Minimization of Energy Consumption for Routing in High-Density Wireless Sensor Networks Based on Adaptive Clone Elite Genetic Algorithm

Jing Xiao¹, a, Chaoqun Li¹, b, Yao Zhang³, c, Jie Zhou¹, 2, *, Yang Liu¹, d and Rui Yang¹, e

¹College of Information Science and Technology, Shihezi University, Shihezi, 832000, China
²Xinjiang Tianfu Information Technology Co., Ltd.e
³University of the Cordilleras, Baguio City 2600, Philippines

Abstract. High-density wireless sensor networks (HDWSNs) perceive environmental information through sensor nodes, connects data to the network, and is widely used in environmental detection, intelligent control, and military fields. Since sensor nodes are usually randomly distributed in the environment and have limited energy, ensuring the energy supply of these nodes is still a difficult problem to solve at present. Therefore, how to effectively reduce network energy consumption, improve algorithm efficiency, and extend network life time is the main problem to be solved by QoS routing in HDWSNs. This paper proposes an adaptive clone elite genetic algorithm (ACEGA) to reduce the energy consumption of HDWSNs routing. The algorithm uses clone operators and elite operators to speed up the convergence speed, and uses adaptive operators to enhance the global search capability of the algorithm. To verify the effectiveness of ACEGA, we compare ACEGA with particle swarm optimization (PSO) and simulated annealing (GA). Simulation results demonstrate that the execution performance of the ACEGA outperforms SA and PSO. In addition, the system energy consumption of HDWSNs using ACEGA is also lower than that of SA and PSO. Therefore, the algorithm we proposed effectively reduces the routing consumption of the entire HDWSNs system.

Keywords. High-density wireless sensor networks, genetic algorithm, energy consumption

1. Introduction
There are large quantities of sensor nodes in high-density wireless sensor networks (HDWSNs). These devices can perceive some physical characteristics of the surrounding environment for obtaining various data information, such as light, sound, humidity, temperature and pressure, etc. [1,2]. Now, HDWSNs are widely used in the fields of environmental quality monitoring, smart home, water resources monitoring, and traffic safety [3,4]. However, as these sensor nodes run out of battery energy, the nodes will also lose their function, which affects the efficiency of the system [5].

In today's wireless sensor networks, most of the nodes are randomly scattered on the target area through airdrops, and humans cannot add node energy and move node locations at will [6]. Therefore, the current bottleneck problem faced by wireless sensor networks is to extend the life of nodes and
optimize routing algorithms [7]. Experts and scholars have optimized and improved the routing algorithms facing bottlenecks in current wireless sensor networks. In paper [8], the author proposes a routing algorithm that optimizes and improves the simulated annealing, using network stratification bands and limiting search angles, introducing the energy distance and gradient function, and adding energy factors to the probability function. As a result, the network cycle can be increased, the optimization ability can be enhanced, and the energy consumption can be reduced. But its algorithm is more complicated. In paper [9], the author proposed a particle swarm algorithm to solve the problem of routing energy consumption, and designed a new forwarding method to choose a path with low energy consumption for forwarding nodes. However, PSO does not meet the convergence criteria.

Genetic algorithm has been studied by scholars. Someone recently proposed that the algorithm should be optimized in the three stages of population initialization, crossover and mutation, and the performance of the algorithm has been greatly improved through multi-style initialization, crossover and mutation methods [10]. Aiming at the problem of minimizing routing energy consumption faced by HDWSNs, an adaptive clonal elite genetic algorithm (ACEGA) is used to solve the routing energy optimization problem, a QoS routing model is designed, and adaptive operators, clonal immune operators and elite operators are applied to genetic algorithms. A fitness function is designed to assess the benefits of the ACEGA. Subsequently, according to the experimental results, the optimized routing strategy of ACEGA makes HDWSNs have the characteristics of minimizing network energy consumption, and provides a low energy consumption and high efficiency method for its system operation.

2. System Model
In this section, a multi-condition constraint QoS routing optimization model is introduced. From a mathematical perspective, the model of HDWSNs can be viewed as an undirected graph composed of a set of sensor nodes and a group of links between each node. Use \( G(V, E) \) to represent the graph theory model. The node set includes a source node \( v_1 \), a terminal node \( v_n \), and a plurality of intermediate nodes \( v_2 \rightarrow \cdots \rightarrow v_i \rightarrow \cdots \rightarrow v_{n-1} \).

