An Improved Coyote Optimization Algorithm-Based Clustering for Extending Network Lifetime in Wireless Sensor Networks

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Abstract

The development of lightweight, low energy and small-sized sensors incorporated with the wireless networks has brought about a phenomenal growth of Wireless Sensor Networks (WSNs) in its different fields of applications. Moreover, the routing of data is crucial in a wide number of critical applications that includes ecosystem monitoring, military and disaster management. However, the time-delay, energy imbalance and minimized network lifetime are considered as the key problems faced during the process of data transmission. Furthermore, only when the functionality of cluster head selection is available in WSNs, it is possible to improve energy and network lifetime. Besides that, the task of cluster head selection is regarded as an NP-hard optimization problem that can be effectively modelled using hybrid metaheuristic approaches. Due to this reason, an Improved Coyote Optimization Algorithm-based Clustering Technique (ICOACT) is proposed for extending the lifetime for making efficient choices for cluster heads while maintaining a consistent balance between exploitation and exploration. The issue of premature convergence and its tendency of being trapped into the local optima in the Improved Coyote Optimization Algorithm (ICOA) through the selection of center solution is used for replacing the best solution in the search space during the clustering functionality. The simulation results of the proposed ICOACT confirmed its efficiency by increasing the number of alive nodes, the total number of clusters formed with the least amount of end-to-end delay and mean packet loss rate.

Keywords: Improved Coyote Optimization Algorithm, Wireless Sensor Networks, Center Solution, Network Lifetime.

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1. Introduction

Recently, smart technologies are considerably utilized in the domains of health, building, home, planes, or ecological monitoring. But these smart technology applications completely depend on sensory data derived from the real-time implementation environment [1]. The recent advancement in the area of microelectromechanical systems (MEMs) technology, wireless communication technologies and digital electronics has visualized the apparition of sensors in smart environments [2]. The sensors used in smart environments are limited in size with the equipped capability of collecting information associated with the environment [3]. Even though sensor networks enable a wide range of diverse applications, sensor nodes are limited by resources such as limited energy, limited computational potential, low memory size and storage, low bandwidth, and poor communication range [4]. In this context, several sensor nodes are deployed and connected for constructing a wireless sensor network in order to protect the consequent space [5]. The energy consumption of each sensor node is regarded as the most important metric for WSNs, as it directly influences the overall network's lifespan [6]. Network performance is dependent on the balance between limited resources and limited sensor energy [7]. When the percentage of nodes in a network is large, direct routing uses a great deal more resources and can drastically reduce the lifespan of the network [8].

The benefits of using cluster-based routing are numerous: seamless connectivity, scalability, and improved quality of service (QoS) [9]. In this case, the network is divided into smaller subnetworks known as clusters, and each cluster is led by a node that has been designated as the cluster head using a cluster-based routing algorithm. These sensor cluster heads are responsible for collection and integration of data from other cluster members. Moreover, communications between and within clusters can take place in a multi-hop fashion in the context of cluster-based routing [10]. When communicating with a neighbor sensor node that is far away, the sensor network attempts to communicate solely with the neighbor sensor node that is nearest to it to conserve its remaining energy and avoid depleting its energy by communicating with the neighbor sensor node that is nearby. The majority of the cluster-based algorithms are considered to be probabilistic in nature [11]. As a result, the technique of clustering in sensing devices continues to be a non-deterministic polynomial (NP) hard optimization issue that has proven to be intractable by conventional approaches [12]. At this juncture, this NP optimization problem of clustering is determined to be accurately resolved through the employment of Computational Intelligence [13]. These computational intelligence-based clustering methods considered biological or environmental activities, and they outperformed traditional clustering algorithms in terms of dependability, network lifetime extension, energy efficiency, and greater coverage, among other metrics [14]. However, the choice of an appropriate computational intelligence technique is vital depending on the kind of application where it is employed by considering the lifetime and network deployment cost into account.

When searching for an optimal solution, meta-heuristic optimization algorithms and clustering approaches outperform other approaches especially when searching for a global optimum which take a long time. The efficiency of the meta-heuristic clustering techniques depends on their effectiveness in generating new and enhanced solutions by potentially covering the solution space. Besides, in order to be effective, meta-heuristic clustering techniques must be able to evade a local position of optimality. Several meta-heuristic strategies, including the Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Monarchy Butterfly Algorithm (MBA), Harmony Search Algorithm (HSA), and Coyotes Herd Optimization (EHO), have been shown in the literary works to be constrained to the local point of optimization problem during the cluster-based procedure. As a result, the meta-heuristic clustering systems must account for the possibility of a trade-off between exploitation and exploration during the process of cluster head selection [15]. This provided the impetus for creating an ICOA to select the cluster head efficiently by leveraging and exploring the search area efficiently, as described above.

In this paper, An Improved Coyote Optimization-based Clustering Technique (ICOACT) is proposed for attaining potential CH selection to boost the lifetime expectancy of the network. This proposed ICOACT integrates the high searching efficiency of ICOA with the inclusion of center solution to replace the best agent of the current generation for efficient selection of cluster heads on the network. By preserving the trade-off between exploitation and exploration, our proposed ICOACT avoided earlier solution trapping in a locally optimal point and prolonged convergence. In experimentation simulation, parameters such as total alive nodes, average residual energy, total dead nodes, and throughput are considered over a number of rounds.

The major contributions of the proposed ICOACT are listed as follows:

i) The proposed work integrates the merits of Improved Coyote Optimization Algorithm and, explored the complete search space of the network for identifying potential sensor node as CH.

ii) The proposed work prevents the problem of convergence by adopting significant factors of fitness that aid in determining potential CH nodes that aided in achieving better network stability and lifetime.

iii) The proposed work balances the deviation between exploitation and exploration through the inclusion of center solution which is used for determining the location of the sensor nodes that can be potentially used as CH in the network.

The article is organized in the following manner. Section 1 deals with the introduction of the work. Section 2 describes the existing techniques of the research. Section 3 explains the contribution of the proposed technique. Section 4 examines the results and discussion of this investigation. Finally, Section 5 concludes the research work along with the future enhancement.

2. Related Work

The section discusses the benefits and limitations of the meta-heuristic clustering techniques and hybrid meta-heuristic clustering techniques that have been added to the recent literature for improving network lifespan in WSNs. A clustering technique based on energy optimization and enhanced PSO has been presented for enabling the option of cluster head selection in reducing the energy consumption in sensor networks [16]. This PSO-based clustering method employs the cluster head selection mechanism by employing the residual energy and distance between member nodes and sink nodes. This PSO-based clustering method was found to have a similar effect on network average lifespan as the competitive clustering technique. The energy consumption rate and throughput of this PSO-based clustering algorithm were found to be much greater than those of the probabilistic clustering systems examined. Then, a clustering technique based on Cat Swarm Optimization was presented for lowering the intra-cluster distances between cluster leaders and their corresponding cluster members in order to optimize the network's energy balance mechanism [17].

For cluster head selection, Cat Swarm Optimization-based clustering algorithm took into account the intra-cluster distance, received transmission power, and residual energy of sensor nodes. It was found to be superior to the centralized LEACH, PSO, and classical LEACH algorithms that were compared during the investigation. The Uneven Dynamic Clustering Process-based on PSO (UDCP-PSO) was developed to address the issue of hotspots by utilizing an energy-balancing mechanism that would shorten the lifespan of the network [18]. This UDCP-PSO enabled a strategy that dynamically changed the distribution of clusters under the influence of failed nodes in the network. It facilitates the option of estimating the area in which the candidate cluster head nodes are located. This UDCP-PSO effectively balanced the network energy consumption rate by incorporating an adaptive clustering process for making the node distribution in every cluster in a reasonable manner. This UDCP-PSO also used the method of connecting line-aided route establishment for confirming the next-hop neighbor that could be more appropriate for enhancing the energy efficiency during multi-hop data transmission. This UDCP-PSO was considered to be significant in prolonging the network lifetime between margins of 7.38% and 74.12% with enhanced scalability under various network sizes.

