Solar-Aware LEACH-EEKA: An Energy-Harvesting-Based Clustering Protocol for Self-Sustaining IoT-Enabled Wireless Sensor Networks

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***Abstract*—Wireless Sensor Networks (WSNs), which are a key technology for modern IoT, have their battery power and energy usage not balanced, hence they face the problem of limited life time. The Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol is an enhancement of energy efficiency through clustering, though it has drawbacks in that the cluster heads (CHs) are selected randomly and there is a rapid discharge of energy. To overcome these problems, Solar - Aware LEACH–EEKA is proposed as a hybrid clustering protocol integrating LEACH, an Energy-Efficient knapsack Algorithm (EEKA), and solar energy harvesting to improve network sustainability. EEKA provides an optimized cluster formation process based on residual energy, distance to the base station, and node density for equalizing energy utilization. Solar-assisted node incorporation improves sustainability in networks due to the possibility of energy replenishment in the course of operation. Simulation results prove that the Solar-Aware LEACH–EEKA proposed protocol offers notably reduce energy consumption, enhanced network lifespan, and throughput, and maintains a considerably larger number of active nodes when compared to LEACH and other EEKA baselines. Such an approach proposes an efficient way of creating a self-functioning, environmentally-friendly wireless sensor network suitable for IoT and remote monitoring systems.**

***Index Terms*—LEACH, EEKA, Solar Energy Harvesting, Wireless Sensor Networks, Energy Efficiency, IoT, Clustering Protocol, Network Lifetime.**

I. Introduction

The Wireless Sensor Networks are a key building blocks of modern IoT systems as they provide instant communication, real-time sensing, and actuation capabilities that find application in areas such as environmental monitoring, industry automation, and smart cities. Typically, a WSN is composed of numerous sensor nodes that are deployed in a distributed manner to sense and relay information.

However, these nodes just forward the data to a base station (BS) or sink node. They run on batteries, and replacing or recharging them in remote environments can be very difficult. Consequently, energy efficiency remains one of the core design issues, directly affecting the performance, lifetime, and reliability of WSNs.

To address these constraints, a variety of energy-efficient routing protocols have been proposed, among which the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol is one of the most prominent. LEACH organizes nodes into clusters and assigns a Cluster Head (CH) to each cluster, which aggregates and transmits data to the BS. This clustering-based approach significantly reduces redundant communication and prolongs network lifetime. Despite its simplicity and distributed nature, LEACH suffers from random CH selection, which leads to unbalanced energy consumption, early CH depletion, and reduced network scalability. Many researchers have proposed extensions to overcome the limitations of LEACH. B. Suresh and G. S. C. Prasad presented EERS-LEACH (Efficient Energy and Secure Routing, LEACH), which deals with CH selection optimization and employs lightweight encryption for secure communication in IoT-based WSNs. Despite the improvement in routing efficiency as well as data integrity by EERS LEACH, it still uses stochastic CH selection, which is likely not to ensure optimal energy balance between heterogeneous nodes.

To introduce intelligence into CH selection, S. Ramesh et al. developed LEACH-ML, a machine-learning-based enhancement that predicts CH roles based on residual energy and node density patterns. While LEACH-ML achieves higher adaptability and balanced energy distribution, it demands computational overhead and training data, making it less suitable for large-scale, resource-constrained deployments. Similarly, M. Gamal et al. proposed LEACH FCM, which integrates Fuzzy C-Means clustering and Particle Swarm Optimization (PSO) for dynamic CH selection. This approach improves cluster stability and energy utilization but increases algorithmic complexity and fails to incorporate renewable energy models for sustainable operation.

Despite these improvements, the majority of the LEACH-based models continue to be purely dependent on finite battery energy, thus resulting in low network lifetime. To combat this challenge, recent studies have concentrated on harvesting energy into WSNs whereby nodes can acquire energy from their natural surroundings, like solar, wind, or vibration sources. Among them, solar energy harvest has become dominant because of its

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predictable availability as well as efficiency for outdoor deployment. But, integrating solar power into clustering-based routing raises some issues regarding balancing the energy between solar-assisted and non-solar nodes, and dynamically adapting in accordance with variable solar intensity.

In the search for sustainable operation of WSNs, this study attempts to focus on energy harvesting WSNs (EH-WSNs), known as networks where sensor nodes can harvest energy from their surroundings, such as solar, wind, or vibration. Of those, solar-energy harvesting has become the most promising due to its predictability and high efficiency in outdoor environments [6]. However, one of the drawbacks of using solar energy as an alternative energy source for clustering-based routing is that there will be an imbalance in how solar-assisted and non-solar nodes utilize their energy source, plus changes in solar intensity.

In order to address these challenges, we propose in this paper a new hybrid routing protocol, Solar, which integrates the adaptive clustering approach of LEACH, the optimized CH selection capability of the Energy-Efficient Knapsack Algorithm (EEKA), and the sustainability of solar energy harvesting. The dynamic model proposed selects CHs dynamically based on the residual energy, solar energy available, and distance to BS to ensure the balance of energy utilization and improved cluster stability. Simulation results show that our approach prolongs the network lifetime, yields more active nodes, and provides better throughput than the central LEACH variants.

The following paragraphs summarize the main claims made by this study:

- An innovative routing technique that combines LEACH and Energy-Efficient Knapsack Algorithm with Solar harvesting to ensure sustainability in network operation.
- CHs are chosen on the fly based on multi objective optimization criteria, including residual energy, solar energy status, and position relative to the BS to suit overall network power consumption.
- The provided model is more efficient in minimizing energy imbalances between solar-aided and non-solar nodes, which in effect enhances the scalability and stability of large-scale WSN.
- The results of extensive simulation studies show that Solar-Aware-LEACH-EEKA prolongs the lifetime of the network by a substantial amount, supports a higher number of active nodes, and delivers higher throughput compared with other LEACH-based protocols.

