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Binary grey wolf optimisation-based topology control for WSNs

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Abstract: Wireless sensor networks (WSNs) are composed of a large number of sensor nodes that are deployed at target locations. Topology control (TC) is one of the significant fundamental challenges in WSNs because of node energy and computing power constraints. TC algorithms try to produce reduced topology by preserving network connectivity. This study presents a novel TC algorithm based on binary Grey wolf optimisation. It uses the active and inactive schedules of sensor nodes in binary format as well as introduces fitness function to minimise the number of active nodes (ANs) for achieving the target of lifetime expansion of the nodes and network. The proposed algorithm is compared with other TC algorithms. The result reduces a minimum of 10% of ANs and energy consumption by 6.84%. The proposed approach also gives maximum coverage and connectivity. The designed fitness function also benefits in the process of selecting a node with low residual energy to join the active topology. The standard deviation in the remaining energy for the proposed algorithms is lower than the other TC schemes.

1 Introduction

Wireless sensor networks (WSNs) have a large number of applications in the Internet of things and machine-to-machine communication along with several others such as environment monitoring, forecasting, traffic control, object tracking, security health care [1]. The diversity of these evolving applications represents the great success of this technology.

Nevertheless, the computation, storage, communication, energy resources, and capabilities are the limitations of WSN [2]. For addressing some of these issues, numerous solutions have been suggested in the literature. In the recent past, lots of efforts have been taken in designing energy-efficient WSNs with proficient packet delivery and data recovering models. By using optimum topology and well-connected nodes in the underlying network, the routeing process, as well as the lifetime of the network and nodes can be improved.

Moreover, change in the nodes' transmitting range and adjustment in its active and inactive schedules can change the network topology. Optimisation of network topology results in energy conservation and leads to network longevity. Deployment of high-density sensor nodes can achieve this dynamic feature, as a retrieval plan for the apparent failure of some of them [3].

Topology control (TC) in a sensor network is an iterative process and has two phases. The first phase is topology construction that builds the reduced topology, whereas the second phase of topology maintenance changes the reduced topology by considering parameters such as residual energy, timeout period, and other parameters. In reduced topology, one can control radio power to accomplish optimised topology, whereas, in the maintenance phase, the topology can be reconfigured as per the schedule of active and inactive nodes. Graph of the initial stage of WSN with high connectivity between the nodes is shown in Fig. 1*a*, which guarantees high coverage and connectivity almost all the time. However, there is a high possibility of the existence of interference and collisions during the involvement of many nodes in conveying and receiving data simultaneously [4]. Besides, sink node, as well as intermediate nodes, will be receiving large redundant data from nearby nodes that results in rapid energy loss, and hence curtail the network lifetime. Interference and collisions also affect data throughput and network performance.

To overcome these drawbacks, topology restructuring is essential, and it can be done by establishing a communication backbone that connects the whole network through the few selected nodes. Reduced topology generated by executing a topology construction algorithm is shown in Fig. 1*b*. In the topology maintenance phase, only active nodes (ANs) will trigger their transceiver while other nodes will go into sleep mode. An efficient and optimised TC algorithm plays a crucial role in data transmission and routeing while protecting connectivity and coverage.

Although researchers have already reported some TC mechanisms, the optimal use of ANs for enhancement of network lifetime and its reliability is still a challenging and open issue. In this paper, we present a novel algorithm for network optimisation, primarily focusing on TC. The developed algorithm is based on binary Grey wolf optimiser, and it minimises the number of ANs in the WSNs and also the overall energy consumption. It produces the reduced topology with lesser number of ANs, without compromising the network performance.

The remaining structure of this paper is organised as: Section 2 presents a literature study related to network TC techniques, while Section 3 describes the continuous and binary format of Grey wolf optimisation (GWO). Section 4 presents the proposed binary GWO for TC (BGWOTC). Section 5 discusses results and performance analysis, whereas this paper is concluded in Section 6.

2 Literature review

The A3 algorithm proposed in [5] for topology construction is a rising tree-based algorithm based on the concept of distance among the nodes, and remaining energy is the metric. The tree is generated by starting with the sink node and then successively nodes with minimal degree neighbours are selected for creating communication backbone. In the process of node selection, one-hop neighbour nodes communicate locally for activation decision because of priority in the metric list. The improved A3 algorithm A3Cov [6] uses sensing range to provide the coverage. It inherits the non-localised and reasonable way of producing a connected

