International Journal of Computer and Engineering Optimization (IJCEO)
Volume 3, Issue 1, January – February (2025)

RESEARCH ARTICLE

HO–WO Hybrid optimization for Improving Energy Efficiency and Extending Network Lifetime in Wireless Sensor Networks

Buchhi Ramakantha Reddy [1, *], Nithya Rekha Sivakumar [2]

[1] Associate Professor, Department of Computer Science and Engineering, Sri Venkateswara college of engineering, JNTU Anantapur, Tirupati, Andhra Pradesh, India

[2] Department of Computer Sciences, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia

*Corresponding e-mail: ramakanthareddy@gmail.com

Abstract – A Wireless Sensor Network (WSN) is a collection of interconnected sensor nodes that communicate wireless to gather information from their environment. However, the existing technique has high delay, low network lifetime and energy consumption. To address these issues, a novel HO–WO Hybrid Optimization for Improving Energy Efficiency and Extending Network Lifetime in Wireless Sensor Networks (HWEL). Initially, C Means clustering is employed in the proposed framework to improve cluster formation. The hippopotamus optimization algorithm (HO) provides an effective way for cluster head selection based on node degree, distance and residual energy. Consequently, the wombat optimization algorithm (WO) is utilized to find a routing path between the source and the destination over the cluster head. The proposed model was compared to existing techniques on energy consumption, throughput, Alive Node, delay and network lifetime are used. The proposed HWEL achieves the higher network lifetime by 95.8% for proposed and 48.17 %, 39.17 % and 20.25% than the LEACH, EBPT-CRA and LCPSO-CRP approaches.

Keywords *– Wireless Sensor Network, Clustering, Hippopotamus Optimization, Wombat Optimization, cluster head selection and routing.*

1. INTRODUCTION

Wireless Sensor Network (WSN) is an interconnected sensor nodes that can connect and communicate with one another to collect and transmit data from their surroundings. WSNs are a key data collecting technology for the Internet of Things (IoT), with several applications including environmental monitoring, target tracking, intelligent transportation and healthcare [1]. WSNs are employed in many security-related applications, such as environmental monitoring, traffic monitoring, smart office settings and battlefield monitoring. Sensors maintain to monitor variables which are processed in the microcontroller and sent to the ground station using the communication unit. Data can be sent directly or through network that relay signals [2]. When a communication protocol is implemented and nodes are assigned to receive or send data depending on the protocol's administration, it will be hard to predict how security features will be implemented in the network. [3].

Sensor nodes collect environmental data and use multicast communication to transmit data to the base station (BS) or sink. Sensor nodes have limited battery life, processing resources, and memory for transmitting and detecting environmental data [4]. Sensor nodes are the basic building components of Wireless Sensor Networks (WSN). The WSN network can only be expanded by adding new sensor nodes, or by adding other sensors or devices to the WSN system. The initial setup of sensor nodes is critical to establishing the network. It should provide wider coverage and link all networks [5]. Sensor nodes include microcontrollers in their circuits to carry out simple tasks using the information that is gathered before sending the semi-processed data to the data center, or simply to another node responsible for processing the data and performing analytics. A single sensor may not have much power, but the combination of hundreds of little sensors creates new possibilities [6].

Routing protocols have emerged as viable options these protocols group nodes into clusters, with a Cluster Head (CH) and Cluster Members (CMs). CHs, as opposed to traditional CMs, are responsible for data receipt, compilation, and transfer, as well as information sensing and transmission. Also, Routing in WSNs involves balancing local energy awareness and global route efficiency [7]. Multi-path routing helps to discover the best route to reduce the energy consumption of sensor nodes. Routing protocols employed in mobile ad hoc networks, such as AODV (Ad Hoc On-Demand Distance Vector) and DSR (Dynamic Source Routing), may not be applicable for WSNs due to resource limitations and their ever-changing topology. Conventional routing approaches may have difficulties maintaining scalability due to increased control message expenses, bigger routing table sizes, and higher latency [8].

Intelligent reflecting surfaces (IRSs) provide a viable solution for real-time reconfigurable propagation settings, improving transmission rates and increasing user capacity. The IRS-assisted communication enhances the usability of the traditional wireless communication systems [9] by optimizing multiple network parameters while finding a balance between exploration and exploitation to efficiently observe different trade-offs. This enhancement is vital for achieving rival objectives [10].

- The primary objective of the work is developed a HO–WO Hybrid optimization for Improving Energy Efficiency and Extending Network Lifetime in Wireless Sensor Networks.
- C means clustering is used to improve cluster formation.
- Hippopotamus optimization which provides an effective way for selecting cluster head selection based on node degree, distance, and residual energy.
- wombat optimization algorithm is utilized for routing path between the source and the destination.
- The proposed model was compared to existing techniques on energy consumption, throughput, Alive Node, delay and network lifetime are used.

