IJAITE

INTERNATIONAL JOURNAL OF ADVANCED INNOVATIVE TECHNOLOGY IN ENGINEERING

Published by Global Advanced Research Publication House Journal

Home page: www.ijaite.co.in

Integrated Deep Temporal Learning and Reinforcement Optimization for Energy-Efficient Routing and Clustering in Wireless Sensor Networks

[1]Prof. Kalyani S. Tidke

[1]Department of Electronics and Telecommunication, Dr. Rajendra Gode Institute of Technology and Research, Amaravati, Maharashtra, India

[1]kt20.entc@gmail.com

Article History

Received on: 25 Dec 2026

Revised on: 28 Jan 2026

Accepted on: 02 March 2026

Keywords: Wireless Sensor Network, Energy Optimization, Particle Swarm Optimization, Actor-Critic reinforcement

e-ISSN: 2455-6491

DOI: 10.65809/IJAITE/26/v11i02/001

Production and hosted by
www.insightiveinc.org

ABSTRACT

These Wireless Sensor Networks are widely used in applications such as environmental monitoring, smart cities, and industrial automation, where energy efficiency remains a critical challenge due to limited battery resources of sensor nodes. This paper proposes a Hybrid Energy-Efficient Intelligent model that integrates deep learning, swarm optimization, and reinforcement learning to minimize energy consumption and enhance network lifetime. The model combines a Bidirectional Long Short-Term Memory model for energy prediction, Particle Swarm Optimization for optimal cluster head selection, and an Actor-Critic reinforcement learning model for adaptive routing. The proposed approach used temporal energy patterns to prevent premature node failures, balances energy distribution through optimized clustering, and dynamically selects routing paths to reduce communication overhead. Extensive simulation results demonstrate that the proposed HEEIF framework achieves up to 80% energy reduction, improves network lifetime by 20-25%, and maintain a high packet delivery ratio of 94-96% compared to conventional methods such as LEACH, LSTM-based, and RL-based approaches. Additionally, the framework improves throughput, reduces delay, and enhances load balancing. The results indicate that integrating prediction, optimization, and adaptive learning that allows the scalable and efficient solution for next-generation energy-aware WSNs.

1. INTRODUCTION

The Wireless Sensor Networks (WSN) have become a cornerstone technology for modern intelligent systems, enabling real-time monitoring and data acquisition in diverse applications such as environmental surveillance, smart agriculture, industrial automation, healthcare monitoring, and smart cities [1], [2] . A typical WSN comprises a large number of spatially distributed sensor nodes that collaboratively sense, process, and transmit data to a centralized base station. Despite their wide applicability, sensor nodes are inherently constrained by limited battery resources, making energy efficiency a critical challenge that directly impacts network lifetime, reliability, and scalability [3]. Efficient energy management is therefore essential to ensure prolonged operation and sustainable network performance.

Traditional energy-efficient routing and clustering protocols, such as LEACH and HEED, rely on probabilistic or heuristic-based approaches for cluster head selection and routing decisions. While these methods are simple and scalable, they often suffer from uneven energy distribution, frequent node failures, and suboptimal routing, leading to rapid network degradation. To overcome these limitations, recent research has explored the use of machine learning, deep learning, and optimization algorithms for improving energy efficiency [4]. However, most existing approaches focus on isolated components, such as energy prediction, clustering, or routing, without considering the interdependency among these processes [5]. This lack of integration results in inefficient decision-making and limits network performance. The core problem addressed in this work is the absence of a unified, intelligent framework that simultaneously optimizes energy prediction, cluster formation, and routing decisions in WSNs. Existing models either rely solely on predictive mechanisms without adaptive routing or employ optimization techniques without leveraging temporal energy patterns. As a result, they fail to achieve a balance between energy consumption, network lifetime, and communication reliability, especially in dynamic and large-scale WSN environments [6].

This research stems from the need to develop a holistic and adaptive energy management framework that can intelligently coordinate multiple network operations. By integrating predictive intelligence with optimization and learning-based decision-making, it is possible to significantly enhance energy utilization and extend network longevity. Inspired by recent advancements in deep learning and reinforcement learning, this study aims to bridge the gap between prediction-driven and decision-driven energy optimization strategies. This paper proposes a Hybrid Energy-Efficient Intelligent Framework (HEEIF) that combines three complementary techniques: (i) Bidirectional Long Short-Term Memory (BiLSTM) for accurate prediction of node energy based on historical patterns, (ii) Particle Swarm Optimization (PSO) for optimal cluster head selection considering energy, distance, and node centrality, and (iii) Actor-Critic reinforcement learning for adaptive and energy-aware routing decisions. The integration of these components enables proactive energy management, balanced load distribution, and dynamic routing optimization, resulting in improved network performance and reliability. The main contributions of this paper are summarized as follows:

- A novel hybrid framework (HEEIF) that integrates deep learning, swarm optimization, and reinforcement learning for energy-efficient WSN operation.
- A BiLSTM-based energy prediction model that captures temporal dependencies to prevent premature node failures.
- A PSO-based clustering mechanism that ensures optimal cluster head selection and balanced energy consumption.
- An Actor-Critic reinforcement learning approach for adaptive routing, reducing communication overhead and packet loss.

The remainder of this paper is organized as follows. Section II presents the related work on energy-efficient WSN techniques. Section III describes the proposed HEEIF framework, including energy prediction, clustering optimization, and routing mechanisms. Section IV outlines the simulation setup and performance metrics. Section V presents the experimental results and comparative analysis. Finally, Section VI concludes the paper and discusses future research directions.