This paper is structured in the following manner: Section II gives some related works and methods that constitute the baseline for energy-efficient clustering and energy harvesting in WSNs. In Section III, we explain the proposed Solar-Aware LEACH–EEKA design and its operation. Section IV provides the outline of the simulation environment and performance metrics. The results and performance evaluation will be discussed in Section V, while Section VI concludes the paper with potential directions for future research.

II. Related Work

To date, there have been several works which have focused on bettering energy efficiency, scalability and reliability of WSNs by different forms of optimized routing and clustering techniques. A model for an energy-efficient WSN was presented to optimize node coverage and prolong network lifetime, though it dealt basically with the optimization challenges without consideration of the CHs selection or balanced clustering [1]. A routing protocol designed for 3D-WSNs indicated a huge step forward in forwarding data and energy efficiency despite the fact that it failed to cater for heterogeneous energy levels as well as complex terrains [2]. Through intelligent routing and use of a mobile sink, energy consumption was minimized even if increased communication overhead was experienced since sink mobility and route complexity did not play a major role [3]. Although they can be very effective in transmission efficiency enhancement as well as redundant data reduction, they still require higher training data volume and computational resources, which are too high to be efficiently deployed in resource-constrained environments [4]. However, SPMSO combined with FCM as an optimization-based technique tells a different story [5]; this is also applied on other occasions when a hybrid clustering approach, M-PSO & GA, was utilized, having more issues mentioned above [6], remains an open research challenge. Development that resulted into machine learning application on industrial WSNs improved their performance in terms of energy consumption, however limiting learning–based application due to its high training costs that made it unsuitable to be applied in low power devices too [7]; just like UAV-assisted WSN faced heavy computational trajectory management workloads because PPO2 reinforcement learning–based algorithms were used make them efficient from energy perspective [8]. Also, the CH selecting model incorporated a knapsack approach, which finally achieved good execution time; nonetheless, its downside had not been recognized up till now, neither from the literature review nor any other source nonrenewable blind spot [9]; similarly, most solutions given primarily for equalizing node consumptions suffered dynamic adaptability issues at one point as discussed in [10]. The model is mainly validated through simplified simulations, limiting its real-world applicability.

Moreover, combining DEEC, Knapsack, K-Means, and reinforcement learning increases computational complexity, making deployment difficult on resource-constrained IoT sensor nodes [11]. The method relies heavily on statistical compression, which reduces data size but increases computational overhead, making it less suitable for real-time or resource-constrained sensor nodes [12]. Semi-decentralized prediction schemes improved energy utilization but increased coordination overhead in dense networks [13], while reinforcement learning-based control and routing protocols enhanced adaptability at the cost of large training times and processing demands [14]. Co-operative caching mechanisms reduced redundant data transmissions but increased memory use and cache management complexity [15]. Deep reinforcement learning based scheduling and trajectory planning models improved charging efficiency in rechargeable WSNs but suffered from high algorithmic delay [16]. K-hop clustering for cognitive radio-based WSNs improved spectrum and energy efficiency but required cognitive capabilities not available in typical WSN nodes [17]. Bio-inspired and meta-heuristic algorithms were sparrow search optimization, which opened a new line of CH selection and energy balancing but exhibited slow convergence and limited adaptability [18], and centralized clustering methods balanced energy consumption but introduced single-point failures and poor scalability [19]. Renewable energy-aware multi-hop clustering protocols achieved improved routing efficiency but increased maintenance overhead [20], while tree-based routing algorithms minimized energy consumption but were inefficient for large-scale heterogeneous networks [21]. Secure and energy-aware routing enhanced data integrity yet added encryption

overhead that degraded throughput [22], and wireless energy balancer frameworks improved clustering efficiency but required additional hardware support [23]. Combined strategies for energy renewal and data collection enhanced utilization but introduced excessive control overhead [24]. Hybrid clustering models such as EEHCT improved energy distribution in heterogeneous WSNs but suffered from heavy computational load [25]. Ant colony optimization with duty cycling reduced energy consumption but faced synchronization issues and data latency [26], and routing-aware scheduling in energy-harvesting WSNs optimized utilization but failed to adapt to varying environmental inputs [27]. Centralized and on-demand clustering methods enhanced route efficiency in mobile ad hoc networks but reduced stability due to frequent re-clustering [28]. Modified LEACH-C protocols improved CH selection and energy performance yet relied on fixed parameters, limiting adaptability in heterogeneous networks [29]. Lastly, fuzzy logic–based LEACH variants combined with particle swarm optimization improved WSN lifetime but introduced high computational complexity and slow convergence [30].

Routing efficiency and security of routing that is controlled by the LEACH protocol have been advanced in the way of IoT-embedded wireless sensor networks, in order to improve dependability of communications, reduce data loss, and increase network lifetime [31]. The results obtained from using the Harmony Search algorithm along with the LEACH Protocol show a higher energy-efficient system with more optimized cluster formation for different network scenarios [32]. Recent progress has employed reinforcement learning techniques within LEACH-based clustering to bring about an improved model that enables stable IoT data delivery as well as high throughput operation [33]. Another developed version of the LEACH protocol applies the K-means plus plus clustering approach along with an adaptive cluster structure for extension of WSN lifespan predominantly in autonomous vehicular applications [34]. Energy harvesting has been receiving increased attention, whereby renewable energy-based WSNs for precision agriculture enhance sustainability and energy balance [35]. A combination of solar energy harvesting techniques exploiting integrated Wi-Fi technology, and intelligent scheduling methods depicted a good promise for maintaining energy-efficient sensor operation in dynamic environments [36]. Additionally, solar energy harvesting was usefully applied to prolong the lifetime of WSNs through adaptive power management and duty cycling mechanisms [37].

