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CLUSTER HEAD SELECTION OPTIMIZATION IN WIRELESS SENSOR NETWORK VIA GENETIC-BASED EVOLUTIONARY ALGORITHM

Vincent Chung[1], Hamzarul Alif Hamzah[2], Norah Tuah[3], Kit Guan Lim[4], Min Keng Tan[5] and Kenneth Tze Kin Teo[6]

[1,2,4,5,6]*Modelling, Simulation and Computing Laboratory, Faculty of Engineering, Universiti Malaysia Sabah, Malaysia*
[3]*Faculty of Computer Science and Mathematics, Universiti Teknologi MARA, Malaysia*

Abstract

Wireless sensor network (WSN) is an embedded system comprises of spatially distributed sensor nodes where an energy-efficient mechanism is needed to prolong the network lifetime. Existing approaches for this optimization problem have several drawbacks, including non-adaptive network configuration that may cause premature death of sensor nodes. Genetic-based evolutionary algorithms such as Genetic Algorithm (GA) and Differential Evolution (DE) have been popularly used to optimize cluster head selection in WSN to improve energy efficiency for the extension of network lifetime. Therefore, the performances of GA and DE are evaluated through comparative analysis to determine their efficiency in cluster head selection optimization. Simulation results show that GA outperforms DE with higher round number for first node dies (FND) but lower round number for last node dies (LND) in terms of network lifetime. Besides, GA also leads to a network with lower number of transmission failures than DE. On the other hand, fitness convergence of GA is slower but it has higher fitness value of population.

Keywords:

Brent's Method, Optimal Power Allocation, Ant Colony Optimization, Secrecy Rate

1. INTRODUCTION

Wireless sensor networks (WSN) has become an essential part of many applications over the past decade [1]. Nowadays, WSN has gained importance and has been focused by many researchers due to the application system in many industrial and consumer applications [2]. Normally, WSN is made up of numerous low-cost sensing devices. It consists of a set of nodes in which every node has its own functions. These nodes can be functioned as a receiver, a transmitter, a sensor or a processor. They are portable and small in size, at the same time do not require large processing unit. All these sensor nodes are used for data collection in a particular area and the data are sent to a base station (BS). Thus, WSN offers wide range of applications in intelligent buildings, medicine, preventive maintenance, biodiversity mapping, precision-agriculture and so on [3].

In 1900s, Defense Advanced Research Project Agency (DARPA) at United States had carried out a series of WSN researches [4]. Due to the technology limitation at that time, development of small size sensor node is a challenging task. Recent advancement in micro-electro-mechanical system (MEMS) has led to the emergence of WSN. The advanced MEMS technology has significantly reduced the size and development cost of a sensor node. WSN has shown wide range of potential applications, therefore various studies have been carried out to improve the constraints of WSN. These constraints include scalability, reliability and energy efficiency.

Sensor nodes are deployed over the area of interest to continuously monitor the physical phenomena for a few months or even a year [5]. This would demand the sensors to have large battery capacity to support their long-time operation. In other words, WSN is strongly dependent on the battery life of the sensor nodes [6]. Besides, WSN is usually applied in remote area where it is hard to recharge the battery, such as battlefield and unexplored jungle. Thus, limited network lifetime is a serious issue in WSN system.

Several conventional routing protocols had been proposed for energy efficiency optimization in WSN. The function of a routing protocol is to manage the network traffic, so that it can provide data transmission with higher energy efficiency. One of the well-known routing protocols is the low-energy adaptive clustering hierarchy (LEACH). It is a communication protocol that divides sensor nodes into different clusters with a cluster head in each cluster [7]. Nevertheless, these conventional routing protocols have a common drawback, which is the non-adaptive network configuration due to the lack of global information during decision-making. Randomized cluster head placement without the consideration of global information may lead to uneven cluster head placement that causes inefficient clustering network [8].

