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Original Article

Energy-Aware Cluster-Optimized Intelligent Routing Protocol for WSN-based IoT Networks

Pravin Yallappa Kumbhar[1], Apurva Abhijit Naik[2]

[1,2]Department of Electrical and Electronics Engineering, Dr. Vishwanath Karad, MIT World Peace University, Pune, Maharashtra, India.

[1]Corresponding Author : pravinkumbhar03@gmail.com

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Abstract - *Wireless Sensor Networks (WSNs) use resource-constrained sensor nodes to continuously monitor ambient conditions and serve as data sinks for various Internet of Things (IoT) applications. However, maximizing Energy Efficiency (EE) while maintaining reliable data delivery remains a significant challenge. Existing clustering and routing algorithms struggle with issues such as uneven energy consumption, premature node failures, and poor network performance. Additionally, many existing metaheuristic schemes are not adaptable to dynamic network environments, which leads to ineffective energy management. To address the above issues and enhance the energy efficiency of IoT-based WSN, this research introduced a novel Energy-Aware Cluster-Optimized Intelligent Routing (EACO-IR) protocol. The EACO-IR protocol performs in three stages: stable cluster formation, Cluster Head (CH) selection, and energy-aware route finding. At first, stable clusters are formed using the Hybrid Fuzzy–Density Adaptive Kronecker Clustering (HF-DAC) algorithm. Subsequently, CHs are optimally selected using the Mutation-Enhanced Armadillo–Devil Optimization (MEADO) based on a multi-objective function for the Base Station (BS). Finally, the Multi-level Energy-Aware Attention Transformer- Based Reinforcement Learning is introduced to create intra and inter-cluster data travel ways to minimize communication overhead from SNs to the BS. Experimental results show that the proposed protocol yields an average throughput of 4 Mbps, an average Packet Delivery Ratio (PDR) of 98.71%, and an end-to-end latency of 0.06 seconds, outperforming current state-of-the-art clustering and routing algorithms. Ultimately, this framework establishes a highly adaptable template for deploying self-optimizing, long-lasting IoT architectures capable of supporting real-time data streaming without premature network degradation.*

Keywords - *Energy-efficient routing, Kronecker clustering, Metaheuristic energy-optimization, Wireless sensor networks, Reinforcement learning.*

1. Introduction

In recent years, WSNs have developed as one of the world's most significant technologies. WSN is a self-organizing network system, which is identified by several energy-constrained micro sensors and a minimum of one sink Base Station (BS) [1, 2]. The fundamental component of WSNs is usually a large number of small sensors. Heat, humidity, vibrations, noise, item presence, and other physical system measures are made possible by these sensors [3]. The development of wireless sensor technology is initiating the contemporary ubiquitous and intelligent IoT application. Since its inception, the IoT has greatly benefited the world as a WSN, particularly in acquiring data from critical situations [4, 5]. The long-term viability of IoT-enabled WSNs depends on effective and flexible routing. WSNs are appealing for a variety of IoT applications due to their many benefits [6]. Initially, they may be deployed even in remote or wide-area contexts since many WSN nodes are inexpensive and need little infrastructure. Furthermore, WSNs offer automatic data gathering and real-time monitoring, which allows quick reactions to system events or environmental changes [7].

Numerous industries, including the military, healthcare, smart buildings, and agriculture, are investigating the topic of WSNs to monitor and collect physical data. As a result, WSN applications have been linked to the physical environment, the computing industry, and society [8]. To collect data on a periodic or event-driven basis, the sensor nodes are dispersed evenly or at random. Wireless broadband channels enable end users to access the necessary sensor data from the BS over the internet [9]. Improving WSN energy efficiency with timely data transmission is the most significant issue among these constraints for many applications [10, 11]. WSN architecture is distinct from standard ones because of its self-configured, ad-hoc, and simple installation and maintenance features. In order to achieve power efficiency in WSNs, hierarchical routing techniques have been put into practice [12]. The WSN clustering method that splits the linkage into hierarchies to accomplish load balancing as well as other goals like scalability, lifetime maximization, and energy minimization [13, 14].

A crucial component of WSNs is scalability, which has not been well demonstrated in many protocols due to the original assumptions made [15]. Due to these factors, WSNs are not scalable and lead to communications that use too much power. Therefore, with the increasing number of IoT devices, the network face overloading issue [16, 17]. A WSN's efficiency can be increased by developing methods that can decrease node energy degradation and lengthen network lifetime. Sensor nodes are considered autonomous once they are installed, but their lifespan will rely on how efficiently they control their energy use. Compared to networks that depend on direct links, WSNs frequently combine multilayer designs to ensure a longer-lasting network [18-20].

In recent years, several researchers have designed clustering and EE routing approaches to effectively enhance the lifetime and EE of WSNs in IoT networks. For instance, the simple contrastive graph approach was introduced in dynamic clustering optimization for EE IoT networks [21] to enhance the quality of clustering and energy utilization. To increase the network communication stability, a fuzzy logic-based clustering approach with optimized EE routing [22] was introduced. Similarly, the optimized rank-based key management for Secure and EE Routing (SEER) [23] is designed for security and energy saving of routing in IoT-enabled WSNs. An EE Artificial Intelligence-Based Routing Protocol (EE-AIRP) [24] was created to enhance the performance of packet transmission and energy efficiency. To enhance QOS, packet delivery, and energy efficiency of IoT-enabled WSN, the optimal cluster-based EE routing scheme [25] was introduced. These methods have provided efficient improvement in IoT-enabled WSN, but they have unresolved several critical challenges.

Most of the existing approaches in the field rely on cluster formation, cluster head selection, and security-aware routing without considering their overall impact on network lifetime and communication reliability [26, 27]. Furthermore, some state-of-the-art techniques are unable to perform efficiently in dynamic IoT situations with different node densities, traffic types, and energy constraints [28-30]. It leads to imbalanced energy usage, high complexity, increased packet loss, higher latency, and reduced network scalability. Hence, an intelligent and adaptive routing framework to ensure stable cluster formation, minimize energy consumption of the clusters, optimize the routes dynamically based on the energy consumption of the cluster head, and achieve high packet delivery performance is required. To tackle these issues, this paper proposes an EACO-IR protocol. The major contribution of the EACO-IR protocol is:

- To improve the network lifespan and EE, the EACO-IR protocol is proposed. This protocol jointly performs cluster formation, cluster head selection, and routing optimization.
- To introduce a Hybrid Fuzzy-Density Adaptive Kronecker Clustering (HF-DAC) algorithm that integrates fuzzy-density learning and Kronecker–based structural representation to ensure that the network structure doesn't collapse, and an adaptive cluster node group under dynamic conditions.
- To select optimal cluster heads, a Mutation-Enhanced Armadillo–Devil Optimization (MEADO) is introduced. Through this optimization, optimally choose the CHs based on the communication distance and node density residual energy.
- To adaptively find the best routes for data, Energy-Aware Attentive twining Transformative Reinforcement Learning is employed that minimizes communication overhead and transmission delay while improving routing reliability.

The rest of the article is prepared by: Section 2 provides the recent research based on an intelligent routing protocol for WSN-based IoT networks; Section 3 describes the proposed methodology with detailed architectures; Section 4 provides the results and discussion with performance comparison; as well as last section 5 includes the conclusion and future scope.

2. Related Works

In WSN-based IoT applications, EE routing is an important research field since the sensor nodes are often deployed in unreachable areas and have limited battery power. Energy-efficient clustering and routing mechanisms can help save energy, enhance packet delivery performance, and prolong network lifetime.

To overcome these problems, researchers have suggested different clustering-based, optimization-based, machine learning-based, and reinforcement learning-based routing protocols. The recent trends have been on incorporating adaptive routing methods with intelligent optimization techniques for enhancing communication efficiency and network stability in dynamic operating conditions.

Rahmani et al. [31] developed a method called the GWFCCV direction-finding strategy for IoT-based WSN networks. Through this approach, incorporated with gray wolf and fuzzy c-means clustering and multi-criteria based ranking approaches. The approach effectively increases the network lifetime, but requires more computational cost.

To reduce the WSN energy consumption, Zhang et al. [32] introduced an EE adaptive clustering routing algorithm. The algorithm produces better energy efficiency and reduces delay. However, it is sometimes difficult to replace the nodes' energy in complicated application settings since they are usually supplied by batteries or micro-energy harvesting devices.

The Hybrid Memetic Evolutionary Algorithm (HMEA) developed by Vimalarani et al. [33] to solve the high EE clustering and routing. By this approach, strong resource allocation strategies for long-term WSN operations are advanced. Still faces a high scalability issue.

