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An intelligent framework for energy optimization in IoT networks using LSTM and multi-criteria decision making

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ABSTRACT

Intelligent agriculture, digital health, or smart cities are only a few out of multiple uses of the Internet of Things. The limited energy supply of the IoT nodes, specifically battery-run sensor nodes, prevents them from maintaining consistent work and hinders the network's functioning. In this regard, a smart framework that utilizes the progressive machine learning models with multi-criteria decision-making should ensure higher energy efficiency in the IoT networks. While the existing researches have attempted to decrease energy levels in the IoT networks, most of them apply primitive concepts: clustering, routing, and node sleep, and do not use the most efficient machine learning algorithms for energy prediction. Indeed, several people have tried using machine learning algorithms, like decision trees, linear regression, and elementary ANN for energy prediction. However, most of these algorithms are efficient if they considered as individual ones, and people almost never combine energy prediction and node priority. As a result, we propose a complex system of several designed operations that result in increased energy efficiency. First, the data on energy consumption are gathered at regular intervals and preprocessed: normalized, denoised, and empty value-imputed. Then the LSTM model is used to find temporal patterns and predict the future changes. After node ranking, various dynamic strategies like routing, some of the nodes put to sleep, and traffic are optimized. As a result, the lifetime of the network increases by 35 % whereas the energy consumption decreases by 23 %.

1. Introduction

The main problem addressed in this study is the excessive and unbalanced energy [22] consumption among IoT nodes, which significantly limits network lifetime. As one of the key technologies in the digital age, IoT [36]networks play an important role in connecting devices and sensors to each other (Maraveas) [23]. These networks are used in various applications such as smart cities, e-health, smart agriculture, and Industry 4.0 (Infant) [17]. However, one of the main challenges in IoT networks is energy consumption [10]. Many nodes, such as sensors and devices, are battery-operated and have limited energy [9]. On the other hand, replacing or recharging batteries in some applications (such as environmental sensors in remote areas) is costly and difficult [19]. Therefore, optimizing energy consumption [39] in these networks has become a critical issue [12]. Previous research on energy optimization in IoT networks has proposed various approaches [29]. Some of these studies have focused on using traditional algorithms [15] such as node sleeping and energy-efficient routing [32]. Others have used machine learning methods to predict energy consumption [34]. However, the following research gaps still exist:

1. **Not paying attention to node prioritization:** A lot of current research treats nodes as if they were all the same and doesn't think about things like how important the data is, where it is, and how much energy [8] is left. Because of this lack of care, important nodes fail early, which makes the network as a whole work worse. 2**. Insufficient application of sophisticated machine learning:** While some research has employed basic neural networks as machine learning algorithms [1], fewer studies have examined the use of more sophisticated models, such as LSTM, to forecast energy consumption in Internet of Things networks (Reddyboina) [33]. The ability of LSTM [21] to learn long-term dependencies, however, improves the accuracy of its predictions. 3. **Methods not working together:** Most of the time, research only looks at one method (like machine learning or node prioritization [2]) and doesn't combine them to get the best results [6].

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This paper aims to present an intelligent framework for optimizing energy consumption in IoT networks by combining advanced long-short-term memory machine learning and node prioritization. The proposed method includes the following steps:

Data on energy consumption for IoT nodes is collected at different time intervals. Then, these data are preprocessed (such as noise removal, missing value imputation, and data scaling).

A long-short-term memory model is designed to predict the future energy consumption of nodes based on past data. Due to its ability to learn long-term dependencies, this model can identify complex patterns in time-dependent data. The next step is to prioritize nodes. Nodes are ranked based on criteria such as data importance, remaining energy, and geographic location. Multi-criteria decision-making algorithms are used to determine these priorities. Based on the predictions of the long-short-term memory model and the results of prioritization, strategies such as reducing data traffic volume, shutting down less important nodes, and rerouting data transmission are implemented. These strategies are updated dynamically according to network conditions. This paper presents the following main contributions:

- An integrated predictive–decision framework is developed that jointly utilizes Long Short-Term Memory (LSTM) for energy consumption forecasting and Multi-Criteria Decision Making (MCDM) for node prioritization — a combination that, to the best of our knowledge, has not been jointly explored in previous IoT energy optimization studies.
- A hybrid decision mechanism is proposed, where the predicted energy consumption, residual energy, and task importance are fused through the TOPSIS technique to dynamically control node sleep scheduling and energy balancing.
- A comprehensive performance evaluation is conducted under various network conditions, demonstrating superior energy efficiency, reduced latency, and extended network lifetime compared to existing schemes such as LEA-RPL and DRL-ICSSS.

Scalability and computational efficiency of the proposed framework are analyzed, confirming its practicality for large-scale IoT networks.

As for the structure of document, In the second section, the literature pertaining to the reduction of energy consumption in IoT networks is analyzed, and the gaps in the literature are outlined. In Section 3, the complete methodology for the approach which consists of data collection and preprocessing, LSTM networks for energy consumption forecasting, and multi-criteria decision-making based node prioritization is described. In Section 4, evaluation and comparative analysis of the results are provided in the form of graphs with concise explanatory analysis, enabling unfettered comparison to the baseline methods.Section 5 goes into great detail about the results in relation to the study's goals and lists the main reasons why performance improved. Lastly, Section 6 is where the summary of the most important points and the rest of the text are set aside so that the results and suggestions for more research can be talked about.

2. Related work

Researchers have come up with smart and flexible ways to deal with the growing complexity and variety of modern IoT-based smart environments. This is especially true when it comes to managing energy [40], routing, and allocating resources. Reinforcement learning (RL) and deep learning (DL) are becoming more popular because they help you make decisions faster and use less energy. Ahmad et al. [3] found a way to pick more than one node for underwater IoT networks that works with RL-based algorithms like DQN-SEC and DDPG-SEC. Their method greatly reduced end-to-end delay and made data delivery more reliable by adapting to the changing conditions of the underwater acoustic channel. But the way they do things costs a lot of money and doesn't always help people learn. Mishra et al. [24], on the other hand, created a two-stage DL-RL caching protocol for smart grid IoT that cut delays by up to 55 % and increased throughput by 170 %. But it is still limited by how hard it is to understand the model and how few edge devices there are. RL is also used a lot in theoretical resource management for the whole Internet of Things (IoT) [18]. Musaddiq et al. [28] made a general RL-based framework that uses FL (Federated Learning) to solve the problems of training in distributed environments with few resources. Their method seems good, but it takes a long time to find a solution, and the reward design has to be very careful. Bereketeab et al. [7] used a hybrid PPO-Clip framework to cut down on HVAC energy use and make people more comfortable in building energy management. They found that this made things work up to 12.6 % better. But it's still hard to use in real life because it needs data and is hard to connect to other systems. Also, RL-driven multi-agent systems, like the one by Ordouei et al. [30], have shown that cooperative clustering can save a lot of energy (about 40 %) in smart cities. Liu et al. [20] also used two DQN models to find out how IoT devices can connect to channels that are changing. They got a lot better at spectral efficiency, but the training is still not stable. Prasad and Periyasamy [31] looked at older clustering protocols such as HEED and LEACH. They found that these protocols are easier to use and use energy more evenly, but they have problems with security and scaling. There has been new research on DL in smart cities. Aljohani [5] says that a predictive load management system that uses feedforward and recurrent networks can help lower energy use and carbon emissions. Sivakumar et al. [38] built on this idea by combining AI-based energy optimization with sensor frameworks that can detect changes in Industry 4.0. This used less than 95 % of the power when the machines weren't doing anything. These models, on the other hand, need a lot [25[of computing power and strong datasets, which makes them hard to use in nodes that don't have a lot of resources. Another new area that looks at security is energy optimization. He et al. [14] looked at lightweight cryptographic methods that work with energy management strategies to keep threats like DoS attacks at bay without using more power. In service composition scenarios, group-teaching-based optimization algorithms like the GT-EQCA proposed by Hameche et al. [13] also improve both QoS and energy at the same time. They can save up to 94 % of energy, but so far they have only been tested on fake sequential datasets. Managing grids and moving cars in real time is easy with multi-agent deep learning frameworks like ORA-DL [37] and OptiE2ERL [16]. These models are very accurate (over 93 %) and stable, but you can only use them if you have centralized infrastructure or if the initial costs are very high. These features get even better when you add edge computing, digital twins, and federated learning to integrated IoT-AI architectures to make the most of building energy [35]. They keep people comfortable at the right temperature and cut CO_2 emissions by as much as 40 %. Routing protocols that use particle swarms, like LEA-RPL [26], and hybrid metaheuristics, like MPA-based routing [11], have been shown to help sensor networks send and receive packets faster. We don't know if these methods will work on mobile devices yet, though. In IoT [41] networks that collect energy, ML-based routing [4] handles the uncertainty of random energy arrival and transmission, but it often has trouble with high data needs and slow convergence. Montoya et al. Montoya [27] came up with a mathematical optimization model for smart cities with limited resources to use when deciding which routes to take first. Finding the best energy-aware service routing is done with linear programming. These methods are great for analysis, but they need a lot of computer power and very accurate energy data. Finally, human-centered models use both IoT and ML to improve the thermal environments for taking care of the elderly. It costs a lot to build, but it makes things more comfortable for everyone and uses less energy. When read together, these works show us how to use energy more wisely and how to control devices in IoT settings in a smart and flexible way. There are still some big gaps, especially when it comes to finding the right balance between how hard it is to compute, how well it scales, how quickly it responds in real time, and how easy it is to use. We want to use a framework that combines hybrid learning methods and dynamic resource scheduling to fix these problems with as little extra work as possible. Table 1 shows a full summary of related works to make it easier to compare different approaches. This table lists the most important things, such as the methods used (whether they are mathematical or heuristic), how they affect delay, load balancing, fault tolerance, energy cost, and reliability, as well as their main pros and cons.