The Harmony Search Algorithm-based Clustering Head Selection Technique (HSA-CHST) was introduced for optimizing network operation to increase the lifetime of the network [19]. This HSA-CHST was used to lower the estimated distances between intra-clusters between cluster leaders and cluster members to optimize the network's energy distribution. In order to achieve an efficient and appropriate energy balance in the networks, an integrated Cuckoo and Harmony Search-based Clustering Head Selection Technique (ICHSA-CHST) was presented [20]. This ICHSA-CHST was explored to reduce the mean consumption of energy rate and the number of dead nodes while increasing the lifetime of the network and the number of live nodes. A hybrid ACO and PSO-based clustering algorithm was developed to accelerate data dissipation while remaining energy efficient and to increase network lifespan expectancy [21]. This hybrid ACO and PSO-based clustering technique incorporates a substantial data aggregation procedure. Based on the problem statement of a multi-objective fitness function, an ABC-based clustering process was proposed for strengthening the objective of cluster head selection [22]. The goal of this ABC-based cluster creation process is to minimize consumption while maintaining a low hop count with the intention of reliable data transfer. This ABC-based cluster formation mechanism was determined to have potential in minimizing mean energy with increased packet delivery rate, mean throughput and network lifetime.

A Hybrid PSO and HSA-based clustering mechanism is proposed for improving the lifetime expectancy of the network by incorporating the dynamic potential of HSA and the high search efficiency of PSO [23]. This hybrid PSO and HSA-based clustering mechanism were proposed as a reliable attempt for facilitating rapid convergence with global search potential during the process of energy-efficient cluster head selection. Moreover, this hybrid PSO and HSA-based clustering mechanism prevent the issue of exploitation and exploration tradeoff and the constraints of local search. This hybrid PSO and HSA-based clustering mechanism confirmed an enhancement in throughput and residual energy by 29.12% and 83.89% compared to the PSO algorithm used for benchmarking. An enhanced Firefly Metaheuristic-based clustering algorithm was contributed to improve the reliability of data aggregation and data transmission to the base station [24]. This enhanced Firefly Metaheuristics-based clustering algorithm confirmed an average decrease in the packet loss rate of 9.63% on par with the compared LEACH and centralized LEACH. In addition, this mechanism is responsible for the optimal selection of cluster heads by effective stabilization of parameters that are related to minimizing delay, minimizing distances between nodes and reduction in energy consumption [25]. This mechanism integrates the benefits of the Grey Wolf and Firefly Optimization algorithm for the objective of optimal cluster head selection with the view to improve the life expectancy of the network. This mechanism was significant in prolonging the network lifetime based on the statistical investigation. The most significant disadvantage of this is that it does not meet the fundamental requirements of communication and computation, and that power failures in the system cause changes in topology [26]. This CH selection incorporates the goal of data aggregation to reduce superfluous data dissemination while simultaneously increasing energy and lifetime. This method makes use of the GA's local search advantages as well as the KHOA's global optimization capability in identifying potential CHs that contribute to energy stabilization and network lifetime sustenance, respectively [27]. To avoid fault propagation to upper layers, CH uses hypothesis testing and a majority vote to identify and decommission defective nodes. Although it keeps adding to the complexity of the system, the backup node monitors the progress of the member nodes and stores all the data collected by the cluster member sensor nodes [28]. For further node activation, a distributed categorization for WSN is used in conjunction with a biological lateral induction model [29]. In this context, some of the researchers have considered the traffic which exists in the network paths as discussed in [30 - 32]. Comparative summary is given in **Table 1**.

Table 1. Comparative summary of literature review

Author	Algorithm Used	Advantage	Disadvantage
Shankar et al [23]	Hybrid PSA and HAS Clustering Mechanism	Rapid convergence with global search	Exploitation and exploration trade off between the local search is low
Sakar et al [24]	Firefly Algorithm	Improved the reliability of data	Convergence speed of data transmission is not high
Murugan et al [25]	Enhanced Firefly Algorithm	Decreased the packet loss rate	Delay in data transmission
Sarkar Amit et al [26]	Grey wolf and Firefly optimization	Improved the life expectancy of network	Does not meet the fundamental requirement of communication
Balamurugan et al [27]	Genetic Algorithm	Identify potential cluster head	Added complexity to the system
Ramesh et al [28]	Firefly and Grey Wolf Optimization	Optimal routing to the nodes	Computation time is high
Vijayalakshmi et al [29]	Cuckoo search and PSO Optimization	Improved network performance incorporating balanced energy dissipation	Time complexity is high

The preponderance of extant meta-heuristic cluster head selection algorithms is considered to be noteworthy in either exploitation or exploration, never both, because they do not optimize parameters in a way that balances the pace of exploration and exploitation. Additionally, it is established that the majority of present meta-heuristic cluster head selection strategies are deficient in global search capability on par with the utilization frequency of local search.

Furthermore, the existing meta-heuristic cluster head selection techniques confirmed that integration of a global search improved meta-heuristic algorithm will be the best option for balancing the tradeoffs between exploitation and exploration rate. Besides, ICOA as a single meta-heuristic was unable to optimize the parameters associated with cluster selection due to their tendency to fall into a local optimum value and exhibit prolonged convergence. As a result, a need to enhance the cluster head selection technique by hybridizing ICOA with a global search enhancing meta-heuristic algorithm such as HSA in order to demonstrate the procedure's efficiency and effectiveness.

3. Proposed Improved Coyote Optimization Algorithm-based Clustering Technique (ICOACT) for Optimal Cluster Head Selection

The proposed Improved Coyote Optimization Algorithm-based Clustering Technique (ICOACT) contributes to optimal cluster head selection in the sensor networks by deriving the common properties of COA and central solution with replacement. The COA algorithm can generate new solutions by permitting the solution to escape from local optima for enhancing the global optimal prediction of the algorithm. For this reason, the central solution is integrated with COA to balance the rate of exploitation and exploration in high-dimensional issues like cluster head selection.

In the COA, the exploited population is partitioned into NP_C (number of coyote packs) and NC_P (the number of coyotes in each pack). This COA also considered that the number of coyotes associated with each pack (sensor nodes in each cluster) is static. Thus, the total number of coyotes (sensor nodes) in the population is determined by multiplying NP_C and NC_P. In COA, each coyote pertains to the feasible solution associated with the optimization problem. It depends on various social conditions (influencing factors under the cluster head selection process) that are used for deriving the objective function cost. These social conditions influencing the coyote optimization are extrinsic or intrinsic, which is similar to the behavior exhibited by sensor nodes (energy, distance between the sink and base stations and distance between sensor nodes and base station). Hence, the social constraint (collection of decision variables) associated with the decision variables that aid in the process of cluster head selection is represented based on Eq. No. (1)

$$COND^{pc,t} = \vec{c} = (c_1, c_2, \ldots\ldots, c_D) \tag{1}$$

where, $COND^{pc,t}$ represents the social conditions (collection of decision parameters, c) pertaining to the m^{th} coyote of the n^{th} pack at any time instant t. It also implies the adaptation of coyotes into the environment which is like the adaptation of sensor nodes deployed in a monitored environment (the objective function cost determined based on fitness function)