An ideal routing strategy to lower energy usage in WSN is presented by Kooshari et al. [34]. It utilized the WSA to cluster wireless sensor nodes in the initial stage. The study's purpose is to increase the lifetime of the WSN while reducing energy consumption and packet error rates, but it requires high-level data.

To ensure safe information transmission, Verma et al. [35] developed a Mutation- grounded Multilayer Perceptron (MUMLP) for energy and security- conscious optimum routing. Nonetheless, the developed method faces high model complexity.

Zhang et al. [36] introduce a deterministic routing system for static heterogeneous WSNs that utilizes three complementary advances to solve scalability and energy imbalance issues. To prevent premature convergence, an Enhanced IPSO method was initially utilized with a cosine-modulated mechanism to dynamically modify learning factors and inertia weights. Then, it utilizes a heterogeneity-aware design that ensures optimum resource allocation across various node types. Still, the method face high computational cost.

The efficient quantum particle swarm optimization clustering approach and deep reinforcement learning-based routing strategy were developed by Guangjie et al. [37]. The developed method performed effectively in WSN data transmission, but the model produced higher delay.

Silambarasan et al. [38] presented the Improved Golden Eagle Optimization Algorithm (IGEOA) to optimize the formation of clusters in WSN-based IoT systems with energy efficiency. The method optimizes cluster head selection with multiple objective functions based on energy awareness and has a cluster maintenance mechanism to ensure network performance. Simulation results showed tremendous EE and network lifetime enhancement. But the algorithm suffers from a computational overhead problem.

An efficient Greylag Goose-based Optimized Clustering (GGOC) algorithm was developed by Malik et al. [39] for heterogeneous WSNs. This approach uses 5 fitness parameters for selecting the cluster heads. The experimental results indicate improved throughput and residual energy. Nonetheless, the GGOC algorithm limits adaptability in real-world WSN.

To solve the scalability problem in real-world WSN, Akram et al. [40] developed an EE Machine Learning-based Clustering and Routing (EEMLCR) framework. The strategy integrates intelligent cluster formation and routing path optimization and achieves excellent performance. Still, the model required high computational and training resources.

The Multi-Agent Deep Reinforcement Learning-based Adaptive Routing framework (MADII) was created by Yang et al. [41] for efficient energy optimization in WSN. The MADII approach utilizes a multi-agent Markov decision process with informer-based learning and an imitation learning strategy to boost the convergence speed of energy optimization. This method efficiently enhances the network lifetime and energy efficiency. But the learning process of reinforcement learning takes a lot of time.

Kiruthika et al. [42] designed a novel Energy-Centric Fossa Optimization (NECFO) framework. The method combines energy-distance-based clustering and fossa optimization for CHs selection and EE routing optimization. Experimental results of the designed framework show better network stability. Still, the framework performance reduces in a highly dynamic network environment. Saroit et al. [43] designed an Energy-Driven K-Means-Based LEACH routing protocol. The protocol design optimizes the placement of the CHs and greatly boosts the EE performance. However, the clustering process affecting performance in highly heterogeneous network scenarios.

Although analysis of existing studies the EE clustering is the main three directions, such as EE clustering, optimization-based cluster head selection, and intelligent routing using machine learning or reinforcement learning techniques, despite these methods having proven to be very useful. Moreover, most approaches are based on a static scenario and on a high idealized deployment setting, or on complex and time-consuming optimization algorithms, which are not readily applicable to real IoT-driven WSN deployments.

While there have been great developments, there are still a few important issues that need to be addressed. These existing solutions typically emphasize cluster formation, cluster head selection, or route optimization separately without taking into account the impact of these three on the overall network performance. This can lead to early node failures, high latency, packet loss, uneven energy consumption, routing overhead, and low scalability. Thus, there is a requirement for a common and flexible routing mechanism to guarantee stable cluster formation, energy-aware cluster head selection, and intelligent route optimization simultaneously. This paper suggests an EACO-IR protocol that combines the Hybrid Fuzzy-Density Adaptive Kronecker Clustering (HF-DAC), Mutation-Enhanced Armadillo–Devil Optimization (MEADO), and an Energy-Aware Attentive Twining Transformative Reinforcement Learning model to improve the EE, reliability of routing, and network life time in WSN-based IoT networks.

3. Materials and Methods

This section discusses the proposed EACO-IR protocol to improve the operational lifespan and energy efficiency of IoTs, as shown in Figure 1. Initially, stable clusters are formed using the HF-DAC algorithm. In the final phase, the Multi-level Energy-Aware Attention Transformer- Based Reinforcement Learning is used to create both intra- and inter-cluster data transmission paths to minimize communication overhead from SNs to the BS.

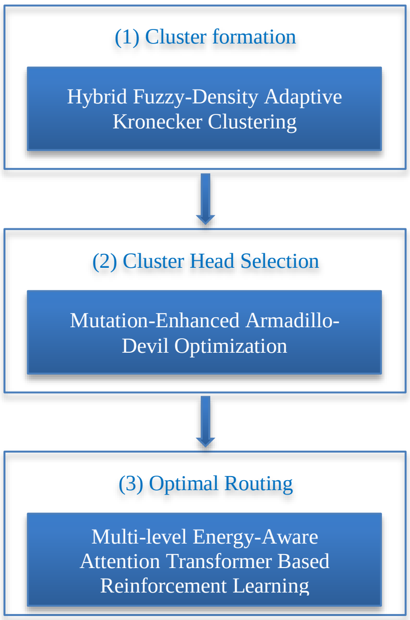

Fig. 1 Architecture of the proposed methodology workflow

3.1. Initialization

During the initialization period, the WSN is generated with a total of 500 heterogeneous sensor nodes. Each IoT node becomes self-configured by calculating the important communication parameters to connect to the network. The initialization is expressed in Equation (1).

$$initial\ sensor\ nodes\ (g_k) = \{g_{k1}, g_{k2}, \dots, g_{k500}\} \quad (1)$$

Here, $g_k$is denoted as the set of all deployed sensor nodes, like 1 to 500 sensor nodes in the heterogeneous WSN. The communication parameter configuration for each node is expressed as Equation (2).

$$parameter\ setup(p_k) = \{p_{k1}, p_{k2}, \dots, p_{k500}\} \quad (2)$$

Here,p_kThe communication parameters associated with each sensor node are denoted. Each p_{k500}includes specific attributes such as node density, network topology, and environmental conditions assigned to the node environment information for setting up the sensor nodeg_{k500}. The adjacency matrix Crepresents the sensor nodes' connectivity, defined as Equation (3).

$$(C) = \begin{bmatrix} C_{1(1)} & C_{1(2)} & \cdots & C_{1(500)} \\ \cdots & \cdots & \cdots & \cdots \\ C_{500(1)} & C_{500(2)} & \cdots & C_{500(500)} \end{bmatrix} \quad (3)$$

Here, C is denoted as the network topology adjacency matrix, and$C_{500(500)}$ is denoted as the connection between the g_k sensor nodes. Then$n_{500(500)}$ value of 1 means a connection, and equal to 0 means no connection. This representation in the form of a matrix provides a scalable and efficient means of handling the connections in the network among all sensor nodes in the WSN.

3.2. Hybrid Fuzzy–Density Adaptive Kronecker Clustering (HF-DAC) Algorithm

The EACO-IR protocol operates in 3 systematic phases: stable cluster formation, CH selection, and energy-aware route finding. In the initial phase, stable clusters are formed using the proposed HF-DAC algorithm, which integrates fuzzy clustering [44], density-adaptive similarity, and alignment-free structural Kronecker encoding to improve clustering robustness in heterogeneous IoT environments. Fuzzy C-Means is a dataset $A = \{i_1, i_2, i_3, \dots, i_N\}$ wherei_x =∈ R^a $c$clusters are formed by minimizing as expressed by Equation (4)

$$J_{FCM}(M, E) = \sum_{x=1}^{N} \sum_{y=1}^{c} m_{x,y}^{u} \left\| i_x - e_y \right\| \quad (4)$$

Let$M = [m_{xy}] \in R^{N \times c}$ denotes the fuzzy membership matrix, $\sum_{y=1}^{c}\{e_1, e_2, \dots., e_c\}$is the cluster centroid, $u >$ 1indicates the fuzziness parameter controlling overlap, and$\|i_x - e_y\|$ Represents the Euclidean distance.