2. RELATED WORK

Recent research in energy-efficient WSN has explored machine learning, deep learning, and optimization techniques to address energy constraints and improve network longevity. Despite significant advancements, existing approaches often operate in isolation, focusing either on prediction, clustering, or routing optimization without a unified framework.

Pande K. et al. (2025) proposed an adaptive multi-hop routing protocol based on machine learning to reduce energy consumption in wireless sensor networks. The approach dynamically selects optimal routes to minimize transmission overhead. The proposed model was compared with conventional protocols such as LEACH and Directed Diffusion. Experimental results demonstrated improved packet delivery ratio and enhanced communication reliability. The method achieved a 25% reduction in energy consumption. Additionally, the network lifetime increased by 35%, showing the effectiveness of the adaptive routing mechanism [7].

Mabunga Z. P. et al. (2024) presented an LSTM-based model for predicting energy consumption in wireless sensor network nodes. The study focused on handling time-series energy data for both static and dynamic sensor nodes. The model was trained using historical node energy usage patterns. Experimental evaluation showed that LSTM outperformed traditional prediction models. The approach achieved an RMSE of 213.39 joules for static nodes. For dynamic nodes, the model obtained an RMSE of 293.26 joules, demonstrating accurate forecasting capability [8].

Sollapure N. S. et al. (2025) proposed a machine learning framework integrated with a Kalman filter to optimize energy consumption in WSNs. The model combines prediction and filtering to reduce unnecessary data transmission. This approach improves energy utilization while maintaining communication quality. The framework was evaluated using multiple performance metrics. Experimental results showed an overall accuracy of 98.36%. The proposed method also extended network lifespan and improved stability [9].

Bagwari A. et al. (2023) introduced an energy optimization model for Industrial Wireless Sensor Networks. The proposed approach focused on reducing transmission and idle energy consumption. The model also optimized sleep-mode energy usage for sensor nodes. Experimental results showed improved received energy efficiency. The system achieved 64.72% transmission energy consumption. Additionally, the model provided 35.28% transmission energy savings, improving overall efficiency [10].

Chauhan N. et al. (2025) evaluated machine learning techniques for residential energy consumption forecasting. The study compared multiple deep learning models for prediction accuracy. Among them, the BiLSTM model demonstrated superior performance. The approach provided accurate energy demand forecasting using time-series data. The model achieved an RMSE of 2.3774 and MAE of 1.2388. It also obtained an R^2 value of 0.9412, indicating strong prediction performance [11].

Sibi S. A. et al. (2024) proposed an ARIMA-driven feature selection method combined with Actor-Critic reinforcement learning. The model was designed to optimize energy consumption in wireless sensor networks. The reinforcement learning agent dynamically selects energy-efficient routing paths. Experimental results demonstrated reduced energy consumption. The proposed method achieved energy usage of 0.32 mJ. Additionally, the network lifetime was extended to 1501 rounds with 98% prediction accuracy [12].

Balakumar D. et al. (2025) introduced a DP-LSTM model to reduce energy consumption in WSNs. The model combines deep learning prediction with dynamic optimization. It was compared with existing algorithms such as ELR, HLMS, and TDPA. Experimental results showed significant improvement in energy efficiency. The proposed model reduced energy consumption by 71.54% compared to ELR. It also achieved reductions of 53.90% and 27.15% over HLMS and TDPA respectively [13].

Surenther I. et al. (2023) proposed a Deep Learning-based Grouping Model Approach (DL-GMA) for energy-efficient communication. The model groups sensor nodes to minimize redundant transmissions. This approach improves network stability and data delivery performance. The proposed system enhanced overall quality of service. Experimental results showed energy efficiency of 88.7%. The method also achieved network stability of 90.8% and QoS of 93.4% [14].

Vijayakumar K. et al. (2025) presented DeepCuckoo, a deep learning-based optimization framework. The model integrates deep belief networks, convolutional neural networks, and recurrent neural networks. The approach improves routing efficiency and reduces node energy usage. Experimental results showed significant improvement in network performance. The proposed method achieved up to 55% energy savings. Additionally, network lifetime increased by 36% [15].

Hakkem B. et al. (2024) proposed an AI-driven adaptive clustering mechanism for wireless sensor networks. The model dynamically selects cluster heads based on energy availability. This reduces communication overhead and improves load balancing. The proposed system was compared with LEACH and HEED protocols. Experimental results showed approximately 30% reduction in total energy consumption. The method also improved network lifetime by 25% and throughput by 20% [16].

Sivasankar C. et al. (2024) employed machine learning techniques for predictive energy management in WSNs. The proposed model analyzes node behavior and predicts energy requirements. This helps in optimizing communication scheduling. Experimental results demonstrated improved system reliability. The model reduced node energy consumption by 40%. Additionally, data transmission efficiency improved by 28.6% [17].

Anshad A. S. et al. (2025) proposed a Hybrid Quantum-Deep Reinforcement Learning framework for WSNs. The model combines quantum optimization with reinforcement learning-based routing. This approach improves energy-efficient path selection. The proposed system enhanced network performance and stability. Experimental results showed 35% reduction in energy consumption. The model achieved 98.6% accuracy with improved routing efficiency [18].

