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# Quantum Genetic Uneven Clustering Algorithm for Wireless Sensor Networks

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Abstract. *Network clustering mechanism is one of the effective ways to save energy for wireless sensor networks (WSN). In this paper, we propose a quantum genetic uneven clustering algorithm (QGUC). The algorithm takes into account the calculation of optimal cluster number, cluster head selection, calculation of cluster radius. At the same time, the clustering parameters are optimized by quantum genetic algorithm based on double-chain encoding method. In order to improve the adaptability to cluster structure of wireless sensor networks, the rotation angle and fitness function of quantum gate have been improved. Besides, we propose a solution to increase the number of initial individual in evolution. The simulation results show its superiority in terms of network lifetime, the number of alive nodes, and the total energy consumption.*
**Keywords:** Wireless sensor networks, Energy optimization strategy, Quantum genetic algorithm, Uneven clustering algorithm

1. **Introduction.** Wireless sensor networks (WSN) typically consist of a large number of energy-constrained sensor nodes with limited onboard battery resources. The node energy is difficult to renew. Therefore, energy optimization is a critical issue in the design of wireless sensor networks [1, 2]. At present, many techniques have been proposed to improve the energy efficiency in energy-constrained and distributed wireless sensor networks [3, 4, 5]. Among these techniques, energy efficiency routing protocol has been widely considered as one of the most effective ways to save energy.

LEACH protocol [6] is one of the most popular hierarchical routing protocols for wireless sensor networks. However, there are also some shortcomings. The residual energy of node is not taken into consideration during the cluster head selection. Uneven distribution of cluster heads and cluster sizes may causes the decline in the balance of network load. In large-scale network, single-hop data transmission will lead to some cluster heads die in advance. To avoid uneven distribution problem of cluster heads and cluster sizes in LEACH, some improved protocols are proposed, such as LEACH-C [7], LEACH-F [8], V-LEACH [9], and LEATCH algorithm [10]. Reference [11] proposes HEED protocol. During each iteration, a node becomes a cluster head with a certain probability which considers the mixture of energy, communication cost, and average minimum reachable power (AMRP). HEED creates well-balanced clusters. It has more balanced energy consumption and longer network lifetime.

To avoid "hot spot" problem, reference [12] proposes an unequal clustering size (UCS) model for network organization, which can lead to more uniform energy consumption among the cluster head nodes and prolong network lifetime. Reference [13] proposes and evaluates an EEUC mechanism for periodical data gathering applications. Simulation results show that EEUC successfully balances the energy consumption over the network and achieves a remarkable network lifetime improvement. The EEMDC algorithm [14] divides the network area into three logical layers by doing the partition of the network area. The distance of the nodes to the cluster head and the cluster head to the base station is taken into account when considering the hop-count value of the nodes. Cluster head is elected by acquiring the average leftover energy of the nodes. The fused data are delivered to the base station using the minimum distance path to the base station. The mechanism is more effective in prolonging the network lifetime than LEACH and fix the "hot spot" problem. Reference [15] reduces energy consumption by proposing a new algorithm. It allows control and management of the topology of each network. The architecture operation and the protocol messages are described. Measurements from a real test-bench will show that the designed protocol has low bandwidth consumption and also demonstrates the viability and the scalability of the proposed architecture. Reference [16] proposes an uneven clustering routing algorithm based on optimal clustering. Some new methods are proposed to obtain the optimal cluster number, select cluster heads, calculate the cluster radius, and deal with isolated nodes. The experiment results show it is effective in reducing the energy consumption and prolonging the network lifetime.

In order to optimize the clustering parameters, genetic algorithm is used as the multi-objective optimization methodology [17]. An appropriate fitness function is developed to incorporate many aspects of network performance. The optimized characteristics include the status of sensor nodes, network clustering. Fitness function is designed according to the application of open-pit mine slope detection system [18]. In the same conditions, it uses serial genetic algorithm, parallel genetic algorithm, and quantum genetic algorithm for network energy optimization. The clustering algorithm for energy balance based on genetic clustering [19] combines genetic algorithm and Fuzzy C-means clustering algorithm. It can form the optimal clustering, furthermore to balance the network energy consumption and improve the performance of the network.

In this paper, we propose a quantum genetic uneven clustering routing algorithm (QGUC) for wireless sensor networks. The rest of this paper is organized as follows. In Section 2, the uneven clustering routing algorithm (UCRA) based on optimal clustering is analyzed. In Section 3, we present the parameters optimization method based on quantum genetic algorithm. In Section 4, shows the simulation and numerical analysis. Final conclusion remarks are made in section 5.

