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Energy-Efficient Edge Intelligence in IoT Environment Using Cross-Layer Bio-Inspired Optimization with Deep Learning Framework

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ABSTRACT

The rapid rise of Internet of Things (IoT) applications has increased the demand for energy-efficient or computationally sustainable Wireless Sensor Networks (WSNs). This paper proposes a hybrid optimization Bio-Inspired Deep Learning and Edge–Cloud (BIO-DLEC) framework with the Whale Optimization Algorithm (WOA) and the Grey Wolf Optimizer (GWO) for energy-aware clustering and routing to address these challenges. The hybrid framework incorporates the exploration capability of WOA to diversify candidate solutions, and GWO exploits them, thus achieving a balance process. During the clustering stages, optimal cluster heads (CHs) are selected based on a multi-objective fitness function that ensures overall optimality from the use of residual energies, intra-cluster compactness, and load balancing. In the routing stage, energy-efficient routing paths are established by minimizing communication cost, hop count, and latency within a multi-hop topology. The experimental setup uses a hybrid NS-3 and iFogSim2 simulation environment. The BIO-DLEC improved overall network performance achieving a 25.5% longer lifetime, 21.8% less energy dissipation, 17.3% lower end-to-end latency, and a packet delivery ratio (PDR) higher than 95%. Overall, the results indicate the benefits of BIO-DLEC frameworks improved throughput reliability and enhanced sustainability for next-generation IoT-enabled WSNs.

1. INTRODUCTION

The rapid evolution of the IoT has fundamentally changed data driven applications in many industries, including agriculture, healthcare, smart cities, and industry 4.0. In fact, given the potential scale and future of IoT a key enabling technology for Internet of Things is the Wireless Sensor Networks (WSNs) which enables a network of collaborating sensor nodes to collect, process, and transmit data. The majority of sensor nodes are energy-constrained and unfortunately do not have frequently replacing batteries. Therefore, routing in WSNs along with effective task management are indispensable for networks to maximize their lifespan while maintaining quality of service (QoS) especially across large-scale IoT. To address the energy consumption and enabling effective routing, bio-inspired and evolutionary algorithms are intriguing options to consider for energy optimization and adaptive routing. For instance, bio-inspired and evolutionary strategies [1] are based on natural phenomena including swarm intelligence, genetic evolution, and predator-prey dynamics can be simple yet effective. Another example of a bio-inspired hybrid optimization algorithm showed prominent results for clustering, load balancing, and energy efficiency in WSNs [2]. Similarly, bio-inspired neural networks demonstrated abilities for optimal cluster head selection that resulted in efficient energy distributions and improved scalability within a low power wireless personal area network [3]. Moth-Flame Optimization (MFO) and variants are also one of many metaheuristics and provided a great deal of flexibility in dynamic environments by maintaining a controlled balance between exploration and exploitation of the optimization space [4].

Few researchers have found that metaheuristic clustering protocols outperform the heuristic-based clustering schemes in terms of energy consumption and packet delivery performance [5]. The papers strongly suggest that evolutionary computing should be included when quantifying the performance of WSNs. As routing optimization matured, started investigating the application of edge and fog computing to enhance efficiency in IoT ecosystems. Deep learning is a promising approach for real-time analytics that can be performed using IoT data is an extremely energy intensive computing technology. Recent efforts to benchmark the energy efficiency of deep learning across models and edge devices continue to emerge [6, 7]. These articles outline the trade-offs between accuracy, latency, and energy efficiency. The need for adaptive frameworks for both computation and communication overhead. Task offloading is another important domain where energy efficiency has implications for IoT performance. Recent advances in reinforcement learning (RL) and deep reinforcement learning (DRL) frameworks can optimize the migration of computations among IoT devices, fog nodes, and cloud infrastructure. The use of Deep Q-Networks (DQNs) demonstrated promising results for latency-aware, energy-efficient offloading strategies. Here, the computational load is balanced while minimizing delay [8]. Fuzzy logic enhanced DRL approaches demonstrate further adaptability for IoT application within a fog-cloud three-tier architecture [9]. Earlier works also recognize the critical aspects of an energy-scheduling while identifying that issues to ensure Quality of Service [10].

Despite the progress in the literature, there remain significant gaps. A systematic review of energy-aware resource management techniques in fog-enabled IoT highlights the absence of a unified framework that accounts for communication, computation, and routing optimization at the same time [11]. To make further progress, we also find that many of the existing techniques are domain or application-specific, or static, and research in these areas neglects the unpredictable nature of IoTs. There are current constraints that require an efficient evolutionary computing framework that combines multi-objective energy-aware routing and adaptive cluster head selection with intelligent task offloading. For an efficient evolutionary computing framework, bio-inspired algorithms should be utilized for exploration, reinforcement learning for variability, and multi-objective optimization to balance energy efficiency, latency, and reliability.

This paper addresses the above challenges by contributing the following:

- An innovative evolutionary computing Bio-Inspired Deep Learning and Edge–Cloud (BIO-DLEC) framework for routing and energy-aware clustering in IoT-based WSNs.
- Identifying an optimized route and task offloading selection using bio-inspired optimization and reinforcement learning.
- A multi-objective fitness function including residual energy, latency, link reliability, and cost for offloading.
- Detailed simulations and comparisons with clustering, routing and offloading protocols.

The structure of the remainder of the paper is detailed as follows: In Section 2, we review related literature in bio-inspired optimization, deep learning compression for edge devices and fog-cloud offloading. In Section 3, we describe the proposed BIO-DLEC framework along with the mathematical model and optimization process. In Section 4, we present the experimental protocol and details. In Section 5, we conclude with a summary and future research.

2. RELATED WORK

Energy-efficient routing in WSNs has seen remarkable growth due to the resource-limited nature of IoT devices. More recently, design approaches have emphasized using evolutionary computing, methodology fuzzy heuristics, and other hybrid metaheuristic techniques to optimize energy consumption by extending the lifetime of the network. Shokouhifar et al. [12] provided an extensive survey of AI-based cluster-based routing protocols. The study indicated how fuzzy heuristics, metaheuristic, and some machine learning based models had been used extensively to provide energy efficiency. Though the applications reviewed regarding AI showed some improvements in clustering and routing stability required intensive computational costs that would not be feasible for ultra-low-power WSNs. Zaier et al. [13] examined a mechanism of interval type-2 fuzzy unequal clustering and sleep scheduling for IoT based WSNs. The draw for this model was the improved energy balanced values, as well as overall network life to provide continuous service, however challenges with scaling to the entire physical area of interest, and latency, especially in dense networks, remained problematic.

Wang et al. [14] developed fuzzy logic and applied it with a quantum annealing algorithm for cluster-based routing. While they used extensive algebra to show improvements with energy aware cluster head (CH) selection, many are concerned with implementation at the hardware or silicon level due to complexity attributable to the quantum annealing algorithm. Cherappa et al. [15] developed an Adaptive Swarm-Based Fuzzy Optimization (ASFO) for clustering and also proposed a cross-layer expedient routing protocol. While the protocol was efficient in reducing communication costs, it was not reliable in environments with high mobility. Also, Dev and Mishra [16] created a hybridization of Grey Wolf Optimizer (GWO) and Firefly Algorithm for heterogeneous WSNs, which provided significant longevity; nevertheless, their hybrid framework required a lot of tuning to parameters, which complicated deployment in everyday scenarios.