Depuru S. et al. (2025) presented a hybrid transformer and graph neural network model. The model predicts energy consumption in wireless sensor networks. It captures spatial and temporal relationships among sensor nodes. The proposed system improves prediction accuracy and energy management. Experimental results showed a Mean Squared Error of 0.034. The model also achieved an R-squared value of 0.92 [19].

Haripriya R. et al. (2025) proposed a hybrid ANNMLP-PSO optimization algorithm for energy-efficient WSNs. The model optimizes cluster selection and routing paths. The approach was evaluated using 300 sensor nodes. Experimental results showed reduced energy consumption compared to GA, GWO, PSO, and RPSO. The proposed model achieved energy consumption of 0.43J. It also improved packet delivery ratio and network lifetime [20].

Hachicha M. et al. (2024) proposed a probabilistic estimation approach for energy management in WSNs. The model evaluates battery charge retention and energy usage. The proposed method improves decision-making for periodic applications. Experimental results demonstrated high prediction accuracy. The system achieved 98.65% accuracy. Additionally, battery life improved by up to 75%, enhancing network longevity [21].

Table 1: Comparative Analysis of Energy Consumption in WSN.

Author's	**Year**	**Model Used**	**Dataset**	**Findings**	**Limitations**
Pande K. et al. [7]	2025	ML-based Adaptive Multi-hop Routing	WSN simulation	Energy consumption reduced by 25%, packet delivery ratio improved by 18%, network lifetime increased by 35%	Limited evaluation on large-scale heterogeneous WSN
Mabunga Z. P. et al. [8]	2024	LSTM	Static and dynamic WSN nodes	RMSE = 213.39 J (static), 293.26 J (dynamic) showing accurate prediction	High computational complexity for real-time deployment
Sollapure N. S. et al. [9]	2025	ML + Kalman Filter	WSN simulation dataset	Accuracy = 98.36%, improved energy utilization and lifetime	Requires parameter tuning and filtering overhead
Bagwari A. et al. [10]	2023	Energy Optimization Model	Industrial WSN dataset	Transmission energy consumption = 64.72%, energy saving = 35.28%	Tested only in industrial environment
Chauhan N. et al. [11]	2025	BiLSTM	Residential energy dataset	RMSE = 2.3774, MAE = 1.2388, MSE = 5.6522, R^2 = 0.9412	Not specifically designed for WSN routing
Sibi S. A. et al. [12]	2024	ARIMA + Actor-Critic RL	WSN simulation	Accuracy = 98%, energy consumption = 0.32 mJ, lifetime = 1501 rounds	Increased training time
Balakumar D. et al. [13]	2025	DP-LSTM	WSN dataset	Energy reduction = 71.54%, 53.90%, 27.15% over ELR, HLMS, TDPA	Deep model requires high memory
Surenther I. et al. [14]	2023	DL-GMA	WSN simulation	Energy efficiency = 88.7%, network stability = 90.8%, QoS = 93.4%	Limited real-time validation
Vijayakumar K. et al. [15]	2025	DeepCuckoo (DBN + CNN + RNN)	WSN simulation	Energy saving = 55%, network lifetime improved by 36%	Complex hybrid architecture
Hakkem B. et al. [16]	2024	AI-based Clustering	WSN dataset	Energy consumption reduced by 30%, lifetime increased by 25%, throughput improved by 20%	Cluster overhead increases with node density
Sivasankar C. et al. [17]	2024	ML Predictive Model	WSN dataset	Energy reduction = 40%, transmission efficiency improved by 28.6%	Requires training data for prediction
Anshad A. S. et al. [18]	2025	Quantum + DRL	WSN simulation	Accuracy = 98.6%, precision = 97.8%, ROC-AUC = 99.1%, energy reduction = 35%	High computational complexity
Depuru S. et al. [19]	2025	Transformer + GNN	WSN dataset	MSE = 0.034, R^2 = 0.92 indicating high prediction accuracy	Requires large training dataset
Haripriya R. et al. [20]	2025	ANNMLP-PSO	300-node WSN	Energy consumption = 0.43 J, better than GA (0.88 J), GWO (0.72 J)	Performance depends on node density

Hachicha M. et al. [21]	2024	Probabilistic Estimation Model	WSN periodic applications	Accuracy = 98.65%, battery life improved by 75%	Limited evaluation scenarios

3. PROPOSED METHODOLOGY

A. Overview of Proposed Framework

This research proposes a Hybrid Energy-Efficient Intelligent Framework (HEEIF) for Wireless Sensor Networks (WSNs). The framework integrates:

- Deep Learning (BiLSTM / LSTM) for energy prediction
- Optimization algorithm (Particle Swarm Optimization – PSO) for clustering
- Reinforcement Learning (Actor-Critic model) for adaptive routing

The objective is to minimize energy consumption while maximizing network lifetime and communication efficiency.

