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Research article

Enhancing sensor duty cycle in environmental wireless sensor networks using Quantum Evolutionary Golden Jackal Optimization Algorithm

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Abstract: Environmental wireless sensor networks (EWSNs) are essential in environmental monitoring and are widely used in gas monitoring, soil monitoring, natural disaster early warning and other fields. EWSNs are limited by the sensor battery capacity and data collection range, and the usual deployment method is to deploy many sensor nodes in the monitoring zone. This deployment method improves the robustness of EWSNs, but introduces many redundant nodes, resulting in a problem of duty cycle design, which can be effectively solved by duty cycle optimization. However, the duty cycle optimization in EWSNs is an NP-Hard problem, and the complexity of the problem increases exponentially with the number of sensor nodes. In this way, non-heuristic algorithms often fail to obtain a deployment solution that meets the requirements in reasonable time. Therefore, this paper proposes a novel heuristic algorithm, the Quantum Evolutionary Golden Jackal Optimization Algorithm (QEGJOA), to solve the duty cycle optimization problem. Specifically, QEGJOA can effectively prolong the lifetime of EWSNs by duty cycle optimization and can quickly get a deployment solution in the face of multi-sensor nodes. New quantum exploration and exploitation operators are designed, which greatly improves the global search ability of the algorithm and enables the algorithm to effectively solve the problem of excessive complexity in duty cycle optimization. In addition, this paper designs a new sensor duty cycle model, which has the advantages of high accuracy and low complexity. The simulation shows that the QEGJOA proposed in this paper improves by 18.69%, 20.15% and 26.55% compared to the Golden Jackal Optimization (GJO), Whale Optimization Algorithm (WOA) and the Simulated Annealing Algorithm (SA).

Keywords: duty cycle optimization; Golden Jackal Optimization Algorithm; exploration operators; network lifetime

1. Introduction

Environmental monitoring is one of the key directions in ecological protection. Wireless sensor networks (EWSNs) are a highly effective technology for environmental monitoring, which can be used for large-area and long-term monitoring tasks. EWSNs are designed to deploy sensor nodes within the target monitoring area, allowing for the remote collection of physical or environmental information from the region. Regarding ecological quality monitoring, EWSNs can monitor temperature, humidity and carbon dioxide in real-time to detect changes in environmental conditions and pollutants. In disaster prevention, EWSNs respond quickly to natural disasters, which is conducive to controlling danger and facilitating human resource investment.

Since EWSNs are limited by the sensor battery capacity and data collection range, the sensing resources are limited [1, 2]. Traditional EWSNs deployment schemes usually increase the sensor node density per unit area to compensate for the limited monitoring range of a single sensor [3]. However, this deployment scheme often leads to uneven distribution of sensor nodes, which can cause repeated node coverage, resulting in a waste of sensor resources. When sensor resources are wasted due to recited ranges of nodes, this can reduce the overall service life of the network. Therefore, the main objective of this paper is to investigate EWSN using the traditional deployment scheme, meaning the distribution of the original sensor nodes and monitoring target locations should remain the same throughout the entire research process. The paper aims to satisfy the requirements above by achieving complete monitoring coverage while minimizing the number of nodes used, extending the network's lifespan and optimizing sensory and communication coverage in the target monitoring zone.

Within the literature that pertains to this matter, Sanjay et al. [4] limit the power of WSNs to prolong network life. Although this method can extend the network life, it affects the coverage quality of a single sensor. Zhang et al. [5] proposes an applied probabilistic sensing model (PSM), which is optimized by adjusting the detection radius of the sensor, which also affects the coverage quality of a single sensor. Liao et al. [6] To avoid the hardware cost of battery replacement and the energy consumption of wireless power transmitters, the method of solar-powered sensor network is adopted. This method can effectively prolong the network's life, but it dramatically increases the cost and price of optimizing the network. Not suitable for large-scale promotion. Solar energy utilization is added in paper [7], combining the above two methods while designing the optimization algorithm for the PSM model. Still, there is also the problem of high optimization costs.

The best solution to this problem is optimizing the duty cycle. Unfortunately, this is an NP-Hard problem and as the number of sensor nodes increases, the complexity of the problem search grows exponentially. Non-heuristic algorithms often need help finding a deployment plan that meets the requirements in a reasonable amount of time.

In recent years, heuristic algorithms have become more and more widely used, not only in the field of resource allocation but also play an essential role in many other fields [8, 9]. Compared with traditional optimization algorithms, heuristic algorithms can provide better optimization results because they can not only use their search strategies to find optimal solutions in local and global searches but also optimize the performance of the algorithms through continuous iterations and adaptive adjustments to better adapt to the characteristics and needs of the problem [10–15]. The Golden Jackal optimization (GJO) algorithm is a novel heuristic optimization algorithm proposed in 2022. Compared with traditional algorithms, this algorithm has better robustness and global search capability and thus is suitable for large-scale and high-complexity sensor duty cycle problems. However, the GJO algorithm is prone to fall into local optimality when dealing with the sensor duty cycle problem because the search strategies may be different. To solve this problem, the authors of this paper propose a new heuristic algorithm based on the quantum evolution strategy, which aims to extend the network lifetime and solve the duty cycle optimization problem in EWSN.

The main innovation points of the research are as follows:

1) The new QEGJOA is designed for duty cycle optimization in EWSN, which has excellent performance. In the case of multi-sensor nodes, QEGJOA can quickly obtain the duty cycle design and significantly extend the network life. Moreover, QEGJOA has good robustness and can maintain high performance to handle different duty cycle optimization.
2) The new quantum exploration operator and quantum exploitation operator are designed, which greatly enhances the algorithm's ability to search the entire solution space and enables the algorithm to effectively solve the problem of excessive complexity in duty cycle optimization.
3) A novel sensor duty cycle model is designed, which is more accurate than the traditional model. The model can simulate the exact location of all sensor nodes and monitoring targets, reflecting the EWSNs system more accurately.
4) A new experiment is designed to test the algorithm's performance. The simulation results show that the network lifetime expectancy with QEGJOA is 20.53% higher than that of the whale optimization algorithm (WOA) and 26.87% higher than that of the analog annealing algorithm (SA). Moreover, QEGJOA has better stability and converges faster than the other two algorithms.

The remainder of the paper is shown below. Part 2 presents the relevant research on EWSNs coverage optimization, Part 3 shows the sensor duty cycle model, Part 4 uses QEGJOA to solve duty cycle optimization problem in EWSN, Part 5 verifies and discusses the effectiveness of QEGJOA in extending network lifetime through simulation experiments, and Part 6 is the conclusion part.

2. Related work

There are currently four main categories of research focused on optimizing duty cycles in EWSN: the development of routing protocols, the use of artificial intelligence techniques for processing sensor data, the application of mathematical models to optimize node duty cycles and the utilization of clustering algorithms for efficient sensor data aggregation and duty cycle management.