In summary, although many studies have addressed energy efficiency in IoT networks using traditional or learning-based techniques, few have jointly applied deep temporal prediction (LSTM) with multi-criteria decision making for adaptive energy management, which constitutes the main novelty of this paper.

3. Proposed method

The proposed method of this research aims to improve energy consumption in Internet of Things networks by introducing a smart and multi-stage efficient method that combines advanced machine learning techniques and multi-criteria decision-making algorithms. It comprehensively attempts to simultaneously predict accurate energy consumption and energy consumption decisions regarding energy resource management in nodes. In the first step, data related to network energy consumption are collected in continuous intervals and are prepared for analysis after performing preprocessing steps including noise removal, incomplete completion, and smoothing. In the next step, LSTM-type recurrent neural networks are used to predict the energy consumption trend in nodes in order to accurately model the future behavior of the network. After prediction, using multi-criteria decision-making algorithms, networks are ranked and prioritized based on factors such as remaining energy, most important production data, and location. This ranking is used to make management decisions regarding the application of policies such as sleeping low-value nodes, reducing unnecessary traffic, and optimizing forwarding routes. Fig. 1 shows the flowchart of the proposed method.

3.1. Optimization process

The optimization process begins by defining the main objectives and identifying the existing challenges. The main objective in this context is to reduce the energy consumption of sensor nodes in the IoT network and, as a result, increase its operational lifespan. In this step, key parameters affecting decision-making, such as the energy level of the nodes, traffic density, data importance, and the topological state of the network, are identified and evaluated. Eq. (1) defines the target variable for modeling as the sum of all nodes' total energy consumption.

$$\min E_{\text{total}} = \sum_{i=1}^{N} E_i \tag{1}$$

Where E_i is the energy consumption of node i and N is the total number of nodes. The lifetime of nodes is also modeled as Eq. (2).

$$T_i = \min\{t : E_i(t) = 0\} \tag{2}$$

3.2. Collecting energy consumption data

In this step, data related to the energy consumption of nodes is collected at different time intervals. This data includes instantaneous

Table 1
Summary of recent works on energy-efficient IoT network optimization.

Ref.	Year	Method	Math.	Heuristic	Delay	Load	Fault	Cost	Reliability	Advantage	Shortcoming
Ahmad [3]	2024	RL-SEC, DQN-SEC, DDPG-SEC	×	×	✓	×	×	✓	✓	Improved throughput, reduced delay, enhanced battery life	Execution complexity, memory need, learning instability
Mishra [24]	2023	DRL, Edge, Caching	×	×	✓	✓	×	✓	✓	Energy and throughput efficiency, cost-saving	High implementation complexity, resource demands
Musaddiq [28]	2023	Reinforcement Learning	✓	×	✓	×	×	×	✓	Smart decisions, reduced delay, better energy use	Slow convergence, large state space
Bereketeab [7]	2024	PPO-Clip, Offline+Online	✓	✓	✓	×	✓	✓	✓	Reduced energy use, improved stability	High complexity, long training time
Ordouei [30]	2024	Q-Learning (multi-agent)	×	✓	×	✓	×	✓	✓	Lower energy, longer network life	High complexity, coordination needed
Liu [20]	2023	DRL, Dual-DQN, FDMA+NOMA	×	✓	✓	✓	✓	×	✓	High throughput, optimal spectrum usage	Convergence fluctuation, high complexity
Prasad [31]	2023	Clustering: LEACH, HEED, etc.	✓	✓	✓	✓	✓	✓	×	Longer network life, balanced load	Low security, clustering instability
Aljohani [5]	2024	Deep Learning (ANN, RNN)	×	×	✓	×	×	✓	✓	Accurate prediction, cost and energy saving	High processing need, hard integration
Sivakumar [38]	2024	Reinforcement Learning + AI	✓	✓	✓	✓	×	✓	✓	High savings, 96 % sensitivity	Complex implementation, processing overhead
He [14]	2024	Energy-aware ML + Blockchain	✓	×	×	×	✓	✓	✓	Energy-efficient security	Device diversity, limited resources
Hameche [13]	2025	GT-EQCA, GTO, Pareto	✓	✓	×	×	×	✓	✓	Up to 94 % energy saving	Static environment limits, simulated data
Singh [37]	2025	ORA-DL (RL+DL+IoT)	×	×	✓	✓	✓	✓	✓	93 % accuracy, lower cost and energy	Processing complexity, high security demand
Hussain [16]	2025	OptiE2ERL, Q-Learning, MDP	✓	×	✓	✓	×	✓	✓	High stability, reduced energy use	Base station dependency
Rojek [35]	2025	IoT + AI (LSTM, CNN, RL)	✓	×	✓	✓	✓	✓	✓	Lower CO_2, accurate prediction, high ROI	High initial cost, data security concerns
Mokrani [26]	2025	LEA-RPL, PSO, LSTM	✓	✓	✓	✓	✓	✓	✓	49 % energy reduction, 43 % delivery gain	Not tested in dynamic environments
Darabkh [11]	2025	MPA, Data Fusion, RDFCF	✓	✓	✓	✓	✓	✓	✓	300 % lifetime, 264 % energy saving	Depends on specific parameters
Alamu [4]	2025	ML (RL, DL, DRL)	✓	×	✓	✓	✓	✓	✓	Automated decisions, longer network life	High data requirement, slow convergence
Montoya [27]	2025	Math Model + LP (Pyomo)	✓	×	✓	✓	✓	✓	✓	Precise allocation, scalable to large networks	Needs accurate energy data

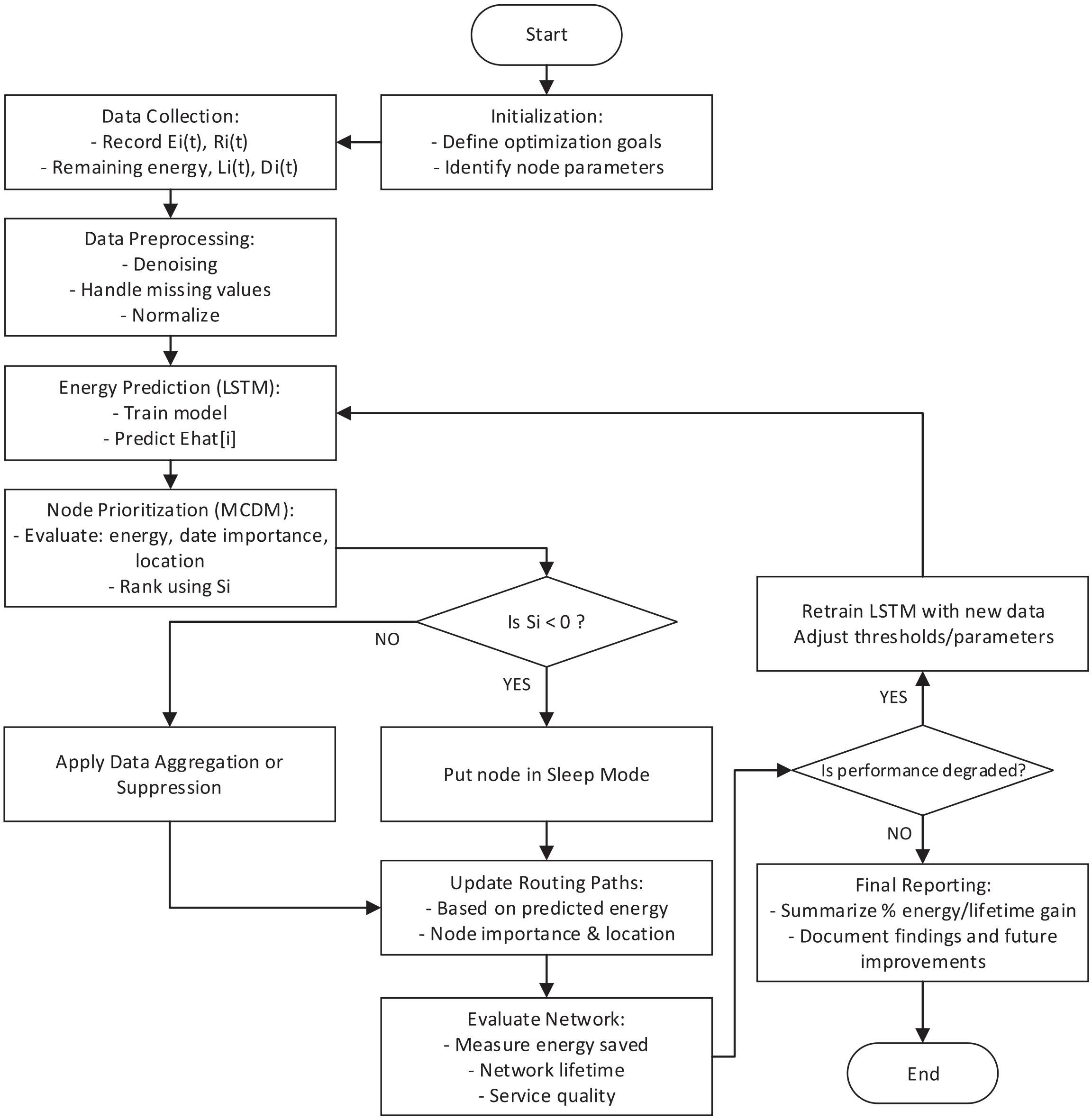

Fig. 1. Flowchart of the proposed method.