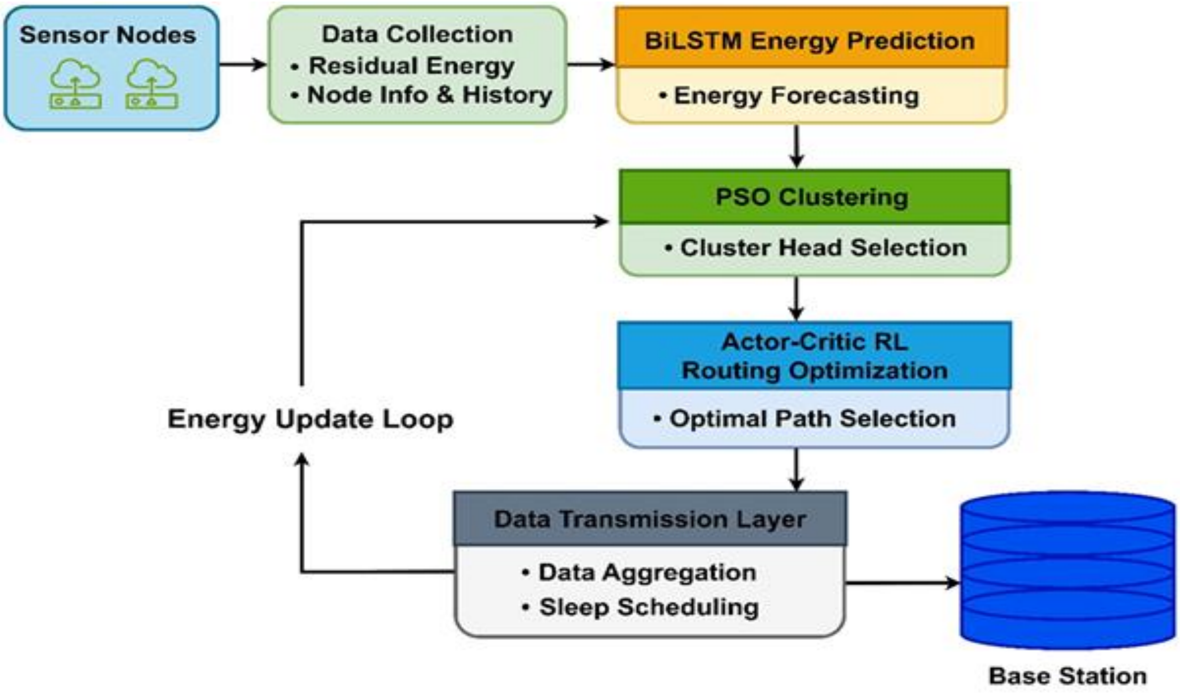

Figure 1: Proposed HEEIF model for Wireless Sensor Networks

Figure. 1. Architecture of the proposed HEEIF for Wireless Sensor Networks. The framework begins with sensor nodes that collect environmental data, followed by a data collection module that gathers residual energy and node information. A BiLSTM-based model predicts future energy levels to support intelligent decision-making. The PSO-based clustering module selects optimal cluster heads based on energy and distance metrics. An Actor-Critic reinforcement learning approach is employed for adaptive routing and optimal path selection. The data transmission layer ensures efficient communication using aggregation and sleep scheduling techniques. An energy update feedback loop continuously refines the system to enhance network lifetime and energy efficiency.

Sensor Nodes Layer: The sensor layer consists of spatially distributed nodes responsible for sensing environmental parameters and transmitting data to the base station. Each node operates under strict energy constraints, making efficient energy utilization essential. The WSN consisting of N sensor nodes distributed over an area

A. Each node i is initialized with energy

$$E_i(0) = E_0 \tag{1}$$

The residual energy of a node at time t is defined as:

$$E_i(t) = E_i(t-1) - (E_{tx}(k,d) + E_{rx}(k) \tag{2}$$

Where: $E_{tx}(k,d)$ = transmission energy, $E_{rx}(k)$= reception energy, k = packet size, d = transmission distance

Using the first-order radio model:

$$E_{tx}(k,d) = kE_{elec} + \mathrm{k}E_{amp}d^2 \quad (3)$$

$$E_{rx}(k) = kE_{elec} \quad (4)$$

This formulation captures the energy depletion behaviour of sensor nodes.

Data Collection Module: The state of each node is represented as a feature vector:

$$S_i = \{E_i, D_i, p_i, T_i, H_i\} \quad (5)$$

The dataset for prediction is:

$$D = \{\, S_1, S_2, \dots, S_N \,\} \quad (6)$$

This structured representation enables efficient input to the learning model.

Energy Prediction using BiLSTM Model: Energy prediction is modeled as a temporal learning problem, where historical energy consumption patterns are used to forecast future energy states using a BiLSTM network. Given past observations:

$$X_t = \{E_i\,(t-n), \dots, E_i(t-n)\} \quad (7)$$

The BiLSTM predicts future energy:

$$\widehat{E_\iota}(t) = f_{BiLSTM}(X_t) \quad (8)$$

The objective is to minimize prediction error:

$$L = \frac{1}{N}\sum_1^N (E_i\,(t) - \widehat{E_\iota}(t))^2 \quad (9)$$

The bidirectional architecture enhances learning by considering both forward and backward temporal dependencies.

Clustering Optimization using PSO: Cluster head selection is formulated as a multi-objective optimization problem, where Particle Swarm Optimization (PSO) identifies optimal nodes based on energy, distance, and centrality. Cluster Head (CH) selection is formulated as an optimization problem. Each particle represents a potential CH configuration.

