Fine-tuning approach in metaheuristic algorithm to prolong wireless sensor networks nodes lifetime

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ABSTRACT

Wireless sensor networks (WSN) have evolved a vibrant and lively research field. It comprises numerous wise and low-power consumption devices for gathering the contiguous atmosphere's data. However, the energy dissipation matter that distorts network lifetime remains the challenge since the sensor node battery is non-rechargeable and irreplaceable. Clustering and routing protocol has become the furthermost solutions and invariably minimizes depletion and prolongs the sensor node lifetime. Such protocols have adopted metaheuristic algorithms to secure the efficiency of the clustering and routing protocols. However, the cluster head's extensive task favors consuming and draining more energy. This study proposed a fine-tuning solution for the sensor node's population and generation sizes. It benefits from the modified problem-oriented genetic algorithm parameters in securing the sensor node lifetime. Besides, the solution works effectively to balance the load of the cluster head nodes. A set of simulations has been performed using MATLAB R2018b on the proposed solution, namely the energy efficient of genetic (EEG) algorithm and has revealed that the solution outperforms the network lifetime and cluster head load of the existing solution.

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1. INTRODUCTION

Wireless sensor network (WSN) is a self-configured, infrastructure-less wireless network type. It consists of low-power practice embedded wireless devices known as sensor nodes arbitrarily positioned in a geographical area [1], [2]. The sensor nodes have been used in diverse tangible applications (e.g., electronic, biotechnology, chemical, and so forth) to accomplish many tasks, such as detecting, discovering, processing, and transmitting sensitive data to the knowledge station, referred to as a sink node [3], [4]. Furthermore, energy proficiency, precision, robustness, reliability, and data throughput make the WSN widely functional in healthcare, traffic controls, home appliances control, industrial diagnostic, natural disaster prevention, surveillance, and precision agriculture [5]-[7]. Figure 1 depicts the elemental architecture of a WSN. Such challenges of the WSN are quality of service (QoS), security issues, energy efficiency, network throughput and performance, cross-layer optimization and scalability to the large-scale deployment.

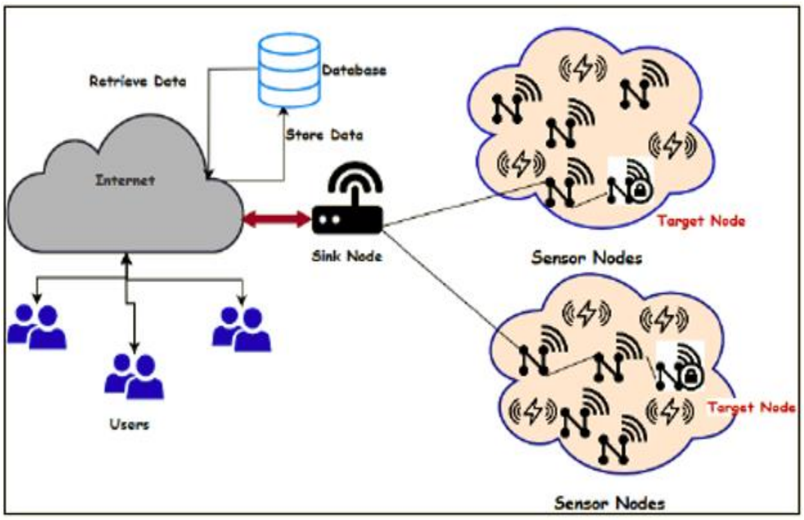


Figure 1. The WSN architecture

WSN sensor nodes' energy depletion remains the most challenging in WSN due to the node's lifetime furnished with non-chargeable and irreplaceable low-powered batteries [8]-[10]. Likewise, the energy depletion is due to their immense participation in a routing procedure while relaying data to the desired destination nodes. Therefore, the respective clustering approach was the most effective technique to attenuate energy-wasting and strengthen the sensor node's network lifetime [11]-[15]. The network field splits into various clusters where the local communications between the sensor nodes are controlled through a cluster leader, known as a cluster head (CH). The CH is responsible for data collection as well as sensitive data accumulation. Nevertheless, fixing the best CH from the available clusters is formidable.