energy consumption, data transmission rate, location, and type of data generated. The collected data for each node is defined as a feature vector of Eq. (3).

$$X_i(t) = [E_i(t), R_i(t), L_i(t), D_i(t)] \tag{3}$$

Where E_i *(t)* is the energy consumption, R_i *(t)* is the transmission rate, L_i *(t)* is the location, and D_i *(t)* is the data type at time *t* for node *i*. The sum of these vectors forms a feature matrix of Eq. (4) for the entire network.

$$X(t) = [X_1(t), X_2(t), \ldots, X_N(t)] \in \mathbb{R}^{N\times d} \tag{4}$$

3.3. Data preprocessing

The collected raw data may contain noise, missing values, or features with different scales. First, the noise is removed using the moving average in Eq. (5).

$$\widehat{E}_i(t) = \frac{1}{k}\sum_{j=0}^{k-1} E_i(t-j) \tag{5}$$

Then, the missing values in Eq. (6) are replaced by time averaging. Finally, to avoid the negative impact of different scales on model learning, all features are normalized by Eq. (7).

$$E_i(t_{\text{missing}}) = \frac{E_i(t-1) + E_i(t+1)}{2} \tag{6}$$

$$\widetilde{X}_i(t) = \frac{X_i(t) - \min(X)}{\max(X) - \min(X)} \tag{7}$$

3.4. Predicting future energy consumption with LSTM model

To predict future energy consumption, recurrent neural networks with long short-term memory are used, which are capable of modeling temporal dependencies in data. This model, by receiving a sequence of previous data, predicts the future energy consumption of each node based on Eq. (8).

$$\widehat{E}_i(t+1) = f_{\text{LSTM}}(X_i(t-h:t)) \tag{8}$$

Here h is the time window size, and f_"LSTM" is the learning function of the model. The cost function for training the model is defined as the mean squared error with Eq. (9).

$$L = \frac{1}{N}\sum_{i=1}^{N}\left(\widehat{E}_i(t+1) - E_i(t+1)\right)^2 \tag{9}$$

Table 2 shows the pseudocode of the proposed method.

In our implementation, the LSTM network consisted of two stacked layers with 64 and 32 hidden units, respectively. The *tanh* activation function was applied to capture nonlinear temporal dependencies. A dropout rate of 0.2 was introduced to mitigate overfitting. The model was trained using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and a total of 100 epochs. The mean squared error (MSE) was used as the loss function, while the root mean squared error (RMSE) and mean absolute error (MAE) were employed as evaluation metrics. Early stopping was applied to halt training when the validation loss showed no improvement for 10 consecutive epochs. This configuration ensured a good balance between accuracy and computational efficiency.

3.5. Prioritizing nodes with multi-criteria decision making

After predicting future consumption, nodes should be prioritized based on several criteria, such as remaining energy, data importance, and distance from the central node. For this purpose, a multi-criteria decision-making technique such as TOPSIS is used. First, the criteria are normalized with Eq. (10). Then, the distance of each node from the positive and negative ideal is calculated with Eq. (11). And the final node score is obtained with the Eq. (12):

$$r_{ij} = \frac{c_{ij}}{\sqrt{\sum_{i=1}^{n} c_{ij}^2}} \tag{10}$$

$$D_i^+ = \sqrt{\sum_{j=1}^{m}\left(r_{ij} - r_j^+\right)^2}, D_i^- = \sqrt{\sum_{j=1}^{m}\left(r_{ij} - r_j^-\right)^2} \tag{11}$$

Table 2
Pseudocode of the proposed method.

```
Input:
  - Time-series energy consumption data from IoT nodes
  - Node metadata: location, remaining energy, data importance, transmission rate
  - Network parameters: sleep threshold, routing table, traffic load status
Output:
  - Predicted energy usage of nodes
  - Node priority scores (MCDM-based)
  - Energy-aware actions: sleep scheduling, traffic suppression, path optimization
Start
Initialize()
define_optimization_goals()
identify_node_parameters()
While network_is_active:
data = collect_data()
preprocessed_data = preprocess(data)
energy_prediction = LSTM.predict(preprocessed_data)
for each node i:
Si = MCDM_rank(energy_prediction[i], data_importance[i], location[i])
if Si < 0:
put_node_to_sleep(i)
else:
apply_data_aggregation_or_suppression(i)
update_routing_paths(energy_prediction, node_importance, locations)
metrics = evaluate_network()
if performance_degraded(metrics):
retrain_LSTM(preprocessed_data)
adjust_thresholds()
else:
generate_report(metrics)
break
End
```

$$S_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{12}$$

3.6. Applying optimization strategies

According to the prioritization of nodes, strategies to reduce energy consumption are applied. For nodes with low importance and high consumption, it is recommended to enter sleep mode according to Eq. (13).

$$\text{If } S_i < \theta \text{ and } \widehat{E}_i(t+1) > E_{\text{thresh}} \Rightarrow \text{Sleep Mode} \tag{13}$$

In other cases, duplicate data is removed, and aggregated to reduce network load. Furthermore, data transmission paths are optimized according to energy consumption and node location. The edge weights used for routing are defined in Eq. (14).

$$\text{Cost}(i,j) = \frac{d_{ij}}{E_i(t)} \tag{14}$$

Table 3 lists the most important symbols and notations used in the mathematical modeling, algorithm design, and performance evaluation to make the proposed framework easier to understand and follow. In later sections, these definitions will help you understand how to read equations and how parameters are related to each other.

3.7. Architecture of the proposed method

This architecture consists of four main layers, each of which performs specific tasks for the optimal management of sensor networks. The upper layer, known as the application layer, provides features like monitoring dashboards, network performance reporting, and decision support. Users and system administrators can analyze energy consumption, quality of service, and network lifetime using the final output this layer provides. The next layer, the control and intelligence layer, is responsible for implementing prediction and decision-making algorithms. In this layer, nodes are prioritized based on criteria such as remaining energy, data importance, and physical location. A deep learning model is also used to predict future energy consumption to make decisions more accurate. If the network performance decreases, this model is retrained.

The third layer is the data processing layer, which is responsible for collecting information from nodes, cleaning noise, completing incomplete data, and normalizing it. At this stage, data such as the amount of energy consumed, the amount of information received or sent, and the location of the nodes are recorded. Then, unnecessary data is compressed or deleted to reduce energy consumption. In the lowest layer, the network layer, and the sensor layer, there are sensor nodes that are responsible for sensing the environment and sending information. These nodes have limited energy resources and must be managed in a way that increases the life of the network. This layer also houses a wireless communication infrastructure that facilitates data transfer between nodes and the central server. The connection between these four layers forms an intelligent structure that adapts to environmental changes. Fig. 2 shows the subject of our proposed method.

In this section, a multi-layer architecture was presented to optimize energy consumption and extend the life of wireless sensor networks in the context of the Internet of Things. This architecture enables effective resource management by dividing tasks into four layers: application, control and intelligence, data processing and network, and sensing. In the intelligence layer, the combination of deep learning algorithms and multi-criteria decision-making provides an accurate mechanism for predicting energy consumption and prioritizing nodes. Also, the use of a deep learning algorithm based on recurrent networks in predicting future energy consumption has increased the accuracy of decision-making and reduced network load. On the other hand, the data processing layer provides the basis for reducing unnecessary transfers and

Table 3
Symbols of the proposed method.

Symbol	Definition	Unit/Explanation
N	Total number of nodes in the network	Unitless
E_i	Energy consumption of node i in a time interval	Joule (J)
E_{total}	Total energy consumed by all nodes	Joule (J)
T_i	End of life time of node i (when it runs out of energy)	Second (s)
$X_i(t)$	Feature vector of node ii at time t	Numerical vector
$R_i(t)$	Data sending rate by node ii at time t	Byte/second
$L_i(t)$	Spatial coordinates of node i	Meter (m)
$D_i(t)$	Type or importance of data sent by node i	Numerical value (normalized)
$\hat{E}_i(t)$	Mean smoothed energy consumption of node i	Joule (J)
$\tilde{X}_i(t)$	Normalized feature vector of node i	Unitless
f_{LSTM}	LSTM model for energy prediction	Learning function
$\hat{E}_i(t+1)$	Predicted energy of node i for next step	Joule (J)
L	Error function of LSTM model	Unitless
c_{ij}	Metric value of j for node ii in MCDM	Variable
r_{ij}	Normalized value of j for node i	Unitless
D_i^+	Distance of node i to positive ideal solution	Unitless
D_i^-	Distance of node i to negative ideal solution	Unitless
S_i	Final score of node i in MCDM	Between 0 and 1
θ	Score threshold for node to enter sleep state	Unitless
E_{thresh}	Energy consumption threshold for optimization decision	Joule (J)
$Cost(i,j)$	Path cost between nodes i and j	Unitless
d_{ij}	Physical distance between nodes ii and j	Meter (m)
T_{net}	Network lifetime (based on percentage of nodes outage)	Second (s)
α	Percentage of nodes whose outages indicate end of network lifetime	Percent (%)
ΔE	Percentage of energy reduction compared to baseline	Percent (%)
ΔT	Percentage Increased lifespan compared to the baseline	Percent (%)

saving energy by cleaning and compressing data. Nodes that have low energy or are less important are dynamically put into sleep mode to prevent rapid resource depletion. Finally, the proposed system adapts itself to environmental changes by adaptively retraining the model and updating communication paths. Also as you can see in Fig. 3.