The remaining portion of the work has been followed by section 2 which contains the literature review of the work, section 3 which shows the proposed methodology, section 4 which displays the result and discussion, and section 5 which explains the conclusion of the future works.

2. LITERATURE SURVEY

Recently, a lot of research has been done to address the problem of power consumption in WSNs. This section explains the most recent routing and clustering strategies used in WSNs.

In 2023, Fan et al. [14] proposed a LEACH-based clustering algorithm enables water quality monitoring in locations with varying levels of contamination. The LEACH protocol has gained popularity due to its simplicity, scalability, and capability of prolonging the network lifetime. The utilization of K-means clustering improves the efficiency of decisions in the context of water quality monitoring applications.

In 2025, Zhang et al. [15] proposed Energy-Efficient Multi-Hop LEACH protocol for WSN that incorporates Artificial Bee Colony (ABC) clustering and routing. Simulation results for several different cases, including centralized, edge, and corner base station placements, demonstrate that the proposed protocol is more energy efficient than existing approaches, such as MHCRP and SBOA. Furthermore, it improves First Node Death (FND) by 216%, and achieves a 29% increase in packets delivered to the base station.

In 2023, Hosseinzadeh, M., [16] proposed a cluster-based trusted routing solution with fire hawk optimizer (CTRF), enhances network security with the value of limited energy value of nodes in the WSN. The primary aspect of this trust mechanism relies on the use of exponential coefficients, reception rate, redundancy rate, and energy state, in order to reduce the trust level of sensor nodes based on hostile or friendly behaviors. In this study we propose to compare the performance of two secure routing systems for their energy, throughput, packet loss rate, delay, detection ratio, and accuracy.

In 2025, Rahmani et al. [17] proposed Gray Wolf and Fuzzy Clustering with Critique and Fuzzy Viktor methods (GWFCCV) is a new routing method based on WSN for IoT networks. Cluster-based approaches are key to the network, expanding network life and efficiency through reduced energy use. The suggested method extends the network lifetime by 5.43%, 8.3%, and 23.26%, respectively, depending on the circumstances.

In 2025 Fan, B.et al.,[18] suggested energy-balanced path tree-based clustering and routing algorithm (EBPT-CRA) for large-scale WSNs. the energy balanced path tree (EBPT) structure is built, and we assess the aggregation relationships amongst nodes, together with competition coefficients of potential cluster heads. According to simulation results, EBPT-CRA can more efficiently sustain and balance energies of the nodes, while enhancing both the network's lifetime, throughput, and service capacity across larger WSNs.

In 2025, Ridwan, M., et al.,[19] suggested Adaptive Grid-Based LEACH clustering approach is based on dynamic grid partitioning to enhance cluster formation for CHs concerned with transferring data. Classic clustering protocols such as LEACH often experience challenges related to unequal energy consumption and transmission of data, which can lead to failures in network performance. AG-LEACH employs adaptive grid size, and adaptive cluster head selection based on changing node energy and changing network structure. The results show that Ag-LEACH outperforms the outcome protocols in many ways such as power, data rates, and dropping packets.

In 2024 Luo, T., al.,[20] suggested levy chaos-based particle swarm optimization routing protocol (LCPSO-CRP) in Industrial Wireless Sensor Networks (IWSNs) can increase the lifetime of the system. Sensor nodes have limited energy and existence, thus developing an efficient routing protocol can be a substantial challenge. Cluster routing is an effective way to reduce energy consumption in the network, thus extending its lifespan. The results of our experiments indicate that LCPSO-CRP is able to decrease energy consumption, relative to typical cluster routing protocols such as LEACH, LEACH-C, SEP, DEEC, and LEACH-kmeans by at least 22.91%, while increasing the lifespan of the IWSN network by at least 13.93%.

To optimize multiple networks there is a challenge in designing an algorithm that can efficiently search for Pareto optimal solutions in high-dimensional solution spaces, considering the conflicting objectives and resource constraints. the problem is that these existing reviews often rely on simulation-based or theoretical solutions that may not address real-world challenges effectively. Using the Extreme Learning Machine (ELM) for real time event detection becomes a problem since with increasing occurrences of updates for different patterns in the agricultural data, the process becomes a tedious and time-consuming process since it involves retraining the model every time it is fed with new information which increases the rate of power consumption due to the computational requirement. To overcome this issue, HO–WO Hybrid Optimization for Improving Energy Efficiency and Extending Network Lifetime in Wireless Sensor Networks (HWEL) has been proposed.

