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An African vulture optimization algorithm based energy efficient clustering scheme in wireless sensor networks

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Energy efficiency plays a major role in sustaining lifespan and stability of the network, being one of most critical factors in wireless sensor networks (WSNs). To overcome the problem of energy depletion in WSN, this paper proposes a new Energy Efficient Clustering Scheme named African Vulture Optimization Algorithm based EECS (AVOACS) using AVOA. The proposed AVOACS method improves clustering by including four critical terms: communication mode decider, distance of sink and nodes, residual energy and intra-cluster distance. Through mimicking the natural scavenging behavior of African vultures, AVOACS continuously balances energy consumption on nodes resulting in an increase in network stability and lifetime. For CH selection, we use AVOACS, which considers the following parameters: communication mode decider, the distance between sink and node, residual energy, and intra-cluster distance. In comparison to the OE2-LB protocol, simulation findings demonstrate that AVOACS enhances stability, network lifetime, and throughput by 21.5%, 31.4%, and 16.9%, respectively. The results show that AVOACS is an effective clustering algorithm for energy-efficient operation in heterogeneous WSN environments as it contributes to a large increase of network lifetime and significant enhancement of performance.

Keywords AVOA, WSNs, Cluster Head, Sensor Networks, CMD

In recent years, Wireless Sensor Networks (WSNs) have become indispensable in many applications such as healthcare systems, environmental monitoring and military surveillance or smart cities et cetera[1]. These networks are composed of an assemblage of physically disseminated sensor nodes which all together operate to collect, process and transport data/mote towards impel sink node[2]. These devices face serious energy considerations, even though they are used for many purposes. While sensor nodes are normally battery powered, and the small energy available in them limits life of an operating network[3,4]. Therefore, prolonging the lifetime of wireless sensor networks along with their stable and efficient performance have been important issues addressed in design of WSNs. WSN can enable such virtual and real-world connections. Nonetheless, sensor nodes have limited computing power, memory, and battery[5]. They require batteries and are commonly employed in large-scale unsupervised environments where battery maintenance or recharge is challenging.

In clustering is a major technique where many researchers focus to increase energy efficiency in WSNs. It utilizes cluster-based protocols, i.e., it groups sensor nodes into clusters that consist of a CH to aggregate data and deliver these to the sink[6]. The selection of CHs and the management of clusters are key factors which influence network performance even though this method reduces energy consumption[7]. Intra-cluster communication should be reduced to a minimum for energy efficiency and an ideal clustering algorithm helps in distributing the workload of all nodes across individual clusters, as well as minimizing intra cluster hops. Every cluster has a CH whose main responsibility is to collect data from the other members of the cluster. CH is chosen depending on several important factors such as intra-cluster distance, CMD, residual energy, etc. Using a meta-heuristic method in CH selection has proved attractive in achieving optimum network performance[8,9]. When

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intra-cluster communication occurs, the nodes closest to the sink use much energy. This issue is known as the hot-spot problem because these relaying nodes quickly consume energy[10,11].

However, the existing cluster-based algorithms suffer from drawbacks: shorter operational duration of sensor nodes, high energy expenditure, delay in data delivery, hot-spot problems in large-scale applications, residual energy dependence, connection failure, etc[12–16]. From this current perspective, several studies have been conducted, each suggesting a unique energy-efficient routing strategy with the goal of extending the network's useful life by reducing the drain on the sensor nodes' batteries: the proposed approach analyses and monitors data from the wireless sensor networks[17–19]. However, despite its benefits of energy efficiency and network lifetime extension effect, there are limitations if the African Vulture Optimization Algorithm-based Energy Efficient Clustering Scheme (AVOACS) is applied. Among its drawbacks, it does not have the strong scalability powered by being enormous and possessing many clusters along with cluster heads that large-scale WSNs do; The resulting conciliation of both processing time as well as energy consumption is increased.

In this paper, we design a new energy efficient clustering scheme for WSN named AVOACS that is nature motivated approach of scavenging behavior in Africa vultures. The AVOACS (An algorithm for Optimization in energy Consumption using the four mandatory factors which improves network life) that is an efficient method to reduce power consumption and lifetime of networks by having four important parameters Based on communication mode decider, Sink –node distance, residual energy & intra cluster distance. AVOACS uses these parameters to dynamic cluster head selection and optimizing the clustering process for reducing energy consumption. The proposed AVOACS method is experimentally validated in terms of performance by comparing it with the performances for some well-known existing state-of-the-art clustering algorithms: PSO-ECSM, HWSHO, OE2-LB and ABC-DE. Experimental results indicate that AVOACS not only has better network stability, but also prolongs the lifetime of a wireless sensor network compared with another algorithm. Thus, a retrospective assessment reveals a few characteristics that might significantly increase network lifetime

The major contributions of this paper are highlighted as follows:

- The proposed AVOACS for WSNs formulated the cluster formation through several essential parameters such as communication mode decider, distance to sink, residual energy of sensors and intra-cluster distance.
- The optimal selection of cluster heads is compatible with the characteristics shown in AVOACS which demonstrated significant advantages on energy efficiency for network Longevity.
- The dynamic clustering adapts cluster head selection and communication strategies by considering factors such as node energy levels or distance to the sink, optimizing energy usage and load sharing based on network conditions.
- To test and validate the proposed methodology with the state-of-the-art optimized routing methods based on particle search, such as PSO-ECSM[7], HWSHO[20], OE2-LB[21], and ABC-DE[22], and it is shown to have achieved higher overall performance.

The remainder of the manuscript is summarised in the sections below. Sect "Literature review" provides the background research, while Sect "Preliminaries"describes the proposed strategy. The simulation findings are detailed in Sect "Proposed methodology", and the conclusion is in Sect "Experimentation, results and analysis".

Literature review

Clustering algorithms have an important role to play in the energy efficiency of a Wireless Sensor Network (WSN), and lot of research has been done on developing efficient clustering algorithm for increasing the lifetime of network. Existing optimization-based clustering schemes are good energy conservation approaches, and some further improved by utilizing certain issues regarding cluster formation to verify their performance under different conditions. However, most of them experience difficulties in scalability as they adapt into a large-scale network rather than the target one for which these were proposed initially[23–26]. This part presents major works in energy-efficient clustering algorithms, mainly influenced by nature-based optimization methods[27].

Deepa et al.[28] proposed multi-path routing protocol utilizing swarm optimization. The cluster head is selected near the sink coverage area, and the energy hole problem is solved by using a modified Particle Swarm Optimization (PSO)-based clustering algorithm. A particle swarm optimization-based clustering technique with a mobile sink was suggested by Wang et al.[29]. Rambabu et al.[30] suggested a HABC-MBOA algorithm for CH selection. HABC-MBOA was found to be useful in preventing sensor node overloading when used as CH. Thrun et al.[31] presented the databionic swarm system. As a result, while Swarm-based algorithms are task-centred and data independent approaches for WSN optimization issues they struggle with premature convergence problems leading to suboptimal performance in Heterogeneous networks due to their static approach of deployment irrespective the network dynamics and heterogeneous energy-based node implementation[32].

Palattella et al.[33] proposed that IoT-based WSN universality may be hindered by the need for reliable, scalable, and cost-effective connectivity. It has been pointed out that these technologies may be used in diverse contexts, such as for consumer IoT and industrial IoT. The article focuses on the significant developments of 5G technology in IoT and the commercial implications that follow from them. Ilango et al.[34] used mapper and reducer programming to implement the ABC Algorithm in a Hadoop environment. The suggested ABC was shown to reduce execution time and fault of classification for a collection of ideally designed clusters in empirical testing. The findings show that the suggested ABC scheme outperforms differential evolution and PSO[35].

In this paper, Gaikwad et al.[36] has presented an enhanced ABC that optimizes large-scale data clustering. By using the modified ABC, the cluster consumes less power. For selecting CHs, the protocol methodology uses a distributed technique, and K-means is utilized to fix the threshold power based on experimental data. Amiri et al.[37] proposed a novel fuzzy algorithm with enhanced discrete ABC for data clustering.