The first step of the COA algorithm concentrates on the initialization of the global population with randomly set social conditions for each coyote, since it is one of the vital stochastic algorithms. This initialization of the global population in the search space is achieved by assigning random values for each m^{th} coyote of the n^{th} pack at any time instant t based on j^{th} dimension is represented based on Eq. No. (2)

$$COND^{pc,t} = LB + r_j * (UB - LB) \tag{2}$$

where, LB and UB represents the lower bound and upper bounds of the decision variable associated with the j^{th} decision variable. r_j is the random variable pertaining to the 'D' dimensional search space that ranges between 0 and 1 determined based on uniform probability. Then, the adaptation of the coyotes (sensor nodes) with respective to the present social constraints is estimated based on Eq. No. (3)

$$Fit^{pc,t} = f(COND^{pc,t}) \tag{3}$$

In the process of initialization, the coyotes are randomly allocated to the packs. But the coyotes are considered to leave their packs and transform into a solitary or integrate with a pack instead. Further, the movement of the coyote from the packs purely relies on the number of coyotes residing inside each pack based on the Occurrence Probability ($Pr\,o\,b_{COA}$) depicted in Eq. No. (4)

$$Pr\,o\,b_{COA} = 0.005NC_p \tag{4}$$

The above-mentioned Equation $\Pr ob_{COA}$ is greater than 1 when the value of NC_pgreater than$\sqrt{200}$. This probability $\Pr ob_{COA}$ aids in facilitating the COA towards diversification (global optimization) which provides a kind of cultural exchange. The COA algorithm generally utilizes two alphas. However, only one alpha is utilized for simplicity in the proposed approach. The alpha pertaining to each coyote of the pack at any time instant based on dimension is represented based on Eq. No. (5)

$$Alpha^{pc,t} = \{COND^{pc,t} |\, arg_{SOC=[1,2,\ldots,NP_C]}\, M\,inf(\,COND^{pc,t})\} \tag{5}$$

Moreover, the COA algorithm is potent in integrating the complete set of information shared between the coyotes (sensor nodes) for the purpose of calculating the cultural tendency related to each pack determined based on Eq. No. (6)

$$CULT^{pc,t} = \{ \begin{matrix} RSC_{SOC(\frac{(NP_C+1)}{2},j)} & NP_C is \quad odd \\ \frac{(RSC_{SOC(\frac{(NP_C)}{2},j)} + RSC_{SOC(\frac{(NP_C+1)}{2},j)})}{2} & NP_C is \quad even \end{matrix} \tag{6}$$

where, $C^{pc,t}$ portrays the ranked social conditions associated with the complete collection of each m^{th} coyote of the n^{th}pack at any time instant t based on D. The cultural tendency associated with the coyote pack (cluster of sensor nodes) is determined based on the average social conditions of all coyotes (complete sensor nodes of the cluster) belonging to each specific pack. In this context, the birth and death of COA (the selection or de-selection of a specific sensor node as cluster head) depends on the integration of the social conditions related to the two parents (two randomly selected sensor nodes) and the impacting environmental factors as depicted in Eq. No. (7)

$$POP^{pc,t} = \{ \begin{matrix} COND_{SOC(r1,j)} & rnd_j < P_{PS} & (or) & j = j_1 \\ COND_{SOC(r2,j)} & rnd_j \geq P_{PS} + P_{PA} & (or) & j = j_2 \\ R_{VAR(DV)} & . & Otherwise & . \end{matrix} \tag{7}$$

$$RSC_{SOC(\frac{(NP_C+1)}{2},j)}$$

Here, j_1 and j_2 represents two random perspectives of the problem with r_1 and r_2 as the random coyote (sensor nodes) derived from the m^{th} pack. $R_{VAR(DV)}$ refer to the random number inherent to the boundary decision variable under P_{AS} and P_{PS} as the association probability and scatter probability in the j^{th} dimension. In particular, the association probability and scatter probability useful for controlling the diversification (exploration towards global optimization) process is determined based on Eq. No. (8) and (9) respectively.

$$P_{PS} = \frac{1}{D} \tag{8}$$

$$P_{AS} = \frac{(1-P_{PS})}{2} \tag{9}$$

The exploitation and exploration balance inside the clusters of sensor nodes are achieved by assuming the behavior of coyotes (behavior of sensor nodes) under the influence of two vital such as pack impact factor δ_1 and alpha influence factor δ_2 respectively. The pack impact factor δ_1 aids in estimating the deviation in behavior existing between the first random coyote (sensor node randomly selected) and alpha coyote (the fittest coyote individual). The alpha influence factor δ_2 plays a vital role in estimating the difference between a second random coyote and the tendency inherent to a specific coyote pack (sensor node clusters). Thus, the pack impact factor δ_1 and alpha influence factor δ_2 are represented based on Eq. No. (10) and (11) respectively.

$$\delta_1 = ALPHA^{pc,t} - COND^{pc,t} \tag{10}$$

$$\delta_2 = CULT^{pc,t} - COND^{pc,t} \tag{11}$$

Thus, the social constraint related to the coyote (sensor nodes' location) is updated using Eq. No. (12) based on the pack impact factor δ_1 and alpha influence factor δ_2 respectively.

$$NEW\_COND^{pc,t} = COND^{pc,t} + \beta_1 * \delta_1 + \beta_2 * \delta_2 \tag{12}$$

where β_1 and β_2 are the weights associated with the pack impact factor δ_1 and alpha influence factor δ_2, respectively. Thus, weight factors β_1 and β_2 are random numbers that range between 0 and 1 determined based on the uniform distribution. The fitness of the newly updated social condition (the fitness value of the newly selected cluster head position) is determined based on Eq. No. (13)

$$NEW\_FIT^{pc,t} = f(NEW\_COND^{pc,t}) \tag{13}$$

Finally, the decision of the cluster head selection is facilitated when the newly updated social condition is superior on par with the older social condition as represented in Eq. No. (14)

$$COND^{pc,t} = \begin{cases} NEW\_COND^{pc,t} & NEW\_FIT^{pc,t} < FIT^{pc,t} \\ COND^{pc,t} & Otherwise \end{cases} \tag{14}$$

Thus, the phenomenon related to the social condition of the coyote is suitably adapted to achieve predominant cluster head selection with high energy balance in the network.

Algorithm 1: Proposed ICOACT-based CH selection

$\boldsymbol{Begin}$

$\boldsymbol{Process\ of\ initialization}$

- $Initialize\ the\ generation\ counter\ 'GC_t = 1'.$
- $Set\ the\ population\ search\ space\ SP_{pop} with\ N_i number\ of\ Coyotes\ individuals\ (number\ of\ sensor\ nodes)\ randomly\ based\ on\ a\ uniform\ distribution$
- $Initialize\ the\ number\ of\ Coyotes\ (C_{kept})\ (\ the\ Coyotess\ (sensor\ nodes)\ identified\ as\ fittest\ in\ the\ previous\ generation, Maximum\ Generation\ Count\ (MGC),\ the\ number\ of\ Coyotess\ (number\ of\ sensors) in\ each\ clan\ C_i\ (cluster), number\ of\ clans\ N_c\ (clusters), factor\ of\ scaling\ \alpha\ and\ \beta.$

$\boldsymbol{Objective\ function}: FIT^{pc,t} = f(COND^{pc,t})$

$\boldsymbol{While}\ (t < MGC)\ do\ the\ following$

$Arrange\ the\ coyotes\ based\ on\ their\ estimated\ fitness\ value$

$The\ estimated\ fitness\ value\ of\ coyote\ is\ the\ input\ to\ ICOA\ algorithm$

$\boldsymbol{If}(Termination\ criterion\ is\ not\ achieved)$

$\boldsymbol{do}\{$

$\boldsymbol{for}\ each\ n\ pack\ \{$

$\boldsymbol{Define\ alpha\ cyote\ sensor\ node\ based\ on}$

$$CULT^{pc,t} = \begin{cases} RSC_{SOC(\frac{(NP_C+1)}{2},j)} & NP_C is \quad odd \\ \frac{(RSC_{SOC(\frac{(NP_C)}{2},j)} + RSC_{SOC(\frac{(NP_C+1)}{2},j)})}{2} & NP_C is \quad even \end{cases}$$