Designing a routing protocol is a relatively common method to deal with the duty cycle optimization problem, which can reduce the communication cost of sensors in EWSNs to a certain extent, thereby reducing the energy loss [16–24]. In the paper [25], Li et al. propose an energy-saving data aggregation scheme, which reduces the communication cost through the balanced energy of the nodes to prolong the network's life while protecting data privacy. Zhang et al. [26] propose a triple integration scheme with duty cycle-based energy saving and responsive congestion control to achieve seamless transmission, minimize energy utilization of nodes and prolong network lifetime with low control overhead. In the study by Liu et al. [27], the authors modeled the distribution of sensor nodes and proposed a method to optimize the paths of sensor nodes to reduce communication overhead. These studies can reduce energy consumption to a certain extent and increase network life, but they are only suitable for small numbers of nodes and are difficult to optimize for large-scale EWSN.

When compared, it becomes evident that artificial intelligence technology can significantly enhance the network's duty cycle and eliminate any unnecessary nodes. In the paper [28] by Zhu et al., the overlay network is optimized to prolong service life and coverage, and Ant Colony Optimization (ACO) is used to optimize multi-node distribution. The global layout is changed to improve network life, and the method can also increase the stability of sensor connections. Huang et al. [29] propose a Voronoi bee colony algorithm (VABC) for the global deployment of sensor nodes, which improves the coverage of WSNs and achieves the optimal range of the network. The above methods can eliminate redundant nodes and extend the network's life. However, the convergence speed of the above algorithm could be faster, and there are easy to converge prematurely, which are difficult to solve the problem of duty cycle optimization in EWSN.

In addition to the two research methods discussed above, another critical approach that has been widely studied in recent years is clustering algorithms. Clustering algorithms are an effective way to extend the lifetime of wireless sensor networks by grouping nodes into clusters and assigning different roles and responsibilities to the nodes in each set. In paper [30], Tsiropoulou et al. apply clustering algorithms to improve the energy efficiency among wireless sensor devices and thus extend the lifetime of wireless sensor networks. In addition, Liu et al. [31] proposed a new heuristic-based clustering method: improved adaptive clone jellyfish search (DCC-IACJS). This method combines the swarm optimization algorithm and Ant Colony Optimization (ACO) algorithm with a new clustering process and periodic protocol operation, aiming to reduce the energy consumption of nodes and the duty cycle of the network by dynamically changing the state of nodes, thus improving the energy efficiency of the network. Although the clustering algorithm can solve the sensor duty cycle problem and achieve specific results, it has some drawbacks. First, it is susceptible to parameter settings and requires fine-tuning to obtain optimal results. Second, the assumptions on data distribution are strict, and the clustering results may fail if the data do not meet the beliefs. In addition, the number of clusters is usually unknown and needs to be determined by experiments and adjustments, and these increase the workload when using it. More importantly, compared to heuristic algorithms, clustering algorithms are more likely to fall into local optima, which affects the final optimization results.

Considering the enhancements to the methods mentioned earlier, the new research adopts an applied mathematics approach to model WSNs. It optimizes the node duty cycle through artificial intelligence technology. About two research papers, Li et al. [32] present a fresh approach to parallel hybrid grey wolf optimization (PHGWO) that optimizes the duty cycle of high-density wireless sensor networks (HDWSNs) to extend network lifespan and enhances system efficiency. In contrast, Wang et al. [33] proposes a novel sensor duty cycle model (SDCM) for industrial wireless sensor networks (IWSNs) and devises a new optimization algorithm called quantum clone gray wolf optimization (QCGWO). However, the algorithms examined earlier tend to become trapped in local optima, exhibit inadequate performance when dealing with extensive WSNs, and need help to optimize the duty cycle of EWSNs completely.

To sum up, previous studies on extending the lifetime of EWSNs have limitations, such as difficulty in optimizing the duty cycles of large-scale networks and low efficiency or using heuristic algorithms that may converge prematurely and fail to increase network lifetime effectively. The QEGJOA presented in this paper is an efficient solution that can quickly generate high-quality deployment plans for large-scale EWSNs, effectively avoid local optima and significantly extend network lifetime compared to existing methods.

3. EWSNs duty cycle model

EWSNs are typically used for environmental monitoring in large areas such as forests, ocean. These networks consist of small sensor nodes with limited battery capacity and detection range. In order to ensure full coverage of the monitored targets, a dense deployment of sensor nodes is required, which leads to the generation of redundant nodes. To address this challenge, this paper presents a sensor duty cycle model that takes into account the presence of redundant nodes and is mathematically modeled. The symbols involved in this section and their comments are shown in Table 1.

Table 1. Note sheet.

Letter	Paraphrase	Letter	Paraphrase
S	Sensor node	I	Monitoring target
N	Number of sensors node	M	Number of monitoring target
C	Coverage relationship matrix	R	Work relationship matrix
L	Working life of each sensor	NL	Maximum lifetime rounds
RC	Deployment matrix		

3.1. 2D duty cycle model

In practice, the distribution of sensor nodes and monitoring targets can be abstracted as a distribution problem on a two-dimensional plane. An example is given in this paper to facilitate the understanding of the model. In Figure 1, it is assumed that four sensor nodes and three monitoring targets are randomly distributed in a plane area. Dots represent the sensor nodes, respectively $S1$, $S2$, $S3$ and $S4$; the monitoring targets are represented by triangles, respectively $I1$, $I2$ and $I3$. The sensor node is positioned at the center of a circle, and the range in which it can detect objects is determined by the radius of the circle.

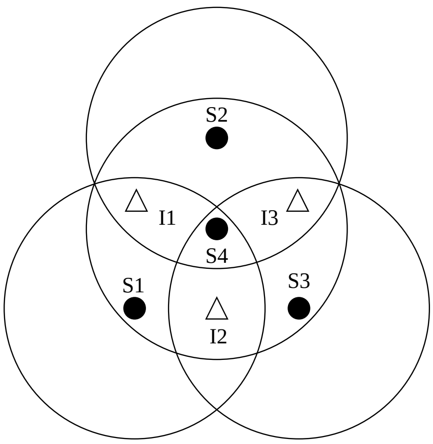
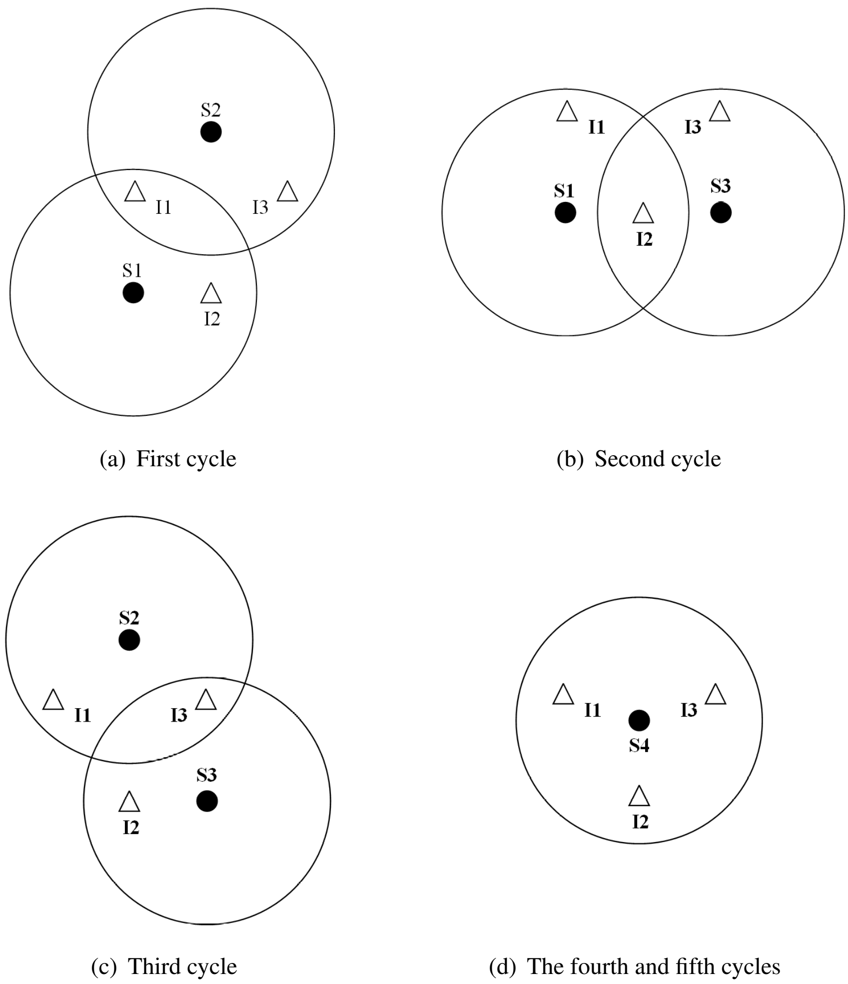


