A NOVEL AI-ASSISTED ENERGY EQUALIZATION AND COMPRESSION ENABLED ROUTING FRAMEWORK FOR WSNS

Amirmasoud Soltanzadeh and Zbigniew Dziong

ETS, Montreal, Canada

ABSTRACT

Wireless Sensor Networks (WSNs) have transformed monitoring and tracking applications across diverse domains. These networks, comprised of small sensor nodes transmitting data to a central base station (BS), face a significant challenge due to limited energy resources, impacting operation allongevity.This study addresses this challenge by proposing an innovative energy-efficient routing protocol. The primary aim is to develop an optimized routing model based on clusters, enhancing energy efficiency, through put, and reducing delay and dead nodes in the network. To achieve this, clustering with the k-means algorithm is employed, followed by the selection of cluster heads using PSO-mutation, optimizing for suitable cluster heads. Subsequently, the routing between cluster heads is optimized using the Golden Eagle algorithm(GEO),with benchmark comparison against Leach-CR. Leveraging the Golden Eagle algorithm, the protocol optimizes communication paths by intelligently selecting routes to minimize energy consumption.

Motivated by the limitations of existing energy-efficient routing protocols, which struggle to comprehensively address diverse applications and energy constraints, this study proposes amore robust and adaptable routing protocol. Rigorous validation through extensive Matlab simulations evaluates metrics such as dead nodes, throughput, energy consumption, and network delay. Simulation results in Matlab show ssignificant enhancements over the benchmark model GA-PCT& Leach-CR routing protocol, demonstrating substantial energy savings and extended network lifespan.

KEYWORDS

Genetic algorithm (GA), Predictive coding theory (PCT), Cluster-low energy adaptive clustering hierarchy (C-leach), Golden eagle optimization (GEO), Particle swarm optimization-mutation (PSO-Mutation), Energy efficiency routing protocol (EERP). Wireless sensor networks (WSNs).

1. INTRODUCTION

A Wireless Sensor Network is a combination of hundreds of electromagnetic devices installed in precise locations in the field for monitoring and tracking. The sensor nodes can transmit and receive data wirelessly to the BS. As sensor nodes have limited energy resources, they introduce issues in wireless sensor networks, potentially causing them to die earlier and compromising performance. To avoid the setback of SNs' earlier depletion, several approaches have been used in the past; one of the best is the development of a routing protocol. They provide some considerable solutions, but the space improvement still exists. This article provides an in-depth analysis and review of existing studies to develop a novel routing protocol for improving energy efficiency in WSNs. To begin, we will introduce the specific issue that is the primary focus of our research work, as outlined in this article.

In the current times, Multifunctional SNs are facilitating the development of WSN applications to automate environmental impact monitoring and tracing multiple domains in practical life. The most commonly utilized areas where WSN applications are worthwhile are agriculture, industry, homes, the military, healthcare, and farms. WSNs, which provide significant benefits to users, also face critical issues, such as security, connectivity, and energy efficiency. However, addressing energy efficiency is a critical challenge. Due to the critical data communication in WSNs, a balance between efficiency and energy efficiency is always required. In existing research, we found that the development of the EERP is encouraged by examples of traditional and advanced approaches that offer efficient solutions; however, an improvement gap persists. Still, some deep-seated issues persist, including unbalanced energy expenditure and excessive energy consumption, as well as the ineffective utilization of AI techniques to achieve efficient performance.

This article presents a model that addresses existing issues more effectively by integrating AI techniques, focusing on key issues to develop a novel EERP for WSNs. The main contribution focuses on the use of advanced techniques, including tK-means for clustering, PSO-Mutation for selection within each cluster, and GEO for efficient node selection during data broadcasting between H and BS. All these factors can help distribute energy consumption, save significant energy, and maximize the network's lifespan.

To validate the model's performance, MATLAB simulations are performed with specific parameter values and performance matrices, including total energy consumption, the number of dead nodes, throughput, and delay. The results will be evaluated using a genetic algorithm and a predictive coding theory-based model, Leach-CR, and justified as a more effective and efficient approach. This article further details the background studies, methodology, simulation, results, and conclusions.

2. LITERATURE REVIEW

Multiple research efforts have been made in the past to address the energy problem considered in this research on WSNs. Here is the detailed literature review of the study.

A study presents a k-means clustering method for large-scale WSNs (LSWSNs). The immediate objective of this model is to achieve improved performance in terms of throughput and delay, including enhancements to overall operating time [1]. The PSO algorithm is an intelligent metaheuristic inspired by the social behaviour of bird flocks, operating in two phases: position representation and the steady-state phase. In the first step, it considers particle potential cluster heads in WSNs. In the PSO, the fitness function used for CH selection considers the residual energy of nodes and their communication gap to the CH. It uses an algorithm to explore the search space and selects the best CH that distributes the energy load among the SNs. It also updates the particle's velocity and location iteratively, based on both personal and global best solutions.