In WSN, cluster head selection optimization is essential to increase the energy efficiency. However, a lot of parameters need to be taken into consideration to achieve effective optimization. Thus, evolutionary algorithm plays an important role in solving this issue because it can solve complex problem adaptively in polynomial time. Based on the reviews, genetic-based evolutionary algorithms such as Genetic Algorithm (GA) and Differential Evolution (DE) are suiTable.to optimize the cluster head selection process. GA has outperformed Particle Swarm Optimization (PSO) in terms of energy efficiency and fitness value although its execution time is slightly longer [9]. This is further proved through a statistical analysis [10]. The analysis showed that GA has higher number of alive nodes than swarm intelligence-based evolutionary algorithms such as Cuckoo Search (CS) and PSO. Therefore, the efficiencies of GA and DE in optimizing cluster head selection are analyzed in this work.

This paper is organized as follows: section 2 discusses the review of cluster head selection optimization algorithms. Section 3 introduces the network model which will be implemented as the testbed to evaluate the robustness of GA and DE. Section 3 explains the development of GA and DE in optimizing cluster head selection, including their genetic operators in metaheuristic optimization. Section 4 presents the parameter settings used in this work. Section 5 discusses the performance evaluations of GA and DE in terms of network lifetime, residual energy, transmission failure and fitness consumption. Section 6 summarizes the findings of this work and provides a recommendation on future study.

2. LITERATURE REVIEW

Many optimization algorithms for cluster head selections had been studied. Among these algorithms, LEACH routing protocol and genetic-based evolutionary algorithms are popularly used. LEACH routing protocol is the most common routing protocol in WSN. Cluster heads are randomly selected with the condition that each sensor node can only be selected as cluster head once in a cycle for equal distribution of workload. LEACH routing protocol also applies time-division multiple access (TDMA) to avoid data collision. It is a powerful and simple routing protocol, but it faces a few drawbacks. For example, selection of cluster head in any round is random and does not consider information like residual energy, geographical location and cluster head number, which can lead to inefficient transmission. This routing protocol also cannot be used in large-scale network as single-hop transmission is used between cluster heads and BS.

An improved LEACH routing protocol based on energy-consumption optimization (LEACH-EO) was proposed [11]. The cluster head selection is improved by introducing residual energy of sensor node into the LEACH threshold function. However, it faces the issue of uneven cluster head placement as energy-LEACH routing protocol does not consider the location information. Meanwhile, data redundancy of WSN is exploited to optimize the data transmission according to the characteristics of WSN. Sensor nodes that have collected data similar to previous round do not need to forward the data to reduce communication traffic. This can be helpful in reducing the energy consumption, but it is achieved with certain expense of data accuracy.

A modified LEACH (MG-LEACH) routing protocol that utilizes the correlated nature of data inside the clusters was proposed to prolong the network lifetime [12]. It divides the sensor nodes into sub-groups according to their locations. The number of sub-groups is depending on the density of sensor nodes. These sub-groups work on alternate basis, so the energy of sensor nodes depletes slower. Meanwhile, MG-LEACH routing protocol includes the information of residual energy in the threshold function of LEACH routing protocol to improve the cluster head selection process. Although MG-LEACH routing protocol does prolong the network lifetime, there are certain drop in data accuracy. Furthermore, single-hop transmission used between cluster heads and BS has low energy efficiency.

GA was developed to form predefined clusters for shortening the total transmission distance [13]. It has decreased the total transmission distance by 80% as compared to single-hop transmission. The number of cluster heads over number of sensor nodes is 10%. This algorithm was extended by improving the fitness function to achieve better performance [14]. Few parameters such as population size, mutation rate and crossover rate are tuned. Results showed the energy consumption has been decreased using this extended GA. Besides, another GA for energy efficient clusters in WSN was proposed [15]. BS is loaded with GA to calculate the suiTable.cluster heads for the network in each round. Fitness parameters used to evaluate the performance of cluster heads are direct distance to sink, cluster distance, transfer energy and number of transmissions. Simulation results indicate that GA-based hierarchical clusters can improve the network lifetime as compared to the conventional cluster-based protocols.

A hybrid GA and artificial bee colony (GA-ABC) was proposed for energy efficient clustering in WSNs [16]. To solve the NP-Hard problem in clusters selection, researchers have been utilizing GA to search for number of clusters and their cluster head placement. ABC is employed into GA to overcome the problem of assigning sensor nodes and which cluster to join. Simulation results demonstrated that the proposed algorithm outperforms LEACH and GA based clustering scheme.

