Quantum Genetic Energy Efficient Iteration Clustering Routing Algorithm for Wireless Sensor Networks

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Abstract—Hierarchical routing algorithm as an energy optimization strategy has been widely considered as one of the effective ways to save energy for wireless sensor networks. In this paper, we propose a quantum genetic energy efficient iteration clustering routing algorithm (QGEEIC) for wireless sensor networks. To select the optimum cluster heads, the algorithm takes into account the balance of energy consumption by proposing an cluster selection method based on energy efficient iteration. 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 the superiority in terms of network lifetime, the number of alive nodes, and the total energy consumption.

Index Terms—Wireless sensor networks, energy optimization strategy, quantum genetic algorithm, iteration routing algorithm, routing algorithm

I. Introduction

Wireless Sensor Networks (WSN) typically consist of a large number of energy-constrained sensor nodes with limited onboard battery resources which form a dynamic multi-hop network. In a lot of applications supported by wireless sensor networks, node energy is difficult to renew [1]. Therefore, energy optimization is a critical issue in the design of wireless sensor networks [2]-[4].

At present, many techniques have been proposed to improve the energy efficiency in energy-constrained and distributed wireless sensor networks. These techniques include energy optimization strategy based on node transmission power, such as common power (COMPOW) protocol [5]; energy optimization strategy based on routing protocol, such as low energy adaptive clustering hierarchy (LEACH) protocol [6]; energy optimization strategy based on medium access control (MAC) protocol, such as sensor MAC (SMAC) protocol [7]; energy optimization strategy based on data fusion, such as maximum lifetime data gathering with aggregation (MLDA) algorithm [8]; energy optimization strategy based on node sleeping scheme, such as dynamic balanced-energy sleep scheduling scheme [9]. Among these techniques, energy efficiency routing protocol has been widely considered as one of the most effective ways to save energy. Existing routing protocols can be generally divided into two categories: flat routing and hierarchical routing. Flat routing protocol is easy to implement, without additional cost of topology maintenance and packet routing. However, it has several shortcomings such as message implosion, overlay, and resource blindness [1]. Hierarchical routing protocol, also known as clustering routing protocol, such as LEACH protocol [6] and hybrid energy-efficient distributed clustering (HEED) protocol [10], has proposed the methods that using cluster heads to form the clusters. Researches show the hierarchical routing protocol is better than flat routing protocol in adaptability and energy efficiency.

LEACH protocol is one of the most popular hierarchical routing protocols for wireless sensor networks. The whole network is divided into several clusters. The cluster head node is used as a router to base station. All members in cluster transmit their data to the cluster head. The cluster head aggregates and compresses all the received data and sends them to the base station. The operation of LEACH is divided into rounds. Each round includes a set-up phase and a steady-state phase. In set-up phase, each node has the equal probability to become a cluster head randomly by using a distributed algorithm. Based on the received signal strength of the advertisement from each cluster head, each non-cluster head node determines its cluster in this round. It chooses the cluster head as minimum communication energy. The cluster head node sets up a time division multiple address (TDMA) schedule and transmits this schedule to the nodes in cluster. This method ensures that there are no collisions among data messages and allows the radio components of each non-cluster head node to be turned off at all times except during their transmission period. In steady-state phase, the time is divided into frames. Nodes send their data to the cluster head at most once per frame during their allocated transmission slot. Non-cluster head nodes send the collected data to the cluster head node. Once the cluster head receives all the data, it performs data aggregation and sends them to the base station directly. Compared with flat multi-hop routing algorithm and static hierarchical algorithm, the network lifetime of LEACH can be prolonged by 15%. However, there are also some shortcomings. The residual energy of node is not taken into consideration during the cluster head

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selection. Uneven distribution of cluster heads and cluster sizes, due to the random cluster head selection mechanism, 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, which are far away from the base station. So the lifetime of the whole network will be affected.

