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Energy aware clustering protocol using chaotic gorilla troops optimization algorithm for Wireless Sensor Networks

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Abstract
Energy efficiency is treated as a challenging problem in Wireless Sensor Networks (WSNs) which involves limited non-replaceable and non-rechargeable inbuilt batteries. Optimal utilization of available energy in the sensor nodes is an effective way to improve the lifetime of the WSN with assured quality of service (QoS). Clustering can be employed as an efficient approach for enhancing network lifetime and scalability. Since clustering is considered an NP-hard problem, several metaheuristic algorithms are utilized for accomplishing energy efficiency. With this motivation, this study proposes an energy-aware clustering protocol utilizing a chaotic gorilla troops optimization algorithm (EACP-CGTOA) for WSN. The proposed EACP-CGTOA model derives a CGTOA by replacing the population initiation with circle chaotic mapping to explore the solutions with a high convergence rate and sensitivity. The CGTOA helps to increase the population diversity and overall performance of the optimization algorithm. Besides, the EACP-CGTOA model derives a fitness function involving three input parameters namely distance to neighbours (DTN), distance to base station (DBS), and energy ratio (ER). To ensure the enhanced performance of the EACP-CGTOA technique, a wide range of simulations were carried out and the outcomes are examined under several aspects. The experimental results ensured that the network lifetime and energy efficiency are considerably improved by the EACP-CGTOA model over the existing methods.

Keywords Energy efficiency · Network lifetime · WSN · Clustering · Metaheuristics · Fitness function

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1 Introduction

Wireless sensor networks (WSN) consist of multiple wireless sensor nodes that are deployed in a field to gather information [19]. They are armed with sensor devices that have wireless communication capabilities and limited processing power. WSN is the better option to monitor and observe the environment and security purposes [2]. WSN has been widely used and greatly developed in transportation systems, industry, medical industry, agriculture, smart home, environmental monitoring, etc. [20], due to numerous benefits of WSN namely low cost, easy deployment, unattended operation, and self-configure ability. With the current advancement, sensors to supply energy are still based on low-power batteries. As well, due to the employment of WSNs in an inaccessible environment, it can be impossible to replace or recharge the battery of sensors [3]. However, there is a major constraint that the deployed sensors are constrained by computational capability, memory, energy, and bandwidth. Amongst others, the energy limitation of the sensors plays an important part in affecting the network lifetime. Furthermore, the communication cost of the network overtakes the computation and sensing costs [23]. Therefore, the energy of the node i.e., available for access needs to be efficiently utilized for lessening the transmission cost and for augmenting the lifetime of networks. The clustering method is a crucial technology in handling the energy constraint of the sensors. Figure 1 illustrates the structure of WSN.

Layered architecture cut down the energy utilization of the network, particularly a huge WSN [4]. Clustering is a typical layered architecture. Nodes are classified as distinct clusters, and all the clusters have a node named cluster head (CH) which gathers information from another node in the cluster. CH aggregates information beforehand transmitting them to BS since the information from nodes in the cluster is the same [9]. The clustering approach reduces the network load by data aggregation which leads to a long network lifetime [10]. Numerous studies provide a system for selecting CHs. The CH selection is of great importance. Some choose the CH according to the backpropagation technique of ANN to enhance the robustness and network energy efficacy [18]. Others choose Energy Effective Quad Clustering to enhance the efficiency of WSN in terms of network lifespan [5].

WSNs comprise massive nodes, which can make it difficult to cluster the nodes effectively. New clustering protocols can be designed to improve the scalability of WSNs, enabling them to handle larger numbers of nodes. Since the CH selection process can be considered as a Non-Deterministic Polynomial (NP)-hard optimization problem to select m optimum CHs amongst n sensors giving nC_m possibility. Therefore, metaheuristic optimization algorithms can be used for clustering and CH selection in WSN. Metaheuristic optimization algorithms can search the solution space proficiently, resulting in high-quality clustering solutions to enhance the performance of WSNs. By using metaheuristic optimization algorithms, clustering protocols can potentially achieve better cluster formation, cluster head selection, and data aggregation, resulting in improved network throughput, reduced energy consumption, and extended network lifetime.

This study proposes an energy-aware clustering protocol using a chaotic gorilla troops optimization algorithm (EACP-CGTOA) for WSN. The proposed EACP-CGTOA model derives a CGTOA by replacing the population initiation with circle chaotic mapping to explore the solutions with a high convergence rate and sensitivity. In addition, the EACP-CGTOA model derives a fitness function (FF) involving three input parameters namely