Apart from that, multi-objective two-nested GA (M2NGA) is developed for optimal energy-efficient clustering [17]. The objectives of the algorithm are the optimizations of energy consumption and delay. M2NGA consists of two-layers node clustering. Simulation result showed that M2NGA has less energy consumption per bit and has better performance with increased node number. However, M2NGA has poor performance in dynamic network.

GA-based cluster head selection (GACH) was proposed to optimize communication in WSN [18]. In GACH, distance between sensor nodes and residual energy are the key factors in selecting the cluster head. Average residual energy will be calculated and used as the first condition in cluster head selection. Sensor node with residual energy greater than the average residual energy will be selected as cluster head if it is near to other sensor nodes. After all data are received from the sensor nodes in the cluster, cluster head will communicate with mobile sink (MS) to send data to the appropriate cluster head that is nearer to the destination. Overall, GACH outperforms PSO-based cluster head selection (PSOCH) in terms of throughput, packet delivery ratio and energy efficiency.

To address the shortcomings of traditional LEACH routing protocol, an improved LEACH routing algorithm based on differential evolution (DE) algorithm is developed. It is known as DE-LEACH routing algorithm [19]. The DE-LEACH algorithm takes energy and distance distribution of neighbor nodes inside clusters into account to optimize cluster head selection. The algorithm has advantages in effectively preventing premature blind nodes and reducing network energy consumption. Simulation results proved that this proposed algorithm can avoid blind nodes effectively in normal clustering routing algorithm and improve the life cycle of large scale WSN.

A novel DE based clustering algorithm for WSN named DECA was developed [20] to balance the cluster heads' energy consumption, which is indicated by the rate of residual energy, as energy consumption delays the death of first cluster head. Traditional DE is introduced by a local improvement phase via DECA to help DE based approach converges faster. Simulation results demonstrated that DECA is superior to the traditional DE in terms of network lifetime, energy consumption of network, number of dead sensor nodes and convergence rate.

A switching DE (S-DE) algorithm was proposed for clustering and cluster head selection in WSN [21]. Instead of running the optimization algorithm every round, this algorithm applies switching to select cluster heads based on the residual energy of sensor nodes between specific rounds. DE with switching decreases the complexity of network effectively. This helps to reduce the computation power and time.

Table.1. Summary of the Reviewed Cluster Head Selection Optimization Algorithms

Algorithm	Functionality	Author
LEACH	Utilize randomized cluster head rotation for equal distribution of workload among all the sensor nodes	Heinzelman et al. [7]
LEACH-EO	Introduce the residual energy into the threshold function and reduce communication traffic	Zhang et al. [11]
MG-LEACH	Utilize the correlated nature of data inside the clusters to reduce the communication traffic	Ouldzira et al. [12]
GA	Form predefined clusters to shorten the total transmission distance	Jin et al. [13]
	Tune parameters such as population sizes, mutation probability and crossover probability	Ferentinos et al. [14]
	Utilize the objective functions of direct distance to sink, cluster distance, transfer energy and number of transmissions	Hussain et al. [15]
GA-ABC	Search for number of clusters and their cluster head placement	Mehrjoo et al. [16]
M2NGA	Employ two-layers node clustering to optimize energy consumption and delay	Peiravi et al. [17]
GACH	Choose the node with residual energy greater than average residual energy as cluster head if it is near to other nodes	Palani et al. [18]
DE-LEACH	Takes energy and distance distribution of neighbour nodes inside clusters into account	Li et al. [19]
DECA	Implement an efficient vector encoding scheme and perform a local improvement phase to delay the death of first cluster head	Kuila and Jana [20]
S-DE	Employ switching to select cluster heads based on the residual energy to decrease the network complexity	Gaur and Kumar [21]

Fitness function of S-DE comprises of three objective functions, which are residual energy, distance between cluster heads to BS and total intra-cluster communication distance. This fitness function leads to the generation of better solution, so the energy consumption in network is reduced. In short, S-DE is capable to prolong network lifetime and decrease network complexity. These reviewed cluster head selection optimization algorithms are summarized in Table.1 with a description of their functionalities.