To avoid uneven distribution problem of cluster heads and cluster sizes in LEACH, references [11] and [12] propose LEACH-C (LEACH-Centralized) and LEACH-F (LEACH with Fixed clusters) algorithm. However, both of them are centralized based approaches and not suitable for large-scaled networks. To avoid cluster heads premature death in LEACH, reference [13] proposes V-LEACH algorithm. V-LEACH is a new version of LEACH protocol to reduce energy consumption. The main concept behind V-LEACH is that, besides having a cluster head in the cluster, there is a vice-cluster head that takes the role of the cluster head when the cluster head dies. So cluster nodes can send data to the base station without the need to select a new cluster head each time, which can prolong network lifetime. But the protocol can't solve uneven distribution problem of cluster heads and cluster sizes. To avoid cluster head premature death, reference [14] proposes a new threshold including the node energy, the distance between node and base station, the distance between cluster head and base station. Simulation results show that the algorithm is better in balancing the node energy and prolonging the network lifetime. Reference [15] proposes an improved LEACH algorithm, in which residual energy and distance between node and base station are considered as parameters to select cluster head. To save energy, the authors proposes to start the steady-state operation of a node only if the value sensed by a node is greater than the predetermined threshold value. The threshold value will be set by the terminal user at the application layer. Reference [16] presents a new protocol called Low Energy Adaptive Tier Clustering Hierarchy (LEATCH), which offers a good compromise between delay and energy consumption. The two level hierarchical approach has been proposed. Every cluster is divided into small clusters called Mini Clusters. For each Mini Cluster, the authors define a Mini Cluster Head (MCH). In addition, the algorithm improves the procedure of cluster head and mini cluster head election. Reference [17] proposes M-LEACH algorithm, a multi-hop version of the LEACH protocol. It outperforms the single-hop version of the protocol.

All improved protocols based on LEACH presented above can't solve the uneven distribution problem of cluster heads and cluster sizes. Reference [10] proposes HEED protocol. However, the clustering process requires a number of iterations. During each iteration, a node becomes a cluster head with a certain probability which considers the mixture of energy, communication cost, and average minimum reachability power (AMRP). All other nodes, which are not cluster heads, select the cluster head which has the lowest intra-cluster communication cost and directly communicate with cluster heads. Unlike LEACH, HEED creates well-balanced clusters. It has more balanced energy consumption and longer network lifetime. To achieve a longer network lifetime and better cluster formation than HEED protocol, reference [18] presents a distributed dynamic clustering protocol based on HEED which exploits non-probabilistic approach and Fuzzy Logic (HEED-NPF). In this protocol, cluster head selection is finished by Fuzzy Logic which uses node degree and node centrality as input parameters. The output is the Fuzzy cost. Every node selects the cluster head with least cost and join it. Non-probabilistic cluster head selection is implemented through introducing delay, which is inversely proportional to residual energy for each node. Consequently node with more residual energy has more chance to become cluster head. The approach is more effective in prolonging the network lifetime than HEED and provides better cluster formation in the field.

To avoid "hot spot" problem, reference [19] 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. At the same time the authors expand this approach to homogeneous sensor networks. The simulation results show that UCS model can lead to more uniform energy consumption in a homogeneous network as well. However, the assumptions in UCS are not in accordance with the actual situation. Reference [20] proposes and evaluates an Energy-Efficient Unequal Clustering (EEUC) mechanism for periodical data gathering applications in WSN. It wisely organizes the network via unequal clustering and multi-hop routing. EEUC is a distributed competitive algorithm. Unlike LEACH and HEED, the cluster heads are selected by localized competition without iteration. The competition range of the node decreases with decreasing distance to the base station.The node's competition range decreases as its distance to the base station decreasing. The result is that clusters closer to the base station are expected to have smaller cluster sizes. They will consume lower energy during the intra-cluster data processing and preserve more energy for the inter-cluster relay traffic. In the proposed multi-hop routing protocol for inter-cluster communication, a cluster head chooses a relay node from its adjacent cluster heads according to the node's residual energy and its distance to the base station. Simulation results show that EEUC successfully balances the energy consumption over the network and achieves a remarkable network lifetime improvement. The fuzzy energy-aware unequal clustering algorithm (EAUCF) [21] aims to decrease the intra-cluster work for the cluster heads which are either close to the base station or have low remaining power.