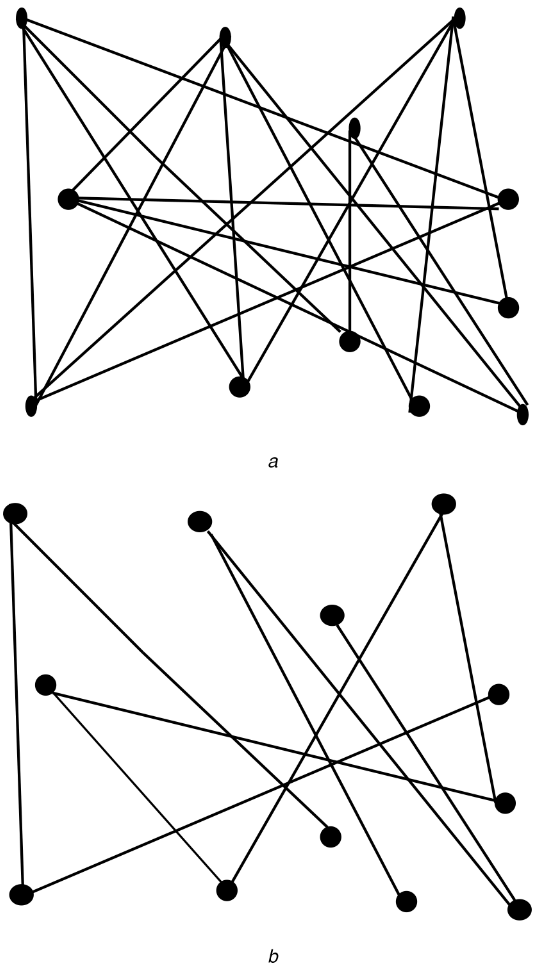

Fig. 1 *Initial stage of WSN with high connectivity between the nodes*
(a) Original network, ***(b)*** Reduced topology

backbone and includes additional nodes to generate coverage solution. A3Cov provides better coverage and network lifetime than A3 at the cost of increased energy consumption. Connected dominating set (CDS) Rule-K topology construction algorithm in [7] is distinct from the original CDS-based algorithms [8] that generate communication backbone by combining, marking, and snipping rule. A3 and CDS algorithm uses received signal strength indicator and residual energy of the receiver node as metrics. Energy-efficient CDS algorithm [9] follows a different procedure that of the A3. It creates multiple maximal independent sets (MISs) of CDS tree and then the choice of proper MIS is made for generating optimal communication backbone. Local minimum spanning tree (MST) uses the same approach as of k-local MST, and it is wholly distributed TC algorithm [10]. Simulated annealing algorithm is used to convert local MST into an MST with degree constraint [11, 12]. Addition of one or more constraints to the fundamental MST problem changes it to a multi-objective problem, which is the nondeterministic polynominal time-hard problem.

Swarm intelligence plays a crucial role in adaptive TC and sensor deployment due to the resemblance of the nature of swarm intelligence and WSNs routine. Glowworm swarm optimisation-based wireless sensor deployment [13] scheme shows improvement in coverage after the initial placement. Every sensor node in a network is treated as individual glowworms, whereas the intensity of the firefly is nothing but distance between the sensor node and its neighbours. Sensor deployment by this approach achieves maximum coverage with restricted movement of the sensor nodes. Particle swarm optimisation (PSO)-based algorithm [14] is proposed to achieve optimal solutions such as minimising energy consumption for global connectivity. The simulation result shows that it performs better than the conventional MST algorithms. To address the issue of the existence of high connectivity and low coverage in conventional methods, optimised MST TC using PSO is proposed [15]. It converges to the reduced topology evenly with lower-energy consumption and has a robust structure. However, the time complexity is very high. PSO TC algorithm for WSNs for dynamic adjustment of transition radius between the nodes [16] achieves the lesser average number of neighbours and the energy consumption.

Vertex sort TC (VSTC) algorithm [17] adjusts the transition radius of nodes. A location of each node is used and characterised in a binary system to augment the coverage area and decrease the quantity of ANs. Swarm intelligence-based modified bat optimisation algorithm [18] is used to determine the accuracy of node localisation problem in WSNs. It increases the localisation success ratio and achieves fast convergence. TC is considered as a multi-objective – constrained MST problem, and the discrete version of PSO is used for generating optimal topology schemes. Discrete PSO and local MST-based topology scheme are introduced in [19]. Distance between nodes, coverage of each edge, and residual energy are considered to reduce the topology. GWO [20] is one of the most recent bio-inspired optimisation methods; it mimics hunting procedure of a pack of Grey wolves. It has effective imitation more than hunting in the pack and can be used in network optimisation.

A three-level hybrid clustering routeing algorithm based on the GWO is used in [21]. A centralised cluster head is selected in level one, whereas GWO-based routeing is performed in level two. Distributed clustering based on a cost function is proposed in level three. The proposed algorithm performs better than other well-known algorithms in terms of network lifetime, stability period, and residual energy. Being new metaheuristic approach, not much research is addressed in the literature on the use of GWO and BGWOTC in WSN.