3.8. Scalability and computational complexity

The proposed framework is designed to be scalable with respect to the number of IoT nodes (N) and decision parameters (M). The LSTM-based prediction stage operates independently for each node and has a computational complexity of $O(N \times T \times h)$ where T is the number of time steps and h is the number of hidden neurons. This component can be parallelized across nodes, which ensures scalability under distributed or edge-computing environments. The MCDM-based prioritization (TOPSIS) stage has a complexity of $O(N \times M)$ as it computes normalized scores and distances for each node. The total space complexity of the system is $O(N \times (T + M))$ dominated by the data storage for recent time-series measurements and decision parameters.

Therefore, under the assumption that LSTM prediction is executed in a distributed or edge-enabled manner, the overall system scales linearly with the number of nodes, making it practical for large-scale IoT deployments.

4. Evaluation and comparison

To evaluate the effectiveness of the proposed method, its performance has been compared with two previous approaches that have structural and objective similarities with this research. First, the two-stage protocol based on the Internet of Things and Deep Reinforcement Learning (DRL) [24], which uses multi-hop routing and DRL-based policies to dynamically and optimally allocate resources in smart energy networks. This method, by simultaneously using historical and real-time data, has been able to significantly reduce network latency and increase energy efficiency. Second, the LEA-RPL algorithm [26], which intelligently reduces energy consumption and network overhead in the routing process by combining the LSTM prediction model and PSO-based multi-criteria optimization. Compared to these two approaches, the proposed framework of this research has been able to achieve a more effective balance between prediction accuracy, management flexibility, and energy consumption reduction by designing a multi-stage structure including data preprocessing, energy consumption prediction using LSTM, and multi-criteria decision making for ranking and managing node resources. Also, this method offers exclusive advantages over similar approaches by applying policies such as sleeping low-value nodes and optimizing the data transmission path.

This study used the IoT-SmartHome Energy Dataset. It gets information in real time about how much energy different smart home IoT devices use. The dataset shows all the ways energy is used, such as temperature, humidity, occupancy, and the loads on different systems, like HVAC, lighting, and plug loads. These features help the proposed model make good decisions and guesses.

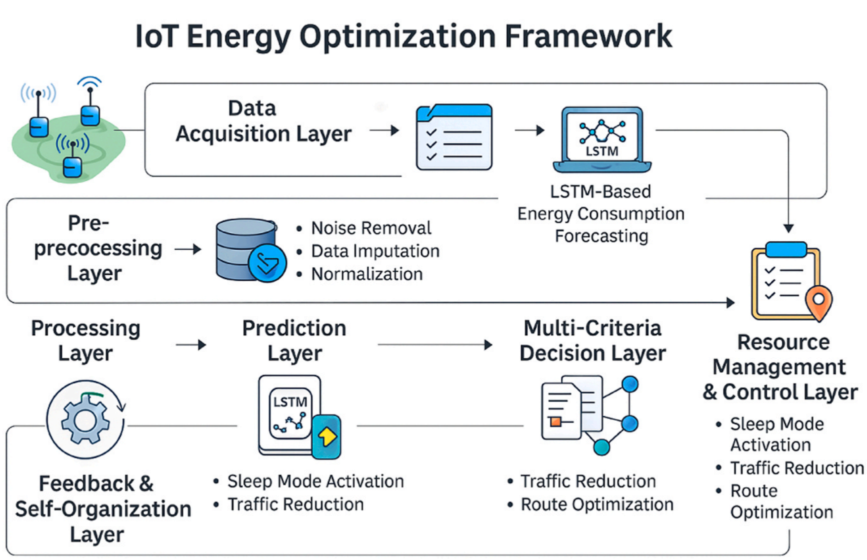

Fig. 2. Architecture of the proposed method.

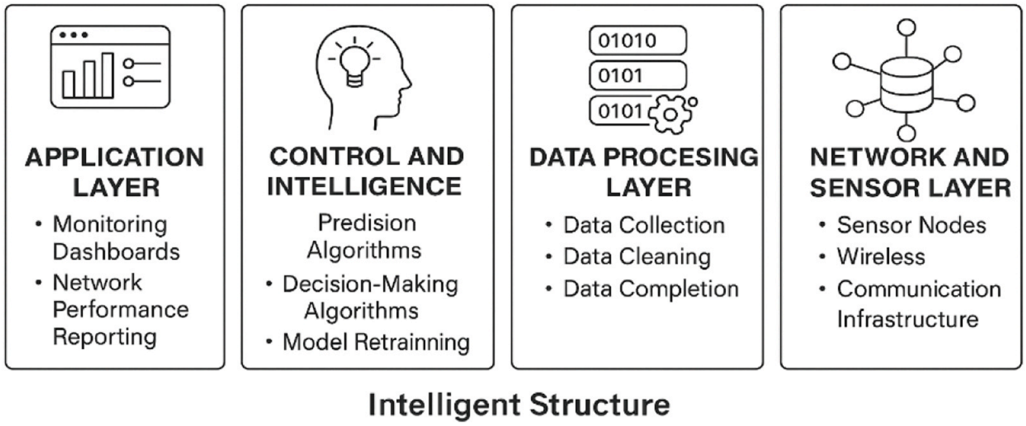

Fig. 3. Intelligent architecture consisting of four main layers including application layer, control and intelligence, data processing and network, and sensor.

Table 4 goes into great detail about the structure and features of the dataset.

This example IoT-SmartHome energy dataset in Table 5 shows time-stamped energy consumption records across various home systems. The dataset has rows that show detailed information recorded every 15 min, such as total energy use, indoor temperature and humidity, occupancy status, and the specific energy loads for appliances, lighting, and HVAC systems. This wide range of features gives LSTM models useful information that helps them make better time series predictions. These data points also help IoT networks make better decisions, especially when it comes to things like optimizing energy policy and prioritizing nodes. The dataset is great for building smart home systems that can use resources wisely and work on their own because it has a lot of detail and a well-organized structure.

Table 4
Source: IoT-SmartHome Energy Dataset – Key features for energy usage analysis and forecasting.

Category	Item	Description
Dataset Name	IoT-SmartHome Energy Dataset	Real-time energy usage data collected from smart home IoT devices.
Features		
	Timestamp	Exact time when each record was captured (e.g., every 15 min).
	Household id	Unique identifier for each IoT-enabled smart home or sensor node.
	Energy consumption	Total power usage in kilowatt-hours (kWh); the primary target for forecasting.
	Temperature	Indoor temperature (in °C); may influence HVAC operation and energy demand.
	Humidity	Indoor relative humidity (%); relevant for evaluating energy patterns.
	Occupancy	Indicates if the house is occupied (1) or vacant (0); derived from sensors.
	Subsystem Loads	Energy usage by specific appliances/ systems (when available):
	→ HVAC usage	Power consumed by heating/cooling systems.
	→ lighting load	Energy used for lighting across the house.
	→ plug loads	Power drawn by plug-in devices (e.g., TVs, laptops, chargers).
	Weather conditions	(Optional) Outdoor weather description (e.g., sunny, cloudy); if included.
Record Count	~120,000 – 200,000	Number of time-stamped records depending on duration and home count.

4.1. Evaluation criteria and parameters

To ensure that the proposed framework is evaluated fairly and thoroughly, a standardized set of simulation parameters and evaluation criteria is followed in this study. Firstly, KPIs such as energy use, packet delivery ratio, average delay, and network lifetime are calculated to determine how well the system functions over time, how reliable it is for inter-node communication, and how efficient it is in terms of energy consumption. Secondly, simulation parameters, such as packet size, transmission range, data generation rate, initial energy levels, and node density, are selected based on what is commonly used in the literature. Through using such standardized settings, the IoT network will simulate as it would in reality under different conditions, enabling the systematic comparison to the base-line approaches.

1. **Energy Consumption:**
   Energy consumption: This is the aggregate amount of energy consumed by all nodes while the network is running. Thus, for the efficiency of the proposed framework on energy reduction through predictive modelling and node prioritization, the lesser the better. The Eq. 15 for this metric is as follows:

$$E_{\text{total}} = \sum_{i=1}^{N} \sum_{t=1}^{T} P_i(t) \times \Delta t \tag{15}$$

2. **Packet Delivery Ratio (PDR):**
   PDR measures the percentage of data packets that are successfully delivered out of the total packets sent over the network. It indicates the reliability of the connection under energy-aware decisions. A higher PDR means better data integrity and a stable connection, the Eq. (16) for which is given below.

$$\text{PDR} = \frac{\text{Total Delivered Packets}}{\text{Total Sent Packets}} \times 100 \tag{16}$$

3. **Average Delay:**
   The average latency represents the average time it takes for data packets to travel from source nodes to destination nodes. This metric helps to assess whether proposed resource management policies have a negative impact on data transmission timing. Minimizing latency is crucial to maintaining quality of service, as the Eq. (17) for this measure is given below.

$$\text{Average Delay} = \frac{1}{N} \sum_{i=1}^{N} \left(t_i^{\text{receive}} - t_i^{\text{send}}\right) \tag{17}$$

4. **Network Lifetime:**

   The network lifetime is defined as the time elapsed until the first

Table 5
Sample entries from the IoT-SmartHome Energy Dataset showing time-based energy usage and contextual features.