3. PROPOSED METHODOLOGY

In this section, a novel HO–WO Hybrid Optimization for Improving Energy Efficiency and Extending Network Lifetime in Wireless Sensor Networks (HWEL) has been proposed. Initially, sensor nodes are first grouped into clusters. C Means clustering is used to improve cluster formation. Next, the hippopotamus optimization (HO) algorithm is introduced as an effective method for selecting cluster heads based on node degree, distance and residual energy. Then wombat optimization (WO) algorithm is utilized to routing path between source and the destination across the cluster head selection. Figure 1 shows the proposed methodology.

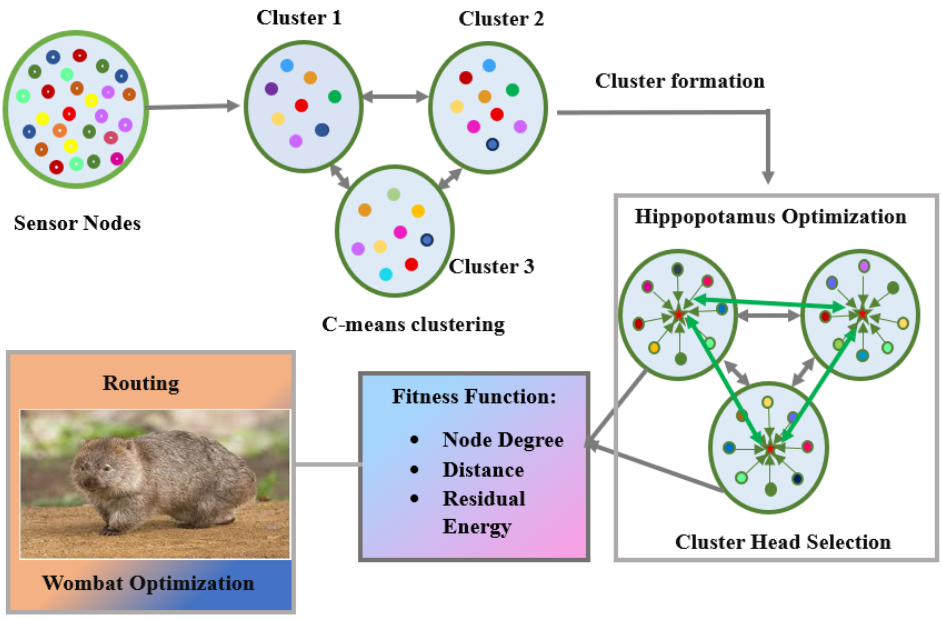

Figure 1. Proposed Methodology

3.1 Cluster Formation via C-means Clustering

In this section, c-means clustering is used for cluster formation. C-means clustering is a type of unsupervised machine learning algorithm that separates data points into C different groups based on the features. For single-view data, one of the most well-known types of clustering algorithms is C-means algorithm. There is a need for an algorithm that can handle all of these concerns and automatically choose the best number of clusters when clustering multi view data.

$$M_{FCJ}(V,U) = \sum_{i=1}^{n} \sum_{i=1}^{C} V_{JI}^{A} \left\| Y_J - U_I \right\| \tag{1}$$

$$\text{T.s} \sum_{i=1}^{n} v_{ji} =1, i=1,\ldots,N \tag{2}$$

FCM can only assign one sample to an imprecise cluster, it is difficult to produce appropriate results for some samples that overlap between several clusters.

$$J_{MCN^{T,I,K,U)}} = \sum_{J=1}^{N} \sum_{I=1}^{C} \{\varpi_1 T_{ij}\} \| Y_J - U_I \| \, 2 \tag{3}$$

$$\text{T.s} \sum_{i=1}^{n} T_{ij+y_{j+k_j}} =1, 0 < T_{ji}, Y_J K_I \ < 1 \tag{4}$$

J_{MCN} is the inaccurate cluster center for y_j, and δ is a parameter to detect outliers. The weight factors are $\varpi 1$, $\varpi 1$, and $\varpi 3$; β is the same as MCN. N

$$u_i = \frac{\sum_{J=1}^{n} (\varpi_1 K_{ji}) \ y_j}{\sum_{J=0}^{n} (\varpi_1 K_{ji})} \tag{5}$$

The support degree of Y_i to the accurate cluster is represented by y_j , whereas the support degree of y_j. The support degree of y_(i) to outliers is shown by k_{ji} .

3.2 Hippopotamus optimization algorithm

In this section Hippopotamus optimization (HO) is used for cluster head selection (CHs). The HO is a population-based optimization strategy that makes use of hippos as search agents. Hippopotamuses are prospective solutions to the HO technique's optimization problem. Therefore, the updated search space positions correlate to decision variable values. During the beginning stage of HO, solutions are started at random, just like in traditional optimization methods.

Phase 1: initialization phase: in initialization phase Each position of a hippopotamus in the search space is linked to the values of the decision variables. Each hippopotamus is defined as a vector, and thus, the hippopotamus population can also be defined as a matrix. With most optimization algorithms, the initialization step for HO consists of producing random initial solutions.

