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Energy-aware dynamic adjustment integrated kookaburra optimization based efficient routing in WSN

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ABSTRACT

In this paper a novel kookaburra optimization algorithm based dynamic adjustment strategy (KOA-DAS) method has been proposed in this paper for the energy efficient (EE) clustering and routing in wireless sensor network (WSN). The satin bowerbird optimization (SBO) is utilized for optimum cluster head (CH) selection. The proposed KOA-DAS model is utilized for an efficient routing through considering the fitness functions like distance from CH to base station (BS), remaining energy and intra-communication cost. The suggested framework has been assessed using a MATLAB simulator. The efficacy of the suggested KOA-DAS framework has been determined using evaluation metrics including execution time, average residual energy, network lifetime (NL), latency, packet delivery ratio (PDR), computation cost, energy consumption (EC), and alive nodes. The suggested KOA-DAS framework achieves the lowest energy efficiency by 23.44%, 19.31%, and 14.44% than the ASFO, EELCR, and K-LionER approaches. The proposed model effectively selects the CH and routing through dynamically adjusting parameters, which results in minimum EC and extending NL.

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1. INTRODUCTION

Wireless sensor networks (WSNs) are primarily developed as monitoring system which involves various distributed sensor nodes (SNs) for different applications such as transmission, military, data gathering, and so on [1]. Because of the minimum life time of batteries in sensor networks of WSN, an optimal energy consumption becomes more challenging [2]. The energy effectiveness of sensor nodes becomes an important part because of their restricted resources with respect to communication as well as processing [3]. Thus, it is important for developing an effective energy consumption approach to enhance a NL as well as stability of WSN. Clustering is an important approach for attaining an optimal energy efficiency in WSN [4], [5]. In clustering, WSN is devided into groups called clusters and maintained through cluster heads (CHs) [6]. An attached CH are the first level nodes, and rest are the second level nodes [7]. CH in every cluster collects data from the neighbour sensor node and transmits it to the base station through the support of neighbour nodes [8]. In clustering, an arbitrary CH selection impacts worst connectivity, failure of the nodes, and constrained network lifetime [9]. Simultaneously, optimal CH selection improves an effectiveness and lifetime in WSNs. An optimized routing approach with optimal CH selection is important for better scalability WSNs [10], [11].

Energy optimization to enhance network lifetime is greatly needed for real-world applications of WSNs. Previously, various clustering as well as routing protocols have been developed to address an issue of excessive energy consumption and limited network lifetime [12]. Clusters are grouped to arrange arbitrarily deployed nodes in clustering and routing protocols, that involves CH and cluster members (CMs) [13]. Commonly, CHs are more important to the network than CMs due to their additional capabilities, which include data collecting, aggregation, forwarding, and cluster administration [14]. Thus, researchers put forward introducing EE models and nodes for maintaining various tasks. Thus, an efficient routing approach is targeted to minimize EC and enhance the NL [15]. In recent years, researchers have been basically concentrated on introducing multi-objective optimization approaches for solving energy challenges. The recently developed optimization approaches like genetic algorithms (GAs), sunflower optimization algorithm (SFO), and ant colony optimization (ACO) [16], [17]. These approaches are supportive in maintain network effectiveness of efficient routing. In previous research works, the model impacts constrained battery power as well as minimum resources at end-to-end transmission [18].

In recent years, a number of research have used a variety of methods for CH selection and routing in WSN. A number of the contemporary evaluation techniques are discussed in the part that follows, along with some of their drawbacks: In 2023, Cherappa *et al.* [19] developed an adaptive sailfish optimization (ASFO) approach with K-medoids for the effective CH selection in sensor nodes. The EE cross-layer-assisted expending routing protocol (E-CERP) approach was utilized for a determination of best route, dynamically reduced the network overhead. Performance findings for QoS criteria include PDR (100%), latency (0.05 s), throughput (0.99 Mbps), EC (1.97 mJ), NL (5908 cycles), and PLR (0.5%) for 100 nodes. In 2024, Roberts *et al*. [20] suggested an enhanced two-phased paradigm for cluster-based, EE routing in WSNs. The advanced meta-heuristic models such as spotted hyena optimization (SHO) and sailfish optimization (SFO) were integrated into the suggested approach. The developed hybrid framework performed higher than the previous single-algorithm approaches in terms of increasing data transmission reliability, maximizing EC, and prolonging NL. In 2024, El Khediri *et al*. [21] introduced a novel hybrid metaheuristic that integrated artificial bee colony (ABC) and ACO principles to improve the solution search process and reduce the total EC of WSNs. According to the findings, the method used a lot less energy than BeeSensor, LEACH, iABC, and Beecluster, with reductions of 22.20%, 47.25%, 27.38%, and 32.40%, respectively.