In order to optimize the clustering parameters, genetic algorithm is used as the multi-objective optimization methodology [22]. 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 [23]. 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 [24] 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 energy efficient iteration clustering routing algorithm (QGEEIC) for wireless sensor networks. The rest of this paper is organized as follows. In Section II, considering the residual energy and distance between node and base station, we select the optimum cluster heads according to factor value. At the same time, the related parameters are optimized by quantum genetic algorithm. In Section III, shows the simulation and numerical analysis. Final conclusion remarks are made in section IV.

II. Quantum Genetic Energy Efficient Iteration Clustering Routing Algorithm

A. The Cluster Head Selection Based on Energy Efficient Iteration

In clustering phase, the cluster heads are selected based on energy efficient iteration. The node with maximum residual energy will become cluster head in its communication range. After several times of iteration, all selected cluster heads will be the nodes with maximum residual energy in their communication range.

The steps of the energy efficient iteration clustering are described as the following.

1) Calculating the optimal number of clusters

In the set-up phase, we need the optimal number of clusters which can be obtained by using energy model. A radio model proposed in LEACH [6] is shown in Fig. 1.

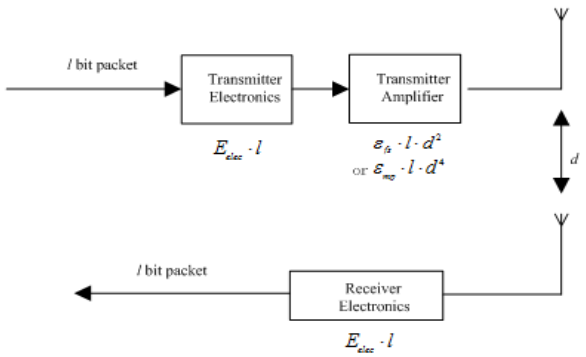

Fig. 1. The radio energy consumption model

where E_{elec} is the transmitter energy consumption per bit, l is the number of bits, ε_{fs} is proportional constant of the energy consumption for the transmit amplifier in free space channel model ($\varepsilon_{fs} l d^2$ power loss), ε_{mp} is proportional constant of the energy consumption for the transmitter amplifier in multipath fading channel model ($\varepsilon_{mp} l d^4$ power loss), the distance between transmitter and receiver is d , the transmitter energy consumption to run the transmitter or receiver circuitry is $E_{elec} l$, the energy consumption in transmitter amplifier is $\varepsilon_{fs} l d^2$ or $\varepsilon_{mp} l d^4$.

In this model, the free space channel model and multipath fading channel models are used, which depend on the distance between transmitter and receiver. If the distance is less than a threshold, the free space model is used; otherwise, the multipath fading channel model is used.

Assume there are N nodes distributed uniformly in an $M \times M$ region. There are k clusters, each has N/k nodes in average (one cluster head node and $N/k-1$ non-cluster head nodes). Since the base station is far from the nodes, we can assume that the energy consumption follows the multipath fading channel model. Therefore, the energy consumption of a cluster head in a round can be obtained as

$$E_{CH} = l\left[\left(\frac{N}{k}-1\right)E_{elec} + \frac{N}{k}E_{DA} + f_{agg}\left[\varepsilon_{mp}E\left(d_{toBS}^4\right) + E_{elec}\right]\right] \quad (1)$$

where E_{DA} is the energy consumption for data fusion per bit, d_{toBS} is the distance between node and base station, $E\left(d_{toBS}^4\right)$ is the expectation of d_{toBS}^4 , f_{agg} is fusion rate .The energy consumption of the cluster head includes the energy consumed by data transmission in the cluster, data compression, and sending data to the base station.