The genetic algorithm (GA) is a metaheuristic algorithm that establishes the clustering and routing protocol's efficiency. Hallam *et al*. [16], Cheng *et al*. [17], and Zhou *et al*. [18], both population and generation sizes are the significant keys to GA's robustness and necessitate determining by exploring different sizes to perform an optimal performance. Low energy adaptive clustering hierarchy (LEACH) is the significant clustering and routing algorithm for WSNs [19]. In LEACH, the network lifetime was diverged into several rounds to ensure all sensor nodes participated as CH, easing the communication costs between CH, nodes, and sink. However, the nodes' uneven dispersal in different clusters and residual energy is not counted during CHs selection. The GA algorithm based energy-efficient clustering and routing (GECR) has been proposed to lessen the permanent CH energy depletion and balance their load in each network round [20]. Even though the GECR produced the obtained CH with optimal living sensor nodes, it performs poorly when the CHs being formed temporarily. To lessen energy wastage during cluster formation in the LEACH, two cluster algorithms, namely GA-optimized fuzzy logic (CGAFL) and fuzzy inference system (FIS) been proposed [21]. The selection of CHs like the LEACH, but a fuzzy inference system was applied for ordinary nodes to join any CH. The FIS computation is based on the CH residual energy, the number of neighboring nodes, and the minimum distance between the CH and sink node. Therefore, node members can join with CH having maximum value to form the cluster with the time-consuming process. genetic algorithm optimized clustering (GAOC) and multiple data sinks GAOC (MS-GAOC) [22] are further solutions to decrease CH energy depletion. The GAOC algorithm relies upon aggregated data to sink and take full advantage of the network's stability period, while the MS-GAOC algorithm shortens the CH communication using multiple sinks to solve the hotspot difficulty in WSN. The algorithms achieved a better network lifetime, but the selection of CH was incapable due to the CH distribution range and distance.

Integrating the particle swarm optimization (PSO) algorithm and the LEACH algorithm results in energy efficiency [23]. However, the iterative nature of PSO itself prevents its usage for real high-speed applications like the WSN. The combination of glowworm swarm optimization (GSO) and fruitfly optimization algorithm (FFOA) was proposed in choosing the best CH [24]. Compared to the conventional algorithms (e.g., GA, PSO), this hybrid algorithm produces the highest number of alive nodes, prolongs the network period, and decreases cost function. Anurag *et al.* [25] proposed an energy-efficient GA-based approach to intensify the sensor nodes' lifetime and reduce energy wastage. The algorithm demonstrates that the CH has static behaviour in maintaining the network and is partly involved in dispensing the WSN. Due to the static behaviour of CH, the CH wastes energy and causes other nodes to die early. A combination of GA and an adaptive neuro-fuzzy inference system (ANFIS) to lessen energy usage, CH workload, and sensor node wastage in WSN has been proposed by [26]. A weighted trust evaluation had introduced to sense malicious nodes during data transmission and intensify the lifetime of the WSN. From the above literature, the following discoveries which affect the sensor nodes and the WSN network lifetime have been observed: i) removing the redundant, aggregating, and routing data packets to the sink favour the CHs consuming more energy; ii) the short transmission distance between CH and sink node depletes more energy and dies quickly; and iii) relaying sensitive data to the sink through multi-hop makes CHs nearer to the sink nodes drain more energy.

The remainder of this paper is organized as follows. Section 2 discusses how the energy efficient of genetic (EEG) algorithm lessens the sensor nodes' energy depletion and balances the CH loads. Section 3 provides the methodology used in proposing the EEG algorithm and the simulation works details. The performance evaluation of the study is discussed in section 4, while section 5 presents the conclusion.

2. ENERGY EFFICIENCY OF GENETIC (EEG) ALGORITHM

The GA can utilize both the sensor node's population and generation size parameters in finding the right clustering and routing protocols. The EEG algorithm aims to reduce sensor node energy depletion by re-tuning the population and generation sizes in the benchmark GA. Several simulations were performed with various population sizes and generation iterations established on various scenarios to identify the best population size for raising the benchmark algorithm performance. Hence, the two concentrations of the proposed EEG algorithm are: i) optimize the clustering and routing protocol during the transmission of sensitive data to the sink node, and ii) distribute the CH energy dissipation by adding the earlier hops to balance the various CH loads.