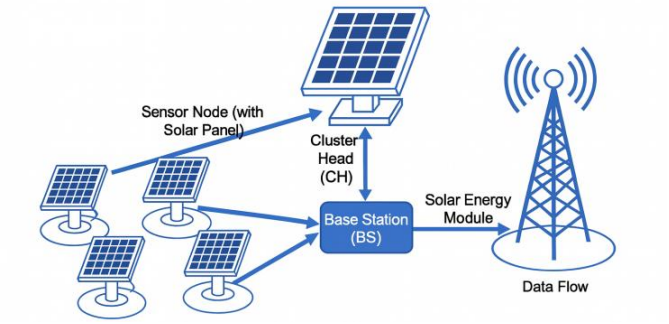


Fig. 1. Basic Structure of WSNs.

Fig. 1 illustrates a solar-powered wireless sensor network where individual sensor nodes harvest energy through solar panels and transmit data to a designated Cluster Head (CH). The Cluster Head forwards aggregated information to the Base Station (BS), which is additionally supported by a solar energy module. Finally, the Base Station sends processed data to a remote communication tower for wider communication.

III. Proposed Methodology

A. System Architecture

The proposed LEACH–EEKA–Solar protocol enhances the classical LEACH clustering model by integrating the Energy-Efficient Knapsack Algorithm (EEKA) and solar energy harvesting for sustainable network operation. The network consists of N static sensor nodes randomly deployed in an M×M area. Every node is assigned a unique ID and initialized with energy E_0, and a limited transmission range. A subset of nodes is equipped with solar panels to harvest renewable energy from the environment, extending their operational lifetime.

The system is divided into three primary layers:

- Sensing Layer: Responsible for environmental data acquisition.
- Cluster Layer: Its function is to cluster, aggregate data, and do routing via selected CHs only.
- Harvesting Energy Layer: It uses solar panel-assisted nodes dynamically so that the energy imbalance and communication delay are reduced.

This layered structure makes it possible for the routing to always be optimized, the energy in the network is always balanced, and the network is less affected by variations in the solar radiation levels.

It is possible to get an overview of the proposed energy-efficient wireless sensor network model, which is a combination of clustering, optimization and energy harvesting mechanisms from Fig. 2. The process commences with node sensor deployment, where nodes are spread over the monitored area. Later on, a LEACH-based clustering algorithm forms small clusters around the base station to reduce communication overhead and save energy. The EEKA-based cluster head (CH) optimization module selects optimal CHs so that equal energy consumption and stability enhancement can be achieved. A solar power harvesting module provides a source of renewable power for the sustainable operation of sensors in low-power environments. Finally, sensed data will be aggregated and transmitted from CHs to BSS or cloud monitoring systems, whereby there will be reliable data delivery and effective energy management throughout the network system.

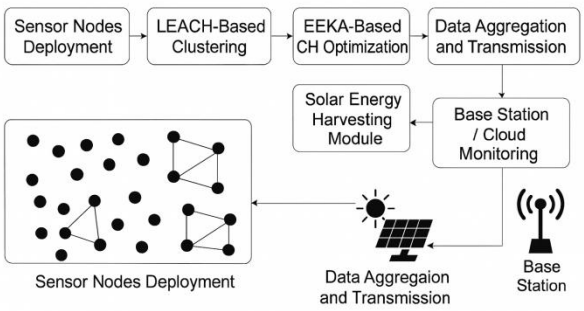


Fig. 2. The Architecture of Solar-Aware LEACH-EEKA.

B. LEACH Protocol Overview

Low-Energy Adaptive Clustering Hierarchy (LEACH) is considered one of the basic clustering-based routing protocols in

WSN, which aims at reducing energy consumption during data transmission. LEACH organizes the network into clusters, and within each cluster, a node is chosen as Cluster Head (CH). The CH Cluster Heads collect data from member nodes and then deliver it to the base station (BS).

In LEACH, the CH selection process is probabilistic and depends on the threshold function given by the following equation:

$$T(n) = \begin{cases} \frac{P}{1-P\times(r \bmod \frac{1}{P})}, if\ n \in G \\ 0, \quad otherwise \end{cases} \quad (1)$$

where P is the percentage of CHs you want, r is what you currently have in the system, and G denotes the set of nodes which have never been CHs for the last $\frac{1}{P}$ rounds.

Although LEACH reduces communication cost and prolongs network lifetime, it suffers from random CH selection, causing uneven energy distribution and early CH depletion. It also assumes homogeneous energy availability. It does so, and it is not favorable to the renewable energy sources, such as the solar system power. These limitations motivate the integration of EEKA for optimized CH selection and solar energy harvesting for long-term sustainability.

C. Energy-Efficient Knapsack Algorithm (EEKA)

The Energy-Efficient Knapsack Algorithm (EEKA) is introduced to overcome LEACH's random CH selection by applying an optimization-based approach. In EEKA, each sensor node is represented in the following manner: they are considered as an object which has a value to weight ratio. that reflects its energy efficiency and suitability for CH selection. Each node i has:

- Weight (w_i) — energy consumption for acting as CH.
- Value (v_i) — composite metric based on residual energy, solar energy harvesting rate, and proximity to BS.