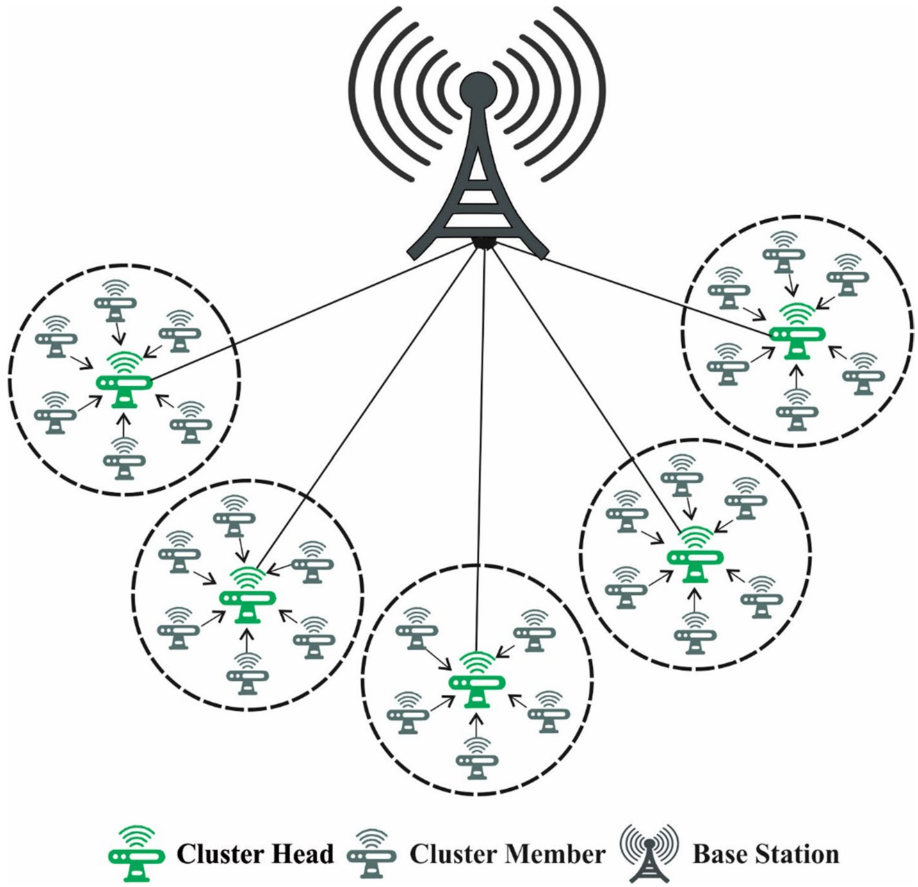

Fig. 1 Structure of WSN

distance to neighbours (DTN), distance to base station (DBS), and energy ratio (ER). For ensuring the improved performance of the EACP-CGTOA model, a wide range of simulations were carried out and the outcomes are investigated in various aspects.

2 Literature review

In [11], an effectual CH selection (CHS) process was created by the established Taylor-Spotted Hyena Optimization (Taylor-SHO) that combines the Taylor series with SHO. The presented technique was utilized for the effectual CHS procedure utilizing fitness measures dependent upon delay, energy, and distance. Next, the data routing was completed by the modified k-Vertex Disjoint Path Routing (mod-kVDPR) technique that is developed by mod-kVDPR employing the parameters namely throughput and link reliability. In [17], a hybrid grey wolf and crow search optimization algorithm-based optimal CHS (HGWC-SOA-OCHS) technique is presented to improve the lifespan probability of the network by focusing on minimized delay, minimized distance amongst nodes, and energy stabilisation. This hybridization of GWO and CSO technique from the procedure of CHS continues the trade-off amongst the exploitation as well as exploration degrees under the searching space.

In [7], a whale optimization algorithm (WOA) based technique was presented for expanding the lifespan of the system. Besides, a novel FF was determined to reduce the energy consumption (ECM) of networks, load balancing (LB), and node coverage. The clustering was completed unequally; it represents that CHs neighbouring to BS are further energy to data relay. During this case, to decrease the count of messages, the clustering phase is more at the start of the meta-round. Wang et al. [21] optimized the APTEEN routing protocol by integrating GA with the fruit-fly optimization algorithm (FFOA). With adding residual energy (RE), distance from the node to BS, distance from the node to the geometric centre of entire networks, node degree, and other selective features from CHS, the GA and FFOA are utilized for CHS to the primary time, and the secondary time of CHS dependent upon density adaptive technique.

Kotary et al. [12] examined the many-objective WOA (MaOWOA) for handling robust distributed clusters from WSN. Primarily, a swarm-based MaOWOA was discussed in which a reference point-based leader selective process was employed to upgrade the solution rather than grid-based leader selective as in a multi-objective approach. Bhushan et al. [6] presented a Fuzzy Logic-based Energy Adequate Clustering (FLEAC), a clustering protocol which generates utilize of the fuzzy if-then rule to choose suitable CH on the fundamental of 5 fuzzy descriptors such as compaction degree, node history, RE, average intra-cluster distance, and packet drop probability. In addition, the presented protocol assumes the selection of relay nodes (RNs) to alleviate extreme ECM of CHs. Improved GOA was utilized to select suitable RNs.

In [8], an effectual technique named Tunicate Swarm Butterfly Optimization Algorithm (TSBOA) was established to choose CH for accomplishing effectual data broadcast amongst the sensor node. The presented TSBOA was resultant of the integration of the Tunicate Swarm Algorithm and BOA correspondingly. Reddy et al. [16] presented a novel cluster-based routing method by choosing the optimum CH. Furthermore, a novel technique called grey wolf upgrade WOA was established. At this point, a novel multi-objective function has been determined in terms of distinct constraints such as delay, energy, distance, and security correspondingly. Raslan et al. [15] presented a new technique for selecting optimum CHs from the IoT-WSN. The new technique is named as Improved Sunflower Optimization Algorithm (ISFO). During the ISFO, it integrates the SFO with the lèvy flight (LF) function. Such appeal is the balance of the diversification and intensification procedures of the presented technique and avoids being trapped from a local minimum.

3 The proposed model

In this study, a novel EACP-CGTOA model has been developed for lifetime maximization and maximum energy efficiency in WSNs. Initially, the nodes in the WSN are randomly deployed in the target region and then the initiation process takes place. The BS broadcast a beacon signal to the whole network. All the nodes in the network receive the beacon signal and determine its estimated distance to BS based on RSSI. Followed by, the nodes transmitting a handshaking message in its communication radius to collect data regarding the neighbouring nodes. The handshaking message comprises node ID, remaining energy level, and its distance to BS. For instance, Once a neighbouring node j receives a handshaking message from node i, it stores the received details and replies with its information to node i. Now, node i will update its node degree by one as well as calculates the distance to its neighbouring node j using the node j's distance to BS and stores the information of node j. Likewise, node i will get information from each of the other nearby nodes and then the distance to neighbours can be computed. Using this procedure, every node gathers information about its neighbours as well as updates its information and then the clustering process will be initiated. Then, the BS executes the proposed model for the effective selection of CHs. The proposed EACP-CGTOA model derives a CGTOA by replacing the population initiation with circle chaotic mapping to explore the solutions with a high convergence rate and sensitivity. In addition, the EACP-CGTOA model derives a FF involving three input parameters namely DTN, DBS, and ER. Figure 2 depicts the block diagram of the EACP-CGTOA technique. The nodes with maximum fitness value will be chosen as CH and transmit CH_WON to the nearby nodes. A node may get multiple CH_WON from its nearby nodes. In those situations, it sends a CH_JOIN message and joins to the nearer CH. When the clusters are constructed and then the data transmission process takes place between nodes and BS via CHs.