3. THE FINE-TUNING ALGORITHM

3.1. Energy depletion radio model

This study employs the standard first-order radio model in computing the sensor nodes' energy dissipation. The following equations calculate the energy dissipation for transmitting *f*-bits of data for short and long ranges. Parameter descriptions for both equations are described in Table 1.

$$ETx(f, d^2) = f * E_{elc} + f * \varepsilon_{fs} * d^2, if\ d^2 < d_0 \quad (1)$$

$$ETx(f, d^4) = f * E_{elc} + f * \varepsilon_{mp} * d^4, if\ d^4 \geq d_0 \quad (2)$$

Table 1. First radio model parameters

Parameter	Description
E_{elc}	Energy dissipation per *f*-bit by the transmitter/receiver
ε_{mp}	Energy expended by signal amplification when conveying *f*-bit data
ε_{fs}	Factors for the free space used for long-distance
d^2	Energy dispels by the amplifier for a short transmission range
d^4	Energy dispels by the amplifier for a long transmission range
d_0	The distance threshold ($\sqrt{\varepsilon_{fs}/\varepsilon_{mp}}$

3.2. Network period round structure

Figure 2 depicts the structure of the EEG approach. The network period is diverged into several rounds (known as the time interval) in the initial phase. First, the ordinary node members successfully dispatch the sensed data to CHs, combining the received data before it transmits to the sink through multi hops. Next, managing the cluster (which consists of ordinary nodes and CH) in the setup phase. This phase aims to accumulate the collected data from regular nodes and remove redundant data before dispatching the data directly to the sink or via multi hops. Finally, in the steady phase, each CH utilizes the optimal clustering and routing scheme to gather sensed data from the ordinary node, merge the collected sensed data, and forward the aggregated sensed data to the multi-hops sink node.

The time division multiple access (TDMA) scheduling is used to allocate time slots for the CH. The main reason is that the TDMA scheduling can avoid collisions by silencing every CH node's interferers in each time slot and minimizing the time slot numbers, hence the latency. However, the more significant latency may require a higher data rate and energy consumption.

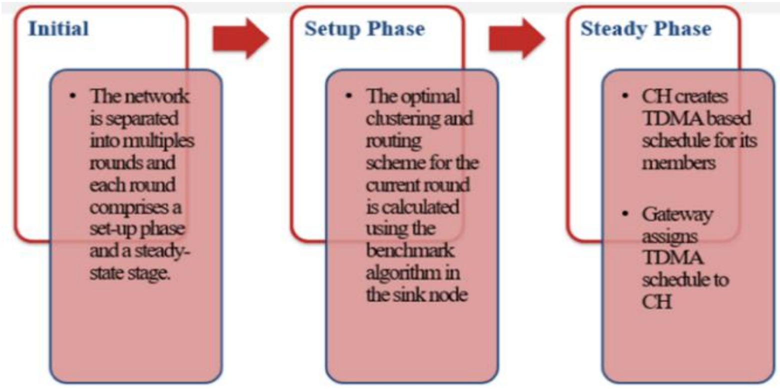


Figure 2. Round structure in EEG algorithm

3.3. Cluster formation and routing scheme

Generally, all the sensor nodes have insufficient energy. Hence it is essential to lessen the total energy depletion of nodes for cluster establishment and routing sensed data. Thus, the chromosome length, denoted by *nodes_count*, which excludes the sink node and the identification of CH nodes, is represented as in (3).

$$id_{n\_hj} = \int_{nodes\_count}^{j} \begin{matrix} if\ j\ \leq n\_h \\ if\ j = n_h + 1 \end{matrix} \tag{3}$$

Parameters j, n_h and n_h+1 refer to CH's identity, cluster head and the sink node. Hence, the new identities for the next hop of the routing scheme denoted by $next_{n\_h\_g}$ are given as in (4).

$$next_{n\_h\_g} = \int_{n\_h+1}^{n\_hj} \begin{matrix} if\ scheme[g] & g\ \leq n\_hj, j\ \leq n\_h \\ if\ scheme[g] & nodes\_count, g \leq n\_h \end{matrix} \tag{4}$$

Parameter n_hj defines the next hop as the head node, while n_h+1 designates the next hop as the sink node. Therefore, the new identity for the next hop of the encoding clustering scheme g denoted by $CSn\_mg\ n\_H$ is given as in (5).