In 2024, Manoharan *et al*. [22] offered a novel method for achieving the best energy-efficient routing in WSNs by combining density-based adaptive soft clustering with adaptive entropy bald eagle search optimization. When compared to the several current methods, the suggested methodology achieved better performance in terms of energy (1.92 j), latency (6.5 ms), throughput (320.1 kbps), and PDR (218.7%). In 2024, Sulthana and Duraipandian [23] suggested an EE lifetime-aware cluster-based routing (EELCR) for WSN. The EELCR approach introduced the modified giant trevally optimization (MGTO) model for effective balanced clustering that reduced EC. The suggested EELCR strategy works noticeably better than current routing techniques, showing an average NL gain of 52.625% in simulation rounds and 51.88% in node density considerations. In 2024, Rekha and Garg [24] introduced the hybrid K-means and lion optimization (K-LionER) method for EE clustering-based routing model for WSN supported by the IoT. The objective of the developed K-LionER is to increase EC and network longevity. The suggested K-LionER routing model extended the NL by 10% to 48% as compared to the previous methods. In 2025, Mabunga and Cruz [25] presented a novel multiobjective CH selection and routing method for providing energy-aware data transmission in WSN. Here, CH selection was carried out using the developed chronological wild geese optimization (CWGO) technique based on multiple constraints. The proposed CWGO was examined considering metrics, like energy, trust, distance, and delay, and was found to have attained superior values of 0.963 J, 0.700, 19.468 m, and 0.252 s, respectively. To tackle these issues, a novel kookaburra optimization algorithm based dynamic adjustment strategy (KOA-DAS) method has been developed for the EE clustering and routing in WSN. The key contributions of the developed KOA-DAS have been given as follows.

- The key goal of the developed model is to improve the NL and reduce EC by introducing novel optimization algorithms.
- The CH is selected using the SBO algorithm, which considers fitness parameters involving distance from CH to BS, remaining energy and intra-communication cost.
- After CH selection, a novel KOA-DAS technique has been utilized for efficiently selecting the optimal data transmission route.
- The execution time, average residual energy, latency, PDR, NL, computation cost, EC, and alive nodes of the suggested approach have been thoroughly assessed.

The remaining sections of the proposed KOA-DAS technique are arranged in the following order. Section 2 describes the related works for energy-efficient clustering-based routing and section 3 describes the proposed KOA-DAS methodology in detail. The simulation findings and discussion are covered in section 4, and the conclusion is presented in section 5.

2. PROPOSED KOA-DAS SYSTEM

In this section, a novel KOA-DAS method has been developed for EE clustering and routing in WSN. Initially, the SNs are randomly deployed in the WSN environment. In the CH selection phase, the key parameters like location and energy are initiated, and the nodes are evaluated based on the fitness metrics including distance from the CH to the BS, remaining energy, and intra-communication cost. Here, the SBO algorithm is utilized to select the optimal CHs. The suggested KOA-DAS is then used in the routing phase to calculate the best routes. Finally, the routing phase determines the most efficient path for data transmission from each CH to the BS. Figure 1 demonstrates the workflow of the suggested KOA-DAS technique.