3 Grey wolf optimisation

Generally, Grey wolves choose to reside in a group. Average group size is 5–12. They have extremely strict regulations in the leading social hierarchy. In a Grey wolf group, wolves are categorised as alpha (α), beta (β), omega (ω), and delta (δ). Here α, generally a pair of wolves leads the pack and liable for making decisions and hunting. Decisions of α wolves are communicated to the group. βs are secondary wolves; they assist in judgement building or added actions to the αs. βs are possibly the pre-eminent candidates to be α. Here, β wolf respects the α but rules the other lower-level wolves as well. β fortifies α's orders all over the pack and provides feedback to α. Here, ω wolves are nothing but scapegoats in the group. They have to capitulate to the remaining leading wolves. ωs belong to final layer of wolves that are permitted to eat. Here, δ wolves have to follow to αs and βs; however, they rule ω. Detectives, guards, elders, seekers, and wardens belong to this class. Detectives watch the margins of the terrain and inform the group if some risk. Guards shelter and guarantees the security of the group. The proficient wolves, those who were α or β, are seniors. Hunters assist the αs and βs in hunting prey and providing food for the group. Finally, the wardens are accountable for helping the fragile, sick, and wounded wolves in the group.

3.1 Mathematical model for continuous GWO

In GWO, there are three prime solutions, namely α, β, and δ. Solution α is derived from α wolves and is the best solution, while β and δ solutions are from β and δ wolves, treated as second- and third-best solutions, respectively. All other solutions are considered to be ω solutions that are evolved from ω wolves. Hunting in the pack is directed by α, β, δ, and ω trail these three candidate solutions. The first step in the hunting process is encircling the prey, and it can be modelled as

$$\bar{S}(t+1) = \overline{S_{\mathrm{p}}}(t) - \bar{U} \cdot \bar{\boldsymbol{V}} \tag{1}$$

$$\bar{\boldsymbol{V}} = \left|\bar{W} \cdot \overline{S_{\mathrm{p}}}(t) - \bar{S}(t)\right| \tag{2}$$

where $\overline{S}$ is the location of a Grey wolf, $\overline{S_{\mathrm{P}}}$ is the location of prey, t is the iteration number, and $\bar{\boldsymbol{V}}$ is the distance vector. $\bar{\boldsymbol{U}}$ and $\bar{\boldsymbol{W}}$ are coefficient vectors given by

$$\bar{\boldsymbol{U}} = 2k \cdot \bar{r}_1 - k \tag{3}$$

$$\bar{\boldsymbol{W}} = 2 \cdot \bar{r}_2 \tag{4}$$

where k is linearly reduced from 2 to 0 during the consecutive iterations, and $\bar{r}_1$, $\bar{r}_2$ are the random vectors in [0, 1]. Here, α generally leads the hunt. Occasionally, the β and δ wolves also contribute to hunting. To imitate the hunting nature of Grey wolves mathematically, α (best candidate solution), β (second-best candidate solution), and δ (third-best candidate solution) are expected to have improved information regarding the possible position of prey. The first three most excellent candidate solutions attained so far are saved and communicated with the other hunt managers, together with ωs for updating their locations concerning the location of the best hunt managers. For updating the wolves location, we have

$$\bar{S}(t+1) = \frac{\overline{S_1} + \overline{S_2} + \overline{S_3}}{3} \tag{5}$$

$$\overline{S_1} = |\overline{S_\propto} - \overline{\boldsymbol{U}_1} \cdot \overline{\boldsymbol{V}_\propto}| \tag{6}$$

$$\overline{S_2} = |\overline{S_\beta} - \overline{\boldsymbol{U}_2} \cdot \overline{\boldsymbol{V}_\beta}| \tag{7}$$

$$\overline{S_3} = |\overline{S_\delta} - \overline{\boldsymbol{U}_3} \cdot \overline{\boldsymbol{V}_\delta}| \tag{8}$$

where $\overline{S_1}$, $\overline{S_2}$, and $\overline{S_3}$ are the first three best solution candidates in the group at a given iteration t. $\overline{\boldsymbol{U}_1}$, $\overline{\boldsymbol{U}_2}$, and $\overline{\boldsymbol{U}_3}$ are as defined in (3), and $\overline{\boldsymbol{V}_\propto}$, $\overline{\boldsymbol{V}_\beta}$, and $\overline{\boldsymbol{V}_\delta}$ are position vectors defined as

$$\overline{\boldsymbol{V}_\propto} = |\overline{\boldsymbol{W}_1} \cdot \overline{S_\propto} - \bar{S}| \tag{9}$$

