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Energy-efficient intelligent management for smart grids using AI

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ABSTRACT

The increasing penetration of renewable energy sources, electric vehicles, and distributed energy resources introduces significant uncertainty and operational complexity in modern smart grids. To address these challenges, this paper proposes an integrated artificial intelligence (AI)-driven energy management framework that combines hybrid deep learning, reinforcement learning, and data-driven anomaly detection. A hybrid ResNet-LSTM architecture is employed for short-term load and renewable generation forecasting, leveraging residual learning to enhance feature extraction and improve temporal prediction accuracy. The forecasting outputs are utilized within a reinforcement learning-based demand response model, where an optimal control policy is learned to minimize energy cost and peak demand through a reward-driven optimization mechanism. Furthermore, an autoencoder-based anomaly detection module is incorporated to identify deviations between predicted and measured grid states using reconstruction error thresholds, enabling early detection of cyber-attacks and system faults. The framework is validated using time-series historical load and renewable datasets with appropriate preprocessing and normalization. Quantitative evaluation using mean squared error and cost-related metrics demonstrates superior performance compared to baseline models. The proposed approach provides a scalable, robust, and unified solution for intelligent, secure, and energy-efficient smart grid operation.

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1. INTRODUCTION

The rapid evolution of modern power systems, driven by the large-scale integration of renewable energy sources, increasing penetration of electric vehicles (EVs), and the deployment of advanced communication infrastructures, has transformed conventional grids into complex cyber-physical smart grid systems. These next-generation grids require intelligent, adaptive, and energy-efficient management strategies to ensure reliable and sustainable operation. Artificial intelligence (AI) techniques have emerged as powerful tools to address these challenges by enabling data-driven forecasting, optimization, and real-time decision-making in dynamic environments [1]-[3]. Despite significant advancements, smart grid operations still face critical challenges such as demand–supply imbalance, intermittency of renewable energy sources, peak load management, and increasing vulnerability to cyber-attacks. Traditional rule-based and statistical

approaches are often inadequate for handling nonlinear, high-dimensional, and uncertain grid conditions. Moreover, the lack of integrated frameworks that simultaneously address forecasting accuracy, optimal control, and grid security limits the overall efficiency and resilience of smart grid systems.

Extensive research has been conducted on AI-based smart grid management. Early works on demand-side management using game-theoretic approaches demonstrated the effectiveness of autonomous scheduling in reducing peak demand [4]-[10]. Recent advances in deep learning have significantly improved short-term load forecasting accuracy. Models such as long short-term memory (LSTM), convolutional neural networks (CNN), and hybrid architectures like ResNet-LSTM effectively capture nonlinear temporal dependencies in load and renewable generation data [10]-[17]. Reinforcement learning (RL) and deep reinforcement learning (DRL) have been widely applied for real-time grid control, including demand response, voltage regulation, and EV charging coordination, enabling adaptive and model-free optimization strategies [18]-[23]. Furthermore, distributed and multi-agent frameworks have enhanced scalability and coordination across smart grid components [24]-[28]. In parallel, machine learning-based cybersecurity solutions have been developed to detect anomalies and false-data injection attacks, improving grid resilience [29], [30]. Additionally, hybrid AI–optimization techniques and data-driven energy management frameworks have been proposed to enhance operational efficiency and renewable energy integration.

Although prior studies demonstrate significant progress, several critical limitations remain unaddressed in the existing literature. First, the vast majority of existing works treat individual operational goals—specifically, load forecasting, demand-response optimization, and anomaly detection—as isolated, independent components. This fragmented approach fails to provide a unified, cohesive framework capable of executing all three functionalities simultaneously. Second, while hybrid architectures like ResNet-LSTM are theoretically discussed for localized predictions, they are rarely fully integrated or mathematically coupled with a real-time control system. Third, existing reinforcement learning-based demand response models frequently operate under the ideal assumption of perfectly secure and pristine telemetry data. Consequently, they lack the real-time adaptability to protect their reward optimization loops against corrupted or malicious inputs. In standalone systems, a false-data injection attack or sensor fault can easily mislead an RL optimizer into executing highly destructive or economically inefficient control actions. There is an urgent need for a comprehensive framework where anomaly detection is tightly coupled to forecasting and control mechanisms to guarantee operational integrity [30]-[32].