2. **The Uneven Clustering Routing Algorithm (UCRA).** The operation of hierarchical routing for WSN can be divided into set-up phase and steady-state phase. In [16], we proposes an uneven clustering routing algorithm by taking into account the calculation of optimal cluster number, cluster head selection, cluster radius calculation. A radio model proposed [6] in LEACH is shown in Figure 1.
where $E_{elec}$ is the transmitter energy consumption per bit, $l$ is the number of bits, $\varepsilon_{fs}$ is proportional constant of the energy consumption for the transmit amplifier in free space channel model ($\varepsilon_{fs} \cdot l \cdot d^2$ power loss), $\varepsilon_{mp}$ is proportional constant of the energy consumption for the transmitter amplifier in multipath fading channel model ($\varepsilon_{mp} \cdot l \cdot d^4$ power loss), the distance between transmitter and receiver is $d$, the transmitter energy consumption to run the transmitter or receiver circuitry is $E_{elec} \cdot l$, the energy consumption in transmitter amplifier is $\varepsilon_{fs} \cdot l \cdot d^2$ or $\varepsilon_{mp} \cdot l \cdot d^4$.

Assume there are $N$ nodes distributed uniformly in a $M \times M$ region. There are $k$ clusters, each has $N/k$ nodes in average. $E_{DA}$ is the energy consumption for data fusion

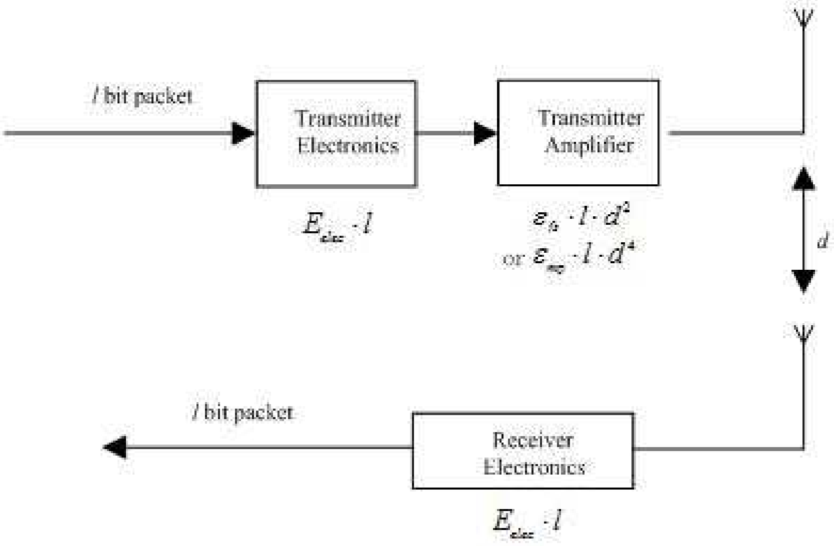


FIGURE 1. The radio energy consumption model

per bit, $d_{toCH}$ is the distance between the node and the cluster head. $d_{toBS}$ is the distance between node and base station. $f_{agg}$ is fusion rate. In each frame, all the nodes expend

$$
\begin{aligned}
E_{total} &= k \cdot \left[E_{CH} + (\frac{N}{k} - 1) \cdot E_{NCH}\right] \\
&= l \cdot k \cdot \left\{\left(\frac{N}{k} - 1\right) \cdot E_{elec} + \frac{N}{k} \cdot E_{DA} + f_{agg} \cdot \left[\varepsilon_{mp} \cdot E\left(d_{toBS}^4\right) + E_{elec}\right]\right. \\
&\quad \left. + \left(\frac{N}{k} - 1\right) \cdot [E_{elec} + \varepsilon_{fs} \cdot d_{toCH}^2]\right\} \\
&\approx l \cdot \left\{N \cdot E_{elec} + N \cdot E_{DA} + k \cdot f_{agg} \cdot \left[\varepsilon_{mp} \cdot E\left(d_{toBS}^4\right) + E_{elec}\right]\right. \\
&\quad \left. + N \cdot \left[E_{elec} + \varepsilon_{fs} \cdot \frac{M^2}{2\pi k}\right]\right\}
\end{aligned} \tag{1}
$$

By making the derivative of the function $E_{total}$ equal to 0, the optimal number of $k$ can be obtained as

$$
k = \left\lceil \sqrt{\frac{\varepsilon_{fs} \cdot M^2 \cdot N}{2\pi f_{agg} \cdot [\varepsilon_{mp} \cdot E\left(d_{toBS}^4\right) + E_{elec}]}} \right\rceil \tag{2}
$$

where $\lceil a \rceil$ denotes the smallest integer which is greater than or equal to the argument $a$.

After obtaining the optimal cluster number, the next step is to choose appropriate nodes as cluster heads which can gather data from intra-cluster nodes, compress data and send them to the base station. Considering all the factors above, in UCRA, we introduce factor of energy consumption $E_{avecon}/E_{con}$ [20, 21], factor of node degree $N_{NN}/N_{AN}$ [11], factor of distance between the node and base station $(d_{toBS\_MAX} - d_{toBS})/(d_{toBS\_MAX} - d_{toBS\_MIN})$ to determine the selection probability of cluster head.

$$
P_U = \max\left(\frac{k}{N} \cdot \left(\frac{E_{res}}{E_{\max}} \cdot \frac{E_{avecon}}{E_{con}}\right) \cdot \left(\eta_1 \cdot \frac{N_{NN}}{N_A} + (1-\eta_1) \cdot \frac{d_{toBS\_MAX} - d_{toBS}}{d_{toBS\_MAX} - d_{toBS\_MIN}}\right), P_{\min}\right) \tag{3}
$$

where $\eta_1$ is a constant coefficient between 0 and 1, $E_{con}$ is the energy consumption of the $i^{\text{th}}$ node, $E_{avecon}$ is the average energy consumption of the whole network during the last round of data transmission, $N_{NN}$ is the number of neighbor nodes, $N_A$ is the number of alive nodes.