2.1. Energy Consumption Model
The power consumption can be calculated by formula (1).

\[
C(e) = C_s + C_r
\]  

In (1), \( C(e) \) represents the whole power consumption among two adjacent nodes, \( C_s \) denotes the power consumption for data transmission, \( C_r \) stands for the power consumption of receiving information between two nodes.

Suppose \( d \) represents the distance between two nodes and the quantity of transmitted information is \( t \) bits, the power consumption for the transmitted information can be expressed as equation (2).

\[
C_s(t, d) = E_e \cdot t + \eta_{\text{amp}} \cdot t \cdot d^3
\]  

In (2), \( E_e \) is the electronics energy parameter. \( C_s \) is the transmitter dissipated energy. The power amplification parameter for multipath fading \( \eta_{\text{amp}} \) determine the energy of the amplifier. the distance between two nodes \( d \) and the length of bits \( t \). The power consumption of receiving information is shown as equation (3).

\[
C_r(t) = E_e \cdot t
\]  

In (3), For example, when the two sensor nodes are 0.3m apart and \( t = 2 \text{ Mbit} \). We can set \( \eta_{\text{amp}} = 10pJ / \text{bit} / m^3 \).
2.2. Route Functions
In this part, route functions, bandwidth functions, delay functions, delay jitter functions, and loss packet rate functions on the path from \( v_1 \) to \( v_n \) are respectively represented by the formula (4)(5)(6)(7)(8).

\[
C(r(v_1,v_n)) = \sum_{e \in r(v_1,v_n)} C(e)
\] (4)

\[
B(r(v_1,v_n)) = \min \{ B(e) \}
\] (5)

\[
D(r(v_1,v_n)) = \sum_{e \in r(v_1,v_n)} D(e)
\] (6)

\[
D_J(r(v_1,v_n)) = \sum_{e \in r(v_1,v_n)} D_J(e)
\] (7)

\[
P_L(r(v_1,v_n)) = 1 - \prod_{e \in r(v_1,v_n)} (1 - P_L(e))
\] (8)

2.3. Objective Function
In HDWSNs, many limitations of the QoS routing model can be formed by the graph model. According to the multi-condition delay energy consumption model, the purpose of QoS routing is to find a route with the lowest power consumption. The evaluation function can be calculated by formula (33).

\[
f_{\text{fitness}} = \min \{ C(r(v_1,v_n)) \}
\] (9)

2.4. Restrictions
Data communication starts at the source node \( v_1 \) and ends at the terminal node \( v_n \). The links between adjacent nodes on this route need to meet the following restrictions (10) (11) (12) (13).

\[
D(r(v_1,v_n)) \leq D_{\text{max}}
\] (10)

\[
B(r(v_1,v_n)) \geq B_{\text{min}}
\] (11)

\[
D_J(r(v_1,v_n)) \leq D_{J_{\text{max}}}
\] (12)

\[
P_L(r(v_1,v_n)) \leq P_{L_{\text{max}}}
\] (13)

3. ACEGA-Based Routing Minimize Energy Consumption in HDWSNs
ACEGA is a swarm intelligence approximation optimization technology used to achieve efficient routing performance and reduce energy consumption. To enhance the effectiveness of the program, we use real number codes to simulate the genetic codes of organisms. In order to prevent the algorithm from prematurely converging and falling into a local optimum, an adaptive mechanism is used to control the probability of crossover and mutation. The purpose of using clone operators and elite operators is to increase the optimization ability of the algorithm, thereby minimizing the energy consumption of the routing problem.

This paper discusses ACEGA from the aspects of parameter and population initialization, fitness calculation, selection and crossover, adaptive mutation, evaluation of fitness, and cloning of elite chromosomes.

3.1. Coding Scheme
The program coding scheme is the first step for ACEGA to solve the routing problem. In the implementation of ACEGA, a good coding method will have a great impact on routing energy
consumption, fitness assessment and population changes. There are many coding methods. This article uses real number coding to increase the algorithm search space.