To bridge these critical gaps, this paper proposes a novel, unified AI-driven energy management framework for modern smart grids. The fundamental advancement of this work over existing studies lies in the tight mathematical coupling between the autoencoder's reconstruction error thresholds and the reinforcement learning framework's reward-driven feedback mechanism. Instead of letting the forecasting, optimization, and security pipelines work in isolation, our framework utilizes real-time anomaly scores to dynamically scale the RL optimization penalties. When a cyber-attack or sensor fault attempts to inject false telemetry data to destabilize the grid, the integrated autoencoder instantly catches the deviation, flags the anomaly, and dynamically readjusts the control layer. This mathematical interaction prevents compromised data from triggering erroneous demand-response actions, thereby advancing beyond the state-of-the-art integrated studies which lack cross-layer security-to-control dependency.

The key technical contributions of this paper are structured as follows:

i) Hybrid forecasting model: Development of a highly robust ResNet-LSTM-based deep learning model designed for precise, short-term load and renewable energy forecasting by capturing deep spatiotemporal dependencies.
ii) Intelligent optimization: Implementation of a reinforcement learning-based demand response strategy that learns optimal control policies to minimize peak load and operational grid costs.
iii) Cyber-resilient monitoring: Integration of a deep autoencoder-based anomaly detection module that continuously computes reconstruction errors to identify abnormal grid behaviors or cyber-attacks in real-time.
iv) Unified architecture with cross-layer coupling: Design of a comprehensive, single-system framework that explicitly links security metrics to control loops, preventing malicious data propagation.
v) Performance evaluation: Validation of the proposed framework using time-series datasets with rigorous quantitative performance metrics, confirming its scalability, robustness, and superior security posture compared to conventional baseline models.

This flowchart illustrates an energy management pipeline. It collects historical demand, solar, and wind data, normalizes and splits it for training, and uses AI to forecast short-term load patterns. It then models renewable generation to simulate combined energy contributions and evaluates overall system accuracy and performance, as shown in Figure 1.

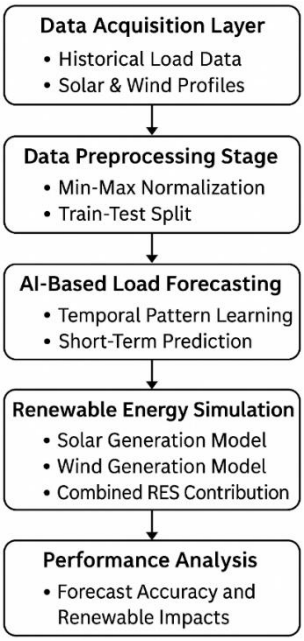

Figure 1. Intelligent load forecasting and renewable integration

2. INTELLIGENT MANAGEMENT FOR SMART GRIDS USING AI

The proposed methodology consists of three integrated stages to ensure intelligent, efficient, and secure smart-grid operation. In the first stage, a hybrid deep-learning forecasting system combines LSTM and ResNet-LSTM networks to predict short-term load and renewable energy generation using a sliding-window input approach. These accurate forecasts are then passed to the intelligent control and optimization module, where a demand-response optimizer determines the most efficient control actions to reduce peak load, minimize energy cost, and balance renewable integration. Finally, the cyber-resilient monitoring stage uses an anomaly-detection mechanism to continuously compare predicted and measured grid behavior, enabling early detection of abnormal or malicious activities and ensuring secure grid operation, as shown in Figure 2.