$Z_j: z_{ji} = u\ell_i + n.(bu_i - u\ell_i), j = 0,2,\ldots,\gamma, i = 0,2,\ldots,m$ (1)

Where z_j is the location of i th candidate solution, n denote as random number between 0 and 2, then $u\ell$ and bu indicate upper and lower bounds of the i th decision variable

$$Y = \begin{bmatrix} Y1 \\ \vdots \\ Yi \\ \vdots \\ Y\mathcal{N} \end{bmatrix}_{m\times n} = \begin{bmatrix} y1,1 & \ldots & \ell1,_j & \ldots & y1,m \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ yi,1 & \cdots & yi,_j & \cdots & yi,m \\ \vdots & & \vdots & & \vdots \\ y\mathcal{N},1 & \cdots & y\mathcal{N},_j & \cdots & y\mathcal{N},m \end{bmatrix} \quad (2)$$

Phase 2: Exploration phase: in exploration phase hippopotamuses position update in the pond or river. Hippopotamus has multiple adult females, calves, numerous adult males, and dominant males make up a herd of hippopotamuses. The male hippopotamuses are surrounded by several female hippo. The male hippo includes the other males from the group once they grow adulthood.

$$yj^{\mathcal{N}hippo}: y_{ij}^{\mathcal{N}hippo} = y_{ji} + x1.(Ahippo\_\mathcal{H}1_{yj}) \quad (3)$$

$$\mathcal{F}or j = 0,2,\ldots,\left[\frac{\mathcal{N}}{2}\right] and_i = 0,2,\ldots,m \quad (4)$$

The male hippopotamus position is represented by y_j^{nhippo}, while the dominant hippopotamus position is indicated by A^{hippo} . From 0 to 2, $\rightarrow h$ 0….4 is a random vector, and $h5$ is a random integer.

$$h = \begin{cases} H_2 \times \overrightarrow{h_1} + (\sim\varrho_1) \\ 2 \times \overrightarrow{h_2} - 1 \\ \overrightarrow{h_3} \\ H_1 \times \overrightarrow{h_4} + (\sim\varrho_2) \\ h_5 \end{cases} \quad (5)$$

Illustrate the location of a female or young hippopotamus among the group $Y_i^{\mathcal{F}Bhippo}$ Most young hippopotamuses stay close to their mothers; however, the age of curiosity may take the young hippo away from the mother or the group. If T > 0.5, the young hippo has separated from its mom or in the group.

$$Y_i^{\mathcal{F}Bhippo}: Y_{ij}^{hippo} = \{Y_{ij} + h1.(A^{hippo} -. H_2MG,)T > 0.5 \quad (6)$$

Using h vectors, the H1 and H2 conditions improve the methods global search and exploratory phases; the global search is improved and the exploration phase is enhanced in the suggested method.

$$for_i = 0,2,\ldots,\left[\frac{\mathcal{N}}{2}\right] and_j = 0,2,\ldots,m, \quad (7)$$

Phase 2: Exploitation phase: in exploitation phase Hippopotamus Escape from Predator Action by another hippopotamus - A hippo escapes from a predator action when it is facing a group of predators or cannot repel a predator through protective behavior. In this case, the hippopotamus is trying to leave the area.

$$Y_{ij}^{\mathcal{B}hippo}: Y_{ij}^{\mathcal{B}hippo} = x_{ij} + k_{10}\left(\ell m_i^{local} + \left(bm_i^{local} - \ell m_i^{local}\right)\right) \quad (8)$$

$$j = 1,2\ldots,\mathcal{N}, i = 1,2\ldots,m \quad (9)$$

E_j^{hippo} represents the starting point of the hippopotamus, which we looked to establish the nearest safe spot. y_j a random vector or integer taken from three situations y_j.

$$y_j = \begin{cases} y_j^{hippo} \; E_j^{hippo} < y_j \\ y_j E_j^{hippo} \geq y_j \end{cases} \quad (10)$$

When updating the population using the HO algorithm, we did not distinguish between immature, female, and male hippopotamus by creating three separate hippopotamus categories, although it would provide a better modeling of their nature, it would determine the optimization algorithm's performance.

3.2.1 Fitness Function

The fitness value is set to CH, which considers the degree of CH, energy, and distance from conventional nodes. As shown in (18), the fitness value is calculated.

$$\text{fitness(i)} = M1\frac{E_{res-i}}{E_0} + M2\left(1 - \frac{degree_i}{N}\right) + M3\left(1 - \frac{d_{to\_i}}{d_{to\_Bs}}\right)$$

The weight variables are M1, M2, and M3, which add up to 1. N represents the total number of sensor nodes, E_{res-i} represents the RE of CH_i , E_0represents the starting energy ofCH_i, represents the distance from ordinary nodes toCH_i, and d_{to_Bs} represents the distance from ordinary nodes to B_s.