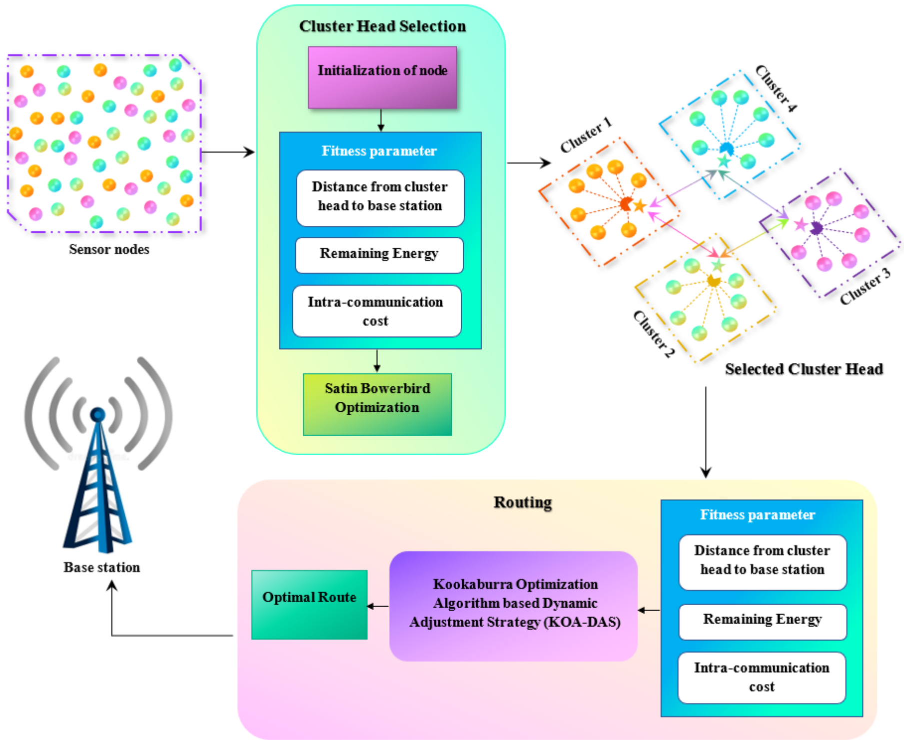


Figure 1. Overall workflow for the proposed KOA-DAS method

2.1. Cluster head selection using SBO algorithm

In this work, the SBO is employed to select optimal CHs based on the fitness metrics including distance from CH to BS, remaining energy, and intra-communication cost. The initialization people of the SBO method are generated at random as a collection of locations. The following relationship in (1) provides the locations of the individuals.

$$pop(x).pos = rand(1, i_{var}) * (var_{max} - var_{min}) + var_{min} \; for \; x \in i_{pop} \tag{1}$$

The attraction probabilities of males (or females) to the other bowers are then calculated (2) and (3), just like in the ABC optimizer.

$$pb_x = \frac{cost_x}{\sum_y cost_y} \; for \; x \in i_{pop} \tag{2}$$

$$cost_x = \begin{cases} \frac{1}{1+f(n_x)} & for \; f(n_x) \geq 0 \\ 1 + |f(n_x)| & for \; f(n_x) < 0 \end{cases} \tag{3}$$

$$n_{x,y}^{new} = n_{x,y}^{old} + \alpha_y \left(\frac{n_{k,y}+n_{elite,n}}{2} - n_{x,y}^{old}\right) \tag{4}$$

The SBO approach was used in this work to identify the more likely bowers ($n_{k,y}$). The iteration amount for selecting the aiming bower is indicated by α_y in (5), and it may be found for each variable by (5).

$$\alpha_y = \frac{\beta}{1+prop_x} \tag{5}$$

Then, using a normal distribution (with $n_{x,y}^{old}$ mean and ρ variance), $n_{x,y}$ will be randomly altered with a certain probability by (6) and (7).

$$n_{x,y}^{new} \sim n_{x,y}^{old} + \rho^* N(0,1) \tag{6}$$

$$\rho = Z^*(var_{max} - var_{min}) \tag{7}$$

At the conclusion of each iteration, the old persons are combined with the accomplished individuals using the specified process to create the new individuals.

2.2. Routing using KOA-DAS

In this work, KOA-DAS is utilized to determine the optimal route from each CH to the BS. The KOA approach is population-assisted approach which is capable to offer appropriate solutions for optimization issues in an iterative-assisted procedures according to an arbitrary search in a problem-solving manner. The location of Kookaburra at the implementation of KOA's beginning is formulated in (8) and (9).

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,d} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,d} & \cdots & x_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,d} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \tag{8}$$

$$x_{i,d} = lb_d + r.(ub_d - lb_d) \tag{9}$$

A group of estimated outcomes for a function is demonstrated in (10).