Recent studies have explored bio-inspired optimization for energy-efficient WSN routing. For example, the EEM-LEACH-ABC protocol applies the Artificial Bee Colony (ABC) algorithm to dynamically select cluster heads and optimize routing paths based on residual energy and transmission distance, demonstrating substantial improvements in network lifetime, packet delivery ratio, and energy consumption compared to conventional methods[11].

In the context of IoT-based WSNs, hybrid metaheuristic approaches have been proposed to enhance energy efficiency and network lifetime. For instance, a bi-objective clustering protocol integrating Tabu Search and Ant Colony Optimization (ACO) demonstrates significant improvements in network stability, residual energy, and transmission delay compared to conventional methods, highlighting the potential of hybrid optimizers for effective cluster head selection and data routing[12].

The time-variant inertia weight variant uses PSO to balance exploration and exploitation during the search. It also leverages PSO's potential to provide an efficient solution to NP-hard clustering problems [8]. GWO is a metaheuristic algorithm inspired by the leadership hierarchy and hunting behaviour of grey wolves. Here, a modified version, identified as HMGEO, is used, proposed to enhance its performance by selecting optimized cluster sets in heterogeneous WSNs. To tailor the fitness function in HMGWO, it considers specific factors related to HWSNs [2]. Another study uses a genetic algorithm to reduce energy consumption and minimize communication gaps among SNs. It is a faster technique for approximating the system's current state to schedule the route [9]. Another study uses a genetic algorithm and a multi-hop route optimization approach for wireless sensor networks. It is a multi-hop route discovery algorithm that optimizes a new fitness function to enhance the energy efficiency of WSNs [3].

Golden Eagle Optimization for Energy-Aware Cluster Head Selection and Routing addresses energy issues in WSNs. It mimics the hunting behaviour of golden eagles, in which a population of search agents (representing golden eagles) explores the solution space to identify optimal solutions. Each GEO agent represents a potential set of cluster heads, and the fitness function aims to reduce energy consumption and intra-cluster distances. The GEO algorithm effectively handles the multi-objective problem by exploring trade-offs among differing intents during optimization. After forming the clusters using GEO, inter-cluster routing employs the improved shuffled frog leaping algorithm (SFLA). This technique is most supportive in finding an efficient route for communicating data on flowcharts and at waste stations. It also ensures network energy efficiency [8]. Another data compression approach uses a routing protocol that provides highly robust solutions for wireless sensor network applications across various areas [6]. The designed model uses the Grey Wolf Optimization technique, a nature-inspired algorithm for data clustering and cluster head selection, which considers the residual energy of the SNs and the distance between communication devices. It also creates a 3-level hierarchy using the clustering technique. Moreover, it uses the fitness function to reduce energy expenditure in the network and extend the network's lifetime [4]. Another routing protocol, a hybrid of the well-known routing protocols Leach-C and Leach-R, primarily uses the properties of these models to select the cluster head, then uses the closely located CH toward the sink as an intermediate CH to receive data from CHs positioned farther from the sink, and then performs routing. In this way, it distributes the energy usage load among the SNs, thereby enhancing the network lifespan and energy efficiency of the WSNs [7]. Another routing protocol is the ad hoc on-demand distance vector (AODV), designed for mobile ad hoc networks and operating reactively, meaning it responds only when needed. This concept conserves energy for wireless, limited-energy device systems, such as WSNs. This model also diminishes the routes and transmits signals—the AODV [9]. An energy-efficient routing protocol based on the genetic algorithm and predictive coding theory, which predicts whether transmission will occur, thereby reducing the number of transmissions and enhancing network energy efficiency and lifetime [10].

3. METHODOLOGY

3.1. Overview

The proposed model for this research leverages several AI techniques to reduce energy consumption, optimize routes, and prevent excessive or unbalanced energy consumption across the network.

To begin, we apply the k-means algorithm to cluster sensor nodes based on their spatial proximity or similarity. This step establishes the network's foundational structure and supports efficient organization. K-means is selected because it effectively partitions nodes into well-defined clusters, simplifying network management and intra-cluster communication.

Following the clustering phase, the PSO-mutation algorithm determines the cluster heads within each group. This algorithm is chosen for its strong optimization capabilities, enabling the selection of nodes with adequate residual energy and favorable positions. Optimizing cluster-head selection helps distribute energy consumption more evenly across the network and reduces the risk of early node depletion.

After identifying the cluster heads, the Golden Eagles algorithm selects the inter-cluster routing path. Inspired by the predatory behavior of golden eagles, has the potential to establish efficient and reliable routing paths. It enables smooth data transmission from sensor nodes to the base station while minimizing latency and reducing packet loss. Recent work surveying clustering-based routing in WSNs highlights the growing use of AI techniques — including fuzzy heuristics, metaheuristics, and machine learning — to design more adaptive and energy aware protocols[13].