Node Degree

Node degree refers to the number of connections between nodes and may be used in a variety of fitness functions. For example, the fitness function can employ the degree's dynamic attitude, or it can serve as a foundation for defining a node's intrinsic fitness, which remains constant over time but effects its capacity to attract future linkages.

Distance

Distance metrics to evaluate how well a set of clusters fits the data by minimizing the sum of intra-cluster. Common distance metrics like Euclidean or Manhattan distance are used to calculate this intra-cluster distance, and the goal of the fitness function is typically to minimize this overall distance, indicating compact and well-separated clusters.

Residual Energy

It is a statistic used to choose the optimal cluster heads, with the primary goal of enhancing the network's overall lifetime by evenly distributing the energy consumption load. The cluster member nodes with the smallest distance to the Cluster Head are the most qualified for the CH position.

3.3 Routing via Wombat Optimization

In this section, the selected cluster head is used for routing shortest path using wombat optimization (WOA). The WOA operates in three basic steps: initialization, exploration, and exploitation. In the initialization step, the method generates a set of random solutions. During the exploration stage, the wombats wander in various directions in quest of better solutions.

Phase 1: Initialization phase: in initialization phase WOA provided techniques for creating members of the algorithm's population. For visualization and thinking, the wombat habitat in the wild represents the problem-solving space, while the individual wombats in the habitat represent a candidate solution's location in the problem-solving space.

$$Y = \begin{bmatrix} Y1 \\ \vdots \\ Yi \\ \vdots \\ Y\mathcal{N} \end{bmatrix}_{m\times n} = \begin{bmatrix} y1,1 & \dots & \ell 1,_j & \dots & y1,m \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ yi,1 & \cdots & yi,_j & \cdots & yi,m \\ \vdots & & \vdots & & \vdots \\ y\mathcal{N},1 & \cdots & y\mathcal{N},_j & \cdots & y\mathcal{N},m \end{bmatrix} \quad (1)$$

$$x_{i,d} = lb_d + r.(ub_d - la_c) \quad (2)$$

X is the WOA population matrix, y_j is the $\ell 1_j$, $y_{i,j}$is its $x_{i,d}$ parameter in the search space. N is the total number of wombats, m represents the number of selected variables, r is a random number from [0, 1], and lb_i and bu_i are the lower and upper bounds of the y_i decision variable, respectively.

$$E = \begin{bmatrix} E_1 \\ \vdots \\ E_j \\ \vdots \\ E_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} E(Y_1) \\ \vdots \\ E(Y_i) \\ \vdots \\ E(Y_N) \end{bmatrix}_{N\times 1} \quad (3)$$

Here E is the vector representing the evaluated objective function, and E_j is the evaluated objective function for the ith wombat.

Phase 2: Exploration phase: in exploration phase Wombat animals have a very high hunting search ability within a large spatial habitat. A model of the change in position of the wombat species would result in a large change in the position of the WOA members achieving a problem-solving task, thereby increasing the hunting search ability of the algorithm in administering the global search.

$$\mathrm{DE}O_j = \{y_l : L_l < L_j \; and \; l \neq j\}, where \; j = 1,2\ldots, N \; and \; l \in \{1,2\ldots, N \quad (4)$$

Here, $\mathrm{DE}O_j$ refers to the potential foraging locations for the jth wombat, y_l is the member of the population that has a better objective function value than the ith wombat, and $L_l$is the objective function value of y_l

$$y_{j,i}^{O_1} = y_{j,i} + q_{j,i}.(SEO_{j,i} - I_{j,i}.y_{j,i} \quad (5)$$

$$y_j = \begin{cases} y_j^{O_1}, E_j^{O1} & \leq E_{j,} \\ y_j, \; else, & \end{cases} \quad (6)$$

Here, $SEO_{j,i}$is the selected forage position for the jth wombat, $SEO_{j,i}$is its jth dimension, $y_j^{O_1}$ j is the new position calculated for the jth wombat based on the foraging phase of the proposed WOA

Phase 3: Exploitation phase: in exploitation phase, the shifts in the wombats' position when escaping from the hunter to the tunnel demonstrates small shifts in the position of WOA members in the problem-solving space, thus enhancing the exploitation power of the algorithm's abilities to perform local search.

$$x_{i,j}^{p2} = y_{j,i} + (1 - 2\, q_{j,i}).\frac{va_i - la_i}{t} \quad (7)$$

Here $x_{i,j}^{p2}$ is the new position computed for the ith wombat based on the escape phase of the proposed WOB, and t is the iteration timer.

$$y_i = \begin{cases} y_j^{p2} & , k_j^{p2} < k_j \\ y_j & \end{cases} \quad (8)$$

Here, k_j is the newly calculated location of the ith wombat according its escape phase with respect to the proposed WOA, k_j^{p2} is its jth dimension, y_j^{p2} represents the objective value of the location, k_j represents random integers sampled from the interval of [0, 1], and t is the timer for iterations.

