

A Hybrid SCO–BiLSTM–DRL Framework for Intelligent Smart Grid Energy Management and Energy Demand Forecasting

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Received: 20 March 2026 | Revised: 29 April 2026 | Accepted: 17 May 2026

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ABSTRACT

Smart grid technologies have evolved rapidly to enable intelligent monitoring, forecasting, and control of modern energy systems. However, the increasing integration of renewable energy sources, variable demand, and dynamic grid conditions poses significant challenges for effective energy management. Traditional methods are often not well-suited to handling the nonlinear and time-varying nature of smart grid data, which can lead to reduced prediction accuracy and scheduling efficiency. To address these challenges, this paper proposes a hybrid Sine Cosine Optimization (SCO)–Bidirectional Long Short-Term Memory (BiLSTM)–Deep Reinforcement Learning (DRL) framework for smart grid energy management. The BiLSTM model is employed to accurately forecast energy demand, whereas the SCO algorithm optimizes model parameters to enhance prediction performance. Experimental results show that the proposed model achieves lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values and higher prediction accuracy than conventional models, including Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and BiLSTM. The proposed framework improves energy utilization efficiency, reduces operating costs, and enhances electrical grid stability. Overall, the proposed approach provides a scalable and efficient solution for next-generation smart grid energy management.

Keywords–smart grid energy management; Deep Reinforcement Learning (DRL); Bidirectional LSTM; Sine Cosine Optimization (SCO); energy demand forecasting; renewable energy integration; intelligent energy scheduling

I. INTRODUCTION

The rapid evolution of modern power systems has given rise to smart grids, which use advanced communication technologies, intelligent control systems, and distributed energy sources to ensure the efficiency, reliability, and sustainability of electricity networks [1, 2]. Smart grids differ significantly from conventional grids in that they enable two-way communication between suppliers and consumers, real-time monitoring, demand response, and efficient energy utilization. The development of technologies such as the Internet of Things (IoT) and blockchain has promoted transparency, automation, and security in energy transactions and grid operations [1, 2]. In addition, the increasing deployment of solar and wind power plants, together with the growing penetration of renewable

energy sources and distributed generation, requires effective grid management to ensure system reliability and efficient utilization of distributed energy resources.

Furthermore, artificial intelligence and machine learning techniques have been widely adopted to improve load forecasting, demand response management, and energy resource planning due to their ability to process large volumes of energy data [3, 4]. Game theory is also commonly used to model the behavior of energy stakeholders and to determine optimal energy transfer and consumption strategies [5]. In addition, advanced communication infrastructures and emerging technologies have been explored to improve connectivity and coordination in smart grid systems [6]. However, the complexity of smart grid infrastructures

introduces challenges related to privacy, regulatory compliance, and system security, requiring robust data management and protection strategies [7, 8].

A number of research works have been developed for smart grid energy management using various computational and analytical techniques. Optimization-based energy management models have been proposed to coordinate smart grid systems with demand response programs and energy storage systems, aiming to improve operational efficiency and reduce costs [9]. In the same direction, hierarchical decentralized multi-agent frameworks have been introduced to enable distributed monitoring and decision-making across different units in smart grid systems [10]. Furthermore, forecasting-based optimization approaches have been applied to day-ahead energy scheduling and microgrid management, leading to improved planning of distributed energy resources and demand response strategies [11].

Apart from optimization methods, hardware-oriented energy management approaches have also been considered to improve power conversion efficiency and system stability in smart grids; for instance, hybrid grid-tied inverter systems [12]. Recently, Deep Reinforcement Learning (DRL) has been proposed for smart microgrid control due to its adaptive and autonomous decision-making capabilities in real environments [13]. Moreover, deep learning models have been widely used for time-series forecasting in smart grid systems. To enhance forecasting accuracy, hybrid deep learning models such as VMD-SSA-BiLSTM have been developed, where time-series signals are decomposed into sub-components prior to prediction [14]. In addition, optimization-integrated machine learning approaches such as SCO-GBDT have been used for efficient management of hybrid AC/DC microgrids and renewable energy resources [15].

Recent studies have also explored the integration of deep learning and reinforcement learning for smart grid energy management. Authors in [16] proposed a real-time load prediction and management framework combining these techniques, achieving improved forecasting accuracy and adaptive control, although without advanced optimization for parameter tuning in complex systems.

Despite these advances, most existing studies focus on either energy demand forecasting or optimization-based scheduling as separate tasks. Traditional forecasting methods often struggle in dynamic environments, whereas optimization-based approaches typically rely on predefined models that may not fully capture the complex temporal behavior of energy demand and renewable generation. Furthermore, only a limited number of studies have investigated the combined use of deep learning-based forecasting, metaheuristic optimization, and reinforcement learning within a unified framework. Therefore, there is a need for an integrated hybrid framework that combines accurate forecasting, efficient optimization, and adaptive energy management strategies to improve smart grid performance.