Figure 1. 2D duty cycle model.

According to Figure 1, sensor $S1$ covers detection targets $I1$ and $I2$, $N2$ covers $I1$ and $I3$, $S3$ covers $I2$ and I3, and $S4$ covers $I1$, $I2$ and $I3$.

Assuming that each sensor node has a life cycle of 2 rounds, the EWSNs' coverage time would be 2 rounds if no duty cycle operations are implemented and all sensor nodes are active. This implies that during the first round, $S1$, $S2$, $S3$ and $S4$ are active, and they remain active during the second round as well. To attain complete coverage, the sensors can be classified into different coverage sets.In that case, the number of sensors in each round of EWSNs can be reduced, thereby reducing loss. For example, the sensor is divided into $S1$, $S2$, $S2$, $S3$, $S3$, $S1$ and $S4$ four coverage sets. During the initial stage of the work cycle, the set of sensors $S1$, $S2$ is actively monitoring while the remaining nodes are in a dormant state, completing a round of monitoring tasks for EWSNs.Then in the second and third rounds, respectively, make the coverage sets $S2$, $S3$ and $S3$, $S1$ in the working state, and in the fourth and fifth rounds, make the coverage set $S4$ in the working state, then the entire work cycle of EWSNs Increased to 5 rounds. Figure 2 shows the coverage relationship of each round of the work cycle in EWSNs.



(a) First cycle

(b) Second cycle

(c) Third cycle

(d) The fourth and fifth cycles

Figure 2. Coverage relationship for each round.

From the above, the duty cycle operation can greatly improve the coverage time of EWSNs and prolong the sensor's service life. Therefore, this paper constructs a EWSNs duty cycle model suitable for optimizing artificial intelligence algorithms.

3.2. mathematical model

Suppose there is a duty cycle model in EWSNs with N sensor nodes and M monitoring targets. Equation (1) presents a matrix C, which represents the coverage relationship between sensor nodes and detection targets.

$$C = \begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,M-1} & c_{1,M} \\ c_{2,1} & c_{2,2} & \cdots & c_{2,M-1} & c_{2,M} \\ \vdots & & c_{n,m} & & \vdots \\ c_{N-1,1} & c_{N-1,2} & \cdots & c_{N-1,M-1} & c_{N-1,M} \\ c_{N,1} & c_{N,2} & \cdots & c_{N,M-1} & c_{N,M} \end{bmatrix} (c_{n,m} \in \{0,1\}) \tag{1}$$

Each row in matrix C represents the coverage relationship of a single sensor to all monitoring targets, and each column represents the monitoring of a target by all sensors. If $c_{n,m} = 1$ indicates that the target is within the detection range of the corresponding sensor, $c_{n,m} = 0$ is the opposite. In addition, this paper also constructs another duty cycle sequence matrix to manage the working status of each sensor in each round of monitoring tasks of EWSNs. First, the theoretical lifetime of a single sensor is L rounds, and WSNs contain N sensors. Then the theoretical maximum lifetime of EWSNs is NL rounds, and its duty ratio sequence matrix is expressed as shown in Eq (2).

$$R = \begin{bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,L-1} & r_{1,L} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,M-1} & r_{2,L} \\ \vdots & & r_{i,l} & & \vdots \\ r_{NL-1,1} & r_{NL-1,2} & \cdots & r_{NL-1,L-1} & r_{NL-1,L} \\ r_{NL,1} & r_{NL,2} & \cdots & r_{NL,L-1} & r_{NL,L} \end{bmatrix} (r_{i,l} \in \{0,1\}) \tag{2}$$

In matrix R, if $r_{i,l} = 1$ indicates that sensor l is working in the round i, otherwise it is in a dormant state.

$$RC = \begin{bmatrix} \sum_{n=1}^{N} r_{1,n}c_{n,1} & \sum_{n=1}^{N} r_{1,n}c_{n,2} & \cdots & \sum_{n=1}^{N} r_{1,n}c_{n,M-1} & \sum_{n=1}^{N} r_{1,n}c_{n,M} \\ \sum_{n=1}^{N} r_{2,n}c_{n,1} & \sum_{n=1}^{N} r_{2,n}c_{n,2} & \cdots & \sum_{n=1}^{N} r_{2,n}c_{n,M-1} & \sum_{n=1}^{N} r_{2,n}c_{n,M-1} \\ \vdots & & \sum_{n=1}^{N} r_{i,n}c_{n,m} & & \vdots \\ \sum_{n=1}^{N} r_{NL-1,n}c_{n,1} & \sum_{n=1}^{N} r_{NL-1,n}c_{n,2} & \cdots & \sum_{n=1}^{N} r_{NL-1,n}c_{n,M-1} & \sum_{n=1}^{N} r_{NL-1,n}c_{n,M} \\ \sum_{n=1}^{N} r_{NL,n}c_{n,1} & \sum_{n=1}^{N} r_{NL,n}c_{n,2} & \cdots & \sum_{n=1}^{N} r_{NL,n}c_{n,M-1} & \sum_{n=1}^{N} r_{NL,n}c_{n,M} \end{bmatrix} \tag{3}$$

Multiply matrix C by matrix R to get deployment matrix RC, as shown in Eq (3). Matrix RC is a matrix with NL rows and M columns, representing the monitoring situation of all targets in each round. If there are elements greater than 1 in the matrix, there is redundancy in the scheme, and there is still room for optimization. If there is a 0 element, it means that the round represented by this row has not achieved full coverage, and the deployment plan for this round is invalid. Finally, the number of rows containing 0 elements is subtracted from the maximum number of working rounds NL to obtain the number of working rounds of WSNs corresponding to the deployment scheme. Therefore, the maximum number of work wheels in the EWSNs duty cycle model can be represented by Eq (4), and Eq (5) represents the limit of each sensor on the number of work wheels.

$$f(R) = zero(RC) - 1 \tag{4}$$

$$\sum_{n=1}^{NL} t_{i,n} \leq L, n = 1 \cdots N, \tag{5}$$

Given the above, it can be inferred that the complexity of the model grows exponentially as the number of sensors and working rounds increase.