$$CSn\_mg\_n\_H = n\_h \quad if\ scheme[g] = j, n\_h\ < g < nodes\_count, j \leq n\_hj \tag{5}$$

The CH new identification relates to (3) and the ordinary node n_m. For instance, in Figure 3, the nodes with identities 2, 4, and 6 can directly relay sensed data to the endpoint, which is the sink node 23, while the value of gene locations with sensor nodes identities 1, 3, and 5, which indicates the next hop of the cluster head 2, 4, and 6 respectively. Likewise, the second part, the clustering scheme, specifies the individualities of the ordinary node's members n_m in the network. For instance, sensor nodes 7, 10, and 17 are nodes n_m allocated to cluster leader one, the next hop of CH 2.

3.4. Population initialization and fitness evaluation

The population initialization was used to review valid routing and clustering schemes. Additionally, the sink nodes use GA in each round to obtain the minimum energy and routing clustering scheme. The fitness function is used to evaluate the total energy dissipation by the CHs in every network round. Therefore, the cluster heads' complete energy depletion (denoted by $Total_E$) combines energy depletion for clustering and routing f-bits of data from CHs to the sink. So, (6) is used to minimize energy depletion. Both parameters n_mn_hEij and Bij are communication energy for node member n_mi to relay f-bits of data to CH n_hi and a variable to determine if a node is assigned to a CH, respectively.

$$Total_E = \sum_{i=1}^{n\_m} \sum_{j=1}^{n\_h} n\_mn\_hEij\ * Bij \tag{6}$$

As shown in (7), (8) and (9) show the computation of the node members' energy cost (*sendn_mn_hij* and *receiven_mn_hij*) in sending and receiving f-bits of data to or from the CH. The summation between both is the total communication energy for node members, $n\_mn\_hEij(f)$.

If $d^2 < d_0$, then:

$$sendn\_mn\_hij(f) = f * E_{elc} + f * \varepsilon_{fs} * d^2 \tag{7}$$

else if $d^4 \geq d_0$,

$$sendn\_mn\_hij(f) = f * E_{elc} + f * \varepsilon_{mp} * d^4 \tag{8}$$

and,

$$receiven\_mn\_hij(f) = f * E_{elc} \tag{9}$$

As shown in (10) computes the total energy for the routing scheme.

$$Routing\ Energy = \sum_{g=1}^{n\_h}(En\_h\_g\_n\_h_{n\_h+1}) \tag{10}$$

Parameter $En\_h\_g\_n\_h_{n\_h+1}$ refers to the energy dispels by *n_h* in sending aggregated data to *n_h+1* through the $next_{n\_h\_g}$. If the $next_{n\_h\_g} = n\_h+1$, then $En\_h\_g\_n\_h_{n\_h+1}$ is equal to the energy dispels by the gateway node to relay the sensed data to the sink, denoted by n_hEgn_h+1. If $next_{n\_h\_g}$ is equal to the communication between the previous CH to relay the gateway (*n_hgj*), $En\_h\_g\_n\_h_{n\_h+1}$ is the summation between *n_hEgn_h+1* and the energy required between all CH during the communication, denoted by *n_hEgj*.