To address these limitations, this study introduces a hybrid SCO-BiLSTM-DRL architecture for smart grid energy management. The Bidirectional Long Short-Term Memory

(BiLSTM) network is used to learn historical energy consumption and generation data for predicting future demand-supply patterns. To improve forecasting performance, the Sine Cosine Optimization (SCO) algorithm is employed to optimize BiLSTM parameters, improving both accuracy and convergence speed. In addition, a Deep Reinforcement Learning (DRL) module is integrated to enable adaptive and intelligent energy scheduling and resource allocation in dynamic smart grid environments.

This work proposes a unified framework that integrates optimization, deep learning, and reinforcement learning to address accurate energy forecasting and adaptive energy management in smart grid systems. The main contributions of this research are summarized as follows:

- A hybrid SCO-BiLSTM-DRL framework is proposed for intelligent smart grid energy management, integrating forecasting, optimization, and decision-making in a unified architecture.
- A BiLSTM model is employed to accurately predict energy demand by capturing temporal dependencies and nonlinear patterns in historical data.
- The SCO algorithm is used to optimize BiLSTM parameters, improving convergence and prediction accuracy.
- A DRL module is integrated to enable adaptive energy scheduling through learning optimal control policies in dynamic environments.
- The proposed framework improves energy utilization, reduces forecasting errors, enhances grid stability, and supports better integration of renewable energy sources.

The novelty of this work lies in the integration of metaheuristic optimization, deep learning-based forecasting, and reinforcement learning-based control within a single unified architecture for smart grid energy management. Unlike many existing studies that address these components independently, the proposed framework jointly addresses forecasting, optimization, and control. As a result, it improves prediction accuracy, enhances energy distribution efficiency, and reduces operating costs, supporting scalable next-generation smart grid systems.

II. PROPOSED METHODOLOGY

The proposed system introduces a hybrid SCO-BiLSTM-DRL framework for intelligent smart grid energy management. The objective of this framework is to improve energy demand forecasting, optimize model parameters, and enable adaptive energy scheduling decisions within a dynamic smart grid environment.

A. Proposed Architecture

Due to the large number of distributed energy resources, including renewable energy sources, battery energy storage systems, electric vehicles, and consumer loads, smart grids exhibit complex energy utilization patterns. Conventional energy management systems often cannot effectively handle the nonlinear and time-varying nature of energy data.

Therefore, advanced machine learning and optimization techniques are required to achieve efficient energy management.

Figure 1 shows the proposed architecture. The proposed framework combines three main techniques:

- BiLSTM: Predicts energy consumption and renewable energy generation using historical smart grid data.
- SCO: Optimizes the hyperparameters of the BiLSTM model to improve prediction accuracy and convergence speed.
- DRL: Enables real-time intelligent decision-making for energy scheduling, load balancing, and cost optimization.

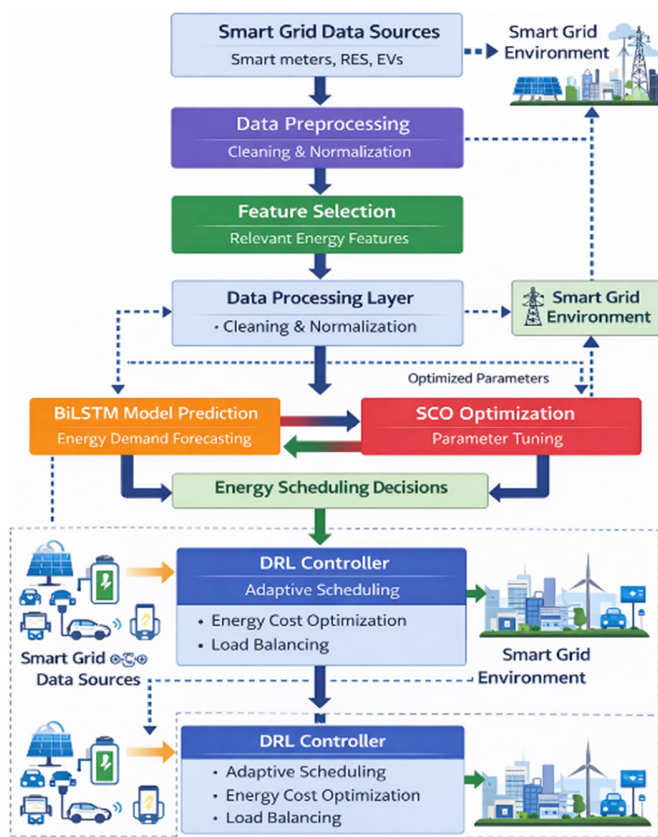


Fig. 1. Proposed architecture.