PFK_j= {YK: pk < Pi and k/= i}, where i = 0, 2, . . . N and k ∈ {0, 2, . . . N} (9)

Here, PFK_j *is* the set of candidates foraging places for the ith wombat, YK is the population member with a higher objective function value than the ith wombat, and Pk is its objective function value.

4. RESULT AND DISCUSSION

In this section, the efficacy of the suggested technique is assessed using matlab-2022b, performance analysis is discussed regarding various calculation metrics such as Residual Energy, Alive Node, Cluster Stability, throughput, and end to end delay. The PC requirements for this experiment comprised an i9-9820X3.30GHz CPU, 2 TB of RAM, and Ubuntu 20.04.1 LTS. The proposed model efficacy is contrasted with Leach [14], EBPT-CRA [18], LCPSO-CRP [20].

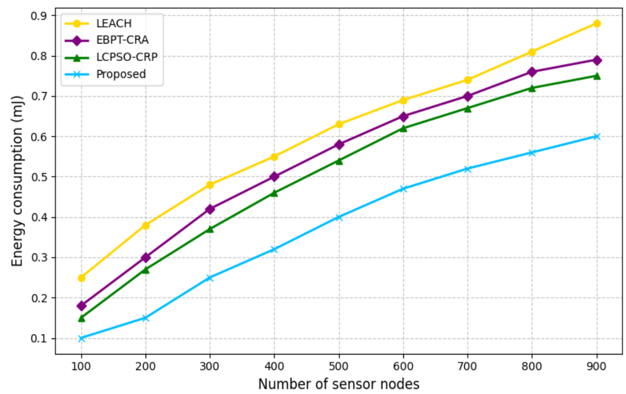

Figure 2. Energy consumption

Figure 2 shows comparison of Energy consumption via number of sensor nodes. The proposed model has lower energy consumption compared to existing techniques such as LEACH, EBPT-CRA and LCPSO-CRP. When a node is 300, the energy consumption of the proposed model is 0.25 mJ and the existing LEACH, EBPT-CRA and LCPSO-CRP yield 0.48 mJ, 0.42 mJ and 0.37mJ respectively. The proposed model lower by 37.3 mJ, 35.1 mJ and 27.5 mJ than the existing techniques.

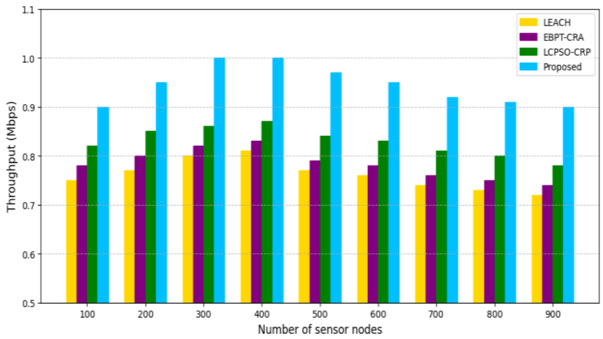

Figure 3. Comparison of Throughput

Figure 3 illustrates Comparision of Throughput via number of sensor nodes. The suggested model has higher than the existing techniques such as LEACH, EBPT-CRA and LCPSO-CRP. When the node is 200, the throughput of the suggested model is 0.95 Mbps, and the existing LEACH, EBPT-CRA and LCPSO-CRP yield 0.76 Mbps, 0.8 Mbps and 0.85Mbps respectively. And when the node is 600, the throughput of the suggested model is 0.96 Mbps, and the existing LEACH, EBPT-CRA and LCPSO-CRP yield 0.94 Mbps, 0.77Mbps and 0.75Mbps respectively. The proposed model higher by 24.0 Mbps, 20.2Mbps and 13.0Mbps than the existing techniques

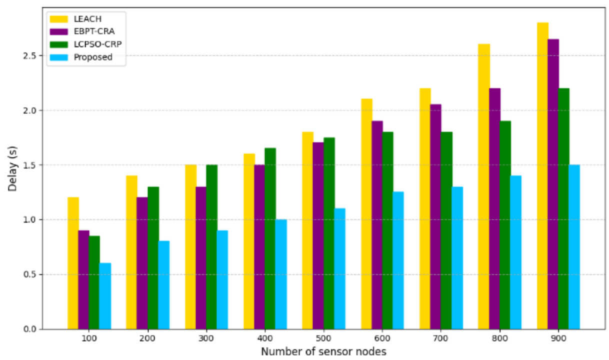

Figure 4. Comparison of Delay

Figure 4 show the Comparision of Delay via number of sensor nodes. The suggested model has lower than the existing techniques such as LEACH, EBPT-CRA and LCPSO-CRP. When the node is 400, the delay of the suggested model is 1.0 s, and the existing LEACH, EBPT-CRA and LCPSO-CRP for the 1.54 s, 1.5 s, and 1.55 s respectively. The proposed model lower by 43.5 s, 39.8 s and 36.6 s then the existing techniques.