Recent studies have demonstrated that hybrid bio-inspired optimization techniques can significantly enhance data transmission efficiency in clustered wireless sensor networks by simultaneously optimizing cluster formation and routing paths [14]. Another study used a modified Ant Colony Optimization approach to improve both energy efficiency and routing reliability in wireless sensor networks, demonstrating that bio-inspired algorithms can effectively balance energy consumption while maintaining high network performance [15].To assess performance, it simulated and evaluated the performance matrices of energy consumption, dead nodes, throughput, and delay. A comparison of the proposed model with benchmark models, Leach-CR and GA-PCT, was performed to validate its effectiveness [10]. The description of the algorithm, including the mathematical model and all details, is as follows.

3.2. Mathematical Model

Randomly deployed SNs are divided into clusters that sense data and transmit it to their respective CHs; a mathematical equation calculates the distance between each SN and its CH.

$$d_{nc} = min(\sum_{m=1}^{M} \sum_{m=1}^{M} d_{nhead}) \quad (1)$$

The above equation 1 demonstrates the **m** CHs and **n** SNs in the appropriate cluster, along with the $\mathbf{d_{nhead}}$ Euclidean distance between the SNs. Further, the CHs broadcast the data to the destination via other CHs in the designed model, equation 2 calculates that

$$d_{cs} = min(\sum_{m=1}^{M} d_{csink}) \quad (2)$$

Equation 2 shows the communication distance between the CHs and the destination through other CH in the system. Further, when a node or CH sends its data to the next destination, the following equation is used to compute it.

$$E_{cn}(t, d_{cn}) = \begin{cases} \mathrm{T}\left(E_{elec} * \left(E_f d_{cn}^2\right)\right), d_{cn} < d_o \\ t\left(\mathrm{E_{elec}} * \left(E_m d_{cn}^4\right)\right), d_{cn} \geq d_o \end{cases} \quad (3)$$

In equation 3, is energy consumption, *represents* the energy consumption of the amplifier, and & is for the Euclidean distance. $\mathbf{E_{elec}}$ energy consumption by CH to transmit data,$\mathbf{E_f} and \mathbf{E_m}$represents the amplifier energy of the signal, $\mathbf{d_{cn}^4}$means theEuclidean distance . Equation 4 computes the overall energy consumption.

$$\mathrm{E_{non_{cn}}}(\mathrm{t}, \mathrm{d_{cn}}) = \begin{cases} \mathrm{T}\left(E_{elec} * \left(E_f d_{cn}^2\right) + tEelec * tE_{elec}, d_{cn}^2\right), d_{cs} < d_o \\ t\left(\mathrm{E_{elec}} * \left(E_f d_{cn}^2\right) + tEelec * tE_{elec}, d_{cn}^2\right), d_{cs} \geq d_o \end{cases} \quad (4)$$

In addition, each CH, which receives the data from the other CH, allows the CHs to transmit data using the following equation

$$\mathrm{E_{cn}}(\mathrm{n}, \mathrm{d_{cn}}) = \mathbf{t}\mathrm{E_{elec}} * \left(\frac{\boldsymbol{N}}{\boldsymbol{M}} - \mathbf{1}\right) \quad (5)$$

In the equation, **M** represents the CHs and **N** represents the SNs in the cluster. Next is the overall energy computation in the designed model that uses the following equation

$$\text{energy } 1 = \begin{cases} \mathrm{MIN}\left(tEelec * \left(\frac{N+2}{M} + 1\right) + tEelec * \left(\frac{N}{M} + 1\right)\right), d_{cs} \\ min\left(tEelec * \left(\frac{N+2}{M} + 1\right) + tEelec * \left(\frac{N}{M} + 1\right)\right), d_{cs} \end{cases} \quad (6)$$

The system also considered energy 2, the energy expenditure of each cluster, based on the number of nodes, using the following equation that combines the number of nodes and the cluster ID to compute the number of nodes in the appropriate cluster and the energy consumed in that cluster.

$$\text{energy } 2 = \begin{cases} d_{no} = \dfrac{\sum_{i=0}^{m}(V_i - u)}{m} & (7) \\ d_{en} = \dfrac{\sum_{i=1}^{m}(E_i - Ue)^n}{m} & (8) \end{cases}$$

In equation 7, **vi** represents the number of SNs in the appropriate cluster, and u represents the average number of SNs in that cluster across the system. In equation 8, **Ei** represents the energy expenditure, and **Ue**use represents the average energy consumption of each cluster. Further, they argue concerning the mathematical model for link quality.

$$ETX\ (k, d) = \min \sum_{i=1}^{n} \sum_{j=1}^{k} \left(\dot{€}_e * n_i * d_{ij}^2\right) + \left(K - 1\right) * d_{jk}^2)(9)$$

In equation 9, the energy consumption constant($\mathbf{€_e}$), the number of nodes in each cluster ($\boldsymbol{ni}$), the distance between nodes within a cluster, the number of clusters ($\boldsymbol{K}$), and the estimated distance between cluster head nodes ($\mathbf{d_{jk}^2}$). The above equation demonstrates the link quality, which signifies the expected energy transmission **ETX**, which has the energy consumption, number of cluster members, intra-cluster distance, and number of clusters considered to compute that. Further, the system models a mathematical equation.