Swarm intelligence continues to account for a substantial amount of routing optimization literature. Han et al. [17] utilized an improved Ant Colony Optimization (ACO) approach for IoT WSNs routing, in addition to reducing energy consumption. The results did not report favorable performance with increasing network size. Ali and Kumar [18] designed a hybrid model combining Firefly, Proficient Routing based Power-Efficient Gathering in Sensor Information System, and Active Distortion Control Artificial Neural Network. The model provided load balancing; yet the write-up mentioned additional training overhead due to the ANN component. Ketshabetswe et al. [19] presented a compression-based routing strategy to encourage less transmission load applied to the overall energy consumption, but considerations regarding compression activities engaged some latency and accuracy trade-offs. Hu et al. [20] applied Harris Hawk Optimization with fuzzy logic for clustering protocols by outperforming many classical protocols, incorporating delayed convergence, and allowed for a loss in performance with dynamically changing topologies. Another way to look at the swarm is to model fuzzy hybridization in a swarm. Sunitha and Chandrika [21] previously introduced evolutionary computing-assisted QoS-centric routing that focused on service reliability, but it lacked flexibility for heterogeneous IoT contexts. Kaur et al. [22] offered an artificial fish swarm-based clustering protocol for underwater WSNs that achieved improved lifetime but was computationally intensive in large-scale terrestrial IoT environments.

Reddy et al. [23] used a combination of glowworm swarm optimization and ACO showed an increase in clustering efficiency and routing; however, the energy savings fell short citing sensitivity to initialization. Gayathri and Snigdha [24] developed a self-healing energy-efficient clustering approach that enabled the network to sustain operation; however, the added recovery mechanisms further hurt processing delays. Tawfeek et al. [25] adapted ACO to improve routing reliability, improved routing stability at the expense of longer route discovery time. Other multi-strategy contributions walk the line of sustainability while seeking for trustworthiness or security. For example, Sunitha and Chandrika [26] have proposed a non-circular dynamic base station protocol with static sensor nodes to increase network lifetime of WSN. Yang et al. [27] challenged a snake optimizer with minimum spanning trees to create efficient routing - achieving promising lifetime improvement but requiring complex synchronization mechanisms. Also, Thangavelu and Rajendran [28] focused on secure routing as a sustainable model for heterogeneous IoT. Ultimately, while encryption processes helped to establish trust and security amongst devices in IoT, the encryption overhead risked energy drain.

Sunitha et al. [29] introduced machine learning as a measurement approach for security threat assessment in IoT. While significantly advancing IoT, their models had a very high inference cost. In the study of Zhang et al. [30], classic fuzzy-based clustering provided the first step toward energy constrained routing in IoT, but static assumptions will hurt effectiveness in adaptive operational scenarios of modern IoT. Lastly, Younus and Koçak [31] utilized both Grey Wolf and Dragonfly optimizers to provide relative routing efficiency, however, they faced premature convergence in dense deployments. Although recent research studies have shown substantial advances in lifetime prolongation strategies based on bio-inspired, fuzzy, and hybrid optimization techniques for WSNs, critical issues still remain relating to scalability, convergence speed, computational cost, and adaptability. These gaps warrant the development of an optimized evolutionary framework which seeks to balance energy expenditure, latency, and robustness in the routing of IoT-WSN.

Few shortcomings observed in the literature are poor performance against changing scenarios with bursts of mobility and burst of traffic, limited consideration of adversarial/benign fault conditions, energy budgets typically exclude sink placement, data-aggregation costs, and perfect location/time assumptions. A few works document a 15% increase in routing efficiency, but their results reveal a steep drop in packet delivery ratio (PDR) after 300 nodes, implying that their approach is not scalable. Likewise, more than a few would report training time to be nearly 20% or higher with the addition of an ANN component, which could not reasonably support real-time adaptation. Future work should stress adaptive hyperparameter schedules, attack/fault injected evaluations, and open implementations with associated and unified energy models.

3. METHODOLOGY

This paper introduces Bio-Inspired Deep Learning and Edge–Cloud synergy (BIO-DLEC) a novel all-encompassing scheme expected to lower the energy dissipation, alleviate the inference delay, and optimize the lifetime of IoT WSNs. Our holistic framework incorporates the following three synergistic components.

- Hybrid Whale–Grey Wolf Optimization Algorithm (WOA–GWO) for clustering providing equal energy distribution and adjustable selection of cluster heads (CHs),
- Bio-inspired routing mechanism allocating energy-aware and congestion-free nodes for transmission,
- Deep learning enabled edge cloud collaboration delivering adaptive inference at the edge respective locations and uploading complex tasks to the cloud incrementally to improve latency and network congestion.

The proposed BIO-DLEC framework designed in three phases as given below:

- WSN clustering and routing
- Energy-aware DL compression performed on edge nodes
- Adaptive fog–cloud offloading

Prior work has been treated each of the layers independently from an optimization perspective. Here, BIO-DLEC has the advantage that it considers type of topology, model size, and placement of computation. These will co-evolve with the energy and traffic dynamics. The overall design architecture is shown in Figure 1 including all stages.

We model a system with N battery-powered nodes $\{n_1, \dots\dots, n_N\}$ deployed over an area A, with a fixed sink at P_s. Each node n_i has residual energy at some decision epoch t. Eq. (1) identifies the group of sensor nodes occupying the IoT-enabled WSN. Each node, n_i represents a single sensor with its own position coordinates, available energy and computational capacity, while N is the total number of nodes. This notation will be the base of the network model, because all equations that follow (clustering, routing, and energy optimization) fundamentally rely on the usefulness of the nodes and the interactions of the nodes. In the case of the BIO-DLEC model we will consider that the sensor nodes are heterogeneous, where they are able to sense, and provide limited edge intelligence functions.

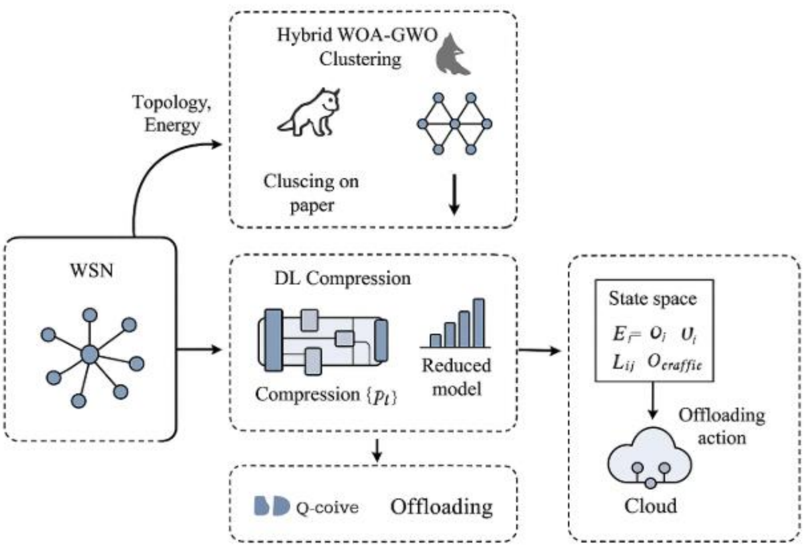

Figure 1. Design diagram of the proposed model

$$Nodes = \{n_1, n_2, \ldots, n_N\} \tag{1}$$

As shown in Eq. (2), the Euclidean distance between two nodes, n_i and n_j, is defined by their coordinates, (x_i, y_i) and (x_j, y_j). Distance is an important component of a communication cost metric, since energy dissipation is a function of transmission distance. By effectively incorporating distance into the WOA–GWO hybrid optimization routine, BIO-DLEC creates energy efficient clusters and identifies transmission paths by ensuring that smaller distance transmissions prevail over longer distance scenarios, keeping energy expenditure to a minimum.