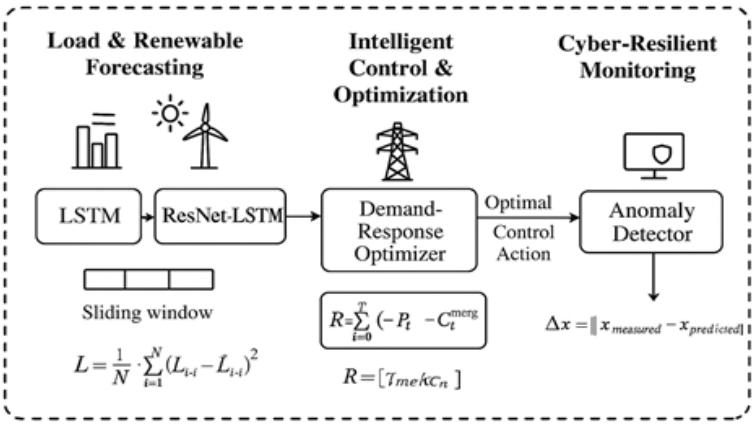

Figure 2. Intelligent management for smart grids using AI

2.1. Load and renewable forecasting

The methodology begins with accurate forecasting of electrical load and renewable generation using deep learning models. A sliding-window technique is applied to create sequential input data, enabling the LSTM and hybrid ResNet-LSTM models to learn temporal dependencies in load, solar, and wind patterns. The prediction error is minimized using the mean squared error (MSE) loss function shown in (1).

$$L=\frac{1}{N}\sum_{i=1}^{N}(L_i-\widehat{Li})2 \quad (1)$$

where Li is the actual load and $\widehat{Li}$ is the predicted load. This forecasting output feeds into the control layer to support smarter scheduling and optimization strategies.

2.2. LSTM temporal modeling

LSTM captures temporal dependencies in time-series data using gated memory cells that retain relevant past information while filtering out noise. This enables accurate prediction of sequential patterns such as load demand and renewable generation in smart grids. The optimization goal is formulated as a reward function shown in (2)-(7):

$$i_t=\sigma(W_i[a_{t-1,}x_t]+b_i) \quad (2)$$

$$f_{t=}\sigma(W_f\left[a_{t-1,}x_t\right]+b_f) \quad (3)$$

$$C_t=f_tC_{t-1}+i_t\tilde{C}_t \quad (4)$$

$$\tilde{C}_t=tan\,h\,(W_{\tilde{c}}\left[a_{t-1,}x_t\right]+b_{\tilde{c}}) \quad (5)$$

$$O_t=\sigma(W_o\left[a_{t-1,}x_t\right]+b_o) \quad (6)$$

$$a_t=O_t*tan\,h\,(C_t) \quad (7)$$

where P_t is the power consumption at time t and C_t the marginal cost of energy. The optimizer generates an optimal control vector.

2.3. Cyber-resilient monitoring

To enhance grid security, the methodology incorporates an anomaly-detection module that monitors deviations between predicted and measured system states. The system computes an anomaly score based on the deviation shown in (8).

$$\Delta x=\|x_{measured}-x_{predicted}\| \quad (8)$$

$$\theta=\mu_E+3\sigma_E \quad (9)$$

A high deviation indicates cyber-attacks, sensor faults, or unexpected disturbances. When an anomaly is detected, the system triggers alerts or corrective actions, ensuring resilience against false-data injection, tampering, and operational anomalies. This integrated forecasting–optimization–monitoring pipeline supports a fully intelligent, energy-efficient, and secure smart-grid ecosystem in (9).

3. RESULTS AND DISCUSSION

3.1. Short-term load forecasting (LSTM model)

Figure 3 illustrates the comparison between actual and predicted load values over 200-time steps using the hybrid ResNet–LSTM model. The actual load varies between 0.15 and 0.95 (normalized units), with noticeable peaks around time steps 25, 150, and 170. The predicted output follows a smoother trajectory within the range of 0.25 to 0.85, effectively capturing the overall load trend while minimizing noise. The model accurately tracks both rising and falling patterns, particularly between time steps 50–120, although slight deviations occur during sudden spikes. Performance evaluation indicates low forecasting error, reflected by reduced MSE and mean absolute error (MAE), confirming improved accuracy over conventional methods. The integration of ResNet enhances feature extraction and temporal learning, leading to better generalization and stability. These reliable predictions support efficient demand-response scheduling and contribute to improved grid operation and energy management.