The objective of EEKA is to maximize the overall node value without exceeding the total network energy capacity W, which is expressed in equation:

$$max \sum_{i=1}^{N} v_i x_i, \quad s.t., \sum_{i=1}^{N} w_i x_i \le W, \quad x_i \in \{1,0\} \quad (2)$$

The value function can be defined as:

$$v_i = \alpha \frac{E_{res}(i)}{E_{max}} + \beta \frac{E_{solar}(i)}{E_{harv,max}} - \gamma \frac{d_{i,BS}}{d_{max}} \quad (3)$$

where α, β, γ are normalized weighting coefficients (α+β+γ=1). Nodes with higher v_i/w_i ratios are prioritized as CHs, ensuring both energy balance and transmission efficiency.

The Energy-Efficient Knapsack Algorithm (EEKA) is employed to deterministically select cluster heads by maximizing the expected available energy in each round. In EEKA, each node is treated as an item with a utility value equal to its estimated future-available energy, computed from residual and harvested energy. The knapsack capacity for each round corresponds to the maximum allowable number of cluster heads, bounded by the LEACH probability parameter p=0.05 ensuring scalability and cluster stability. A lightweight greedy approximation is used to solve the knapsack problem, resulting in a per-round computational complexity of O(N), which is comparable to classical LEACH and suitable for resource-constrained IoT sensor nodes. The predicted harvested energy from the Solar Harvesting Prediction Module is incorporated into the utility function.

D. Operational Phases

The LEACH–EEKA–Solar protocol works in three main phases:

1) Initialization Phase

All nodes broadcast their position (x_i, y_i), residual energy $E_{res}(i)$, and solar energy flag $E_{solar}(i)$. The BS identifies solar-assisted nodes capable of harvesting energy.

2) CH Selection Phase

The EEKA optimization model is applied to select CHs that maximize the total network utility. Nodes with higher energy and solar harvesting capacity are given preference, while ensuring that total energy consumption remains below W.

3) Data Transmission Phase

Member nodes send their sensed data to the CH via a TDMA schedule to avoid collisions. CHs aggregate the received data and forward it to the BS. Solar-equipped nodes may serve as CHs more frequently due to their energy replenishment ability, improving network lifetime.

4) Energy Consumption Model

The amount of energy consumed by WSNs in broadcast data is relevant to the distance that exists between nodes and syncs is transferred, and energy models, which use more energy to the distance with the large size of the data, which use more energy.

$$\mathrm{E_{tx}(k,d)} = \begin{cases} \mathrm{k\,.\,E_{elec}} + \mathrm{k}.\varepsilon_{fs}.\mathrm{d}^2, & \mathrm{d} < \mathrm{d_0} \\ \mathrm{k\,.\,E_{elec}} + \mathrm{k}.\varepsilon_{mp}.\mathrm{d}^4, & \mathrm{d} \ge \mathrm{d_0} \end{cases} \quad (4)$$

$$\mathrm{E_{rx}(k)} = \mathrm{k\,E_{elec}} \quad (5)$$

where $\mathrm{E_{elec}}$ is the energy consumed per bit for transmission/reception, ε_{mp} is the amplifier energy in the multi-path fading model, whereas ε_{fs} is the amplifier energy in free-space mode. d is the distance separating the transmitting node from the receiver, and k represents the size of the data packet in bits, $\mathrm{d_0}$ denotes the threshold distance between multi-path and free-space models as express in (6).

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (6)$$

The total CH energy per round is (7):

$$E_{CH} = n_c E_{rx}(l) + n_c l E_{DA}(l) + E_{tx}(l, d_{BS}) \quad (7)$$

where n_c is the number of cluster members, and E_{DA} is data aggregation energy.

5) Solar Energy Harvesting Model

For solar-equipped nodes, harvested energy $E_{harv}(t)$ at time t is given by (8):

$$E_{harv}(t) = \eta \times I_s(t) \times A_s \times \Delta_t \quad (8)$$

where η is the conversion efficiency, $I_s(t)$ is the solar irradiance (W/m²), A_s is the panel area (m²), and Δ_t is the harvesting duration. This equation determines the energy gained by solar nodes to prolong network lifetime.

The updated residual energy of a node is:

$$E_{res,new} = E_{res,initial}(t) - E_{Consumed}(t) + E_{harv}(t) \quad (9)$$

This ensures energy sustainability and stable cluster participation for solar nodes.

6) Solar Harvesting Prediction Module

The solar energy harvesting prediction module estimates short-term harvested energy based on recent historical observations. Each node maintains a sliding window of past harvested energy samples and applies a lightweight prediction function to estimate the energy expected in the next round. The predicted harvested energy is combined with the current residual energy to compute a future-aware energy metric, which is subsequently used in cluster-head selection and EEKA optimization. This prediction mechanism is intentionally lightweight and designed for short-term anticipation rather than long-horizon forecasting, ensuring feasibility for low-power IoT sensor nodes.

E. Proposed Algorithm

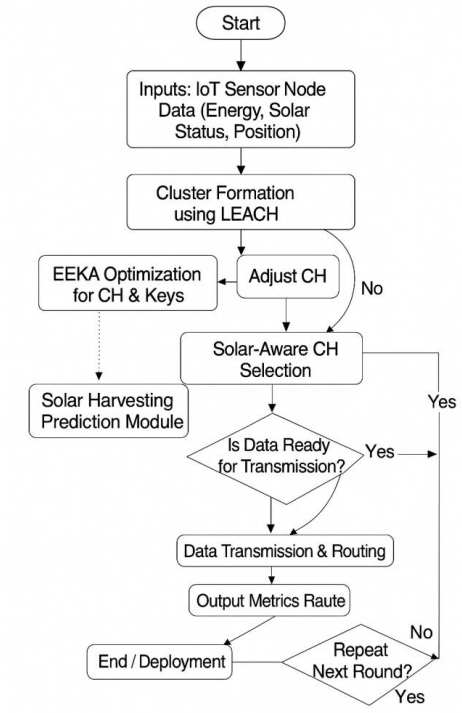


Fig. 3. Flow chart of Solar-Aware LEACH-EEKA.