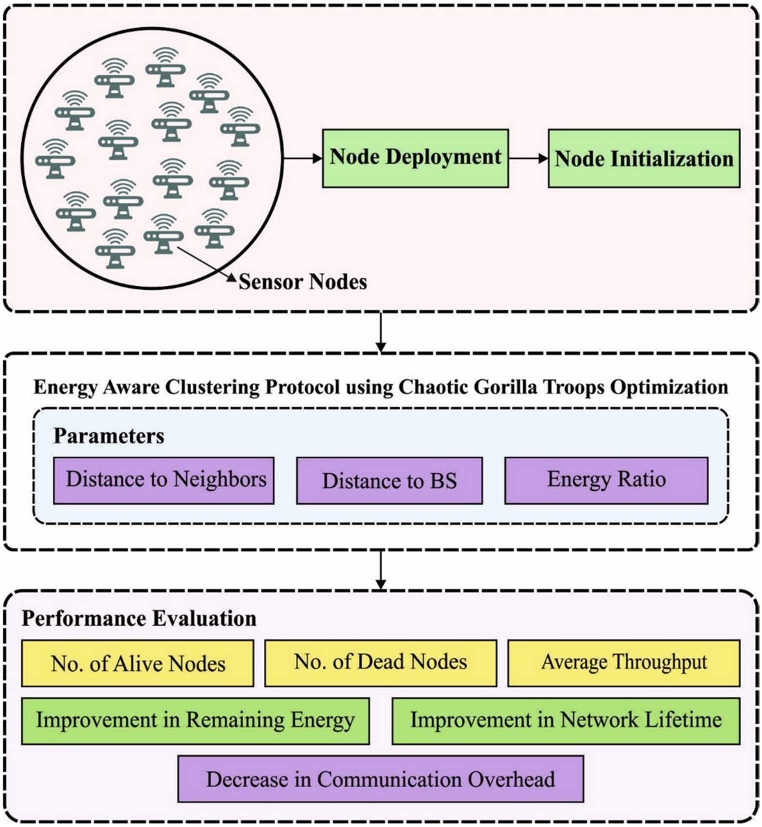

Fig. 2 Block diagram of EACP-CGTOA technique

3.1 Energy model

The first-order radio energy model developed in [3] has been employed. By guaranteeing a reasonable signal-to-noise ratio, the energy utilization for the node transmitting information is given below.

$$E_{Tx}(n,d) = \begin{cases} nE_{elec} + n\varepsilon_{fs}d^2, & d \le d_0, \\ nE_{elec} + n\epsilon_{mp}d^4, & d > d_0, \end{cases} \tag{1}$$

Whereas n represents the number of bits transferred, d indicates the communication distance, E_{elec} denotes the energy utilization to send or receive 1-bit information, ε_{fs} signifies the coefficient of energy utilization to amplify radio at free-space mode, ε_{mp} represents the coefficient of energy utilization to amplify radio at multi-fading mode, and $d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$ denotes the threshold value of distance.

The energy utilization for data received by the node can be denoted as follows.

$$E_{Rx}(n) = nE_{elec} \tag{2}$$

The data fusion from the cluster assumes that CH receives n-bit information transmitted by all the CMs and accumulates them into n-bit information nevertheless of the node count in the cluster.

$$E_{Fx}(n,d) = nE_{DA} \tag{3}$$

Whereas E_{DA} (nJ/bit) denotes the energy utilization for fusing 1-bit data.

3.2 Design of CGTOA

GTOA is a newly presented nature-inspired and gradient-free optimization approach that emulates the gorilla lifestyle [1]. They live in a group named Troop, which is comprised of adult male gorillas named Silverback, many adult female gorillas, and posterity. Generally, gorilla tends to migrate from one place to another. But some male gorilla continues to follow the silverback and choose to stay in the initial troop. When the silverback dies, this male might engage in a brutal battle for mating with adult females and dominance of the group. From the abovementioned, the arithmetical expression for the GTOA has been proposed. Like all other techniques, GTOA comprises initialization, global exploration, and local exploitation that are thoroughly explained in the following [22]:

3.2.1 Initialization phase

Assume that there are N gorillas in the D-dimension. The location of the i-th gorilla is represented by $X_i = (x_{i,1}, x_{i,2}, \cdots, x_{i,D}), i = 1,2,\cdots,N$. This can be expressed in the following equation:

$$X_{N\times D} = rand(N,D) \times (ub - lb) + lb \tag{4}$$

Whereas ub and lb represent the upper and lower limits, rand (N, D) represents the matrix with D columns and N rows, whereby all the elements are in an arbitrary value within [0, 1].

3.2.2 Exploration phase

For precisely simulating the migration behaviour, the location update formula for the exploration phase has been developed by applying three distinct algorithms involving moving to other groups, migrating towards unknown positions, and migrating around familiar locations as follows [22]:

$$GX(t+1) = \begin{cases} (ub - lb) \times r_2 + lb & r1 < p \\ \left(r_3 - C\right) \times X_A(t) + L \times Z \times X(t) & r_1 \geq 0.5 \\ X(t) - L \times \left(L \times \left(X(t) - X_B(t)\right) + r_4 \times \left(X(t) - X_B(t)\right)\right) & r_1 < 05 \end{cases} \tag{5}$$

Whereas t denotes the present iteration, $X(t)$ signifies the existing location of the individual gorilla, and $GX(t+1)$ represents the candidate location of the searching agent from the following iteration. In addition, r_1, r_2, r_3 and r_4 represent the arbitrary numbers within [0,1. $X_A(t)$ and $X_B(t)$ denote the arbitrarily chosen gorilla position in the existing population. p indicates a constant. Z represents a row vector from the problem dimension within $[-C, C]$. Also, the variable C can be estimated as follows.

$$C = \left(\cos\left(2 \times r_5\right) + 1\right) \times \left(1 - \frac{t}{\text{Max } iter}\right) \tag{6}$$

In which $\cos(\cdot)$ indicates the cosine function, r_5 represents an arbitrary value within [0,1], and Maxiter designates the maximal iteration. The variable L can be calculated by the following equation:

$$L = C \times l \tag{7}$$

In which l indicates an arbitrary value within [1, 1].