3. NETWORK MODEL

Wireless communication is the main reason for energy dissipation in wireless sensor nodes. Energy usage in wireless communication is far higher than sensing and computing activity [22]. The tasks for the radio module are: transmitting data, listening at idle state and receiving data. It is important to model the network energy consumption by focusing on the radio energy model for each sensor node.

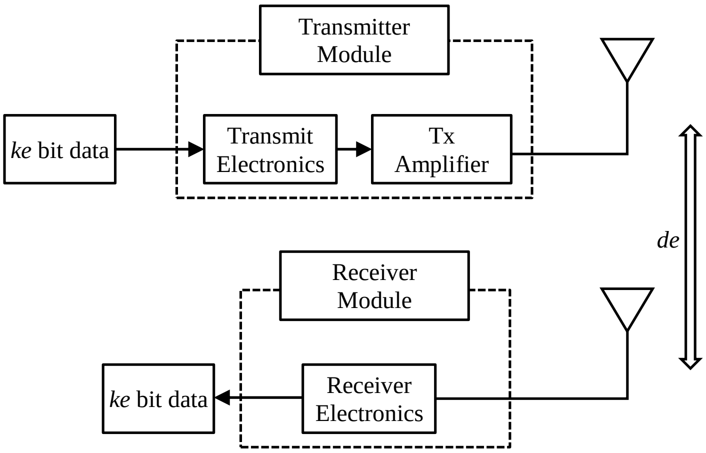

Fig.1. First Order Radio Model

The radio channel used in this work is assumed to be symmetric. For example, the same amount of energy is required to transmit a message from sensor node A to sensor node B and sensor node A to sensor node C with the equal separate distance denoted by *de*.

In order to characterize the energy consumption of wireless communication in WSN, the radio model is implemented into the developed network simulation. The radio model consists of two main components which are the transmitter module and the receiver module as shown in Fig.1 [23].

In the transmitter module, transmit electronics and transmit amplifier are the major causes of energy dissipation. While in the receiver module, receiving data by the receiver module is a not low-cost operation due to the energy drain in the receiver electronics. To transmit *ke* bits of data, the data will go through transmit electronics that convert data from digital signal to analog signal. The converted analog signal will be further amplified by the transmit amplifier for long-range transmission before it reached the antenna. When the receiver antenna receives analog signal, the received analog signal will go through receiver electronics as the data will convert back to the digital data that is understood by its processing unit.

The energy cost to transmit *ke* bits of a data message from the transmitter module to the receiver module and between two sensor nodes separated by a distance of *de* meters is expanded by Eq.(1), where $E_{Tx}(ke,de)$ is overall transmission energy, E_{elec} is electronics energy and $E_{Tx\text{-}amp}(ke,de)$ is transmit amplifier energy [24].

$$E_{Tx}(ke,de)=(ke\times E_{elec})+E_{Tx\text{-}amp}(ke,de) \quad (1)$$

The energy cost to receive *ke* bits of a data message by the receiver module is denoted by Eq.(2), where receiving energy is $E_{Rx}(ke)$ and receiver electronics energy is $E_{Rx\text{-}elec}(ke)$.

$$E_{Rx}(ke) = E_{Rx\text{-}elec}(ke) = ke\times E_{elec} \quad (2)$$

In wireless communication, the communication between nodes will experience energy loss due to channel transmission. However, in the radio model before, $E_{Tx\text{-}amp}(ke,de)$ at transmit amplifier module is assumed to be the minimum energy required by the transmit amplifier to operate and maintain at an acceptable signal-to-noise ratio (SNR). Hence, in order to increase the simulation accuracy, path loss models of free-space and multi-path fading propagations are used. Free space propagation is used for shorter transmission range while the multi-path propagation is used for longer transmission range. The radio energy model in Eq.(3) includes the path loss model [25]. In the path loss model, de is the threshold distance used for swapping amplification models. The threshold distance can be calculated using Eq.(4),

$$E_{Tx}(ke,de) = \begin{cases} ke \times E_{elec} + ke \times \varepsilon_{fs} \times de^2 & if\ de < d_0 \\ ke \times E_{elec} + ke \times \varepsilon_{mp} \times de^4 & if\ de \geq d_0 \end{cases} \quad (3)$$

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (4)$$

where ε_{fs} is the transmit amplifier for free space and ε_{mp} is the transmit amplifier for multi-path.