By combining these techniques, the proposed framework can accurately forecast energy demand, optimize model performance, and manage energy distribution in real time, improving the overall efficiency of the smart grid.

The Data Acquisition Layer collects real-time and historical data from various components of the smart grid environment. These data provide the information required for energy demand forecasting and energy management.

The major data sources include:

- Smart meters,

- Renewable energy sources (solar and wind),
- Energy storage systems (battery storage units),
- Consumer electricity demand,
- Weather information (temperature, solar radiation, wind speed).

These heterogeneous sources continuously generate large volumes of operational data reflecting different states of the smart grid. The collected data are transferred to the preprocessing stage for further analysis. The raw data often contain noise, inconsistencies, and missing values that can negatively affect model performance. Therefore, a preprocessing stage is introduced to improve data quality through:

- Data normalization
- Feature extraction
- Noise removal
- Data transformation

Normalization guarantees that all input variables are within a comparable numerical range, improving the convergence behavior of deep learning models.

The min–max normalization process is defined as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

where:

- X = original data,
- X_{min} = minimum value,
- X_{max} = maximum value.

B. Energy Demand Forecasting Using Bidirectional Long Short-Term Memory

The BiLSTM network is employed to predict future energy consumption using historical demand data. Unlike conventional Long Short-Term Memory (LSTM) networks, the BiLSTM network processes sequential data in both forward and backward directions, enabling the model to capture complex temporal dependencies in energy consumption patterns. The energy demand prediction model is expressed as shown in (2):

$$\hat{Y}_t = f(X_t, X_{t-1}, \dots, X_{t-n}) \quad (2)$$

where:

- X_t represents the input features at time t ,
- n represents the number of previous time steps,
- $f(\cdot)$ represents the BiLSTM prediction function,
- \hat{Y}_t represents the predicted energy demand.

The BiLSTM network predicts future energy demand based on historical data. The simulation parameters used in the proposed framework are presented in Table I.

TABLE I. SIMULATION PARAMETERS OF THE PROPOSED SCO-BiLSTM-DRL FRAMEWORK

Parameter	Value
Learning rate	0.001
BiLSTM hidden units	128
Epochs	100
Batch size	64
SCO population size	30
SCO iterations	50
r_1	[0,2]
r_2	[0,2 π]
r_3	[0,2]
Discount factor γ	0.95
Reward weights (α, β, γ)	0.4, 0.3, 0.3

The LSTM cell operations are defined as shown in (3)–(7).

Forget gate:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (3)$$

Input gate:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (4)$$

Cell state:

$$C_t = f_t C_{t-1} + i_t \tanh(W_c[h_{t-1}, x_t] + b_c) \quad (5)$$

Output gate:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (6)$$

Hidden state:

$$h_t = o_t \tanh(C_t) \quad (7)$$

C. Parameter Optimization Using Sine Cosine Optimization

The SCO algorithm is used to optimize the hyperparameters of the BiLSTM model, including:

- Learning rate,
- Weight parameters,
- Bias values,
- Network configuration.

The SCO algorithm searches for optimal solutions by updating candidate solutions using sine and cosine operators. The position update equations of the SCO algorithm are defined as shown in (8) and (9):

$$X_i^{t+1} = X_i^t + r_1 \times \sin(r_2) \times |r_3 P_i^t - X_i^t| \quad (8)$$

or

$$X_i^{t+1} = X_i^t + r_1 \times \cos(r_2) \times |r_3 P_i^t - X_i^t| \quad (9)$$

where:

- X_i^t = current solution,
- P_i^t = best solution,
- r_1, r_2, r_3 = random parameters, and $r_1 \in [0,2]$, $r_2 \in [0,2\pi]$, $r_3 \in [0,2]$.

The SCO algorithm minimizes the prediction error according to the fitness function shown in (10):

$$Fitness = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (10)$$

D. Energy Scheduling Using Deep Reinforcement Learning

The final layer of the framework employs a DRL model for real-time decision-making in smart grid energy management. The DRL agent observes the current grid state and selects actions to reduce energy consumption and improve operational efficiency. The objective is to maximize the cumulative reward defined in (11):

$$R = -(\alpha C + \beta L + \gamma D) \quad (11)$$

where:

- C = energy cost,
- L = load imbalance,
- D = demand fluctuation,
- α, β, γ = weighting parameters.