Timestamp	Household ID	Energy Consumption (kWh)	Temperature (°C)	Humidity (%)	Occupancy	HVAC Usage (kWh)	Lighting Load (kWh)	Plug Loads (kWh)
2025–05–01 08:00:00	H001	1.32	22.4	45	1	0.68	0.22	0.42
2025–05–01 08:15:00	H001	1.28	22.5	44	1	0.65	0.20	0.43
2025–05–01 08:30:00	H001	1.15	22.3	46	0	0.58	0.15	0.42
2025–05–01 08:45:00	H001	1.48	22.7	43	1	0.72	0.30	0.46
2025–05–01 09:00:00	H001	1.41	22.9	41	1	0.70	0.28	0.43

Table 6
Describing key simulation parameters used for evaluating energy efficiency and network performance.

Parameter	Description	Range	Type	Unit
Initial Energy	Initial energy assigned to each IoT node	0.5 – 2.0	Continuous	Joules (J)
Transmission Range	Maximum distance a node can send data	10 – 30	Discrete	Meters (m)
Data Generation Rate	Rate at which a node generates data packets	1 – 5	Discrete	Packets/minute
Packet Size	Size of each transmitted data packet	64 – 512	Discrete	Bytes
Energy TX per bit	Energy consumed per bit during transmission	$50 - 100 \times 10^{-9}$	Continuous	Joules/bit
Node Density	Number of sensor nodes per unit area	20 – 100	Discrete	Nodes/100 m^2
Sleep Threshold	Threshold energy level below which a node enters sleep mode	0.1 – 0.4	Continuous	Joules (J)
Simulation Time	Total duration of network simulation	1000 – 10000	Discrete	Seconds (s)

node in the network runs out of energy. This indicates the stability of the system under energy-aware scheduling and prediction techniques. A longer network lifetime confirms the effectiveness of the energy optimization mechanisms, as shown in the following Eq. (18).

$$\text{Lifetime} = \min_i \{t||||E_i|(|t|)|=|0\} \tag{18}$$

Table 6 presents the main simulation parameters used in this study, selected based on the structure of the proposed framework and aligned with the baseline methodologies in the reference works. These parameters define the operational conditions of the IoT network, including energy-related thresholds, node density, communication characteristics, and data generation rates. The chosen ranges and types (discrete or continuous) are based on commonly accepted values in the literature to ensure realistic and comparable performance evaluation.

Fig. 4 illustrates the energy consumption of the proposed method in comparison with two baseline approaches—LEA-RPL and DRL-ICSSS—across different levels of initial energy. As shown, the proposed framework consistently achieves lower energy usage at all energy levels, confirming its effectiveness in minimizing energy waste through predictive modeling and intelligent node management. On average, it demonstrates a 26.78 % reduction in energy consumption compared to LEA-RPL and a 32.19 % improvement over the DRL-ICSSS approach, highlighting its superior energy efficiency in IoT networks.

Fig. 5 compares the energy consumption of the proposed method with two baseline approaches—LEA-RPL and DRL-ICSSS—under varying transmission ranges from 10 to 30 m. As the transmission distance increases, energy consumption rises across all methods due to higher communication costs; however, the proposed framework consistently

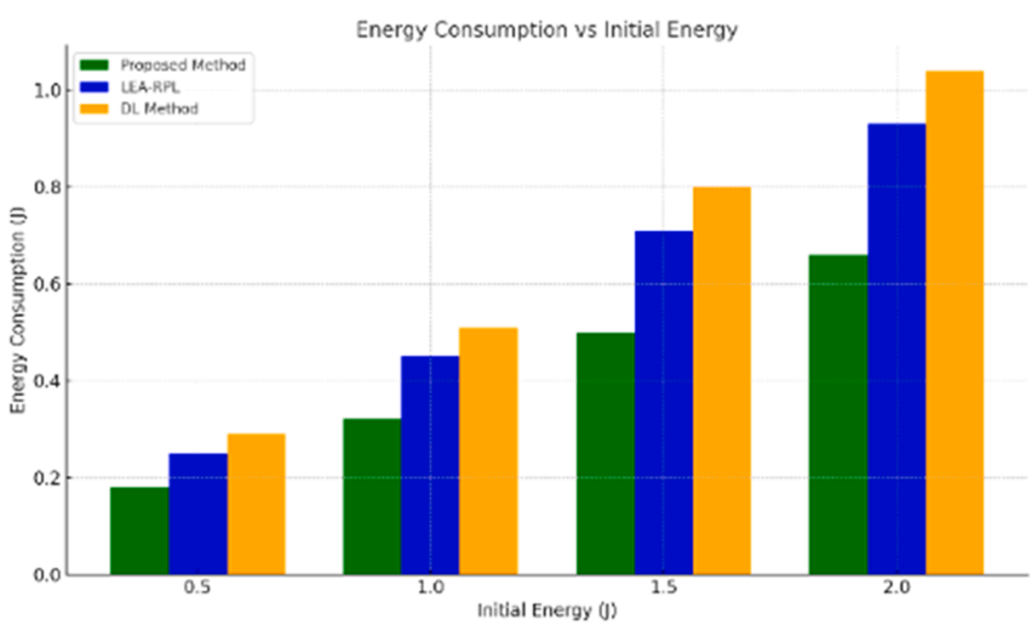

Fig. 4. Reducing energy consumption across different initial energy levels using the proposed framework.

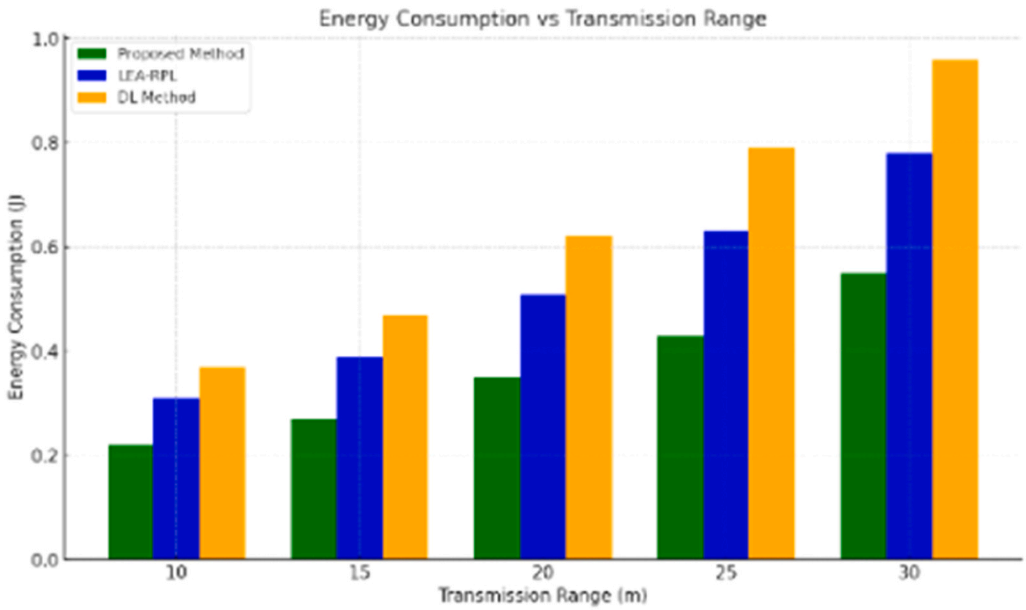

Fig. 5. Comparing energy usage at varying transmission ranges and demonstrating communication cost control.

maintains lower energy usage. On average, it achieves a 30.36 % reduction in energy consumption compared to LEA-RPL and a 37.03 % improvement over the DRL-based approach, demonstrating its superior efficiency and scalability in managing transmission-related energy overheads in IoT networks.

Fig. 6 presents a comparison of energy consumption across three methods—our proposed approach, LEA-RPL, and DRL-ICSSS—under varying data generation rates from 1 to 5 packets per minute. As data generation increases, energy consumption rises in all models; however, the proposed method consistently maintains lower energy usage. On average, it reduces energy consumption by 30.19 % compared to LEA-RPL and 35.09 % compared to the DRL-based approach, demonstrating higher efficiency in handling traffic-intensive IoT environments.

Fig. 7 compares the packet delivery ratio (PDR) of the proposed method with LEA-RPL and DRL-ICSSS under varying initial energy levels ranging from 0.5 to 2.0 joules. Increasing energy availability improves delivery performance across all methods. When more energy is available, all delivery methods work better. The suggested method, on the other hand, always has a higher PDR, with an average improvement of 7.28 % over LEA-RPL and 9.11 % over DRL-ICSSS. These results show that the proposed framework is reliable and can communicate consistently when using energy-efficient and predictive methods.