$\boldsymbol{Estimate\ the\ social\ tendency\ parameter\ using}$

$$POP^{pc,t} = \begin{cases} COND^{pc,t} & rnd_j < P_{PS} & (or) & j = j_1 \\ COND^{pc,t} & rnd_j \geq P_{PS} + P_{PA} & (or) & j = j_2 \\ R_{VAR(DV)} & . & Otherwise & . \end{cases}$$

$\boldsymbol{for}\ each\ m^{th}\ coyote\ of\ the\ n^{th}\ pack\{$

$\boldsymbol{Update\ the\ parameter\ of\ the\ social\ tendency\ using}$

$$P_{AS} = \frac{(1 - P_{PS})}{2}$$

$\boldsymbol{Compute\ the\ value\ of\ the\ new\ social\ tendency\ using}$

$$\delta_1 = ALPHA^{pc,t} - COND^{pc,t}$$

$\boldsymbol{Perform\ adaptation\ process\ for\ Cluster\ Head\ Selection\ using}$

$$\delta_2 = CULT^{pc,t} - COND^{pc,t}$$

$\boldsymbol{End\ for}$

}

$\boldsymbol{Identify\ the\ selection\ and\ re - selection\ of\ cluster\ head\ based\ on}$

$$NEW\_COND^{pc,t} = COND^{pc,t} + \beta_1 * \delta_1 + \beta_2 * \delta_2$$

$\boldsymbol{End\ for}$

}

$Employ\ the\ transition\ between\ clusters\ (Packs)$

$Re - estimate\ and\ update\ the\ fitness\ value\ of\ the\ sensor\ nodes (Coyotes)$

$Update\ MGC\ with\ = t + 1\ .$

$\boldsymbol{End\ While}$

}

$Return\ best\ optimal\ cluster\ head$

End

In addition, Fig. 1 presents the overall view of the proposed ICOACT as depicted as follows.

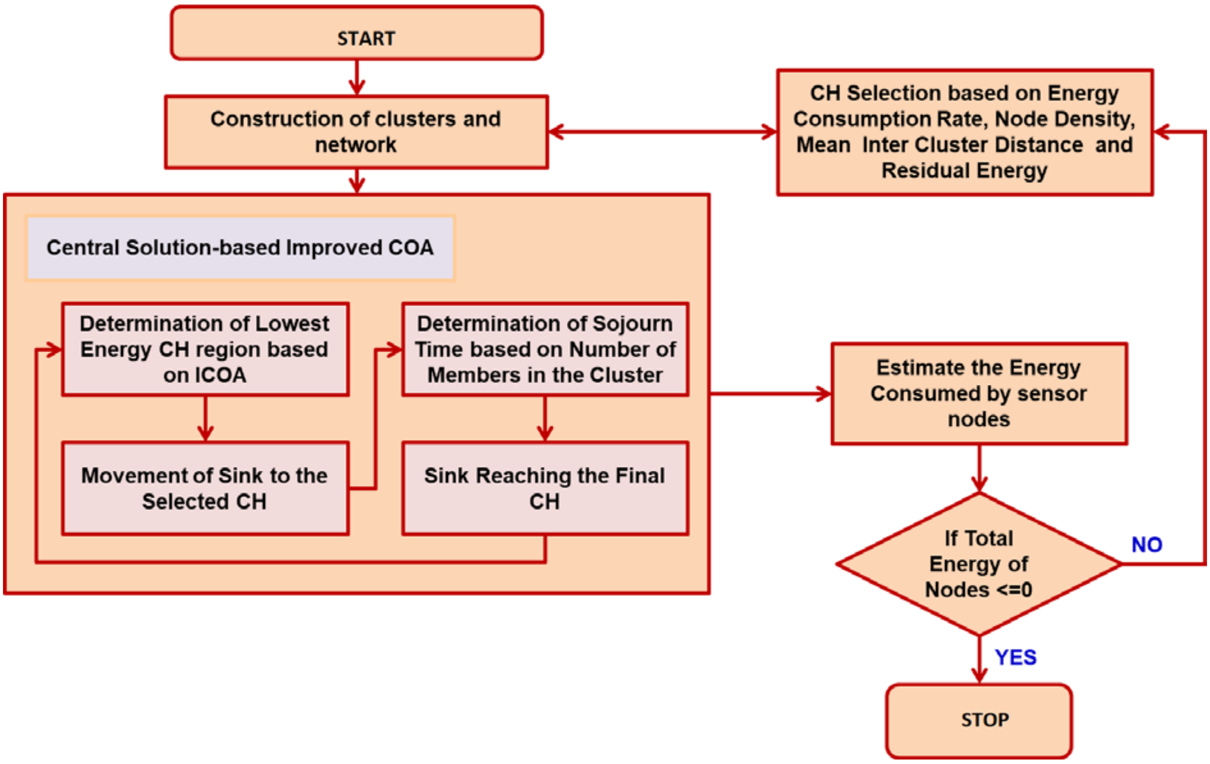

Fig. 1. The architectural view of the proposed ICOACT technique

4. Results and Discussion

MATLAB R2019a is used to implement the proposed ICOACT and benchmarked techniques. For simulation 200 nodes are being considered. The region considered for the simulation environment is 1500 x 15000m topology of network consisting of randomly distributed 200 nodes. with the Base Station (BS) at the location (250m, 50m). Heinzelmann energy model is used in the proposed model. This technique initially, the network lifespan is determined by the death of the first node, half of which are attained by the proposed techniques, and the benchmarked techniques are determined by the increased number of rounds.

Fig 2 & **Fig 3** demonstrate the network lifespan assessed based on the death of first as well as half nodes. In comparison to the benchmarked techniques such as SFACHS, ABCEECR, HSACP, the death of the first node in ICOACT is found to be better, as the presence of a novel searching approach avoids unnecessary energy reduction. As a result of its use of mutation and crossover functions, the proposed strategy is effective in extending the lives of half of the nodes it is designed to protect until they die. The following **Table 2** shows the various parameters used while implementing our proposed ICOACT approach.

Table 2. Parameters fixed for simulation of proposed ICOACT approach

Parameters used	Values
Total amount of sensor nodes	200
Region considered	1500 x 15000 m
The location of the sink node	(250m, 50m)
Amount of power available at the outset for sensor nodes	0.6 J
Size of control packets	1000 bits
Size of data packets	256 bytes
Energy utilized for amplification	100 pJ/bits/sqm

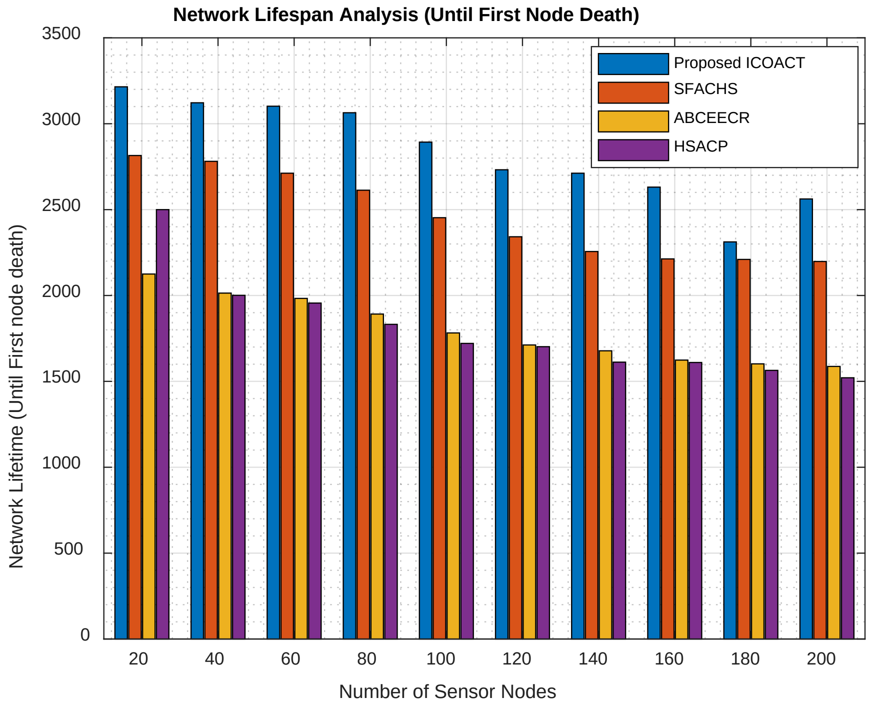

Fig. 2. Network Lifespan (Until first node death) of the Proposed ICOACT for Increasing Amount of Nodes