The reward function in (11) is adapted from reinforcement learning-based energy management formulations [13].

The optimization objective is expressed as shown in (12):

$$\max \sum_{t=0}^T R_t \quad (12)$$

Through continuous interaction with the grid environment, the DRL agent learns optimal energy scheduling strategies.

The overall algorithm of the proposed framework is summarized in Algorithm 1.

Algorithm 1: Hybrid SCO-BiLSTM-DRL Energy Management

1. Collect smart grid data
2. Perform data preprocessing and normalization
3. Train the BiLSTM model using historical energy data
4. Optimize the BiLSTM parameters using the SCO algorithm
5. Generate energy demand forecasts
6. Use the predicted demand as input to the DRL agent
7. Train the DRL agent for energy scheduling
8. Generate optimized energy distribution decisions

The smart grid dataset can be represented as shown in (13):

$$D = \{E_t, G_t, P_t, W_t\} \quad (13)$$

where:

- E_t = energy consumption,
- G_t = renewable energy generation,
- P_t = electricity price,
- W_t = weather parameter.

The reinforcement learning model is defined as follows:

State:

$$S_t = \{E_t, G_t, P_t\} \tag{14}$$

Action:

$$A_t = \{\text{Load scheduling, storage control}\} \tag{15}$$

Policy:

$$\pi(a|s) \tag{16}$$

Value function:

$$Q(s, a) = E[R_t + \gamma \max_{a'} Q(s', a')] \tag{17}$$

where:

- $Q(s, a)$ = expected reward for action a in state s ,
- γ = discount factor.

The DRL agent learns an optimal policy that maximizes long-term energy efficiency and improves overall smart grid operation.

III. RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed SCO–BiLSTM–DRL model for intelligent smart grid energy management. The proposed framework integrates BiLSTM for energy demand forecasting, SCO for model parameter optimization, and DRL for adaptive energy scheduling. The main objective of the evaluation is to assess forecasting accuracy and energy management performance compared with conventional machine learning and deep learning approaches.

The experiments were conducted using a benchmark smart grid dataset [17] containing electricity consumption, renewable energy generation (solar and wind), battery storage levels, electricity prices, and weather parameters.

The dataset was divided into training and testing subsets, with 80% of the data used for training and 20% used for testing. Standard performance metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and prediction accuracy, were used to evaluate model performance. The results demonstrate that the proposed framework outperforms the baseline SVM, LSTM, and BiLSTM models. As shown in Table II, the SCO–BiLSTM–DRL framework achieves the lowest MAE and RMSE values, along with higher prediction accuracy, compared with all benchmark models.

TABLE II. COMPARATIVE PERFORMANCE ANALYSIS OF DIFFERENT MODELS

Model	MAE	RMSE	Accuracy (%)	Operating cost	Energy efficiency
SVM [3, 4]	0.145	0.232	86.5	498	80.4
LSTM [16]	0.118	0.201	90.2	412	88.3
BiLSTM [14]	0.104	0.187	92.1	395	91.2
Proposed SCO–BiLSTM–DRL	0.072	0.141	96.4	342	96.1

The BiLSTM network effectively captures temporal patterns in energy consumption data, whereas the SCO algorithm enhances forecasting performance through hyperparameter optimization. In addition, the proposed framework reduces operating costs and improves energy efficiency compared with the baseline models.

Figure 2 compares the actual and predicted energy demand values generated by the proposed framework. The predicted values closely follow the actual energy demand pattern, demonstrating the ability of the proposed model to capture temporal dependencies in smart grid data.

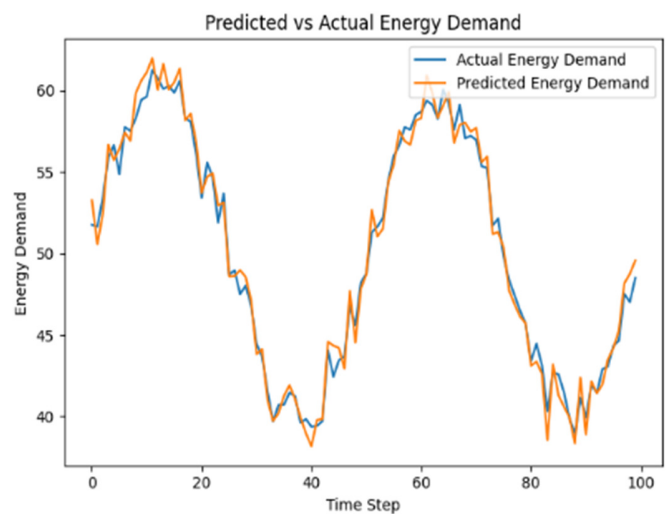


Fig. 2. Predicted vs. actual energy demand using the proposed SCO–BiLSTM–DRL model.