Based on the completion of exploration, the fitness value of the recently generated candidate $GX(t+1)$ solution is computed. Given that GX is superior to X that is, $F(GX) < F(X)$, whereas F indicates the FF for a specific problem, it can be preserved and replace the original solution $X(t)$. Additionally, the optimum solution at this period has been chosen as the silverback $X_{silverback}$.

3.2.3 Exploitation phase

Once the troop was developed, the silverback is healthy and powerful, whereas the other males are still young. Also, the silverback grows older and dies at the end, with the young blackback in the troop may be included in a violent conflict with the other male gorillas to mate with the leadership and the adult females. From the abovementioned, competing for adult female gorillas and two behaviours of the silverback are modelled in the exploitation stage. Simultaneously, the variable W is presented for controlling the switch among themselves. Once the value of C is larger than W, the initial model of following the silverback is selected. It can be mathematically expressed in the following:

$$GX(t+1) = L \times M \times \left(X(t) - X_{silverback}\right) + X(t) \tag{8}$$

Whereas L can be estimated by Eq. (7) $X_{silverback}$ denotes the optimal solution, and $X(t)$ indicates the existing location. Additionally, the variable M is evaluated by the following equation:

$$M = \left(\left|\sum_{i=1}^{N} \frac{X_i(t)}{N}\right|^{2^L}\right)^{\frac{1}{2^L}} \tag{9}$$

Now N denotes the population size, and $X(t)$ signifies the location of the gorilla in the existing iteration. When $C < W$, it represents that the last model is selected, in such cases, the position of the gorilla is upgraded by the following equation:

$$GX(t+1) = X_{silverback} - (X_{silverback} \times Q - X(t) \times Q) \times A \tag{10}$$

$$Q = 2 \times r_6 - 1 \tag{11}$$

$$A = \phi \times E \tag{12}$$

$$E = \begin{cases} N_1, r_7 \geq 0.5 \\ N_2, r_7 < 0.5 \end{cases} \tag{13}$$

where $X(t)$ represents the existing location and Q denotes the impact force, r_6 represents an arbitrary number within [0,1]. Furthermore, the coefficient A utilized for mimicking the violence intensity in the competition in which ϕ indicates a constant and the values of E are allocated. Where r_7 denotes an arbitrary value from 0 to 1. When $r_7 \geq 0.5$,E is determined by a 1D array of standard distribution arbitrary numbers, and D indicates the spatial dimension. When $r_7 < 0.5, E$ is equivalent to the stochastic value which follows the standard distribution [14].

Likewise, during the exploitation stage, the fitness value of recently generated candidate $GX(t+1)$ solutions are evaluated. When $(GX) < F(X)$, the solution GX can be retained and participated in the succeeding optimization, whereas the optimum solution with each individual can be determined by the silverback $X_{silverback}$.

3.2.4 Improvement of GTOA using chaotic mapping

Generally, it is stated that the quality of the individual primary population has a considerable effect on the efficacy of the present metaheuristic algorithm. Although this technique is accessible to perform, still suffers from insufficient ergodicity and is extremely based on the likelihood distribution that could not assure that the population initialization is distributed uniformly from the searching space, thus deteriorating the convergence rate and solution precision [22]. Chaotic mapping is a complex dynamic technique founded in a non-linear system with ergodicity, unpredictability, and randomness properties in comparison with random distribution, chaotic mapping enables the individual initial population for exploring the solution space in detail with sensitivity and high convergence rate such that it is extensively adapted to enhance the optimization accuracy of the algorithm. The experimental result depicts that the presented method has greater performance if compared to the widely employed Tent chaotic mapping and Logistic chaotic mapping. Therefore, to increase the population diversity and make optimal use of the data in the solution space, the presented method aims to enhance the initialization mode of the fundamental GTOA using circle chaotic mapping, called CGTOA. Also, it can be mathematically expressed in the following equation:

$$Zk + 1 = zk + b - \frac{a}{2\pi} \cdot \sin(2\pi z) mod(1), z \in (0,1) \tag{14}$$

Whereas $a = 0.5$ and $b = 0.2$. In the same free independent parameter, the Circle mapping and random searching process are carefully chosen to perform individually. In addition, the attained outcome can be given as follows. Therefore, the presented CGTOA method has a strong global exploration capability afterwards integrating Circle chaotic mapping.

3.3 Application of CGTOA for clustering process

The idea of the EACP-CGTOA method is for selecting a further amount of sensor nodes nearby the BS before being distant in BS. This procedure of selective of CHs helps to the creation of clusters under the cluster formation phase. Assume, f_1 be a function of distance in the neighbour sensor node. This means require for selection of the CHs that are a minimal distance from their neighbour sensor. Require for minimizing f_1 to optimum CH selection (CHS).

DTN It is the minimal distance from their neighbours, i.e., $dis(CHj, si)$. During the communication procedure, every sensor utilizes some part of the energy for sending data to its respective CH. Reducing the energy utilization, require minimizing the distance from their neighbours. In this way, require for selecting the CHs that are nearby the arbitrarily initializing CHs [14].

$$Minimize\, f_1 = \sum_{j=1}^{m} dis(CH_j, s_i) \tag{15}$$

DBS It can be the distance between a CH CH_j and BS, i.e., $is(CH_j, BS)$. The BS distance roles are an essential play in the selection of a further amount of CHs nearby BS. This procedure helps to create of small size cluster nearby the BS.

$$Minimize\, f_2 = \sum_{j=1}^{m} dis(CH_j, BS) \tag{16}$$

ER It is the ratio of energy utilized by CH CH_j to RE of CH_j. When the CH CH_j utilizes minimum energy under the sensing, communication, and computation and further the RE and is minimum energy ratio.

$$Minimize\, f_3 = \sum_{j=1}^{m} \frac{E_c\left(CH_j\right)}{E_R\left(CH_j\right)} \tag{17}$$

At this point, it can utilize a weighted aggregation manner for minimizing every objective, since these objectives aren't strongly conflicting with every other. Thus, utilize the subsequent FF:

$$Fitness = \alpha 1 \times f_1 + \alpha 2 \times f_2 + \alpha 3 \times f_3 \tag{18}$$

The purpose is for minimizing the fitness value. The lesser fitness value, an optimum is the particle place, viz., an optimum is the CHS.