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \tag{10}$$

Where, F denotes a vector of estimated objective function and F_i specifies an estimated objective function according to ith kookaburra. The following section describes how the KOA population is updated into a solution space.

2.2.1. Exploration-hunting strategy

The KOA technique preserves the position of other kookaburras with higher objective function values as the prey's location for each individual kookaburra to mimic their hunting style. Thus, according to a comparison of an objective function values, an accessible prey group for every bird is identified through (11)-(13).

$$CP_i = \{X_k : F_k < F_i \; and \; k \neq 1\}, where \; i = 1,2,\dots,N \; and \; k \in \{1,2,\dots N\} \tag{11}$$

$$x_{i,d}^{p1} = x_{i,d} + r.\left(SCP_{i,d} - I.x_{i,d}\right), i = 1,2,\dots,N, and \; d = 1,2,\dots,m \tag{12}$$

$$x_i = \begin{cases} X_i^{p1}, F_i^{p1} < F_i \\ X_i, else \end{cases} \tag{13}$$

Where, X_i^{p1} demonstrates a new recommended position of ith kookaburra according to initial phase of KOA and $x_{i,d}^{p1}$ denotes a dth dimension.

2.2.2. Exploitation - ensuring that the prey is killed

In the KOA design, to mimic the movement behaviour of kookaburras near their hunting ground, an arbitrary location is generated utilizing (14). A new position estimated for every kookaburra modifies its prior location if it enhances a value of an objective function using (15).

$$x_{i,d}^{p2} = x_{i,d} + (1-2r).\frac{(ub_d - lb_d)}{t}, i = 1,2,\dots,N, d = 1,2,\dots,m \; and \; t = 1,2,\dots,T \tag{14}$$

$$X_i = \begin{cases} X_i^{p2}, F_i^{p2} < F_i \\ X_i, else \end{cases} \quad (15)$$

Where, X_i^{p2} denotes a recommended location of ith kookaburra according another level of KOA. $x_{i,d}^{p2}$ illustrates the dth dimension of KOA; F_i^{p2} means an objective function; t denotes an iteration number of KOA; and T denotes a maximum number of iterations of KOA.

2.2.3. Dynamic adjustment strategy

Based on KOA, a global exploration level for development of new eggs is administered through Levy flight (LF) according to arbitrary walks. Now, the DAS is introduced for step size in actual KOA with Levy flight. In this manner, the step size S_i^{new} is formulated in (16).

$$S_i^{new} = \left(\frac{1}{It}\right)^{\left|\frac{Best\ f(It) - f_i(It)}{Best\ f(It) - Worst\ (It)}\right|} \quad (16)$$

Thus, though a step size is big at beginning, number of iterations enhances, step size minimizes. Hence, the DAS for the step size in actual KOA is determined as well as advantageous to optimization through the faster rate as well as greater quality solutions.

3. RESULTS AND DISCUSSION

In this section, the suggested KOA-DAS framework is implemented in a MATLAB 2020 R with the system configurations of Intel i5 processor, 16 GB RAM, and Windows 10 OS. The data transfer from a SN to the CH is shown in Figure 2. Figure 2 indicates that a cluster's six cluster leaders oversee each of its SNs. In a WSN, there are several SNs that may be active or inactive. The suggested CH model creates groupings based on distances between nodes by routinely monitoring the nodes. Nearby nodes are grouped into clusters using the SBO algorithm, and the CH is chosen based on how much energy the SN uses. The EE SN is selected as CH, though this can be altered at any moment.