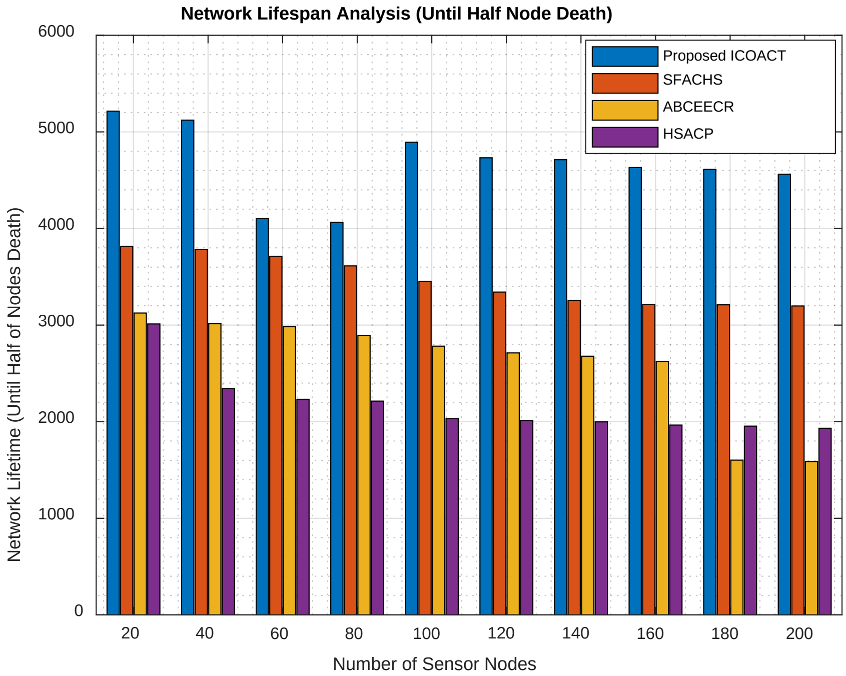

Fig. 3. Network Lifespan (Until half node death) of the Proposed ICOACT for Increasing Amount of Nodes

From **Fig. 4** it is obvious that the suggested technique is consistent in maintaining the network lifespan assessed based on the death of the last node.

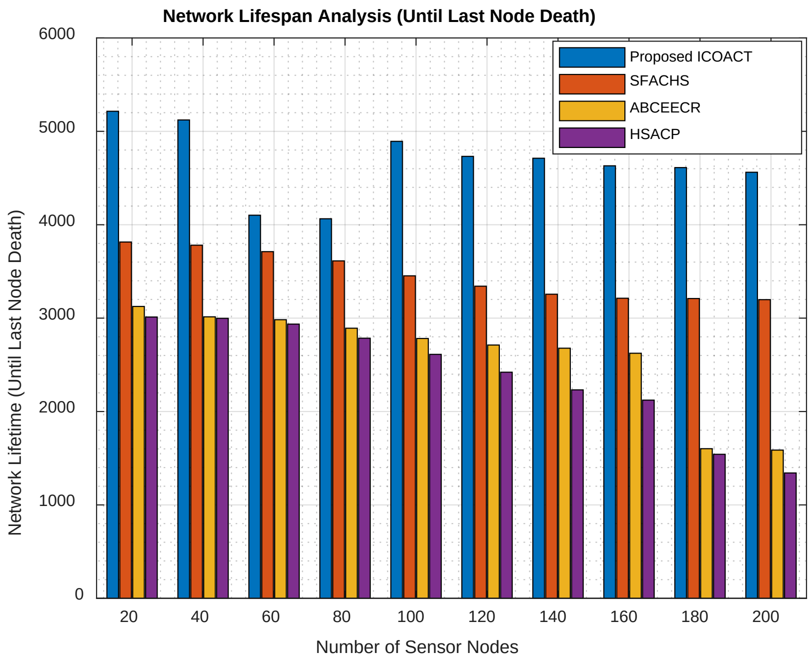

Fig. 4. Network Lifespan (Until last node death) of the Proposed ICOACT for Increasing Amount of Nodes

The network lifespan based on the death of the first node is enhanced by 7.29% and 8.52% when compared to the benchmarked techniques taken into consideration where SFACHAS, ABCEECR and HSACP has 7.12%, 7.08% and 7.01% respectively. Based on the death of half the number of nodes, the proposed technique is found to possess an enhanced lifespan of about 7.45% and 8.84% in contrast to the standard techniques taken for examination. Based on the death of the last sensor node, the network lifespan achieved by the proposed technique is improved by 6.98% and 7.79% in contrast to the benchmarked techniques.

Figs. 5 -6 depict the predominance of the proposed ICOACT in contrast to the benchmarked techniques examined in terms of network lifespan, throughput and energy consumption. From this investigation, it is evident that the network lifespan is significantly improved by the suggested technique on an average of 8.64% and 9.33% in contrast to the benchmarked mechanisms. The throughput of the proposed technique with an increase in node density is improved on an average by 8.22% and 9.54% in contrast to the benchmarked mechanisms taken for investigation. The proposed technique under a varying number of nodes is found to be improved on an average by 7.56% and 8.54% in contrast to the standard mechanisms considered for this investigation.

