Optimization of Low Power Wireless Sensor Network Lifetime Using Improved Clone Elite Monkey Algorithm

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Abstract. Recent advances in efficient software algorithms, electronics and networking technologies have promoted the development of low computational complexity, low-cost, low storage, and intelligent tiny nodes. Low power wireless sensor networks (LPWSNs) are composed of some sensing units with limited communications as well as sensing capabilities. LPWSNs are approaches in a good deal of domains such as traffic control, automated assistance for the elderly monitors and so on. Recently network lifetime optimization has been receiving a lot of attention for wide applications of LPWSNs. Achieving a longer network lifetime under the restricted power source has a large calculation difficulty, which can be regard as an NP-hard problem. An improved clone elite monkey algorithm (ICEMA) to determine the network lifetime optimization in LPWSNs is given. In this paper, in order to achieve maximum network lifetime with full coverage, we first build a system model to calculate a better network lifetime. It is designed to increment the lifetime of the nodes for LPWSNs. The ICEMA has many advantages by combining the clone strategy as well as elite strategy. The simulations verify the robust and efficiency of ICEMA when compared with strategies based on evolutionary algorithm (EA), particle swarm algorithm (PSO) and artificial fish swarm algorithm (AFSA) under a LPWSNs conditions. The outcomes demonstrate that the proposed ICEMA can achieve a longer network lifetime than EA, PSO and AFSA while taking the same computational complexity.

Keywords. Wireless sensor networks, Monkey algorithm, Duty cycle design, Network lifetime

1. Introduction
The rapid development of efficient software algorithms, system-on-chip design and wireless communications has made it possible to deploy small-size, numerous, low storage, and networked wireless sensors [1]-[4]. Low power wireless sensor networks (LPWSNs) have a large number of tiny sensors with communications, sensing, processing, free-infrastructure capabilities [5]. LPWSNs support important practical applications in tracking, medical diagnostic, home automation, environment surveillance, deploying network in battlefield, commercial management, etc [6][7].

The network lifetime optimization problem attracts attention of researchers who are in industry, and military department. Sensor nodes mainly use tiny sensing units and they are limited in sensing capability [8]. They affect the effective optimization means for achieving maximum network lifetime as well as the lifetime optimization greatly.
Many heuristics techniques have been developed to improve the efficiency of the network lifetime optimization scheme through duty cycle design. In [9], a network lifetime optimization strategy that enables the performance between the computation complexity and a better lifetime is researched utilizing evolutionary algorithm (EA). In their work they increment of the number and the lifetime of the nodes without considering restricted power source constraint. However, EA suffer from low performance. A simple network lifetime optimization scheme using particle swarm algorithm (PSO) while simultaneously evaluating effective optimization means for achieving maximum network lifetime has also been attempted in [10]. Nevertheless, the computational cost is too large. In [11], an artificial fish swarm algorithm (AFSA) scheme is designed for achieving a longer network lifetime in LPWSNs. The proposed method uses a hybrid heuristic technique. However, it suffers from stagnation after only a few generations.

An improved clone elite monkey algorithm (ICEMA) is given to determine the network lifetime optimization in LPWSNs in our works. We first formulate a network optimization model as objective function. After that, in order to improve the system performance of ICEMA based network lifetime optimization issue, we put clone as well as elite strategies into the ICEMA to enhance the quality of solutions and avoid local optima.

The simulations are executed to validate the efficiency gain in terms of a better lifetime when compared with the techniques depending on EA, PSO and AFSA. Experiments indicate that the profitable optimization means for achieving maximum network lifetime of the proposed ICEMA method has a better performance than that of EA, PSO and AFSA respectively with different quantity of sensor nodes and targets.

2. System Model
In this section, the system model of the network lifetime optimization problem is built with respect to the constraints of restricted power source and the duty cycle design.