In round $R$, the larger energy consumption is, the smaller $E_{avecon}/E_{con}$ is and the lower probability to be a cluster head in the next round. On the contrary, the probability to be a cluster head in next round will be larger. At the same time, the larger $N_{NN}/N_A$ is, the larger probability to be a cluster head.

In addition, the node should have larger probability to be cluster head when its distance from the base station is short. So $(d_{toBS\_MAX} - d_{toBS})/(d_{toBS\_MAX} - d_{toBS\_MIN})$ is used to solve the problem. In (3), $\eta_1$is used to make $P_U$ more reasonable and will be optimized in Section 3.

After the cluster heads have been selected, the cluster heads will broadcast an advertisement message (ADV) to let all the other nodes know the cluster information for the current round. We introduce node degree to improve the adaptation. In UCRA, the uneven cluster radius is

$$R_U = \left(1 + \frac{d_{toBS} - E(d_{toBS})}{\eta_2 \cdot (d_{toBS\_MAX} - d_{toBS\_MIN})}\right) \cdot \left(1 - \frac{N_{NN}}{\eta_3 \cdot N_A \cdot R_L}\right) \cdot R_L \tag{4}$$

where $\eta_2$ and $\eta_3$ is constant coefficients, $R_L$ is the cluster radius designed in LEACH. The three parameters will be optimized in Section 3.

In (4), cluster radius can be adjusted according to the distance between node and base station. When $d_{toBS}$ is larger, the cluster radius is larger too. On the contrary, the radius will be smaller. In addition, the node degree has influence on the radius. The larger the node degree is, the smaller the cluster radius is.

Once receiving ADV, each non-cluster head node determines its cluster for this round by choosing the cluster head that requires the minimum communication energy. After each node having selected the cluster it belongs to, it must inform the cluster head node that it will be a member of the cluster. Each node transmits a join-request message (Join-REQ) to the chosen cluster head. The cluster head node sets up a TDMA schedule and transmits this schedule to the nodes in its cluster. After the TDMA schedule has been known by all nodes in cluster, the set-up phase is completed and the steady-state operation will begin. Once the cluster head receives all the data, it performs data aggregation to enhance the common signal and reduce the energy consumption. The resultant data are sent to the base station in routing path.

3. **Parameters Optimization Based on Quantum Genetic Algorithm.** Quantum Genetic Algorithm (QGA), is a probability optimization algorithm combining Genetic Algorithm (GA) and Quantum Algorithm (QA). In QGA, the chromosomes are encoded by quantum bits and updated by quantum rotation gates. Then each chromosome is evaluated by its fitness value. The fitness of a chromosome depends on some fitness factors. The best chromosomes are selected by using a specific selection method based on their fitness values. QGA applies crossover and mutation to produce a new population better than the previous one for the next generation [22]. QGA has been proposed for some combinatorial optimization problems. It still has some shortcomings. Firstly, binary coding has randomness and blindness to measure the state of quantum bit. Some chromosomes are possible to degenerate as the majority of chromosomes in population evolve. Secondly, binary coding is not suitable for numerical value optimization such as function extreme and neural network weight optimization. Thirdly, the direction of rotation angle is usually determined by a query table, which is inefficient to deal with many conditional judgments. In this paper, we propose a self-adaptive updating method for rotation angle. The rotation angle gradually decreases with the increase of the optimization steps.

Aiming at the above parameter optimization, we propose an parameter optimization method based on improved double-chain encoding QGA. The steps of parameter optimization are described as the following.

3.1. **Encoding quantum chromosome and initializing the population with new method.** In quantum computation, the basic unit of information is described by a quantum bit, which coded in binary can be expressed as

$$|\phi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \tag{5}$$

where the pair of $\alpha$ and $\beta$ is called quantum bit probability amplitude of the $|\phi\rangle$. Many QGAs proposed currently are coded in binary. To avoid its randomness and blindness, the probability amplitudes of quantum bits are directly regarded as the coding of chromosome. According to the nature of probability amplitude, the quantum bit can also be expressed as

$$\begin{bmatrix}\alpha\\ \beta\end{bmatrix} = \begin{bmatrix}\cos\phi\\ \sin\phi\end{bmatrix} \tag{6}$$

where the quantum bit $|\phi\rangle$ is $|\cos\phi\rangle$ or $|\sin\phi\rangle$.