Fig. 8 compares the packet delivery ratio (PDR) of the suggested method to that of LEA-RPL and DRL-ICSSS. The transmission ranges are between 10 and 30 m. As the distance between transmissions increases, PDR tends to go down because of more transmission errors and weaker signals. The suggested strategy keeps getting higher PDR values, even though this trend is happening. This keeps communication reliable. The average improvement in packet delivery of 8.96 % over LEA-RPL and 10.96 % over the DRL-based approach shows that it can handle long-range IoT situations.

Fig. 9 Comparisons show that with increasing generation rates (from

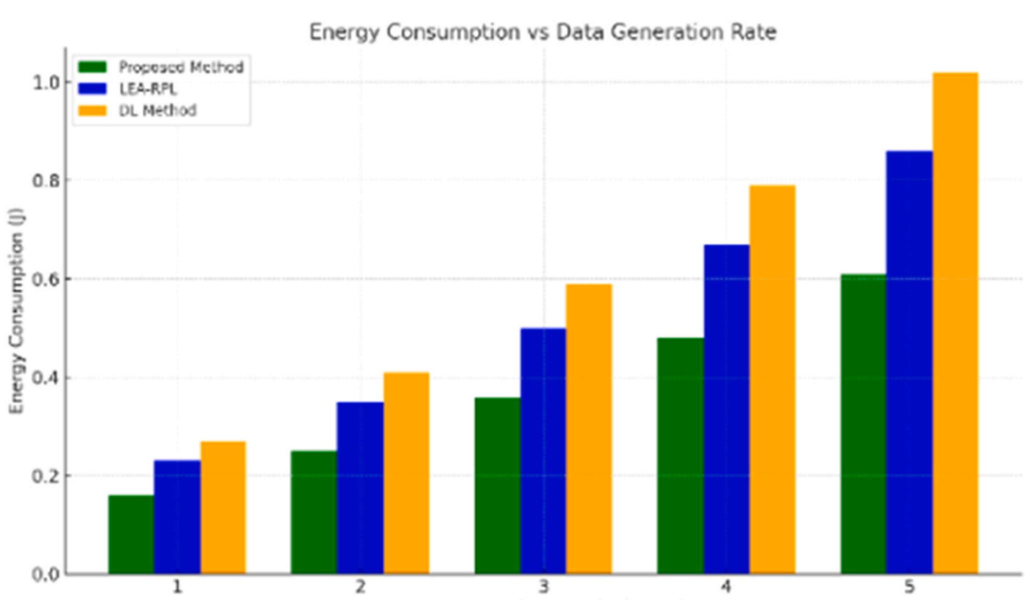

Fig. 6. Evaluating the impact of data generation rate on energy consumption and maintaining performance under high traffic.

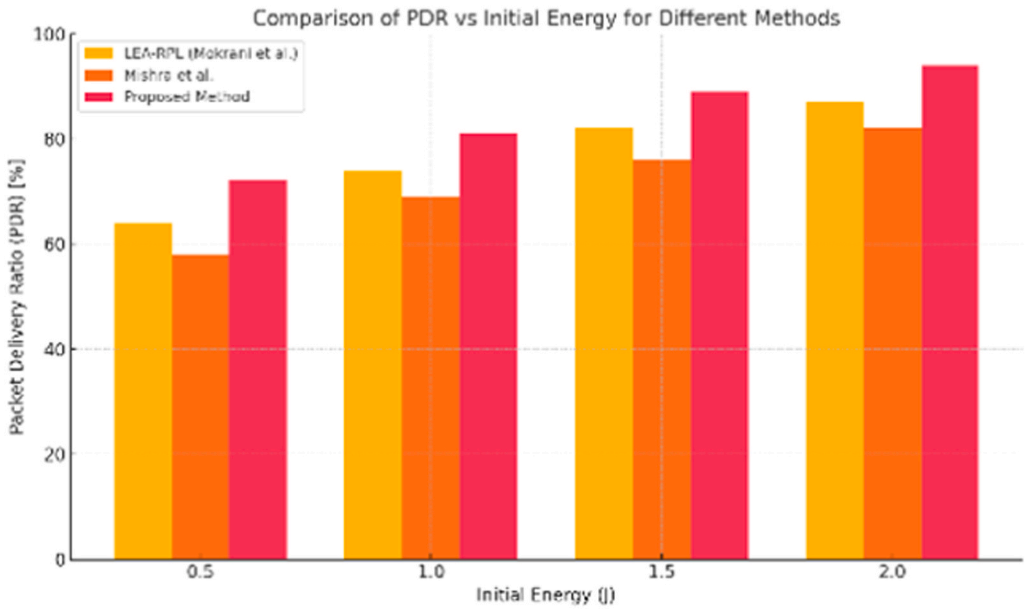

Fig. 7. Enhancing packet delivery ratio (PDR) under different initial energy levels using predictive prioritization.

Fig. 8. Maintaining higher PDR at increased transmission ranges with stable communication strategies.

1 to 5), the packet delivery rate (PDR) decreases in all methods. However, the proposed method shows better performance. On average, the proposed method has improved packet delivery by about 7.3 % compared to the Mokrani method and by about 9.8 % compared to the Mishra method. This indicates that the proposed method has been more successful in managing traffic and avoiding network congestion.

Fig. 10 by increasing the initial energy of the nodes from 0.5 to 2 J, the average delay in all three methods decreases slightly, which is due to the greater stability of the paths and the reduced need for rerouting the paths. The proposed method always has lower delay than the two reference methods, which indicates its high efficiency in using energy to maintain optimal scheduling in the network. On average, the delay reduction compared to the Mokrani method was about 16.7 %, and compared to the Mishra method, it was about 24.6 %. These results prove that the proposed method is very effective in reducing delay and improving the user experience in time-sensitive applications.

Fig. 11 as the transmission range increases from 10 to 30 m, the average delay for all methods rises proportionately. This is due to the fact that signal collision and interference are more likely to occur at greater distances. With an average reduction of about 17.5 % compared to Mokrani and 25.5 % compared to Mishra, the proposed method consistently demonstrates a lower delay than the two reference methods across all transmission ranges. This reduction in latency demonstrates how effectively the proposed algorithm controls energy consumption and communication channels in Internet of Things networks.

Fig. 12 illustrates how the average latency for all three approaches rises as the network's data generation rate rises (from 1 to 5 packets/s), which is typical given the rise in traffic load.However, the proposed method consistently has lower latency than the Mokrani and Mishra methods. At the highest data generation rate (5 pkt/s), the latency in the proposed method is up to 20 % lower than Mokrani and 26 % lower than Mishra. These results indicate that the proposed method has a better

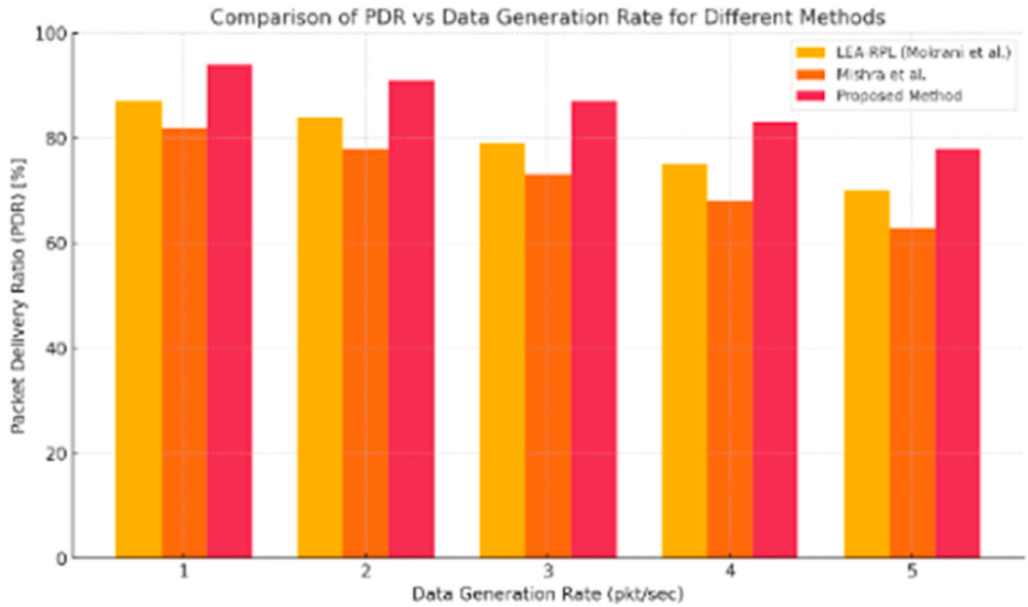

Fig. 9. Managing traffic load effectively and improving PDR under various data generation rates.