Supposed that $I$ sensor nodes and $J$ targets are deployed in the monitored region. The sensing relationship matrix is described as following formula.

\[
E = \begin{bmatrix}
e_{1,1} & e_{1,2} & \cdots & e_{1,J-1} & e_{1,J} \\
e_{2,1} & e_{2,2} & \cdots & e_{2,J-1} & e_{2,J} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
e_{i-1,1} & e_{i-1,2} & \cdots & e_{i-1,J-1} & e_{i-1,J} \\
e_{i,1} & e_{i,2} & \cdots & e_{i,J-1} & e_{i,J}
\end{bmatrix}
\]

(1)

In (1), $e_{i,j}$ represents the monitoring relationship among the $i_{th}$ sensor and the $j_{th}$ target, $e_{i,j} \in \{0, 1\}$, and $e_{i,j} = 1$ indicates that the $i_{th}$ target located at the coverage range of the $j_{th}$ node. $e_{i,j} = 0$ is the opposite.

Due to energy limitation, the maximum working lifetime of each sensor in the $I$ sensor nodes is $R$ rounds, $r \in \{1, 2, \cdots, R\}$, then the maximum working lifetime of the network is $IR$ rounds, that is, the round matrix $S$ of the sensors can be written in (2):

\[
S = \begin{bmatrix}
s_{1,1} & s_{1,2} & \cdots & s_{1,J-1} & s_{1,J} \\
s_{2,1} & s_{2,2} & \cdots & s_{2,J-1} & s_{2,J} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
s_{IR-1,1} & s_{IR-1,2} & \cdots & s_{IR-1,J-1} & s_{IR-1,J} \\
s_{IR,1} & s_{IR,2} & \cdots & s_{IR,J-1} & s_{IR,J}
\end{bmatrix}
\]

(2)
Where \( s_{i,j} = 1 \) denotes that the \( i_{th} \) node is in an active state in the \( r_{th} \) round, \( s_{i,j} \in \{0,1\} \), \( s_{i,j} = 0 \) indicates that the \( i_{th} \) sensor node is in the dormant state in the \( r_{th} \) round.

If we multiply the two matrixes, we can get the monitoring relationship among the \( i_{th} \) sensor as well as the \( j_{th} \) target in each round.

\[
ES = \begin{bmatrix}
\sum_{i=1}^{I} e_{i,j} s_{i,1} & \cdots & \sum_{i=1}^{I} e_{i,j} s_{i,J} \\
\cdots & \cdots & \cdots \\
\sum_{i=1}^{I} e_{i,j} s_{IR,i} & \cdots & \sum_{i=1}^{I} e_{i,j} s_{IR,J}
\end{bmatrix}
\]

In (3), \( \sum_{i=1}^{I} e_{i,j} s_{i,r} > 0 \) means that the \( j_{th} \) target in the \( r_{th} \) round is monitored by at least one sensor, and \( \sum_{i=1}^{I} e_{i,j} s_{i,r} = 0 \) means that the \( j_{th} \) target in the \( r_{th} \) round is not monitored by any one of the sensors.

In (4), the fitness function \( f \) represents the number of rows in which the first zero element in \( ES \). The mathematical model of the lifetime optimization of the wireless sensor network can be expressed as follows:

\[
f = \text{row\_zero}(ES) - 1
\]

Subject to:

\[
\sum_{r=1}^{R} s_{ir,r} \leq R, i = 1, 2, \ldots, I
\]

(5) indicates that each sensor has a maximum working life, which is less than \( R \) rounds.

3. Optimization of network lifetime using improved clone elite monkey algorithm

The proposed ICEMA combines the merits of both clone operator and elite operator based on the traditional monkey algorithm. The proposed ICEMA mainly includes initialization, fitness calculation, the climbing process, the lookout process and the flipping process.

3.1. Population Encoding and Initialization

The initialization of the population has an influence on the global convergence and effect of the algorithm. Therefore, the ICEMA uses random initialization in the solution space. Discrete ICEMA is applied to solve network lifetime problem.