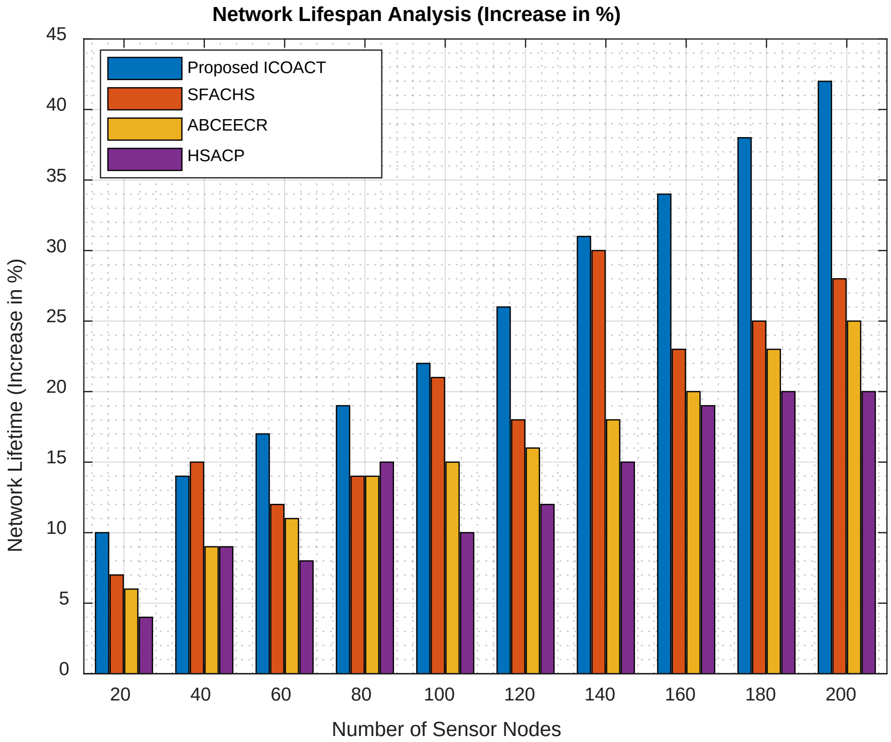

Fig. 5. Network Lifespan of the Proposed ICOACT for Increasing Amount of Nodes

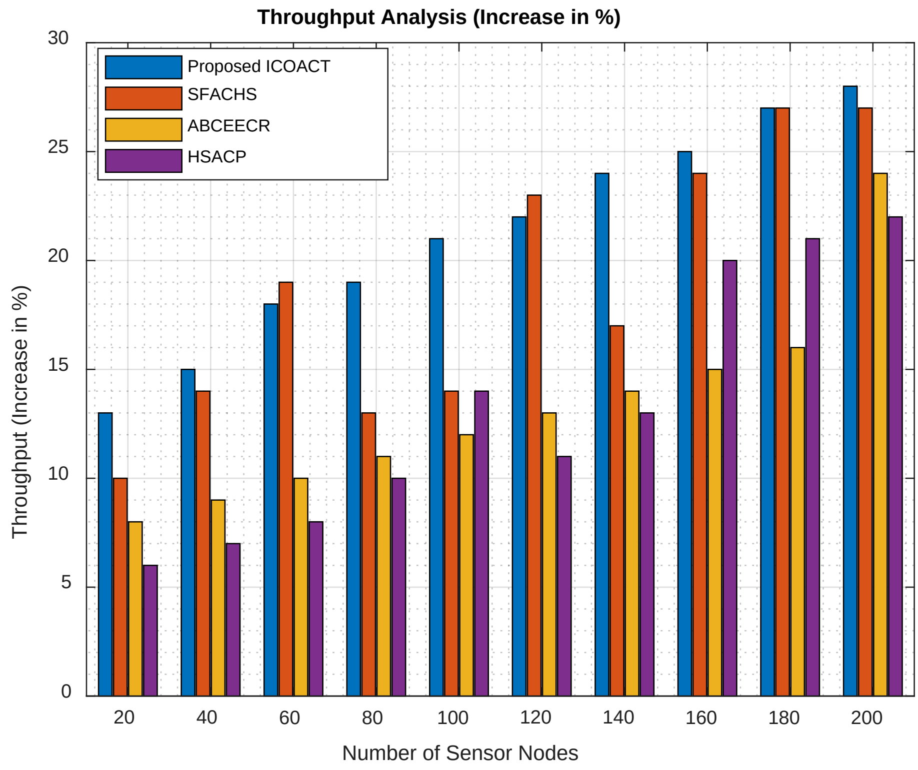

Fig. 6. Throughput of the Proposed ICOACT for Increasing Amount of Nodes

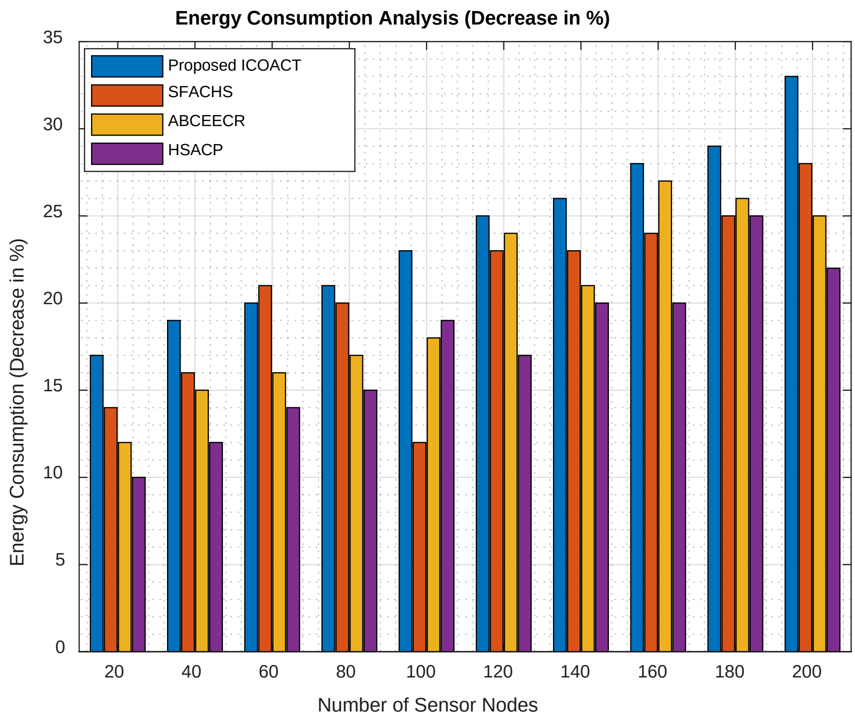

Fig. 7. Energy Consumption of the Proposed ICOACT for Increasing Amount of Nodes

Fig. 7 depicts the energy consumption of the proposed technique at various nodes.

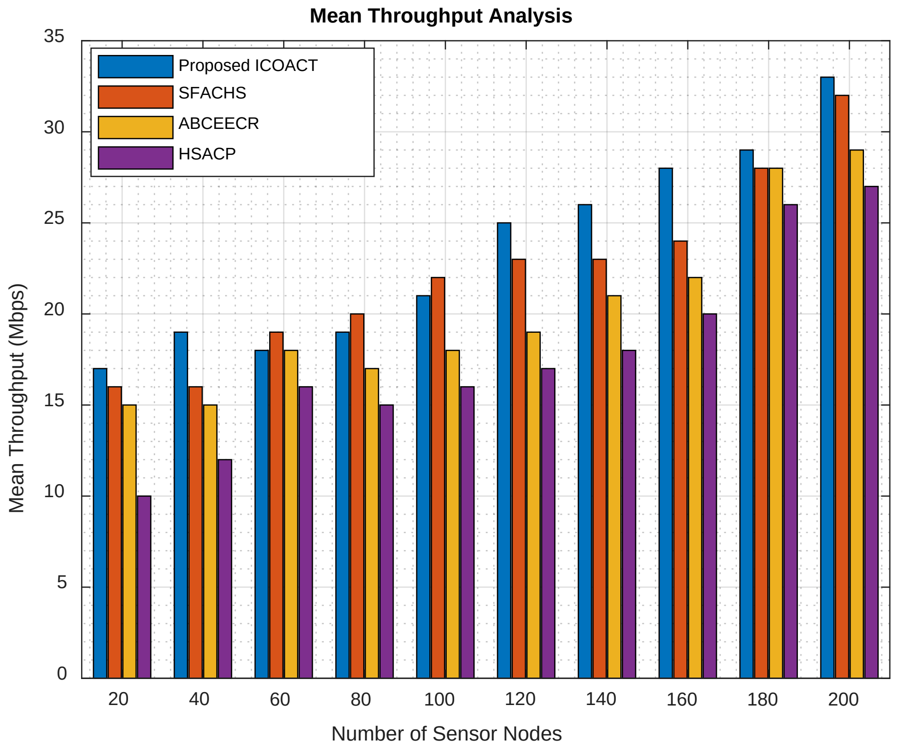

Fig. 8. Mean Throughput of the Proposed ICOACT for Increasing Amount of Nodes

Fig. 8 depicts the mean throughput of the proposed technique at various node densities. The suggested technique has a better mean throughput compared to the benchmarked methods, regardless of the frequent increase in the number of nodes, since it determines the appropriate criteria for selecting the CH. When compared to the other techniques, the proposed technique mean throughput is estimated to be 5.98 % and 6.84 % higher.