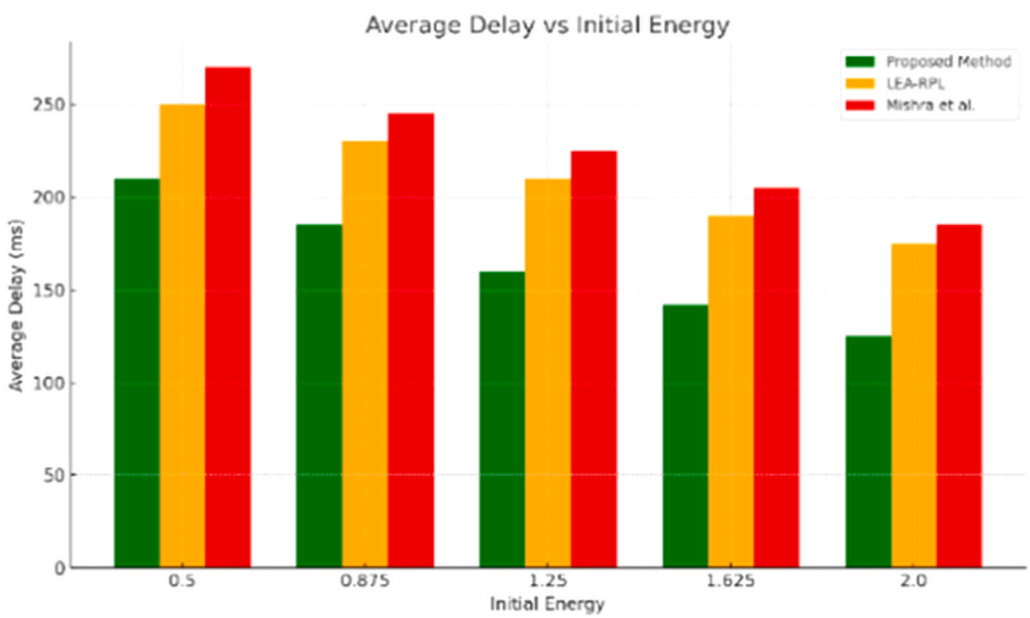

Fig. 10. Reducing average delay under various initial energy levels via efficient scheduling.

ability to manage network loads and optimize packet queuing under heavy load conditions.

Fig. 13 The results indicate that the proposed method has a better network lifetime than the two reference methods at all initial energy levels. On average, the improvement in network lifetime is about 16 % compared to the LEA-RPL method and about 22 % compared to the DRL-ISSS method. This improvement is due to better optimizations in energy management and intelligent use of resources in the proposed method, which leads to more efficient use of energy and increased network operational lifetime.

Fig. 14 The results show that with increasing transmission range, the network lifetime increases in all three methods, but the proposed method consistently outperforms LEA-RPL and DRL-ISSS. On average, the proposed method improves the lifetime by about 17 % over LEA-RPL and by about 24 % over DRL-ISSS. This improvement is due to better optimizations in energy management and routing protocols, which reduce energy consumption and increase network stability at higher transmission ranges.

Fig. 15 As can be seen, with increasing data generation rate, the network lifetime decreases for all three methods, which is due to increased workload and higher energy consumption. The proposed method performs better than LEA-RPL and DRL-ISSS in all cases, and on average, it provides about 18 % improvement over LEA-RPL and about 29 % over DRL-ISSS in network lifetime. This indicates that the optimizations made in the proposed method are more effective for energy management and network efficiency under high load conditions.

The recommended framework did better than the two reference approaches, LEA-RPL and DRL-ICSSS, in all evaluation scenarios. This advantage in four critical areas—energy use, packet delivery ratio, average latency, and network lifetime—was maintained and even increased, even in difficult and high-density situations. The Discussion section goes into detail about these results and how they can be

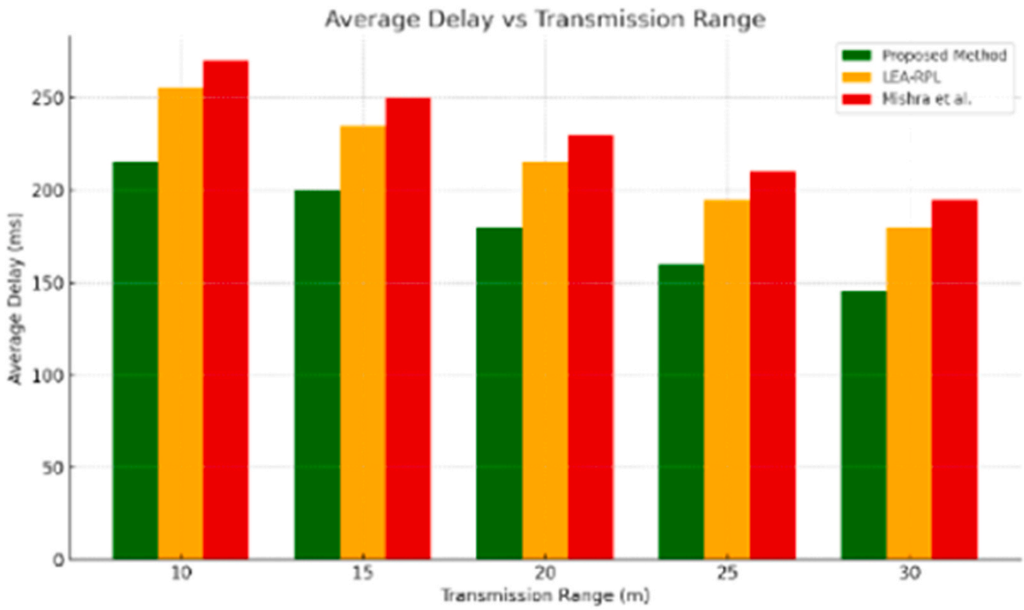

Fig. 11. Managing delay across transmission distances with optimal path selection.

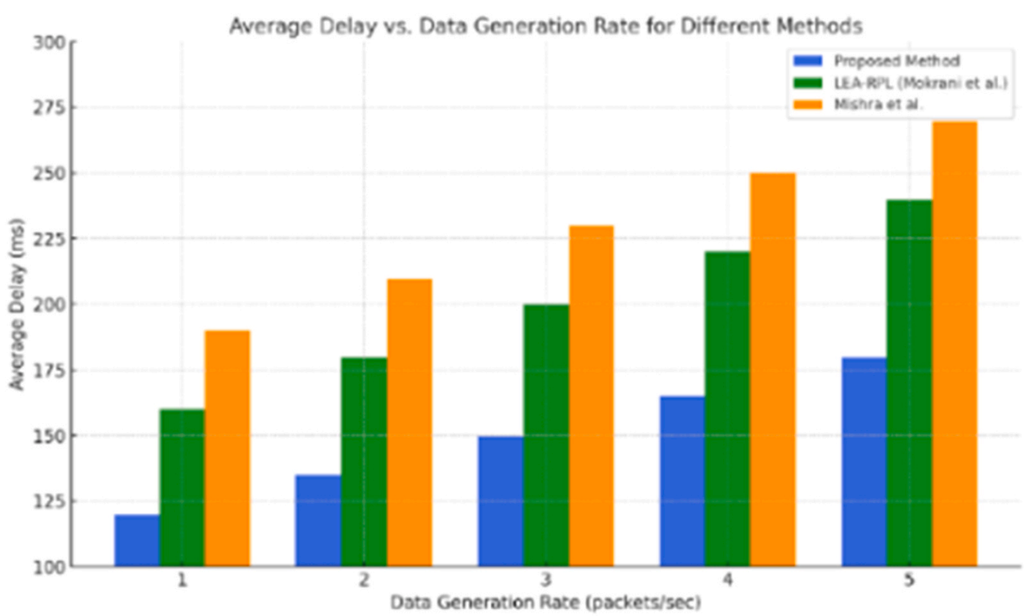

Fig. 12. Controlling average latency under increasing data generation rates.

understood in a technical way. It also looks at how useful they are for the study's major goals.

5. Discussion

The findings of this study show that the proposed framework directly achieves the initial research objectives mentioned in the introduction. The main goal of this study was to fill three main gaps: the lack of sufficient attention to node prioritization, the limited use of advanced machine learning models such as LSTM for energy consumption prediction, and the lack of combining energy consumption prediction with multi-criteria management policies. The simulation results indicate that the proposed method, by accurately predicting energy and applying multi-criteria decision-making, has been able to cover these gaps and simultaneously reduce energy consumption, increase network stability, and maintain quality of service.

5.1. Performance improvement analysis based on indicators

1. **Energy Consumption**
   The proposed model has succeeded in significantly reducing energy consumption in all scenarios (changing initial energy level, transmission range, data generation rate, packet size, transmission energy per bit, network density, and sleep threshold). The average energy consumption reduction in the range of 26–37 % compared to LEA-RPL and 32–36 % compared to DRL-ICSSS shows that accurate prediction and application of dynamic sleep policy play a key role in optimal resource management.
2. **Packet Delivery Ratio (PDR)**
   The use of a prioritization mechanism and the reduction of unnecessary traffic loads have ensured that the PDR remains higher than the reference methods in all conditions. This increase is especially important in high-density and long-range scenarios, as the PDR

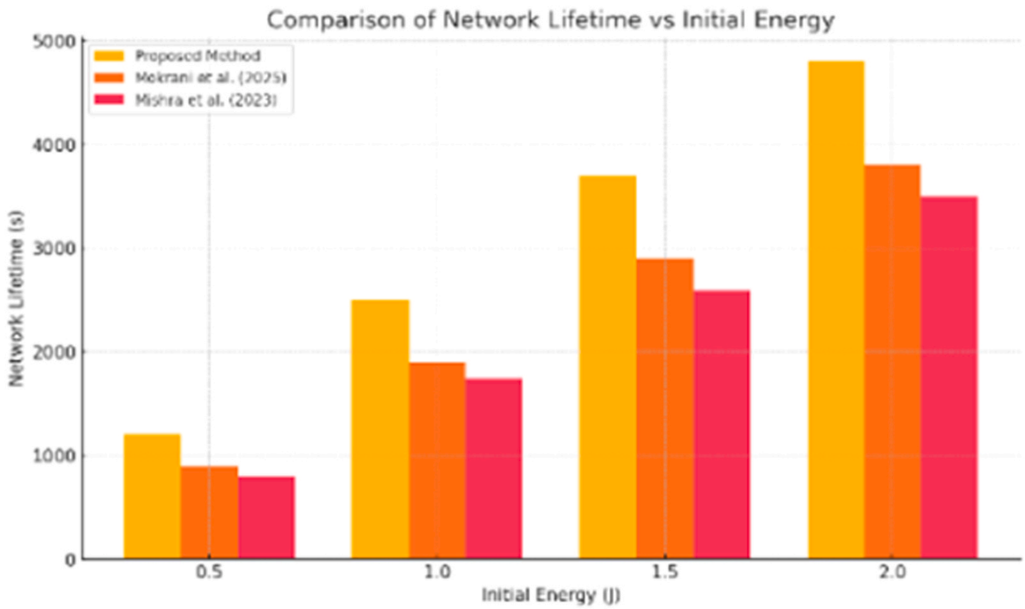

Fig. 13. Increasing network lifetime under varying initial energy levels with the proposed energy optimization strategy.