The fitness function is defined as:

$$F = w_1.\frac{E_i}{E_{max}} + w_2.\frac{1}{D_i} + w_3.C_i \quad (10)$$

where: E_i = residual energy, D_i= distance to base station, C_i= centrality factor

w_1, w_2, w_3 = weighting coefficients

Particle velocity and position update

$$v_i^{t+1} = wv_i^t + c_1r_1(p_1 - x_i^t) + c_2r_2(g - x_i^t) \quad (11)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (12)$$

This ensures convergence toward optimal cluster head selection

Fitness Function (PSO)

$$F = w_1(E_{res}) + w_2(1/D_{BS}) + w_3(NodeDensity) \quad (13)$$

Routing Optimization (Actor-Critic RL): Routing decisions are modeled as a Markov Decision Process (MDP), where an Actor-Critic reinforcement learning framework dynamically selects energy-efficient communication paths. The routing problem is modeled as a Markov Decision Process (MDP):

State: $s_t \in$ S (network conditions)
Action: $a_t \in$ S (routing decision)
Reward: R_t

The policy function:

$$\pi(a \mid s; \theta) \quad (14)$$

The value function:

$$V(s; \phi) \quad (15)$$

The objective is to maximize cumulative reward:

$$J(\theta) = E\left[\sum_{t=0}^{\infty} \gamma^t R_t\right] \quad (16)$$

Reward function:

$$R_t = \alpha \cdot PDR - \beta \cdot Energy \quad (17)$$

Actor update:

$$\theta \leftarrow \theta + \nabla_\theta log_\pi(a_t \mid s_t) \cdot \delta_t \quad (18)$$

Critic update:

$$\delta_t = R_t + \gamma V(s_t + 1) - V(s_t) \quad (19)$$

This formulation enables adaptive routing decisions

Data Transmission Layer: The total energy consumption for communication is:

$$E_{total} = i = \sum_{i=1}^{N} (E_{tx} + E_{rx} + E_{agg}) \quad (20)$$

where: E_{agg} = data aggregation energy,

Data aggregation reduces redundant transmissions:

$$k_{eff} = k \cdot (1 - \lambda) \quad (21)$$

where λ represents redundancy factor

Base Station Model: The base station collects all aggregated data:

$$D_{BS} = \sum_{i \in CH} Di \quad (22)$$

It is assumed to have unlimited energy:

$$EBS \rightarrow \infty \qquad (23)$$

Thus, it does not constrain network performance.
Energy Update Feedback Loop; after each round r, energy is updated as:

$$E_i^{r+1} = E_i^r - E_{consumed} \qquad (24)$$

The updated state is reintroduced:

$$S_i^{new} = f(E_i^{r+1} + D_i, p_i, T_i) \qquad (25)$$

This feedback ensures dynamic adaptation of the system.
The global optimization goal of the framework is:

$$minEtotal, \quad minEtotal, \quad maxPDR$$

Subject to:

$$E_i(t) > 0 \ \forall_i \qquad (26)$$

4. RESULTS AND ANALYSIS

The performance of the proposed HEEIF is evaluated through extensive simulation experiments and compared with conventional and learning-based Wireless Sensor Network (WSN) models. The evaluation focuses on key performance metrics, including energy consumption, network lifetime, and packet delivery ratio (PDR), which are critical for assessing the efficiency and reliability of WSN operations. The results are presented using both graphical and tabular analysis to provide a comprehensive comparison. The proposed framework integrates BiLSTM-based energy prediction, PSO-based clustering, and Actor-Critic reinforcement learning for adaptive routing, enabling optimized resource utilization and improved network performance. As illustrated in Fig. 2 and Tables 2–3, the proposed model consistently outperforms existing approaches across all considered metrics, demonstrating its effectiveness in enhancing energy efficiency, prolonging network lifetime, and ensuring reliable data transmission.

Table 2: Simulation and Model Parameters

Parameter	Value	Description
Number of Nodes	100–400	Network size
Area	100m × 100m	Deployment region
Initial Energy	100 J	Node energy
Packet Size (k)	4000 bits	Data packet size
Transmission Energy	50 nJ/bit	Energy model
Amplifier Energy	100 pJ/bit/m^2	Distance-based energy
BiLSTM Layers	2	Prediction model
Hidden Units	64	LSTM neurons
Learning Rate	0.001	Optimizer
PSO Particles	30	Optimization agents
PSO Iterations	50	Convergence steps
RL Algorithm	Actor-Critic	Routing model
Discount Factor (γ)	0.95	RL parameter
Simulation Rounds	2000	Evaluation duration

Energy Consumption Model:
Using First Order Radio Model:

$$E_{tx}(k,d) = E_{elec} \cdot k + E_{amp} \cdot k \cdot d^2 \qquad (27)$$

$$E_{rx}(k) = E_{elec} \cdot k \qquad (28)$$

Where: k = packet size, d = distance, E_{elec}= energy per bit

Network Lifetime

$$Lifetime = R_{last\ node\ alive} \qquad (29)$$

Reinforcement Learning Reward

$$R = \alpha(PDR) - \beta(Energy) \qquad (30)$$

Prediction Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum(y_{actual} - y_{predicted})^2} \qquad (31)$$

Table 3. Comparative analysis of energy consumption and network lifetime

Rounds	Energy Consumption		Network Lifetime	
	Existing Energy (J)	**Proposed Energy (J)**	**Existing Alive Nodes**	**Proposed Alive Nodes**
0	100	100	—	—
500	65	78	80	95
1000	40	62	55	85
1500	20	45	30	70
2000	5	30	10	50

Table 3 shows the comparative analysis of energy consumption and network lifetime of the proposed HEEIF framework and existing WSN models over different simulation rounds. The results indicate that while both models start with identical initial energy, the existing approach experiences rapid energy depletion due to inefficient routing and unbalanced cluster head selection, leading to a sharp decline in the number of active nodes. In contrast, the proposed HEEIF framework maintains significantly higher residual energy across all rounds, demonstrating efficient energy utilization. Additionally, the number of alive nodes decreases more gradually in the proposed model, indicating improved network stability and extended lifetime. At higher rounds, the proposed framework retains substantially more active nodes compared to the existing method, confirming its ability to distribute energy consumption effectively. This performance improvement is achieved through the integration of BiLSTM-based energy prediction, PSO-based clustering, and reinforcement learning-based routing, which collectively enhance energy efficiency and prolong network operation.