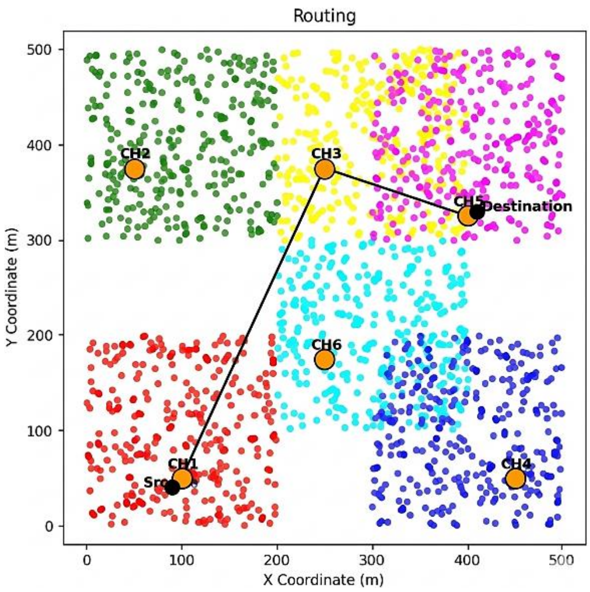


Figure 2. Performance analysis of CH selection and routing

Figure 3 shows the CH selection system's efficacy over time. The proposed technique demonstrates superior performance by reducing execution time compared to conventional CH selection methods. Compared to the current CH selection processes, the suggested approach was faster to implement. The time will be prolonged if there are more CHs. As shown in Figure 3, comparing the proposed technique to other existing strategies, the proposed system achieved an execution time of just 67 seconds for 4 CHs.

Figure 4(a) illustrates the suggested KOA-DAS method's CH selection is compared to three traditional approaches including ASFO, EELCR, and K-LionER. According to the average residual energy, the suggested method's CH selection in 250 rounds is 39.2337 J, while the current approaches like ASFO, EELCR, and K-LionER have 34.3295 J, 32.4351 J, and 29.4253 J, respectively. This demonstrates that the suggested KOA-DAS model outperforms the traditional CH selection process. As a result, the suggested approach selects the CH for the identifying cluster effectively. One practical assessment criterion for determining the longevity and operational effectiveness of network nodes in WSNs is the number of living nodes. Figure 4(b) shows the comparison of the number of rounds and the overall efficacy evaluation of the alive node count. It is evident from the overall comparison that the suggested KOA-DAS algorithm sustains a higher number of living nodes throughout a range of rounds. Additionally, it is demonstrated that the suggested approach significantly outperforms other algorithms by maintaining the number of alive nodes for a variable number of rounds, improving by about 3% to 20%. This shows that the suggested algorithm can sustain the node's energy, hence increasing the network's operational lifetime.

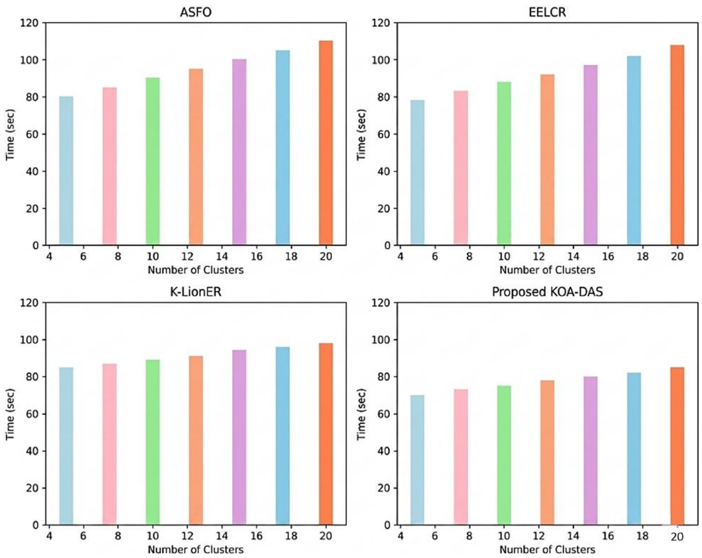
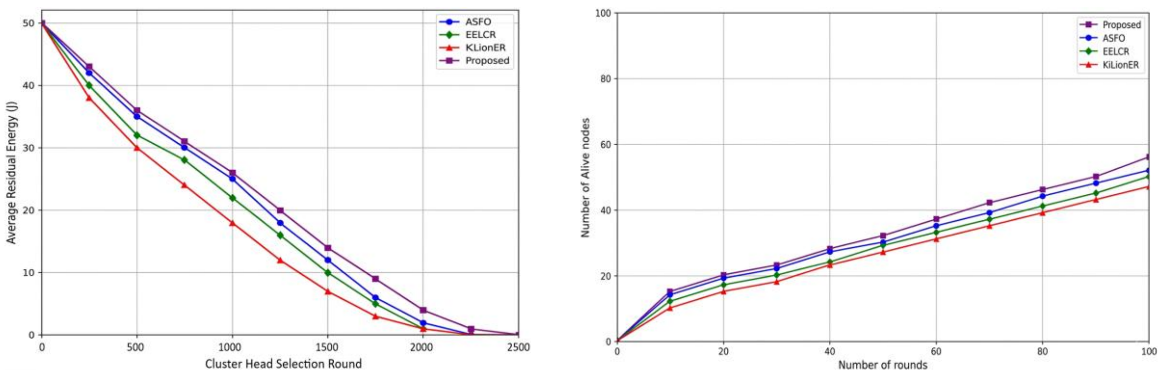