3.2.1. HF-DAC Algorithm

The hybrid approach, called the Isolation Kernel (IK), which is in the data space, is repeatedly partitioned using randomly selected nodes. Two nodes are considered similar if they frequently fall into the same partition. The isolation is defined based on data-dependent portioning and is mathematically defined by Equation (5).

$$K_{\varphi}(i, j|A) = E_{p\varphi(A)}[X(i, j \in \theta | \theta \epsilon P)] \quad (5)$$

Here $P_{\psi}(A)$ is the set of all partitions generated using ψsampled pointsθ. A partition (region) in\ P, $X(\cdot)$denotes the indicator function (1 if true, 0 otherwise), and the kernel measures the probability that $i$and $y$fall into the same partition. Afterward, the Euclidean distance measure is density adaptive, and nodes in sparse regions are not unfairly separated. Enables detection of clusters with varying density and irregular shapes, which are common in IoT deployments. Actually, a limited number of partitions$r$, can be used to approximate K defined by Equation (6)

$$K_{\psi}(i, j|A) \approx \frac{1}{r} \sum_{x=1}^{r} X(i, y \in \theta | \theta \in P_x) \quad (6)$$

Where $r$denotes the amount of random partitioning iterations, and $P_x$is the partition generated at iteration x. It leads to the fundamental characteristics of IK: given coordinates i,j in a sparse area and i' j', with equal inter-point distances in a dense area, is computed as Equation (7).

$$K_\psi(i,j) > K(i',j') \tag{7}$$

It indicates that similarity is higher in sparse regions, enabling adaptive clustering. Following the FCM-IK- based binary proximity encoding, each node is transformed into a binary vector. In each iteration, a node is assigned to its nearest partition center. This assignment is encoded as a binary vector concatenating across iterations creates a robust feature representation.

For each iteration:

- To create A, choose $\psi_r$points at random from $A$to form $A' \in \Re^{\psi\times a}$.
- Determine the pairwise distances between points. A'_r and A, yielding $S_r \in \Re^{\psi\times N}$.
- To assign each point$A$to the closest division, make a binary matrix $B_r \in \{0,1\}^{N\times\psi}$and set $B_{r(y,k)} = 1$, where $k$indicates the index of the smallest distance in the row $y$of S.
- To care about the outcome, $B \in \{0,1\}^{N\times\psi r}$ concatenate $B = B||B_r$repeatedly.

The cluster centers $E$and memberships matrix $M$are then obtained by applying FCM clustering on B. The use of cosine distance in the goal function is a crucial change to the approach is defined by Equation (8).

$$J_{IK-FCM}(M,E) = \sum_{x=1}^{N}\sum_{y=1}^{c} m_{xy}^{u} \cdot cos\,i\,ne\_dis\,tan\,c\,e(i_x, e_y) \tag{8}$$

It reduces sensitivity noise and feature scaling, while converting complex spatial relationships into computationally efficient binary features.

3.2.2. Adaptive Kornecker (Alignment structural encoding)

Previously, the IK-DFM effectively addressed density variation and non-linear separability, but it did not explicitly capture structural relationships with the encoded feature space. As a result, nodes with similar distributions but different internal feature arrangements can still be misclustered. To address the issues solved by the Adaptive Kronecker-based transformation, by encoding pairwise positional relationships of active features in the binary representation. It makes the model alignment-independent and robust to feature permutations. Consequently, it enhances clustering stability by preserving local structural patterns, which are critical in heterogeneous IoT environments.

Local distance is defined by Equation (8).

$$d(p,q) = |p-q| \tag{9}$$

The Kronecker Delta Function is defined by Equation (9).

$$\delta(a,b) = \begin{cases} 1, & if\, a = b \\ 0, & otherwise \end{cases} \tag{10}$$

Kronecker-based Transformation is defined by Equation (10)

$$T_k(B_i) = \delta(|p-q|)\delta(B_{ip},1)\delta(B_{iq},1) \tag{11}$$

Here $B_i$is the binary vector of the node i, $k \in \{1,\ldots,n\}$, indicating the distance index and counts pairs of active features (1s) separated by distance k. The developed HF-DAC objective function is mathematically expressed in Equation (12).

$$J_{HF-DAC}(M,E) = \sum_{x=1}^{N}\sum_{y=1}^{c} m_{xy}^{u} \cdot (1 - K_\psi(i_x - K_\psi(i_x, e_y)) + \lambda \sum_{x=1}^{N}\sum_{k=1}^{n} T_k(B_i) \tag{12}$$

Finally, traditional clustering approaches, HF-DAC does not rely on a fixed notion of distance. Instead, it learns similarity from data distribution, encodes relationships structurally, and applies fuzzy logic for flexible membership assignment. Algorithm 1 presents the Pseudo-code of the HF-DAC algorithm.

Algorithm 1: Pseudo-code of HF-DAC algorithm

Input:

Dataset $A = \{i_1, i_2, i_3, \ldots, i_N\}$, clusters c, parameter u, ψ,r

Output:

Cluster centers$E$ \ and membership matrix$M$

Begin

1. Initialize the membership matrix Mrandomly
2. Generate Binary Representation (IK encoding)

 To $l = 1$ $r$do

  Select ψrandom samples from A

  Assign each data point to its nearest sample

  Form a binary matrix B_l

 End for

 Concatenate all $B_l$to obtain B

3. Repeat until convergence

- Compute similarity using IK
- Apply the Kronecker transformation to extract structural features
- Update cluster center
- Update membership matrix

4. End Repeat

Return $\boldsymbol{M}, \boldsymbol{E}$

End

3.3. Mutation-Enhanced Armadillo–Devil Optimization (MEADO)

After the clustering process is done, the optimal CH is selected using the developed MEADO approach. The hybrid strategy incorporates genetic mutation (local search diversity) [45], armadillo-inspired exploration (global search) [46], and Tasmanian devil-based exploitation (local refinement) [47] to attain EE and balanced CH selection in IoT networks.

3.3.1. Mutation Strategy (Local Search Diversity)

To improve the convergence performance and enhance population diversity, the mutation is employed on low-fitness candidate solutions as expressed in Equations (13) and (14).

$$M = \frac{f - f_{min}}{f{min}_{max}} \tag{13}$$

$$f_x^{new} = \begin{cases} f_x + d \cdot (f_x^{max_x} & d \geq 0 \\ f_x + d \cdot (f_x - f_x^{min} & d < 0 \end{cases} \tag{14}$$

here $f$is the fitness value of the solution, $f_{min}$and f_{max}indicates the minimum & maximum fitness in the population, and $d \in [-M, M]$ is the mutation factor. This strategy increases search diversity by perturbing weaker solutions within adaptive bounds. It helps the approach escape local optima and ensures broader exploration of CH candidates. Overall, it enhances strength and prevents during optimization.

3.3.2. Armadillo-Inspired Exploration (Global Search)

This phase updates candidate CH positions using stochastic long-range movements are described in Equations (15) and (16).

$$A_x^{new} = A_x + \alpha \cdot r \cdot sign(r - 0.5) \cdot |ub - x \cdot lb| \tag{15}$$

$$A_x = \begin{cases} A_x^{new}, & F(A_x^{new}) < F(A_x) \\ A_x, & otherwise \end{cases} \tag{16}$$

Here $A_x$denotes the current solution (CH candidate), $\alpha$is the movement of amplitude, and $r \in [0,1]$ is a random number. Where $ub$and lbrepresent the upper and lower bounds, as well as $I \in \{1,2\}$is the directional factor. Large and stochastic allow the discovery of globally optimal CH positions. It reduces the risks of early convergence and ensures better coverage of possible solutions.

3.2.3. Tasmanian Devil-Based Exploitation (Local Refinement)

After exploration, local refinement is enhanced by modeling prey-chasing behavior:

Prey selection is defined by (17)

$$P_x = A_k, k \neq x \tag{17}$$

Position update is defined by (18)

$$a_{x,y}^{new} = \begin{cases} a_{x,y} + r \cdot (p_{x,y} - X \cdot a_{x,y}), & F(P_x) < F(A_x) \\ a_{x,y} + r \cdot (a_{x,y} - p_{x,y}), & otherwise \end{cases} \tag{18}$$

Refinement is defined by (19) to (21)

$$M = 0.001\left(1 - \frac{t}{T}\right) \tag{19}$$

$$a_{x,y}^{new} = a_{x,y} + (2r - 1) \cdot M \cdot a_{x,y} \tag{20}$$

$$A_x = \begin{cases} A_{x,y}^{new}, & F(A_x^{new}) < F(A_x) \\ A_x, & otherwise \end{cases} \tag{21}$$

Where $P_x$is the selected prey (neighbor solution), Mdenotes the shrinking neighborhood method radius, and $t \setminus T$represents the current and maximum iterations. This phase intensifies the search for optimal CH candidates by exploiting local regions. The adaptive neighborhood shrinks over iterations, ensuring precise convergence. It improves solution quality by fine-tuning CH selection based on energy and distance metrics. By leveraging mutation strategy, armadillo-based global search, and devil exploitation (refinement), the MEADO approach obtains a balanced trade-off between exploration and exploitation. The results are optimal EE CH selection, reduced communication overhead, and prolonged network lifetime in IoT-based routing environments. Algorithm 2 shows the Pseudo- code of the MEADO approach.