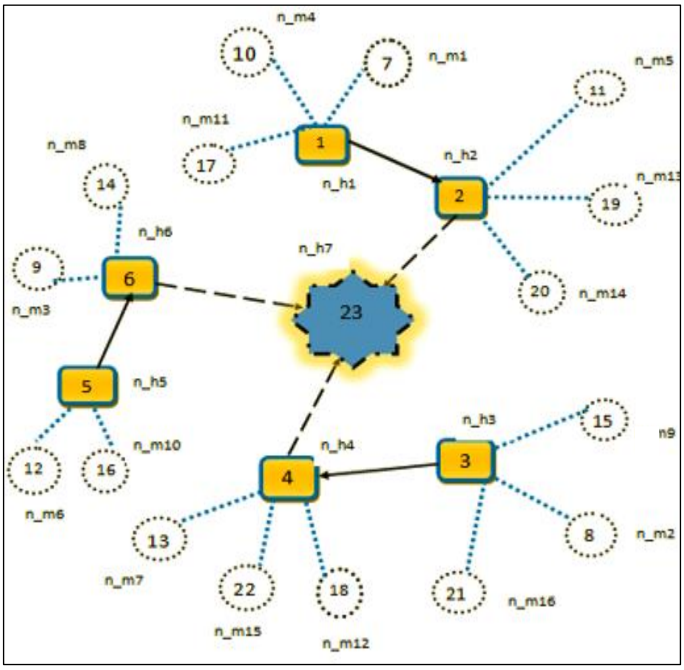


Figure 3. Cluster formation and routing

3.5. Energy load balancing

The second aim is to balance the energy load for each CH in every round. Hence, the residual energy denoted by *RE* for each CH needs to consider for the subsequent rounds. The number of loads (*nF(n_h_j)*) on each gateway CH is computed according to the average remaining energy, denoted by *AverageRj* of each CH. Therefore, the *AverageRj* for each CH is given (11).

$$AverageRj = \frac{RE(n\_h\_j)}{nF(n\_h\_j)} \tag{11}$$

The variance (μ) of *AverageRj* for all clusters is used to ensure the CH has adequate energy to receive and transmit the sensed data for the current round as shown in (12). Moreover, to balance the energy dissipation load of the CH and lengthen the network life cycle, the standard deviation (σ) is employed as shown in (13).

$$\mu = \sum_{i=1}^{n\_h}(AverageRj/n\_h) \quad (12)$$

$$\sigma = \sqrt{\sum_{i=1}^{n\_h}(AverageRj/n\_h)} \quad (13)$$

Thus, σ with the most negligible value will balance CH's energy dissipation and help extend the network lifetime. However, both $Total_E$ in (6) and σ are not in the same range. Hence it is necessary to normalize these two values.

$$\frac{Total_E - Total_{E\_min}}{Total_{E\_max} - Total_{E\_min}} \quad (14)$$

$$\frac{\sigma - \sigma_{min}}{\sigma_{max} - \sigma_{min}} \quad (15)$$

A weight (Lambda) is added since $Total_E$ and σ affect the fitness, therefore, the fitness function is given as $Fit \propto$ Lambda $*$ $Total_E$ + (1 −Lambda) $*$ σ.

3.6. Simulation setup and configuration

The simulation to evaluate the performance of the EEG algorithm was implemented using MATLAB R2018b. The EEG was compared with the GECR using a similar configuration used in [7], and the Lambda's equal value in [20] was used to form the comparisons with the network lifetime, defined as first node death (FND), half node alive (HNA), and last node death (LND).

Two performance metrics, i) network lifetime and ii) CH load variance, evaluate the optimized EEG algorithm. The network lifetime is the time interval from the commencement of the sensor node's operation until the death of the last node in the network field, while the CH load variance indicates how CH workload can accomplish in a given round and finds the variation in the respective CH throughput to ensure that load is balanced. Table 2 concludes the simulation parameters used in the simulation evaluations.

Table 2. Simulation parameters

Parameter	Values
Network field	$100m^2$ x $100m^2$, $200m^2$ x $200m^2$
Maximum communication range	50 /100
Number of sensor nodes (N)	100 & 200
Sink node position in the network field	Center
Energy cost per f-bit by the transmitter and receiver (E_{elc})	50nJ/bit
Free space factor model for a short distance (ε_{fs})	10 pJ/bit/$m2$
Multipath factor model for long-distance (ε_{mp})	0.0013/pJ/bit/m4
Data aggregation energy	5 nJ/bit/$m4$
Ordinary node initial Energy of n_m	0.02J
CH initial energy	0.12J / 0.06J
CH proportion	20 and 40 for N = 100 80 for N =200
Control message	200
Packet size	4000 bits
Numbers of rounds	250, 400, & 500
Population size	10, 25, 50, 100
Generation size	10, 25, 50, 100
Mutation	0.0050

4. RESULT AND DISCUSSION

Both Tables 3 and 4 represent the network lifetime for different lambda values in various population and generation size scenarios. As shown in Table 3, the population size of 25 has the highest number of exceeding performances based on the weight of lambda. Although the population size of 10 has the fastest execution time, it has a lower performance. Consequently, it is trapped within the optimal local search that no longer enhances fitness value. However, the result shows more significance than the population size of 50 and 100. On the other hand, the population size of 50 and 100 have the lowest number of exceeding performances. Also, the population size of 50 and 100 requires much more computational time for sorting and assessing every candidate solution than the population size of 10 and 25.