3.2. Population Initialization and Fitness Calculation
The population is coded based on the routing energy consumption model. Its purpose is to establish a problematic and abstract connection between routing energy consumption and ACEGA. Therefore, before the algorithm starts, $M$ individuals are created randomly as the first biological population. The first biological population is described as $H = \{H_1, H_2, \ldots, H_N\}$.

In the ACEGA process, the fitness function is the basis for the selection operation, and it is also the key to choosing which individuals to retain to the next-generation population. It determines whether ACEGA can solve the possibility of the optimal value. This paper adopts Formula (9) calculates the fitness value, which is also the energy consumption value of the route. The routing communication energy consumption of each individual is evaluated as fitness. In our proposed ACEGA, the better the route represented by the individual code, the smaller the value of fitness.

3.3. Selection and Crossover
In ACEGA, the selection of parents is determined by the rules of roulette. Roulette describes the reproduction opportunities of chromosomes in the previous generation population. High fitness individual is more likely to be chosen. After initialized the population, start the selection operation from the population. The number of chromosomes selected needs to be the same as the number of the initial population. In the selection process, if a pair of chromosomes is determined to be selected under the constraints of the relative view, then this pair of chromosomes will be inherited into the next generation population to continue to evolve.

The recombination of genes is important in evolution. When the routing does not reach the optimal solution, it needs to be modified. One point crossover is the simplest crossover method. By randomly selecting a crossover point from two parent individuals, we can select the structure before or after the crossover point in the parent individuals to exchange, so as to generate two new children. Whether the newly generated offspring can be directly retained in the next generation depends on whether the fitness value of the two individuals becomes larger and the survival ability is improved. The crossover probability of ACEGA is 0.96. Crossover process is an important means to search for the global optimal solution.

3.4. Adaptive Mutation
To avoid premature and maintain the diversity of the population, the mutation operation is applied to the new species. Mutation operation is an auxiliary operation in the process of crossover. Every individual has a chance of mutation. In the traditional genetic algorithm, the crossover probability and mutation probability are usually a certain value. If the mutation probability is too large, the individual structure with higher fitness value will be easily destroyed which will lead to poor performance of the algorithm; if the mutation probability is too low, it will lead to the stagnation of the evolution process and fall into local optimum. Therefore, when using ACEGA to solve different problems, we need to constantly adjust and select the appropriate mutation probability. What’s more, the mutation probability should also change slowly and maintain at a lower level when the individual fitness value is high. That is to say, the mutation probability should change adaptively with the individual fitness value.

3.5. Clone elite Preservation
In ACEGA, the process of evolution is carried out by preserving individuals with excellent genes. Through fitness evaluation, several elite individuals are found after sorting. The fitness values of several elite individuals are grouped into roulette, and selected according to a certain probability and cloned into the next generation population. This method of cloning elite individuals is very effective in increasing the algorithm's ability to find the best individuals.
During the execution of the algorithm, the population is selected, adaptive crossover and mutation are performed, and this process is performed cyclically. If the algorithm reaches the predetermined termination condition, the iterative process of ACEGA algorithm is terminated. The criterion for algorithm convergence is to reach the set number of iterations. After evolution, the algorithm finds an individual with the highest fitness value, which is the approximate optimal solution to the routing energy consumption problem.

4. Simulation and Results
In the simulation part, we will test the algorithm performance of ACEGA in HDWSNs routing energy consumption problem, and compare the results with the simulation results of SA and PSO in HDWSNs routing energy consumption problem. The experiment platform is an Intel(R) Core (TM) i7 2.40GHz CPU computer, RAM is 12GB, and the programming language is MATLAB. Under the same other experimental conditions, we used a different number of sensor nodes for comparison.

To validate the effectiveness of ACEGA, we discontinued ACEGA, PSO and SA after 150 iterations. The parameters of the three algorithms are as follows: we set the population size to 50, the crossover probability of ACEGA to 0.96, and the mutation probability to 0.07. In SA, the initial temperature is set to 100, and the annealing coefficient is 0.98. In PSO, the values of social learning factor and individual learning factor are both defined as 2, and the absolute value of speed limit is defined as 10.

In Figure 1, the energy consumption of ACEGA, PSO and SA after 150 generations with 70 sensors is shown. The energy consumption of the three algorithms of ACEGA, PSO and SA are 1.396 J, 1.631 J and 1.954 J respectively after 150 iterations. It can be seen that ACEGA with adaptive operators, clone operators and elite operators can significantly reduce routing energy consumption.