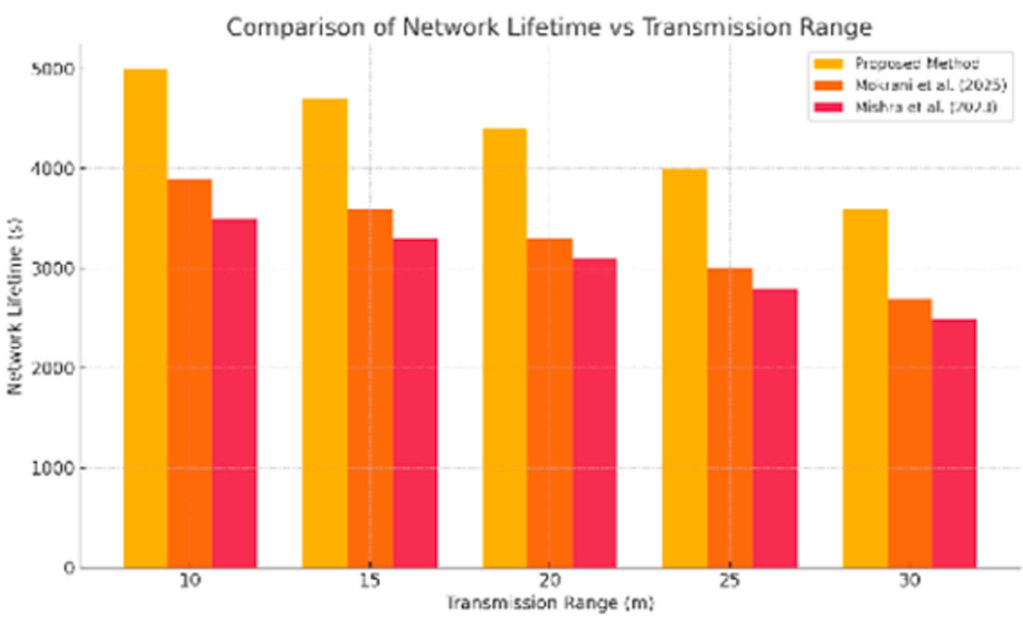

Fig. 14. Extending network lifetime at higher transmission ranges through improved routing efficiency.

degradation is usually significant in such conditions. The average improvement of 7–9 % over LEA-RPL and 9–12 % over DRL-ICSSS confirms the stability of the communication.

3. **Average Delay**

   The proposed framework with intelligent path management and node sleep-wake scheduling has been able to reduce the delay between 16 % and 20 % compared to LEA-RPL and 23 % and 26 % compared to DRL-ICSSS. This is especially important in time-sensitive applications (such as live monitoring or industrial control).

4. **Network Lifetime**

The increase in network lifetime is evident in all scenarios and varies between 14 % and more than 33 % compared to LEA-RPL and 20 % and more than 56 % compared to DRL-ICSSS. The greatest improvement is achieved in conditions of high density and high transmission energy per bit, which shows that the proposed framework is more efficient, especially in environments with high energy pressure.

5.2. Summary table of percentage improvement of the proposed method compared to the basic methods

The Table 7 below shows the percentage improvement of the proposed method over the two reference methods, LEA-RPL and DRL-ICSSS, in four key performance indicators. These values are extracted from simulation results in different scenarios and provide a summary picture of the quantitative advantages of the proposed framework. As can be seen, the largest improvement is achieved in network lifetime and the smallest in PDR index, while the better performance is maintained in all metrics.

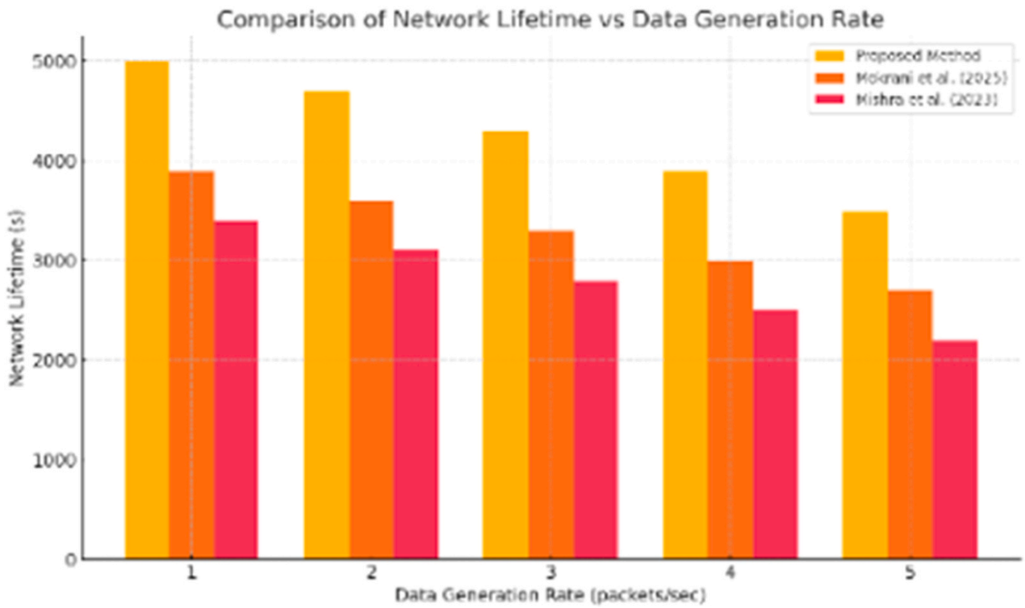

Fig. 15. Enhancing network sustainability under high data generation rates using predictive management.

Table 7
Summary of the percentage improvement of the proposed method in key performance indicators.

Performance index	Improvement range compared to LEA-RPL	Improvement range compared to DRL-ICSSS
Energy consumption	26 % – 37 %	32 % – 36 %
Packet delivery ratio (PDR)	7 % – 9 %	9 % – 12 %
Average latency	16 % – 20 %	23 % – 26 %
Network lifetime	14 % – 33 %	20 % – 56 %

5.3. General interpretation of the results

The results show that using LSTM-based prediction along with multi-criteria decision-making not only uses less energy but also makes communication better and the network more stable. This improvement is due to three main things:

- being able to accurately predict energy consumption trends and avoid making reactive and late decisions;
- making policies that are flexible and change priorities based on the current state of the network;
- managing network paths and load intelligently to avoid congestion and waste of energy.

In short, the proposed framework has been able to find a good balance between energy efficiency and quality of service and keep it in different situations with different conditions.

6. Conclusion

This study presents a comprehensive and intelligent framework for optimizing energy consumption in Internet of Things (IoT) networks by integrating Long Short-Term Memory (LSTM) neural networks with Multi-Criteria Decision Making (MCDM) techniques. By accurately predicting the temporal patterns of energy usage and prioritizing nodes based on key factors such as residual energy, data importance, and location, the proposed method enabled dynamic energy-aware decisions such as putting low-priority nodes to sleep, reducing redundant traffic, and optimizing routing paths. Simulation results demonstrated that the framework outperformed existing baseline methods—such as LEA-RPL and DRL-ISSS—by significantly reducing energy consumption and extending the operational lifetime of the network.

Despite the promising outcomes, the framework's performance remains sensitive to factors such as network topology, real-time data quality, and computational capabilities of nodes. Therefore, future work may focus on incorporating reinforcement learning for adaptive policy refinement, real-time feedback mechanisms, and edge intelligence to enhance scalability and responsiveness. Overall, the proposed approach provides a robust, scalable, and energy-efficient solution suitable for smart city applications, smart homes, and other resource-constrained IoT environments.

CRediT authorship contribution statement

Ali Asghar Pour Haji Kazem: Writing – review & editing, Resources, Methodology, Conceptualization. **Abbas Mirzaei:** Writing – review & editing, Validation, Supervision, Methodology. **Nahideh Derakhshanfard:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Conceptualization. **Hossein Heydari:** Writing – original draft, Validation, Resources, Methodology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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