4. QEGJOA-based duty cycle for boosting the lifespan in EWSNs

The paper focuses on the challenge of extending the lifespan of EWSNs in the duty cycle problem, which is known to be an NP-Hard problem. As the number of sensor nodes increases, the problem search complexity grows exponentially, making it difficult to find a deployment plan that meets the requirements within a reasonable time using non-heuristic algorithms. The paper proposes a novel heuristic optimization algorithm that combines the golden jackal optimization algorithm (GJO) with a new quantum evolutionary strategy to address this. GJO is an intelligent optimization algorithm with few parameters, fast execution and high efficiency, but its global search capability and applicability are limited. The proposed algorithm, the quantum evolutionary golden jackal optimization algorithm (QEGJOA), overcomes these limitations and provides better results.

The process for QEGJOA consists of several steps, which include problem description, initialization of prey populations, calculation of fitness and screening, updating of male and female golden jackal positions, calculation of evading energy, hunting, exploration, quantum evolution updating of populations and termination conditions. The symbols involved in this section and their comments are shown in Table 2.

Table 2. Note sheet.

Letter	Paraphrase	Letter	Paraphrase
C	Coverage relationship matrix	R	Work relationship matrix
L	Working life of each sensor	N	Number of sensors
NL	Maximum lifetime rounds	E	Evading energy
E_1	Prey energy descent process	E_0	Prey energy initial state
r	Random number in [0,1]	T	Maximum iterations
c	Current number of iterations	t	Constant

4.1. *Problem coding*

The key to solving the duty cycle problem is to plan a reasonable sensor working time, reduce redundant nodes and reduce the energy consumption of the network. It is first assumed that all sensors have the same operating lifetime. A binary code is used to indicate the sensor status, where 0 means the sensor is in a sleep state, and 1 means the sensor is in a working state. The sensor duty cycle problem involves two essential matrices: the coverage relationship matrix C and the work relationship matrix R. The coverage relationship matrix C represents the coverage of each sensor towards all monitoring targets, while the work relationship matrix R denotes the working status of each sensor in each round of work. To optimize the work relationship matrix R, this article proposes using the QEGJOA algorithm until a final solution is achieved. For instance, suppose there are three sensors in the sensor duty cycle model, and the lifespan of each sensor is two rounds. In that case, the encoding of matrix R can be expressed as Eq (6).

$$R = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{6}$$

In Eq (6), the sum of each column is 2, representing a single sensor with a working lifetime of 2 rounds. The three columns indicate that sensor one works in the second and fifth rounds, sensor two works in the first and third rounds and sensor three works in the fourth and sixth rounds, respectively.

4.2. Population prey initialization

In the process of duty cycle optimization of EWSNs by QEGJOA, the distance of each sensor relative to the monitored target is first calculated, and if that distance is less than the detection distance of the sensor, the target is covered by that sensor, which produces the coverage matrix C. The initialized population is encoded in three dimensions, and each two-dimensional matrix represents the location of one prey. Assuming that each sensor has an operating lifetime of L and a number N, the maximum number of possible lifetime rounds in the entire network is the number of sensor lifetime rounds multiplied by the number of sensors NL. the population contains A individuals, so the initialized population can be expressed as Eq (7).

$$chrom(NL, N, A) = 1 \tag{7}$$

4.3. Calculation fitness and screening

In the process of duty cycle optimization of EWSNs by QEGJOA, the network lifetime of the scheme represented by an individual is the fitness of that individual, and the final solved optimal individual is the optimal deployment scheme solution.

The working relationship matrix must be multiplied by the coverage relationship matrix to determine an individual's fitness. This will identify all rows containing 0 elements. These rows will then be removed at the maximum lifetime number using Eq (8). The resulting value is the individual's fitness.

$$Fitness = fitness - 1 \tag{8}$$

Following the completion of the fitness calculation for all individuals, two individuals with the highest performance were chosen. The position of the male golden jackal was determined based on the individual with the best performance, while the position of the female golden jackal was determined based on the individual with the second best performance.

4.4. Calculation of evading energy

After completing the adaptive selection operation, the algorithm enters the iterative process and in each round of iteration, the evading energy in the current iteration is first calculated, and according to its magnitude, it determines whether it is exploration or hunting. Its calculation formula is shown in Eq (9).

$$E = E_1 \times E_0 \tag{9}$$

E_1 represents the descent process of the prey energy, calculated as shown in Eq (10); E_0 represents the initial state of the prey energy, calculated as shown in Eq (11). The value of r is a randomly generated number that falls within the range of [0,1].

$$E_0 = 2 \times r - 1 \tag{10}$$

T is the maximum iterations; c is a constant with a value of 1.5; t is the current iterations. Throughout the iteration, E decreases linearly from 1.5 to 0.

$$E_1 = c_1 \times (1 - t/T) \tag{11}$$

4.5. Exploring

If the current evading energy exceeds 1, the jackal enters the exploration phase. Due to the unique nature of the duty cycle problem, the traditional exploration scheme is not suitable for this problem. This paper proposes a new quantum mutation scheme to replace the traditional exploration scheme. First, the algorithm randomly generates an individual mutation scheme based on the actual problem, which represents the mutation position and direction of the prey individual and has a certain probability of variation. To enhance the algorithm's global search capability and increase randomness, a quantum revolving gate is utilized to update the individual mutation scheme, thereby achieving the quantum mutation of a target individual.

In this paper, taking the example of 8 sensors with 2 rounds of working life for each sensor, a variant scheme individual is shown in Eq (12). In this example, the maximum number of working rounds is 16 rounds, and the decimal number corresponding to each 4-digit binary code from front to back in Eq (12) represents that sensor needs to work in that round, and the last 3-3 digits indicate the sensor number to designate the sensor. This individual designates the third sensor in rounds 3 and 6.

$$V = \begin{bmatrix} 0 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \end{bmatrix} \tag{12}$$

4.6. Hunting

Hunting occurs when evading energy is less than 1. In this process, the algorithm uses a more conservative quantum crossover operator for hunting. The working principle of the quantum cross operator is similar to that of quantum mutation, and the individual prey is changed through the quantum cross scheme individual.

4.7. Quantum evolution updating of populations

After updating an individual according to the above scheme, since the male and female jackals are updated simultaneously at each update, two new prey positions will eventually be generated. The population will retain one prey position with better performance, thus completing the population update.