Algorithm 2: Pseudo- code of MEADO approach

Input: IoT nodes d, population size N_p, iterations T

Output: CH^*optimal cluster heads

Begin

1. Initialize population $A_x$randomly
2. Evaluate the fitness of each solution
3. To $t = 1$ Tdo

Mutation strategy

4. For each solution A_x:
    - Apply random mutation based on fitness
    - Keep the solution if fitness improves

Exploration phase:

5. Update each solution using random long-range movement
6. Preserve the current solution if fitness improves

Exploitation phase:

7. Select a random neighbor P_x
8. Move toward $P_x$based on fitness
9. Apply local refinement
10. Preserve the solution if fitness improves
11. Update best solution CH^*

End For

Return CH^*

End

3.4. Multi-Level Energy-Aware Attention Transformer-Based Reinforcement Learning

This study designed an MLEA^{2}T-RL for effectively optimizing a WSN energy –aware routing conditions, as shown in Figure 2. This approach provides discriminative state representations and optimal routing decisions in the context of reinforcement learning.

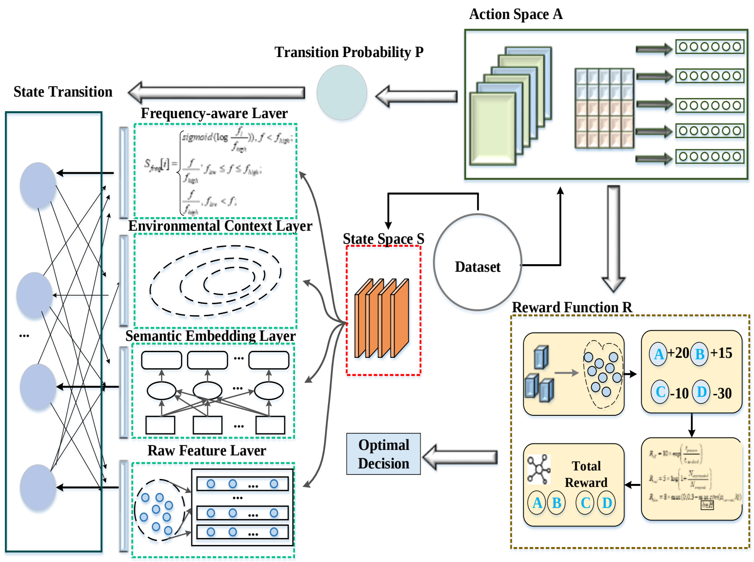

Fig. 2 Architecture of MLEA^{2}T-RL

Figure 2 illustrates a reinforcement learning-based model that is aimed at making optimal decisions. The first stage is the processing of the raw input features by a multi-layered process that includes the raw feature layer, semantic embedding layer, environmental context layer, and frequency-aware layer to produce a comprehensive representation of the state space$S$. Depending on the information about this state and the dataset, the model identifies an action space (P), which is composed of all possible decisions. The transition probability (P) is a factor that determines the way the system will move between states after an action is taken. A Reward Function (R) is then used to assess the effectiveness of each action by giving scores, and the summed reward is calculated. The model uses this feedback mechanism to learn to choose the most appropriate action and ultimately arrive at an optimal choice.

3.4.1. Decision-Making Process Modeling

The Markov Decision Process (MDP) [48], formulated as the routing decision- making is denoted as(S, A, P, R, γ). In this case, $S$is significance of the network feature state, $A$is significance of the space of routing strategies in action, $P$is significance of the transition dynamics, $R$is significance of the reward of evaluation, and $\gamma$is significance of the discount factor.

3.4.2. State Space

State space Sinvolves using four layers to represent robust features. The raw feature layer $S_{raw} \in R^{n1}$captures simple features, including node ID, residual energy, packet time, queue length, and distance to base station. The frequency-conscious layer $S_{freq} \in R^{n2}$arbitrarily scales the values of the frequency of transmission of packets logarithmically, within limits f_{low}andf_{high}, namely:

$$s_{freq}[i] = \begin{cases} Sigmoid(log(f_i)), & f > f_{high} \\ f, & f_{low} \leq f \leq f_{high} \\ f, & f < f_{low} \end{cases} \quad (22)$$

The semantic embedding layer$S_{semantic} \in R^{n3}$ encodes routing-related properties like priority of data, quality of service demands, and type of traffic. The environmental context layer $S_{contex} \in R^4$captures the external network conditions, like node density, link quality, and network congestion, to optimize context awareness. To enhance the state representation, this study introduces a multi-level attention transformer.

3.4.3. Action Space

The action space defined a$A = \{a_0, a_1, a_2, a_3, a_4\}$. Here a_0 is the significance of intelligent suppression of redundant transmissions, a_1 significance of the EE neighbor routing, a_2 significance of the normal routing via the cluster head, a_3 significance of the prioritized routing of critical data packets, and a_4 Significance of the aggregated batch data forwarding.

3.4.4. Transition Probability

The transition probability $P(s_0|s, a)$ represents the probabilistic change of state $s$to states_0 Due to action a, it has been estimated through statistical analysis of past routing information and model learning.

3.4.5. Reward Function

The $R(s, a, s_0 The$ reward function assesses the feature of this transition. Here R_{energy} signifies energy efficiency, R_{eff}represents transmission efficiency, R_{load}represents load balancing and R_{disc} Represents adaptive routing capability. The specific formulation is as following Equation (23) to (26).

$$R_{energy} = \begin{cases} +20, & successfulenergy - efficientrouting \\ +15, & balancedenergyusage \\ -30, & energydepletionofnode \\ -10, & inefficientenergyutilization \end{cases} \quad (23)$$

$$R_{eff} = 10 \times exp - \left(\frac{t_{process}}{t_{s\tan dard}}\right) \quad (24)$$

$$R_{load} = 5 \times log - \left(1 + \frac{N_{aggregated}}{N_{original}}\right) \quad (25)$$

$$R_{disc} = 8 \times max - \left(0{,}0.3 - \max_{h \in H} sim(s_{current}, h)\right) \quad (26)$$

The R_{energy} highlights efficient utilization of node energy to prolong network lifetime. R_{eff} is calculated by the actual transmission delay function ($t_{process}$) and standard delay ($t_{s\tan dard}$), decaying as latency increases. R_{load} is an incentivizes aggregation and balanced traffic distribution, defined by the ratio of aggregated packets ($N_{aggregated}$) to original packets($N_{original}$). R_{disc} targets adaptive routing behavior by calculating a comparison between the current network state ($s_{current)}$and historical state patterns(H). The total reward (R_{total})is defined as Equation (27).

$$R_{total} = \alpha \cdot R_{energy} + \beta \cdot R_{eff} + \gamma \cdot R_{load} + \delta \cdot R_{disc} \quad (27)$$

In this case,α,β, andδ are weighting coefficients satisfying$\alpha + \beta + \gamma = 1$. This approach overcomes the traditional protocols in routing by modeling routing.

3.4.6. Multi-Level Attention -Based Transformer

A Multi-Level Attention Transformer with DQN is utilized to boost state representation and decision-making ability.

First, the resulting state values of Section 4.3.2 are encoded via a two-path encoding architecture, which aims at capturing both high-frequency changes and complicated contextual dependencies.

The dual-path encoder consists of a fast as well as details encoding path. The faster route employs a lightweight multilayer perceptron to handle network traffic characteristics of high frequencies. s_{freq} is defined by Equation (28).

$$h_{fast} = Re\,L\,U(W_2 \cdot Re\,L\,U(W_1 \cdot s_{freq} + b_1) + b_2) \quad (28)$$

In this case, $W_1 \in R^{64\times 8}, W_2 \in R^{32\times 64}$there $b_1, b_2$are biases. This route quickly extracts important information from high-frequency data transmission patterns. Subsequently, the detail route is built on a transformer that has eight attention heads, four encoder layers, and handles concatenated features. $s_{raw}, s_{semantic}, s_{content}$], which is mathematically expressed in Equation (29).

$$h_{det\,ailed} = Transformer\big(concat(s_{raw}, s_{semantics}, s_{context})\big) \quad (29)$$

For balancing the two encoding paths, the multi-head attention fusion [49] module is introduced. Through this fusion technique, effectively adjusting the traffic features weight and it's defined by Equations (30) to (32).

$$h_{fused} = \gamma(h_{fast}, h_{det\,ailed}) \quad (30)$$

$$\alpha = \sigma\big(W_f \cdot s_{freq} + W_c \cdot s_{complexity} + b\big) \quad (31)$$

$$h_{final} = \alpha \cdot h_{fast} + (1 - \alpha) \cdot h_{det\,ailed} \quad (32)$$

The gating coefficient$\alpha$is adaptively learned. It dynamically switches between the Fast route ($\alpha \approx 1$for high-frequency traffic) and the detailed route ($\alpha \approx 0$for complex routing conditions), balancing the accuracy.