$$\sum_{j=1}^{k} d_j >= \alpha \quad (10)$$

$$\sum_{i=1}^{n} D_i \leq \beta \quad (11)$$

$$\sum_{j=1}^{k} E_{cn} + E_{no_i} + E_{en_j} \leq \gamma \quad (12)$$

$$\sum_{j=1}^{k} ETX_i \leq \delta \quad (13)$$

The equations demonstrated above represent the intra-cluster distance; Equation 10 demonstrates the alignment purpose and explains the cluster distance in the system. Equation 11 demonstrates the constraint that controls multiple cluster heads and the clustering of multiple head nodes within the clusters, while Equation 12 focuses on minimizing energy expenditure in the system. Equation 13 focuses on limiting the delay in data broadcasting in the system by ensuring on-time packet delivery. All the above equations represent the constraints on the system for achieving energy-efficient routing in WSNs.

3.3. K-Means Algorithm

K-means was selected as the clustering technique in this study because it remains one of the most lightweight and computationally economical algorithms available—an important consideration in Wireless Sensor Networks, where processing power and energy are limited. Unlike more complex approaches such as hierarchical clustering, density-based algorithms, or fuzzy clustering, K-means operates with minimal overhead and reaches stable partitions quickly. Its efficiency and predictable behavior make it well suited for large-scale node deployments, where rapid grouping based on spatial or similarity metrics is required.Below is the pseudo-code for the K-means clustering algorithm adopted in this model.

Algorithm 1: K-means clustering
Input : Randomly deployed SNs of WSNs
Output: Clustered network
1. Initialization with random nodes
2. Define numbers of centroids
3. Loop of centroids
for i to n # max numbers of SNs
4. Computing distance nodes to centroids
N_C(i)=min(N_{Dist})
5. C_A(k) = N_C(i)
6. Assign k to nearest C
7. Update C
8. End process

3.4. Pso Mutation

The next phase of cluster head selection uses the PSO mutation algorithm, which is inspired conceptually by birds' forgiving behaviour. It enables each particle to evaluate the potential positions of other particles by adjusting its speed and position in response to local and global interactions with them. The wireless sensor network chose the CH node with the highest potential. The equation below updates the position and velocity in each movement, serving this purpose.

$$V_t(i+1) = wV_t + C_1R_1\left(P_{best} - X_t(i) + C_2R_2\left(G_{best} - X_t(i)\right)\right) \quad (15)$$

$$X_t(i+1) = X_t(i) + V_t(i+1) \quad (16)$$

The above equation updates the particle's position; the particle swarm optimization algorithm updates the velocity based on the current position, computed using the velocity updating equation above. The particle's movement is based on these updated values and considered the global best position for the best solution.

$$T_{val} = \frac{1}{\mu}(1 - maxgen^{-1}) \quad (17)$$

$$N_{x^t} = T_{val} * (X_{max-1} - X_{min-1}) \quad (18)$$

$$T_{bt} = X_t - N_{x_t} \quad (19)$$
$$U_{bt} = X_t - N_{x_t} \quad (20)$$

These equations threshold-based mutation in the hybrid designed algorithm, and then it computes the position within the search space by ensuring they stay within allowed limits based on the mutation factor and position range because of attaining the improvements in the solution. The pseudo-code for particle swarm optimization is shown here.

Algorithm 2: Particle swarm optimization –Mutation for CH selection
Input : Clustered network **Output**: Cluster heads **1.** Initialization with clustered network **2.** For j=1 to m # max iterations **3.** Velocity updation for each particle $V_t(i+1) = wV_t + C_1R_1\left(P_{best} - X_t(i) + C_2R_2\left(G_{best} - X_t(i)\right)\right)$ **4.** Particles positions $X_t(i+1) = X_t(i) + V_t(i+1)$ **5.** Fitness Evaluation process If $N_{RE} > N_{EO} / 2$ # until half energy consumed Else N_{Dist} / N_{RE} **6.** Update the personal best If $C_F > P_{Best\_}$ **7.** Update the Global best If $C_F > G_{BF}$ **8.** Repeat process upto maximum numbers of iterations **9.** End Process

3.5. Golden Eagle Optimization

After these, the next step in data communication is to use the golden eagle optimization algorithm to select hops among the CHs toward the BS. The golden eagle's hunting behaviour inspires the concept of the golden eagle, balancing the exploitation and exploration phases to locate the best solution. Golden eagles adjust their speeds dynamically during the search phase and cruise to spot potential prey. In the attack phase, they target the prey with focused precision. The mathematical module, Golden Eagle Optimization algorithm, focuses on finding new solutions while refining promising ones. The fitness function equation for the algorithm

$$F_f(D_i, E_i) = D_i \quad (21)$$

Used for the SN energy and communication gap to determine the efficiency. The memory stores each golden eagle's distance to the BS to make the following hope selection process in the designed algorithm. In contrast, each iteration's memory for storing information as shown in the equation

$$M_{ij} = CH_{d_{bs}}(P_s, 1) \quad (22)$$

Based on the equation, design the memory and update the information for each golden eagle. Moreover, the next hope is selected based on the highest values in the memory; for this reason, this equation is used