4.8. Termination condition

The above process is repeated in each iteration. The algorithm terminates until QEGJOA reaches the specified number of iterations and outputs the individuals and adaptations represented by the male golden jackets, i.e., the final deployment scheme and its maximum number of working rounds.

4.9. The algorithm's process

Below is a presentation of the detailed procedure for QEGJOA.

$Step$ 1. QEGJOA started by initializing its parameters, randomly placing sensors and targets within a 200×200 square area, and establishing coverage relationships between them. A population size of 50 was specified, and the number of iterations was set to 100. Finally, an initial prey population was generated.

$Step$ 2. After generating the initial prey population, the fitness of each individual in the population is calculated. The individual with the highest fitness score is designated as the male golden jackal, while the second-best individual is selected as the female golden jackal.

$Step$ 3. Calculate evading energy to determine whether to explore or hunt next.

$Step$ 4. Enter the iterative process and start updating the population.

$Step$ 5. Calculate evading energy to determine whether to explore or hunt next.

$Step$ 6. Explore or hunt to generate quantum evolution solutions to update individuals.

$Step$ 7. The quantum revolving gate updates the quantum evolution scheme to update all individuals, replacing the corresponding individual in the original population with the best of the two new individuals produced in each update.

$Step$ 8. The iteration number is updated. If the iteration number is not reached, return Step 4.

$Step$ 9. Once the algorithm reaches a certain number of iterations, it outputs the corresponding individuals and adaptations of male golden jackets. This output represents the final deployment scheme and the number of working rounds. Following this output, the algorithm terminates.

The algorithm flow chart of QEGJOA is shown in Figure 3.

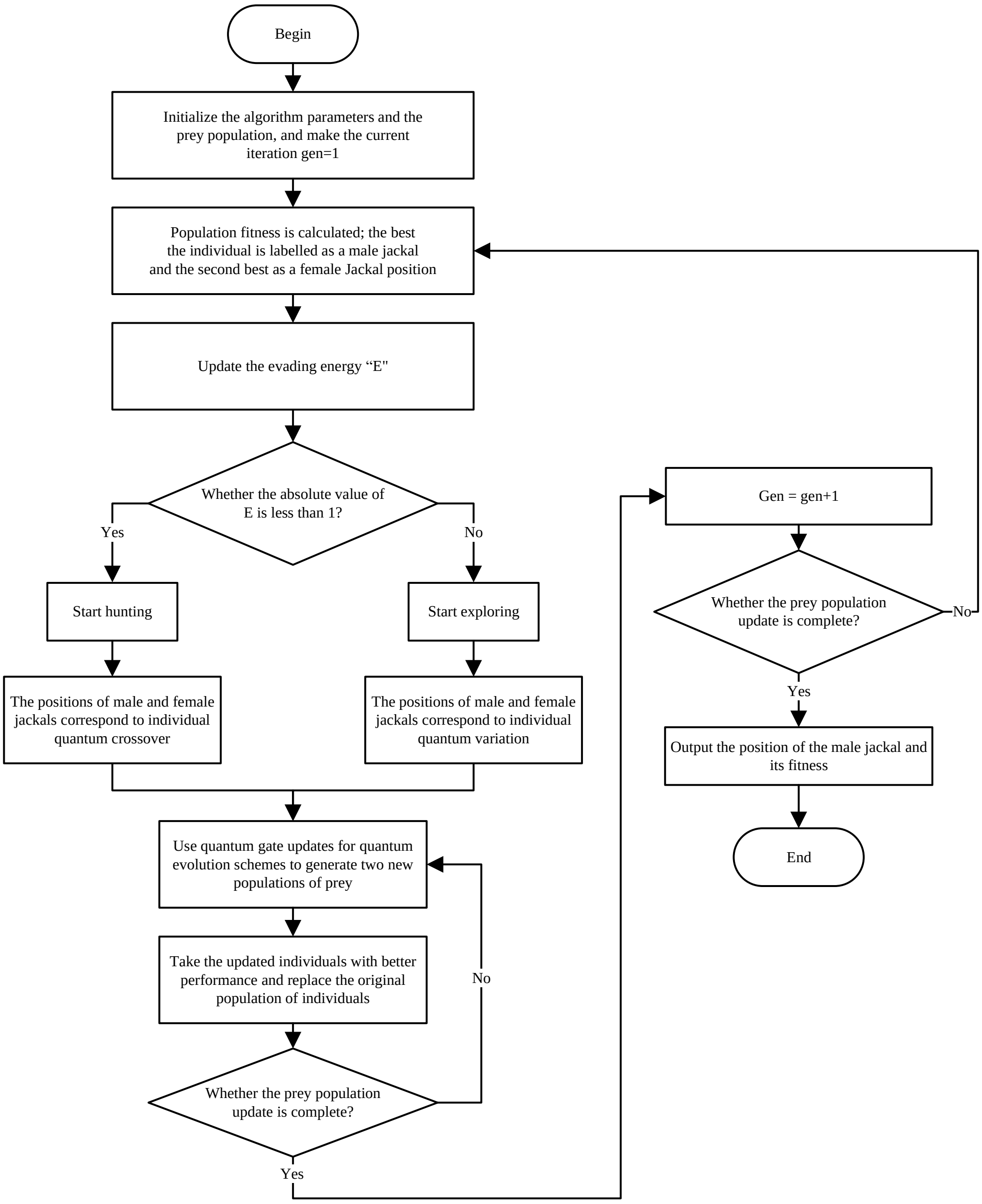


Figure 3. 2D duty cycle model.

4.10. Algorithm complexity analysis

This paper introduces an algorithm and analyzes its time and space complexity. The time complexity is determined by factors like the population size, problem dimensionality, number of quantum bits, binary encoding length and iterations. Meanwhile, the space complexity is determined by variables that need to be stored. The algorithm's time complexity is expressed as

$O(Max_iter * (D + sensor_num^2 + sizepopD/(2Len) + Lenx/(2ITER)))$, while the space complexity is expressed as $O(Max_itersensor_num + 3sensor_num + Max_iter + Max_iter)$. The analysis shows that the algorithm's time complexity increases with the problem size, while the space complexity remains low. Additionally, the algorithm requires few computational resources and can run on an average computer. The algorithm's running times are shown in Table 3, and they indicate that the algorithm can run in real-time or near real-time.

Table 3. Note sheet.

Parameter Source	Running time (s)	Parameter Source	Running time (s)
Figure 4(a) condition	6.41	Figure 4(b) condition	9.99
Figure 4(c) condition	12.68	Figure 4(d) condition	19.07

5. Results and discussion

The proposed QEGJOA and EWSNs duty cycle models were subjected to experiments and compared with GJO, WOA and SA to verify their effectiveness. The algorithms are compared under different conditions, such as different numbers of sensors and monitoring targets and sensor monitoring radii. Tables 4–7 show the system parameters for each simulation in Figures 4–7, including the number of nodes, detection targets, individual sensor operating rounds and monitoring range. This study assumed that the locations of sensors and monitoring targets were randomly generated within a square area with a side length of 200. All results presented were averaged over 100 experiments. The simulations were conducted on a computer running MATLAB R2022a and equipped with an Intel(R) Core(TM) i7-7700HQ CPU @ 2.80 GHz, 8 GB RAM and NVIDIA GEFORCE GTX1050 graphics card.