First define \( H \) as the size of the population \( P \) in ICEMA. A round matrix \( S \) is an individual, which consists of 0 and 1. The population \( P \) is made up of round matrixes. An individual \( P_h \) can be demonstrated by the following example in (6):

\[
S_1 = \begin{bmatrix}
0 & 1 & 1 \\
0 & 0 & 1 \\
1 & 0 & 0
\end{bmatrix} = [0, 1, 1, 0, 0, 1, 0, 0] = P_1
\]

Where a matrix \( S_h \) \((3 \times 3)\) should be converted into a matrix \( P_h \) \((1 \times 9)\) to represent the \( h_{th} \) individual. In other words, a matrix \( S_h \) \((IR \times I)\) should be converted into a matrix \( P_h \) \((1 \times I^2R)\) to
represent the $h_{th}$ individual. Moreover, a population which has $H$ individuals consists of a $I^2 R$-dimensional matrix $(H \times I^2 R)$.

In (7), randomly generate $H$ individuals to create an initial population, indicating the number of monkeys. The population consists of randomly generated binary codes.

$$P = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,i^2 R-1} & p_{1,i^2 R} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,i^2 R-1} & p_{2,i^2 R} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ p_{H-1,1} & p_{H-1,2} & \cdots & p_{H-1,i^2 R-1} & p_{H-1,i^2 R} \\ p_{H,1} & p_{H,2} & \cdots & p_{H,i^2 R-1} & p_{H,i^2 R} \end{bmatrix}$$ (7)

Where $P = (P_1, P_2, \ldots, P_H), h = \{1, 2, \ldots, H\}$. $P_n = (p_{h,1}, p_{h,2}, \ldots, p_{h,i^2 R})$. The position can be represented as a solution to the network lifetime optimization problem.

3.2. Fitness Calculation

The objective function can be calculated in (8) to optimize the network lifetime. The monkeys will be selected to the next iteration if the network lifetime is longer.

$$f(P_h) = \text{row } \_ \text{zero}(ES) - 1$$ (8)

3.3. Climbing process

The climbing operator is a process in which each monkey searches for the best network lifetime of the optimization problem by iterations in the current range. Due to the binary encoding method, the climbing step is generally set to 1. For the monkey $h$, the climbing process is designed as following:

Step1: Randomly generate vectors $\Delta P_h^\uparrow$ and $\Delta P_h^\downarrow$. $\Delta P_h^\uparrow = (\Delta p_{h,1}^\uparrow, \Delta p_{h,2}^\uparrow, \ldots, \Delta p_{h,i^2 R}^\uparrow)$, $\Delta P_h^\downarrow = (\Delta p_{h,1}^\downarrow, \Delta p_{h,2}^\downarrow, \ldots, \Delta p_{h,i^2 R}^\downarrow)$. The climbing step $w$ in climbing process is 1.

$$\Delta p_{h,i^2 R}^\uparrow, \Delta p_{h,i^2 R}^\downarrow = \begin{cases} w \text{ probability } = 0.5 \\ -w \text{ probability } = 0.5 \end{cases}$$ (9)

Step2: If the value of $(i^2 R)_{th}$ of vectors $\Delta P_h^\uparrow$ or $\Delta P_h^\downarrow$ is 1, the value of $(i^2 R)_{th}$ of $P_h$ is unchanged; otherwise, 0 is changed to 1 or 1 is changed to 0. In this way, two new individuals $P_h^\uparrow$ and $P_h^\downarrow$ are formed according to the current individual $P_h$.

Step3: If $f(P_h^\uparrow) > f(P_h^\downarrow)$ and $f(P_h^\downarrow) > f(P_h)$, set $P_h = P_h^\downarrow$. If $f(P_h^\uparrow) > f(P_h^\uparrow)$ and $f(P_h^\downarrow) > f(P_h)$, set $P_h = P_h^\uparrow$.

Step4: Repeat step1 to step3 until the number of climbs is satisfied for a given number of executions $N_c$.

3.4. Lookout process

At the end of the climbing process, each monkey looks around and sees if there is a higher point than the current one. If there is, then it jumps from the current point to the higher position. The process of lookout in ICEMA is described as following.