Each non-cluster head node only needs to transmit its data to the cluster head once during a frame. Assume the distance to the cluster head is small, the energy consumption follows the free space channel model. The energy consumption of a non-cluster head node in a round can be obtained as

$$E_{NCH} = l\left[E_{elec} + \varepsilon_{fs}E\left(d_{toCH}^2\right)\right] \quad (2)$$

where d_{toCH} is the distance between the node and the cluster head, $E(d_{toCH}^2)$ is the expectation of d_{toCH}^2 . In each frame, all the nodes expend

$$\begin{aligned} E_{total} &= k\left[E_{CH} + \left(\frac{N}{k}-1\right)E_{NCH}\right] \\ &= lk\left\{\left(\frac{N}{k}-1\right)E_{elec} + \frac{N}{k}E_{DA} + f_{agg}\left[\varepsilon_{mp}E\left(d_{toCH}^4\right) + E_{elec}\right]\right. \\ &\left. + \left(\frac{N}{k}-1\right)[E_{elec} + \varepsilon_{fs}d_{toCH}^2]\right\} \\ &\approx l\left\{NE_{elec} + NE_{DA} + kf_{agg}\left[\varepsilon_{mp}E\left(d_{toCH}^4\right) + E_{elec}\right]\right. \\ &\left. + N\left[E_{elec} + \varepsilon_{fs}\frac{M^2}{2\pi k}\right]\right\} \end{aligned} \quad (3)$$

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

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

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

2) Selecting cluster head by iteration

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. There are two kinds of algorithms to choose cluster heads, random probability selection as LEACH and probability iteration selection as HEED. The selection probability for the ith node to become a cluster head in LEACH [6] is given by

$$P_L(i) = \begin{cases} \dfrac{k/N}{1-\dfrac{k}{N}\left[R \bmod \left(N/k\right)\right]} & i \in G \\ 0 & \text{other} \end{cases} \tag{5}$$

where k is the optimal cluster number, G is the set of nodes that have not been selected as cluster heads in the last $R \bmod N/k$ rounds. The distribution of cluster heads and cluster sizes are uneven because the cluster heads are selected randomly. HEED protocol [10] takes residual energy and AMRP into consideration. The probability for the ith node to become a cluster head is given by

$$P_H(i) = \max\left(\frac{k}{N}\frac{E_{res}}{E_{\max}}, p_{\min}\right) \tag{6}$$

where k/N is the rate of the optimal cluster number to the node number, E_{res} is the estimated node residual energy and $E_{\max}$ is a reference maximum energy (corresponding to a fully charged battery), which is typically same for all nodes. The $P_H(i)$, however, is not allowed to fall below a certain threshold p_{min} (e.g. 10^{-4}). p_{min} is inversely proportional to $E_{\max}$.

HEED only take the residual energy and AMRP into consideration while choosing the cluster heads. More factors such as initial energy, distance between node and base station, node degree, and average energy consumption should be considered.

In the energy efficient iteration clustering routing algorithm, a packet containing the residual energy value of node will be broadcasted in one iteration. After receiving the packet, the node will make a table that includes the ID number of the broadcasting nodes, their residual energy, and the own residual energy. Then the algorithm selects the best node with the maximum factor value in the table as a temporary cluster head. The factor function is defined as

$$F = \eta_1 \cdot f_{RED} + (1\text{-}\eta_1) \cdot f_{BSD} \tag{7}$$

where η_1 is a constant coefficient. It will be optimized by quantum genetic algorithm. $f_{RED} = E_{res}/E_{\max}$ is the energy factor. $f_{BSD} = d_{toBS}/d_{toBS\_MAX}$ is the distance factor. E_{res} is the residual energy of node. $E_{\max}$ is the reference maximum energy. d_{toBS} is the distance between node and base station. d_{toBS_MAX} is the distance maximum value between all the nodes and base station.

The node will become a temporary cluster head if its factor value is the maximum one in its table. Then it broadcasts cluster head message including the broadcasting radius. The nodes that received the cluster head message will join the cluster established by the temporary cluster head.