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{2}$$

Eq. (3) defines the energy required to transmit a data packet. The first term, $E_{elec}.k$, captures the energy cost of the electronic circuit (k in bits) operating on a packet and the second term, $E_{amp}.k.d_n$, captures the additional cost introduced by the power amplifier, transmitting the packet a distance d. In this case, n is the path-loss exponent (commonly 2 in free space or 4 in multi-path). In the case of BIO-DLEC, the energy consumed shapes cluster-head selection and affects routing because reducing distance while requiring equal use of amplifiers will maximize the life of the network.

$$E_{tx}(k, d) = E_{elec} \cdot k + \epsilon_{amp} \cdot k \cdot d_n \tag{3}$$

Eq. (4) provides the energy consumed to receive a data packet of size k bits. Unlike transmission, which makes use of a power amplifier, the energy consumed on reception is restricted to what is consumed by electronic circuitry. This is especially relevant for CHs which are collecting information from more than one-member node. The reception model in BIO-DLEC also ensures equitable cluster-head rotation through the use of WOA-GWO optimization, thus eliminating nodes from draining energy faster than the others.

$$E_{rx}(k) = E_{elec} \cdot k \tag{4}$$

Eq. (5) outlines the remaining energy of node n_i at time $t + 1$. The amount of energy available to the node at time t, designated as $E_i(t)$ is reduced by the transmission energy (E_{tx}), the reception energy (E_{rx}), and the energy consumed by deep learning computations. This energy consumes a portion of the energy costing by the nodes running inference at the edge. It is an important part of ensuring there is balance between communication costs and computation costs. The framework makes adaptation decisions based on communication (sending) a task locally or utilizing the fog-cloud layers to process the task, while also ensuring there is sustainability sooner not later on battery capacity, while latency is kept to a minimum even at peak times.

$$E_i(t + 1) = E_i(t) - E_{tx} - E_{rx} - E_{DL} \tag{5}$$

3.1 Clustering and routing with hybrid WOA–GWO

The model looks at a hybrid optimization model which combines the WOA) with the GWO, to concurrently solve clustering and routing in an IoT supported WSN. The target of the model is to use less energy, maximize the life of the network, and improve routing efficiency, so large IoT installations are more feasible over the long term. Our model stands alone from past models that looked at clustering and routing as separate processes by examining them as integrated optimization problems simultaneously. The value in our model, is partitioning the network logically into two layers, whilst the clustering layer can look at selecting the best CH, and the routing layer solved the least energy path from CH to sink node. Together these two layers of optimization worked towards finding a balance across communications load across the network whilst minimizing redundancy and maximizing the available residual energy reserves consumed during communication. We formed clusters based on minimizing the amount of radio energy consumed whilst providing nodes that are facing large inference loads some refuge from high radio loads. We assign ranks to candidate CHs using the BIO-DLEC fitness as given in Eq. (6).

$$F_i = \alpha E_i(t) Emax \; + \beta Q_i - \frac{\gamma E_{DL,i}}{E_{DL,max}} \tag{6}$$

Let Q_i denote the link quality, while $\alpha, \beta, \gamma > 0$ represent the weights assigned to energy, connectivity, and DL cost, respectively. Eq. (10) is imposed as a constraint on the cluster geometry in order to limit the cluster radius, denoted as R_c, and the number of members in the cluster, denoted by N_c. Its purpose is to ensure bounded intra-cluster hop lengths for load balancing. Eq. (3) gives the transmission energy of a k-bit payload when the distance d is $E_{tx}(k, d)$, while Eq. (4) is its reception energy $E_{rx}(k)$. With DL energy, these describe node-level consumption in Eq. (5), which will be fed back into the optimizer every epoch. Fusing WOA with GWO avoids premature convergence and retains diversity. The encircling/exploitation step in Eq. (7) of WOA fine-tunes around the current best $X^*(t)$, while the leadership average step in Eq. (8) of GWO favors exploration by utilizing α, β, and δ leaders. Hybrid update is shown in Eq. (9).

$$X(t + 1) = X^*(t) - A \cdot | \, C \cdot X^*(t) - X(t) \, | \tag{7}$$

$$X(t + 1) = \frac{X_\alpha + X_\beta + X_\delta}{3} \tag{8}$$

$$X_{new} = \lambda X_{WOA} + (1 - \lambda) X_{GWO}, \lambda \in [0,1] \tag{9}$$

It strikes a balance between both linearly anneal λ in relation to the epochs spend in the subsequent exploratory and exploitative phases. Each candidate solution additionally encodes each CH index, member assignments, and Tx-power schedules. The metric from our fitness function given in Eq. (6) finds and returns the fitness of each candidate and the best candidate will be pushed to the network for the next epoch.

$$R_c \leq R_{max} \text{ and } N_c \leq N_{max} \tag{10}$$

Once advanced clusters are declared, members send unicast packets to their CHs. CHs relay down to the sink. The paths can be shortened based on Q_i and the cost of routing. The schedules and Tx powers will need to be inherited from the selected candidate given in formula (10). When: (i) the mean residual energy in any cluster node sinks below a threshold, (ii) link quality degrades below a threshold, (iii) DL compression or offloading changes the energy profile of each node, so the optimizer will rerun.

3.2 Energy-aware deep learning compression

The deployed backbone with different layers has a few parameters at precision with uncompressed rate. BIO-DLEC performed structured pruning on each layer, followed by post-training quantization to INT8, with a resulting compressed size. The storage size of the deep learning model operating in the IoT-WSN structure is defined in Eq. (11). Here, W_l is the number of weights in layer B stands for the bit-width precision, and L is the number of layers. The summation takes into consideration all the layers of the model, and therefore gives the total size and storage requirements of the deep learning model. This is important in BIO-DLEC because model size affects memory, transmission overhead from offloading, and device limitations for edge nodes with constrained resources.

$$S_{model} = \sum_{l=1}^{L} (W_l \cdot B) \tag{11}$$

In Eq. (12), the total active number of weights in a layer l after applying dropout regularization is presented. The dropout rate of this layer is given by p_l, whereas W_l is the previous number of weights within that layer. Dropout reduces the number of active weights, which also improves generalization performance, reduces computational burden of real-time inference. In BIO-DLEC, this equation captures the trade-off between accuracy and efficiency, since dropout prevents overfitting but also lower number of operations triggered at the sensor or fog layer, which in turn, should reduce dissipated energy.