In clustering protocol, the cluster head transmits only a single packet to the BS instead of the multiple packets collected from cluster members. Data aggregation is the process to combine the multiple packets into a single packet. Data aggregation scheme can reduce the received data size into a single packet. Hence, to model the real situation that cluster head experienced extra works, a data aggregation model is added into cluster head during data transmission to the BS. The data aggregation model together with transmitter module for cluster head can be expressed in Eq.(5) [26], where ke_{DA} is the number of bits subjected to data aggregation and E_{DA} is the energy of data aggregation. The Table.2 shows the involved default parameter values.

$$E_{Tx}(ke,de) = \begin{cases} ke\left(E_{elec} \times \varepsilon_{fs} \times de^2\right) + ke_{DA} \times E_{DA} & if\ de < d_0 \\ ke\left(E_{elec} + \varepsilon_{mp} \times de^4\right) + ke_{DA} \times E_{DA} & if\ de \geq d_0 \end{cases} \quad (5)$$

Table.2. Radio Model Parameter Setting

Operation	Symbol	Value
Electronics Energy	E_{elec}	50 nJ/bit
Transmitter Amplifier	$E_{Tx\text{-}amp}$	100 pJ/bit/m^2
Transmitter Amplifier (Free Space)	ε_{fs}	10 pJ/bit/m^2
Transmitter Amplifier (Multi-Path)	ε_{mp}	0.0013 pJ/bit/m^4
Energy of Data Aggregation	E_{DA}	5 nJ/bit

4. EVOLUTIONARY ALGORITHM

Genetic-based evolutionary algorithm is a search and optimization algorithm based on the principle of natural evolution. In the genetic-based evolutionary algorithm, a population of solutions are modified repetitively, choosing potential solutions as parents to generate new children. At the end of the generation, the population will eventually result in an optimum solution. During the generational process, the variation of operators is implemented to search for a global optimum from a population of possible solutions. The formulated genetic-based evolutionary algorithms are GA and DE. Both algorithms have operators with similar functions. The main difference between GA and DE is the order of these operators. The formulations of GA and DE are demonstrated as follows:

4.1 GENETIC ALGORITHM

GA is a search and optimization algorithm based on the principle of natural evolution [25] [26]. GA originates from the principle of natural selection and survival of the fittest. It evolves a population of initial chromosomes into a population of high-quality chromosomes, in which these chromosomes represent solutions. The operators involved in evolution are selection, crossover, mutation and replacement. These operators work in conjunction with one another to guide the algorithm towards an optimum solution of a given problem.

4.1.1 Selection:

Selection is the operator for parent selection to produce the next generation. Roulette wheel selection (RWS) has been known for its simplest selection scheme in which the chromosomes are mapped to the contiguous segments that resemble a roulette [29]. The size of each segment is associated with their fitness. Thus, the probability of each chromosome to be selected from the roulette wheel can be expressed in Eq.(6). The greater the fitness value of chromosome, the higher the probability for it to be selected. The pseudo-code of RWS algorithm is shown in Algorithm 1.

Probability = Fitness Value of Chromosome / Total Fitness Value of Population (6)

Algorithm 1: Roulette Wheel Sampling Algorithm

Step 1: Roulette Wheel Sampling Algorithm

Step 2: Initialize the population

Step 3: Map the chromosomes in population into contiguous segments

Step 4: Generate a pointer randomly

Step 5: Select the chromosome whose fitness spans the position of pointer

4.1.2 Crossover:

Crossover is the operator analogous to biological crossover. One-point crossover is the most common crossover technique, in which a random crossover point will be selected to decide the gene position for swapping [30]. Through the crossover at this gene position, two offsprings will be generated. However, this crossover between two parents occurs only with a pre-defined crossover probability. If no crossover occurs, the offspring will be the exact same as the parents. The pseudo-code of one-point crossover is given in Algorithm 2.