The merged feature representation is then considered the state input to the DQN. DQN approximates the action-value function and chooses the best routing action, which maximizes the cumulative reward.

The agent obtains feedback through constant interaction with the network environment as rewards (as defined in Section 4.3.5) and modifies its policy through temporal difference learning.

Lastly, the framework suggested allows for adapting, EE, and delay-conscious routing choices, which can contribute to the substantial performance enhancement of the network in the context of WSN-based IoT.

4. Results and Discussion

The EACO-IR protocol was developed to design the energy efficient cluster based optimization protocol. The proposed model was implemented using python tool. The system configuration comprised a model Intel Core i7-4770 CPU @ 3.40GHz 3.40 GHz processor, 16.0GB RAM, and a 64-bit operating system, x64 -based processor. Table 1 shows the simulation parameters of the EACO-IR protocol.

Table 1. Simulation parameters

Parameters	Values
Number of nodes	500
Network area	200m x 200m
Initial energy	1J
Packet length	4000 bits
Number of grouped clusters	5
Cluster head	5
Base station	1
Tool	Python

4.1. Performance Measures

The model performance was validated with diverse existing protocols like Fuzzy-PSO energy -aware routing (FPEAR), TPSO-CR, LEACH, and PSO-C [50].

Figure 3 and Table 2 show the energy consumption analysis. In WSN, efficient energy consumption analysis is essential for increasing operational lifetime and balancing node traffic to avoid early network collapse. The offered model uses multi- objective fitness function to ensure the uniform distribution of CH. But existing models suffer from higher energy depletion due to the random selection of cluster heads and single- hop transmission. In addition, these models struggle with high control packet overhead and slow convergence.

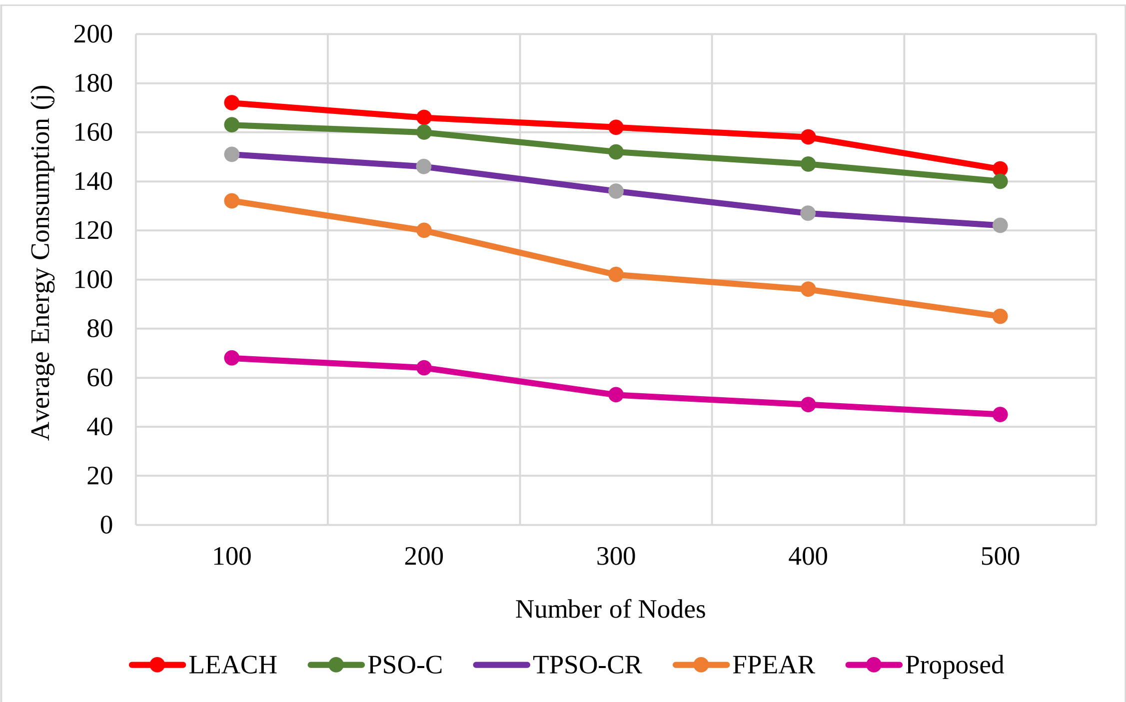

Fig. 3 Energy consumption comparison

Table 2. Energy consumption comparison

Number of Nodes	Methods				
	LEACH	PSO-C	TPSO-CR	FPEAR	Proposed
100	172	163	151	132	68
200	166	160	146	120	64
300	162	152	136	102	53
400	158	147	127	96	49
500	145	140	122	85	45

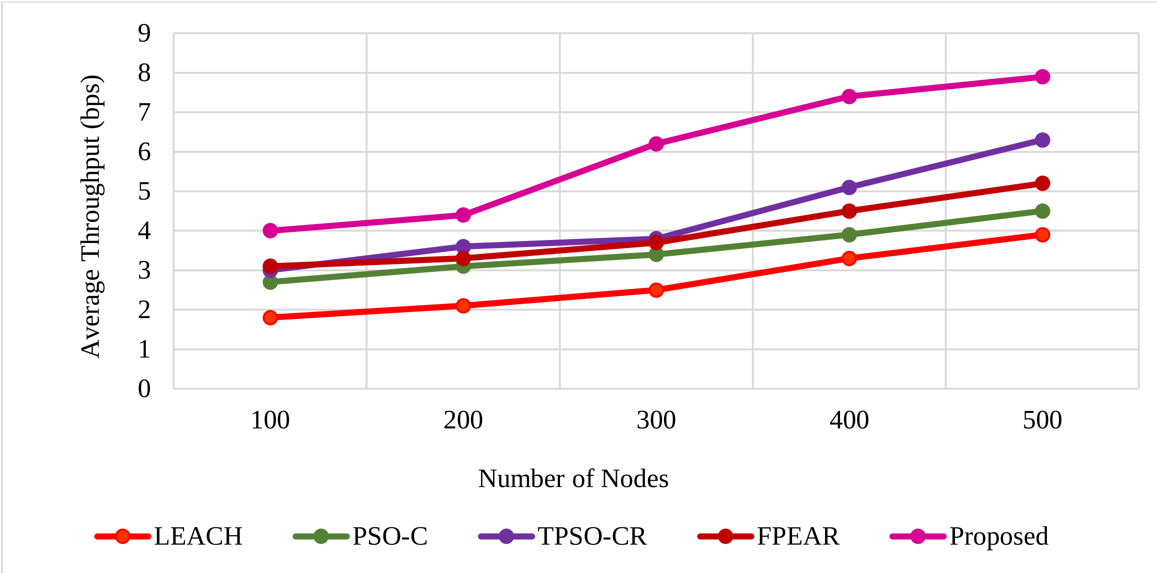

Fig. 4 Analysis of throughput

Throughput analysis is shown in Figure 4 and Table 3. The EACO-IR model attained a higher value than the other models. The proposed model maximizes the throughput value by optimizing cluster formation, which maintains a stable data channel as the network grows. But existing models suffer from low throughput due to frequent packet collisions and early node death caused by their randomized clustering approach. These models dropped packets under heavy traffic due to computational overhead and slow path convergence. Thus, the offered protocol maximizes network stability and data reliability to ensure balanced energy distribution and optimized data routing.