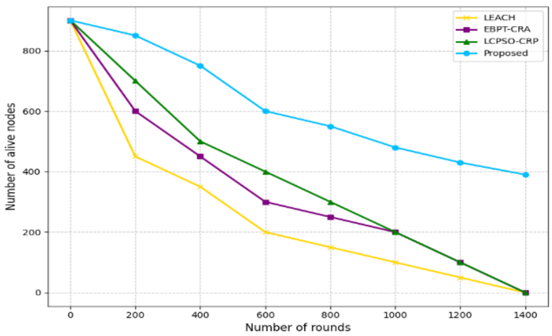

Figure 5. Comparison of Alive node

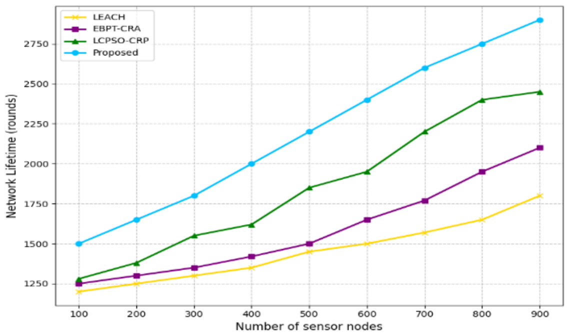

Figure 6. Network lifetime

Figure 6 displays the Comparision of network lifetime via number of sensor nodes. The proposed model is higher than the existing techniques such as LEACH, EBPT-CRA and LCPSO-CRP. When the node is 100, the alive node of the proposed model is 1500 and the existing LEACH, EBPT-CRA and LCPSO-CRP for the 1230 rounds (r), 1250 r and 1340 r respectively. The proposed model higher by 59.0 r, 67.3 r and 78.0 r then the existing techniques.

5. CONCLUSION

This paper presents, a novel HO–WO Hybrid Optimization for Improving Energy Efficiency and Extending Network Lifetime in Wireless Sensor Networks (HWEL) has been proposed. Initially C Means clustering is used to improve cluster formation and reduce communication costs. The proposed HWEL techniques mainly uses the HO (hippopotamus optimization) approaches to select cluster head. The WO (wombat optimization) utilized best route path from source to destination, then cluster head uses the best route to send data to the basestation. Proposed HWEL framework achieves network lifetime by 95.8% for proposed then 48.17 %, 39.17 % and 20.25% than the LEACH, EBPT-CRA and LCPSO-CRP approaches. In future work, Machine learning can be used to predict energy levels and make better clustering and routing decisions.

CONFLICTS OF INTEREST

The writers say they have no competing interests.

FUNDING STATEMENT

Not applicable.