Algorithm 2: One-Point Crossover Algorithm

One-Point Crossover Algorithm

Step 1: Initialize the crossover probability

Step 2: Select parents from the population

Step 3: If randomly generated probability ≤ crossover probability

a. Generate a random crossover point

b. Perform one-point crossover

Step 4: Else

c. Clone the parents

Step 5: End if

4.1.3 Mutation:

Mutation is the operator used to maintain the diversity in the population. If the mutation probability is too low, premature convergence may occur. Nevertheless, a too high mutation probability may also lead to the difficulty of convergence. Hence, an optimum mutation probability is required. One of the popular mutation techniques is a multi-fit flip mutation, in which a random number of genes are selected for mutation [31]. The selected genes will be bit flipped with a pre-defined mutation probability. The pseudo-code of the multi-bit flip mutation algorithm is given in Algorithm 3.

Algorithm 3: Multi-Bit Flip Mutation Algorithm

Step 2: Initialize the mutation probability

Step 3: Select genes from offspring chromosome

Step 4: For number of selected genes until maximum number of selected genes

a. if randomly generated probability ≤ mutation probability

i. Perform the bit flipping

b. else

i. Maintain the selected gene

c. end if

Step 5: end for

4.1.4 Replacement:

Replacement is the operator used to form a new population. It is the last step in breeding for any GA cycle. Unfit parent replacement is a steady-state replacement technique. With this replacement technique, the fitter chromosomes will replace the parent chromosomes [32]. The pseudo-code of this algorithm is given in Algorithm 4.

Algorithm 4: Weak parent Replacement Algorithm

Step 1: If fitness of trial offspring chromosome > fitness of parent chromosome

a. Replace parent chromosome with offspring chromosome

Step 2: Else

a. Abandon the offspring chromosome

Step 3: End if

4.2 DIFFERENTIAL EVOLUTION

DE is a stochastic optimization algorithm with vector as solution representation [33]. The main operators of DE are mutation, recombination and selection. These operators have similar function with the operators of GA. Recombination and selection have the functions of crossover and replacement.

4.2.1 Mutation:

Mutation operator will first select four vectors from population using the sampling algorithm in Algorithm 5. They are one target vector and three parameter vectors. The parameter vectors are used to generate a donor vector using Eq.(7) [34]. The weighted difference will dwindle as the vectors in population converge.

$$\vec{V}_{i,G} = \vec{X}_{r_1^i,G} + F \cdot \left(\vec{X}_{r_2^i,G} - \vec{X}_{r_3^i,G}\right) \quad (7)$$

where $\vec{X}_{r_1^i,G}$, $\vec{X}_{r_2^i,G}$ and $\vec{X}_{r_3^i,G}$ are the first, second and third parameter vectors respectively, F is the differential weight which is a constant between 0 and 2, and $\vec{V}_{i,G}$ is donor vector.

Algorithm 5: Vector Sampling Algorithm

Initialize the population

Map the vectors in population into contiguous segments

Generate four pointers randomly

Select the four vectors whose fitness spans the positions of pointers

4.2.2 Recombination:

Recombination operator will generate a trial offspring vector by mixing bits from target and donor vectors. This operator is based on Eq.(8) and its pseudo code is given in Algorithm 6 [35],

$$u_{j,i,G} = \begin{cases} v_{j,i,G} & if \left(rand_{i,j}[0,1)\right) \le C_r \ or \ j = j_{rand} \\ x_{j,i,G} & otherwise \end{cases} \quad (8)$$

where $u_{j,i,G}$, $v_{j,i,G}$, $x_{j,i,G}$ are the bits of trial offspring, donor and target vectors respectively, C_r is the crossover probability, and j_{rand} is the number of bits that is chosen randomly between 1 and vector length to avoid an exact clone of target vector.