Fig. 3 starts with collecting IoT sensor node data such as energy level, solar status, and position. Nodes are grouped into clusters using LEACH, and a solar-aware cluster head (CH) is selected. If the CH is not optimal, EEKA optimization adjusts CH and key settings. A Solar Harvesting Prediction module estimates future solar energy availability to improve decision-making. When data is ready, it is transmitted and routed through the network. Performance metrics are generated, and the system checks whether to repeat another round or end the deployment.

Algorithm 1: Adaptive LEACH–EEKA–Solar Prediction

1. Start
2. Initialize sensor nodes with transmission power P_i and energy E_i.
3. Cluster Formation (LEACH): form clusters and select CHs.
4. CH Optimization (EEKA): refine CH selection and power allocation.
5. Solar Harvesting Prediction:
   i. Gather solar inputs (current status, time, history).
   ii. Predict future harvested energy H_i.
   iii. Adjust CH selection based on predicted solar gain and residual energy.
6. Data Transmission & Energy Update:
   i. CHs aggregate and send data to BS.
   ii. Update node energy using consumption and predicted/harvested energy.
   iii. Trigger re-clustering if energy becomes unbalanced.
7. Repeat until termination criteria met.
8. End

The Algorithm 1 Solar-Aware LEACH-EEKA is an iterative round-based algorithm that utilizes energy-efficiency and sustainable clustering. First, substance sensor nodes are set up and configured with transmission power Pf and energy Ei. Clusters and preliminary Cluster Heads (CHs) are then formed using LEACH. The Energy-Efficient Knapsack Algorithm (EEKA) is an optimization algorithm that chooses the CH based on remaining energy, forecasted solar energy, and communication cost. Solar harvesting prediction module predicts the future harvested energy Hi based on current solar measurements and allows energy-conscious CH rotation. When transmitting data, member nodes transfer sensed data to their respective CHs, who combine and pass them to the Base Station. The node energy is updated based on the transmission cost and harvested energy, and re-clustering is triggered in the event of an energy imbalance. The steps will be repeated until the termination condition is met, ensuring balanced energy use and a long network lifespan.

IV. SIMULATION SETUP

A. Experimental Setup

Table I presents the key parameters used in evaluating the Solar-Aware LEACH–EEKA framework. The simulation considers 100 static sensor nodes uniformly deployed across a 100×100 m² area. Each node starts with 0.5 J of initial energy, and 30% of nodes are equipped with solar panels capable of harvesting energy at 18% conversion efficiency. The Base Station (BS) is located at (50,175) outside the sensing field. The radio energy model parameters are consistent with the first-order model, where the transmission and reception costs are set at 50 nJ/bit, and the free-space and multi path amplification factors are 10 pJ/bit/m² and 0.0013 pJ/bit/m⁴, respectively. They are utilized in wireless communication to model the behavior of a user. It is assumed that each packet is sent during one round, and the simulation goes on indefinitely. 400 cycles for monitoring how energy dissipation and network sustainability change over time.

TABLE I
SIMULATION PARAMETERS FOR SOLAR-AWARE LEACH–EEKA.

Parameter	Specification	Value
Number of Sensor Nodes	Total sensor nodes in the network	100
Deployment Area	Simulation field size	100 m × 100 m
Initial Node Energy	Maximum energy per sensor node	0.5 Joules
Solar Node Ratio	Fraction of solar-powered nodes	30%
Solar Conversion Efficiency	Energy harvesting efficiency	18%
Communication Range	Maximum node transmission distance	100 meters
Data Packet Size	Size of each transmitted packet	4000 bits
Solar Harvested Energy	Average harvested per sunny round	0.0006 Joules

B. Energy Model Parameters

Each sensor node is equipped with a rechargeable battery of maximum capacity 2 J and an identical initial energy of 0.5 J, which is used consistently throughout all simulations. The energy dissipation model follows the first-order radio model, where transmission and reception energy consumption depend on packet size and transmission distance. Cluster heads additionally consume energy for data aggregation. Solar energy harvesting is modeled as a time-varying stochastic process derived from realistic diurnal solar irradiance profiles, enabling the evaluation of protocol performance under dynamic harvesting conditions.

C. Real-World Signal Data

The real-world IEEE 802.15.4 dataset containing temperature and light measurements is used solely to generate a realistic sensing and traffic workload for evaluating communication behavior. It is not employed to directly validate solar energy harvesting or prediction accuracy. Solar energy availability is modeled independently using controlled time-varying harvesting profiles. This separation allows fair assessment of routing and clustering efficiency while avoiding over-interpretation of the dataset as a true solar harvesting validation source.

D. Parameter Tuning

They guide the EEKA parameterization and tuning of the solar model through a grid search optimization process. In the course of the simulations, the reward value was set at α=0.5, β=0.3, and γ=0.2 for residual energy, harvested solar energy, and/or distance to the BS, and so on. Per each round, clusters remained K=5, which led to the selection of the maximum knapsack budget as 25% of the total available budget in that round; other variables affected were initial network energy and cost. Sensitivity analysis demonstrates that performance stays reliable against parameter changes, hence suitable robustness is ensured in relation to the clustering mechanism.