Betzler et al.[38] developed an IoT- based WSN technique for estimating round-trip times that incorporates the age factor for retransmission timeouts. Cluster formation is most important part of clustering process which has been accentuated by several researchers[9,10]. Das et al.[39] presented a new clustering technique by utilizing probability-based selection mechanism for allocation of a set of data in each cyclic rotation. Rani et al.[40] presented dynamic clustering-based technique utilizing Genetic algorithm. The CHs selection was made based on residual energy and node's location. Pan et al.[41] proposed a search model utilizing best-of-random mutation strategy. The performance assessment was done by employing various optimization techniques. The results obtained strengthen the claim made by suggested method as it depicted significant gain in performance[42,43]. Bagirov et al.[44] suggested approach's performance is compared to that of other methods, and the findings demonstrate that the suggested method outperforms its rivals. The performance of Bee Colony Optimization (BCO) in clustering datasets may be an essential research component, even if there are various clustering applications of BCO in the literature. It is combined the suggested approach with k-means algorithms to improve its performance and provide optimum solution[45–47].

Verma et al.[20] introduced the HWSHO approach in order to address the problem of green communication in 6G-enabled large WSN devices. This was accomplished by using cluster-based data distribution in the network. This method is an excellent example of a solution that may be useful for a variety of malicious apps that are interested in green communication via 6G-enabled Internet of Things devices. CH selection is found to be an NP-Hard problem, and achieving optimal network performance is one of the difficult tasks that must be accomplished. As a consequence of this, there is a requirement for a metaheuristic strategy that is able to meet crucial characteristics in an optimum fashion. These critical parameters are necessary for CH selection[48]. As a result, many different metaheuristic approaches such as GA[49], PSO[50,51], WOA, MFO[52], and were presented in order to optimize the cluster selection[53]. The existing metaheuristic algorithms used for routing have several limitations like lack of scalability, unbalanced exploration and exploitation and ineffectiveness in handling the dynamics of the network. Beside that the existing algorithms are still not able to truly optimize the decision of clustering and routing leading to ineffective energy consumption. The proposed optimization algorithm addressed these deficiencies and improves the performance on various metrics. Among the several metaheuristic algorithms available, AVOA is used in this research to enhance network efficiency. AVOA is used in this study to improve the efficiency of decision-making in order to provide the best possible value throughout the clustering process. The current routing protocols cannot provide an energy-efficient solution for routing in wireless sensor networks. AVOA may reduce application complexity by using the fitness function[54].

Nature-inspired optimization algorithms are promising for real-world engineering problems. One such technique is the Arithmetic Optimization technique (AOA), designed for optimization[23]. AOA helps engineers with constraint management tasks like resource allocation and system optimization traverse and use the solution space. Kumar et al.[24] proposed chaotic marine predators algorithm (CMPA) has promise. Chaos theory and predator-prey interactions improve optimization exploration and convergence. CMPA optimises mechanical and structural designs that traditional approaches struggle with. Optimizing shell and tube heat exchangers has been successful. The AVOA solves complicated multi-dimensional and non-linear optimization problems by balancing efficiency and accuracy[25]. These methods improve exploration-exploitation harmony to solve optimization problems. Engineering situations benefit from convergence rates and effective constraint management. Data transmission mechanisms are essential for optimizing energy efficiency and network durability. The ELFO algorithm is inspired by eel foraging[26]. ELFO's adaptive foraging technique allows efficient network exploration to find optimum paths while reducing energy. PROA uses reinforcement learning and optimization to improve decision-making in scenarios like tuning automobile suspension elements for performance[55]. It might improve clustering and node communication in WSNs, ensuring network stability even when circumstances change. These methods may improve energy utilization and operating efficiency in WSN installations, overcoming optimization challenges. Though, much work has been done on Energy efficient clustering algorithms but still there is a requirement of adaptive and scalable solutions, especially for WSNs having heterogeneous nodes with varying capabilities as well energy levels. Table 1 shows the reference study of the optimization methods on IoT based WSN.

Preliminaries

In this part, we outline the network assumptions before proposing the suggested work's operational structure.

AVOACS network assumptions

It is vital to note that while replicating the proposed study, several network assumptions about medical things must be considered.

1. The network is composed of randomly deployed sensor nodes, with node uniformly placed in a two-dimensional region. The nodes are battery-powered and, after deployment, do not move from their respective locations for the lifetime of the network. The nodes have the ability to sense, process and transmit data.
2. A single sink node or base station is located inside the sensor field between sinks and source nodes. Sensor nodes are presumed to be limited in power and incapable of remote recharging. Nonetheless, the sink has no energy constraints since it gets a constant source of energy.
3. The network is clustered where sensor nodes clustered in clusters. In each cluster, a specific node called the Cluster Head (CH) is responsible for collecting data from all the member nodes of her corresponding in its hotspots and then transmit it directly to Sink. The cluster head is dynamically selected each round according to residual energy, distance to the sink and intra-cluster communication costs.
4. The nodes are considered homogeneous, meaning they possess processing, initial energy, and sensing range configurations.

References	Method	Objective	Research gaps
Pravin et al.[56]	Genetic Algorithm for Stochastic cluster head selection	Cluster head selection, energy balancing in IoT-WSN	Energy balancing in IoT-WSN is considered, but the optimization technique used there is crude.
Sahoo et al.[57]	Metaheuristic (CBA-EH) Method	Network longevity, Cluster head selection, and energy harvesting in WSN	Application in WSNs restricted to IoT with wok on multiple objective optimizations for energy conservation.
Moghaddasi et al.[58]	DRL method	Energy consumption, resource efficiency and task offloading	It concentrates on offloading efficiency but has a shallow clustering mechanism for WSNs.
Moghaddasi et al.[59]	DDQN method	Multi-objective optimization and task offloading	Thoroughly discusses security but do not emphasize energy efficiency in WSN clustering.
Gharehchopogh et al.[60]	Dynamic Harris Hawks optimization (HHO)	IoT security, botnet detection and dynamic HHO	Security in IoT is the focus, but the main goal of this paper is not energy-efficient clustering.
Gharehchopogh et al.[61]	AVOA optimization Method	Multilevel thresholding and image segmentation	For image processing; not applicable for WSN clustering or energy efficiency.
Gharehchopogh et al.[62]	Chaotic Quasi-oppositional farmland fertility algorithm	Optimization, solving optimization engineering problems	Strictly related with engineering optimization, for signals from a controlled experiment are not directly applicable to optimizing the energy efficiency of WSNs.
Kumar et al.[63]	Caddisfalcon optimization algorithm	Optimization and energy transfer in IoT network	Only high-level energy transfer — not clustering in WSNs.
Zhou et al.[64]	GSHFA-HCP clustering method	Performance monitoring, Clustering with agricultural IoT	Applicability mostly on agriculture IoT system not suitable for wider range of WSN applications.

Table 1. References study of the optimization methods on IoT based WSN.

Energy consumption model

Energy consumption of the Network is one important factor which directly impacts on network lifetime and performance as a whole, hence in the proposed AVOACS by considering energy consumed by each node. Energy model. The energy consumption model used in this work is based on a generic radio power dissipation that accounts for transmission and reception cost of the whole communication protocol. It includes the following assumptions and equations for them as energy consumption model of sensor nodes in network. A distance $\mathrm{d_{ij}}$ between two nodes i and j is expressed as follows. The energy used by node i during the transmission of z-bit data to node j is

$$\mathrm{E_{tx}}\,(\mathrm{z},\mathrm{d_{ij}}) = \begin{cases} z*\mathrm{E_{el}} + z*\mathrm{E_{efs}}*\mathrm{d_{ij}}^2 \;\; for\ \mathrm{d_{ij}} \le do \\ z*\mathrm{E_{el}} + z*\mathrm{E_{amp}}*\mathrm{d_{ij}}^4 \;\; for\ \mathrm{d_{ij}} > do \end{cases} \tag{1}$$

The energy spent rather than starting a transmitter and reception circuit is denoted by E_{el}, and 'd_o' denotes a minimum distance and has to be written as in Eq. (2).

$$\mathrm{d_o} = \sqrt{\frac{\mathrm{E_{efs}}}{\mathrm{E_{amp}}}} \tag{2}$$

Where, Eqs. (3), (4) $\mathrm{E_{rx}}\,(\mathrm{z})$ represent the energy spent by a node in accepting and aggregating z-bit data packets, and $\mathrm{E_{dx}}\,(z)$ represent the consumption of energy throughout aggregation of data respectively.

$$\mathrm{E_{rx}}\,(\mathrm{z}) = z*\mathrm{E_{el}} \tag{3}$$

And

$$\mathrm{E_{dx}}\,(z) = \mathrm{x}*z*\mathrm{E_{da}} \tag{4}$$

Equation (5) calculates the overall energy E_{Total} spent in packet forwarding, processing, and data aggregation.

$$\mathrm{E}_{Total} = \mathrm{E_{tx}} + \mathrm{E_{el}} + \mathrm{E}_{dx} \tag{5}$$

Proposed methodology

We aim to build a cluster-based data aggregation routing scheme in WSNs using the network above paradigm. Using four important parameters, the proposed method extends the life of the network. As a result, the primary goal to be explored is creating a load-balanced data aggregation routing scheme that efficiently links all sensors to the sink node. The remaining energy usage among multiple sensors in the Network utilizes a modified energy-aware AVOA algorithm to choose the optimal CH for each cluster. AVOACS presents the Network's energy usage and reduces the Network's overall energy transmissions. The AVOA meta-heuristic method was first presented by Abdollahzadeh et al.[54] in the year 2021. Since that time, it has been implemented in a variety of real-world engineering applications. In order to build the AVOA, simulations and models were used that were based on the feeding behaviors and daily routines of African vultures. The following considerations are taken into account in order to carry out the simulation that is known as AVOA. This simulation recreates the life patterns and foraging strategies of African vultures, and it is carried out by using the following elements.