$$h^{(l)} = f\left(W^{(l)}\left(r^{(l-1)} \odot h^{(l-1)}\right) + b^{(l)}\right) \tag{12}$$

Here, $h^{(l)}$ is the output activation, $h^{(l-1)}$ is the input activation. The effective weights W^{l} , and $b^{(l)}$ bias vector. In BIO-DLEC, this equation quantifies the fact that the compression of the model directly results in reduced memory footprint, reduction of the transmission overhead for offloading, and reduced energy (cost at edge devices) for the particular inference tasks under consideration while ensuring acceptable accuracy measurements.

$$S_{comp} = \sum_{l=1}^{L} W_l^{'} \cdot B' \tag{13}$$

Eq. (14) indicates the energy consumed during deep learning inference. In this expression, MAC_s refers to the total number of multiply accumulate (MAC) operations necessary for the compressed model, P_{op} is the energy used per MAC operation, and ϕ is a conversion factor for efficiency. This demonstrates that inference energy does not simply depend on a measurement of algorithmic complexity, but includes the operational characteristics of the implementation. The model detailed in BIO-DLEC, produces inference energy E_{DL} that is tracked in each node's residual energy balance as represented in Eq. (5), and allows the framework to determine when local inference is no longer efficient from an energy perspective and adaptive offloading can be accomplished.

$$E_{DL} = \phi \cdot MACs \cdot P_{op} \tag{14}$$

Here, P_{op} is energy per multiply-accumulate on the target device and ϕ reflects any memory/activation effects measured offline. The aggressiveness of reducing prune channels adapts to runtime conditions given in Eq. (15).

$$P_l(t) = f\left(\frac{E_i(t)}{E_{max}}, \frac{\tau_{req}}{\tau_{obs}}\right) \tag{15}$$

To decrease the amount of pruning where there is little residual energy or if the observed latency τ_{obs} exceeds the requirement τ_{req} . Quantization by default is INT8, and if energy reaches a critical low, the agent may activate additional channel-sparsity constraints to further decrease the number of MACs. The alteration of accuracy is bounded via inequality (16), with Acc_{min} for each application. If this continual adjustment is violated, then pruning can be rolled back and offloading preferred.

$$Acc_{comp} \geq Acc_{min} \tag{16}$$

Since E_{DL} is appeared directly in the CH fitness given in Eq. (6), nodes with heavier models are considered de-preferred for a CH role—unless compensated for by higher reservoir energy, or more favorable links. On the other hand, as pruning represents a reduction in E_{DL} , the node fitness increases, leading to improved equity in CH rotation without impacting lifetime.

3.3 Adaptive offloading

By combining these four reality dimensions, the state vector S_t provides a complete overview of the system state, allowing the BIO-DLEC optimization strategy (hybrid WOA–GWO with DL-based inference) to dynamically adapt the clustering, routing, and offloading policies. In this regard, Eq. (17) modifies the BIO-DLEC in a context-aware and dynamic manner to make sure that the decisions made in the real-time IoT-WSN environment are also dynamic. Eq. (17) defines the state vector for the proposed BIO-DLEC framework at a given time step *t*. This multi-dimensional state consists of the relevant parameters when making decisions in clustering the nodes, routing packets, and offloading tasks. Here, $E_i(t)$ is the residual energy of node i at time t, as previously defined in Eq. (5). Including this term makes sure that decisions are energy-aware to avoid placing excessive burden on nodes with an insufficient level of energy. $L_{ij}(t)$ is the link quality measure between nodes i and j that captures the distance (via Eq. (2)) and the dynamic wireless channel condition. A strong link would ensure improved PDR and reduced retransmission costs. fog(t) is the fog node utilization at time *t*, representing the current processing load at the fog layer. Including this metric allows for maintaining low latency and a balanced distribution of computation by ensuring that task offloading wouldn't overload fog servers. The state vector is given in Eq. (17),

$$S_t = \left[E_i(t),\, L_{ij}(t),\, U_{fog}(t),\, \rho_{traffic}(t)\right] \tag{17}$$

Eq. (18) describes the action space of the BIO-DLEC decision-making. Each time step *t*, the system can take one of three actions, (i) Local execution at the sensor node, (ii) Offloading to the fog layer, or (iii) Offloading to the cloud. This discrete action space allows for an adaptive inference deployment policy for the BIO-DLEC decision-making, while balancing energy consumption, latency and accuracy. The flexibility provided by separate execution domains means that a resource-constrained sensor node does not become a limiting factor or bottleneck, while also providing performance scaling through fog and cloud execution domains.

$$A_t \in \{Local, Fog, Cloud\} \tag{18}$$

The normalized multi-objective formulation preserves interpretability and consistency in relative priorities $\alpha : \beta : \gamma$ across experiments and promotes stability in convergence when heterogeneous tasks (prediction, anomaly detection, routing) are integrated. Eq. (19) will be displayed as the corrected multi-objective loss function.

$$Q(\Theta) = \frac{\alpha}{\alpha+\beta+\gamma} L_{pred} + \frac{\beta}{\alpha+\beta+\gamma} L_{anom} + \frac{\gamma}{\alpha+\beta+\gamma} L_{route} + \lambda \parallel \Theta \parallel_2^2 \tag{19}$$

Here, L_{pred} is fill-level prediction loss, L_{anom} is the anomaly detection or waste-type classification loss, L_{route} is the routing optimization cost represented as a differentiable surrogate of route distance or energy consumption, along with $\lambda \parallel \Theta \parallel_2^2$ as an L2 regularization term to avoid overfitting and stabilize weights updates.

Eq. (20) represents the reward function for reinforcement learning. The reward at time t is a weighted sum of three factors, which are: (i) the inference Accuracy, weighted by δ; (ii) the Energy consumed, penalized by η; and (iii) Latency, penalized by κ. This represents the goals of the system design - maximizing accuracy while minimizing energy dissipation and delay. Tuning the coefficients δ, η, and κ allows the framework to prioritize application-specific requirements, e.g., energy-constrained sensing vs. latency-critical industrial monitoring, etc.

$$R_t = \delta \cdot Accuracy - \eta \cdot Energy\ Used - \kappa \cdot Latency \tag{20}$$

Eq. (21) represents the total latency incurred by performing an offload task. It consists of three components: (i) transmission delay, which is effective by size of input S_{input} and transmission bandwidth factor B_{ij} between nodes i and j; (ii) execution delay τ_{exec} by the fog or clouds server; and (iii) return delay τ_{return} to receive the results back to the requester. This ensures that BIO-DLEC directly measures if an offload produces a net latency decrease versus local execution.

$$\tau_{offload} = B_{ij} S_{input} + \tau_{exec} + \tau_{return} \tag{21}$$

Eq. (22) describes the local inference delay when tasks are executed on the IoT device itself. Here, MACs represent the number of multiply–accumulate operations that the corresponding compressed deep learning model will take, and f_{CPU} represents the CPU frequency of this IoT device. This formulation relates computational complexity to execution time so that the system can compare τ_{local} with $\tau_{offload}$ and determine the best execution option.