The simulation experiments were conducted to establish the algorithm parameters for solving the duty cycle optimization problem in EWSN. The initial population size for all three algorithms was 50, and the number of iterations was 100. In QEGJOA, the probability of quantum variation was set to 0.1, and the likelihood of quantum crossover was set to 0.1. As the duty cycle problem in GJO and WOA has unique features, the simulation experiments utilized the variation operator to update the whale's and golden jackal's position, and the probability of variation was set to 0.1. In the simulated annealing algorithm (SA), the initial temperature is set to 1000, the cooling factor is 0.89, the termination temperature is 1e-8 and the number of iterations at each temperature is 100. This setting ensures that the algorithm performs 100 iterations per run to compare with other algorithms under the same conditions. Adaptation Eq (4) was utilized to calculate the results.

Table 4. The conditions tested in Figure 4 experiment.

	Sensors	Targets	Maximum lifespan	Radius of observation (m)
Figure (a) condition	40	15	10	200
Figure (b) condition	60	20	10	200
Figure (c) condition	80	30	10	200
Figure (d) condition	100	40	10	200

Table 5. The conditions tested in Figure 5 experiment.

	Sensors	Targets	Maximum lifespan	Radius of observation (m)
Figure (a) condition	30	10	10	220
Figure (b) condition	40	18	10	220
Figure (c) condition	50	23	10	220
Figure (d) condition	65	30	10	220

Table 6. The conditions tested in Figure 6 experiment.

	Targets number	Maximum lifespan	Radius of observation (m)
Figure (a) condition	30	10	200
Figure (b) condition	35	10	200
Figure (c) condition	30	8	200
Figure (d) condition	30	10	300

Table 7. The conditions tested in Figure 7 experiment.

	Sensors	Targets	Maximum lifespan	Radius of observation (m)
Figure (a) condition	40	15	12	180
Figure (b) condition	60	20	12	180
Figure (c) condition	80	30	12	180
Figure (d) condition	100	40	12	180

Figure 4 illustrates the convergence speed of the three algorithms. In particular, QEGJOA achieved a maximum network lifetime of 83.2 rounds in Figure 4(a). However, GJO, WOA and SA obtained optimal 65.0, 68.0 and 64.2 games, respectively. The solutions provided by QEGJOA were 27.91%, 22.35% and 29.60% higher than those offered by GJO, WOA and SA, respectively. In Figure 4(b), QEGJOA converged significantly faster than GJO, WOA and SA, maintaining a fast convergence rate throughout the iterations. In contrast, GJO combined prematurely in the 30th generation, WOA converged prematurely in the 50th generation and SA merged prematurely in the 70th generation and failed to obtain a more efficient solution. In Figure 4(c), QEGJOA maintained a fast convergence rate until the optimal solution of 97.2 was obtained in 90 generations. The optimal solutions obtained by GJO, WOA and SA were only 83.2, 82.0 and 72.6, respectively, indicating that their optimization effects were inferior to that of QEGJOA. In Figure 4(d), WOA and SA encountered local optimal search stagnation in the 50th generation, while GJO encountered local optimal search stagnation in the 30th generation. In contrast, QEGJOA, with its excellent global search capabilities, maintained a good convergence speed until an optimal solution was obtained. This result shows that QEGJOA is able to consistently maintain its optimization effectiveness over other algorithms in solving the sensor duty cycle problem as the problem size increases. Table 8 presents the solution quality pairs of the three algorithms in the figure.

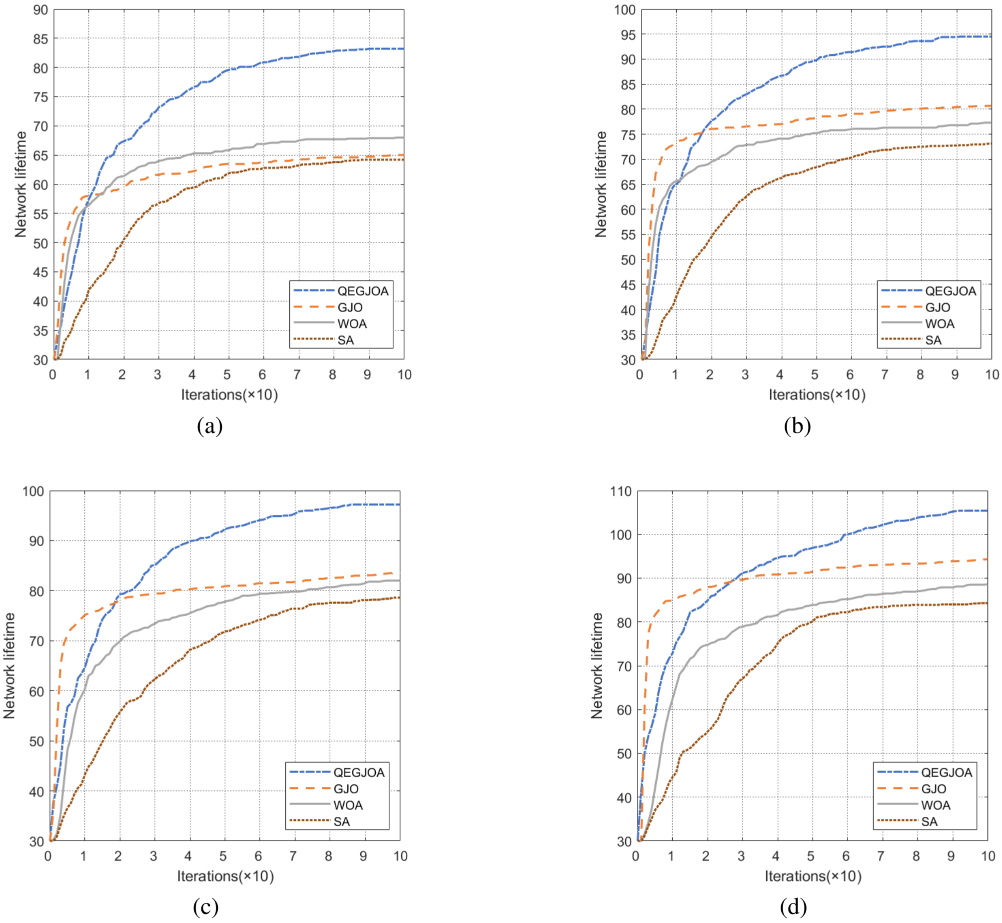


Figure 4. The network's lifespan was assessed using three algorithms, each with different numbers of sensors and targets: (a) 15 targets and 40 sensors; (b) 10 targets and 50 sensors; (c) 25 targets and 60 sensors; (d) 30 targets and 80 sensors.

Table 8. Comparison of solution excellence.