The chromosome in our quantum genetic algorithm is coded as

$$p_i = \left[\begin{array}{c|c|c|c}\cos(t_{i1}) & \cos(t_{i2}) & \cdots & \cos(t_{in})\\ \sin(t_{i1}) & \sin(t_{i2}) & \cdots & \sin(t_{in})\end{array}\right] \tag{7}$$

where $t_{ij} = 2\pi \cdot Rnd$, $Rnd$ represents a random number in $(0,1)$, $i = 1,2,\cdots,m$, $j = 1,2,\cdots,n$. $m$ represents the number of initial population and $n$ represents the number of quantum bits. The whole network in one round with one set of parameter values will be one individual in evolution. The energy consumption in each round is different. So we set one same set of parameters for every five rounds and calculate the average energy consumption in fitness function. Besides there are 4 parameters in the new clustering routing algorithm. Considering the above conditions, $m$ is set to 16, $n$ is set to 4. The chromosome is encoded as

$$p_i = \left[\begin{array}{c|c}\alpha_{\text{i}1} & \alpha_{i2}\\ \beta_{i1} & \beta_{i2}\end{array}\right] = \left[\begin{array}{c|c}\cos(t_{i1}) & \cos(t_{i2})\\ \sin(t_{i1}) & \sin(t_{i2})\end{array}\right] \tag{8}$$

where $\begin{bmatrix}\alpha_{i1}\\ \beta_{i1}\end{bmatrix}$ represents parameter $\eta_1$, $\begin{bmatrix}\alpha_{i2}\\ \beta_{i2}\end{bmatrix}$ represents parameter $\eta_2$, $\begin{bmatrix}\alpha_{i3}\\ \beta_{i3}\end{bmatrix}$ represents parameter $\eta_3$, $\begin{bmatrix}\alpha_{i4}\\ \beta_{i4}\end{bmatrix}$ represents parameter $R_L$.

Each chromosome contains 2n probability amplitudes of n quantum bits. Each of probability amplitudes corresponds to an optimization variable in solution space. If the quantum bit on chromosome is $[\alpha_{\text{ij}}, \beta_{ij}]^T$, the corresponding variables in solution space $\Omega$ can be computed as

$$\begin{aligned} X_{ic}^j &= \frac{1}{2}[A_{\min}(1+\alpha_{ij}) + A_{\max}(1-\alpha_{ij})]\\ X_{is}^j &= \frac{1}{2}[A_{\min}(1+\beta_{ij}) + A_{\max}(1-\beta_{ij})] \end{aligned} \tag{9}$$

where, $A_{\min} = 0.2$, $A_{\max} = 0.9$ for coefficient $\eta_1$ in (3), $A_{\min} = 0.2$, $A_{\max} = 0.9$ for coefficient $\eta_2$ in (4), $A_{\min} = 1$, $A_{\max} = 5$ for coefficient $\eta_3$ in (4), $A_{\min} = 35$, $A_{\max} = 86$ for parameter $R_L$ in (4).

3.2. **Calculating the fitness with proposed self-adaptive fitness function.** After initializing the chromosome and population, the chromosome need to be evaluate by fitness value. In order to make the algorithm clear and concise, the fitness function $f(r)$ at round $r$ only involves the average energy consumption of the whole network. The less the average energy consumption is, the larger change rate of fitness function is. The rotation angle should be inversely proportional to $E_{avecon}$. So the fitness function can be defined as

$$f(r) = \exp(-E_{avecon}(r)/E_{\max}) \tag{10}$$

where $E_{avecon}$ is the average energy consumption of the whole network during the past five rounds. $E_{\max}$ is a reference maximum energy consumption of the whole network.

3.3. **Evolving into the next generation group by improved self-adaptation quantum rotation gate.** When Q-gate is

$$U(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \tag{11}$$

The quantum bit in next generation will be

$$\begin{bmatrix} \overline{\alpha} \\ \overline{\beta} \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} \cos\phi \\ \sin\phi \end{bmatrix} = \begin{bmatrix} \cos(\theta+\phi) \\ \sin(\theta+\phi) \end{bmatrix} \tag{12}$$

It is clear that the Q-gate $U(\theta)$ causes the phase rotation of $\theta$.

In $U(\theta)$ , the phase rotation of $\theta$ can be defined as

$$\theta = -\mathrm{sgn}(A) \cdot \theta_0 \cdot \exp(-\frac{|\nabla f(r)| - \nabla f_{\min}}{\nabla f_{\max} - \nabla f_{\min}}) \cdot \exp(-\frac{r}{r_{\max}}) \tag{13}$$

where $A$ is defined as

$$A = \sin(\theta - \theta_{opt}) \tag{14}$$

and $\theta_{opt}$ is the probability amplitude of a quantum bit in the global optimum solution, $\theta$ is the probability amplitude of the corresponding quantum bit in the current solution. $\theta_0$ is the initial value of rotation angle and $\theta_0 \in (0.005\pi \sim 0.1\pi)$. $\nabla f(r)$ is the gradient of fitness function at round $r$. $\nabla f_{\min}$ and $\nabla f_{\max}$ are respectively defined as

