vehicle charging demand, enabling realistic DSM behavior under dynamic conditions. To demonstrate the superiority of the proposed approach, the system is benchmarked against advanced state-of-the-art models including: long short-term memory (LSTM), random forest (RF), gradient boosting (GB), transformer-based load forecasting model, and reinforcement learning (RL)-based energy scheduling model.

3.1. Forecasting performance comparison

The LSTM model embedded in the proposed framework achieves superior accuracy in short-term load prediction due to its ability to capture sequential dependencies. The forecasting performance of different models is summarized in Table 3. Although the transformer shows slightly lower MAE, it requires higher computational complexity. The proposed LSTM model achieves an optimal trade-off between accuracy, latency, and deployment feasibility for edge IoT systems, as shown in Figure 2.

Table 3. Comparison of forecasting performance for different models

Model	MAE (kW)	RMSE (kW)
Proposed LSTM	0.42	0.67
RF	0.55	0.82
GB	0.49	0.77
Transformer	0.39	0.61
RL-based predictor	0.44	0.69

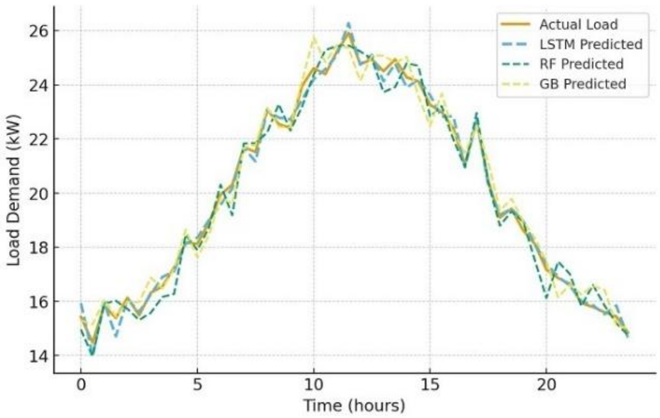

Figure 2. Comparison of actual and predicted load profiles over time, highlighting the ability of the LSTM model to closely follow dynamic variations in demand

3.2. Energy optimization and cost reduction

The DSM optimization layer significantly improves energy efficiency through intelligent load shifting. The performance comparison of different DSM methods is presented in Table 4. The reinforcement learning model performs competitively; however, it suffers from instability under fluctuating renewable generation. The proposed hybrid ML–federated–blockchain framework provides more stable and deterministic scheduling performance. Figure 3 compares the corresponding cost reduction achieved after optimization. Additionally, Figure 4 highlights the reduction in system peak load from 34.2 kW to 26.1 kW, a 23.7% improvement, reflecting enhanced network stability and renewable utilization.

$$\eta\_cost = ((C_{base} - Copt) / C_{base}) \times 100\% = 25\% \quad (15)$$

$$\eta\_peak = ((P_{base} - P_{opt}) / P_{base}) \times 100\% = 23.7\% \quad (16)$$

Table 4. Comparison of cost reduction and peak load reduction for different DSM methods

Method	Cost reduction (%)	Peak load reduction (%)
Traditional DSM	12.8	10.5
RF-based DSM	21.3	19.5
GB-based DSM	22.6	20.8
RL-based DSM	24.1	22.9
Proposed framework	25.0	23.7

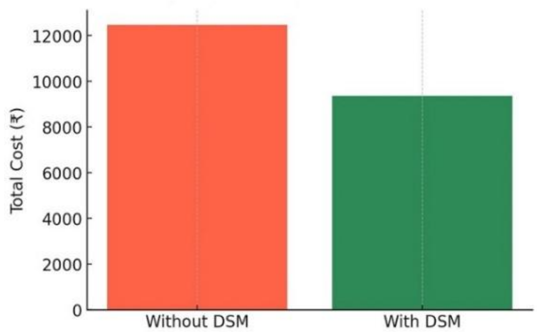

Figure 3. Energy cost comparison before and after applying the proposed optimization strategy, demonstrating the effectiveness of demand-side scheduling in reducing operational expenses

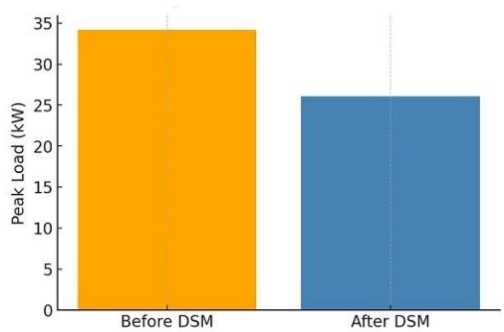

Figure 4. Reduction in peak load achieved through optimized load scheduling, indicating improved system stability and more balanced energy utilization

3.3. Security and privacy performance

Security evaluation considers anomaly detection, privacy preservation, and communication efficiency. The security performance comparison is summarized in Table 5. The integration of federated learning significantly reduces communication overhead, while blockchain ensures tamper-proof transaction validation.