	QEGJOA compared to GJO boosting effect	QEGJOA compared to WOA boosting effect	QEGJOA compared to SA boosting effect
Figure 5(a)	26.31%	20.73%	29.60%
Figure 5(b)	17.02%	22.35%	29.19%
Figure 5(c)	16.80%	18.54%	22.36%
Figure 5(d)	14.60%	18.96%	25.03%

Table 8 shows that QEGJOA's solutions, regardless of the size of EWSNs, have been a huge improvement over GJO, WOA and SA.

Figure 5(a)–(d) illustrates more prominently the distinctions among various algorithms in a line graph format. In Figure 5(a),(c), QEGJOA provides a solution that outperforms the other three algorithms from beginning to end until the 90th generation to obtain an optimal solution. At the same time, GJO, WOA and SA perform inferior to QEGJOA to perform more efficient searches for optimal solutions. Figure 5(b),(d) show that both QEGJOA, GJO and WOA converged very quickly in early iterations. However, WOA and GJO fell into local optimality and could only get local optimal solutions. The above results can demonstrate that QEGJOA has excellent global search capability by using quantum evolutionary operators, and can effectively avoid falling into local optimal solutions when solving the sensor duty cycle problem. Compared with other algorithms, QEGJOA can obtain a more efficient sensor node deployment scheme.

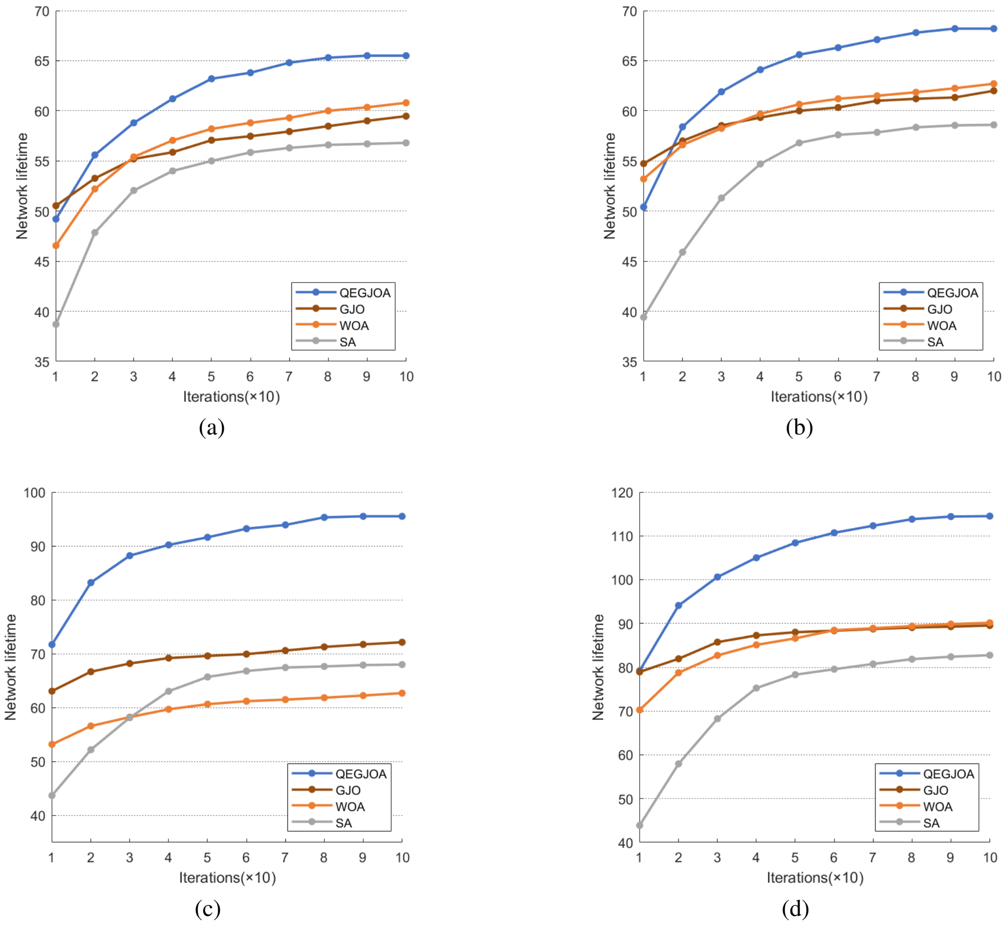


Figure 5. The network's lifespan was assessed using four algorithms, each with different numbers of sensors and targets: (a) 10 targets and 30 sensors; (b) 18 targets and 40 sensors; (c) 23 targets and 50 sensors; (d) 30 targets and 60 sensors.

The line graphs in Figure 6(a)–(d) compare the performance of four algorithms with varying numbers of sensors. Specifically, the QEGJOA optimization's network lifetime is compared to that of GJO, WOA and SA. The results demonstrate that for small sensor counts, QEGJOA has a comparable or superior network lifetime to WOA and GJO. However, as the number of sensors increases, QEGJOA's optimization is significantly more effective than the other algorithms. In Figure 6(b), the network lifetime of QEGJOA improves notably with an increased number of sensors. In Figure 6(c), as the working rounds of individual sensors decrease and the monitoring range expands, WOA's optimization becomes unstable and unable to improve network lifetime. Similarly, GJO may become trapped in a local optimum, unable to find a more efficient solution. In comparison, SA performs moderately but still significantly lower than QEGJOA. In Figure 6(d), while maintaining the results from Figure 6(a), QEGJOA consistently performs better than the other algorithms as the number of working rounds of individual sensors increases. The above data demonstrates that QEGJOA can maintain excellent performance in solving high complexity sensor duty cycle problems, with better performance and robustness compared to other algorithms