3.4 Cluster construction process

The CGTOA derives the fitness values of the nodes in the network and the nodes with maximum fitness will be considered as CHs. Once the CHs are chosen, the advertisement process takes place where the nodes are aware of the CHs with their fitness value. Then, the nodes in the nearby region reply to the CH advertisement message to indicate the willingness of CM under the specific CH. In addition, the CMs can turn off their transmitter to save energy in case of no data is available for transmission. During the setup phase, the receiver of the CHs gets data from CMs and then the aggregation process is carried out. Lastly, the aggregated data will be transferred to BS via CHs.

4 Experimental validation

The proposed EACP-CGTOA model is simulated using the MATLAB tool. The parameter settings are given in Table 1 and the results are examined under distinct rounds of operations.

Table 2; Fig. 3 investigate the comparative number of alive nodes (NOAN) inspection of the EACP-CGTOA technique with existing models [13]. The experimental results highlighted the betterment of the EACP-CGTOA model with maximum NOAN under all rounds. For instance, with 100 rounds, the EACP-CGTOA model has resulted in a higher NOAN of 99.73% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO models have obtained lower NOAN of 98.46%, 98.46%, 96.68%, and 96.43% respectively. Likewise, with 700 rounds, the EACP-CGTOA model has resulted in a higher NOAN of 96.17% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO methodologies have reached a minimal NOAN of 84.98%, 52.67%, 44.27%, and 32.31% correspondingly. Similarly, with 1000 rounds, the EACP-CGTOA algorithm has resulted in a higher NOAN of 78.36% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO models have achieved minimal NOAN of 44.53%, 24.43%, 17.56%, and 9.93% correspondingly.

Table 1 Simulation settings

Simulation parameters	Values
Node count	1000
Target regions	400*400 square meters
Count of rounds	2000
Initial energy	0.5 Joules
Packet length (bits)	4096 bits
Node deployment	Random
Energy used for data aggregation	5 nJ/bit/signal
Energy used for transmission	50 pJ/bit/square meters
Energy used for power amplification	10 pJ/bit/square meters

Table 2 NOAN analysis of EACP-CGTOA technique with recent approaches under distinct rounds

No. of alive nodes (%)					
No. of rounds	EACP-CGTOA	HABC-MBOA	FFCGWO	FFOCR	HAS-PSO
100	99.73	98.46	98.46	96.68	96.43
200	98.72	98.46	98.46	95.41	93.37
300	98.21	97.95	96.43	93.63	89.56
400	97.44	96.43	90.07	82.43	79.63
500	97.44	94.39	78.62	67.93	58.26
600	97.19	89.05	65.39	51.65	43.25
700	96.17	84.98	52.67	44.27	32.31
800	90.32	72.26	42.24	32.06	23.66
900	83.70	65.39	35.11	21.88	12.47
1000	78.36	44.53	24.43	17.56	9.93
1200	66.91	32.06	13.74	3.31	0.51
1400	58.77	23.66	8.40	0.77	0.00
1600	42.24	14.76	2.29	0.00	0.00
1800	32.06	0.77	0.00	0.00	0.00
2000	17.81	0.00	0.00	0.00	0.00

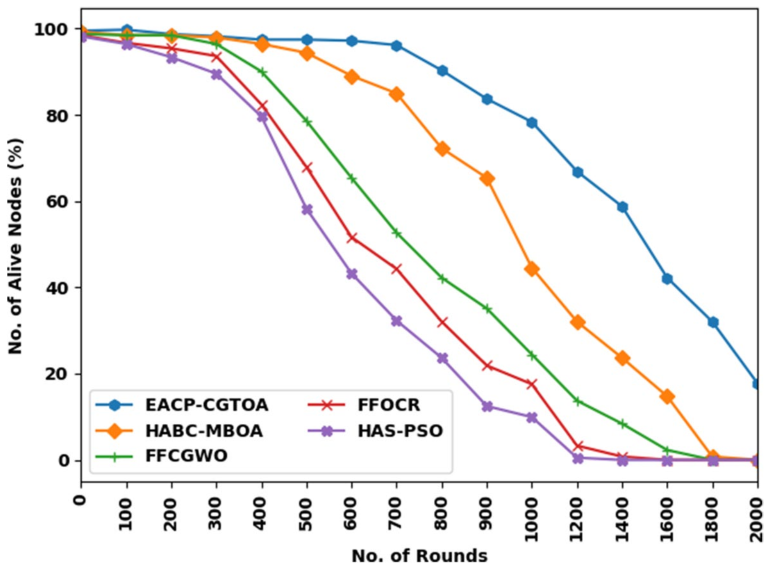

Fig. 3 NOAN analysis of EACP-CGTOA technique with recent approaches

A detailed number of dead nodes (NODN) examinations of the EACP-CGTOA model with recent models are provided in Table 3; Fig. 4. The simulation results pointed out that the EACP-CGTOA model has accomplished an enhanced lifetime of WSN with minimum NODN under every round. For instance, with 100 rounds, the EACP-CGTOA model has provided decreased NODN of 0.27% whereas the HABC-MBOA, FFCGWO, FFOCR,

Table 3 NODN analysis of EACP-CGTOA technique with recent approaches under distinct rounds