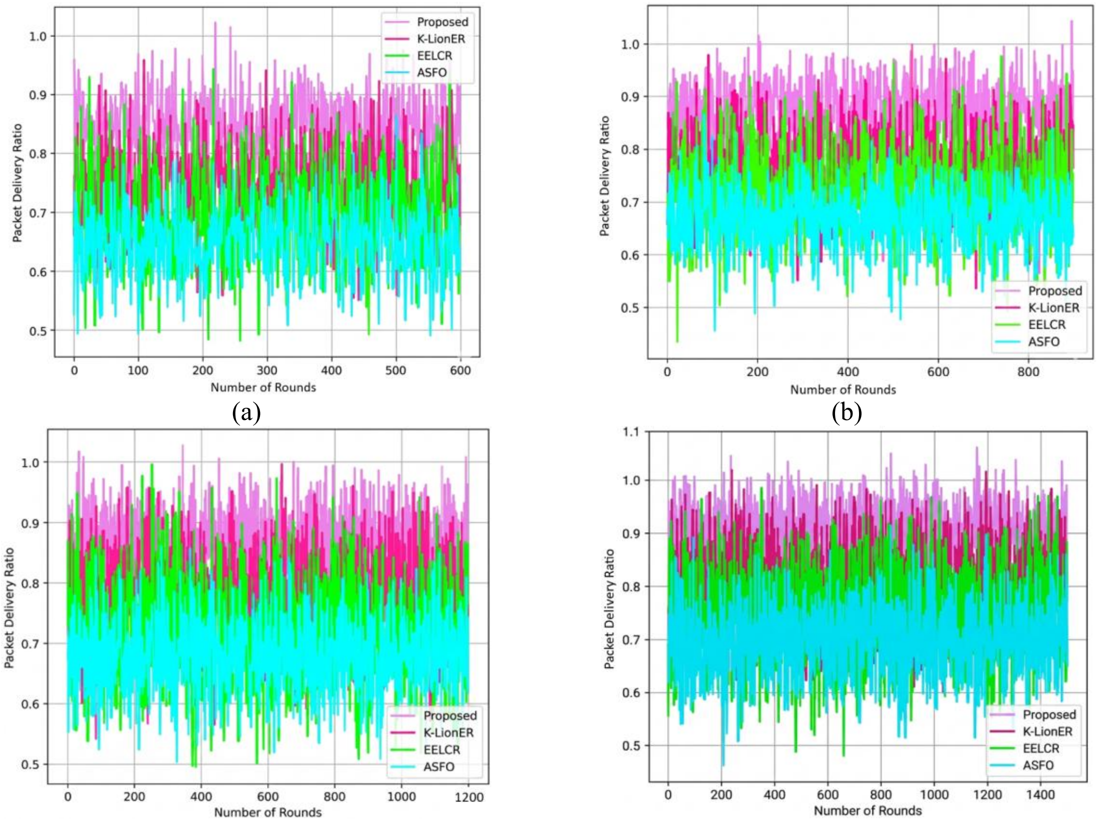
Figure 3. Time taken for CH selection in WSN



(a) (b)

Figure 4. Suggested KOA-DAS method's CH selection: (a) comparison of average residual energy and (b) comparison of alive nodes

Figure 5 illustrates a comparison of the PDR over different numbers of rounds for four different approaches, such as proposed KOA-DAS, ASFO, EELCR, and K-LionER. Figures 5(a)-5(d) represent different scenarios or timeframes with increasing numbers of rounds ranging from 600 to 1500. In all scenarios, the proposed KOA-DAS model consistently achieves a higher PDR compared to the existing systems. The findings indicate that the developed KOA-DAS framework provides a more reliable communication with higher PDR in WSNs across various scenarios.