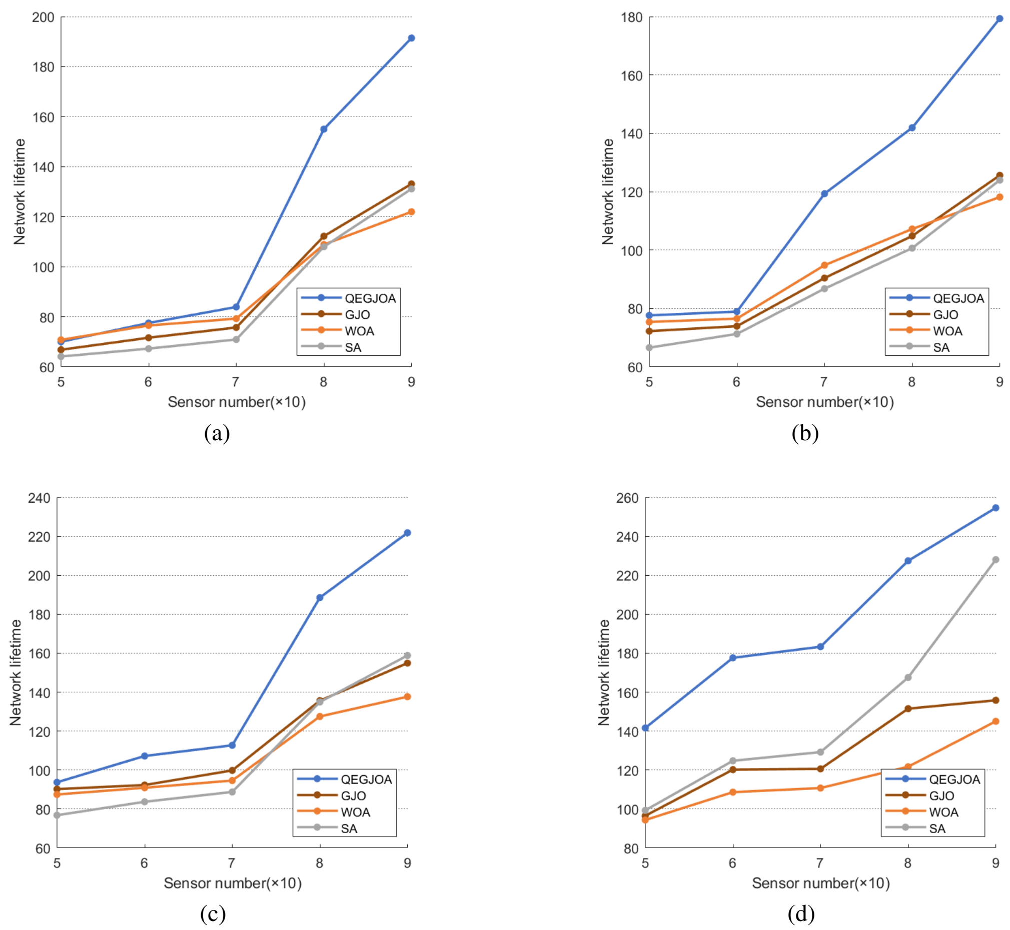
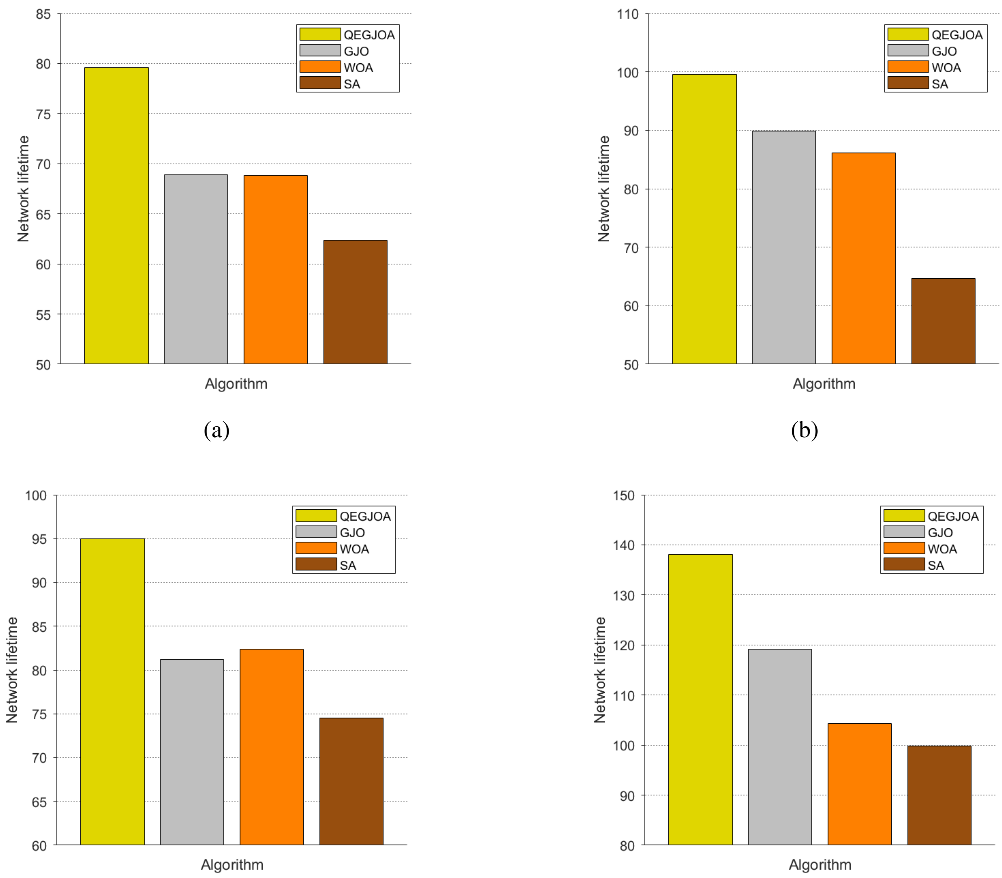


Figure 6. Comparison chart of the four algorithms with different number of sensors.

Figure 7(a)–(d) provides a more visual comparison of the network lifetimes optimized by the three algorithms through bar charts. In Figure 7(a), QEGJOA, GJO, WOA and SA obtain maximum network lifetime values of 79.60, 68.92, 68.80 and 62.35, respectively. In Figure 7(a)–(d), QEGJOA obtains the highest network lifetimes of 99.60, 95.00 and 138.10, respectively. In contrast, WOA obtains only 86.10, 82.35 and 104.30, GJO obtains only 89.80, 81.20 and 104.30, respectively, and SA obtains only 64.70, 74.55 and 119.20. Describe in detail QEGJOA effectively avoids evolutionary stagnation by introducing the new quantum exploration operator and quantum exploitation operator, which dramatically improves the algorithm's performance and can better handle the duty cycle optimization problem. Overall, QEGJOA is always better than GJO, WOA and SA in dealing with the issue of duty cycle optimization.



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

Figure 7. The network's lifespan was assessed using four algorithms, each with different numbers of sensors and targets: (a) 10 targets and 30 sensors; (b) 18 targets and 40 sensors; (c) 23 targets and 50 sensors; (d) 30 targets and 65 sensors.

6. Conclusions

The network life cycle is crucial for the continuous operation of wireless sensor networks. To improve the duty cycle and extend the network lifetime, a novel quantum evolutionary gold jackal optimization algorithm (QEGJOA) is designed in this paper. The innovation of the QEGJOA algorithm lies in adopting a series of optimization operators to improve the algorithm's performance. In particular, the quantum exploration and exploitation operators are designed, which significantly boost the global search capability of the algorithm and enables it to solve the duty cycle optimization problem effectively. Then, this paper compares the algorithm with GJO, WOA and SA to demonstrate the algorithm's effectiveness in improving the network's duty cycle and extending the network lifetime. The simulation results show that the QEGJOA proposed in this paper significantly improves the duty cycle of EWSNs and effectively extends the network lifetime, which provides a research basis for further development of sensor networks.

Although QEGJOA proves its superior performance through simulations, it still needs further improvement due to the limitations of research capability and environmental conditions. In this paper, the sensor node distribution of QEGJOA is static and randomly distributed in a two-dimensional monitoring area, however, in some application scenarios, the dynamic changes in the sensor node distribution need to be considered. In the future, the authors plan to investigate the effects of sensor node distribution, mobile monitoring data and environmental variables (e.g., temperature, humidity, etc.) on the network life cycle. In addition, the authors plan to extend the study to the location of sensor nodes in 3D space to improve the utility and adaptability of the algorithm.

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Conflict of interest

The authors declare no competing interests.

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