3) Clustering phase

When the iteration is over, all temporary cluster heads broadcast cluster head messages again. The other nodes decide which cluster they should join by the received message and the distance to cluster heads.

4) Steady-state phase

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 by routing path.

B. Parameters Optimization Based on Quantum Genetic Algorithm

Genetic Algorithm (GA) is based on the process of biological evolution and natural selection. GA is a direct search method based on probability. In the very weak condition, the algorithm converges probability to the optimum. By increasing the iteration number, the probability of the optimum tends to 1. At each step, one of the individuals is selected randomly from the current population. This individual becomes a parent that produces the children for the next population. After some steps, the population starts to evolve towards an optimal solution [27].

Quantum Algorithm (QA) is based on the quantum theory. QA direct uses quantum-mechanical phenomena, such as superposition and entanglement, to perform data operations. Different from digital computation, quantum computation uses quantum bits, which can be in superposition of states. QA solves problems faster than classical algorithms.

Quantum Genetic Algorithm (QGA), is a probability optimization algorithm combining GA and 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 [28]. 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.

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

$$|\phi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{8}$$

where the pair of α and β 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

$$\begin{bmatrix} \alpha \\ \beta \end{bmatrix} = \begin{bmatrix} \cos\varphi \\ \sin\varphi \end{bmatrix} \tag{9}$$

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

The chromosome in our quantum genetic algorithm is coded as

$$p_i = \begin{bmatrix} \cos(t_{i1}) & \cos(t_{i2}) & \cdots & \cos(t_{in}) \\ \sin(t_{i1}) & \sin(t_{i2}) & \cdots & \sin(t_{in}) \end{bmatrix} \tag{10}$$

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 2 parameters in the new clustering routing algorithm. Considering the above conditions, m is set to 16, n is set to 2. The chromosome is encoded as

$$p_i = \begin{bmatrix} \alpha_{i1} & \alpha_{i2} \\ \beta_{i1} & \beta_{i2} \end{bmatrix} = \begin{bmatrix} \cos(t_{i1}) & \cos(t_{i2}) \\ \sin(t_{i1}) & \sin(t_{i2}) \end{bmatrix} \tag{11}$$

where $\begin{bmatrix} \alpha_{i1} \\ \beta_{i1} \end{bmatrix}$ represents parameter η_1. $\begin{bmatrix} \alpha_{i2} \\ \beta_{i2} \end{bmatrix}$ 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 $[\alpha_{ij}, \beta_{ij}]^T$, the corresponding variables in solution space Ω can be computed as

$$\begin{aligned} X_{ic}^{j} &= \frac{1}{2}[A_{\min}(1+\alpha_{ij}) + A_{\max}(1-\alpha_{ij})] \\ X_{is}^{j} &= \frac{1}{2}[A_{\min}(1+\beta_{ij}) + A_{\max}(1-\beta_{ij})] \end{aligned} \tag{12}$$

where $A_{\min} = 0.2$, $A_{\max} = 0.99$ for coefficient η_1 in $E_{res}/E_{\max}$, $A_{\min} = 35$, $A_{\max} = 86$ for parameter R_L.

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

$$f(r) = \exp(-E_{avecon}(r)/E_{\max}) \tag{13}$$

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) Evolving into the next generation group by improved self-adaptation quantum rotation gate

When Q-gate is

$$U(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \tag{14}$$

The quantum bit in next generation will be

$$\begin{bmatrix} \overline{\alpha} \\ \overline{\beta} \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} \cos\varphi \\ \sin\varphi \end{bmatrix} = \begin{bmatrix} \cos(\theta+\varphi) \\ \sin(\theta+\varphi) \end{bmatrix} \tag{15}$$