Table 3. The living nodes based on population size

Population Size	Lifetime/lambda	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	FND (%)	27	26	16	18	25	32	45	71	38	43	42
	HND	90	91	91	91	91	91	91	92	92	92	92
	LND	96	199	149	131	104	148	400	400	400	400	400
Remaining node alive (%)	Execution Time: 1966.7317	0	0	0	0	0	0	1	1	2	4	6
25	FND	14	29	30	30	24	44	44	67	68	86	78
	HND	91	91	92	92	91	91	91	92	92	93	92
	LND	97	104	97	101	131	145	169	168	400	400	400
Remaining node alive (%)	Execution Time: 4083.647	0	0	0	0	0	0	0	0	1	3	6
50	FND	15	32	28	39	31	22	47	56	86	88	73
	HND	90	91	91	91	91	91	92	91	91	92	91
	LND	96	145	97	112	157	147	400	400	400	400	400
Remaining node alive (%)	Execution Time: 7993.0463	0	0	0	0	0	0	1	1	2	1	5
100	FND	21	27	43	38	24	35	36	80	54	62	86
	HND	90	91	90	91	91	91	91	91	92	92	92
	LND	98	97	97	117	106	186	226	400	364	400	400
Remaining node alive (%)	Execution Time: 14787.8569	0	0	0	0	0	0	0	1	0	1	7

Table 4. The living nodes based on generation size

Generation Size	Lifetime/lambda	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
10	FND	14	28	30	30	24	44	44	67	69	85	78
	HND	91	91	90	91	90	91	91	91	91	92	91
	LND	97	104	97	101	131	145	169	168	400	400	400
Remaining node alive (%)	Execution Time: 1966.7317	0	0	0	0	0	0	0	0	3	1	6
25	FND	9	32	37	30	28	44	74	86	69	44	87
	HND	91	91	91	90	91	91	91	92	92	92	92
	LND	96	97	97	96	98	146	170	400	400	400	400
Remaining node alive (%)	Execution Time: 4083.647	0	0	0	0	0	0	0	1	3	6	5
50	FND	11	6	29	22	32	58	74	86	69	44	87
	HND	91	91	91	91	91	91	91	92	92	92	92
	LND	98	97	98	96	98	109	400	400	400	400	400
Remaining node alive (%)	Execution Time: 7993.0463	0	0	0	0	0	0	2	2	7	9	9
100	FND	11	29	17	28	32	46	38	87	66	72	85
	HND	90	91	91	90	91	91	92	92	92	92	92
	LND	96	96	97	98	97	133	400	400	400	400	400
Remaining node alive (%)	Execution Time: 14787.8569	0	0	0	0	0	0	1	2	3	5	10

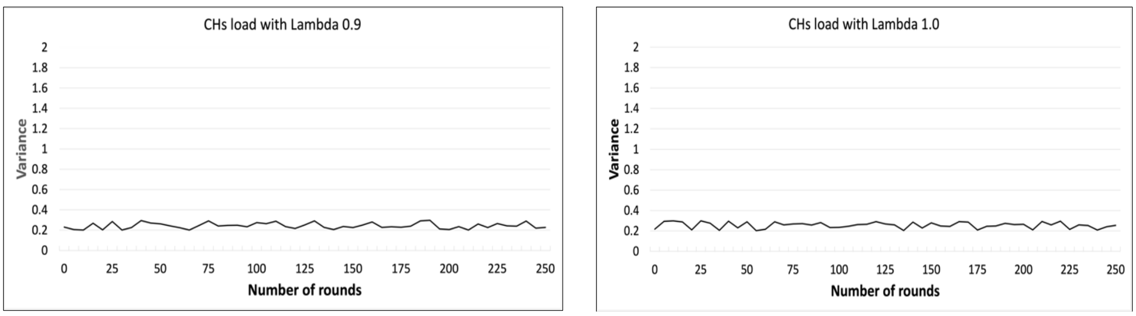
In Table 4, the optimal population size is 25. However, since a small population tends to give a quicker convergence speed than a large population, it is essential to run on an appropriate number of generations. Therefore, another simulation testing based on four generations, 10, 25, 50, and 100, examines the suitable generation number to give an accurate solution. Therefore, an equivalent population size of 25 was used for the test, and other energy consumption parameters remained the same as in the previous simulation testing. As tabulated in Table 4, the Lambda values increase the nodes' performance, where Lambdas 0.7, 0.8, 0.9, and 1 have the highest performance. Next, the simulation validated the EEG results by comparing the result with the benchmark results using the same scenarios (the CH proportion). Finally, the summary of the result is given in Table 5.