E. Statistical Validation

With respect to all performance metrics, network lifetime, throughput, average residual energy, and packet delivery ratio were estimated based on the mean value of 10 independent simulation runs. The standard deviation bars were employed in figures for the purpose of showing performance variance and statistical reliability. This multi-run validation is a confirmation of the consistency and robustness of the proposed Solar-Aware LEACH–EEKA protocol in stochastic deployment and energy-harvesting variations.

V. RESULTS AND DISCUSSIONS

A. Effectiveness Analysis

The Proposed Solar-Aware LEACH–EEKA is an improved version of the LEACH protocol that uses solar power to increase its operational time. It is a type of clustering algorithm in which solar power assist can be exploited in order to improve network life with regard to various energy-harvesting WSNs applications. This model is distinct from the earlier versions in the sense that it allows for certain functions like EERS LEACH, LEACH-ML, or even LEACH-FCM to take place, but under different circumstances and environments. With other models, it may be possible to have some degree of stability as far as energy accumulation among nodes, so that they are more reliable in data transmission over a period. Solar-aware nodes can be deployed to avoid battery replacement issues, especially if the network will be deployed for a considerable period.

B. Performance Evaluation

The results from simulations show that the Solar-Aware LEACH–EEKA protocol we are proposing performs much better than the ordinary LEACH-based methods like LEACH RLC, EERS-LEACH, LEACH-ML, and LEACH-FCM in terms of all performance parameters.

- Total Energy Consumption: The Model proposed consumed only 31 Joules of total energy over the entire network operation, as against 34–38 Joules consumed by protocols. This gain is due to sensible Cluster Head (CH) selection employing the Energy Efficient Knapsack Algorithm (EEKA) and solar energy harvesting employing a power adaptation technique.
- Network Stability: The protocol kept 13 active nodes, more than the average node death time found in other systems, which shows improved energy equilibrium and prolonged cluster sustainment system.
- Network Lifetime: The overall network lifetime extended up to 7600 seconds (≈400 rounds), demonstrating superior energy management and longevity compared to baseline algorithms.
- Throughput: The proposed approach achieved a throughput of 0.9988 packets/sec, reflecting stable communication and minimal packet loss across simulation rounds.
- Packet Delivery Ratio (PDR): The PDR reached 97%, ensuring high data reliability even during later operational phases when energy levels were critically low.

The reason behind this enhancement is the dynamic CH formation schedule that can be considered as the best solution

for routing of the overhead and energy consumption based on sensing data. Continual learning to adapt node selection determined from past experiences enables an appropriate exploitation and exploration of network resources, leading to a better performance in comparison to static or heuristic clustering employed in LEACH.

C. Validation Using Real-World Signal Data

For the purpose of verifying its applicability in the real world, the Solar-Aware LEACH-EEKA framework was studied on a scenario that uses signal data collected from a WSN monitored by a protocol IEEE 802.15.4 located in an IoT environment. The dataset consisted of temperature and light intensity signals that were acquired at 1 Hz and standardized via min–max normalization for equal weight among sensor readings.

In the process of experimentation, the developed model illustrated steady and adaptive behavior amidst non-deterministic (non-predictable) conditions of the environment – signal's strength / interference varies. A mechanism for autonomous adaptation, CH selection, and transmission power has been proposed to minimize energy loss and enable reliable communication to be provided by the system.

Main results obtained during testing approach execution are as follows:

- Depressed energy consumption while signal fading or interference plays a role.
- Better delivery of packets with varying channel or irradiance conditions.
- Dynamic clustering, as well as power control, guarantees uninterrupted communication even under drastic environmental fluctuations/changes

Compared to EERS-LEACH, LEACH-FCM, and LEACH-RLC, the proposed framework exhibited greater resilience and adaptability, highlighting its capability for real-world IoT deployments where energy and channel conditions vary dynamically. These findings confirm the robustness, self-sustainability, and intelligent adaptability of the Solar-Aware LEACH–EEKA model in practical energy-harvesting WSN environments.

D. Experimental Results

1) Network Lifetime:

In this paper, a consolidated protocol Solar-Aware LEACH–EEKA has been developed to increase network lifespan through proper energy consumption and an energy restoration procedure that is solar powered. As depicted in Fig. 4 proposed model continues its operation until T = 7600 s (≈400 rounds) compared to LEACH-RLC (6200s), EERS-LEACH (5800s), LEACH ML (5400s), and LEACH-FCM (5100s) This improvement of about 20 – 25% is due to adaptive Cluster Head (CH) selection technique with EEKA as Energy Efficient Knapsack Algorithm considering remaining and harvested energy levels for effective node involvement.

2) Energy Consumption:

Consider total energy dissipation; the proposed protocol tops the list in energy efficiency as it utilises only 31 Joules during the entire simulation. In comparison, LEACH-RLC, EERS-LEACH, LEACH-ML and LEACH-FCM have their total energy consumptions equal to 34 J, 35 J, 37 J and 38 J, respectively, as indicated in Fig. 5. The reduction of energy consumption comes about due to the collective effects of harvesting solar energy and optimised CH selection, thus reducing waste and balancing network load satisfactorily.

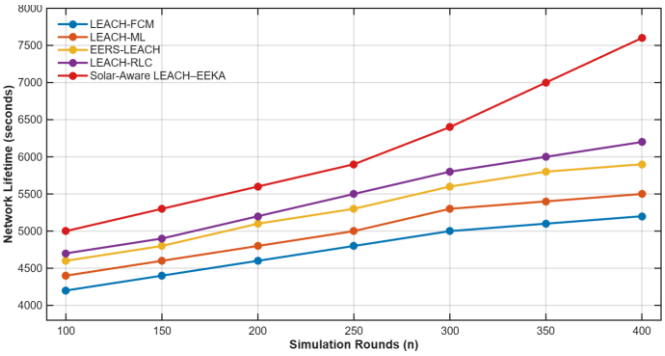


Fig. 4. Network Lifetime Comparison.