Algorithm 6: Recombination Algorithm

Step 1: Initialize the crossover probability

Step 2: for number of bits until vector length

Step 3: If randomly generated probability ≤ crossover probability

a. Take the bit from donor vector

Step 4: else number of bits = randomly chosen number of bits

a. Take the bit from donor vector

Step 5: Else if

a. Take the bit from target vector

Step 6: End if

Step 7: End for

4.2.3 Selection:

Selection operator applies the principle of survival of the fitter. The trial offspring vector will replace the target vector only if it is fitter as denoted in Eq.(9) [36]. The pseudo code of selection algorithm is given in Algorithm 7.

$$\vec{X}_{i,G+1} = \begin{cases} \vec{U}_{i,G} & if \ f\left(\vec{U}_{i,G}\right) \ge f\left(\vec{X}_{i,G}\right) \\ \vec{X}_{i,G} & otherwise \end{cases} \quad (9)$$

Where $\vec{U}_{i,G}$ and $\vec{X}_{i,G}$ are the trial offspring and target vectors respectively.

Algorithm 7: Selection Algorithm

Step 1: if fitness of trial offspring vector > fitness of target vector

a. Replace target vector with trial offspring vector

Step 2: else

a. Abandon the trial offspring vector

Step 3: end if

5. PARAMETER SETTING

The BS and sensor nodes are deployed over two-dimensional network topology. In the network topology model development, each sensor node and the BS will be assigned with a specific *x* and *y* coordinate. The distance parameters used in the radio model can be obtained by using Euclidean distance between two points. Given the coordinate for the first sensor node as (x_1, y_1) and the second sensor node as (x_2, y_2) respectively, the Euclidean distance, *d* between both sensor nodes can be calculated using Eq.(10).

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \quad (10)$$

The Table.2 and Table.3 show the parameter settings of WSN and genetic-based evolutionary algorithms respectively.

Table.2. Parameter Settings of WSN

Parameter	Value
Base Station Coordinate	x=-80 m, y=-80 m
Sensor Nodes Number	200
Network Dimension	100 m×100 m
Initial Energy	0.05 J
Bit Number	1000 bits

Table.3. Parameter Settings of GA and DE

Parameter	Symbol	Value
Generation Number	G_n	1000
Population Size	P	50
Crossover Probability	Cr	0.9
Mutation Probability	M_r	0.3
Differential Weight	F	2

6. RESULTS AND DISCUSSION

In the formulations of GA and DE, the cluster head selection mechanism of the improved LEACH routing protocol is integrated into the population initializations of both algorithms to initialize a fitter population. This is important as it will lead to a faster fitness convergence of population with higher fitness value. In evolutionary algorithm, higher fitness value indicates higher quality of solution in solving a specific optimization problem. The evaluation and assessment of both algorithms are conducted through the comparative analysis in terms of network lifetime, residual energy, transmission failure and fitness convergence. Based on the results summarized in Table.4, GA outperforms DE with higher round number for first node dies (FND), lower number of transmission failures and higher fitness value of population upon convergence, although the round number for last node dies (LND) is lower with GA.

Table.4. Simulation Results of GA and DE

Algorithm	GA	DE
FND (round)	205	15
LND (round)	558	629
Number of Transmission Failures	798	901
Convergence Speed (generation)	568	151
Fitness Value of Population	957.5	816.8

6.1 NETWORK LIFETIME

The Fig.2 illustrates the network lifetime of WSN with GA and DE by showing the number of alive sensor nodes.

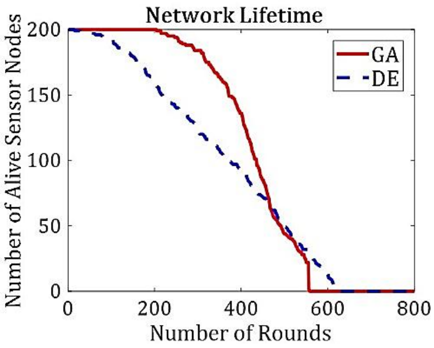

Fig.2. Network Lifetime

As compared to DE, GA delivers higher round number for FND but 11.29% lower round number for LND. FND is the one desired as WSN requires all sensor nodes to be cooperative to achieve the common objectives. Higher round number for FND indicates longer stability period. GA gives longer stability period than DE because its obtained fitness value of population is higher with better ability in searching the solution space. The lower round number for FND and higher round number for LND with DE indicates that it causes longer instability period. This is because the workload is not equally distributed but concentrated on some sensor nodes. By contrast, the workload is more equally distributed among all alive sensor nodes with GA.