Fig. 9 shows the mean residual energies of the existing and the proposed techniques for an increasing number of nodes in the network. It is observed that the proposed technique has more residual energy when compared to the existing techniques independent of the drift in the number of nodes in the network. This enhancement of the suggested technique primarily owes to the merits of both the individual as well as population knowledge used in enumerating the impact of every criterion over the choice of suitable CH selection. The proposed technique sustains an increased amount of mean residual energy on an average of 6.24% and 7.18% in contrast to the baseline SFACHS, ABCEECR and HSACP techniques taken for examination. SFACHS, ABCEECR and HSACP has an increased amount of mean residual energy of an average of 6.19%, 6.15% and 6.10% respectively.

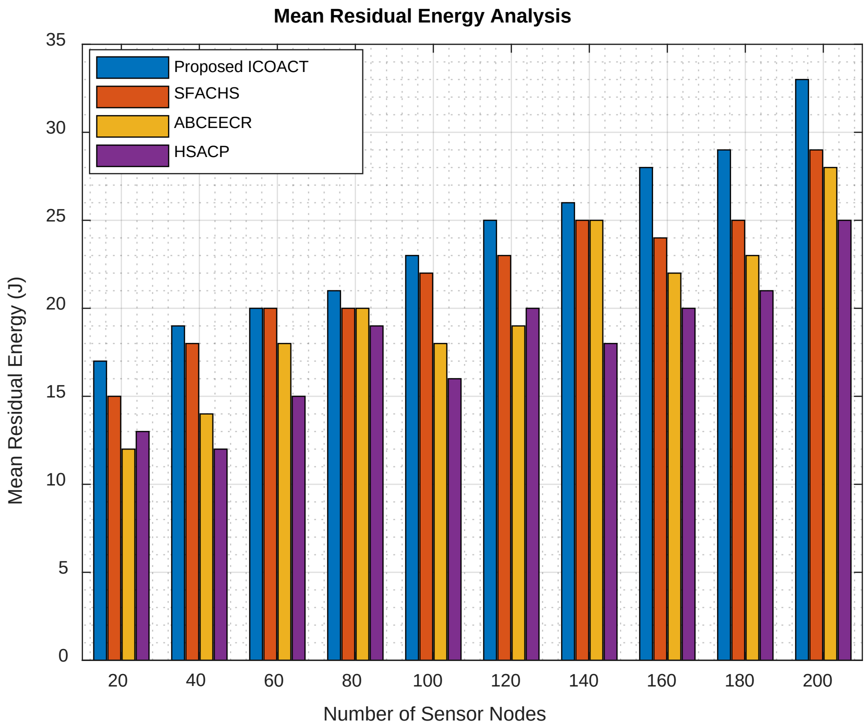

Fig. 9. Mean Residual energy of the Proposed ICOACT for Increasing Amount of Nodes

Table 3 displays the mean, median, and standard deviation based on the proposed ICOACT technique's number of alive nodes and normalized energy (SD). The results reveal that the proposed technique's mean and median are superior to the traditional techniques. The substantial performance of the suggested approach is mostly due to the selection of arbitrary sample solutions derived not only from the cluster where the commander solution exists but also from the solution gained from the remainder clusters. 5.48 %, 5.91 %, and 6.79 % of nodes are alive as a result of the proposed ICOACT mechanism. Compared to the standard techniques, the mean normalized energy is 6.24 % and 7.64 % higher. It also increases median node life expectancy by 6.76 and 7.43 % with median normalized energy maintained by 4.69, 6.13 and 7.26 % in comparison to typical techniques. Compared to the traditional techniques, the proposed approach reduces SD in the number of alive nodes and normalized energy by 7.82 % and 8.94 %.

Table 3. Mean, Median and SD based on the Number of Alive Nodes and Sustained Normalized Energy of the Proposed ICOACT

CH Selection Mechanisms	Mean Number of Alive Nodes	Mean Normalized Energy	Median number of alive nodes	Median in Normalized Energy	SD in the Number of Alive Nodes	SD in Normalized Energy
Proposed ICOACT	73.8	1.50621	66	0.42724	33.244	0.4553
SFACHS	66.18	1.47456	61	0.39282	35.842	0.4785
ABCEECR	62.62	1.45828	59	0.389641	40.181	0.4984
HSACP	59.68	1.44742	55	0.37764	40.828	0.5051

Table 4 compares the provided technique's temporal complexity to those of the conventional techniques under consideration and reflects the worst, best, mean, median, and standard deviation. From the outcomes, it is obvious that the proposed technique offers improved results as it includes the advantages of COA with a central solution which in turn reduces the complexity of CH selection. The proposed technique involves 6.14%, 7.93% and 8.29% reduced time complexity in contrast to the standard mechanisms. The proposed ICOACT technique offers 4.56%, 5.12% and 7.69% reduced time complexity in contrast to the standard mechanisms. The proposed technique involves 5.24%, 6.82% and 7.56% reduced average time complexity in contrast to standard mechanisms. The proposed ICOACT technique offered 4.78%, 5.91% and 6.34% reduced median time complexity in contrast to the conventional techniques. Moreover, the proposed ICOACT technique achieved 4.52%, 6.88% and 8.79% reduced SD in time complexity when compared to the technique conventional techniques.

Table 4. Best, Worst, Mean, Median and SD based on Time Complexity of the Proposed ICOACT

CH Selection Mechanisms	Best	Worst	Mean	Median	Standard Deviation
Proposed ICOACT	3.2474	4.6723	4.1116	2.3616	0.4512
SFACHS	3.5341	6.9087	4.2341	2.4716	0.4643
ABCEECR	3.6542	13.4242	4.6164	2.8742	0.4742
HSACP	3.7724	14.5063	5.1212	3.2841	0.5644

5. Conclusion

In this article, the proposed Improved Coyote Optimization Algorithm-based Clustering Technique (ICOACT) was able to increase the life and maintain a balance between exploitation and exploration for efficient cluster head selection. A centre solution was included in this proposed ICOACT, which assisted in replacing the optimal solution in the search space throughout the clustering algorithm, preventing premature convergence. As the number of sensor nodes increased, the ICOACT technique mean throughput improved by an average of 5.98% and 6.84 % compared to the other systems tested. The suggested ICOACT, on the other hand, maintained an average of 6.24 % and 7.18 % more than the conventional techniques for residual energy. In the future, an improved hybrid spotted hyena-based clustering technique can be devised and tested against the ICOACT to observe the better performance.

References

[1] X.Cheng, C.Xu, X.Liu, J.Li, and J.Zhang, "LEACH Protocol Optimization Based on Weighting Strategy and the Improved Ant Colony Algorithm," *Front Neurorobot*, vol. 16, pp. 1-13, March 2022. Article(CrossRef Link).

[2] P.Sengottuvelan, and N.Prasath, "BAFSA: Breeding Artificial Fish Swarm Algorithm for Optimal Cluster Head Selection in Wireless Sensor Networks," *Wireless Pers Commun.*, vol.94, pp.1979–1991, June 2017. Article(CrossRef Link).

[3] S.Potthuri, T.Shankar, and A.Rajesh, "Lifetime Improvement in Wireless Sensor Networks using Hybrid Differential Evolution and Simulated Annealing (DESA)," *Ain Shams Engineering Journal*, vol.9, no.4, pp.655-663, Dec 2018. Article(CrossRef Link)

[4] S.S.Harakannanavar, H.Jayalaxmi, H.Shridhar, R.Premananda, H.J.Jambukesh, and V.Puranikmath, "Huffman coding: Energy efficient algorithm in wireless networks," *International Journal of Health Sciences*, vol.6, no.S3, pp.3624-3641, Apr. 2022. Article(CrossRef Link).