Table 3. Throughput performance comparison

Number of Nodes	Methods				
	LEACH	PSO-C	TPSO-CR	FPEAR	Proposed
100	1.8	2.7	3	3.1	4
200	2.1	3.1	3.6	3.3	4.4
300	2.5	3.4	3.8	3.7	6.2
400	3.3	3.9	5.1	4.5	7.4
500	3.9	4.5	6.3	5.2	7.9

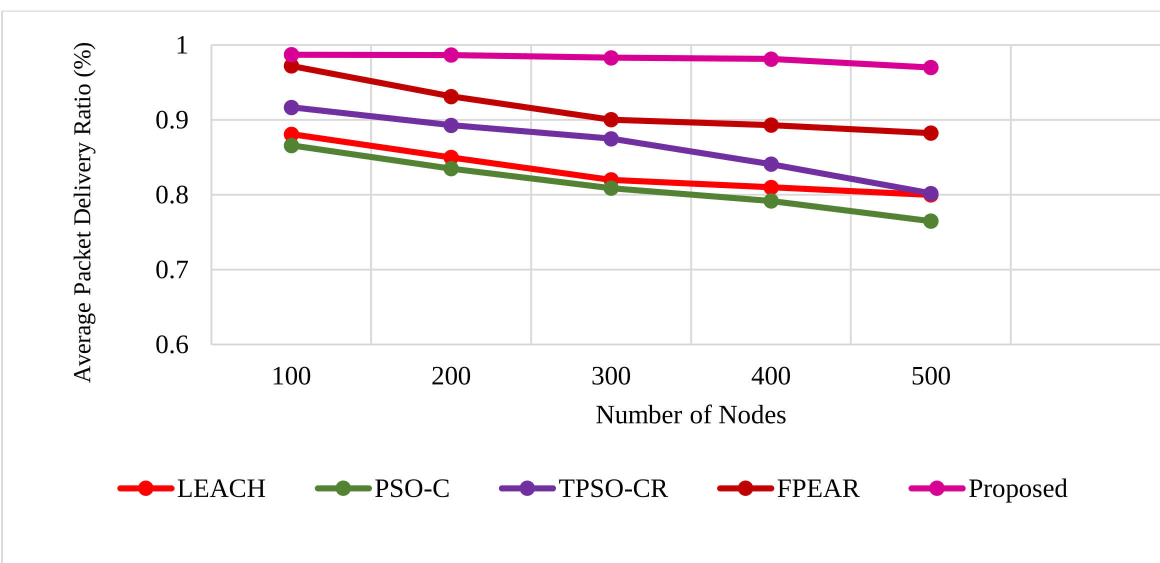

Fig. 5 Analysis of PDR

The PDR analysis is shown in Figure 5 and Table 4. The proposed model increases the packet delivery rate by establishing stable, multi-hop routes and prioritizing nodes with high residual energy to prevent data loss during transmission. Existing models suffer from a low packet delivery ratio due to their lack of a relay mechanism, which leads to frequent packet drops as distant nodes die prematurely. Furthermore, current models are vulnerable to delays and congestion, which can causes packets delay in high- density situations. Thus, the offered protocol enhances network sustainability and reliability by utilizing multi objective fitness function.

Table 4. Comparison analysis of PDR

Number of Nodes	Methods				
	LEACH	**PSO-C**	**TPSO-CR**	**FPEAR**	**Proposed**
100	0.881	0.866	0.917	0.9722	0.9871
200	0.85	0.835	0.893	0.9315	0.9867
300	0.82	0.809	0.875	0.9005	0.9832
400	0.81	0.792	0.841	0.8932	0.9815
500	0.8	0.765	0.802	0.8825	0.9702

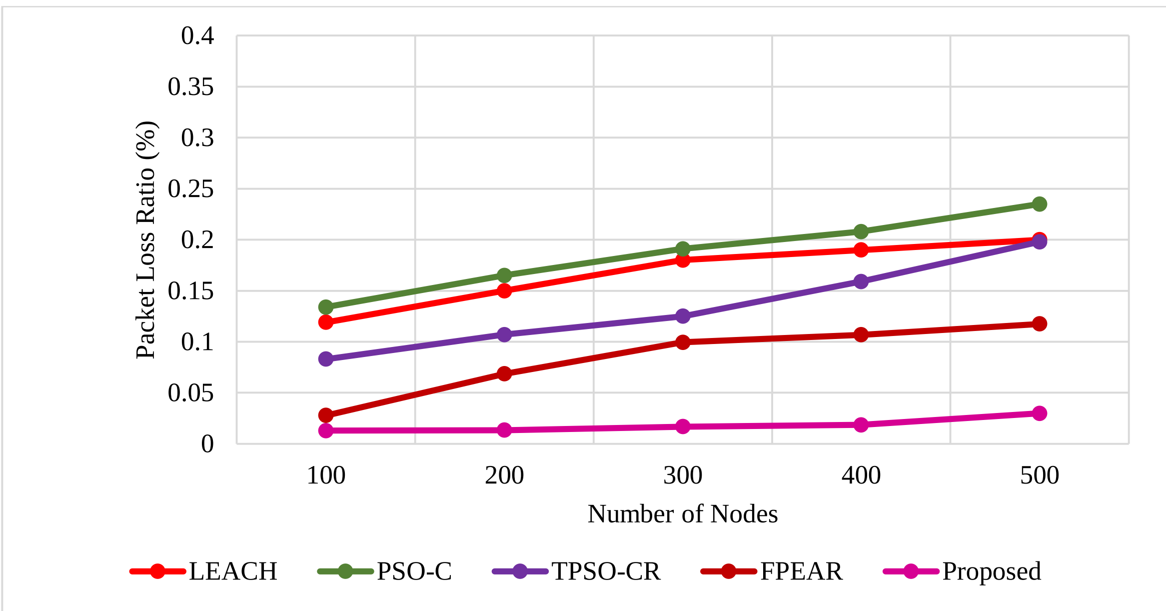

Fig. 6 Analysis of Packet Loss Ratio

Figure 6 and Table 5 show that the proposed model outperform lowest packet loss ratio when compared with other existing algorithms. The existing models exhibit a high packet loss ratio because of their random clustering and suffer from packet drops during traffic due to slow optimization convergence and localized congestion. But the offered model reduces the packet loss ratio by dynamically choosing robust routing paths and high-energy cluster heads, which ensures continuous connectivity even as node energy changes. Therefore, the protocol maximizes network lifetime and reliability by balancing energy consumption and optimizing data transmission paths via multi objective fitness function.

Table 5. Packet Loss Ratio evaluation

Number of nodes	Methods				
	LEACH	**PSO-C**	**TPSO-CR**	**FPEAR**	**Proposed**
100	0.119	0.134	0.083	0.0278	0.0129
200	0.15	0.165	0.107	0.0685	0.0133
300	0.18	0.191	0.125	0.0995	0.0168
400	0.19	0.208	0.159	0.1068	0.0185
500	0.2	0.235	0.198	0.1175	0.0298

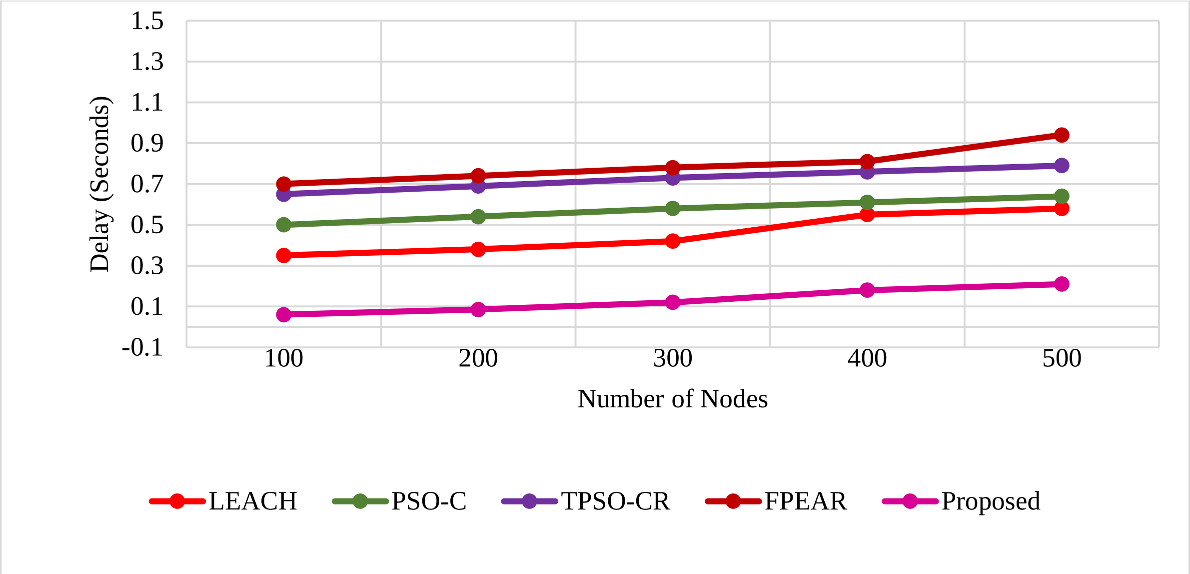

Fig. 7 Delay analysis

Figure 7 and Table 6 describe how the proposed model reduces the delay performance related to the current protocols. Because the offered model reduces the delay which uses optimize routing protocol that selects the shortest, most energy -efficient optimal path, which reduces the overall time. But the existing model increases the delay rate due to the slow convergence speed, which introduces significant computational lag when distant nodes attempt to communicate directly with the sink. Thus, the offered protocol significantly increases network efficiency and reliability to ensure faster and more consistent data flow.