No. of dead nodes (%)					
No. of rounds	EACP-CGTOA	HABC-MBOA	FFCGWO	FFOCR	HAS-PSO
0	0.52	0.78	1.28	1.54	1.79
100	0.27	1.54	1.54	3.32	3.57
200	1.28	1.54	1.54	4.59	6.63
300	1.79	2.05	3.57	6.37	10.44
400	2.56	3.57	9.93	17.57	20.37
500	2.56	5.61	21.38	32.07	41.74
600	2.81	10.95	34.61	48.35	56.75
700	3.83	15.02	47.33	55.73	67.69
800	9.68	27.74	57.76	67.94	76.34
900	16.30	34.61	64.89	78.12	87.53
1000	21.64	55.47	75.57	82.44	90.07
1200	33.09	67.94	86.26	96.69	99.49
1400	41.23	76.34	91.60	99.23	100.00
1600	57.76	85.24	97.71	100.00	100.00
1800	67.94	99.23	100.00	100.00	100.00
2000	82.19	100.00	100.00	100.00	100.00

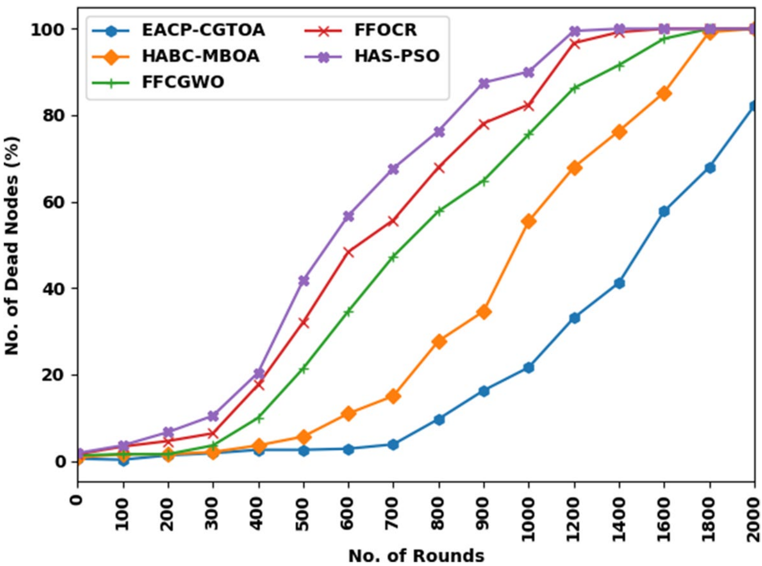

Fig. 4 NODN analysis of EACP-CGTOA technique with recent approaches

and HAS-PSO models have accomplished increased NOAN of 1.54%, 1.54%, 3.32%, and 3.57% respectively. Along with that, with 1000 rounds, the EACP-CGTOA method has provided decreased NODN of 21.64% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO algorithms have accomplished an increased NOAN of 55.47%, 75.57%,

Table 4 Average throughput analysis of EACP-CGTOA technique with recent approaches under distinct rounds

Average throughput (Mbps)					
No. of rounds	EACP-CGTOA	HABC-MBOA	FFCGWO	FFOCR	HAS-PSO
100	8.40	6.93	4.00	3.37	1.90
200	12.38	9.66	7.35	4.84	4.21
300	15.95	13.01	9.03	6.51	4.42
400	18.67	15.95	10.92	8.82	6.93
500	23.29	20.56	14.06	10.92	8.40
600	29.16	24.75	17.42	14.06	9.45
700	34.40	29.58	21.61	16.37	12.59
800	40.27	36.71	23.71	18.05	15.32
900	47.40	43.21	28.95	21.40	18.05
1000	57.67	53.90	31.67	27.27	20.77

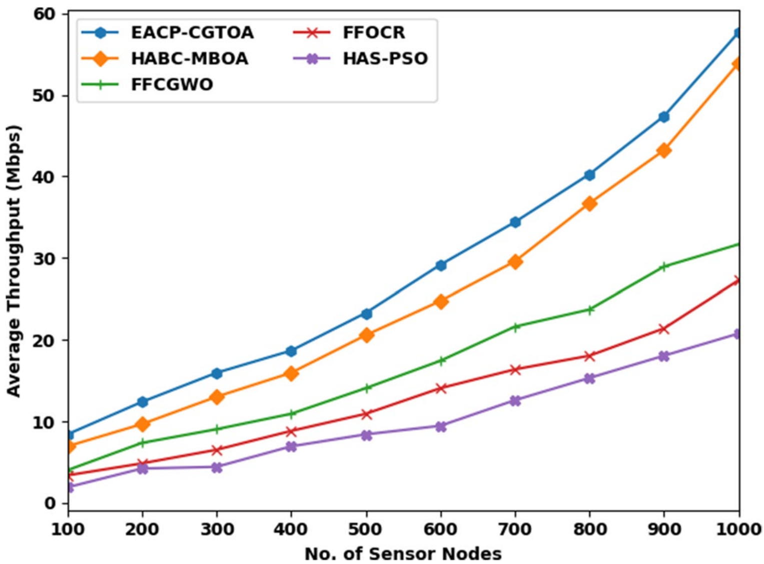

Fig. 5 ATHRPT analysis of EACP-CGTOA technique with recent approaches

82.44%, and 90.07% respectively. In line, with 1200 rounds, the EACP-CGTOA system has provided decreased NODN of 33.09% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO models have accomplished increased NOAN of 67.94%, 86.26%, 96.69%, and 99.49% respectively.