$$\overline{\boldsymbol{V}_\beta} = |\overline{\boldsymbol{W}_2} \cdot \overline{S_\beta} - \bar{S}| \tag{10}$$

$$\overline{\boldsymbol{V}_\delta} = |\overline{\boldsymbol{W}_3} \cdot \overline{S_\delta} - \bar{S}| \tag{11}$$

where $\overline{\boldsymbol{W}_1}$, $\overline{\boldsymbol{W}_2}$, and $\overline{\boldsymbol{W}_3}$ are as given in (4). The parameter k controls the trade-off between the searches for prey (exploration) and converges while attacking prey (exploitation) in successive iterations. To update parameter k linearly in each iteration [19] with the range from 2 to 0 can be written as

$$k = 2\left(1 - \frac{t}{T}\right) \tag{12}$$

where T is the total number of iterations allowed for the optimisation. Grey wolves diverge from each other during exploration and converge during the exploitation process. The choice of k speeds up the algorithm to move toward the best candidate solution. $\bar{\boldsymbol{U}}$ can be used to decide divergence or convergence as given:

$|\bar{U}| > 1$ enforces divergence and moves to find the next better position.
$|\bar{U}| < 1$ enforces convergence and updates the position as the best solution.

The objective function for GWO mainly focuses on finding the optimal solution say x in the particular search space as represented by

$$\text{minimise } f(x), \quad x = (x_1, x_2, x_3, \ldots, x_n) \in R^n \tag{13}$$

where n is the number of dimensions contained in a solution. $x \in F \in S$, where F is the feasible region in the search space S, which defines an n-dimensional rectangle R. The domain size for rectangle R is $l_\mathrm{b}(i) \le x(i) \le u_\mathrm{b}(i)$. l_b and u_b are lower and upper bounds, respectively. Constraints in the feasible region can be given as

$$g_j(x) \le 0, \quad \text{for} \quad j = 1, 2, \ldots, r \tag{14}$$

$$h_j(x) = 0, \quad \text{for} \quad j = r + 1, \ldots, m \tag{15}$$

If any solution x satisfies the constraint g_j or h_j in region F, then g_j is considered to be an active constraint at x.

3.2 Binary GWO

The wolves in continuous GWO (CGWO) change their positions in the space continuously. The solutions of active or inactive nodes in WSN are constrained to the binary {0, 1} values that induce an additional form of the CGWO, called as BGWO. A group of binary form solutions at any given time are generated. We propose the use of the enhanced version of the CGWO, along with BGWO for the topology construction. For such approach, the pool of solutions will always be in binary format, and every solution will be on the corner of a hypercube [19].

The locations of a given wolf are updated according to the CGWO strategy while keeping the binary representation based on (16). To crossover initial solution (x_1, x_2, x_3),, we have applied crossover mechanism per dimension as defined in the equation below:

$$s_t = \begin{cases} l_t & \text{if}\left(\text{rand} < \frac{1}{3}\right) \\ m_t & \text{if}\left(\frac{1}{3} < \text{rand} < \frac{2}{3}\right) \\ n_t & \text{otherwise} \end{cases} \tag{16}$$

where s_t is the output of the crossover at dimension t; l_t, m_t, and n_t are binary values of the first, second and third parameters in dimension t, and *rand* is a number randomly chosen from 0 to 1. To crossover initial solution (x_1, x_2, x_3), we have applied crossover mechanism per dimension as defined in (16). It is a suitable crossover between x_1, x_2, x_3 and $\boldsymbol{s}_1$, $\boldsymbol{s}_2$, $\boldsymbol{s}_3$ are the binary vectors, representing the effect of wolf move toward the α, β, and δ in sequence. $\boldsymbol{s}_1$, $\boldsymbol{s}_2$ and $\boldsymbol{s}_3$ are determined as

$$s_1^t = \begin{cases} 1 & \text{if } (\boldsymbol{s}_\alpha^t + r\text{step}_\propto^t) \ge 1 \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

$$s_2^t = \begin{cases} 1 & \text{if } (s_\beta^t + r\text{step}_\beta^t) \ge 1 \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

$$s_3^t = \begin{cases} 1 & \text{if } (s_\delta^t + r\text{step}_\delta^t) \ge 1 \\ 0 & \text{otherwise} \end{cases} \tag{19}$$

where $\boldsymbol{s}_\alpha^t$ is the position vector of the α wolf in dimension t and $r\text{step}_\propto^t$ is binary step in dimension t that can be given as

$$r\text{step}_\propto^t = \begin{cases} 1 & \text{if } k\text{step}_\propto^t \ge \text{rand} \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