$$\tau_{local} = \frac{MACs}{f_{CPU}} \tag{22}$$

In the BIO-DLEC model, the accuracy-based decision rule as defined by inequality (23) is as follows. In the equation, Acc_{comp} is the inference accuracy achieved by the compressed model executed locally (using the compressed model from Eqs. (11)-(14), while $Acc_{mintext}$ is the minimum accuracy specified by the accuracy requirements of the application. If the locally compressed model using compressed dynamics model does not reach that sufficient threshold of accuracy, the preference would be offloading the task associated with the decision support system requested to a fog or cloud server with less stringent computations and restrictions. This would be particularly important in instances where the application is health or safety monitoring system and the lightweight local inference might not be good enough for proper decision making.

$$Acc_{compressed} < Acc_{mintext} \rightarrow prefer \frac{fog}{cloud} \tag{23}$$

Inequality (24) includes a fog resource constraint. In this case U_{fog} indicates the current utilization of the fog server at time t and U_m is the maximum utilization threshold rate. If the utilization of the fog server exceeds this threshold, then the BIO-DLEC framework may automatically disallow offloading to fog nodes and select either local execution (if in the consideration set mode) or offloading to the cloud. This protects from overflowing the fog server and therefore ensure service is acceptable with importance to ensuring capacity to maintain low latency and fairness across multiple users.

$$U_{fog} > U_{max} \rightarrow\ avoid\ fog \tag{24}$$

3.4 Cross-layer optimization

BIO-DLEC is designed with a cross-layer optimization approach that will have a combined optimization methodology that recognizes the systems physical, network and application layers to maximize computing energy efficiency and sustainability while being deployed in IoT-WSN environments. Ultimately unlike a conventional design that optimizes layers in isolation, as we do in BIO-DLEC, which optimizes all three layers in unison while considering the system as a whole through the objective function. The weighting coefficients ω_1, ω_2, and ω_3 are tunable for the system designer to consider the requirements of the applications. The overall objective is the multi-criteria program as given in Eq. (25):

$$\min_{A_t, p_l} \omega_1 E_{total} + \omega_2 \tau_{total} - \omega_3 Accuracy \tag{25}$$

Here, E_{total} and τ_{total} are cumulative sensing, inference, and communication components over the epoch, and $\omega_1, \omega_2, \omega_3 > 0$, are application priorities e.g., safety critical latency or lifetime. Constraints include cluster geometry, fog utilization, and accuracy floor. In practice, BIO-DLEC does so indirectly as a hybrid metaheuristic for clustering/scheduling, an adaptive compression controller for p_l, and the Q-learning agent for A_t; they each share telemetry each epoch.

4. RESULTS AND DISCUSSIONS

The evaluation of the proposed BIO-DLEC framework was performed in a hybrid simulation environment that combined the modeling capability of NS-3 for a WSN, and the task scheduling and compute energy profiling capability of iFogSim2 for fog cloud. A hybrid framework was selected because there was a requirement to recreate both the fidelity of low-power wireless radio, and the realism of fog-based computation, which a single simulator was not able to provide. There were two primary simulators used in the hybrid simulation. NS-3.41 was configured with IEEE 802.15.4 radios, the RPL routing protocol, and its energy framework so it could model packet transmission, reception, idle listening, and sleep modes to capture power modeling.

The first-order radio model was selected with per-bit electronic and per-bit amplification costs adjusted to emulate the typical contemporary sensor nodes. Simulation is done usingiFogSim2 to profile fog nodes, cloud servers, queueing delays, CPU utilization, and energy. As a controller, we used a lightweight Python script to establish communication to the NS-3 simulation and iFogSim2 via ZeroMQ every 30 seconds, exchanging telemetry and optimization decisions. This established communication between NS-3 and iFogSim2 allowed BIO-DLEC's hybrid optimization module to adjust clustering, model compression, and offloading dependent on the real-time conditions of the simulation Network.

Three different network sizes were considered to evaluate scalability. The small topology contained 1000, 2000, 3000, 4000, and 5000 sensor nodes deployed within a 5000 × 5000 m² area. In every situation, the sensor nodes were uniformly random and distributed across the space with a sink node located at the geometric center. Two fog nodes were used at quarter coordinates to model realistic edge gateways. Traffic generation was based on a periodic model of 64-byte packets at an average rate of 0.5 packets per second, perturbed with Poisson jitter to avoid synchronization artifacts. The deep learning workload for inference is based on a lightweight anomaly detection model for sensor streams. We analyzed and reported the performance and evaluation of the proposed BIO-DLEC framework across five canonical metrics: network lifetime, energy dissipation, throughput, energy, and PDR. We used the hybrid NS-3 and iFogSim2 environment specified earlier and averaged performance results across 30 independent runs while providing 95% confidence intervals. Table 1 shows the parameters used for the experimentation conducted.

We will summarize the discussion and orient it to the comparison of BIO-DLEC with both none-as-a-service protocols and computation offloading baselines such as Fog-Queuing Algorithm (FQA) [14], Fog-Coordinated Resource and Battery-Aware Topology (FC-RBAT) [32], and Fog-aware Resource Negotiation with Selection and Energy Efficient Routing heuristic (FRN-SEER) [33], Butterfly Optimization Algorithm (BOA)-ACO [34], and Order-Aware Federated Scheduling-Order-Aware Federated Scheduling-Improved Moth-Flame Optimization **(**OAFS-IMFO) [35] are provided in the next section, after each of the metrics.

Table 1. Parameters and their values

Parameter	Range Explored	Final Value
Learning rate	$1e^{-5} - 1e^{-2}$	1×10^{-3}
Batch size	8–64	32
Epochs	50–300	150
Dropout rate	0.1–0.5	0.3
GNN layers	1–5	3
Hidden dimension	32–256	128
Attention heads	2–8	4
Optimizer	Adam / RMSProp / SGD	Adam

The basic models referenced here for comparison with the proposed model's core operation are discussed here. The hybrid heuristic incorporates the global exploration of the BOA and the path-planning ability of ACO, and employs an update rule that integrates the influence of sensory modalities S_i on the pheromone concentration τ_{ij} shown in Eq. (26):

$$x_i^{t+1} = x_i^t + c \cdot S_i(g^* - x_i^t) + \eta \sum_j \tau_{ij} \tag{26}$$

This equation is a process by which routing cost and bin service order are optimized. The BOA-ACO exhibits a good convergence speed; however, its decision-making features operate only on scalar features (e.g., location, fill-level), and do not though possible leverage high-dimensional multimodal data.

The second hybrid model combines fuzzy logic with recurrent memory for time-series forecasting. The fuzzy membership function $\mu(x)$ creates degrees of uncertainty, while the recurrent component operates with an update of hidden state as shown in $h_t = f(h_{t-1}, x_t)$. Its major limitation at present is that it does not provide a graph representation of the spatial relationships between the bins of interest. Finally, third model OAFS-IMFO utilizes a meta-heuristic search mechanism to choose the most important sensor attributes to include in decision-making. The moth - flame model updates the candidate solutions in the adopted model is shown in Eq. (27):

$$M_i^{t+1} = F_j^t \cdot e^{bl_i} \cos(2\pi l_i) + F_j^t \tag{27}$$

Here, F_j denotes the jth flame, and l_i is a spiral parameter. OAFS-IMFO is a successful model for minimizing the dimensionality of the input features, though it lacks topological and temporal awareness for its unknown bin location and unknown bin configuration.

