Indonesian Journal of Electrical Engineering and Computer Science
Vol. 29, No. 3, March 2023, pp. 1456~1465
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v29.i3.pp1456-1465

Optimization of wireless sensor networks energy consumption by the clustering method based on the firefly algorithm

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Article Info

Article history:

Received Nov 15, 2021
Revised Oct 21, 2022
Accepted Nov 28, 2022

Keywords:

Clustering method
Energy optimization
Firefly algorithm
Network lifetime
Wireless sensor networks

ABSTRACT

Wireless sensor networks (WSNs) contain an inordinate number of sensor nodes that are spatially distributed. The network is composed of entities that determine its lifetime. The WSN nodes are equipped with a battery whose autonomy is limited in duration. In this paper, different solutions are introduced to improve the overall energy consumption of the network in order to improve its lifetime. Contrary to many works considering the clustering algorithm as one potential candidate to improve the network's lifetime, this study has investigated the firefly algorithm optimization where an optimal cluster head is selected from a group of nodes. The set-up process of the cluster head is based on a set of conditions. To measure the performance of the proposed approach, the number of dead nodes and data packets received by the base station (BS) or sink node are considered. The results are tested on 100 nodes for 5000 transmission rounds, the amount of data transported is 20 million bits a little more than the other methods. It has been shown that the proposed solution outperformed the traditional low energy adaptive clustering hierarchy (LEACH), threshold sensitive energy efficient sensor network (TEEN), and developed distributed energy-efficient clustering (DEEC) approaches.

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1. INTRODUCTION

Wireless sensor networks (WSN) technology is widely welcome in many areas such as defense, medical and various commercial and industrial applications [1]. It consists of several low-cost sensor types of equipment with sensing processing functions, information transmission capabilities, and a manageable and easy configuration setup [2]. The sensor nodes are deployed in a given field to collect the environment data. Being compact, WSN sensors have batteries that have limited autonomy to cover the needs of the network. Then, it must be used appropriately as it cannot be swapped or recharged due to the placement of the sensor in a hostile environment and out of human reach. The sensor collects and processes the data before transmitting it to a sink node. The sensor nodes can also act as repeaters for other sensors. At the sink node, data analysis is important for application decision-making. A WSN architecture must consider many factors such as network scalability, energy efficiency sensing and transmitting environment data from any node to the sink node are two factors leading to energy depletion of sensors in a WSN. However, the energy consumed to transmit data in a WSN is higher than the energy consumed to sense and process data from an environment [3].

The WSN differs from standard wireless networks by its sensitivity to energy consumption. Therefore, having a WSN made up of sensors with insufficient power sources is a problem. In a widely deployed network, direct communication between certain remote sensor nodes with the sink node is not recommended because of the energy path loss. Network clustering of sensors is an alternative to minimize energy consumption. In each cluster of the network, a local data aggregator called cluster head (CH) is appointed among the nodes belonging to the cluster [4]. The main research objective is to decrease the energy consumption of a WSN.

This paper proposes to limit the energy consumed during data transmission. Swarm optimization is used for its robustness, self-adaptability, and search capability, while graph theory addresses the shortest path selection. Firefly algorithm (FA) is used to facilitate the CH choices based on the node degree and its centrality, multiple energy consumption objective value, and distance factors. The choice of the FA lies in its lower computational complexity and high stability. The choice of an energy-efficient CH impacts the energy consumption level during the transmission process.

The paper is organized as shown in; section 2 presents a review of clustering techniques. Section 3 illustrates the proposed solution and shows the preliminary steps for the implementation. Section 4 makes a comparative study of the different methods. Finally, the conclusion is the subject of the last part of this paper.

2. OVERVIEW

Many studies on improving the lifetime and minimizing the energy cost of WSNs have been performed. The main research has been oriented on clustering techniques through many approaches. Globally, many works have been done in the field of network coding for the selection of cluster heads [5] considering the residual energy or the distance from the base station (BS).