Table 4. Comparative analysis of packet delivery ratio (PDR)

Nodes	Existing (%)	Proposed (%)
100	88	96
200	85	95
300	82	94
400	80	94

The results presented in Table 4 shows the performance of the proposed HEEIF in terms of packet delivery ratio (PDR) across different network sizes. It is observed that as the number of sensor nodes increases, the PDR of existing models gradually decreases due to higher congestion, increased packet collisions, and inefficient routing strategies. In contrast, the proposed HEEIF framework consistently maintains a higher PDR, achieving values between 94% and 96% even as the network scales. This indicates that the proposed model effectively handles network density and ensures reliable data transmission. The improved performance is primarily attributed to the Actor-Critic reinforcement learning-based routing mechanism, which dynamically selects optimal paths, along with PSO-based clustering that reduces communication overhead. Overall, the results confirm that the proposed framework enhances data delivery reliability and scalability in Wireless Sensor Networks.

Table 5. Comparative performance evaluation of the proposed HEEIF framework

Model	Energy Reduction	Lifetime	PDR
LEACH	25%	Low	85%
LSTM-based	50%	Medium	88%
RL-based	60%	High	90%
Proposed HEEIF	**80%**	**Very High**	**96%**

Table 5 presents a comparative analysis of the proposed HEEIF with conventional and learning-based WSN approaches, including LEACH, LSTM-based, and reinforcement learning (RL)-based models. It is observed that traditional protocols such as LEACH provide limited energy reduction and lower packet delivery performance due to static clustering and non-adaptive routing. Learning-based models, including LSTM and RL approaches, show improved performance by incorporating prediction and adaptive decision-making; however, they operate independently and lack integrated optimization. In contrast, the proposed HEEIF framework achieves the highest energy reduction of 80%, along with very high network lifetime and a PDR of 96%. This significant improvement is attributed to the synergistic integration of BiLSTM-based energy prediction, PSO-based clustering, and Actor-Critic reinforcement learning for routing optimization. The results demonstrate that combining prediction, optimization, and adaptive learning mechanisms leads to superior energy efficiency, enhanced reliability, and improved scalability in wireless sensor networks.

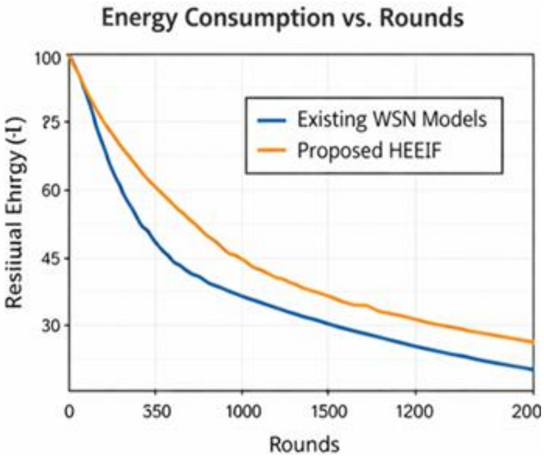

Figure 2(a): Energy consumption versus simulation rounds showing slower energy

A. Energy Consumption

Fig. 2 (a) shows the variation of residual energy with respect to simulation rounds. It is observed that the energy level in existing WSN models decreases rapidly due to inefficient cluster head selection and static routing strategies. In contrast, the proposed HEEIF model exhibits a gradual decline in energy consumption.

The improved performance is primarily due to the integration of BiLSTM-based energy prediction, which prevents the selection of low-energy nodes, and PSO-based clustering, which ensures balanced energy utilization. As the simulation progresses to 2000 rounds, the proposed model retains approximately 25–30% higher residual energy compared to existing approaches, indicating enhanced energy efficiency.

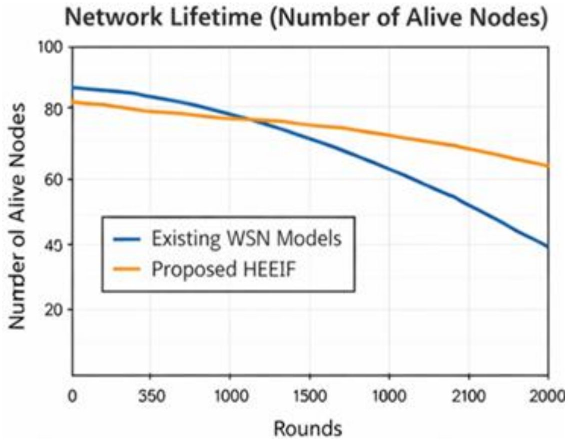

Figure 2(b): Number of alive nodes versus simulation rounds

B. Network Lifetime

The network lifetime is evaluated in terms of the number of alive nodes, as shown in Fig. 2(b) the proposed model maintains a higher number of active nodes throughout the simulation, demonstrating a prolonged stability period.