$$Cn(E_I \cdot D_{ij}) = \{i \mid M_{ij} = max(Cn(E_I \cdot D_{ij}))\} (23)$$

That potential is enough to balance energy expenditure across the selected SNs and extend the cluster head's impact on the overall system. The main goal of the study is to develop a more advanced model that addresses issues in previous models, such as uneven energy expenditure and excess energy consumption. Uneven and excessive energy consumption may lead to earlier depletion of sensor nodes and compromise the overall performance of other critical data-based systems. This study uses a clustering approach, which is very helpful for equalizing the energy dimension, reducing the risk of early node depletion, and improving performance. By strategically selecting routes to balance energy usage, we aim to enhance energy efficiency, minimize delays, and boost data transfer speeds in Wireless Sensor Networks. The figure below shows the system architecture, indicating that the system model is more effective.

Algorithm 3:Golden Eagle Algorithm
Input : cluster heads **Output** : Next Hope Population Initialization of Golden Eagle (CHs) $P_{Size}= T_{CHs}$ *Initilization memory to Golden Eagles* $M_{Mem}= Rand(P_{Size,}1)$ *Fitness Function* $F(i) = N_{Dist} / N_{RE}$ *For r to m # iteration loop* *Fitness evaluation for each Golden Eagle (CH)* *For i to m* $C_{Fit} = N_{Dist}$ *Memory Updation* *If* $C_{Fit<}M_{MEM}$ *(i)* , M_{MEM} *(i)=* C_{Fit} *Position Updation* $P_{Pop} = R_{and} (P_{Size}, CHs)$ *Next Hope selection* $N_{Hope} = min(M_{Mem})$ *Reciever Nodes selection* $N_{Reciever} = N_{Hope}$ *Process repeats as of maximum iteration* *Return the Next hope* *End Process*

The decision to pair GEO with a PSO-based mutation strategy arises from the need to improve the optimizer's balance between global exploration and local refinement. Although GEO is effective at searching broadly within the solution space, it can struggle when faced with highly nonlinear routing environments, occasionally slowing down or converging prematurely. Introducing a mutation mechanism inspired by PSO injects controlled diversity into the population, helping the algorithm escape suboptimal regions and improving its overall convergence speed. This enhancement reduces unnecessary computational repetition and strengthens the stability of the optimization process.

Compared with other hybrid metaheuristic—such as PSO combined with genetic algorithms, firefly-PSO models, or differential evolution paired with swarm intelligence methods—the proposed trio (K-means, PSO-Mutation, and GEO) distributes the computational workload more efficiently. K-means provides fast initial clustering, the mutation layer refines local search adaptively, and GEO manages the broader optimization. This coordinated design leads to improved energy distribution and routing performance while keeping the computational cost appropriate for WSN constraints.

4. SIMULATION

To evaluate the performance of the performance model and the baseline model, and their comparison, we have performed MATLAB simulations. With the uniform performance parameters, these are the performance values you see in the table below. The simulation parameters in Table 1 are uniform across the proposed and baseline models.

The initial energy of 10 J per node reflects typical medium-capacity sensor hardware modeled in many benchmark studies, where initial energies commonly range from 0.5 J to 10 J depending on the intended network lifespan and node capabilities. Using 10 J enables a realistic evaluation of energy-aware routing protocols under extended operation. Similarly, parameters such as node density, packet size, and communication range remain consistent with established simulation standards. To ensure that the proposed approach is not dependent on a specific parameter set, a sensitivity analysis of key variables, including node density and packet size, is conducted to assess their impact on performance.

The results confirm that the proposed method maintains robust energy efficiency and network stability across a range of parameters.

Parameter	**Values**
Simulation tool	Matlab
Network area	100x100
Nodes initial energy	0.5 joules
Packet size	4000
Total nodes	100
Etx(Transferring circuitry)	50x0.000000001
Erx(receiving circuitry)	50x0.000000001
Efs(amplify signal)	10x0.000000000001
Eamp (amplifying circuitry)	0.0013x0.000000000001
Data fusion Energy	5x0.000000001
Location of the base station	(50,50)
Data fusion ratio	0.7
Node mobility	fixed

Table 1. Parameters and values

4.1. Total Energy Consumption

Energy consumption is a critical key performance metric for an energy-efficient routing protocol, as it measures the energy consumed during transmission. To assess the performance of the energy-efficient routing protocol, energy consumption is calculated over the network's lifetime, which is defined by the number of rounds. The model is used to determine the total energy consumed over the number of rounds, illustrating the energy consumption of the sensor nodes in the network. As shown in the graph, the results for the 50- and 100-SN scenarios. These are the two subplots that compare the separate results for each scenario. Subplot II extends this analysis to a network configuration with 100 sensor nodes. Each subplot shows two distinct lines: blue representing the new model (Golden Eagle) and red depicting the LEACH-CR model. In the first subplot, marked as (I), the comparison of the new model to the leach-CR modeling of a randomly organized network with a central.