A hierarchical clustering algorithm for sensor networks named low energy adaptive clustering hierarchy (LEACH) protocol has been implemented for energy-efficient and scalable protocols [6]. The limitation of the LEACH protocol is that a cluster head (CH) can be arbitrarily chosen from a group of nodes. For this reason, researchers have presented in [7], a technique that improves the capability of the traditional LEACH protocol in terms of energy gain. That technique is called LEACH-Impt. The energy expenditure of LEACH-Impt was lower than that of the LEACH protocol. Knowing that WSNs are prone to dynamic energy-sensitive failures, other researchers [8] have implemented a routing protocol that is more tolerant to these ills. Taking into account traffic density, residual energy, and packet error rate, a protocol to help improve route maintenance and load balancing was developed in [9]. The weighted energy-efficient clustering with robust routing (WECCR) provide energy balancing between nodes.

Taking into account the residual energy, the distance between the node and the sink node, and the number of neighboring nodes, in order to have an energy-efficient routing, a routing protocol called weighting and parameter optimization-based energy-efficient clustering routing protocol (WPO-EECRP) was created in [10]. By modifying some clustering parameters, WPO-EECRP provides adequate clustering control and shows good scalability. The aware cluster based routing (AECR) protocol which considers the node’s energy a better need compared to the distance between the nodes was presented in [11].

A harmony search algorithm (HSA) that considers node degree, energy, intra-cluster distance and distance between CH and sink node as fitness functions was proposed in [12]. This algorithm splits the network into clusters and creates the routes in WSN.

The fractional lion clustering algorithm (FLION) which depends on inter-cluster distance and Intra-cluster distance, CH, and ordinary node energy and transmission delay to create an ideal routing way in WSN was developed in [13]. The network lifetime improves due to the fast CH selection. The method of optically inspired optimization (OIO) to determine optimal routing and clustering schemes whose computational complexity increases with the size of the network was developed in [14]. A novel chemical reaction optimization (nCRO) to supply unequal clusters and routing plans was examined in [15]. This technique facilitates the selection of optimal CHs leading to the minimization of unbalanced energy consumption, it should be noted that it lacks plans for fault tolerance.

Ant lion optimization (ALOC) techniques for choosing an optimal CH were deployed in [16]. ALOC acts on the remaining energy, the number of adjacent hubs for each node, the distance between nodes, and the distance between the node and the sink node. An improvement in the energy efficiency of the network was seen. A biogeography-based optimization (BBO) strategy for producing the ideal most brief route between the CH and the sink node was executed in [17]. This technique participated in the reduction of the energy consumption of the network and increase the size of the data packets received by the sink node. To find ideal CHs from the nodes clusters, a gravitational search algorithm (GSA) that considers the residual energy of the node was presented in [18].

The evolutionary multipath energy-efficient routing (EMEER) protocol that relies on the cuckoo search algorithm was developed to cluster the WSN based on similarity and energy level characteristics [19]. The CHs are selected by using energy, confidence value, and the distance between nodes. They then compared their performance in terms of energy cost to those obtained from other methods such as LEACH, power efficient gathering in sensor information systems (PEGASIS), and threshold sensitive energy efficient sensor network (TEEN). From this comparison, it was found that the energy consumption obtained using EMEER is smaller.A fuzzy hierarchical unequal clustering algorithm (HUCFA) has been deployed to reduce the energy consumption of the network [20]. This method first divides the network area into three horizontal layers according to their distance from the sink node, and finally splits each layer into grids. In addition, it includes a fuzzy logic-based CH selection scheme that improves energy efficiency. An optimal routing scheme that selects as CH the node with higher residual energy during clustering was implemented in [21].

Kuila and Jana [22], a new cluster head selection method that uses a weighted sum method to calculate the weight of each node in the cluster and compare it with the standard weight of that particular cluster is proposed in this paper. WSN polynomial temporal clustering algorithms named common scrambling algorithm (CSA) and chaotic particle swarm optimization (CPSO) relying respectively on simulated annealing (SA) and particle swarm optimization (PSO) have been discussed in [23], [24].