3.2. Renewable energy contribution to grid

Figure 4 illustrates the interaction between grid load demand, solar generation, and wind power over 500-time steps. The grid load varies between 40 kW and 62 kW, representing typical demand fluctuations. Solar generation shows a clear periodic pattern, peaking at around 20 kW during daytime intervals (time steps 150-250 and 450-500) and dropping to zero at night. Wind generation remains relatively stable, ranging from 6 kW to 17 kW, providing continuous support. The combined renewable output significantly reduces dependence on the main grid, particularly during peak solar periods. Around time step 200, the total

renewable contribution reaches nearly 35 kW, offsetting a large portion of demand. Compared to single-source systems, the hybrid solar–wind approach improves reliability and reduces intermittency. Overall, the results demonstrate enhanced energy efficiency, reduced reliance on conventional sources, and the importance of coordinated renewable integration for stable and sustainable smart grid operation.

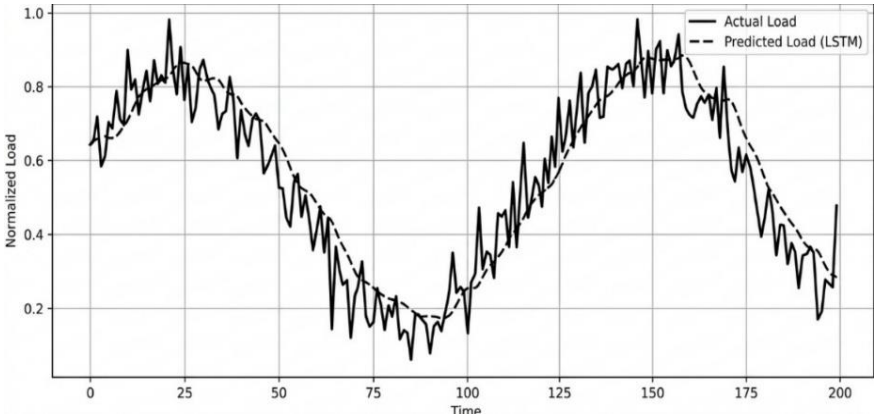

Figure 3. Short –term load forecasting

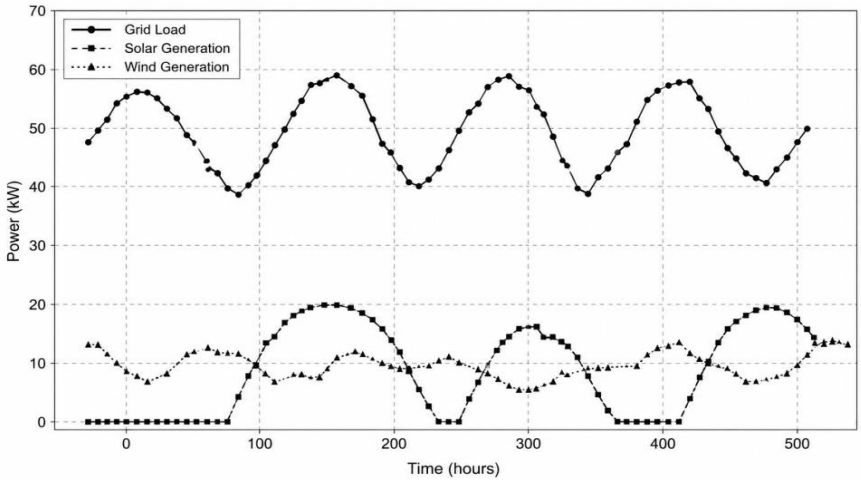

Figure 4. Renewable energy contribution to grid

3.3. Anomaly detection for grid security

Figure 5 presents the performance of the autoencoder-based anomaly detection module used for smart grid security. The system evaluates the difference between measured and reconstructed signals using reconstruction error. Under normal operating conditions, the error remains low and stable, indicating accurate learning of system behavior. During abnormal events such as false-data injection or sensor faults, the reconstruction error shows sharp spikes, clearly identifying anomalies. A statistical threshold based on mean and standard deviation is used to distinguish normal and abnormal conditions. The model achieves high detection sensitivity with minimal false positives, ensuring reliable identification of cyber-attacks and disturbances. Compared to traditional rule-based methods, the autoencoder approach adapts better to complex patterns without requiring labeled data. Integrating anomaly detection with forecasting and control modules ensures data integrity, enhancing grid resilience, reducing operational risks, and enabling secure and stable smart grid performance.