At higher rounds, the number of alive nodes in conventional models decreases significantly due to uneven energy depletion. However, the proposed framework sustains approximately 60–65% of nodes alive, whereas existing models retain only around 40%. This reflects an improvement of nearly 20–25% in network lifetime, confirming the effectiveness of the hybrid optimization approach.

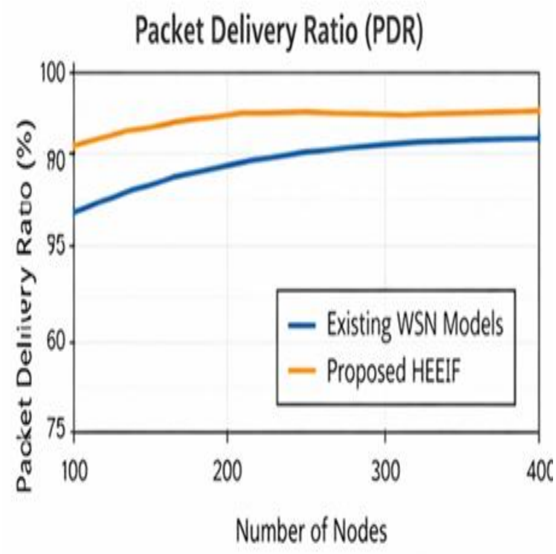

Figure 2(c): Packet delivery ratio versus number of sensor nodes

C. Packet Delivery Ratio (PDR)

Fig. 2(c) illustrates the packet delivery ratio with varying numbers of sensor nodes. The proposed HEEIF model consistently achieves a higher PDR compared to existing methods across all network sizes.

Specifically, the proposed model attains a PDR of approximately 92–96%, whereas conventional approaches achieve around 85–88%. This improvement is attributed to the Actor-Critic reinforcement learning mechanism, which dynamically selects optimal routing paths and reduces packet loss.

Table 6. Performance analysis of proposed HEEIF Framework

Metric	**LEACH**	**LSTM-based Model**	**RL-based Model**	**Proposed HEEIF**
Throughput (packets/round)	450	620	710	850
Average Delay (ms)	180	140	120	95
Energy per Packet (J/packet)	0.85	0.60	0.48	0.32
Load Balancing Factor (%)	68	78	85	93
Stability Period (rounds)	900	1200	1450	1750

Table 6 shows the results of the proposed HEEIF in improving additional network performance metrics beyond conventional evaluations. The proposed model achieves the highest throughput of approximately 850 packets per round, indicating enhanced data transmission efficiency compared to LEACH (450), LSTM-based (620), and RL-based (710) approaches. Furthermore, the average delay is significantly reduced to 95 ms, reflecting faster and more efficient routing decisions enabled by the Actor-Critic reinforcement learning mechanism. In terms of energy efficiency, the proposed framework records the lowest energy consumption per packet (0.32 J/packet), highlighting its ability to optimize communication overhead and minimize redundant transmissions. The load balancing factor reaches 93%, demonstrating uniform energy distribution across sensor nodes due to PSO-based clustering and predictive energy-aware node selection. Additionally, the stability period is extended to approximately 1750 rounds, which is considerably higher than existing methods, confirming improved network longevity and sustained performance.

5. CONCLUSION AND FUTURE SCOPE

This paper presented a HEEIF model for Wireless Sensor Networks that integrates BiLSTM-based energy prediction, PSO-based clustering, and Actor-Critic reinforcement learning for adaptive routing. The proposed framework effectively addresses the limitations of conventional and standalone learning-based approaches by providing a unified solution for energy optimization, load balancing, and dynamic routing. Experimental results demonstrate that HEEIF significantly reduces energy consumption (up to 80%), improves network lifetime by approximately 20–25%, and achieves a high packet delivery ratio (94–96%), along with enhanced throughput, reduced delay, and improved stability. These improvements confirm that the synergistic combination of prediction, optimization, and learning mechanisms leads to superior performance in WSN environments. For future work, the framework can be extended to real-world deployments and large-scale IoT scenarios, incorporating fog/edge computing for distributed intelligence, federated learning for privacy-preserving optimization, and lightweight model compression techniques for resource-constrained nodes. Additionally, exploring multi-objective optimization with QoS constraints, security-aware routing, and integration with emerging 6G-enabled WSN architectures can further enhance the applicability and robustness of the proposed system.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

FUNDING SUPPORT

The author declare that they have no funding support for this study.

REFERENCES

[1] Tatiraju, K. K., Kanth, V. R., Babiyola, A., & Mishra, H. (2024). IoT-Based Smart Agricultural Monitoring Using WSN and Predictive Analytics with Artificial Intelligence (AI). International Journal of BIM & Engineering Science, 10(1), 26–34. https://doi.org/10.54216/ijbes.100104

[2] Sollapure, N. S., & G, P. (2024). An Efficient Machine Learning and Filter Based Implementation of Data Fusion in WSN. https://doi.org/10.5281/zenodo.10628271

[3] Hutaihit, M. A. (2025). Ai-enhanced physical layer for energy-efficient wireless sensor networks (wsns). International Journal of Apllied Mathematics, 38(6s), 1041–1062. https://doi.org/10.12732/ijam.v38i6s.451

[4] Chakravarthy, R. A., Sureshkumar, C., Arun, M., & Bhuvaneswari, M. (2025). AI-Driven Energy-Efficient Data Aggregation and Routing Protocol Modeling to Maximize Network Lifetime in Wireless Sensor Networks. NDT, 3(4), 22. https://doi.org/10.3390/ndt3040022