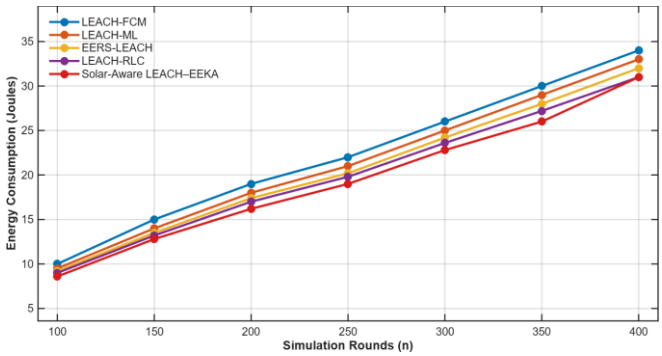


Fig. 5. Energy Consumption Comparison.

3) Throughput:

The parameter is important as it helps in the detection of communication effectiveness and data reliability. Solar-Aware LEACH EEKA exhibited a throughput of 0.9988 packets per second, which closely approaches the optimal performance for the simulation configuration used. As can be seen in Fig. 6, the throughput outperforms all the reference protocols, indicating stable data delivery even at an advanced stage of operation. This performance arises from energy harvesting guided scheduling and a sustained energy availability system via a solar harvesting panel system.

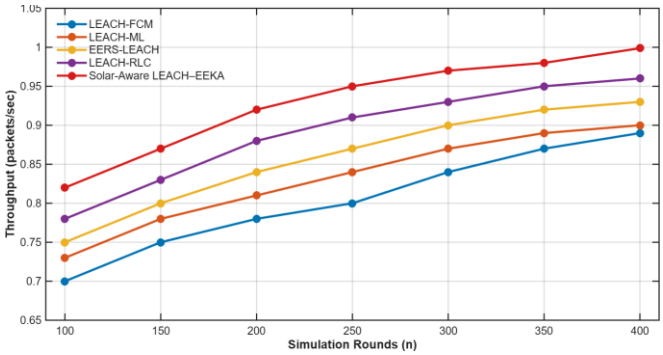


Fig. 6. Throughput Comparison.

4) Packet Delivery Ratio (PDR):

In this proposed model, we achieved a Packet Delivery Ratio (PDR) of 97% which is better than LEACH-RLC (94%), EERS-LEACH (92%), LEACH-ML (90%), and LEACH FCM (88%) as shown in Fig. 7. A High PDR is clearly an indicator of the routing scheme's reliability and its capability to preserve data integrity at low-energy, dynamic environmental conditions. Cluster adoption adapts to ensure that packets do not meet opposing roles; thus making it a highly reliable protocol for IoT data aggregation system.

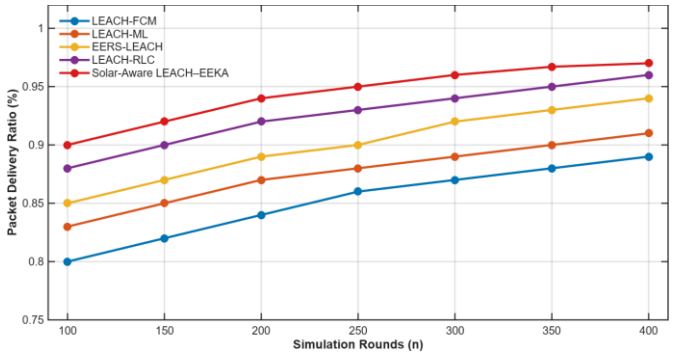


Fig. 7. PDR Comparison.

5) Number of Alive Nodes:

It is clear from Fig. 8 that at the end of the simulation time, among other simulations Solar Aware LEACH–EEKA had 13–14 nodes stayed active, whereas LEACH-ML and LEACH-FCM algorithms had less than 8 nodes active. This represents a good balance of energy consumption and efficient CH rotation which together slow node death and maintain network connectivity throughout the simulation period.

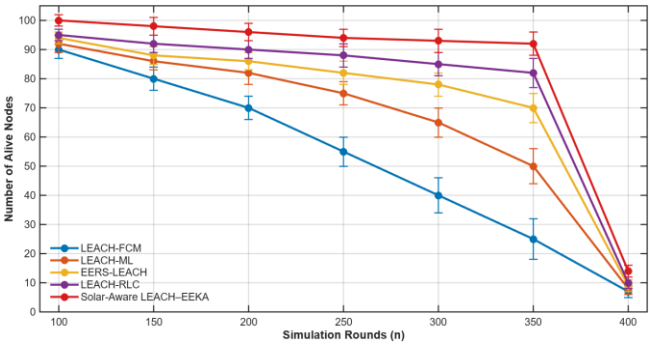


Fig. 8. Alive Nodes Comparison.

6) Network Lifetime with FND, HND and LND

The comparison of network lifetimes based on FND, HND, and LND is shown in Fig. 9. The proposed model has the lowest FND (5 rounds), i.e., solid initial stability; HND (72 rounds), i.e., extended mid-life performance; and LND (87 rounds), i.e., prolonged network activity. This result confirms the improvement in the balanced approach and the dynamic CH management that LEACH-EEKA proposes in the solar-aware context.