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

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

$$\theta = -\mathrm{sgn}(\mathrm{A}) \cdot \theta_0 \cdot \exp\left(-\frac{|\nabla f(r)| - \nabla f_{\min}}{\nabla f_{\max} - \nabla f_{\min}}\right) \cdot \exp\left(-\frac{r}{r_{\max}}\right) \tag{16}$$

where A is defined as

$$A = \sin(\theta - \theta_{opt}) \tag{17}$$

and θ_{opt} is the probability amplitude of a quantum bit in the global optimum solution, θ is the probability

amplitude of the corresponding quantum bit in the current solution. θ_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

$$\nabla f_{\min} = \min\left\{\left|\frac{f(80)-f(0)}{x(80)-x(0)}\right|, \left|\frac{f(81)-f(1)}{x(81)-x(1)}\right|, \cdots, \frac{f(r)-f(r-80)}{x(r)-x(r-80)}\right\} \quad (18)$$

$$\nabla f_{\max} = \max\left\{\left|\frac{f(80)-f(0)}{x(80)-x(0)}\right|, \left|\frac{f(81)-f(1)}{x(81)-x(1)}\right|, \cdots, \frac{f(r)-f(r-80)}{x(r)-x(r-80)}\right\} \quad (19)$$

where $x(r)$ represents the vectors η_1 or 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 (14) respectively.

Where $r_{\max}$ is the maximum number of rounds for evolution.

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 (3) and repeats the procedure of iteration.

III. Simulation and Numerical Analysis

In NS2, we distribute randomly 100 nodes ($N = 100$ in (1)-(6)) in the area of $100 \times 100m^2$ ($M = 100m$ in (3) and (4)). The initial energy of all the sensor nodes are equal ($E_{\max} = 2$ J in (6) and (7)). In (1)-(4), $f_{agg} = 1$, $\varepsilon_{fs} = 10$ pJ/bit/m^2, $\varepsilon_{mp} = 0.0013$ pJ/bit/m^4, $E_{elec} = 50$ nJ/bit. In (6), $p_{\min} = 0.0005$ [6], [10], [12], [20], [25], [26].

Fig. 2 shows the maximum value of fitness for 16 individuals in QGEEIC. The simulation results show that the maximum fitness is 0.98 at 194th round.

Fig. 3 shows the value of fitness in each round for 16 individuals in QGEEIC. The simulation results show that the fitness curve grows variably, but the value of fitness will recover to the best after the fluctuations.