[5] J. Sengathir, A. Rajesh, Gaurav Dhiman, S. Vimal, C.A. Yogaraja, and Wattana Viriyasitavat, "A novel cluster head selection using Hybrid Artificial Bee Colony and Firefly Algorithm for network lifetime and stability in WSNs," *Connection Science*, vol.34, no.1, pp.387-408, 2022. Article(CrossRef Link).

[6] M.Azharuddin, and P.K.Jana, "PSO-based approach for energy-efficient and energy-balanced routing and clustering in wireless sensor networks," *Soft Computing*, vol.21, no.22, pp.6825–6839 Nov 2017. Article(CrossRef Link).

[7] J.Yang, W.Zhao, M.Xu, and B.Xu, "A Multipath Routing Protocol Based on Clustering and Ant Colony Optimization for Wireless Sensor Networks," *Sensors (Basel)*, vol.10, no.5, pp.4521-4540, May 2010, Article(CrossRef Link).

[8] S.Suganthi, N.Umapathi, M.Mahdal, and M.Ramachandran, "Multi Swarm Optimization Based Clustering with Tabu Search in Wireless Sensor Network," *Sensors (Basel).*, vol.22, no.5, pp.1736-1745, Feb 2022. Article(CrossRef Link).

[9] S.Yousefi, F.Derakhshan, H.S.Aghdasi, and H.Karimipour, "An energy-efficient artificial bee colony-based clustering in the internet of things," *Computers & Electrical Engineering*, vol.86, pp.1-14, Sep 2020. Article(CrossRef Link)

[10] P.Singh Mann, and S.Singh, "Energy efficient clustering protocol based on improved metaheuristic in wireless sensor networks," *Journal of Network and Computer Applications*, vol.83, pp.40–52, April 2017. Article(CrossRef Link).

[11] S.S.Ilango, S.Vimal, M.Kaliappan, and P.Subbulakshmi, "Optimization using Artificial Bee Colony based clustering approach for big data," *Cluster Computing*, vol.22, no.4, pp.12169-12177, Sep 2019. Article(CrossRef Link).

[12] A.Gambhir, A.Payal, and R.Arya, "Performance analysis of artificial bee colony optimization based clustering protocol in various scenarios of WSN," *Procedia Computer Science*, vol.132, pp.183–188, Nov 2018. Article(CrossRef Link)

[13] D.Karaboga, S.Okdem, and C.Ozturk, "Cluster based wireless sensor network routing using an artificial bee colony algorithm," *Wireless Networks*, vol. 18, no. 7, pp. 847-860, Oct 2012. Article(CrossRef Link)

[14] Sankalap Arora, and Satvir Singh, "An Effective Hybrid Butterfly Optimization Algorithm with Artificial Bee Colony for Numerical Optimization," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 4, no.4, Aug 2017. Article(CrossRef Link)

[15] B. Rambabu, A.Venugopal Reddy, and S.Janakiraman, "Hybrid Artificial Bee Colony and Monarchy Butterfly Optimization Algorithm (HABC-MBOA)-based Cluster Head Selection for WSNs," *Journal of King Saud University - Computer and Information Sciences*, Vol.34, no.5, pp.1895-1905, May 2022. Article(CrossRef Link).

[16] A.Yadav, S.Kumar, and S.Vijendra, "Network Life Time Analysis of WSNs Using Particle Swarm Optimization," *Procedia Computer Science*, vol.132, pp.805–815, Nov 2018. Article(CrossRef Link)

[17] D.Chandirasekaran, and T.Jayabarathi, "Cat swarm algorithm in wireless sensor networks for optimized cluster head selection: a real time approach," *Cluster Computing*, vol.22, no.7, pp.11351-11361, Sep 2019. Article(CrossRef Link).

[18] Ruan and Huang, "A PSO-Based Uneven Dynamic Clustering Multi-Hop Routing Protocol for Wireless Sensor Networks," *Sensors*, vol.19, no.8, pp.1835-1846, 2019. Article(CrossRef Link)

[19] D.C.Hoang, P.Yadav, R.Kumar, and S.K.Panda, "Real-Time Implementation of a Harmony Search Algorithm-Based Clustering Protocol for Energy-Efficient Wireless Sensor Networks," *IEEE Transactions on Industrial Informatics*, vol.10, no.1, pp. 774-783, Feb. 2014. Article(CrosssRef Link).

[20] G.P.Gupta, and S. Jha, "Integrated clustering and routing protocol for wireless sensor networks using Cuckoo and Harmony Search based metaheuristic techniques," *Engineering Applications of Artificial Intelligence*, vol.68, no.1, pp.101-109, Feb 2018. Article(CrossRef Link)

[21] S.Kaur, and R.Mahajan, “Hybrid meta-heuristic optimization-based energy efficient protocol for wireless sensor networks,” *Egyptian Informatics Journal*, vol.19, no.3, pp. 145-150, Nov 2018. Article(CrossRef Link).
[22] P.S.Mann, and S.Singh, “Artificial bee colony metaheuristic for energy-efficient clustering and routing in wireless sensor networks,” *Soft Computing*, vol.21, no.22, pp. 6699-6712, 2017. Article(CrossRef Link)
[23] T.Shankar, S.Shanmugavel, and A.Rajesh, “Hybrid HSA and PSO algorithm for energy efficient cluster head selection in wireless sensor networks,” *Swarm and Evolutionary Computation*, vol.30, no.1, pp. 1-10, Oct 2016. Article(CrossRef Link).
[24] A.Sarkar, and T.Senthil Murugan, “Cluster head selection for energy efficient and delay-less routing in wireless sensor network,” *Wireless Networks*, vol.25, no.1, pp.303-320, Jan 2019, Article(CrossRef Link)
[25] T.S.Murugan, and A.Sarkar, “Optimal cluster head selection by hybridization of firefly and grey wolf optimization,” *International Journal of Wireless and Mobile Computing*, vol.14, no.3, pp. 296-305, Jan 2018. Article(CrossRef Link)
[26] Sarkar Amit, and T. Senthil Murugan, “Analysis on dual algorithms for optimal cluster head selection in wireless sensor network,” *Evolutionary Intelligence*, vol.15, pp.1471–1485, June 2022. Article(CrossRef Link)
[27] A.Balamurugan, M. Priya, Sengathir Janakiraman, and A. Malar, “Hybrid stochastic ranking and opposite differential evolution-based enhanced firefly optimization algorithm for extending network lifetime through efficient clustering in WSNs,” *Journal of Network and Systems Management*, vol.29, no. 33, pp. 1-31, April 2021. Article(CrossRef Link)
[28] Devika G, D.Ramesh, and Asha Gowda Karegowda, "Firefly and Grey Wolf search based multi-criteria routing and aggregation towards a generic framework for LEACH," *International Journal of Information Technology*, vol.14, pp.105–114, Feb 2022. Article(CrossRef Link)
[29] Jaiswal, Kavita, and Veena Anand, “FAGWO-H: A hybrid method towards fault-tolerant cluster-based routing in wireless sensor network for IoT applications,” *The Journal of Supercomputing*, vol.78, pp.11195–11227, May 2022. Article(CrossRef Link)
[30] J. S. Manoharan, “Double attribute-based node deployment in wireless sensor networks using novel weight-based clustering approach,” *Sādhanā*, vol. 47, no. 3, pp. 1–11, August 2022. Article(CrossRefLink)
[31] J. S. Manoharan, “A Novel Load Balancing aware graph theory-based node deployment in wireless sensor networks,” *Wireless Personal Communications*, vol. 128, pp. 1171 – 1192, January 2023. Article(CrossRefLink)
[32] K.Vijayalakshmi, and P.Anandan, “Global levy flight of cuckoo search with particle swarm optimization for effective cluster head selection in wireless sensor network,” *Intelligent Automation & Soft Computing*, vol. 26, no.2, pp. 303–311, Jan 2020. Article(CrossRef Link)

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