Mekonnen and Rao [25], these clustering methods each include a configuration step where clustering and CH selection are performed. Knowing that the limitation of the LEACH protocol in [6] is that a CH can be chosen randomly from a set of nodes. Therefore, the collection and transmission of information will be disrupted due to changes in the network topology.

Haseeb *et al*. [8], direct data transmission between CH and sink node consumes more energy in WSN, researchers advocated appropriate selection of objective functions to create energy efficiency in WSNs. Indeed, an energy-efficient WSN should work in both small-scale and large-scale applications. Some researchers have recommended a method that prioritizes energy and distance equally leading to a reduction in network energy consumption. For example, WECRR [9] and adaptive energy aware cluster-based routing (AECR) [11] have given higher priority to the residual energy of nodes in clustering. The WSN performance trained by the harmony search algorithm (HAS)-based clustering and routing method proposed in [12] was impacted when a CH had a "high" number of CH members in its cluster.

Given the inadequacy of some of the previously mentioned algorithms, this study advocates that energy and distance be considered to create an energy-efficient WSN. FA is used to determine an optimal cluster head. In the proposed synopsis, nodes are organized as clusters using a K-means clustering scheme. Once the network is set up, the data transmission phase starts as soon as an event is detected.

3. METHOD

This section discusses the choice of the firefly algorithm for the best choice. This method will be implemented in a network organized in k-means clusters. Firefly Algorithm is a bio-inspired metaheuristic algorithm for optimization problems [26]. The algorithm is inspired by the blinking patterns and behavior of fireflies at night. The FA chooses the ideal CHs among all sensors by utilizing node degree, node centrality, distance to neighbors, distance to sink node, and remaining and consumed energy. Firefly algorithm is a bio-inspired meta-heuristic algorithm for optimization problems.

3.1. Network model

This sub-section provides information about the proposed WSN architecture, the energy model, and the description of the firefly optimization algorithm. A sensor can have three functions depending on its rank in the network. A simple sensor (cluster member) transmits data, while a higher order sensor (cluster head) in addition to transmitting, receives and aggregates data. Therefore, the architecture allows to rely on a working model, while the energy consumption modeling helps to list the different functions that can be performed on a sensor node.

3.1.1. Network architecture

In the proposed scheme, an event is defined as the variation of the detected value beyond a certain predefined threshold level. The cluster member node (CM) located near the event area will detect the data and report it to the CH. The detected information is transmitted to the sink node via the CH channels. The scheme of network topology is illustrated in Figure 1.

3.1.2. Energy consumption model

In the free space model, a line-of-sight (LOS) path is considered between the transmitter and receiver nodes, while multipath represents the propagation of the non-line-of-sight (NLOS) signal from various routes at different time intervals and after ground reflection. In this study, a radio model is considered to calculate the energy of the transmitter and receiver. The energy consumed to transmit and collect the packets of bits over the distance d [27] is expressed in (1) and (2) respectively.

$$E_{TX}(k, d_{ij}) = k \times E_{elec} + k \times \mathcal{E}_{amp} \tag{1}$$

$$E_{RX}(k) = k \times E_{elec} \tag{2}$$

where E_{TX}, E_{RX}, k and $\mathcal{E}_{amp}$ represent respectively transmission energy dissipation, reception energy dissipation, the number of bits, the distance between the i^{th} and the j th node, the energy dissipation per number of transmitted or received bits independent of the distance and dependent on the transmitter-receiver model, and the energy consumption of the transmitter amplifier, as shown in (3).

$$\mathcal{E}_{amp} = \begin{cases} \mathcal{E}_{fs} \times {d_{ij}}^2 \; if \; d_{ij} \le d_0 \\ \mathcal{E}_{mp} \times {d_{ij}}^4 \; if \; d_{ij} > d_0 \end{cases} \tag{3}$$

Where $\mathcal{E}_{fs}$, $\mathcal{E}_{mp}$ and d_0 represent respectively the amplification energy for free space and the amplification energy for the multipath model and the threshold distance. The latter is expressed as shown in (4).