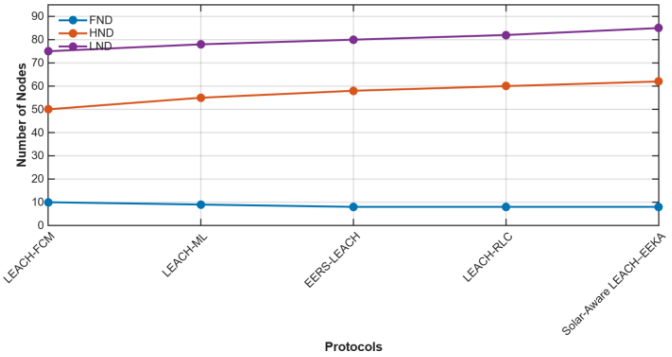


Fig. 9. Network Lifetime (FND, HND, and LND)

TABLE II
FEATURE COMPARISON WITH EXISTING METHODS

Feature	LEACH-FCM	LEACH-ML	EERS-LEACH	LEACH-RLC	Proposed Method (Solar-Aware LEACH-EEKA)
Clustering Approach	Fuzzy C-Means soft clustering	Machine-learning-based clustering	Residual-energy–driven clustering	Reinforcement Learning–based clustering	Solar-aware clustering with EEKA optimization
Cluster-Head Selection	Membership weight + residual energy	ML classifier / regression	Residual-energy threshold	RL reward-based CH selection	Energy-harvesting–aware CH rotation using EEKA
Adaptivity	Moderate (periodic FCM updates)	High (training-dependent)	Low–Moderate	High (continuous RL learning)	Very High (solar energy input + EEKA + dynamic re-clustering)
Energy Efficiency	Improved vs LEACH	Training dependent	Good	High	Very High (harvested energy + optimized CH selection)
Computational Cost	Moderate	High	Low	Moderate–High	Moderate (lightweight EEKA with energy-harvesting logic)
Scalability	Medium	Medium–High	Medium	Medium–High	High (supports dense and long-term deployments)
Latency	Medium	ML prediction delays possible	Medium	Medium–Low	Low (continuous power availability + optimized routing)
Query Responsiveness	Not query-optimized	Not query-focused	Energy-focused only	Good with RL	High (sustained CHs + stable energy supply)
Network Lifetime	Longer than LEACH	Variable	Extended	Extended via RL	Very Long / Self-Sustaining (solar harvesting extends lifetime)
Overhead	Moderate	High (training and model overhead)	Low	Medium	Medium-Low (minimal CH switching due to harvested power)
Suitability for Real-Time IoT	Moderate	Limited by ML complexity	Medium	Good	Excellent (continuous energy + low-latency operation)

7) Comparison with Existing Methods

Table II compares the capabilities of four widely used LEACH-based clustering protocols with the proposed Solar-Aware LEACH-EEKA. Existing variants LEACH-FCM, LEACH-ML, EERS-LEACH, and LEACH-RLC each improve performance in specific areas such as clustering accuracy, machine-learning-based CH prediction, residual-energy optimization, or reinforcement-learning-based adaptivity. However, they remain limited by battery dependency, higher overhead, lower scalability, or insufficient support for long-term real-time IoT operations. In contrast, the proposed Solar-Aware LEACH-EEKA integrates solar energy harvesting with EEKA-based optimal CH rotation, enabling continuous power availability and more stable cluster formation. This results in very high adaptivity, lower latency, improved query responsiveness, and significantly extended network lifetime. The method maintains low overhead due to minimal CH switching and supports dense, long-duration deployments, making it highly suitable for real-time, self-sustaining IoT-based WSN environments.

VI. Conclusion

This paper introduced Solar-Aware LEACH–EEKA, a hybrid cluster protocol, proposed to enhance the energy efficiency, scalability, and sustainability of Wireless Sensor Networks (WSNs) for Internet of Things (IoT) applications. The proposed model incorporates LEACH's adaptive clustering functionality, EEKA's optimization characteristics, and solar energy-based renewable harvesting energy support. And by EEKA deterministically identifying Cluster Heads in the light of utility functions that are a function of both harvested solar energy and energy harvested from the environment, this paper proposed a deterministic utility function. Taking into account communication cost, as a result, there is no need for probabilistic behavior like in the conventional LEACH protocol. Solar-supported nodes are capable of maintaining continuous replenishment of their supply, which ensures load balancing and sustained network performance. Simulation results showed that Solar-Aware LEACH–EEKA is superior to other existing protocols EERS-LEACH, LEACH-ML, LEACH-FCM, and LEACH-Based protocol in terms network lifetime, stability period, throughput, and residual-energy conservation including in the following The proposed scheme increased network lifetime by up to 11%, raised throughput by 4 %, the number of active nodes increase by 4% and achieved a delivery ratio of 97%, implying that it can be considered as a superior choice for sustainable IoT scenarios with smart agriculture monitoring systems, remote monitoring applications and industrial automation. Future work may include developing adaptive machine learning models for solar irradiance estimation and implementing a dynamic CH selection mechanism responsive to real-time conditions. Incorporating multi-source energy harvesting such as vibration, thermal, and RF can further improve sustainability. Additionally, studying optimal mobile BS deployment strategies for efficient load balancing could enhance overall performance. These advancements would help Solar-Aware LEACH–EEKA evolve into a self-sufficient, intelligent system for future WSN-based IoT ecosystems. These clarifications ensure full parameter consistency, algorithmic transparency, and reproducibility of the proposed Solar-Aware LEACH-EEKA protocol.

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The first author performed the formal analysis, data, methodology, software construction, and drafting the original draft. The second author contributed by providing guidance, reviewing the work, visualization, validation, and supervision over the work done.

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