where $k\text{step}_\propto^t$ is continuous valued step size for dimension t, determined by using sigmoid function. As a result, Grey wolf position vectors are updated and converted into binary using

$$S_t^{m+1}(i) = \begin{cases} 1 & \text{if sigmoid}\left(\frac{\boldsymbol{s}_1 + \boldsymbol{s}_2 + \boldsymbol{s}_3}{3}\right) \ge \text{rand} \\ 0 & \text{otherwise} \end{cases} \tag{21}$$

where rand is a random number chosen from a uniform distribution $\in$ [0, 1], $S_m^{t+1}(i)$ is the updated position in dimension t at iteration m for the ith sensor node, and sigmoid*(s)* is defined as

$$\text{sigmoid}(s) = \frac{1}{1 + \mathrm{e}^{-10(s-0.5)}} \tag{22}$$

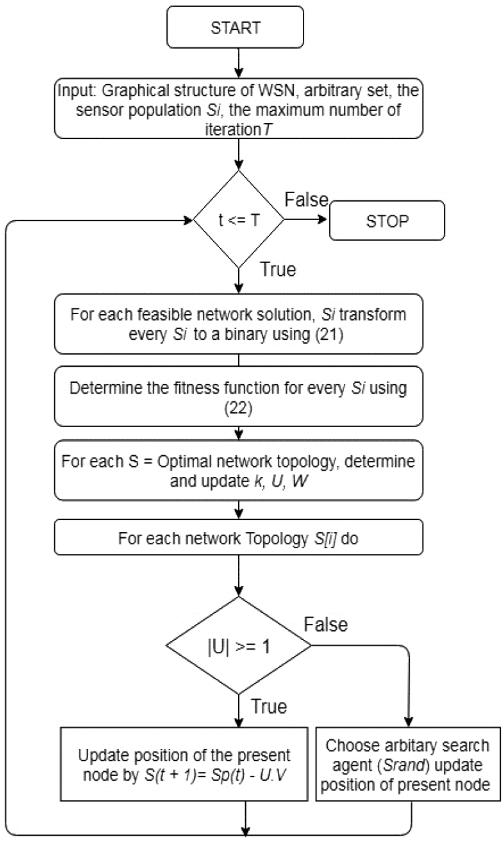

Fig. 2 *Flowchart to find candidate solution and binary form of the sensor node*

4 BGWO model for TC (BGWOTC)

The network lifetime of the deployed WSN is the period for which it performs well for the assigned responsibility. It can be defined as the period between the network deployment time and the time at which the WSN does not assure determined coverage or connectivity assignment. Network lifetime can be extended by using the appropriate subset of sensors dynamically to transfer the data efficiently. In this work, we have measured network lifetime as 50% of nodes dead. By assuming N mobile sensor nodes with uniform initial energy and stationary base station of high-energy node placed in (X_{sink}, Y_{sink}), we applied CGWO for updating positions of sensor nodes. Sensor nodes of WSN are mapped with wolves in the pack for optimisation. To update parameter k in the range of 2 to 0, we have proposed

$$k = 2\left(1 - \frac{t^2}{T^2}\right) \tag{23}$$

CGWO is applied iteratively to update the position of sensor nodes to obtain the candidate solution $S = \{S_1, S_2, S_3, \ldots, S_n\}$. In the next phase, BGWO is applied to convert the candidate solution into a binary vector. The binary format is obtained by using (21) and (22). Each sensor position S_i possesses either the value 1 or 0, to indicate that node i within the topology is active or inactive, respectively. Pseudocode of the algorithm for finding candidate solution and its binary format is outlined in flowchart given in Fig. 2.

When nodes are to be deployed in the monitoring area, the value calculated by (21) and (22) is not able to map to the corresponding sensor node. Hence, we need to define fitness function for corresponding nodes. The fitness function requires knowledge about initial energy, the number of adjacent nodes, and then considers the surplus and the conservation of energy. On the basis of these constraints, sensors are grouped into different sets according to their active/inactive states.

A check procedure is performed on each set to see whether the nodes in the set can provide full coverage or not. As we divide the monitored area into small graphs, for each set S_i, we can count the number of neighbouring nodes that are covered by the sensor nodes in that set.