(a) (b) (c) (d)

Figure 5. Packet delivery ratio comparison: (a) performance of PDR at 600 simulation rounds, (b) performance of PDR at 800 simulation rounds, (c) performance of PDR at 1200 simulation rounds, and (d) performance of PDR at 1500 simulation rounds

Figure 6 demonstrates the performance estimation of EC based on number of rounds. An EC is estimated the total energy leveraged through a whole network according to the number of energies all the node utilizes for the transmission of data packets. The developed KOA-DAS approach attains the minimum energy consumption of 8.32J, 21.49J, 35.64J, 46.65J, and 53.69J on the number of rounds of 1000, 2000, 3000, 4000, and 5000 individually. Also, the proposed KOA-DAS method achieves 23.44% better energy efficiency than ASFO, 19.31% better than EELCR, and 14.44% better than K-LionER on average across the range of sensor nodes. This suggests that the proposed KOA-DAS is more effective in optimizing energy usage, making it a better option for larger WSN deployments.

Figure 7 compares the NL of the proposed KOA-DAS technique with the current models including ASFO, EELCR, and K-LionER based on the number of nodes. The developed approach consistently outperforms the other algorithms, with a significantly higher NL, starting around 1300 for 20 nodes and reaching approximately 6700 for 100 nodes. CIBOA performs moderately, achieving about 4700 at 100 nodes, while DMPRP follows with around 5500 at the same point. This demonstrates the superior efficiency of KOA-DAS in prolonging NL as the number of nodes increases.

Figure 8 illustrates the cost comparison graph for CH selection, which demonstrates the efficiency of the proposed method in minimizing communication and computation costs across varying numbers of clusters. The proposed technique achieves the lowest cost values throughout, with a sharp decline observed as the number of clusters increases from 5 to 30. In contrast, ASFO incurs significantly higher costs with broader error margins, reflecting less stability. The observed cost reduction in the proposed method is attributed to its efficient CH selection mechanism, which minimizes redundant transmissions and optimizes energy usage, thereby enhancing the overall network longevity and performance.

Figure 9 illustrates the comparison of latency versus the number of sensor nodes for four different approaches, such as the proposed KOA-DAS, ASFO [19], EELCR [23], and K-LionER [24]. The findings show that the developed KOA-DAS consistently attains the lowest EEL compared to the other three approaches as the number of SNs increases. ASFO shows the highest delay, followed by EELCR and K-LionER. This shows that the developed KOA-DAS is more efficient in reducing end-to-end delay in WSNs.