6.2 RESIDUAL ENERGY

The Fig.3 shows the residual energy of WSN with GA and DE which drops as number of rounds increases.

The residual energy of WSN with GA depletes faster than DE and the residual energy drops to zero after all sensor nodes die. Even though the drop in number of alive sensor nodes with GA is slower, its drop in residual energy is faster because the residual energy of sensor nodes with DE has larger standard deviation where some sensor nodes are overburdened with excessive workload. In WSN, the workload of cluster head is heavier as it needs to perform extra tasks of data collection within cluster, data aggregation and data transmission to BS. Therefore, it is important to avoid selecting the same sensor node to be cluster head consecutively to avoid the premature death of the sensor node.

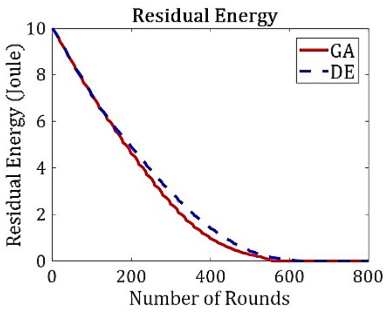

Fig.3. Residual Energy

6.3 TRANSMISSION FAILURE

In this work, transmission failure is due to the insufficient residual energy of sensor node in accomplishing the given tasks. Fig.4 exhibits the transmission failures in WSN with GA and DE.

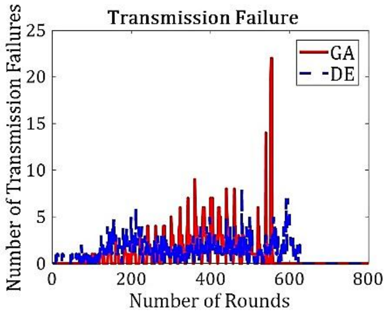

Fig.4. Transmission Failure

The number of transmission failures with GA is 11.34% lower than DE. The fitter solution obtained with GA provides more effective clustering in terms of energy consumption, transmission distance and transmission failure. Hence, GA provides more optimum cluster head placement and even workload distribution for longer network lifetime and lower number of transmission failures. Lower number of transmission failures is important to prevent data loss. In short, the number of transmission failures is greatly affected by the cluster head selection.

6.4 FITNESS CONVERGENCE

The Fig.5 demonstrates the fitness convergences of GA and DE.

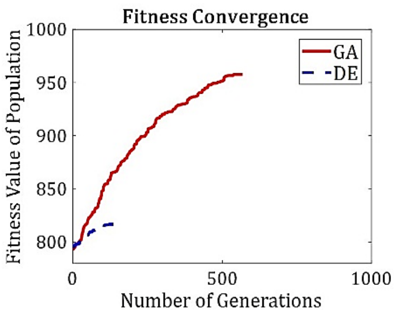

Fig.5. Fitness Convergence

The fitness value of population in GA is 17.23% higher than DE, although the fitness convergence of GA is slower by 417 generations. The fitness convergence of DE is faster but is trapped in the local optimum solution with lower fitness value. This phenomenon is known as premature convergence. By contrast, the ability of GA in exploring and exploiting the large solution space is better, so its fitness value of population is higher. This causes GA to have better performance in terms of both network lifetime and transmission failure with more effective cluster network formation.

7. CONCLUSION

This paper discusses the effectiveness of both DE and GA in improving the energy efficiency of WSN. Both algorithms aim to extend the network lifetime extension via optimizing the cluster head selection. The two algorithms are computed with similar genetic operators and evaluated though comparative analysis in terms of network lifetime, residual energy, transmission failure and fitness convergence. The results show that GA outperforms DE in optimizing the cluster head selection with higher round number for FND, lower number of transmission failure and higher fitness value of population, although GA causes lower round number for LND and slower fitness convergence. Thus, GA can deliver longer stability period with more effective clustering as its better ability in exploring and exploiting the solution space.

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