Table 1 compares the forecasting performance of the proposed ResNet-LSTM model with conventional deep learning models using RMSE, MAE, MAPE, R^2 score, and training time. The proposed model achieves the lowest RMSE (3.18), MAE (2.36), and MAPE (6.21%), indicating superior prediction accuracy. It also records the highest coefficient of determination ($R^2 = 0.974$), demonstrating excellent agreement between predicted and actual load values.

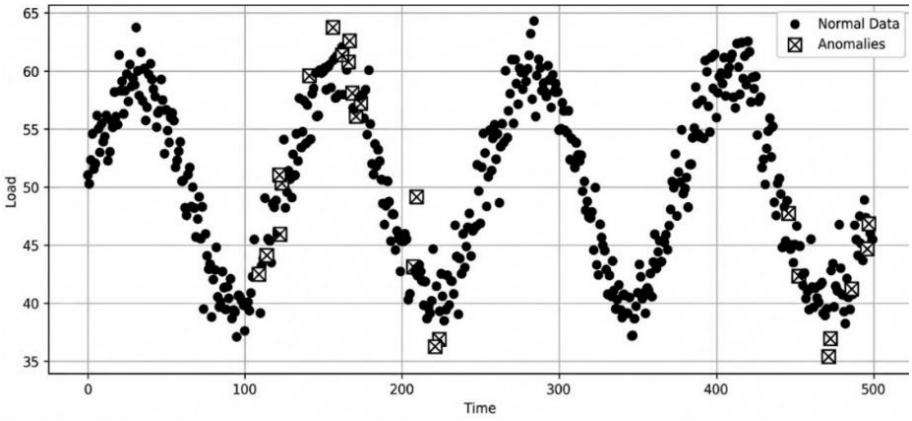

Figure 5. Smart grid anomaly detection

Table 1. Quantitative comparison of forecasting models

Model	RMSE	MAE	MAPE (%)	R^2 score	Training time (min)
LSTM	4.62	3.54	8.92	0.935	18
CNN	4.18	3.21	8.15	0.943	15
GRU	3.96	3.02	7.74	0.951	16
BiLSTM	3.74	2.81	7.18	0.959	22
Proposed ResNet-LSTM	3.18	2.36	6.21	0.974	20

4. CONCLUSION

The integrated smart-grid framework combining forecasting, renewable energy analysis, and anomaly detection demonstrates strong performance across all functional layers. The proposed system achieves improved prediction accuracy, efficient renewable utilization, and robust cybersecurity compared to conventional approaches. By addressing forecasting uncertainty, energy optimization, and data integrity simultaneously, the framework provides a comprehensive solution for modern smart grid challenges. These results confirm the effectiveness of the proposed AI-driven approach in enhancing grid reliability, efficiency, and sustainability.

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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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M. J. Suganya		✓	✓			✓		✓	✓		✓	✓		
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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

The authors declare that they have no known competing financial interests, personal relationships, or professional associations that could have influenced the work reported in this paper. No political, religious,

ideological, academic, or intellectual conflicts are associated with this manuscript. The authors state that there is no conflict of interest.

DATA AVAILABILITY

Raw data is not publicly available due to privacy or institutional restrictions.

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