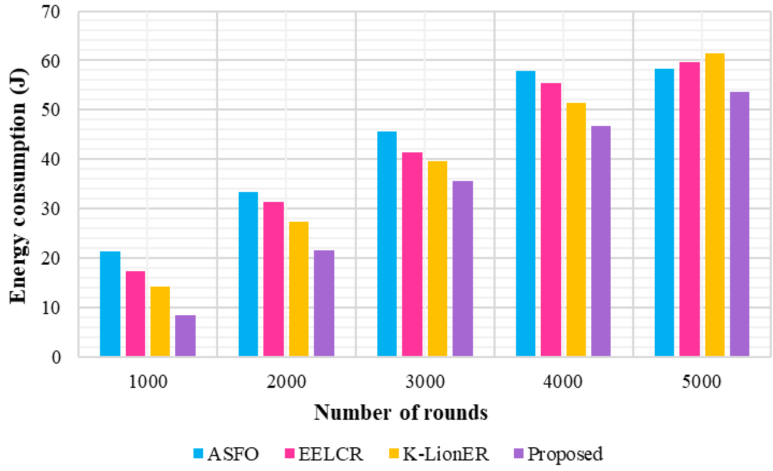


Figure 6. Energy consumption comparison

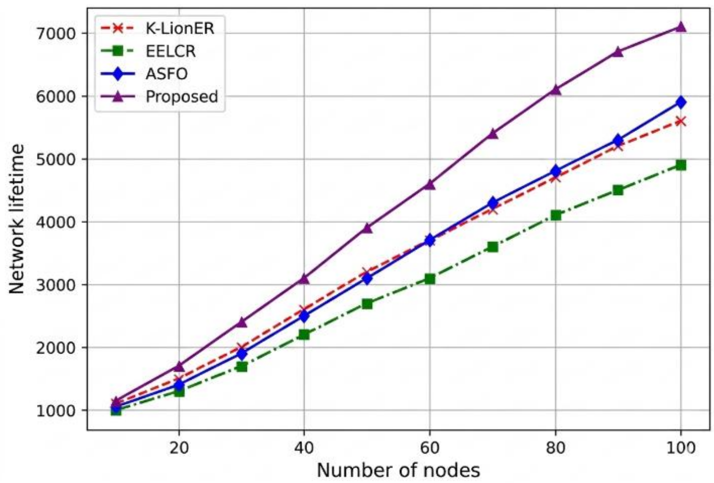


Figure 7. Network lifetime comparison

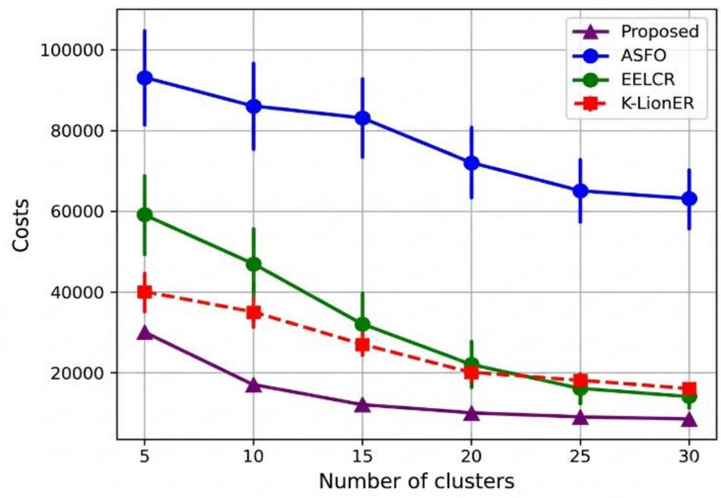


Figure 8. Cost comparison in CH selection

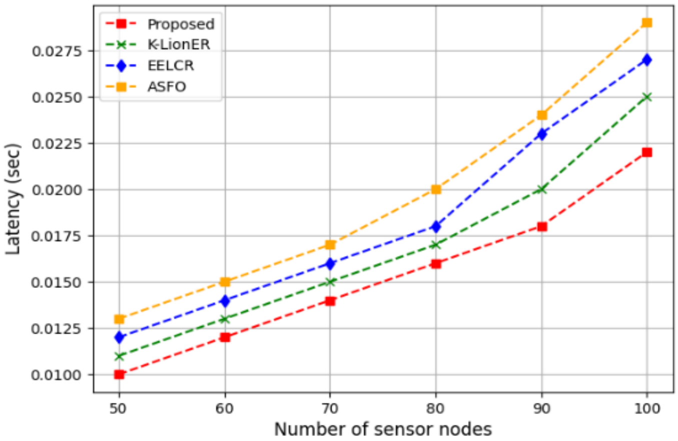


Figure 9. Latency comparison

4. CONCLUSION

In this paper, a novel KOA-DAS method has been developed for EE clustering and routing in WSN. The suggested technique has been evaluated utilizing MATLAB simulator. The experimental findings demonstrate that the suggested framework performs higher than the current approaches such as ASFO, EELCR, and K-LionER in terms of execution time, average residual energy, PDR, NL, latency, computation cost, EC, and alive nodes. According to the comparative analysis, the proposed KOA-DAS method achieves a lowest energy efficiency of 23.44%, 19.31%, and 14.44% than the ASFO, EELCR, and K-LionER techniques. The proposed method also enhances metrics like alive nodes, PDR, energy efficiency, and NL. For future work focus on integrating machine learning for predictive energy management and applying the strategy in real-time IoT applications like smart agriculture and industrial monitoring can broaden its impact.

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R. Karthikeyan		✓		✓		✓	✓			✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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