Table 6. Comparative analysis of delay analysis

Number of nodes	Methods				
	LEACH	PSO-C	TPSO-CR	FPEAR	Proposed
100	0.35	0.5	0.65	0.7	0.06
200	0.38	0.54	0.69	0.74	0.085
300	0.42	0.58	0.73	0.78	0.12
400	0.55	0.61	0.76	0.81	0.18
500	0.58	0.64	0.79	0.94	0.21

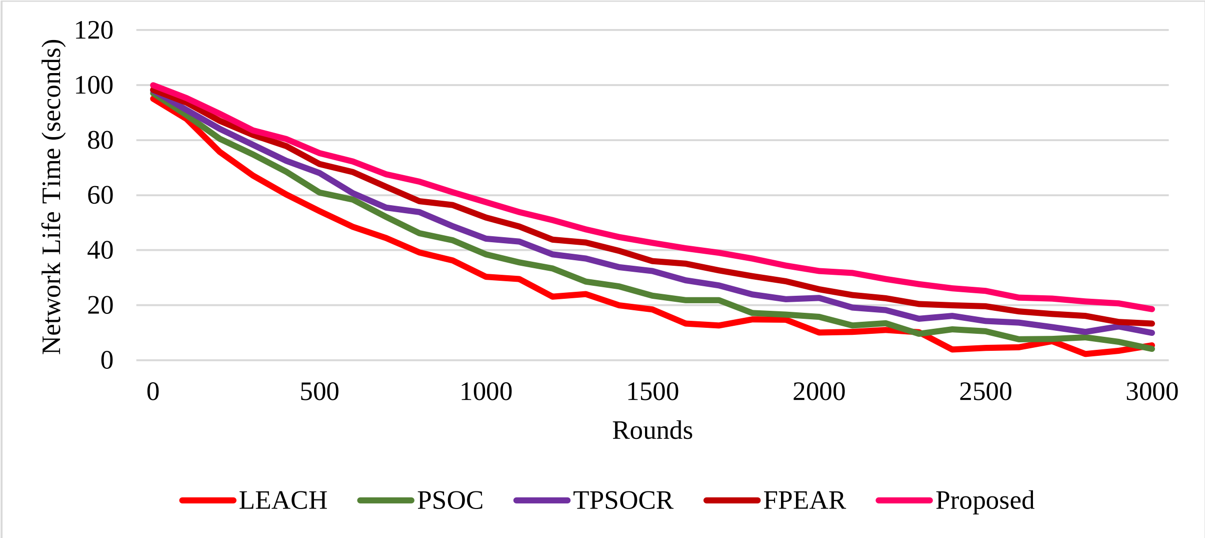

Fig. 8 Network lifetime analysis

Network lifetime analysis was presented in Figure 8. The suggested model attained the highest network lifetime than exiting models. The offered model increases network lifetime by employing a multi-objective function that balances energy distribution and optimal cluster head selection. But existing models possess ineffective energy management during long-range data transmission, early network death rates due to their randomized clustering, which frequently overburdens low -energy nodes. The offered model ensures a more stable and prolonged network existence than existing models. Table 7 shows the Network lifetime analysis.

Table 7. Network lifetime performance values

Number of nodes	Methods				
	LEACH	PSO-C	TPSO-CR	FPEAR	Proposed
0	96	97	98	100	100
500	55.09	61.5	66.6	71.7	75.7
1000	31.65	39.1	45.4	51.3	57.3
1500	18.13	24.8	30.9	36.8	43.5
2000	10.41	15.7	21.1	26.3	32.9
2500	5.97	10	14.3	18.9	24.9
3000	3.43	6.34	9.7	13.5	18.9

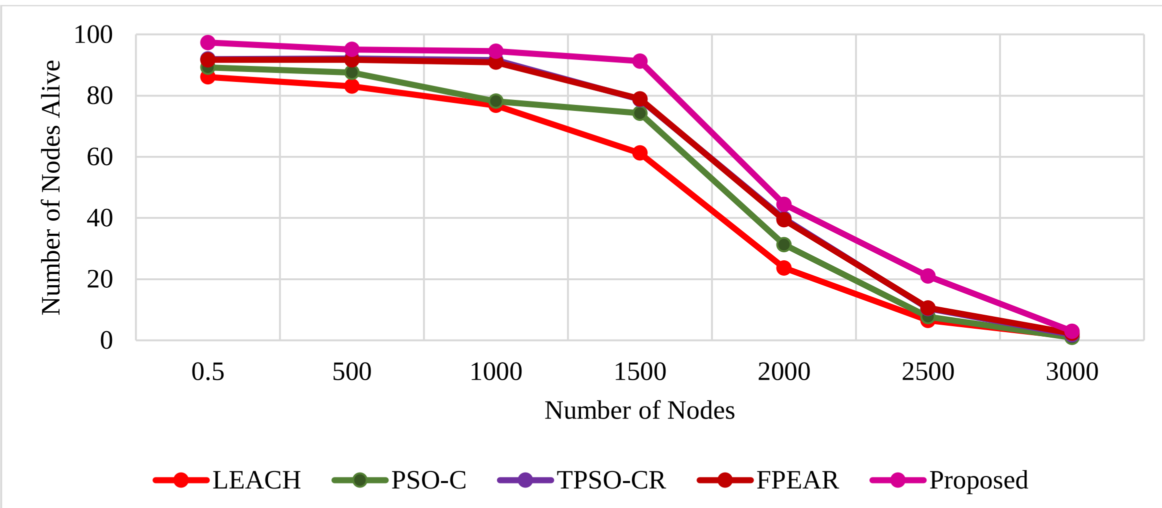

Fig. 9 Alive node analysis

The alive node analysis was shown in Figure 9. The alive node analysis tracks the survival rate of nodes over successive rounds. The offered model maintains a higher number of alive nodes by utilizing an intelligent fitness function that prevents the over- utilization of energy -depleted sensor nodes. The existing models suffer from early network failure as a result of randomized cluster head selection and uneven energy usage. They frequently have substantial packet losses and higher end-to-end delay due to computational overhead and convergence speeds. These models are inability to handle multi-hop routing in dense environments, which leads to fast node depletion and poor data transmission. Thus, the offered model maximizes network reliability, which ensures balanced energy distribution and optimized data routing in a WSN environment. Table 8 shows the Alive node analysis.

Table 8. Comparative analysis of alive nodes

Number of nodes	Methods				
	LEACH	PSO-C	TPSO-CR	FPEAR	Proposed
0.5	86.12	89.26	91.95	91.72	97.33
500	83.09	87.58	92.17	91.72	95.09
1000	76.81	78.15	91.61	90.94	94.53
1500	61.23	74.23	78.72	78.94	91.28
2000	23.66	31.28	39.81	39.36	44.44
2500	6.5	7.68	10.37	10.59	20.96
3000	1.13	0.9	1.79	2.24	2.91

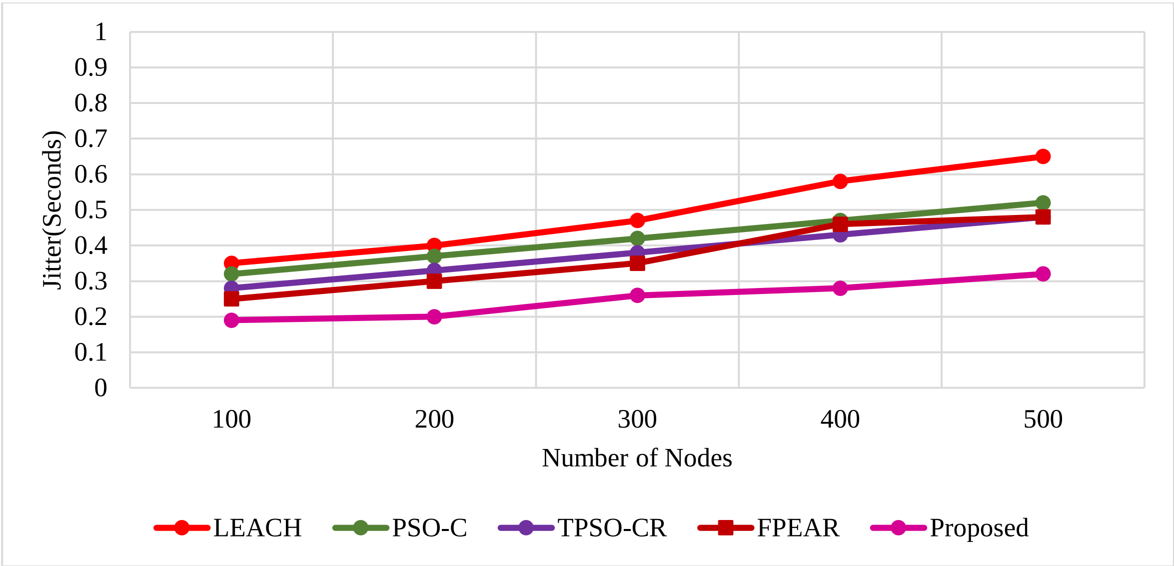

Fig. 10 Jitter analysis

Jitter analysis was shown in Figure 10. The jitter analysis assesses the changes in the delay between data packets in order to ensure constant communication quality in a WSN environment. The offered model reduces jitter value by creating reliable and efficient routing that avoids congestion and lessens variation in packet arrival times. The existing models increase the jitter value because of their frequent and randomized cluster head selection, which creates inconsistent transmission intervals. Additionally, their incapacity to efficiently handle multi - hop routing in congested situation which leads to faster node depletion and poor data transmission. Table 9 shows the Jitter analysis.