Figure 3 compares the RMSE values obtained by the SVM, LSTM, BiLSTM, and SCO–BiLSTM–DRL models. The proposed framework achieves the lowest RMSE value, indicating improved forecasting accuracy and reduced prediction error.

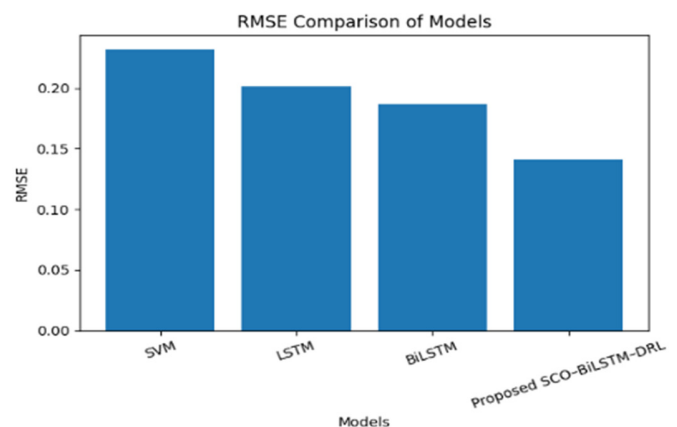


Fig. 3. RMSE comparison of different energy forecasting models.

Figure 4 compares the MAE values of the evaluated models. The SCO–BiLSTM–DRL model achieves the lowest

MAE, demonstrating its ability to minimize forecasting deviations and improve prediction reliability.

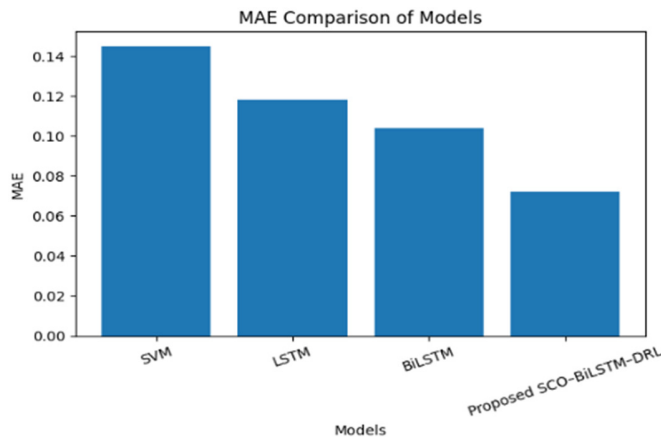


Fig. 4. MAE comparison of different energy forecasting models.

The graphical and numerical results consistently demonstrate the effectiveness of the proposed hybrid framework for accurate energy demand forecasting and efficient smart grid energy management.

IV. CONCLUSION

In this study, a hybrid Sine Cosine Optimization (SCO)–Bidirectional Long Short-Term Memory (BiLSTM)–Deep Reinforcement Learning (DRL) framework was proposed for smart grid energy management. The BiLSTM model effectively captured temporal dependencies in energy consumption data for accurate energy demand forecasting, whereas the SCO algorithm optimized model hyperparameters to improve prediction performance. In addition, the DRL module enabled adaptive energy scheduling in dynamic smart grid environments. Experimental results demonstrated that the proposed framework achieved lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values and higher prediction accuracy than conventional models, including Support Vector Machine (SVM), Long Short-Term Memory (LSTM), and BiLSTM. Furthermore, the proposed framework improved energy utilization efficiency, reduced operating costs, and enhanced grid stability, demonstrating its effectiveness for smart grid energy management applications.

Future work will focus on integrating real-time Internet of Things (IoT) data, exploring advanced reinforcement learning algorithms such as Proximal Policy Optimization (PPO) and Deep Deterministic Policy Gradient (DDPG), and extending the framework to multi-agent environments. In addition, the proposed framework will be validated using large-scale real-world smart grid systems to further improve its scalability and operational performance.

DECLARATION OF COMPETING INTERESTS

Not applicable to this work.

ACKNOWLEDGMENT

Not applicable to this work.

Include sponsor acknowledgments/funding sources in this section. Also, include acknowledgement for people who may have participated/helped but do not qualify for authorship or for institutions/infrastructures.

DATA AVAILABILITY

The dataset used in this study is publicly available and can be accessed at [17].

AI USE AND DECLARATION OF GENERATIVE AI USE

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) to assist in manuscript drafting, content refinement, language improvement, and formatting. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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