Input: Number of deployed sensor nodes (N)
Maximum Iteration (itr_{max}), Sink1
Output: $Best_v$
Begin
Initialization of *population* size V_n .
for each vulture $v \in V_n$ **do** /*Loop to check termination */
Calculate $F = \frac{1}{\alpha * Obj_1 + \beta * Obj_2 + \gamma * Obj_3 + \delta * Obj_4}$ /*Using equation (31) */
end for
Set $t = 1, itr_{max}$
for $t \leq itr_{max}$ ***do***
for each vulture $v \in V_n$ **do**
if $(|F_v| \geq 1)$ **then**
if $(V_1 \geq r_{v1})$ **then**
Update position $V(i)$ using Equation (9)
else
Update position $V(i)$ using Equation (11)
if $(|F_v| < 1)$ **then**
if $(|F_v| \geq 0.5)$ **then**
if $(V_2 \geq r_{v2})$ **then**
Update position $V(i)$ using Equation (13)
else
Update position $V(i)$ using Equation (17)
else
if $(V_3 \geq r_{v3})$ **then**
Update position $V(i)$ using Equation (21)
else
Update position $V(i)$ using Equation (22).
end for
$t = t + 1$
end for
for $i= 1: V_n$ **do**
For $i= 1: N_\omega$ **do**
If $F(i+1) < F(i)$ **then**
$Best_v = F(i+1)$
Else
$Best_v = V(i)$
end for
end for
end for
end

Algorithm 1. AVOACS Procedure.

(i) There are N vultures in the African vulture population, and the user of the algorithm decides how large N should be depending on the conditions at the time of the calculation. The position space of each vulture is represented by a grid with D dimensions; the size of D varies depending on the complexity of the issue.
(ii) The population of African vultures may be broken down into three distinct clusters according to the way in which they make their livelihood. The first cluster determines the most optimal viable solution by using the fitness value of the viable solution as a metric to evaluate the quality of the approach. The second cluster of thought maintains that out of all of the potential solutions, the one that can really be implemented is the one that is second-best. The third and final group is made up of the remaining vultures.

(iii) The vulture hunts in groups throughout the population in which it resides. As a direct consequence of this, several species of vultures fulfil a variety of roles within the community.
(iv) Similarly, if the fitness value of the population's feasible solution may be understood to reflect the advantages and downsides of vultures, then the vultures who are the weakest and most hungry correspond to the vultures that are the worst at the current time. On the other hand, the vulture that is the healthiest and most numerous at this time is the greatest option. Vultures in AOVA strive to position themselves near the greatest and away from the bad.

Based on the fundamental ideas about vultures and the four assumptions used to replicate the artificial vulture's optimization algorithm, the problem-solving process can be broken down into five stages that represent the foraging behaviours of different vultures.

Identifying the best vulture in clusters

After the initial population has been formed, the fitness of each solution is determined, and the best and worst performers are chosen to serve as vultures for the first and second groups, respectively. At each iteration of the fitness test, populations are subjected to a thorough analysis.

$$S\left(i\right)=\left\{\begin{array}{l} Best_{v1}\,if\,f_i=P_1\\ Best_{v1}\,if\,f_i=P_2\end{array}\right.,\,where\,f_i=\frac{F_v\left(i\right)}{\sum_{i=1}^{n}F_v\left(i\right)} \tag{6}$$

The probability that the chosen vultures will lead the other vultures to one of the best solutions in each cluster is determined by Eq. (6), where P_1 and P_2 are the best solutions in the cluster. Both of the search operation's input parameters must have values between 0 and 1, with the total being 1. Using the rank selection to choose the best fitness from each set using $f_i=\frac{F_v(i)}{\sum_{i=1}^{n}F_v(i)}$ increases the probability of selecting the optimal solution.

Vulture hunger rate

Vultures are remaining on the hunt for food, and when they get it, they have a burst of energy that helps them to go further in their quest for more. On the other hand, they are more aggressive when they are hungry since they lack the strength to fly long distances or to hunt for food alongside larger, stronger vultures. This sort of behaviour has been modelled mathematically with the help of Eq. (7). The rate at which the vultures are satiated or hungry has also been used to mark the shift from the exploratory to the exploitative phase. Equation (7), which accounts for the decreasing rate of satisfaction, has been used to predict this phenomenon.

$$F_v=(2*r_1+1)*\Updownarrow*\left(1-\frac{itr_i}{itr_{max}}\right)+\sqcup \tag{7}$$

$$\sqcup=\backslash*\left(sin^{w}\left(\frac{\pi}{2}*\frac{itr_i}{itr_{max}}\right)+cos\left(\frac{\pi}{2}*\frac{itr_i}{itr_{max}}\right)-1\right) \tag{8}$$

In Eqs. (7), (8), the symbol F_v indicates that the vultures have consumed all of the food available to them, iteration i represents the number of the current iteration, itr_{max} represent the overall number of iterations, and $\Updownarrow$ is a random value ranging from − 1 to 1 that fluctuates with each new iteration. $\backslash$ are an integer chosen at random from the range − 2 to 2. rand1 returns a result that is completely random between 0 and 1. If the z value goes below zero, it indicates that the vulture is starving, and if it goes above zero, it indicates that the vulture has satiated.

Exploration

Here, we examine the AVOA exploration phase. Vultures have keen vision, which helps them find prey and dead animals. When searching for food, vultures fly long distances and do detailed observations of their surroundings. The vultures in the AVOA may use one of two methods to explore seemingly random sites, with the method being selected at random. Exploration stage is need to provide a value between 0 and 1 for this option before you can begin the search process. Which method is used is up to it. A random integer between 0 and 1 is created during the exploration phase and used to decide which approach to pursue. The Eq. (9) is utilized if the number is greater than or equal to the parameter. If, however, the digit count is under Eq. (11), the formula will be used. This is shown by Eq. (12).

$$V\left(i+1\right)=S\left(i\right)-\mathcal{D}\left(i\right)*F_v \tag{9}$$

$$\mathcal{D}\left(i\right)=\left|\epsilon\,*S\left(i\right)-V\left(i\right)\right| \tag{10}$$

$$V\left(i+1\right)=S\left(i\right)-F_v+r_2*\left(\left(UB-LB\right)*r_3+LB\right) \tag{11}$$

$$V\left(i+1\right)=\left\{\begin{array}{ll} \left|\epsilon\,*S\left(i\right)-V\left(i\right)\right| & if\,V_1\geq r_{v1}\\ S\left(i\right)-F_v+r_2*\left(\left(UB-LB\right)*r_3+LB\right) & if\,\;V_1<r_{v1}\end{array}\right. \tag{12}$$

The position vector of a vulture in the iteration that follows will be indicated by the $V\left(i+1\right)$, and the satiation rate of the vulture in the current iteration will be denoted by the symbol F_v, which can be determined by using Eq. (7). In Eq. (10), $S\left(i\right)$ is a good example of the kind of vulture that is chosen by Eq. (12). The vultures patrol the area randomly in order to protect their meal from the other vultures. ϵ is created via the formula $\epsilon=r_2$, where r_2 is a randomly produced number between 0 and 1, and ϵ is then utilized as a coefficient vector to enhance the random motion, which shifts with each iteration. r_3 is a randomly generated number between 0 and 1. The vector location is determined by the vulture's V_1. The variable boundaries are shown by LB and UB. r_3 increases the amount of unpredictability. If r_3 is somewhat close to 1, solutions that are comparable are spread, which adds a random motion to the LB.