Step1: Randomly generate a value $t_{h,i^2 R}$ that in matrix $T_h = (t_{h,1}, t_{h,2}, \ldots, t_{h,i^2 R})$ is in the range of $(p_{h,i^2 R} - c, p_{h,i^2 R} + c)$. $c$ represents visual of monkey that is set to 1.
Step2: Because the value of $t_{h,i,r}$ is within the feasible solution area [-1,2], if $t_{h,i,r} < 0.5$, $t_{h,i,r} = 0$, otherwise, $t_{h,i,r} = 1$.

Step3: If $f(T_h) > f(P_h)$, set $P_h = T_h$; otherwise, repeat step1 until the value $T_h$ that satisfies the condition is generated.

Step4: Use $T_h$ as the initial position and repeat the climbing process.

3.5. Cooperation process
Assume the optimal position of the current monkeys is $P^* = (P^*_1, P^*_2, \ldots, P^*_H)$, the position of monkey $h$ is $P_h = (p_{h,1}, p_{h,2}, \ldots, p_{h,H})$. The steps of cooperation process are as follows.

Step1: Randomly generate a number $\alpha$ is within [0, 1].

Step2: If $\alpha < 0.5$, $t_{h,i,r} = p_{h,i,r}$; otherwise, $t_{h,i,r} = -p_{h,i,r}$.

Step3: If $f(T_h) > f(P_h)$, set $P_h = T_h$.

3.6. Flipping process
The main purpose of the flipping process is to ensure that the monkey can find a new search area without falling into a local search. We select the centre of gravity of all monkeys as a pivot point, and then all monkeys will flip in the direction of the pivot point.

Step1: Generate a number $\delta$ in the flipping interval $[e, f]$ of the monkey.

Step2: Randomly generate a number $k$, $k = 1, 2, \ldots, H$. The position of the monkey $k$ is taken as the pivot point.

Step3: Calculate

$$t_{h,i,r} = p_{k,i,r} + \delta(p_{k,i,r} - p_{h,i,r})$$

Step4: If $t_{h,i,r} < 0.5$, $t_{h,i,r} = 0$; otherwise, $t_{h,i,r} = 1$.

Step5: If $f(T_h) > f(P_h)$, set $P_h = T_h$; otherwise, $P_h$ is unchanged.

In order to prevent stagnate, this chapter sets a maximum number of iterations $N_f$ to control the algorithm to fall into local optimum.

3.7. Termination Condition
In the end of ICEMA, when the maximum number of iterations is reached, the algorithm ends and the results are output.

3.8. Clone Operator
The clone operator is inspired by the artificial immune system and has many excellent characteristics. It can improve the convergence speed of the algorithm while maintaining the diversity of the population. It can also overcome the problem of premature convergence. In this paper, the clone operator is applied in the ICEMA based on the advantages of clone strategy. The main steps of ICEMA based clone strategy is described as following:

Step1: Determine the antigen, which is the network lifetime of problem to be optimized, generating the initial antibody population $P$, and the initial antibody is the population of the network lifetime problem;

Step2: Calculate the affinity of the antibody, which represents the network lifetime. In ICEMA, the affinity is $f(P)$;

Step3: Select antibodies with the better network lifetime from the population $P$ to form a collection of temporary antibodies;
Step 4: Clone the individuals with better network lifetime and form a new antibody population for the next iteration calculation.
Step 5: When the maximum number of iterations is reached. The algorithm terminates execution and outputs the optimal solution.

3.9. Elite Operator
In the ICEMA, the elite strategy is also introduced, which balances the relationship between global search and local search. The behaviour of monkeys in the ICEMA with elite strategy increases the diversity of the population, effectively avoids the algorithm falling into local optimum.

Every time the monkey arrives at a new location in each generation, the network lifetime of the monkey needs to be accessed again. Compare the network lifetime of the monkey in the current generation and in the previous generation, select a set of monkey with longer network lifetime, and choose the longest network lifetime from these solutions as an elite solution.