$$\nabla f_{\min} = \min\left\{ \left|\frac{f(80) - f(0)}{x(80) - x(0)}\right|, \left|\frac{f(81) - f(1)}{x(81) - x(1)}\right|, \cdots, \frac{f(r) - f(r-80)}{x(r) - x(r-80)} \right\} \tag{15}$$

$$\nabla f_{\max} = \max\left\{ \left|\frac{f(80) - f(0)}{x(80) - x(0)}\right|, \left|\frac{f(81) - f(1)}{x(81) - x(1)}\right|, \cdots, \frac{f(r) - f(r-80)}{x(r) - x(r-80)} \right\} \tag{16}$$

where $x(r)$ represents the vectors $\eta_1$, $\eta_2$, $\eta_3$, $R_L$ in solution space. If the current optimum solution is cosine solution, then $x(r) = x_{ic}^j$, else $x(r) = x_{is}^j$. $x_{ic}^j$ and $x_{is}^j$ can be computed by (9) respectively.

3.4. **Judging whether it meets with the termination condition.** If the stop condition is met, the iteration ends. Otherwise updating the global optimum solution and the corresponding chromosome. The results can be encoded. The system returns to step **a)** and repeats the procedure of iteration.

4. **Simulation and Numerical Analysis.** In NS2, we distribute randomly 100 nodes ($N = 100$ in (1)–(3)) in the area of $100 \times 100\,\mathrm{m}^2$ ($M = 100$ in (1) and (2)). The initial energy of all the sensor nodes is equal ($E_{\max} = 2J$ in (3)). In (1) and (2), $\varepsilon_{fs} = 10\,\mathrm{pJ/bit/m}^2$, $\varepsilon_{mp} = 0.0013\,\mathrm{pJ/bit/m}^4$, $f_{agg} = 1$, $E_{elec} = 50\,\mathrm{nJ/bit}$. In (3), $p_{\min} = 0.0005$.

Figure 2 shows the maximum value of fitness for 16 individuals in QGUC algorithm. If a certain individual has a new maximum value of fitness in the current generation, the individual will replace the best one. The others will record the value and iterate towards the best individual. The iteration will end until the maximum value tends to 1 or remains unchanged. The simulation results show that the maximum fitness is 0.8827 at 1094th round. It remains unchanged after 1094th round. The iteration ends.

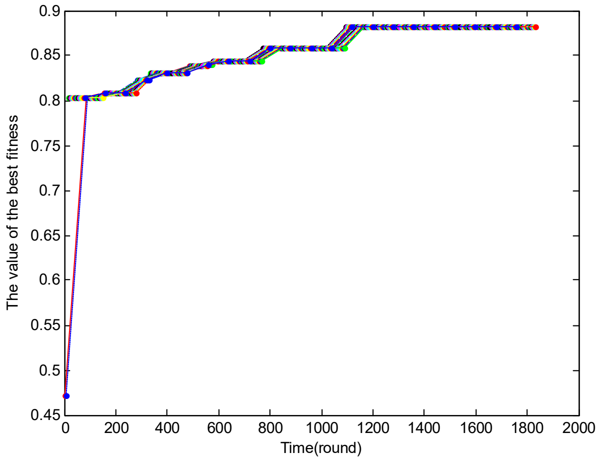


FIGURE 2. The maximum value of fitness for 16 individuals in QGUC algorithm

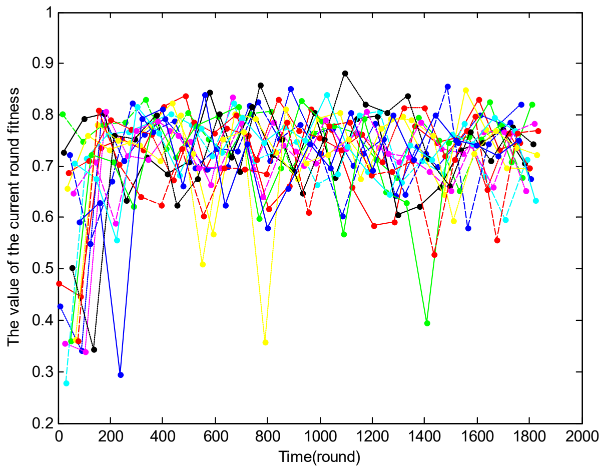


FIGURE 3. The value of fitness in each round for 16 individuals in QGUC algorithm

Figure 3 shows the value of fitness in each round for 16 individuals in QGUC algorithm. Each curve represents the value of fitness in each round for one individual. The best individual is selected by comparing its value of fitness in each generation and recorded by other individuals. Then other individuals iterate towards the best individual. After many times of iterations, the population starts to evolve towards an optimal solution. The simulation results show that the value of fitness grows rapidly in the beginning and turns into small fluctuations as time goes on.