$$d_0 = \sqrt{\frac{\mathcal{E}_{fs}}{\mathcal{E}_{mp}}} \tag{4}$$

Therefore, the residual energy quantities for a cluster member (CM) and for a cluster head (CH) respectively are given by (5) and (6).

$$E_{CM} = E_{init} - E_{TX}(k, d_{ij}) \tag{5}$$

$$E_{CH} = E_{init} - E_{consstd} \tag{6}$$

Where, E_{init}, $E_{consstd}, E_{init}$ and $E_{consstd}$ respectively represent the initial energy of the sensor node and the standard energy consumption of a node participating in the CH selection phase expressed in (7).

$$E_{consstd} = E_{TX}(k, d_{ij}) + E_{DA} + E_{RX}(k) \tag{7}$$

Where E_{DA} represent the energy consumption of the node for the data aggregation process.

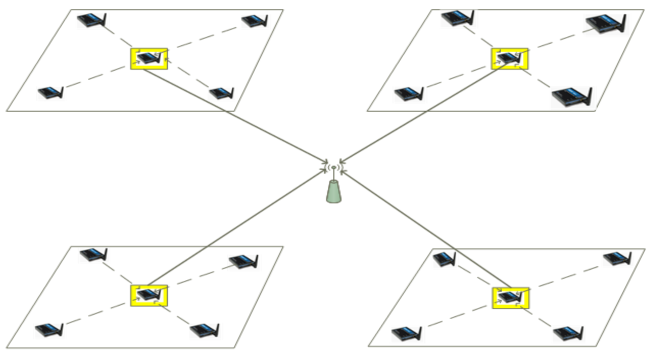


Figure 1. Network topology of the proposed scheme

3.2. Representation and initialization of fireflies

In this step, the firefly indicates a bunch of sensors to be chosen as CH among the sensors in a network. Each size of the firefly is equal to the sum of CH within the network [14]. Each firefly position is initialized as a random node among all nodes. This is modeled for the i^{th} firefly as shown in:

$$f_i = (f_{i,1}(t), f_{i,2}(t), f_{i,3}(t), \dots, f_{i,m}(t)) \tag{8}$$

where each firefly position $f_{i,d}$ $(1 \le d \le m)$ specifies one of all the nodes in the network and m defines the quantity. Each firefly position should be mapped to its sensor node coordinates.

3.3. Representation and initialization of fireflies

It is taken under consideration within the CH choice process. The method agreeing of overhauling the firefly positions [26] is given as takes after. In FA, the fireflies will move to the brightest, and if there is no brighter, it will move randomly. The new fireflies are arbitrarily extemporized with identifier (node ID) of all the nodes within the network. If a firefly located at X_j is more attractive (brighter) than another firefly located at X_i. The firefly located at X_i will move to X_j. The update of the position of the firefly located a X_i will be updated as (9):

$$X_i^{t+1} = X_i^t + \beta_o . e^{-\gamma r_{ij}^2} . \left(X_j^t - X_i^t\right) + \alpha_t . \in_i^t \tag{9}$$

where, X_i^{t+1} represents the new position of the firefly, X_i^t the old position of the firefly, β_o is the attractiveness (when $r = 0$), γ the absorption coefficient, r_{ij} the distance between i^{th} and $j^{\ th}$ fireflies, X_j^t the position of the $j^{\ th}$ firefly, α_t the randomization parameter (with $0 \leq \alpha_t \leq 1$), $\in_i^t$ is the random number drawn from a Gaussian or uniform distribution or other. The fitness function is used for the variation of firefly attractiveness. Its purpose is to select a near optimal set of sensor nodes as CH. To achieve this goal, a fitness function is formulated using intra-cluster distance, consumed energy, residual energy, distance from the CH to the sink node, centrality, and node degree.

3.4. Fitness function (FA)

The FA fitness function is utilized to select the ideal CH within the network sensor group. The chosen parameters are all related to the potential CH of the network. They are the energy consumed, the residual energy, the intra-cluster distance, the distance between a CH and the sink node, the degree of neighborhood and the degree of neighborhood of a CH.