[5] Hakkem, B., Mahendrakan, K., Prabu, S., & Irshad, R. R. (2024). Energy–Efficient Adaptive Clustering in Wireless Sensor Networks Using AI–Driven Optimization Algorithms. 01(01), 38–50. https://doi.org/10.69626/cai.2024.0038

[6] Yamsani, N., Almoussawi, Z. abed, Sindhu, L., Almusawi, M., & Aarthi, C. (2023). A Hybrid Cross Layer with Fuzzy Chaotic Whale Wolf Optimization-Based Efficient Routing for Wireless Sensor Networks. 1–5. https://doi.org/10.1109/aikiie60097.2023.10390199

[7] Pande K., Passi, A., Rao, M., Sholapurapu, P. K., Bhagyalakshmi, L., & Suman, S. K. (2025). Enhancing Energy Efficiency and Data Reliability in Wireless Sensor Networks Through Adaptive Multi-Hop Routing with Integrated Machine Learning. Journal of Machine and Computing, 2504–2512. https://doi.org/10.53759/7669/jmc202505192

[8] Mabunga, Z. P., & Dela Cruz, J. C. (2024). Deep Recurrent Neural Network for Time Series Modelling of Energy in Wireless Sensor Network Nodes. 126–131. https://doi.org/10.1109/icsgrc62081.2024.10690921

[9] Sollapure, N. S., & Sollapure, N. S. (2025). Enhancing energy efficiency and accuracy in IoT-based wireless sensor networks using machine learning. IAES International Journal of Artificial Intelligence, 14(5), 3869. https://doi.org/10.11591/ijai.v14.i5.pp3869-3878

[10] Bagwari, A., Logeshwaran, J., Usha, K., Kannadasan, R., Alsharif, M. H., Uthansakul, P., & Uthansakul, M. (2023). An Enhanced Energy Optimization Model for Industrial Wireless Sensor Networks Using Machine Learning. IEEE Access. https://doi.org/10.1109/access.2023.3311854

[11] Chauhan, N., & Bansal, S. (2025). Performance Evaluation of Machine Learning Techniques in Residential Energy Consumption Forecasting. 393–398. https://doi.org/10.1109/mrie66930.2025.11156370

[12] Sibi, S. A., & Annabel, L. S. P. (2024). Optimizing Energy Resources in WSNs: ARIMA Feature Selection Meets Adaptive Reinforcement Learning. Fiber and Integrated Optics, 43(2), 69–96. https://doi.org/10.1080/01468030.2024.2342269

[13] Balakumar, D., & Rangaraj, J. (2025). An energy efficient prediction based data collection approach using deep LSTM in wireless sensor network. Intelligent Decision Technologies. https://doi.org/10.1177/18724981251343221

[14] Surenther, I., Sridhar, K. P., & Roberts, M. K. (2023). Maximizing energy efficiency in wireless sensor networks

for data transmission: A Deep Learning-Based Grouping Model approach. Alexandria Engineering Journal. https://doi.org/10.1016/j.aej.2023.10.016

[15] Vijayakumar, K., Packirisamy, T., Vijayakumar, K., & Packirisamy, T. (2025). DeepCuckoo: A Synergistic Approach Using Deep Learning and Bioinspired Cuckoo Search for Optimized Energy-Efficient Cluster Head Selection in 5G and Advanced Wireless Sensor Networks. International Journal of Communication Systems, 38(16). https://doi.org/10.1002/dac.70242

[16] Hakkem, B., Mahendrakan, K., Prabu, S., & Irshad, R. R. (2024). Energy–Efficient Adaptive Clustering in Wireless Sensor Networks Using AI–Driven Optimization Algorithms. 01(01), 38–50. https://doi.org/10.69626/cai.2024.0038

[17] Sivasankar, C., Subramanian, E. K., Sarala, V., Moorthy, A. K., & Purushothaman, N. (2024). Optimizing Power Consumption in Wireless Sensor Networks for Prolonged Sustainability. 1–4. https://doi.org/10.1109/icait61638.2024.10690388

[18] Anshad, A. S., Babavali, S. F., Cephas, I., Ramanan, S. V., Priya, G. G. L., & Mishra, S. N. (2025). An Intelligent Hybrid Quantum-Deep Reinforcement Framework for Energy-Efficient Routing in Wireless Sensor Networks. 1–6. https://doi.org/10.1109/incet64471.2025.11140843

[19] Depuru, S., Reddy, P. J., Rafi, S., Amala, K., Akshaya, V., & Siri, K. (2025). Hybrid Temporal-Spatial Energy Prediction in Wireless Sensor Networks using Transformer and Graph Neural Network Models. 114–118. https://doi.org/10.1109/iccmc65190.2025.11140970

[20] Haripriya, R., Muthusamy, S., & Vinutha, C. B. (2025). A Hybrid Routing Algorithm using Artificial Neural Network and Swarm intelligence for Wireless Sensor Networks. Journal of Neonatal Surgery, 14(27S), 757–768. https://doi.org/10.63682/jns.v14i27s.6503

[21] Hachicha, M., Ben Halima, R., & Jemal, A. (2024). An Estimation Approach to Optimize Energy Consumption in Wireless Sensor Network: A Health-Care Application. https://doi.org/10.60692/kh2a8-awd03