Table 4; Fig. 5 investigate the comparative average throughput (ATHRPT) inspection of the EACP-CGTOA model with existing models. The experimental results highlighted the betterment of the EACP-CGTOA algorithm with maximum ATHRPT under all rounds. For instance, with 100 rounds, the EACP-CGTOA approach has resulted in a higher ATHRPT of 8.40Mbps whereas the HABC-MBOA, FFCGWO, FFOCR, and

Table 5 IIRE analysis of EACP-CGTOA technique with recent approaches under distinct rounds

Improvement in remaining energy (%)					
No. of rounds	EACP-CGTOA	HABC-MBOA	FFCGWO	FFOCR	HAS-PSO
100	24.34	22.68	16.22	12.58	9.85
200	22.18	20.53	14.82	11.42	8.69
300	20.86	19.37	12.58	9.85	7.78
400	19.04	17.63	10.84	8.03	6.79
500	17.71	16.55	9.60	7.04	5.96
600	17.38	15.40	8.61	5.63	4.30
700	16.14	13.08	7.62	4.55	3.31
800	14.49	12.66	6.54	3.39	2.40
900	13.24	11.67	5.79	2.32	1.41
1000	11.51	9.85	4.88	1.49	0.50

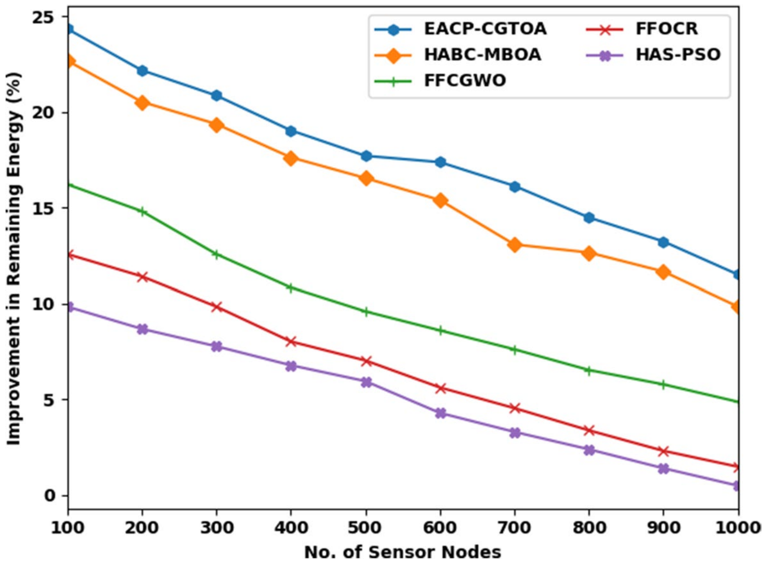

Fig. 6 IIRE analysis of EACP-CGTOA technique with recent approaches

HAS-PSO models have obtained lower ATHRPT of 6.93Mbps, 4Mbps, 3.37Mbps, and 1.90Mbps correspondingly. In addition, with 700 rounds, the EACP-CGTOA algorithm has resulted in a maximal ATHRPT of 34.40Mbps whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO models have obtained lower ATHRPT of 29.58Mbps, 21.61Mbps, 16.37Mbps, and 12.59Mbps correspondingly. Similarly, with 1000 rounds, the EACP-CGTOA technique has resulted in a superior ATHRPT of 57.67Mbps whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO methodologies have obtained a minimum ATHRPT of 53.90Mbps, 31.67Mbps, 27.27Mbps, and 20.77Mbps correspondingly.

Table 6 IINLT analysis of EACP-CGTOA technique with recent approaches under distinct rounds

Improvement in network lifetime (%)					
No. of rounds	EACP-CGTOA	HABC-MBOA	FFCGWO	FFOCR	HAS-PSO
100	38.69	35.96	30.09	26.05	21.10
200	35.70	32.70	27.75	21.36	18.76
300	32.57	30.35	25.27	18.63	15.63
400	30.48	27.62	23.32	17.06	13.55
500	29.05	26.44	21.23	14.98	11.59
600	26.58	24.49	20.19	13.68	9.64
700	24.88	22.80	18.89	11.72	7.68
800	23.45	21.23	17.85	10.55	5.60
900	22.41	20.71	16.02	9.12	4.30
1000	21.62	19.15	13.94	7.81	3.38

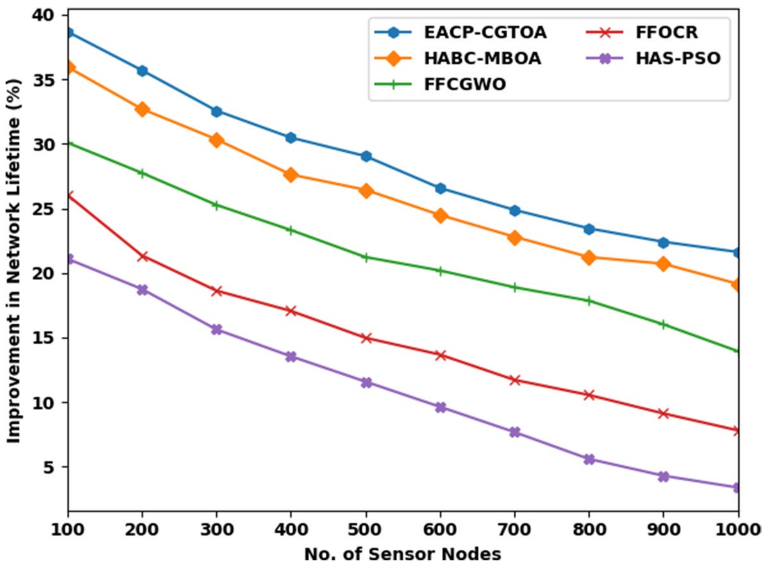

Fig. 7 IINLT analysis of EACP-CGTOA technique with recent approaches

Table 5; Fig. 6 demonstrate the comparative improvement in remaining energy (IIRE) inspection of the EACP-CGTOA method with existing models. The experimental results highlighted the betterment of the EACP-CGTOA system with maximum IIRE under all rounds. For instance, with 100 rounds, the EACP-CGTOA algorithm has resulted in a higher IIRE of 24.34% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO models have obtained lower IIRE of 22.68%, 16.22%, 12.58%, and 9.85% correspondingly. Likewise, with 700 rounds, the EACP-CGTOA model has resulted in a higher IIRE of 16.14% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO models have obtained lower IIRE of 13.08%, 7.62%, 4.55%, and 3.31% correspondingly. In addition, with 1000 rounds, the EACP-CGTOA approach has resulted in a higher IIRE of 11.51% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO techniques have attained minimum IIRE of 9.85%, 4.88%, 1.49%, and 0.50% correspondingly.