ACKNOWLEDGEMENTS

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

REFERENCES

[1] H. Hu, X. Fan, and C. Wang, "Energy efficient clustering and routing protocol based on quantum particle swarm optimization and fuzzy logic for wireless sensor networks," *Scientific Reports*, vol. 14, no. 1, p. 18595, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[2] L. Sahoo, S. S. Sen, K. Tiwary, S. Moslem, and T. Senapati, "Improvement of wireless sensor network lifetime via intelligent clustering under uncertainty," *IEEE Access*, vol. 12, pp. 25018–25033, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[3] A. Alsumayt et al., "Efficient security level in wireless sensor networks (WSNs) using four-factors authentication over the Internet of Things (IoT)," *PeerJ Computer Science*, vol. 10, p. e2091, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[4] H. Muhammad and H. Nam, "Sensor node deployment optimization for continuous coverage in WSNs," *Sensors*, vol. 25, no. 12, p. 3620, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[5] P. Anusuya and C. N. Vanitha, "A comprehensive review of sensor node deployment strategies for maximized coverage and energy efficiency in wireless sensor networks," *PeerJ Computer Science*, vol. 10, p. e2407, 2024. [CrossRef] [Google Scholar] [Publisher Link]
[6] H. Tian, "Enhancing the effectiveness of wireless sensor networks through consensus estimation and universal coverage," *Scientific Reports*, vol. 15, no. 1, p. 24930, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[7] P. Soltani, M. Eskandarpour, A. Ahmadizad, and H. Soleimani, "Energy-efficient routing algorithm for wireless sensor networks: A multi-agent reinforcement learning approach," arXiv preprint, arXiv:2508.14679, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[8] R. Priyadarshi, R. R. Kumar, R. Ranjan, and P. V. Kumar, "AI-based routing algorithms improve energy efficiency, latency, and data reliability in wireless sensor networks," *Scientific Reports*, vol. 15, no. 1, p. 22292, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[9] M. Z. Iskandarani, "Effect of intelligent reflecting surface on WSN communication with access points configuration," *IEEE Access*, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[10] S. Subedi, S. K. Acharya, J. Lee, and S. Lee, "Two-level clustering algorithm for cluster head selection in randomly deployed wireless sensor networks," *Telecom*, vol. 5, no. 3, pp. 522–536, Jun. 2024. [CrossRef] [Google Scholar] [Publisher Link]
[11] A. I. Al-Sulaifanie, B. K. Al-Sulaifanie, and S. Biswas, "Recent trends in clustering algorithms for wireless sensor networks: A comprehensive review," *Computer Communications,* vol. 191, pp. 395–424, 2022. [CrossRef] [Google Scholar] [Publisher Link]
[12] S. Sharmin, I. Ahmedy, and R. Md Noor, "An energy-efficient data aggregation clustering algorithm for wireless sensor networks using hybrid PSO," *Energies*, vol. 16, no. 5, p. 2487, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[13] B. Fan and Y. Xin, "A clustering and routing algorithm for fast changes of large-scale WSN in IoT," *IEEE Internet of Things Journal,* vol. 11, no. 3, pp. 5036–5049, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[14] C. N. Tadros, N. Shehata, and B. Mokhtar, "Unsupervised learning-based WSN clustering for efficient environmental pollution monitoring," *Sensors*, vol. 23, no. 12, p. 5733, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[15] S. Zhang, X. Liu, and M. Trik, "Energy efficient multi-hop clustering using artificial bee colony metaheuristic in WSN," Scientific Reports, vol. 15, no. 1, p. 26803, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[16] M. Hosseinzadeh et al., "A cluster-based trusted routing method using fire hawk optimizer (FHO) in wireless sensor networks (WSNs)," *Scientific Reports*, vol. 13, no. 1, p. 13046, 2023. [CrossRef] [Google Scholar] [Publisher Link]
[17] A. M. Rahmani et al., "A routing approach based on combination of gray wolf clustering and fuzzy clustering and using multi-criteria decision-making approaches for WSN-IoT," *Computers and Electrical Engineering*, vol. 122, p. 109946, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[18] B. Fan and Y. Xin, "EBPT-CRA: A clustering and routing algorithm based on energy-balanced path tree for wireless sensor networks," *Expert Systems with Applications*, vol. 259, p. 125232, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[19] M. Ridwan, T. Wahyono, I. Sembiring, and R. Darmastuti, "Enhancing wireless sensor network performance: A novel adaptive grid-based clustering hierarchy protocol," *Array*, p. 100440, 2025. [CrossRef] [Google Scholar] [Publisher Link]
[20] T. Luo et al., "An improved Lévy chaotic particle swarm optimization algorithm for energy-efficient cluster routing scheme in industrial wireless sensor networks," *Expert Systems with Applications*, vol. 241, p. 122780, 2024. [CrossRef] [Google Scholar] [Publisher Link]

AUTHORS

Ramakantha Reddy received an M.Tech. in computer science and engineering from JNTU, Anantapuramu in 2011 and Ph.D. from Vellore Institute of Technology, Vellore, Tamil Nadu, India in 2025. Currently, he is working as an Associate Professor in the Department of CSE(AI&ML) at Sri Venkateswara College of Engineering, Tirupathi. His current research includes data analytics, Machine learning, and IoT.

Nithya Rekha Sivakumar is currently an Associate Professor in the Department of Computer Sciences, College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University, Riyadh, Saudi Arabia from 2017 till date. She received a grant from UGC and completed Ph.D., as a Full-Time Research Scholar in Periyar University awarded with "UGC BSR Research Fellowship in Science for Meritorious Students" by University Grants Commission, New Delhi, Govt. of India from 2010 to 2013. She received a Travel Grant from the Department of Science and Technology (DST), Govt. of India, to go to the United States of America for her Ph.D. research. She received the "BEST DISTINGUISHED RESEARCHER AWARD" for the year 2015-2016 from the College of Computer, Qassim Private Colleges, Buraydah, Kingdom of Saudi Arabia. She has received a Research grant for Research Identity Fast-track Funding Program from the Deputyship for Research & Innovation, Ministry of Education, and the Researchers Supporting Project Award from Princess Nourah bint Abdulrahman University in Saudi Arabia four times.

Arrived: 07.01.2025
Accepted: 12.02.2025