Figure 4 shows, for cluster head selection, the value of $\eta_1$ in each round for 16 individuals in QGUC algorithm. Each curve represents the value of $\eta_1$ in each round for one individual. After many times of iterations, the population starts to evolve towards an optimal solution. The maximum value of fitness remains unchanged after 1094th round. The parameters in 1094th round are the optimal parameters. The simulation results show that the value of $\eta_1$ is 0.2996 at 1094th round when the value of fitness is maximum.

Figure 5 shows, for cluster radius calculation, the value of $\eta_2$ in each round for 16 individuals in QGUC algorithm. Each curve represents the value of $\eta_2$ in each round for one individual. The parameters in 1094th round are the optimal parameters. The simulation results show that the value of $\eta_2$ is 0.7015 at 1094th round when the value of fitness is maximum.

Figure 6 shows, for cluster radius calculation, the value of $\eta_3$ in each round for 16 individuals in QGUC algorithm. Each curve represents the value of $\eta_3$ in each round for one individual. The parameters in 1094th round are the optimal parameters. The

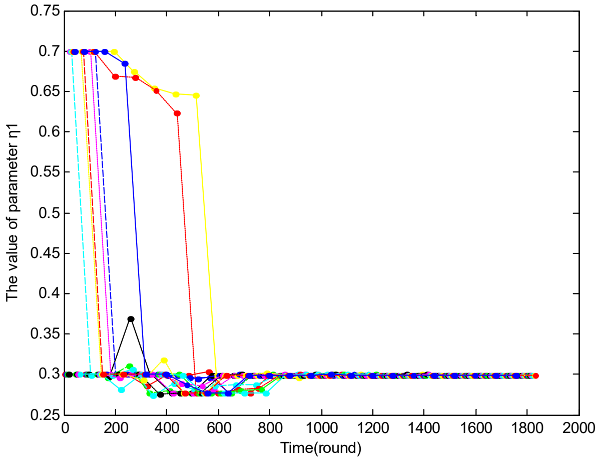


FIGURE 4. The value of $\eta_1$ in each round for 16 individuals in QGUC algorithm

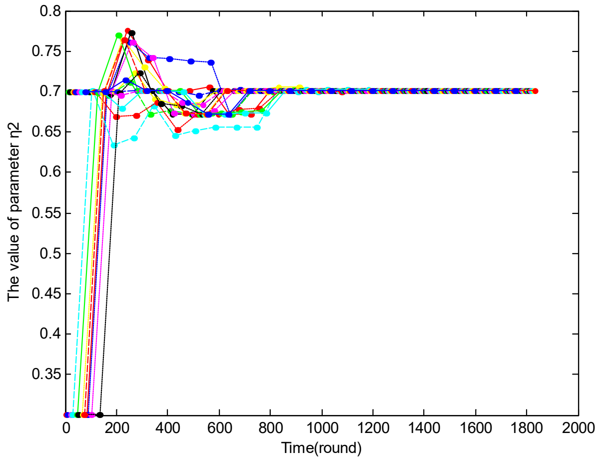


FIGURE 5. The value of $\eta_2$ in each round for 16 individuals in QGUC algorithm

simulation results show that the value of $\eta_3$ is 2.003 at 1094th round when the value of fitness is maximum.

Figure 7 shows the average value of $R_L$ in each round for 16 individuals in QGUC algorithm. Each curve represents the value of $R_L$ in each round for one individual. The parameters in 1094th round are the optimal parameters. The simulation results show that the average value of $R_L$ is 40.01 at 1094th round when the value of fitness is maximum.

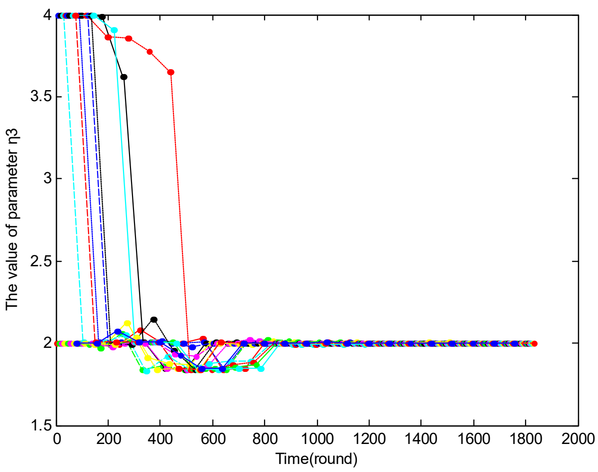


FIGURE 6. The value of $\eta_3$ each round in 16 individuals in the QGUC algorithm

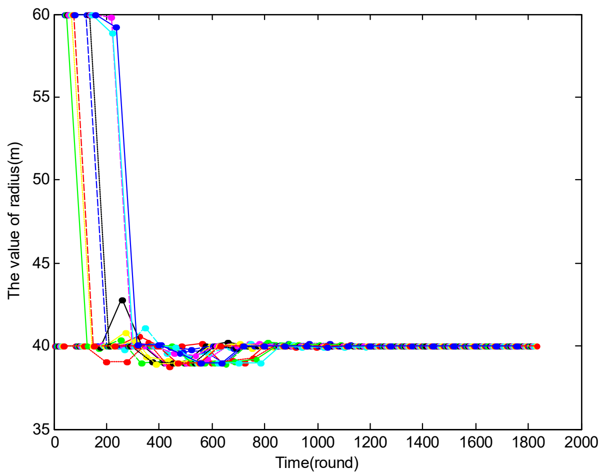


FIGURE 7. The average value of $R_L$ in each round for 16 individuals in QGUC algorithm