Table 6; Fig. 7 examine the comparative improvement in network lifetime (IINLT) inspection of the EACP-CGTOA algorithm with existing models. The experimental results highlighted the betterment of the EACP-CGTOA algorithm with maximum IINLT under all rounds. For instance, with 100 rounds, the EACP-CGTOA system has resulted in a higher IINLT of 38.69% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO models have obtained lower IINLT of 35.96%, 30.09%, 26.05%, and 21.10% respectively. In addition, with 700 rounds, the EACP-CGTOA system has resulted in a higher IINLT of 24.88% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO algorithms have obtained lower IINLT of 22.80%, 18.89%, 11.72%, and 7.68% respectively. Besides, with 1000 rounds, the EACP-CGTOA approach has resulted in a higher IINLT of 21.62% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO models have obtained lower IINLT of 19.15%, 13.94%, 7.81%, and 3.38% respectively.

Table 7; Fig. 8 investigate the comparative Decrease in Communication Overhead (DICOD) inspection of the EACP-CGTOA methodology with existing models. The experimental results highlighted the betterment of the EACP-CGTOA technique with maximal DICOD under all rounds. For instance, with 100 rounds, the EACP-CGTOA approach has resulted in a superior DICOD of 34.86% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO models have attained lesser DICOD of 31.16%, 26.27%, 20.46%, and 15.84% respectively.

In addition, with 500 rounds, the EACP-CGTOA approach has resulted in a higher DICOD of 24.82% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO models have obtained lower DICOD of 22.05%, 18.61%, 14.12%, and 9.11% correspondingly. Likewise, with 1000 rounds, the EACP-CGTOA algorithm has resulted in a superior DICOD of 13.20% whereas the HABC-MBOA, FFCGWO, FFOCR, and HAS-PSO models have obtained lower DICOD of 11.22%, 9.24%, 5.01%, and 3.16% correspondingly. After examining the above results and discussion, it can be ensured that the EACP-CGTOA model has resulted in a maximum lifetime and energy efficiency in WSN.

Table 7 DICOD analysis of EACP-CGTOA technique with recent approaches under distinct rounds

Decrease in communication overhead (%)					
No. of rounds	EACP-CGTOA	HABC-MBOA	FFCGWO	FFOCR	HAS-PSO
100	34.86	31.16	26.27	20.46	15.84
200	31.95	28.91	23.50	19.01	13.60
300	29.97	26.54	21.52	17.95	11.88
400	27.07	24.29	20.59	16.37	10.56
500	24.82	22.05	18.61	14.12	9.11
600	22.31	19.93	16.76	13.33	8.05
700	20.59	17.95	13.46	10.69	6.60
800	17.43	14.52	11.35	8.97	5.28
900	15.44	12.54	9.77	7.39	3.96
1000	13.20	11.22	9.24	5.01	3.16

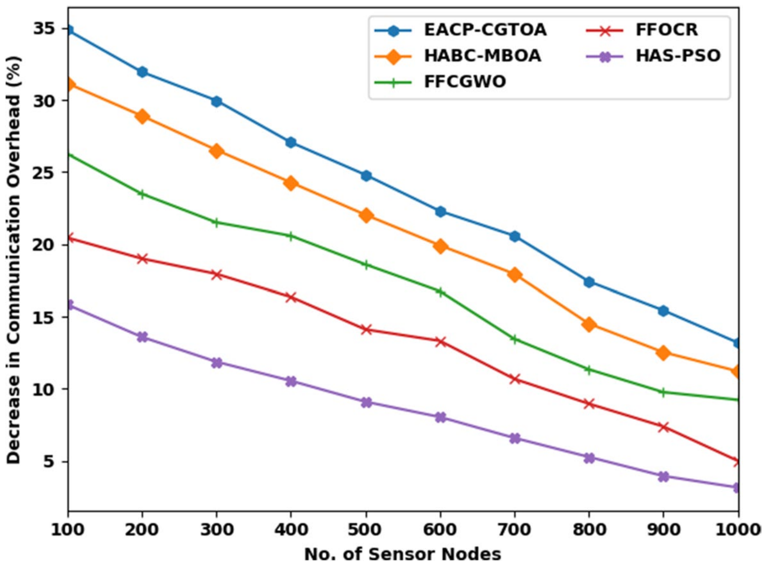

Fig. 8 DICOD analysis of EACP-CGTOA technique with recent approaches

5 Conclusion

In this study, a novel EACP-CGTOA model has been developed for lifetime maximization and maximum energy efficiency in WSNs. Initially, the nodes in the WSN are randomly deployed under the target region and then the initiation procedure takes place. Then, the BS executes the proposed model for the effective selection of CHs. The proposed EACP-CGTOA model derives a CGTOA by replacing the population initiation with circle chaotic mapping to explore the solutions with a high convergence rate and sensitivity. In addition, the EACP-CGTOA model derives a FF involving three input parameters namely DTN, DBS, and ER. For ensuring the enhanced performance of the EACP-CGTOA method, a wide range of simulations are carried out and the outcomes are examined in several aspects. The experimental results ensured that the network lifetime and energy efficiency are considerably improved by the EACP-CGTOA model over the existing methods. Therefore, the EACP-CGTOA approach was employed as an effectual tool to lengthen the lifetime of WSNs. In future, the performance of the EACP-CGTOA is enhanced by the design of a multi-hop routing process. In addition, the proposed model does not support two important network characteristics such as heterogeneity and mobility. Therefore, based on real-world network environments of different WSN applications, future work focuses on the design of clustering techniques that support mobility and heterogeneity needs more attention. In addition, new encryption and authentication techniques can be developed for secure data transmission, as well as investigating methods to detect and prevent attacks on the CHs and BS. Finally, new techniques can be explored to reduce the communication overhead of the protocol, such as data compression or adaptive duty cycling.

Declarations

Human participants and/or animals Not applicable.

Conflict of interest The authors have expressed no conflict of interest.

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