Exploitation stage-1

At this point, the AVOA's efficiency stage is being analysed for its effectiveness. The AVOA will proceed to the exploitation phase if the value of F_v is less than 1, since this indicates that there is room for profit. This phase, like the previous one, is divided into two sections, and each of those portions employs a distinct tactic. Two factors, V_2 and V_3, define the likelihood that each approach will be selected throughout each of the phases that take place internally. The strategy for the first phase is determined by the parameter V_2, whereas the second phase is determined by the parameter V_3. Both of the parameters need to be set to 0 and 1 before the search operation can be carried out. When the value of $|F_v|$ is between 1 and 0.5, the exploitation phase starts. During the initial phase of the battle, both a rotating flying strategy and a siege-fighting strategy will be used. Before performing a searching operation, the value of V_2, which ranges between 0 and 1, will be used to choose which strategy to use. r_{v2} is constructed right at the beginning of this phase. If this amount is more than or equal to V_2, the implementation of the Siege-fight will go more slowly. In the event that the random number is lower than V_2, the rotating flying method will be used. The Eqs. (13), (14) illustrates how to carry out this technique.

$$V(i+1) = \mathcal{D}(i) * (F_v + r_4) - d(t) \tag{13}$$

$$d(t) = S(i) - V(i) \tag{14}$$

The value of $\mathcal{D}(i)$ may be found by using Eq. (10), and the value of F_v can be found by applying Eq. (7) to the satiation rate of vultures. A random number between 0 and 1, r_4 is added to the formula to make the random coefficient even more unpredictable. In Eq. (14), $S(i)$ represents one of the best vultures from the two groups that was chosen using Eq. (17) during the current iteration. $V(i)$ represents the current vector location of the vulture, which is used to calculate the distance between the vulture and one of the best vultures from the two groups.

Vultures typically perform a flying pattern that may be described as a rotating flight, and this flight pattern can be utilized to mimic spiral motion. Mathematical modelling of circular flight has been accomplished via the use of the spiral model. Using this approach will result in the formation of a spiral Eq. (18) involving all of the vultures and one of the top two vultures. Equations (15) and (16) are used to compute a_1 and a_2 and provide an expression for the rotational flight.

$$a_1 = S(i) * \left(\frac{r_5 * V(i)}{2\pi}\right) * cos(V(i)) \tag{15}$$

$$a_2 = S(i) * \left(\frac{r_6 * V(i)}{2\pi}\right) * sin(V(i)) \tag{16}$$

$$V(i+1) = S(i) - (a_1 + a_2) \tag{17}$$

$$V(i+1) = \begin{cases} D(i) * (F_v + r_4) - d(t) & if\ V_2 \geq r_{v2} \\ S(i) - (a_1 + a_2) & if\ V_2 < r_{v2} \end{cases} \tag{18}$$

Exploitation stage-2

During the second stage of the exploitation process, the movements of the two vultures lure many other species of vultures to the food supply, where a siege and a vigorous fight for food ensue. When the value of F_v is lower than 0.5, the transition into this phase begins. During this step, the random number generator r_{v3} will produce a value between 0 and 1. If r_{v3} is more than or equal to V_3, a large number of different kinds of vultures should converge around the source of food. Alternately, the aggressive siege-fight approach described in Eq. (23) is adopted if the value created is less than V_3. This occurs if the value generated is less than V_3.

$$A_1 = Best_{v1}(i) - \frac{Best_{v1}(i) * V(i)}{Best_{v1}(i) - V(i)^2} * F_v \tag{19}$$

$$A_2 = Best_{v2}(i) - \frac{Best_{v2}(i) * V(i)}{Best_{v2}(i) - V(i)^2} * F_v \tag{20}$$

In the last step, the vultures are summed up with the help of Eq. (20), in which A_1 and A_2 come from the previous Eqs. (19), (20), and $V(i+1)$is the vulture vector for the next iteration. The names given to the best vultures in the first and second groups of this iteration are $Best_{v1}(i)$ and $Best_{v2}(i)$, respectively. $V(i)$ stands for the vector position of a vulture at any given moment.

$$V(i+1) = (A_1 + A_2)/2 \tag{21}$$

$$V(i+1) = S(i) - |d(t)| * F_v * levy(d) \tag{22}$$

$$V(i+1) = \begin{cases} (A_1 + A_2)/2 & if\ V_3 \geq r_{v3} \\ S(i) - |d(t)| * F_v * levy(d) & if\ V_3 < r_{v3} \end{cases} \tag{23}$$

When the value of $|F_v|$ is more than 0.5, the head vultures begin to hunger, and as a result, they are unable to compete with the other vultures in terms of strength. Equation (22) is utilized in order to simulate this motion as accurately as possible. $d(t)$ represents the distance that the vulture is from one of the best vultures in the two groups, and this distance is determined by applying Eq. (21) to the equation found in Eq. (22). Patterns of Levy flight[65] have been exploited to improve the performance of the AVOA in Eq. (23), and LF has been recognized and used in the operations of metaheuristic algorithms.

The IPSO-CS method that has been proposed can analyze the fitness population to determine which node is most suitable for becoming CH. The fitness function evaluates each individual, or node, to determine their level of physical fitness and recommends the most effective method for preserving the nodes' available energy. In this particular scenario, one must be careful not to discount the significance of fitness-related factors. It is of the utmost importance to provide those essential physical characteristics that will, in the end, determine whether CH is selected. The parameters of fitness include. To select the optimal CH, we base our decision on four fundamental measures of fitness.

1. Residual energy: The node's remaining energy value, which is the most important parameter. The CH has a higher per-second energy consumption than the other nodes. Therefore, the node with the most energy must be selected. All nodes have access to the starting energy, but their reserves decrease at different rates depending on how close they are to the sink. Therefore, the amount of energy still available plays a role in picking a CH. Through the use of Eq. (26), we can calculate the residual energy of each sensor node, which can then be summed to get the total residual energy.

$$f_1 = \frac{1}{N} \sum {}_{i=1}^{N} E_{(i)} \tag{24}$$

$$f_2 = \frac{1}{cl} \sum {}_{i=1}^{cl} E_{(n)} \tag{25}$$

$$Obj_1 = \frac{f_1}{f_2} \tag{26}$$

2. Distance between sink and node: In this parameter, energy is used to calculate how far away each node in the network is from the sink. In any case, the total amount of energy used by the sink is proportional to its separation from the node. So, the base station may be improved in light of the parameters below the median spacing between the member nodes, which are taken into consideration by the networking approach for CH selection. Instead of basing decision-making on CH proximity, Obj_2 and Eq. (27) with distance is represented as:

$$Obj_2 = \sum {}_{i=1}^{N} \left(\frac{D_{(N(i)-S)}}{D_{AVG(N(i)-S)}} \right. \tag{27}$$

$$D_{AVG(N(i)-S)} = \left(\frac{\sum_{i=1,}^{N} D_{(N(i)-S)}}{N} \right) \tag{28}$$

Evaluating distance costs between nodes *i* and sink using the second fitness parameter (Obj_2) in Eq. (27), and calculating Euclidean distance $D_{N(i)-S}$ and average distance $D_{AVG(N(i)-S)}$ in Eq. (28).

3. Communicating mode decider: The CMD is a crucial parameter in AVOACS that adaptively chooses the communication scheme, which can be used for transmissions between sensor nodes and from them to the sink. It decides some factors like whether the communication between nodes take place in single hop manner and multi hops communication nature of transferring data packet by other nearby cluster head according residual energy, distance with the sink node. Single-hop communication is used for short distances to reduce energy consumption and multi-hop communication for long-distances due the expensive cost of high power. Minimum CMD value for a Network CH node.

Thus, a node's CMD may be calculated using the following formula and the fifth fitness parameter (Obj_3). The total number of CHs or clusters in the Network is denoted by the variable $\mathrm{N_C}$.

$$Obj_3 = \left(\frac{\sum_{i=1,\ j=1}^{N_C} D_{(CH(i)-CH(j))}}{N_C} + D_{(N(i)-S)} \right) \tag{29}$$

The distance between the CHs is represented by $D_{(CH(i)-CH(j))}$ in the Eq. (29), while the distance between the node *i* and sink is represented by $D_{(N(i)-S)}$ in the same equation. If the value of Obj_3, is decreased, the value of 'CMD' will increase in proportion.