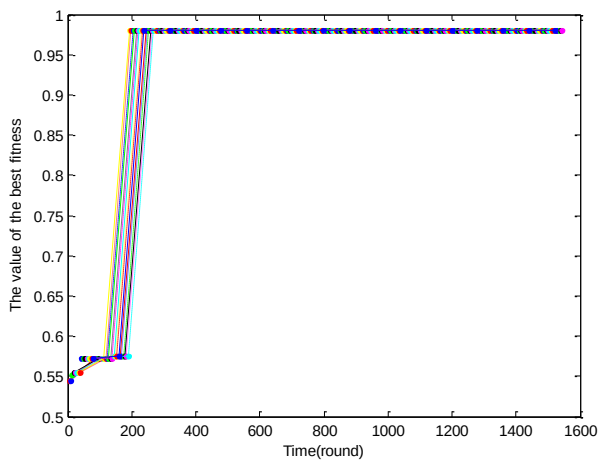

Fig. 2. The maximum value of fitness for 16 individuals in QGEEIC

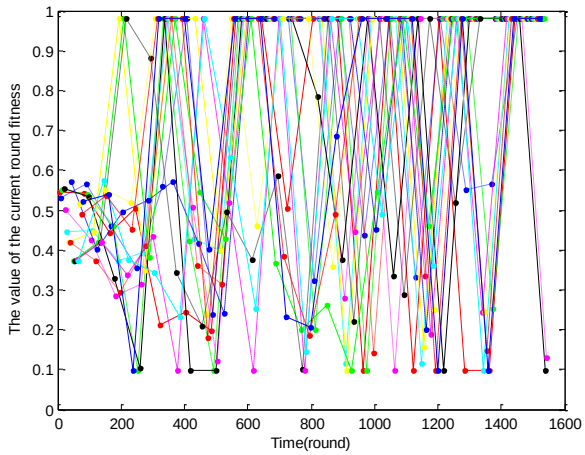

Fig. 3. The value of fitness in each round for 16 individuals in QGEEIC

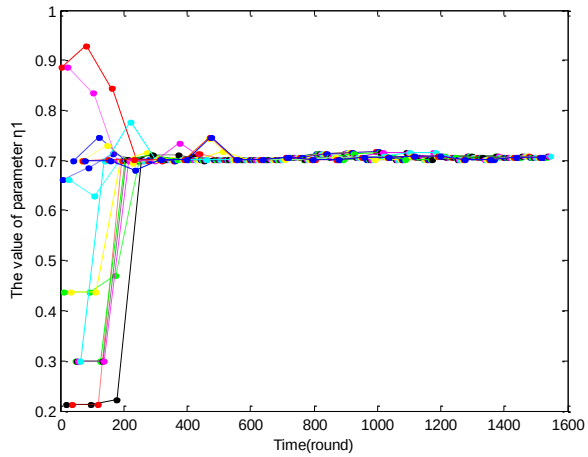

Fig. 4. The value of η_1 in each round for 16 individuals in QGEEIC

Fig. 4 shows, for cluster head selection, the value of η_1 in each round for 16 individuals in QGEEIC. The simulation results show that the value of η_1 is 0.6998 at 194th round when the value of fitness is maximum.

Fig. 5 shows, for cluster radius calculation, the value of R_L in each round for 16 individuals in QGEEIC. The simulation results show that the value of R_L is 62.73 at 194th round when the value of fitness is maximum.