Figure 8 shows the average number of alive nodes in LEACH ($k = 4$), UCRA ($\eta_1 = 0.5$, $\eta_2 = 0.7$, and $\eta_3 = 2$), and QGUC algorithm. The quality of energy optimization strategy can be judged by the average number of alive nodes. We hope that the time that the first node dies and the network no longer provides acceptable quality all is put off. The simulation results show the time that the first node dies is about 330th round in QGUC, which is prolonged by about 175% than that in LEACH ($k = 4$) and about 37.5% than that in UCRA. The time that the network no longer provides acceptable quality results is about 1230th round in QGUC, which is prolonged by about 44.3% than that in LEACH

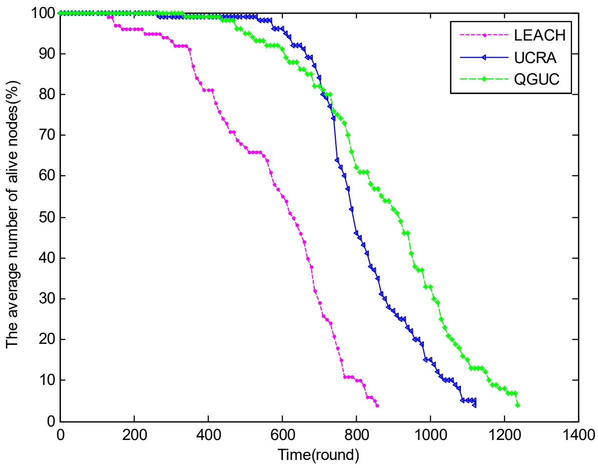


FIGURE 8. The average number of alive nodes in LEACH, UCRA, and QGUC algorithm

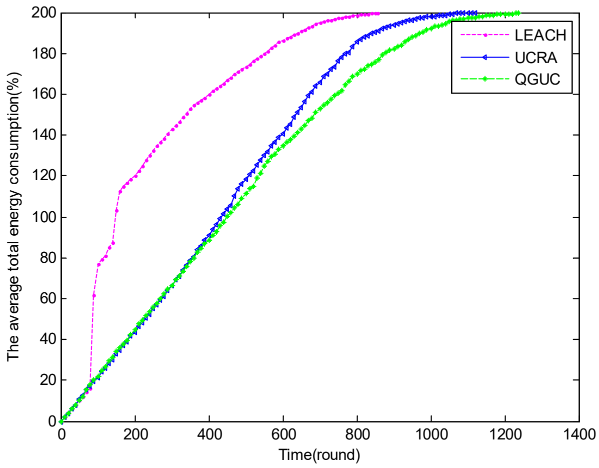


FIGURE 9. The average total energy consumption in LEACH, UCRA, and QGUC algorithm

($k = 4$) and about 5.4% than that in UCRA. So the QGUC algorithm has the superiority in terms of network lifetime and the number of alive nodes.

Figure 9 shows the average total energy consumption in LEACH ($k = 4$), UCRA ($\eta_1 = 0.5$,$\eta_2 = 0.7$, and $\eta_3 = 2$) , and QGUC algorithm. It reflects the balance of energy consumption. The bigger the slope of a curve is, the poorer the balance of energy consumption. The simulation results show that the total energy consumption in QGUC grows more slowly than that in LEACH and UCRA. The average energy consumption in QGUC decreases by 30.7% than that in LEACH and 9.4% than that in UCRA. So the QGUC algorithm has the superiority in terms of network lifetime and the total energy consumption.

5. **Conclusion.** In this paper, we propose a quantum genetic uneven clustering routing algorithm (QGUC) for wireless sensor networks. The algorithm takes into account the calculation of optimal cluster number, cluster head selection, cluster radius calculation. At the same time, the clustering parameters are optimized by quantum genetic algorithm based on double-chain encoding method. In order to improve the adaptability for wireless sensor network cluster structure, the rotation angle and the fitness function of quantum gate have been improved. The time that the first node dies in QGUC is prolonged by about 175% than that in LEACH and about 37.5% than that in UCRA. The time that the network no longer provides acceptable quality results in QGUC is prolonged by about 44.3% than that in LEACH and about 5.4% than that in UCRA. The number of data received at the base station in QGUC is 42.7% more than that in LEACH and 5.5% more than that in UCRA. The average energy consumption in QGUC decreases by 30.7% than that in LEACH and 9.4% than that in UCRA. All these show the QGUC algorithm has the superiority in terms of network lifetime, the total energy consumption, the number of alive nodes, and data transmission. Although the proposed algorithm has some advantages in network lifetime, balance of energy consumption, and data transmission, there is still plenty of work to do in the future. Firstly, we will further study the optimizing algorithm for cluster parameters. Secondly, we will take some measures to improve the search efficiency and convergence rate by optimizing fitness function and the rotation angle of quantum gate.