4. Intra-cluster distance: The chance of becoming a CH increase for nodes that are both more energetic and closer to the control centre. Better distribution of cluster leaders throughout the Network means less variations in inter- and intra-cluster distances. The average distances between cluster members and cluster heads are minimized using the new technique. The Obj_4 represent in Eq. (30) is as follows:

$$Obj_4 = \sum_{i=1}^{N} \left(\frac{D_{(N(i)-S)}}{D_{AVG(N(i)-S)}} \right) * \frac{1}{0.1M} \tag{30}$$

The standard clustering procedure identifies CHs and member nodes for each particle. Subsequently, clusters are established by assigning each member node to the nearest location-based cluster leader. The amount of error for each i^{th} population is assessed using the suggested fitness function. Here, we presuppose that a certain fitness function represents the network's incorporation of four fitness parameters:

$$F = \frac{1}{\alpha \ * Obj_1 \ + \beta \ * Obj_2 \ + \gamma \ * Obj_3 \ + \delta \ * Obj_4} \tag{31}$$

Improving network performance requires minimizing fitness F in Eq. (31). Comprises a wide range of fitness metrics derived by the provided Eqs. (26), (27), (28), (29), (30). Parameters utilized in the integration of the fitness function are given varying degrees of importance according to the weight coefficients in Eq. (31). It is up to the user to fine-tune these settings for their specific sensor network deployment.

To determine the relative relevance of the variables in the fitness function integration, the weight coefficients α, β, γ, and δ are used. It is up to the user to adjust these parameters so the sensor network works as intended. In Eq. (32) the weights of these components are expressed differently.

$$\alpha \ + \beta \ + \gamma \ + \delta \ = 1 \tag{32}$$

Thus, the optimizing Network performance by maximization of this function across metaheuristic processes is the primary focus of search space.

The pseudocode for the suggested AVOACS algorithm is shown in Algorithm 1. The suggested algorithm takes and returns the highlighted phrases as input and output.

As previously mentioned, the procedures outlined in Algorithm 1 are followed while using AVOACS. The sink is positioned in the centre of the network once the nodes have been distributed in the network of given dimensions. The AVOA operation, which involves many steps as previously mentioned, may be used to understand the clustering and CH selection processes. After choosing the CH, the Network enters a steady-state phase. The procedure will now end when all nodes' energy has been utilized. The process of data transmission from CH to sink is shown in Fig. 1.

Complexity analysis of AVOACS

It is essential to perform real-time analysis in terms of the complexity and feasibility of suggested algorithms. The algorithm's complexity is determined to be O ($r_{max} \ \times \ N$), as seen in Algorithm 1, where N denotes the population's size (particle size) and r_{max} denotes the maximum number of rounds for which the Network is conducted. The computational overload of the AVOA algorithm takes place due to two main reasons; first is a number of sensor nodes (N) while secondly, it occurs because several iterations are required for optimization i.e., iteration r_{max}. The O ($r_{max} \ \times \ N$)in this function can be approximated as the number of nodes that need to consider for cluster head selection and r_{max} is another constant-like iteration counts before it converges into a specific value. For each iteration, cluster heads are selected intelligently based on various factors.

Experimentation, results and analysis

This section explores the simulation environment, evaluation metrics, and innovative methodologies for performance assessment and analysis. All simulations were conducted on a system equipped with 8GB RAM, 1 TB HDD, and an Intel i5 CPU with MATLAB R2022a. We have given the simulation Table 2 that mentions the various parameters used in the simulation analysis.

The simulation we performed had 100 nodes spread out throughout the (100 × 100 m). Table 2 summarizes the consistency of sensor nodes and AVOACS parameters, and also offers accurate normative values for the sample size. AVOACS procedures for CH selection use generational counts and other criteria to optimize performance. The assessment of suitable values has been conducted by optimizing the control parameters of proposed AVOACS method and rival methods like PSO-ECSM, HWSHO, OE2-LB, and ABC-DE. This has been executed to ascertain the values that should be used. Three levels were established for control parameter tuning: population size (P) = [20, 30, 40], personal learning coefficient (C_1)= [0.5, 1, 1.5], global learning coefficient (C_2) = [1, 1.5, 2], and total vultures = [10, 30, 50]. The optimal configuration yielded the following results: [P, C_1, C_2, total vultures] = [30, 1, 1.5, 30]. Prior to its finalization, an elitist approach based on rank selection was used. At some point, members of a given cluster may decide to adopt a different aesthetic. The truth is that all node types will operate according to the same rules throughout the network's existence.

Performance metrics

Performance of our proposed AVOACS (African vulture optimization algorithm-based energy efficient clustering scheme) has been assessed in terms of different performance parameters- network lifetime, stability period, energy consumption, and throughput. Lastly, the cluster head selection frequency as well as assessment metrics allow for energy expensive tasks to be evenly distributed on different nodes enhancing network life span by maximizing energy consumption. Together, these metrics validate the contribution of AVOACS in consummate energy efficiency and lifetime expansion to WSNs. For the purposes of measuring the AVOACS against with PSO-ECSM[7], HWSHO[20], OE2-LB[21], and ABC-DE[22] protocols.

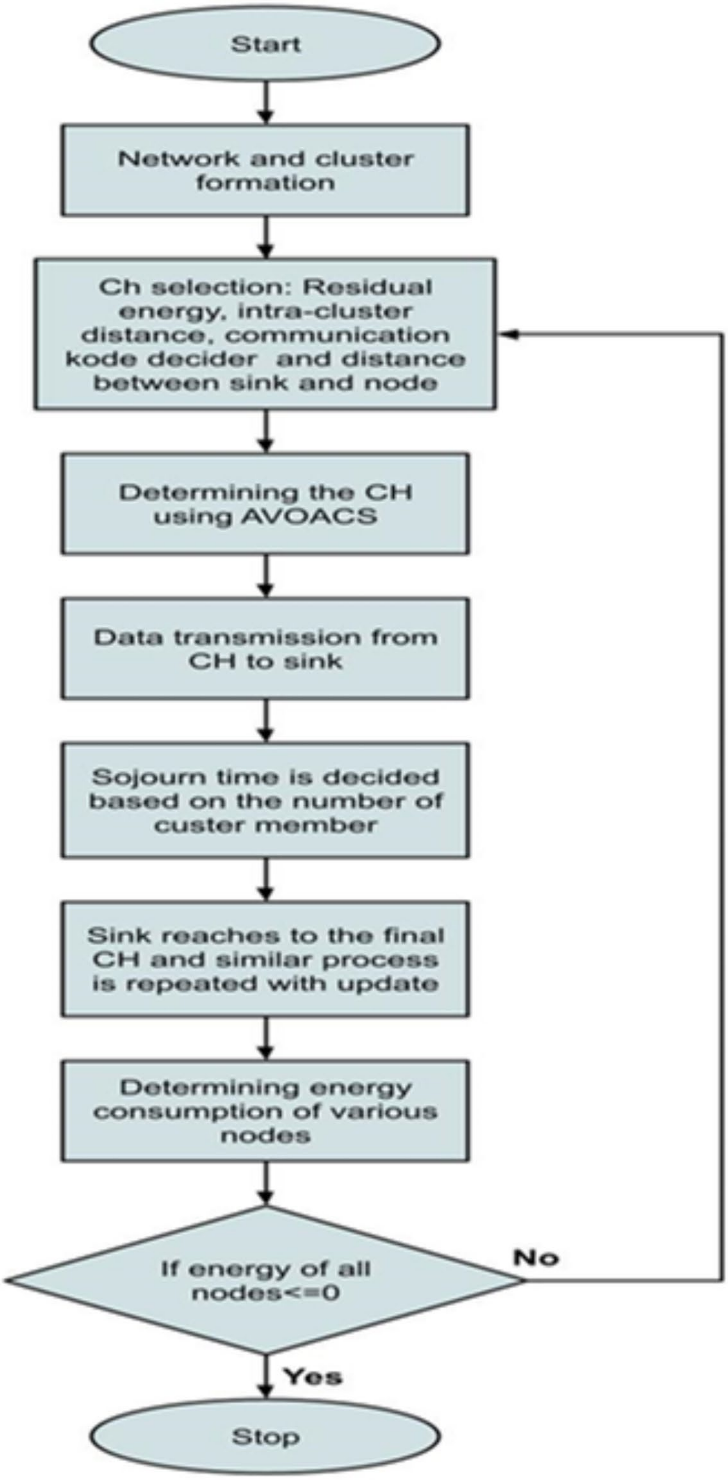

Fig. 1. Proposed method data transmission process between CH and sink.