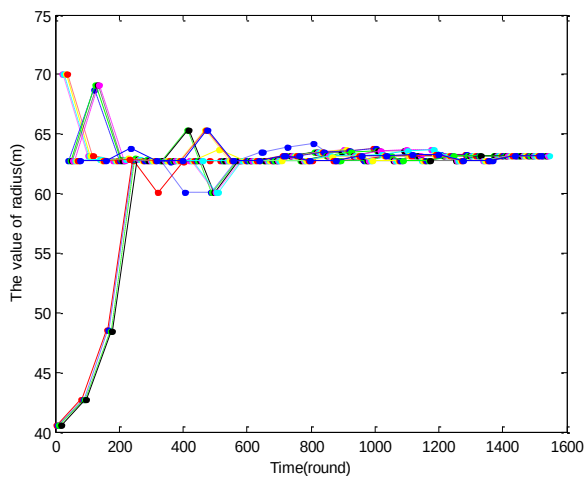

Fig. 5. The value of R_L in each round for 16 individuals in QGEEIC

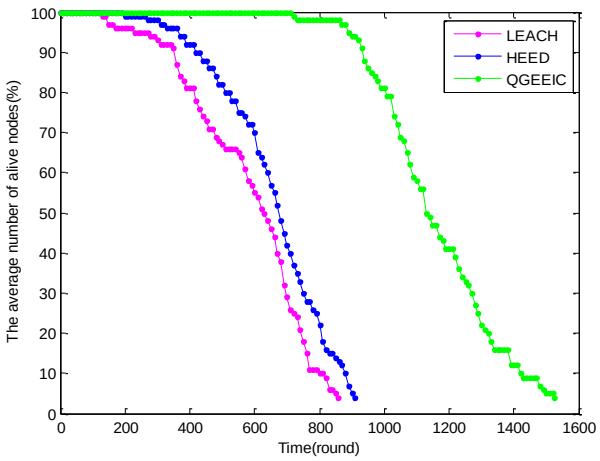

Fig. 6. The average number of alive nodes in LEACH, HEED, and QGEEIC

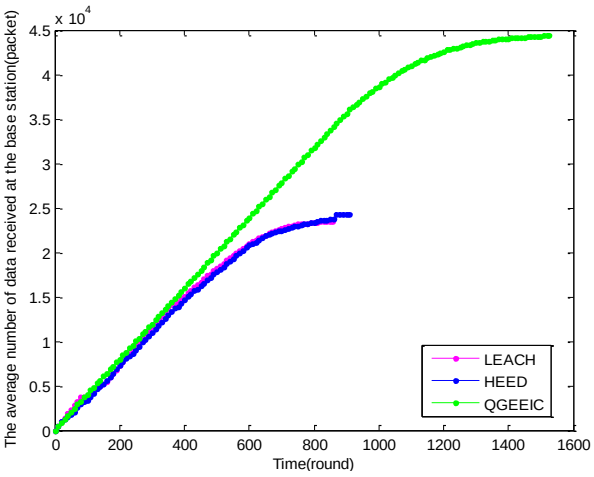

Fig. 7. The average number of data received at the base station in LEACH, HEED, and QGEEIC

Fig. 6 shows the average number of alive nodes in LEACH ($k=4$), HEED and QGEEIC. The simulation results show the time that the first node dies is about 710th round in QGEEIC, which is prolonged by 492.4% than that in LEACH ($k=4$) and 71.8% than that in HEED. The time that the network no longer provides acceptable quality results is about 1520th round in QGEEIC, which is prolonged by 76.9% than that in LEACH ($k=4$) and 40.1% than that in HEED. So QGEEIC has the superiority in terms of network lifetime and the number of alive nodes.

Fig. 7 shows the average number of data received at the base station in LEACH ($k=4$), HEED and QGEEIC. The simulation results show that the number of data received at the base station in QGEEIC is 88.9% and 45.2% more than that in LEACH and HEED respectively.

Fig. 8 shows the average total energy consumption in LEACH ($k=4$), HEED, and QGEEIC. The simulation results show that the total energy consumption in QGEEIC grows more slowly than that in LEACH and HEED. The average energy consumption in QGEEIC for each round decreases by 45.00% and 40.21% than that in LEACH and HEED respectively. So QGEEIC has the superiority in terms of network lifetime and the total energy consumption.

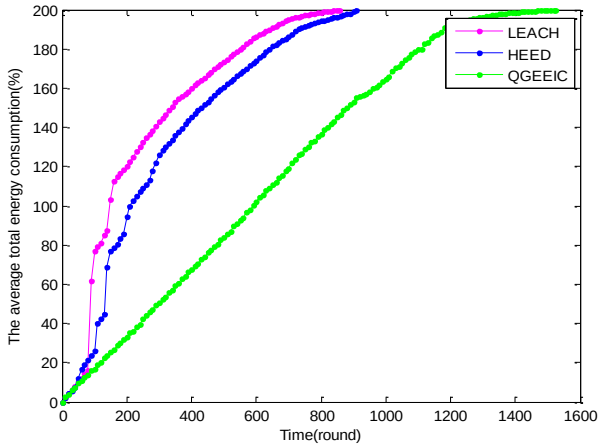

Fig. 8. The average total energy consumption in LEACH, the HEED and QGEEIC

IV. Conclusion

In this paper, we propose a quantum genetic energy efficient iteration clustering routing algorithm (QGEEIC) for wireless sensor networks. QGEEIC includes the cluster head selection based on energy efficient iteration and parameters optimization based on quantum genetic algorithm. The clustering parameters are optimized by quantum genetic algorithm based on double-chain encoding method. The experiment results show the time that the first node dies is prolonged by 492% than that in LEACH and 71.8% than that in HEED. The time that the network no longer provides acceptable quality results in QGEEIC is prolonged by about 76.9% than that in LEACH and 40.1% than that in HEED. The number of data received at the base station in QGEEIC is more than that in LEACH and HEED. The total energy consumption in QGEEIC algorithm grows more slowly than that in LEACH and HEED. All these show the QGEEIC algorithm has the superiority in terms of network lifetime, the total energy consumption, the number of alive nodes, and data transmission.

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