3.10. Algorithm Steps
Based on the above description of the behaviours of the monkeys, the steps that can be attributed to the ICEMA are as follows:

Step 1: Initialize the population and parameters of the ICEMA
Step 2: Calculate the network lifetime, and record the optimal network lifetime of the monkey and the optimal \( P_h \) in the population;
Step 3: Execute the climbing process, calculate the network lifetime of all monkeys according to (8), and compare the network lifetime of current iteration with last iteration.
Step 4: Execute the lookout process, search for a better network lifetime within the range of view. If a better network lifetime is found, update the network lifetime of the monkey; otherwise, execute step 3.
Step 5: Execute the cooperation process to improve the network lifetime.
Step 6: Execute the flipping process to find a new search area. If the network lifetime is improved after the maximum iterations, update the population.
Step 7: When the maximum number of iterations is reached. The algorithm terminates execution and outputs the optimal solution.

4. Simulation and Results
In this experiment, the performance of the proposed ICEMA with the EA, PSO and AFSA for network lifetime optimization in LPWSNs is accessed. To demonstrate the effectiveness of the ICEMA and the proposed objective formulation, simulations are performed. To examine the applicability for practical implementations, we evaluate the performance of the schemes on a PC with Pentium 2.40 GHz, 2G RAM, WIN-7 OS, and MATLAB software.

The ICEMA is analysed with other means over the objective function in section II. Then we generate sensor nodes and targets, and the position \((x, y)\) of sensor nodes are randomly specified within the square area \(500 \times 500\). Each node has their range that is 300m. In the following experiments, we set sensor nodes to 55, 75 and 100, respectively. We also set targets to 10, 20, 30 and 40, respectively. The maximum round is 10. For comparison purpose, the results of EA, PSO and the AFSA are also given out. All comparisons between ICEMA, EA, PSO and AFSA are reported using the same number of iterations and population size.

The parameters of the ICEMA, EA, PSO and AFSA are presented as following. In ICEMA, the number of monkey groups is 50, and the number of iterations is 100. The visual \( c \) is 1 and the step \( w \) is 1. The flip interval \([e, f]\) is \([-1, 1]\). In EA, we investigate the population size 50 that ensures a specified quality of solution. For the crossover probability and mutation probability are employed as 0.85 and 0.05. In PSO, the maximum velocity is definitely 4. The values of cognitive and social are \(c_1=c_2=0.5\). In AFSA, \(v\) is 5. Step is 3. Try number is 5 and congestion factor is 0.62.
Figure 1 shows the average number of generations of ICEMA, EA, PSO and AFSA with 10 targets and 55 sensor nodes. In the beginning, all the heuristics have shown good results when compared with a random search approach. The figure shows that the proposed ICEMA has a better convergence in the first several iterations. Meanwhile, the results of EA, PSO and AFSA are almost consistent. After the iterations, the best result of ICEMA is close to 76. Figure 2 shows the performance of network lifetime with 20 targets and 55 sensor nodes. By comparing with figure 1, when the number of nodes is unchanged and the number of targets is increased, then the round of lifetime is reduced to 69.

Figure 3 and figure 4 show the similar effective optimization for achieving maximum network lifetime of ICEMA, EA, PSO and AFSA with the 30 and 40 targets, respectively, and 75, 100 sensor nodes, respectively. After 100 iterations, the best result of ICEMA is close to 59, and 64 round, respectively. The results shows that the EAPSO has a better performance while optimize the problem of network lifetime.

5. Conclusion
Hence, an improved clone elite monkey algorithm (ICEMA) is presented and applied to network lifetime optimization problem. In this work, we first propose a novel formulation of the objective function to satisfy the lifetime optimization. Numerical simulations are conducted with ICEMA, EA, PSO and AFSA and the results are compared to verify the ICEMA. Results display that the ICEMA provides maintaining full coverage compared with previous EA, PSO and AFSA. It is more powerful and simpler than available heuristics, and can avoid local optima while searching for a better result.
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