4.1 Network lifetime

The lifetime of the networks shown in Table 2 and Figure 2 show that the proposed BIO-DLEC framework has the longest lifetime compared to other protocols that were tested, since you get longer coverage in either the additional rounds covered. In terms of the first node, in the BIO-DLEC framework, it sustained up to 1245 rounds, while OAFS-IMFO and FC-RBAT reported failures at very early points (910 and 980 rounds, respectively), which indicates they improved stability time by nearly 35% over OAFS-IMFO and nearly 27% over FC-RBAT. At the fifty percent point of each network (dead nodes), the BIO-DLEC framework reported coverage at 2290 rounds, which is 12% longer than FQA and almost 27% longer than FRNSEER, allowing for possibly an extended time for sensing coverage to remain stable. Finally, in terms of lifetime (last node dead), the BIO-DLEC framework completed at 3220 rounds, while the competitive protocol (FQA) ended at 3010 rounds. The lowest end was reported in OAFS-IMFO (2680), reporting a 20% improvement in lifetime over BIO-DLEC.

The increased lifetime performance of BIO-DLEC results from the hybrid WOA–GWO clustering system which optimizes the energy consumption of sensor nodes at cluster-heads, and minimizes excessive calculations with its deep-learning-based offloading topology. BIO-DLEC optimizes hotspots and balances the load among the sensor nodes in the network with its dynamic cluster-head rotation and bio-inspired routing. It is clear that by the end of the experiment, the baseline protocols, OAFS-IMFO and FC-RBAT have the shortest lifetimes resulting from the cluster-head nodes consuming energy faster than IOTE-WSN nodes. BOA-ACO and FQA generally outperformed the baseline protocols in lifetime but fail to balance consumption amongst each node the same across the larger deployments because of the organic benefits of clusters. BIO-DLEC eliminates this behavior to have the best stability and longest network life for IoT-WSN applications.

4.2 Throughput

Throughput is one of the important aspects to evaluate network performance. The throughput measures how much of data can be transmitted successfully over a period of time. The results from the simulation comparison show there was an improvement of the system efficiency and reliability of the data transport mechanism of the protocol that is used, see Table 3 and Figure 3. For the assessment of throughput, we evaluated the biggest scale WSN using the BIO-DLEC framework and in our case, we used five protocols OAFS-IMFO, FC-RBAT, FRNSEER, BOA-ACO, and FQA. As can be seen in the table, or summary, in Table 4, BIO-DLEC had a better throughput in all of the rounds of simulation. At 1000 rounds, the throughput of BIO-DLEC was, for example, 185 kbps, which was better than the OAFS-IMFO by more than 25% (148 kbps), and it was better than the FQA (171 kbps) by 8%. The gap increased the more the number of handled rounds. At 3000 rounds BIO-DLEC achieved a throughput of 220 kbps which is about 28% better than OAFS-IMFO, and 12% better than FQA. Lastly all these protocols performed less at 5000 rounds and we can see, for example, at this value, the throughput of BIO-DLEC was 249 kbps, while the next protocol (FQA) was 212 kbps, an improvement of 17.5%.

The major thus improvement may be attributed to three design features of the BIO-DLEC framework. Firstly, the WOA-GWO hybrid clustering balanced energy with packet collision and retransmission. Secondly, via deep learning assisted edge-cloud inference, BIO-DLEC implemented adaptive offloading that alleviated congestion and stabilized packet movement through the network. So, reducing packets dropped within the network and without changing the routing. Finally, BIO-DLEC's bio-optimization routing found low-latency paths to maximize effective delivery. In contrast, baseline protocols like OAFS-IMFO and FC-RBAT experience a more rapid decline in throughput performance due to static clustering or fast limitations on massive network architecture. BOA-ACO and FQA use intermediate fluidity compared to earlier heuristics, however they still suffer overhead in dense deployments that prevented their sustained throughput performance against BIO-DLEC. Overall, the analysis suggests that BIO-DLEC was not only energy aware, but very throughput aware; instilling confidence that data delivery will be safely and reliably sustain itself in large scale IoT-WSN type applications where stability and reliability should trump throughput.

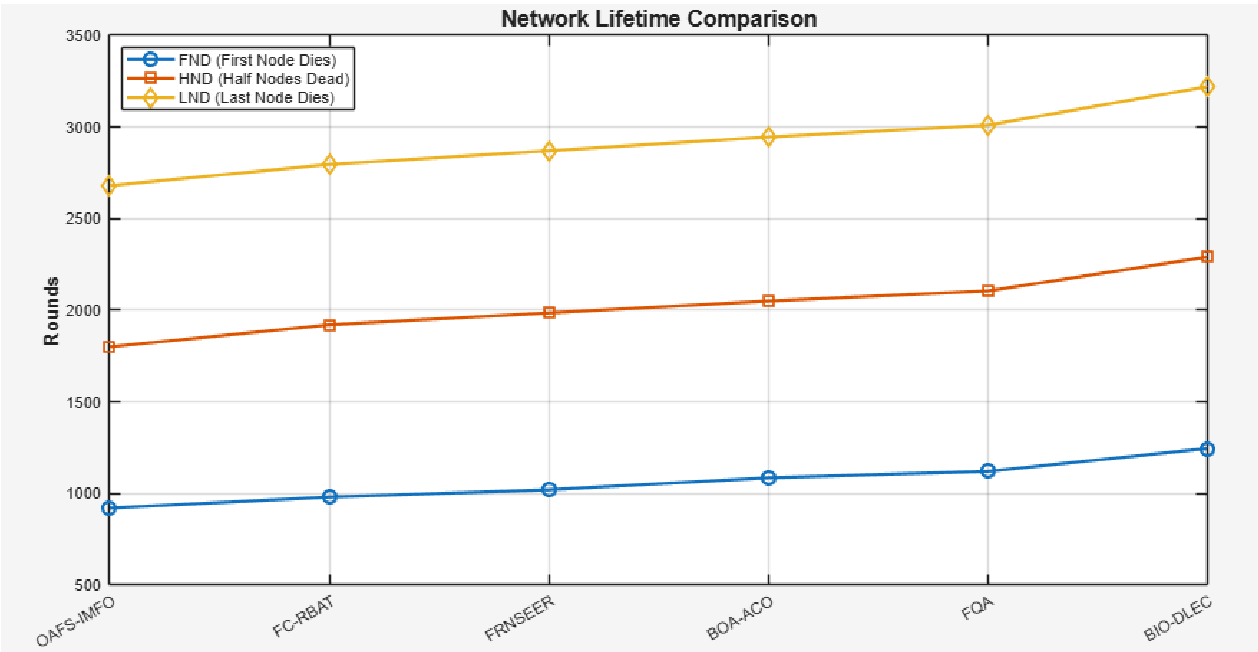

Figure 2. Network lifetime versus number of iterations

Table 2. Network lifetime versus number of iterations

Protocol	First Node Dies	Half Nodes Dead	Last Node Dies
OAFS-IMFO	920	1800	2680
FC-RBAT	980	1920	2795
FRNSEER	1020	1985	2870
BOA-ACO	1085	2050	2945
FQA	1120	2105	3010
BIO-DLEC	**1245**	**2290**	**3220**