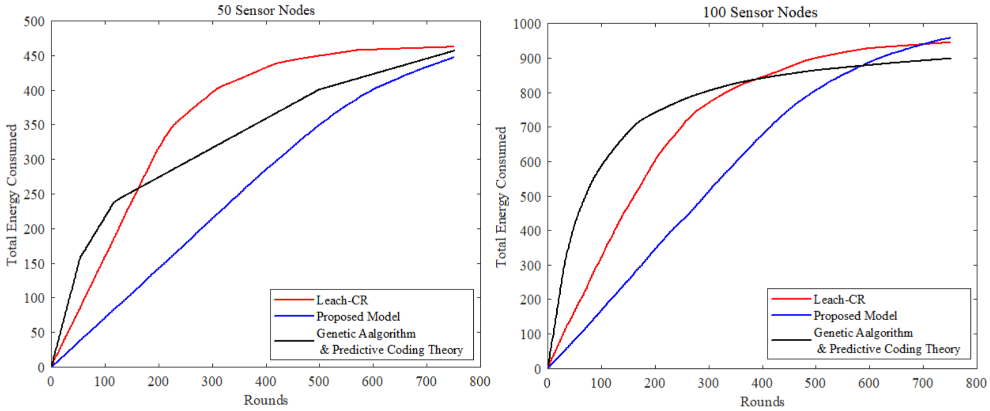

Fig1. Total energy consumption

Fig. 2 illustrates the total energy consumption for the 50 & 100 SNs scenario with 375 rounds, indicating the network's half-life. With 50 SN, consume less energy than benchmark models. At half-time, it shows 57%- 30% improvements, then Leach-CR and GA-PCT. In the overall scenario, it shows a 5-10% increase. Moreover, it achieves 30 % efficiency compared to benchmark models. Over the whole 750-round time, it shows a 10 percent improvement.

These outcomes demonstrate effective utilization of available energy resources for a proposed declarative routine protocol and benchmark models.

4.2. Dead Nodes

The ratio of dead nodes to the total number of rounds refers to the number of nodes that die when they run out of energy resources. Once a node dies, it becomes non-functional in the operation, such as data sensing and transmission, which affects effective routing and performance optimization. The proposed model aims to increase the first-node depletion time in the system and reduce the number of dead nodes per routing, thereby demonstrating the network's effectiveness. Through simulation, we optimized our results, as shown in the figure for the proposed model versus the Leach-CR and GA-PCT models.

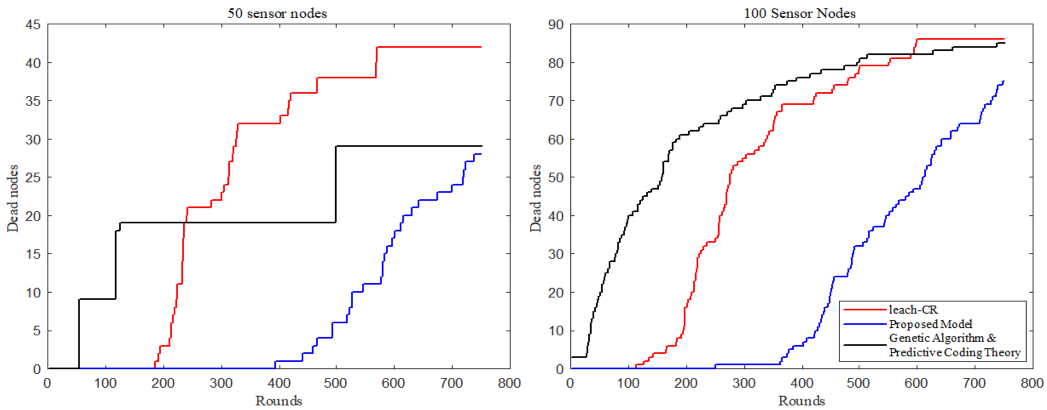

Figure 2.Numbers of dead nodes results

Fig. 3 shows the results of the proposed node-based scenarios. -In the 50 and 100-node scenarios, it outperforms the benchmark models by more than 100 percent in terms of the first node depletion and half of the nodes depletion time, which is absolutely fine. The proposed model is more efficient for broadcasting real-time traffic and critical data and is more scalable for larger networks, offering better performance.

4.3. Throughput

Throughput in WSNs represents the total number of packets transmitted from network SNs to the BS as a function of the number of rounds. Each round is based on the complete data sensing and communication process until it reaches the B. The study enhances the network's lifetime by improving throughput with available resources. We have performed a simulation, and throughput-based results are computed to judge the performance of the proposed model against the