Table 9. Comparative analysis of jitter

Number of nodes	Methods				
	LEACH	**PSO-C**	**TPSO-CR**	**FPEAR**	**Proposed**
100	0.35	0.32	0.28	0.25	0.19
200	0.4	0.37	0.33	0.3	0.2
300	0.47	0.42	0.38	0.35	0.26
400	0.58	0.47	0.43	0.46	0.28
500	0.65	0.52	0.48	0.48	0.32

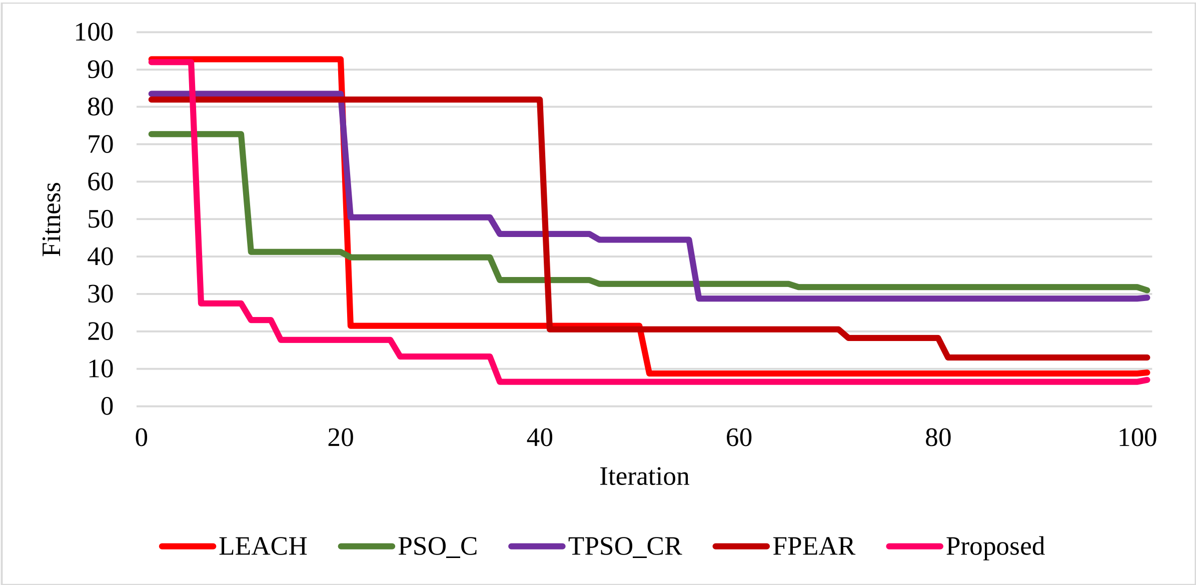

Fig. 11 Convergence loss analysis

Convergence loss analysis was shown in Figure 11. Convergence analysis determines the network capacity to adjust to changes by assessing how quickly and steadily an optimization algorithm arrives at an ideal routing solution. The proposed protocol achieves less loss and more stable convergence by utilizing an enhanced intelligent search mechanism that avoids local optima and reduces the iterations needed for path discovery. The existing model lacks convergence and is computationally expensive, leading to invalid routing decisions in a dynamic network. The offered model ensures the optimal path selection, which minimizes the energy and maximizes network stability and reliability.

4.2. Discussion

This section describes the EACO-IR protocol's effectiveness. Table 10 clearly shows that the proposed EACO-IR protocol outperforms the recent state-of-the-art protocols with the best PDR rate of 98.71%. Because the proposed protocol used an N HF-DAC clustering mechanism, it is significant in improving the stability and reliability of network communication. Some of the previous clustering methods, such as IGEOA [38] and k-means-based leach [43] approaches, are mainly used for distance-based or density-based clustering structures, which can give imbalanced clusters and can generate cluster reformation during dynamic network conditions. The proposed HF-DAC adopts the density-aware fuzzy clustering and adaptive structural learning approach to create self-balanced clusters with less intra-cluster communication cost. It leads to low overhead, high cluster stability, and low unnecessary energy usage.

In contrast, some of the existing approaches, such as GOC [39], QEEC [44], EEART [46] AND P-AODV [47], typically select a cluster head based on a single optimization criterion, causing unequal energy consumption and early node failure. The proposed MEADO algorithm effectively balances global exploration and local exploitation, which optimally selects the cluster head and enhances connectivity. This balanced energy consumption can prevent the occurrence of hot spots and extend the operational life of the sensor nodes, thereby ensuring long-term continuous operation of the network.

Another important reason for the proposed model yet better performance, of included a multi-level energy-aware attention transformer- based reinforcement learning routing framework for improving the network scalability. There are some existing EEMLCR [40] AND DRL ROUTING [41] protocol enhance the adaptability of routing, but they have not totally adopted the stability of clustering and the optimization of the cluster-heads in the routing decision process. But the proposed multi-level energy-aware attention transformer-based reinforcement learning routing framework continuously adapts to network conditions and dynamically adjusts the routing path. The multi-level attention mechanism has the ability to obtain local node behavior and global network context, so that the routing agent can adopt a highly reliable transmission path. Moreover, the proposed framework also addresses scalability issues in dense WSN-IOT deployments. The existing NECFO [42] AND M-EEMH [49] research suffers as the number of nodes grows due to increased performance costs like routing complexity, congestion, and communication overhead.

In contrast, EACO-IR uses traffic balancing and intelligent update routing capabilities to ensure a balanced distribution of traffic across the network. It prevents congestion around cluster heads and relay nodes while ensuring stable data delivery even under high node density conditions. As a result, the proposed framework provides lower packet loss, lower end-to-end delay, lower Jitter, and better throughput than current methods.

Table 10. Comparison between proposed EACO-IR and state-of-the-art approaches

Author name and References	Model used	PDR (%)
Silambarasan et al. [38]	IGEOA	95.24
Malik et al. [39]	GGOC	96.15
Akram et al. [40]	EEMLCR	96.84
Yang et al. [41]	DRL Routing	97.12
Kiruthika et al. [42]	NECFO	97.54
Saroit et al. [43]	K-Means LEACH	96.92
Irine et al. [25]	QEEC	96.356
Rani et al. [51]	EACR	93.67
Goel et al. [52]	EEART	95.92
Aslam et al. [53]	P-AODV	91.89
Hosseinzadeh et al. [54]	DBSCAN	94. 12
Saif et al. [55]	M-EEMH	95.63
Proposed	**EACO-IR**	**98.71**

5. Conclusion

An efficient solution to the crucial problem of energy optimization in WSN for IoT applications was introduced in this study. To overcome the drawbacks of traditional methods, the EACO-IR protocol effectively combines sophisticated clustering, optimization, and intelligent routing techniques. The system guarantees balanced energy consumption, adaptive decision - making in dynamic contexts by utilizing MEADO for optimum cluster head selection.

The HF-DAC for stable cluster formation and an Energy-Aware Attentive twining Transformative Reinforcement Learning model for effective routing. The network lifetime is increased by the frequent rotation of cluster heads, which also improves equity and delays node failures. The suggested EACO-IR protocol outperforms conventional techniques in terms of energy economy, packet delivery dependability, and lower communication overhead according to simulation findings.

In order to further increase efficiency and privacy, future research will integrate sophisticated methods like federated learning or multi-agent reinforcement learning with lightweight security measures. To improve sustainability, cross-layer optimization and energy harvesting methods can also be investigated. In addition, improving computational complexity and scalability will guarantees for large scale resource constrained WSN implementation.

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Conflict of Interest

Authors declare that they have no conflict of interest.

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