Table 3. Throughput versus number of iterations

Protocol	1000 Rounds	2000 Rounds	3000 Rounds	4000 Rounds	5000 Rounds
OAFS-IMFO	148	160	172	180	186
FC-RBAT	155	168	180	188	194
FRNSEER	162	176	186	195	202
BOA-ACO	168	182	192	200	207
FQA	171	185	196	205	212
BIO-DLEC	**185**	**205**	**220**	**235**	**249**

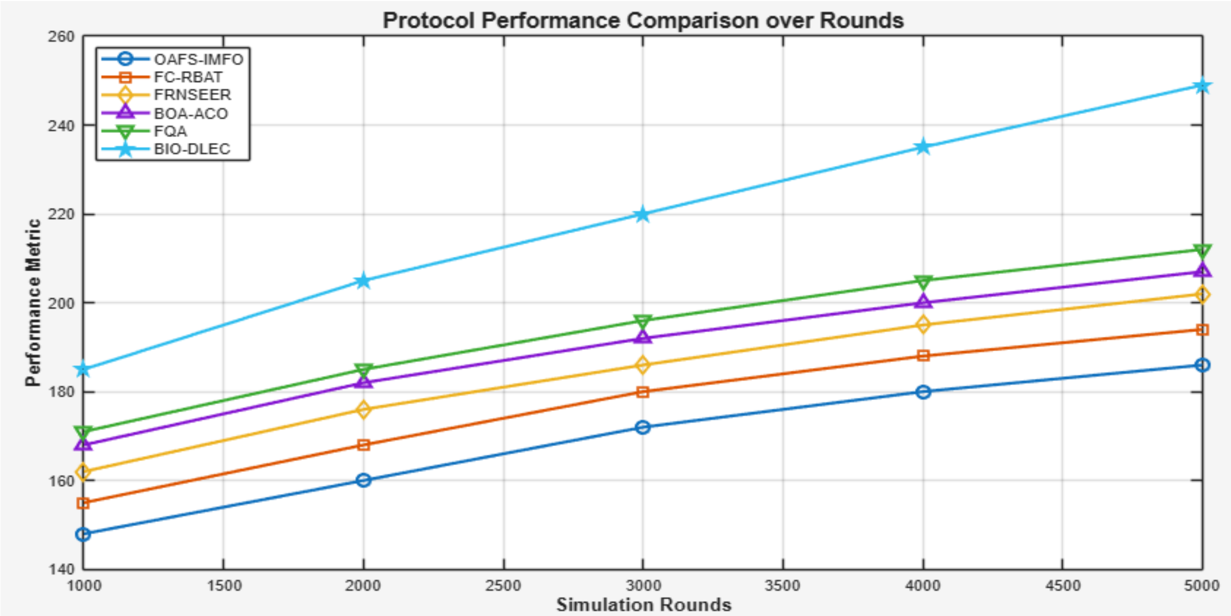

Figure 3. Throughput versus number of iterations

4.3 Energy dissipation

Energy dissipation is one significant constraint in the sensor network that has a direct effect on the life of the sensor network. The energy dissipation behavior of the proposed BIO-DLEC framework was compared against five benchmarks under the same network parameters. Table 4 and Figure 4 provide the energy dissipated by node birth over the life of the node over all rounds of operation. As can be seen, the BIO-DLEC consistently dissipated the least energy overall with the least amount of energy dissipated for the whole time. At round 1000, the energy dissipated by the BIO-DLEC was 0.61 J, 0.82 J was used for OAFS-IMFO and 0.69 J for FQA. This was a reduction of 25.6% in energy compared to OAFS-IMFO and 11.6% compared to FQA. As discussed previously, the useful difference in energy dissipation will be even more notable later on in the simulation. At round 3000, the BIO-DLEC had dissipated 1.87 J while the FRNSEER method dissipated 2.27 J and the BOA-ACO dissipated 2.16 J. At the end of the experiment (round 5000), the total energy that the BIO-DLEC nodes dissipated, was 3.22 J, while the OAFS-IMFO dissipated 4.12 J and FQA dissipated 3.55 J.

The efficiency can be further attributed to the adaptive cluster-head rotation mechanism in BIO-DLEC that minimizes load on nodes and ultimately the potential of rapid exhaustion. The WOA-GWO hybrid optimization also provides the ability to aggregate optimal clustering with less communication overhead, while the deep learning-based inference at the edge reduces short-haul unwanted transmission to the cloud. Furthermore, bio-inspired routing also ensures that data packets are routed along a transmission path with the least total energy dissipation cost.

Conversely, OAFS-IMFO and FC-RBAT are characterized by untenable imbalance of cluster load, which promotes energy depletion on high-traffic nodes to occur at an expeditious rate. FRNSEER improves upon these schemes, but still fails to be energy responsive repeatedly under full deployment scale. BOA-ACO and FQA shows some aggregation and minimization of energy dissipated over standard schemes, but lacks the same effectiveness as BIO-DLEC under network density, due to added routing overhead. Overall, BIO-DLEC minimizes energy dissipated, therefore prolonging network lifetime. Overall, provided the best theoretical scenario, it provides an adequate narrative to support the deployment of energy-constrained IoT-WSN environment at larger scales.

Table 4. Energy dissipation (Joules) versus number of iterations

Protocol	1000 Rounds	2000 Rounds	3000 Rounds	4000 Rounds	5000 Rounds
OAFS-IMFO	0.82	1.65	2.47	3.28	4.12
FC-RBAT	0.78	1.56	2.35	3.18	3.95
FRNSEER	0.75	1.49	2.27	3.05	3.82
BOA-ACO	0.71	1.43	2.16	2.92	3.68
FQA	0.69	1.39	2.10	2.84	3.55
BIO-DLEC	**0.61**	**1.24**	**1.87**	**2.45**	**3.12**