Network's remaining energy

The AVOACS algorithm balance the energy consumption in a better way across the network by having more residual energies of nodes operating different stages on their life. The dynamic cluster head selection mechanism also ensures that nodes with more remaining energy are selected for the tasks which consume lots of power including data aggregation and communicating to sink. It has been shown that the AVOACS protocol expects a decrease in network energy use as a result of data transmission. Networks' residual energy performance improved with the increase of iterations, as predicted. As shown in Fig. 2, AVOACS outperforms other protocols

Parameters	Values
Area covered	100 × 100 m
No of sensor nodes	100, 200
Sink node	1
Initial energy (Eo)	0.5
Essential transceiver energy ($\mathrm{E_{el}}$)	50nJ/bit
Threshold-distance (d_o)	86 m
Packets size	4000bits
E_{efs}	10pJ/bit/m^2
E_{mp}	0.0013pJ/bit/m^4
E_{da}	5nJ/bit/signal
α , β , γ , *and* δ	0.5, 0.25 ,0.15, and 0.1
P_1 and P_2	0.8 and 0.2
Antenna type	Omni Antenna
Simulation time	100 s, 250 s, 400 s
MAC type	IEEE 802.11
Simulation runs	30
w	2.5
Population size	30
Initial position of the vulture	0.5

Table 2. Simulation setting for AVOACS.

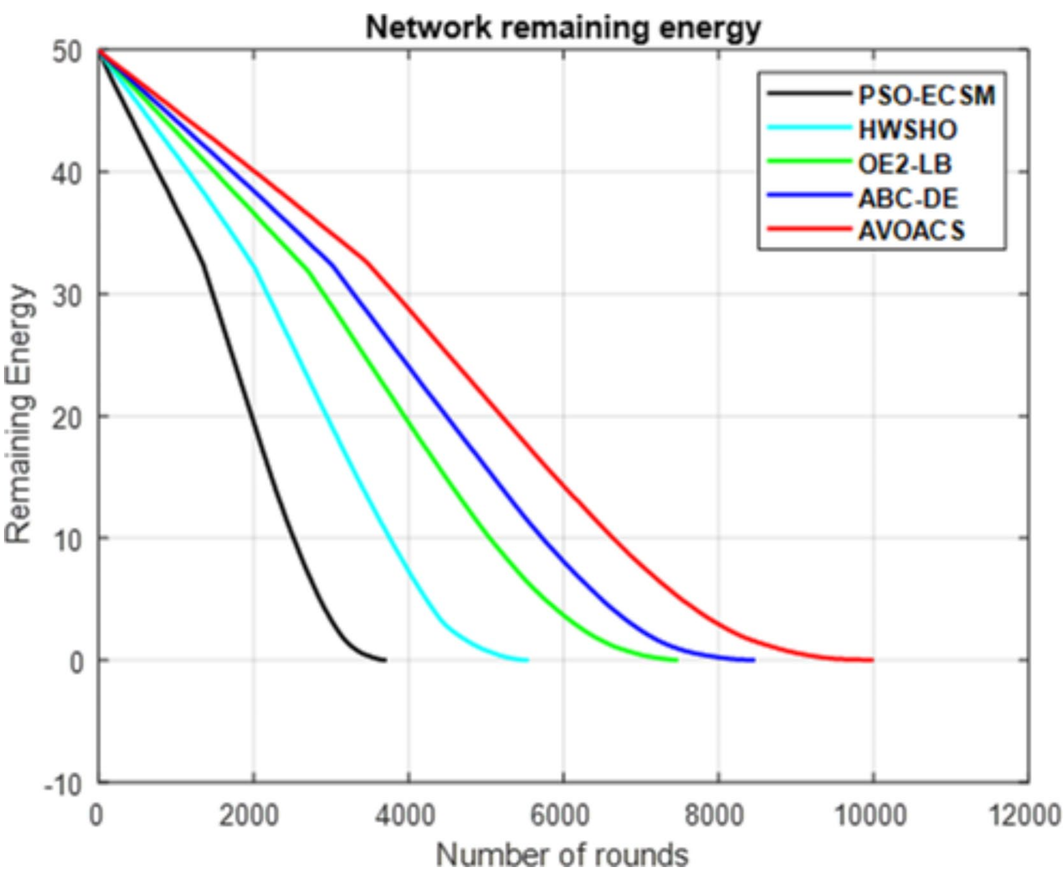

Fig. 2. Network's remaining energy analysis of AVOACS with existing protocols.

like PSO-ECSM[7], HWSHO[20], OE2-LB[21], and ABC-DE[22] because it uses a greater number of iterations and improves data transmission. Furthermore, AVOACS uses less energy each round than competing protocols in dual hop communication.

Network longevity
The AVOACS scheme can prolong the lifetime of a general network, denoted as time duration among arriving alive and leaving away from in valuable nodes. This enhancement is mostly due to the energy consumption model of AVOACS being efficient and has adaptive communication strategies so that both near nodes from sink as well as far away nodes contribute without depleting all their initial energies. AVOACS completed after 9833 rounds, and we can observe that PSO-ECSM[42], HWSHO[43], OE2-LB[21], and ABC-DE[22] all have much shorter network lifetimes (3716) to (8470) rounds. Figure 3 shows that compared to the PSO-ECSM[7], HWSHO[20], OE2-LB[21], and ABC-DE[22] protocols, AVOACS completes 6117, 4285, 2353, and 1363 more cycles. Through the integration of intra-cluster and CMD components into the objective function, AVOACS keeps an eye on the progress made in extending the lifespan of the networks involved. Consequently, the average distance between a node and a CH is greatly reduced when there are several such nodes in proximity.

Dead nodes versus rounds
The AVOACS algorithm shows a slower rate to the number of dead nodes, in contrast with other approaches there are less periodic dead/alive over their round. We compare AVOACS to other protocols; we can observe that it has less rounds for each dead node. Figure 4 shows that the First Node Dead (FND) occurs after 4762 rounds in AVOACS but only after 2096 rounds in PSO-ECSM, 2754 rounds in HWSHO, 3919 rounds in OE2-LB, and 4168 rounds in ABC-DE, and that the Half Nodes Dead (HND) occurs after 7133 rounds in AVOACS but only after 3011 rounds in HWSHO, 4976 rounds in OE2-LB, and 6112 rounds in ABC-DE. And in the improvement of last node dead (LND), also known as the network longevity, AVOACS is also indicated covering 9833 rounds, while PSO-ECSM, HWSHO, OE2-LB, and ABC-DE protocols cover 3716, 5548, 7480, and 8470 rounds, respectively. Higher energy conservation is realized in AVOACS compared to other protocols individually when the CH selection has been improved according to numerous criteria, as discussed above.

Throughput (number of packet delivery)
AVOACS does an improvement with throughput, this combines the total amount of data that has been able to be successfully sent over the wire and received by sink. The introduced method results in enhanced throughput as a result of the reliable network topology and less delays derive from communication. Optimized clustering and