According to Figure 2, with 150 sensor nodes, the energy consumption of the three algorithms of ACEGA, PSO and SA after 150 generations are 6.208 J, 7.698 J and 9.044 J, respectively. It can be seen from Figure 1 and Figure 2 that compared with PSO and SA, ACEGA has good performance and effectively reduces the energy consumption of routing communication under different sensor node scales.

5. Conclusion
The new contribution of this paper is that we combine the advantages of traditional genetic algorithm, adaptive strategy and clone elite strategy, and propose an adaptive clone elite genetic algorithm (ACEGA) for routing energy consumption problems. To demonstrate the effectiveness of ACEGA and the effectiveness of the new clone strategy, adaptive strategy and elite strategy, ACEGA was tested with fitness function. The simulation results show that ACEGA has superior performance and faster execution speed than PSO and SA. Therefore, ACEGA can more effectively find the optimal solution, which means that the method effectively reduces the routing energy consumption.

![Figure 1. Energy consumption of 70 nodes.](image1)

![Figure 2. Energy consumption of 150 nodes.](image2)
Acknowledgments
This paper was funded by the Corps innovative talents plan, grant number 2020CB001, project of Youth and muddleaged Scientific and Technological In-novation Leading Talents Program of the Corps, grant number 2018CB006, the China Postdoctoral Science Foundation, grant number 220531, Funding Project for High Level Talents Research in Shihezi University, grant number RCZK2018C38, Project of Shihezi University, grant number ZZZC201915B.

References
[1] Y. Ji, Q. Tan, H. Wang, W. Lv, H. Dong and J. Xiong 2019 A Novel Surface $LC$ Wireless Passive Temperature Sensor Applied in Ultra-High Temperature Measurement. *IEEE Sensors Journal* 1 pp 105-112.
[2] L. Rodrigues, E. Leão, C. Montez, R. Moraes, P. Portugal and F. Vasques 2018 An Advanced Battery Model for WSN Simulation in Environments with Temperature Variations. *IEEE Sensors Journal* 19 pp 8179-8191.
[3] J. Botero-valencia, L. Castano-Londono, D. Marquez-Viloria and M. Rico-Garcia 2019 Data Reduction in a Low-Cost Environmental Monitoring System Based on LoRa for WSN. *IEEE Internet of Things Journal* 2 pp 3024-3030.
[4] M. A. Mughal, P. Shi, A. Ullah, K. Mahmood, M. Abid and X. Luo 2019 Logical Tree Based Secure Rekeying Management for Smart Devices Groups in IoT Enabled WSN. *IEEE Access* 7 pp 76699-76711.
[5] P. K. Sharma, Y. Jeong and J. H. Park 2018 EH-HL: Effective Communication Model by Integrated EH-WSN and Hybrid LiFi/WiFi for IoT. *IEEE Internet of Things Journal* 3 pp1719-1726.
[6] L. -. Hung, F. -. Leu, K. -. Tsai and C. -. Ko 2020 Energy-Efficient Cooperative Routing Scheme for Heterogeneous Wireless Sensor Networks. *IEEE Access* 8 pp 56321-56332.
[7] W. -C. Yeh, Y. Jiang, C. -L. Huang, N. N. Xiong, C. -F. Hu and Y. -H. Yeh 2020 Improve Energy Consumption and Signal Transmission Quality of Routings in Wireless Sensor Networks. *IEEE Access* 8 pp 198254-198264.
[8] J. Kang, J. Kim, M. Kim and M. Sohn 2020 Machine Learning-Based Energy-Saving Framework for Environmental States-Adaptive Wireless Sensor Network. *IEEE Access* 8 pp 69359-69367.
[9] Y. Cao and H. Pan 2020 Energy-Efficient Cooperative Spectrum Sensing Strategy for Cognitive Wireless Sensor Networks Based on Particle Swarm Optimization. *IEEE Access* 8 pp 214707-214715.
[10] J. Li, Z. Luo and J. Xiao 2020 A Hybrid Genetic Algorithm with Bidirectional Mutation for Maximizing Lifetime of Heterogeneous Wireless Sensor Networks. *IEEE Access* 8 pp 72261-72274.