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## REFERENCES

[1] S. Lonare and G. Wahane, A Survey on Energy Efficient Routing Protocols in Wireless Sensor Network, In *Proceedings of ICCCNT*, 2013.

[2] A. Boonsongsrikul, S. Kocijancic, and S. Suppharangsan, Effective Energy Consumption on Wireless Sensor Networks Survey and Challenges, In *Proceedings of MIPRO*, 2013.

[3] Z. Teng, M. Xu, and L. Zhang, Nodes deployment in wireless sensor networks based on improved reliability virtual force algorithm, *Journal of Northeast Dianli University*, vol.36, no.2, pp.86–89, 2016.

[4] Z. Sun, C. Zhou, Adaptive cluster algorithm in WSN based on energy and distance, *Journal of Northeast Dianli University*, vol.36, no.1, pp.82–86, 2016.

[5] Z. Teng, X. Zhang, The layout optimization of WSN based on inertia weight shuffled frog leaping algorithm, *Journal of Northeast Dianli University*, vol.35, no.6, pp.66–69, 2015.

[6] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, Energy-efficient communication protocol for wireless microsensor networks, In *Proceedings of HICSS*, 2000.

[7] W. B. Heinzelman, Application-specific protocol architectures for wireless networks, *Massachusetts Institute of Technology*, vol.3, no.6, pp.24–35, 2000.

[8] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, An application-specific protocol architecture for wireless microsensor networks, *IEEE Transactions on Wireless Communications*, vol.1, no.4, pp.660–670, 2002.

[9] M. B. Yassein, A. Al-zou'bi, Y. Khamayseh, and W. Mardini, Improvement on LEACH Protocol of Wireless Sensor Network (VLEACH), *International Journal of Digital Content: Technology and its Applications*, vol.3, no.2, pp.132–136, 2009.

[10] W. Akkari, B. Bouhdid, A. Belghith, LEATCH: Low Energy Adaptive Tier Clustering Hierarchy,*In Proceedings of ANT*, 2015.

[11] O. Younis and S. Fahmy, HEED: A hybrid energy-efficient distributed clustering approach for ad-hoc sensor networks, *IEEE Transactions on Mobile Computing*, vol.3, no.4, pp.366–379, 2004.

[12] S. Soro and W. B. Heinzelman, Prolonging the lifetime of wireless sensor networks via unequal clustering,*In Proceedings of IPDPS*, 2005.

[13] G. H. Chen, C. F. Li, M. Ye, and J. Wu, An unequal cluster-based routing protocol in wireless sensor networks, *Wireless Networks*, vol.15, no.2, pp.193–207, 2009.

[14] A. Mehmood, S. Khan, B. Shams and J. Lloret. Energy-efficient multi-level and distance-aware clustering mechanism for WSNs, *International Journal of Communication Systems*, vol.28, no.2015, pp.972–989, 2015.

[15] J. Lloret, M. Garcia, D. Bri and J. R. Diaz, A Cluster-Based Architecture to Structure the Topology of Parallel Wireless Sensor Networks, *Sensors*, vol.9, no.2, pp.10513–10544, 2009.

[16] J. Li and J. Huo, Uneven Clustering Routing Algorithm Based on Optimal Clustering for Wireless Sensor Networks, *Journal of Communications*, vol.11, no.2, pp.132–142, 2016.

[17] K. P. Ferentinos, T. A. Tsiligiridis, Adaptive design optimization of wireless sensor networks using genetic algorithms, *Computer Networks*, vol.51, no.4, pp.1031–1051, 2007.

[18] Y. Wang, X. SHAN, Y. Sun, Study on the application of Genetic Algorithms in the optimization of wireless network, *Procedia Engineering*, vol.16, pp.348–355, 2011.

[19] S. He, Y. Dai, R. Zhou, S. Zhao, A Clustering Routing Protocol for Energy Balance of WSN based on Genetic Clustering Algorithm, In *Proceedings of CSEDU*, 2012.

[20] J. Li, X. Jiang, and I. T. Lu, Energy Balance Routing Algorithm Based on Virtual MIMO Scheme for Wireless Sensor Networks, *Journal of Sensors*, [Online]. vol.2014, Available: http://dx.doi.org/10.1155/2014/589249.

[21] J. Li, X. Jiang, and X. Zhu, LEACH routing algorithm based on energy consumption equalization for WSN, *Process Automation Instrumentation*, vol.35, no.1, pp.51–54, 2014.

[22] P. C. Li, K. P. Song, F. H. Shang, Double chains quantum genetic algorithm with application to neuro-fuzzy controller design, *Advances in Engineering Software*, vol.42, no.2, pp.875–886, 2011.