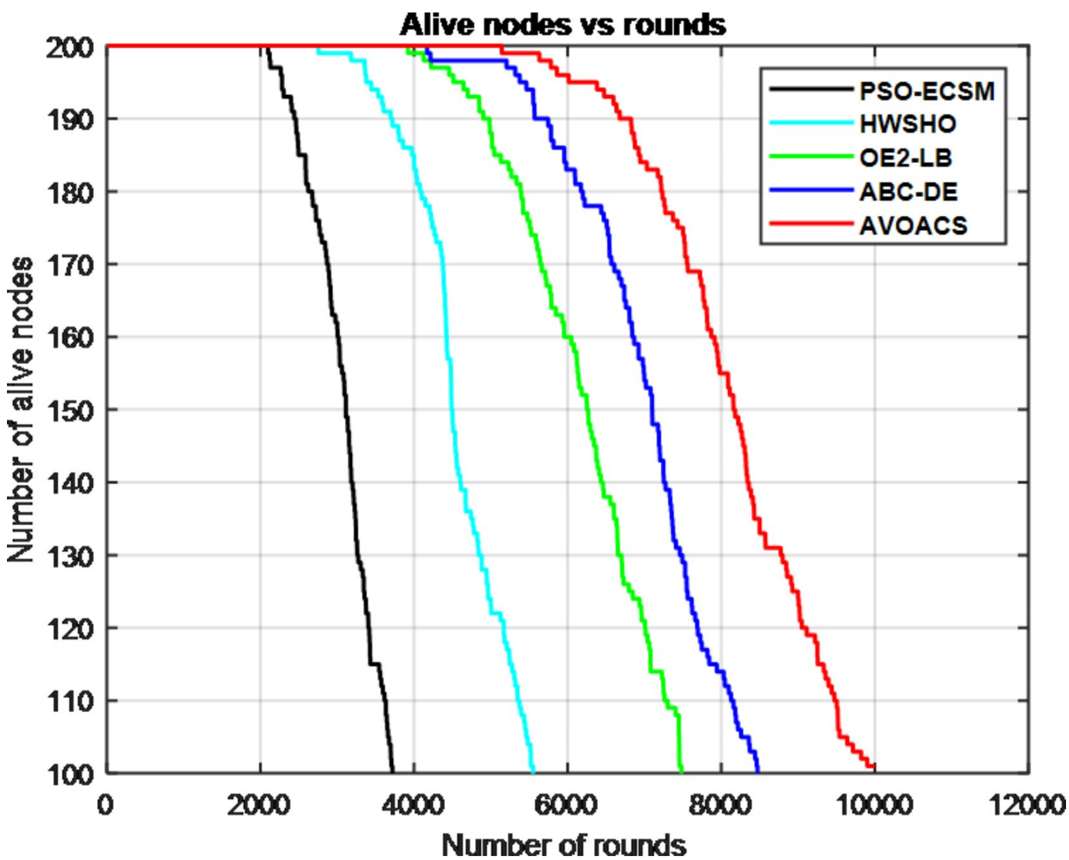

Fig. 3. Comparative analysis of alive node of AVOACS with existing protocols.

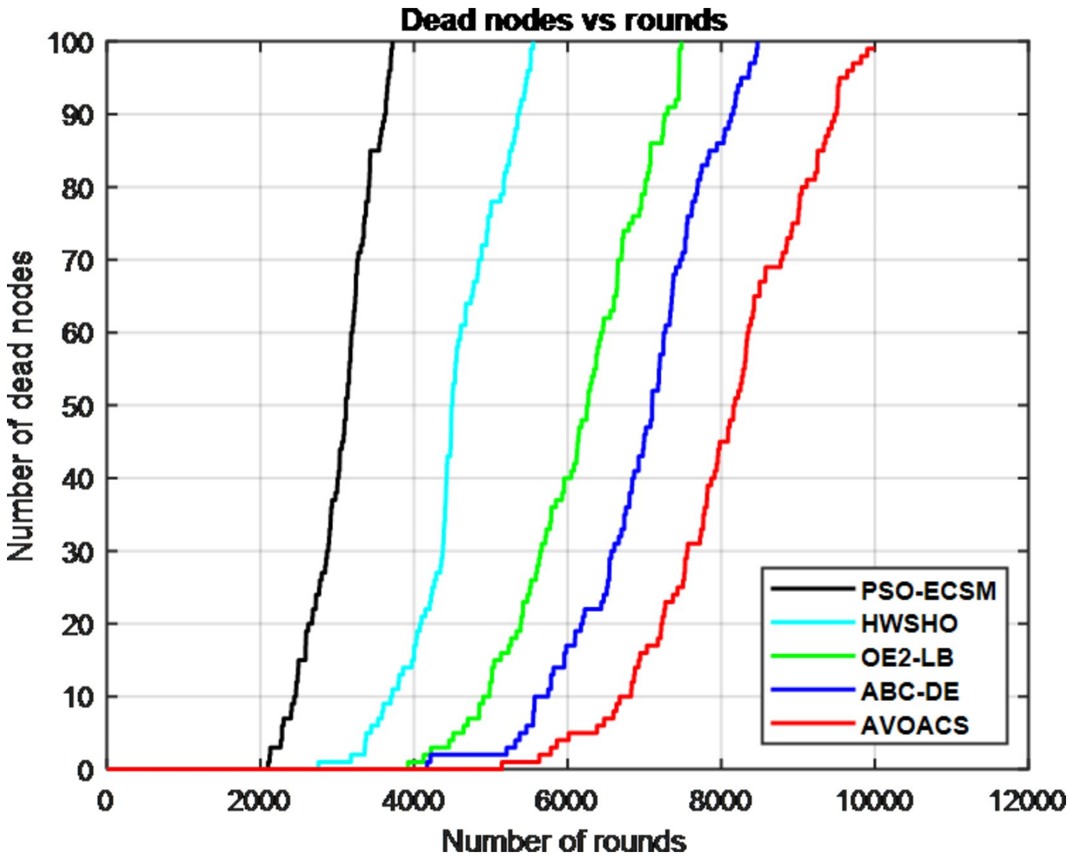

Fig. 4. Comparative analysis of dead node of AVOACS with existing protocols.

communication mode decider to reduce energy wastage while in the transmission of data, for prolonged amount of data transmission before nodes are dead. As illustrated in Fig. 5, AVOACS sends 212,572 data packets whereas PSO-ECSM[7], HWSHO[20], OE2-LB[21], and ABC-DE[22] transmit 80,284, 127,164, 181,726, and 186,841. In terms of throughput, AVOACS improves PSO-ECSM, HWSHO, OE2-LB, and ABC-DE by 164.7%, 67.1%, 16.9%, and 13.7%, respectively. The proposed protocol's throughput enhancements are a direct result of its lower reported loss and its use of increased CH during data packet transfer.

Stability period

The stability period, the time duration where all nodes are observed to be alive (active) in AVOACS method is much enhanced. As a result, by extending the stability period of the new network it is achieved that this network has operational capacity for longer than much time in comparison to before. It can be noted that the first node is eliminated in AVOACS after 4762 rounds, however in the scenario, PSO-ECSM, HWSHO, OE2-LB, and ABC-DE protocols, it is reduced to merely 2096, 2754, 3919, and 4168 rounds, respectively, as shown in Fig. 6. The critical point is having an awareness that knowing AVOACS improves stability period by 127.19%, 72.9%, 21.5%, and 14.2% when compared to the protocols PSO-ECSM, HWSHO, OE2-LB, and ABC-DE, respectively. Unifying four fitness criteria to enable energy saving during data transmission improves both stability period and HND. The distance between nodes and nodes and the sink and nodes has been reduced.

Analysis and interpretation

Table 3 succinctly encapsulates the enhancements recorded by the AVOACS. According to the comparative analysis, AVOACS surpasses other protocols in several performance metrics. Table 4 shows the percentage improvement achieved by AVOACS in terms of FND, HND, LND, and Throughput.

Statistical result

The significance of the AVOACS statistical tests was determined by conducting the tests. Using the F-test, a sample from the same normal group may be evaluated to see whether it has the same variance. When analyzing data from three methods, an F-test (based on analysis of variance (ANOVA)) is used to see whether the data is consistent or significant differences. Thirty samples from each procedure were used to calculate the remaining energy values. In Table 5, the residual energy for each method is described in detail. According to Tables 5 and 6, AVOACS has a greater mean residual energy value (=33.403) than the other algorithms. The remaining energy ANOVA test results are shown in Tables 5 and 6. According to Table 5, p-values of 0.000 to 0.05 are less than 0.05 in the ANOVA test results. Consequently, the efficiency of the algorithm is different.