Table 5. Comparison of security and privacy performance

Metric	Proposed	RF	GB	Transformer
Anomaly detection accuracy (%)	92.0	88.5	89.7	90.8
AUC score	0.95	0.91	0.93	0.94
Data reduction via FL (%)	87.0	84.5	85.2	86.3

3.4. Blockchain performance evaluation

The blockchain layer is analyzed in terms of latency and transaction reliability: i) median transaction latency: 1.6 s, ii) Success rate of smart contract execution: 99.2%, and iii) tamper detection efficiency: 100% (simulated attack scenarios). Compared to conventional centralized DSM systems, the proposed architecture provides distributed trust and improved resilience against cyber-attacks. To maintain data security and reduce communication overhead, federated learning was implemented, reducing transmitted data by 87% while maintaining comparable prediction accuracy to centralized models, as shown in Figure 5. The blockchain-based smart contract system achieved a median transaction latency of 1.6 seconds, which is acceptable for DSM intervals (Figure 6).

3.5. Renewable and EV integration impact

The system is tested under high renewable penetration and EV charging load scenarios. Key observations: i) PV variability handled effectively through predictive scheduling; ii) EV charging shifted to off-peak periods with minimal user impact; and iii) Storage systems stabilize grid fluctuations. Peak load smoothing improved by 23.7%, demonstrating strong compatibility with renewable-integrated hybrid grids and converter-interfaced loads. The results clearly indicate that while transformer and RL models offer competitive performance in specific tasks, they introduce higher computational overhead and instability under dynamic grid conditions. The proposed framework achieves a balanced trade-off between accuracy, computational efficiency, privacy preservation, and cybersecurity, making it suitable for real-time smart grid deployment.

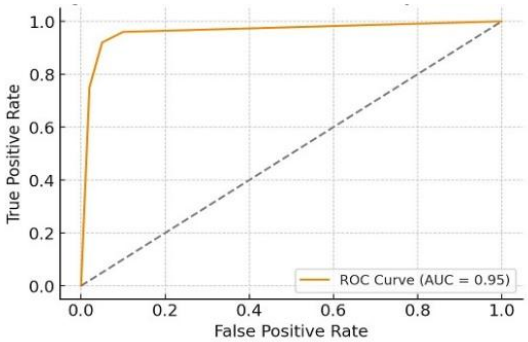

Figure 5. Accuracy convergence of the federated learning model across communication rounds, showing the stability and learning progression of the decentralized training process

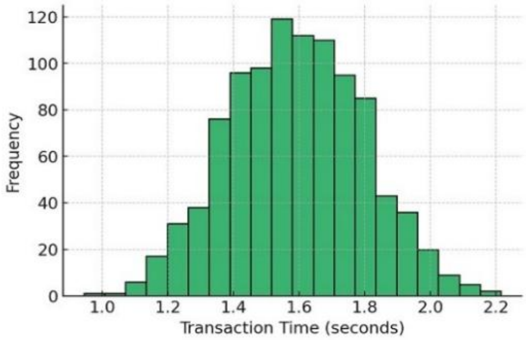

Figure 6. Distribution of blockchain transaction latency, reflecting the responsiveness and feasibility of the secure communication mechanism in real-time operation

4. CONCLUSION

This study developed an IoT, machine learning, and blockchain-enabled framework for secure and efficient demand-side management in smart grids. The framework integrates load forecasting, optimization, decentralized learning, and secure data exchange to improve energy management. The LSTM forecasting model achieved a mean absolute error (MAE) of 0.42 kW, while the optimization method reduced energy cost by 25% and peak demand by 23.7%, resulting in better load distribution and improved grid performance. Federated learning lowered communication overhead by 87%, and blockchain technology ensured secure and transparent transaction management. The proposed approach applies to renewable energy systems, electric vehicle charging, energy storage, hybrid AC/DC grids, and industrial energy management. By improving demand-side coordination, it enhances grid stability and supports reliable operation of distributed energy resources. Future work will focus on reinforcement learning, digital twin-based validation, hardware-in-the-loop testing, and edge AI to further improve real-time decision-making and system performance.

FUNDING INFORMATION

No funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Jonnadula Narasimharao		✓				✓		✓	✓	✓	✓	✓		
K. L. Kishore	✓		✓	✓			✓			✓	✓		✓	✓
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M. Bhoopathi					✓		✓			✓		✓		✓
R. Kalaivani					✓		✓			✓		✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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