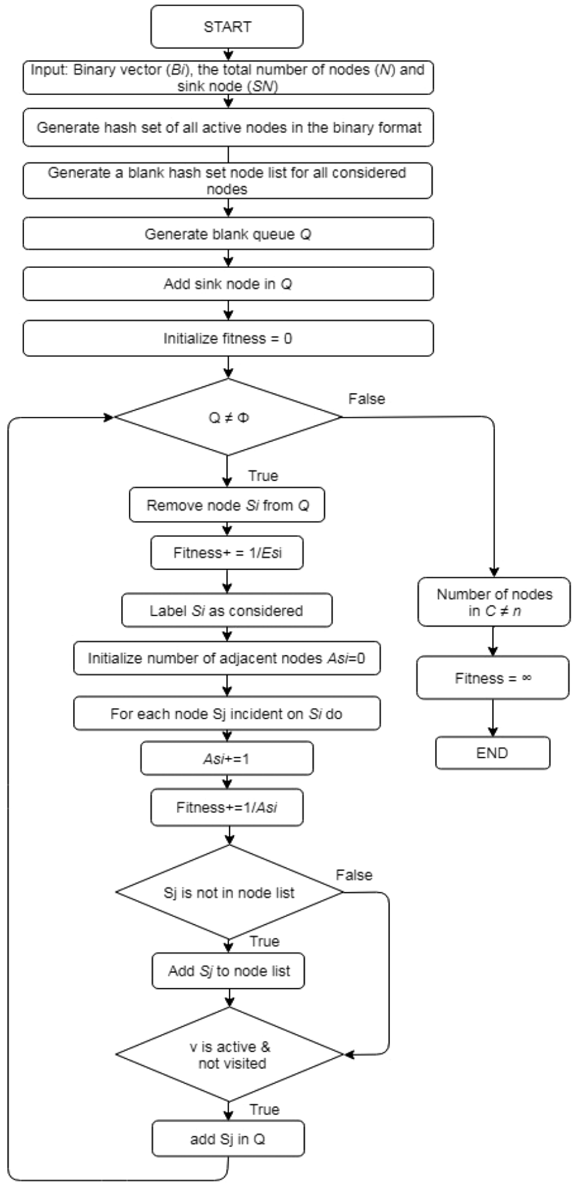

Fig. 3 *Flowchart to evaluate fitness value for the sensor node*

The fitness function used to ensure the final topology covers all the nodes is given as

$$f(x) = \sum_{i=1}^{n} \frac{S_m^{t+1}(i)}{A_i E_i} \tag{24}$$

where A_i is the number of neighbouring nodes to S_i and E_i is the initial energy of sensor node S_i. Pseudocode for determining fitness value for each sensor node in Algorithm II is presented as flowchart as shown in Fig. 3.

5 Results and performance analysis

To test and analyse the performance of the proposed BGWOTC algorithm, extensive simulations were carried out. The characteristics of the nodes in the experimental set up are assumed to be the same as that of the energy model introduced in [22]. For the evaluation of performance and comparison, we considered the A3 algorithm [5], A3Cov [6], particle swarm optimisation based topology control scheme (PSOTCS) algorithm [18], and VSTC algorithm [16]. The performance of these algorithms is measured on the bases of metrics listed in Table 1.

Table 1 Metrics for performance analysis

Metric	Notation and description
total number of nodes in the network	N
number of ANs	AN
total network energy	$\mathrm{TNE} = \sum_{i=1}^{N} E_i$, E_i is the initial energy of node i
energy consumption	$E = E_i - E_c$, E_c is the energy consumed per cycle
transmission amplifier energy for free-space path	E_{TAL}
transmission amplifier energy for multipath	E_{TAG}
coverage	it is the percentage of ANs in the network which represents the degree of coverage of the network in the reduced topology
connectivity	connectivity is the capacity of network nodes to communicate

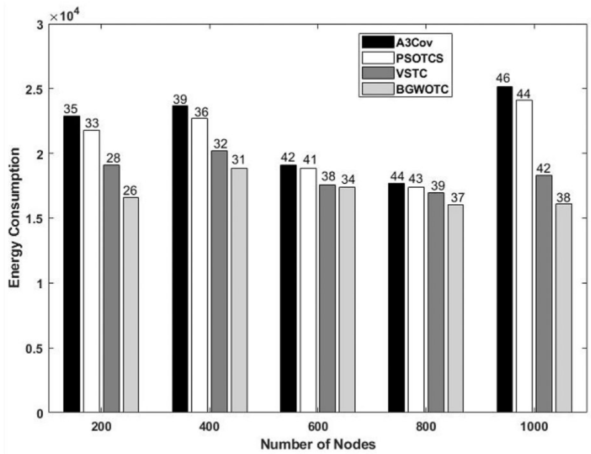

Fig. 4 *Comparison of energy consumption by the reduced topology by different algorithms*

Before the discussion on the result and performance of the proposed algorithm, we define and describe energy consumption, remaining energy, and network lifetime.