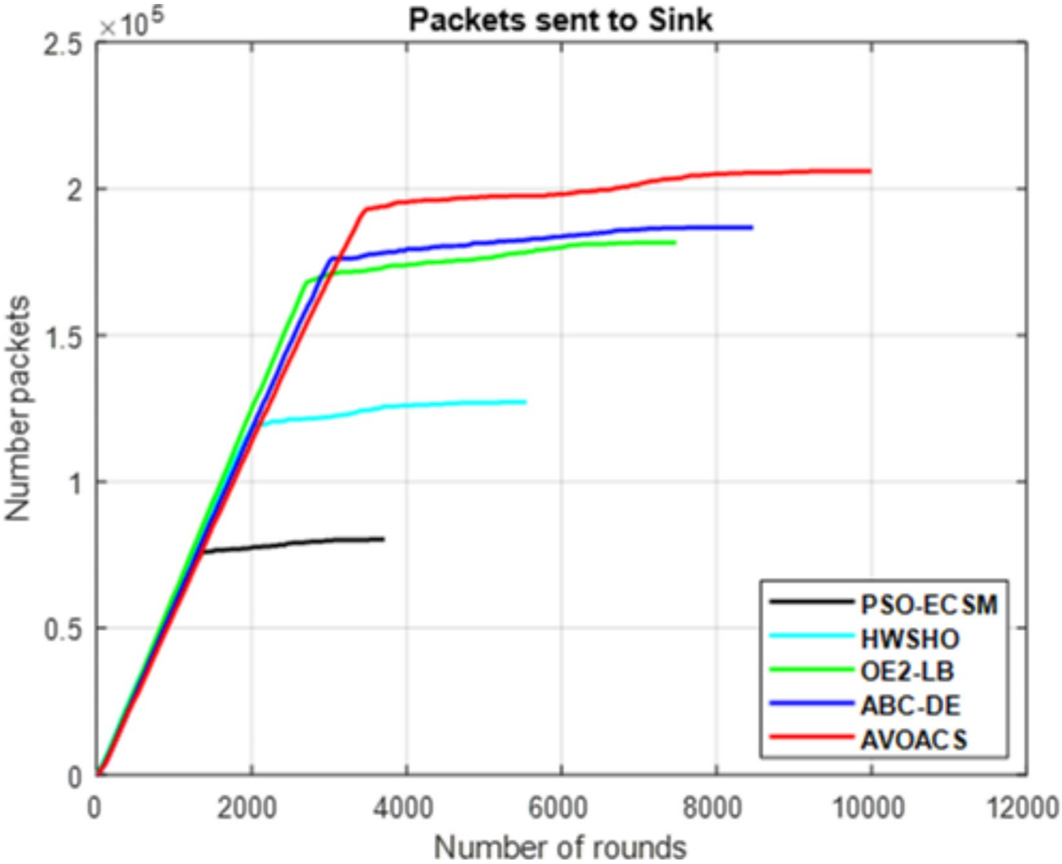

Fig. 5. Comparative analysis of throughput of AVOACS with existing protocols.

Conclusion and future scope

This paper proposed the AVOACS method for Wireless Sensor Networks that aims to solve an essential problem of energy efficiency and prolonging network life in environments with limited resources. The strategies are designed to elect dynamic cluster heads and communication properties based on residual energy, the intravalley of intra-cluster distance between nodes as well and node-to-sink-distance. The superior results of AVOACS using different evaluation metrics demonstrate that the proposed algorithm considerably enhances WSNs with respect to other state-of-the-art methods (PSO-ECSM, HWSHO, OE2-LB and ABC-DE). It has been found that AVOACS elongates the stability period by 127.19%, 72.9%, 21.5%, and 14.2%, and network lifetime by 164.6%, 77.2%, 31.4%, and 16.9% as compared to PSO-ECSM, HWSHO, OE2-LB, and ABC-DE, respectively. The analysis of the remaining energy of network shows that AVOACS always maintains high residual energy over its network, because it properly selects cluster heads and discharges balanced distributed even close nodes along with their different low radii in proportion to their distance from base station. Several key benefits of AVOACS are derived from the enhanced power conservation technique, which includes energy efficiency improvements in WSNs as well as network life and performance. This makes it a promising solution for energy-constrained and mission-critical applications in future WSN deployments, as the protocol is capable of serving heterogeneous network environments; dynamic balancing of power consumption if needed further extend the operational life. In future work, we plan to continue the investigation of our algorithm with respect to mobile nodes and more challenging network conditions.

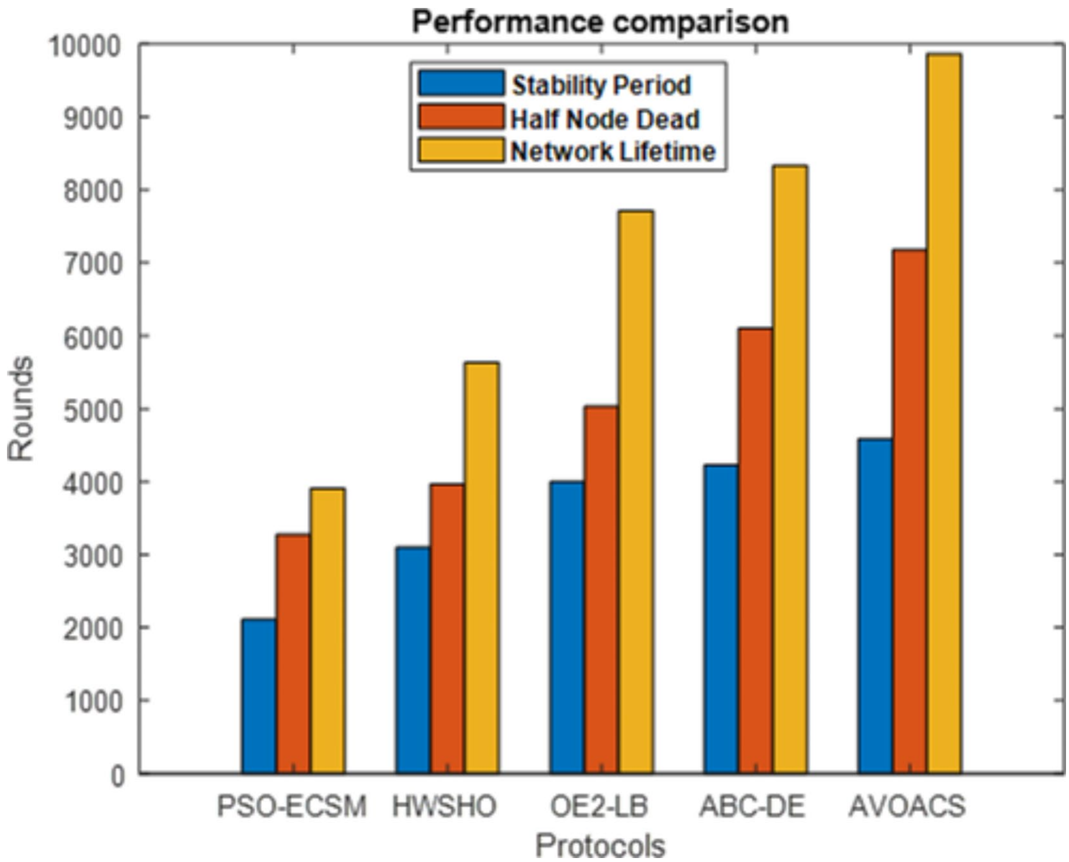

Fig. 6. Performance analysis of AVOACS with existing protocols.

Algorithms	Total energy of network (Joules)	FND	HND	LND	Throughput (packets)
PSO-ECSM[7]	50	2096	3011	3716	80,284
HWSHO[20]	50	2754	3823	5548	127,164
OE2-LB[21]	50	3919	4976	7480	181,726
ABC-DE[22]	50	4168	6112	8470	186,841
AVOACS	50	**4762**	**7133**	**9833**	**212,572**

Table 3. Comparison of AVOACS with existing algorithms for different results. Significant values are given in bold.

Percentage (%) improvement by AVOACS Protocol				
Algorithms	FND	Half node dead	Last node dead	Throughput
PSO-ECSM	127.19	136.8	164.6	164.7
HWSHO	72.9	86.5	77.2	67.1
OE2-LB	21.5	43.3	31.4	16.9
ABC-DE	14.2	16.5	16.09	13.7

Table 4. Percentage improvement by AVOACS to existing algorithms.

Protocols	N	Mean	Std. deviation	Std. error	95% confidence interval for mean Lower bound	Upper bound	Minimum	Maximum
PSO-ECSM[42]	50	1.038	0.069	0.009	0.01	0.012	0.92	1.15
HWSHO[43]	50	15.651	0.186	0.026	0.09	0.11	15.33	15.95
OE2-LB[21]	50	26.372	0.142	0.020	0.10	0.13	26.13	26.61
ABC-DE[22]	50	30.052	0.125	0.017	1.03	1.08	29.84	30.26
AVOACS	50	33.403	0.179	0.021	2.81	2.98	33.27	33.53
Total	250	106.516	0.701	0.093	4.04	4.312	105.49	107.5

Table 5. Remaining energy analysis of respective protocols.

Source of variation	Sum of squares	df	Mean square	F	F crit
Between groups	34563.02	4	8640.756	528217.1	2.408488
Within groups	4.007794	245	0.016358		
Total	34567.03	249			

Table 6. ANOVA test result of remaining energy.

Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on request.

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M.K: concept, design, analysis, writing—original draft. A.K: concept, design, analysis, writing—original draft. S.K: design, analysis. P.C: analysis, writing—review & editing. S.S: analysis, writing—review & editing. All authors contributed equally to the manuscript. All authors reviewed the manuscript.

Declarations

Competing interests
The authors declare no competing interests.

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