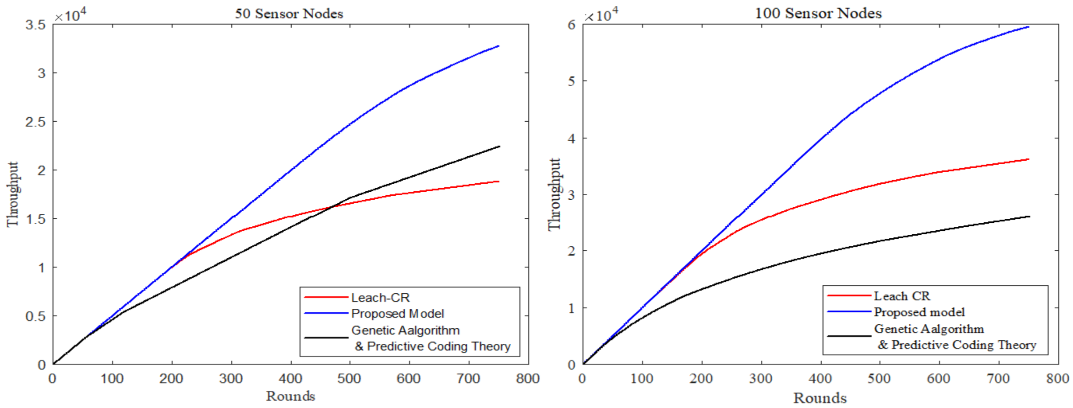

Figure 3.Cumulative throughput

Fig. 4 shows the simulation results for 50 and 100 nodes, where the 50-node PR method achieves a 72-45% improvement. In the scenario of 100 sensor nodes, it gains a percentage improvement of 64-128%. Improvements stated that the proposed model is significantly more robust and scalable for large-scale applications; however, it is also suitable for all types of environments.

4.4. Average Delay

Delay is critical for the network, particularly in systems with limited energy constraints. The proposed model also addresses these issues by reducing the network's average delay. Simulation to assess the average delay of the network with variations in the SNs in WSNs. The figure illustrates the results from the simulation below.

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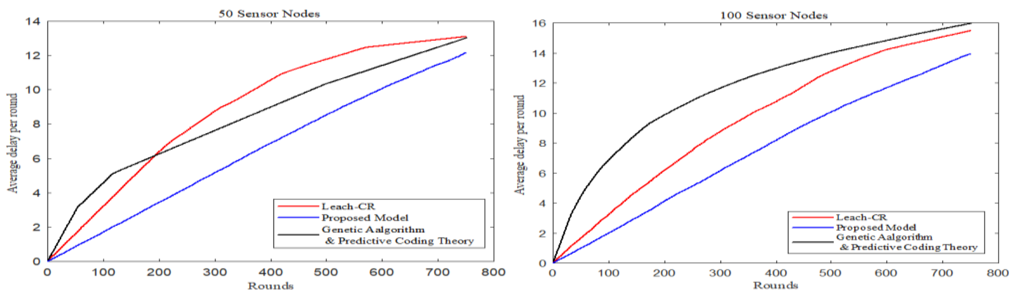

Figure 4: delay of the WSNs

In Fig. 5, the Results show the proposed model with baseline modes in terms of network delay. The 50- and 100-sensor-based results for the proposed model over the Leach-CR and GA-PCT models show a 34-6% improvement. In the 100 SNs nodes scenario, delays shows 36-12% in half and complete rounds, respectively. With more rounds, the network delay remains more efficient than that of baseline models.

Furthermore, the statistical significance and confidence intervals of the multiple-time simulation tests remain above 95 percent, indicating that the proposed model is highly potentiated and performs consistently more efficiently than the baseline model. To conclude, the proposed model demonstrates significant improvement over the benchmarked models for all energy consumption and network lifetime, as well as throughput and delay, and is also suitable for large-scale networks, offering high-quality performance.

4.5. Statistical Validation And Component Contribution Analysis

In simulations, the proposed model results indicate improvements in energy efficiency, throughput, and delay; their statistical significance remains perfect. To ensure the reliability of these performance gains, future simulations will incorporate confidence intervals and statistical testing across multiple runs. It will confirm that the improvements observed are consistent and that there is no serious confidence interval in the simulation outcomes.

Additionally, to better understand the source of these gains, it is essential to examine the contribution of each algorithmic component. The K-means clustering forms compact and cohesive clusters, which reduces intra-cluster communication energy. The PSO-Mutation algorithm optimizes the selection of cluster heads, ensuring that nodes with sufficient energy and favorable positions are chosen, thereby balancing energy usage and prolonging network lifetime. The Golden Eagles Optimization algorithm improves routing paths between cluster heads, enhancing throughput and reducing delay. Conducting an ablation-style analysis, an independent assessment of components, would provide further insight into the specific role and effectiveness of each algorithm in the overall hybrid model.

5. CONCLUSIONS

This study proposes a novel energy-efficient routing protocol for the lingering energy challenge in WSNs, leveraging advanced artificial intelligence techniques. This model performs clustering using the K-means algorithm to select CHs, applies PSO mutation, and optimizes the route among CHs. It uses the golden eagle. The proposed model's assessed performance in terms of total energy consumption, the number of dead nodes, throughput, and delay, as a function of the number of rounds. The proposed model demonstrates with 50-100 nodes scenario, in sense of total energy consumption performance enhanced 57-30% & 30-30%, dead nodes improve performance for first node depletion 100%, for throughput 72-45& 64-128 %, and for delay it shows 34-6 & 36-12% percent improvement against Leach-CR and GA-PCT models. In both scenarios, a higher number of nodes is more efficient than fewer rounds. However, the proposed model is significantly more efficient than the baseline model, including a large-scale network, demonstrating its scalability and improving energy efficiency and network lifetime.