Energy consumption: Summation of energy consumed by each node during sensing and transmission in every cycle. Initially, the maximum numbers of nodes are selected for creating the preliminary topology that assures maximum coverage. In subsequent cycles, redundant and jobless nodes are sent to the inactive mode for energy conservation so that they can be used later. In each optimisation cycle, energy E_c is consumed. The total energy consumed in transmitting the packet of p bits through the distance q between the transmitter and receiver is defined as

$$E_c(p, q) = \begin{cases} pE_D + pE_{\mathrm{TAL}}q^2, & q < q_0 \\ pE_D + pE_{\mathrm{TAG}}q^4, & q \geq q_0 \end{cases} \tag{25}$$

Energy consumed by the receiver to receive the packet of p bits is

$$E_{\mathrm{CM}}(p) = p \times E_D \tag{26}$$

where E_D is the energy dissipation per bit $q_0 = \sqrt{E_{\mathrm{TAL}}/E_{\mathrm{TAG}}}$.

Remaining energy: Average of remaining energy of all the associated nodes with the topology in the network for each cycle. If n is the number of nodes that are associated with the topology, then the energy dissipated in transmitting the packet of p bits through the distance q by the member node of the path per cycle is (see (27)) . The mean dissipated energy for the cycle is

$$\bar{E}_{\mathrm{des}} = \frac{\sum_{x \in n} E^{s}_{\mathrm{des}}(x)}{N} \tag{28}$$

The remaining energy E_R for the next cycle is

$$E_R^{s+1}(x) = E_R^{s}(x) - E_D^{s}(x) \tag{29}$$

The mean remaining energy for the next cycle is

$$\overline{E_R} = \frac{\sum_{x \in n} E_R^{s}(x)}{N} \tag{30}$$

The standard deviation of the remaining energy is

$$\sigma(E_R) = \sqrt{\frac{\sum_{x \in n}\left(\overline{E_R} - E_R(x)\right)^2}{N}} \tag{31}$$

Network lifetime: It is the functioning period of the network until a certain number of nodes are active. For our case, we have considered network lifetime as the period until 10% of the nodes are alive.

Simulations are performed for 1000 m × 1000 m area. We assumed that 100 through 1000 sensor nodes are uniformly distributed in a region. The initial energy of the sensor node is taken as 0.5 J. Energy consumed during idle period is 50 nJ/bit and amplifier energy is $\in$amp = 10 pJ/bit/m^2. Communication and sensing range of each sensor node is 100 and 20 m, respectively. The node energy distribution is uniform. For the performance analysis, we have calculated the average of ten different runs for each network size. Energy consumption for the reduced topology cases for all four algorithms is computed and compared as shown in Fig. 4. The results show that reduced topology generated by BGWOTC algorithm has minimal energy consumption, namely 26.51, 20.62, and 6.84% lesser than that of A3Cov, PSOTCS, and VSTC, respectively. These figures at the top edge of each bar show the minimum number of ANs required for different network sizes for the respective algorithms. It demonstrates that the proposed BGWOTC generate the reduced topology and the average number of ANs is reduced by 21, 18, and 10% in comparison with A3Cov, PSOTCS, and VSTC, respectively. The number of ANs increases with the size of the growing network. BGWOTC has achieved the best result for the ratio of ANs to the rest of the nodes compared with the existing algorithms. It is not only significant to decrease the number of ANs but it is also crucial that the selected nodes should possess enough residual energies. The fitness function proposed in BGWOTC algorithm helps in the process of selecting a node with sufficient residual energy.

We have calculated the remaining energies for different network sizes and all the four schemes. The standard derivation of the remaining energy for the four algorithms is shown in Fig. 5. It can be seen that the remaining energy is more balanced in BGWOTC than the other three. For more number of nodes, standard deviation also increases in most cases.

Fig. 6 shows the percentage of coverage for all four schemes. It illustrates that BGWOTC provides the highest coverage in the network of all sizes since the proposed algorithm periodically reduces ANs while maintaining the required performance of the network. Higher coverage with lesser number of ANs is achieved because of the ability of BGWOTC to escape from the local optimum.

It shows that BGWOTC possesses an ability to tackle coverage problem small as well as large WSN networks. It effectively

$$E^{s}_{\mathrm{des}}(x) = \begin{cases} (n-1)pE_D + npE_{\mathrm{CM}} + pE_D + pE_{\mathrm{TAG}}q^4, & x \in q \\ pE_D + pE_{\mathrm{TAG}}q^2, & x \notin q \end{cases} \tag{27}$$