The results show that the EEG's FND performs better in the first scenario (CH proportion of 20 and 40) than the GECR. Moreover, the EEG outperforms the GECR in all lambda values for both HNA and LND. In the second scenario, the GECR performs better for the FND, but the EEG gives the best result in LND and outperforms all lambda values in HNA. Also, the results show that as the weight (Lambda) increases, the nodes live longer, and there is no early node death in the FND compared with the GECR. Besides, Lambda 0.6 for both scenarios shows that EEG attains a more significant number of alive nodes than the GECR. Therefore, the results have shown that population and generation size significantly enhance the benchmark algorithm's computational performance. Additionally, these results signify that the proposed parameter tuning discovers the optimal path to lessen power consumption and prolong the network lifetime of sensor nodes in WSN.

Last is the load variance, which indicates how much the CH workload can perform in each round. The steadiness load-balancing performance of the proposed EEG algorithm described in Figure 4. Figures 4(a) and (b) show the variances of the CH loads for the Lambda 0.9 and 1 since both weights have the highest number of exceeding performances. This study distributes the CH energy dissipation by adding the earlier hops to balance the various CH loads. Thus, it determines the energy dissipation uniformity and confirms effective communications load among the CH. The average CHs load variance is 0.02 and 0.03. Thus, load balancing is optimal in the proposed fine-tuning approach.

Table 5. The living nodes between the EEG and the GECR

Scenario	Lambda	EEG			Dead (%)	Alive (%)	GECR			Dead (%)	Alive (%)
		FND	HNA	LND			FND	HNA	LND		
1	0	31	91	154	100	0	20	33	36	100	0
	0.1	38	92	136	100	0	43	57	69	100	0
	0.2	22	92	153	100	0	45	56	133	100	0
	0.3	21	91	171	100	0	46	57	161	100	0
	0.4	71	91	140	100	0	46	58	188	100	0
	0.5	34	91	232	100	0	47	58	192	100	0
	0.6	85	92	250	89	11	47	61	214	100	0
	0.7	86	92	250	88	12	51	63	164	100	0
	0.8	52	92	250	88	12	51	64	161	100	0
	0.9	86	92	250	88	12	50	65	170	100	0
	1	87	92	250	85	15	46	63	203	100	0
2	0	15	92	200	100	0	17	56	118	100	0
	0.1	9	93	229	100	0	31	59	229	100	0
	0.2	41	93	257	100	0	33	59	262	100	0
	0.3	17	93	233	100	0	45	60	286	100	0
	0.4	24	92	305	100	0	43	60	312	100	0
	0.5	40	93	341	100	0	45	60	328	100	0
	0.6	46	93	500	77	23	46	60	349	100	0
	0.7	53	93	500	72	28	49	61	365	100	0
	0.8	47	93	500	70	30	51	61	385	100	0
	0.9	33	93	500	74	26	51	64	396	100	0
	1	33	93	500	66	34	49	67	445	100	0



(a) (b)

Figure 4. CH load variance for (a) lambda 0.9 and (b) lambda 1

5. CONCLUSION

This study works on parameter tuning to attain the benchmark algorithm's optimum performance in prolonging sensor nodes' network lifetime and balancing loads of cluster heads in WSN. Several simulations test by fine-tuning the population and generation size was conducted to identify the optimum population and generation size to increase the benchmark algorithm's computational performance further. The benchmark results were analyzed and compared with the fine-tuned results. As a result, the EEG algorithm gain more alive nodes than the GECR as the weight (lambda) increases in the first scenario from the stated lambda values. Similar to the second scenario, the number of alive nodes indicates an addition compared with the GECR. Accordingly, the proposed EEG outperforms the GECR algorithm concerning cluster heads' network lifetime and load balancing to prolong the network lifetime of sensor nodes in WSN. Nevertheless, GA takes a long time to reach an optimal solution. Therefore, combining GA-PSO can improve the time taken to reach an optimal solution in future works.

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