6. FUTURE WORK

In the future, this research can be further extendable by applying data compression techniques to conserve additional energy resources. Additionally, this algorithm supports massive device connectivity. Moreover, this study can identify abnormal energy consumption patterns and optimize routing accordingly.

REFERENCES

[1] R. Gantassi, B. Ben Gouissem, and A. Ajoudani, “Optimizing quality of service of clustering protocols in large-scale wireless sensor networks with mobile data collector and machine learning,” in *Proc. Security and Privacy in Wireless and Mobile Networks*, Wiley, 2021.

[2] X. Zhao, S. Ren, H. Quan, and Q. Gao, “Routing protocol for heterogeneous wireless sensor networks based on a modified grey wolf optimizer,” *Sensors*, vol. 20, no. 10, pp. 1–20, 2020.

[3] M. Al-Shalabi, M. Anbar, T. C. Wan, and Z. Alqattan, “Energy efficient multi-hop path in wireless sensor networks using an enhanced genetic algorithm,” *Information Sciences*, vol. 484, pp. 162–182, 2019.

[4] N. A. Al-Aboody and H. S. Al-Raweshidy, “Grey wolf optimization-based energy-efficient routing protocol for heterogeneous wireless sensor networks,” in *Proc. 4th Int. Conf. Computer and Communication Engineering (ICCCE)*, Kuala Lumpur, Malaysia, pp. 72–77, 2016.

[5] P. Kuila, S. K. Gupta, and P. K. Jana, “A novel evolutionary approach for load-balanced clustering problem for wireless sensor networks,” in *Proc. Swarm and Evolutionary Computation Conf.*, Elsevier, 2013.

[6] Y. Liang and Y. Li, “An efficient and robust data compression algorithm in wireless sensor networks,” *IEEE Communications Letters*, vol. 18, no. 7, pp. 1234–1237, 2014.

[7] N. M. Zamry, A. Zainal, and M. A. Rassam, “LEACH-CR: Energy-saving hierarchical network protocol for wireless sensor networks,” in *Proc. 3rd Int. Conf. Computer and Communication Engineering (ICCCE)*, 2021.

[8] M. Z. Ghawy, G. A. Amran, and H. AlSalman, “An effective wireless sensor network routing protocol based on particle swarm optimization algorithm,” in *Proc. Wireless Communications and Networking Conf.*, Wiley, 2022.

[9] S. K. Gupta, P. Kuila, and P. K. Jana, “GAR: An energy efficient GA-based routing for wireless sensor networks,” in *Proc. 9th Int. Conf. Distributed Computing and Internet Technology (ICDCIT)*, Bhubaneswar, India, pp. 293–298, 2013.

[10] B. Oveisi, “Optimizing energy efficiency and prolonging lifetime in WSNs using the genetic algorithm and predictive coding approach,” M.A.Sc. thesis, Dept. Elect. Eng., École de Technologie Supérieure, Univ. Québec, Montreal, QC, Canada, Dec. 2023.

[11] Zhang S, Liu X, Trik M. Energy efficient multi hop clustering using Artificial Bee Colony metaheuristic in WSN. Sci Rep. 2025 Jul 23;15(1):26803. doi: 10.1038/s41598-025-12321-y. PMID: 40702073; PMCID: PMC12287403.

[12] Kaur, Kirandeep, and Satinder Kaur. "HYBRID BIO INSPIRED OPTIMIZATION BASED ROUTING PROTOCOL FOR ENHANCING DATA TRANSMISSION IN CLUSTERED NETWORK." Array (2025): 100481.

[13] Shokouhifar, Mohammad, et al. "AI-driven cluster-based routing protocols in WSNs: A survey of fuzzy heuristics, metaheuristics, and machine learning models." Computer Science Review 54 (2024): 100684.

[14] Kaur, Kirandeep, and Satinder Kaur. "HYBRID BIO INSPIRED OPTIMIZATION BASED ROUTING PROTOCOL FOR ENHANCING DATA TRANSMISSION IN CLUSTERED NETWORK." Array (2025).

[15] Tawfeek, Medhat A., et al. "Improving energy efficiency and routing reliability in wireless sensor networks using modified ant colony optimization." EURASIP Journal on Wireless Communications and Networking 2025.1 (2025)

AUTHORS

Amirmasoud Soltanzadeh: graduate student in Telecommunication Engineering at École de technologie supérieure (ÉTS) in Montréal, Canada. His research interests include wireless communication systems, network performance, and data transmission optimization.

Zbigniew.Dziong Professor Zbigniew Dziong is a faculty member in the Department of Electrical Engineering at École de technologie supérieure (ÉTS), Montréal, Canada. His research areas include wireless networks, telecommunication systems, network optimization, and performance analysis. He has extensive academic and industry experience and has published numerous works in the field