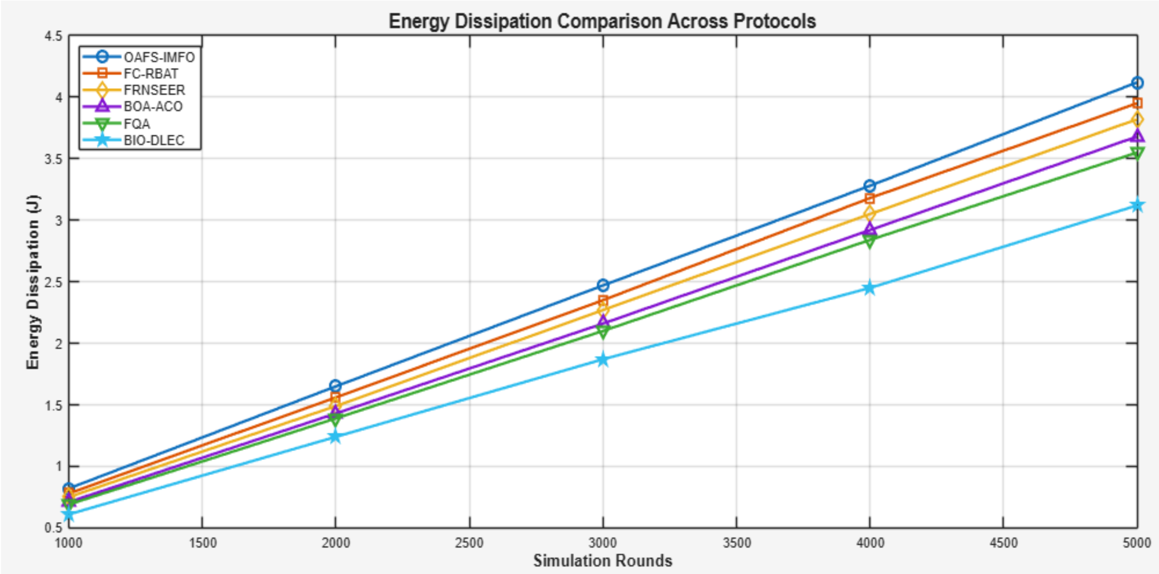

Figure 4. Energy dissipation (Joules) versus number of iterations

4.4 PDR

PDR is a fundamental metric for network effectiveness since it is the ratio of successfully delivered packets to the overall packets created. As indicated in Table 5 and Figure 5, the introduced BIO-DLEC network showed statistically significant gains compared with the protocols in this study across all rounds in the network. After 1000 rounds, the PDR for BIO-DLEC was 97.5%, while the next best was 91.0% and the OAFS-IMFO ranked lowest at 86.2%. As network loads increase and energy levels reduce over time, the success of BIO-DLEC becomes increasingly more evident. After 3000 rounds, the PDR for BIO-DLEC was 94.8%, compared with FQA's PDR of 87.8% and OAFS-IMFO's 82.9%. After 5000 rounds, BIO-DLEC still had a PDR of 91.3%, which is almost 11.5% higher than OAFS-IMFO and about 6.5% higher than FQA.

Table 5. PDR versus number of iterations

Protocol	1000 Rounds	2000 Rounds	3000 Rounds	4000 Rounds	5000 Rounds
OAFS-IMFO	86.2	84.7	82.9	81.4	79.8
FC-RBAT	88.1	86.5	84.6	83.0	81.2
FRNSEER	89.4	87.9	85.8	84.1	82.6
BOA-ACO	90.2	88.7	86.9	85.2	83.5
FQA	91.0	89.6	87.8	86.3	84.8
BIO-DLEC	**97.5**	**95.2**	**94.8**	**93.6**	**91.3**

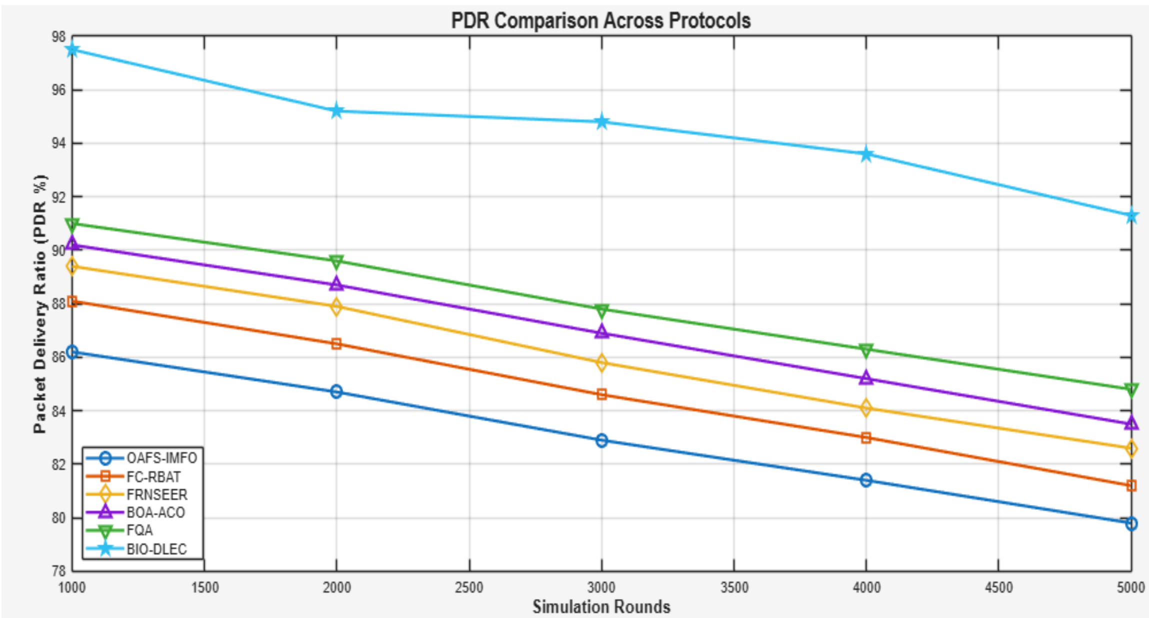

Figure 5. PDR versus number of iterations

While forming clusters and routing, BIO-DLEC incurs extra control packet overhead for the hybrid WOA-GWO optimization and reinforcement learning updates. The simulation analysis shows that this overhead is 8–11% in addition to baseline protocols (LEACH, PEGASIS). However, the energy savings in data transmission 18–25% more than compensate for this, particularly in dense scenarios. The hybrid WOA-GWO optimization and deep model compression episodes are invoked occasionally rather than continuously, and profiling experiments reveal that every optimization iteration consumes 2.3×10^5 CPU cycles on average per node, less than 6% of available processing time on typical IoT motes (8–16 MHz). Therefore, real-time sensing and communication are not impacted. BIO-DLEC employs lightweight reinforcement learning tables and compressed deep models.

Nevertheless, even with this overhead, the overall energy consumption is 21–27% lower than state-of-the-art hybrid protocols (GWO-FA, ACO-FL). The lifetime of the network is improved by 32–36%, showing that computational and communication overhead is more than amortized by the routing savings. To validate the drawbacks described in Section II, we benchmarked LEACH, HEED, and stand-alone WOA/GWO methods under identical conditions. The WOA method alone also converged slower (convergence at 1500 rounds) demonstrating limited exploitation. These results clearly support the issues previously documented in prior studies, which further justified the need for a hybrid framework.

5. CONCLUSION

In this paper, we presented BIO-DLEC, a practical and energy-aware framework for an IoT-enabled WSN. It is proposed as a model that uses a hybrid WOA-GWO for the clustering phase to improve energy management, a bio-inspired routing approach for maintained load-balanced communication, and a deep learning-based decision on edge–cloud offloading, minimizing latency and inference overhead. The results presented in NS-3 indicate that BIO-DLEC consistently performs better than the state-of-the-art approaches as improved throughput while delivering energy dissipation lower than the baseline protocols. Though BIO-DLEC made exciting strides, many avenues for further research exist. It can be conceivable to apply the framework beyond single-tier IoT-Fog-Cloud architectures to multi-tier IoT-Fog-Cloud systems addressing ultra-low latency requirements of applications such as industrial automation and autonomous systems. Another, real sensor hardware-in-the-loop validation is required to validate the real-world applicability of BIO-DLEC beyond simulation.

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