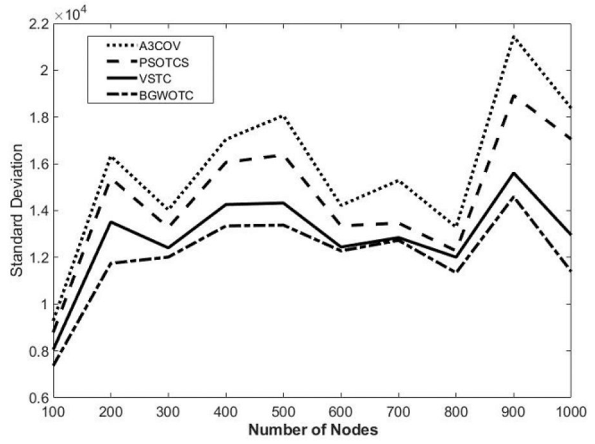

Fig. 5 *Standard deviation of remaining energy*

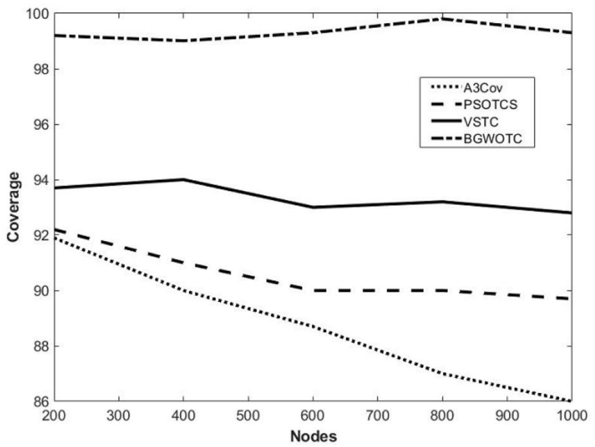

Fig. 6 *Coverage percentage for the reduced topology of different algorithms*

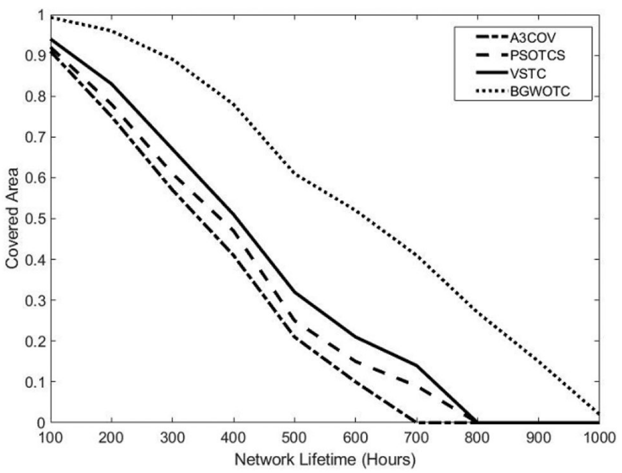

Fig. 7 *Covered area and network lifetime for the reduced topology of different algorithms*

Table 2 Comparison of computation time

Algorithm	A3Cov	PSOTC	VSTC	BGWOTC
time complexity applicable	$O(n \log n)$	$O(n!)$	$O(\Delta n)$	$O(nA \times nD)$
computation time, μs	16,789	18,311	7102	1918

identifies the best distribution of sensor nodes in WSN as the algorithm continues to search until it reaches the optimal solution with better convergence, whereas the A3Cov, PSOTC, and VSTC reach to the inertia state quite in advance leading to the poor search results. We have also determined the influence of different maintenance schemes on the area coverage and the network lifetime with 1000 nodes. The results in Fig. 7 show that BGWOTC provides the best coverage and network lifetime for a substantially longer period compared with the other three algorithms. It extends the coverage almost by 30% for 800 h network lifetime. This happens due to the fact that the algorithm uses lesser number of ANs with more remaining energy than other nodes, so it will not die immediately after being selected.

To analyse the computational performance of our algorithm for a network size of 100 nodes, we calculated the time required for algorithm execution on a standard computer with fifth-generation i5 processor, 8 GB machine.

For BGWOTC, the expected runtime for the optimised topology formation is $O(nA \times nD)$, where nA is the number of ANs and nD is the average node degree. Table 2 shows the time required for the reduced topology creation for each algorithm for 100 node networks.

The proposed distinct approach for selecting the value of parameter k improves the speed to reach optimal candidate solution. The results demonstrate that the proposed BGWOTC is much faster than the other three schemes.

6 Conclusion

We have presented a novel WSN TC algorithm by using BGWO. The proposed fitness function minimises the requirement of the number of ANs in the sensor network and also reduces energy consumption without compromising the network coverage and connectivity. The results demonstrate that the proposed algorithm outperforms the existing optimisation approaches by substantially reducing the number of ANs, maintaining low-energy usage, and giving the highest coverage. The algorithm computes the best candidate solution with lesser time, enabling the faster TC, and improvement in network performance.

7 References

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