3.4.1. Energy consumed

It is the standard energy consumption due to data transmission, reception and aggregation functions. In other words, it corresponds to $E_{consstd}$ defined in section B. The first objective (f_1) is modeled as shown in:

$$f_1 = E_{consstd} \tag{10}$$

3.4.2. Residual energy

In the data transmission phase, the CH performs the tasks of collecting and aggregating data from normal sensor nodes and transmitting data to sink nodes. Therefore, the node with higher remaining energy is favored as a CH. The second objective function with respect to residual energy is f_2 which can be minimized as shown in:

$$f_2 = \sum_{i=1}^{m} {}^{1}\!/_{E_{CHi}} \tag{11}$$

where, E_{CHi} is the residual energy of the i^{th} cluster head.

3.4.3. Intra-cluster distance

The energy dissipation of the node depends mainly on the distance of the transmission path. The energy expenditure of the node is moo when the chosen node has less transmission distance to sink node. Therefore, if the transmission distance is minimal, less energy is required to process the data. The distance between normal and CH sensors is expressed as (12):

$$f_3 = \sum_{j=1}^{m} \left(\sum_{i=1}^{I_j} dis(s_i, CH_j)/I_j \right) \tag{12}$$

where $dis\left(s_i, CH_j\right)s_i$ represents the distance between the cluster head CH_j and I_j the number of sensor nodes belonging to its cluster.

3.4.4. Distance between cluster head and sink node

It defines the Euclidean distance between each CH and the sink node [14]. The energy consumption of the node depends on the transmission distance. If the sink node is located far from the CH, then it needs a large amount of energy for data transmission. Thus, the sudden drop of CH may occur due to higher energy consumption. So, the node with less distance from sink node is preferred during data transmission. Therefore, CH with minimum Euclidean distance from sink node is a more preferable choice. Thus, the objective function of the distance between the cluster head and the sink node (f_4) can be minimized as shown in (13):

$$f_4 = \sum_{i=1}^{m} dis(CH_j, BS) \quad (13)$$

where, $dis(s_i, CH_j)$ is the distance between the cluster head CH_j and the sink node (BS).

3.4.5. Degree of node

This is the number of sensor nodes belonging to the respective CH. If CHs have a smaller number of members, then it lasts longer because CHs with higher cluster members lose their energy in less time. Therefore, CH with less node degree is preferred. The node degree (f_5) expressed in (14) can be minimized as:

$$f_5 = \sum_{i=1}^{m} I_i \quad (14)$$

3.4.6. Centrality of a node

It shows how far a node is located from the center of neighboring nodes and is expressed in (15):

$$f_6 = \sum_{i=1}^{m} \frac{\sqrt{\left(\sum_{j\in n} dist^2(i,j)\right)/n(i)}}{Network\ dimension} \quad (15)$$

where $dist(i,j)$ represents the distance between a sensor node S_j and the cluster head CH_i and $n(i)$ the number of nodes neighboring CH_i.

All the above criteria are non-conflicting in nature, so instead of minimizing them separately, these objectives are converted into a single objective function using a weighted sum approach and minimize. The weighting value is allocated for each objective value. In this case, different targets are changed into a single objective function. The weighted values are $\rho_1, \rho_2, \rho_3, \rho_4, \rho_5$ and ρ_6 .The unique objective function is shown in (16):

$$\begin{cases} f = \rho_1(f_1) + \rho_2(f_2) + \rho_3(f_3) + \rho_4(f_4) + \rho_5(f_5) + \rho_6(f_6) \\ \qquad \forall \sum \rho_i = 1;\ and\ \rho_i \in [0; 1] \end{cases} \quad (16)$$

These values are assigned based on the following considerations:
- ρ_2 is chosen as the higher priority to dodge failure of the node as CH.
- ρ_4 is the second priority to be considered to minimize the distance between CH and the sink node.
- ρ_1 and ρ_3 are taken as the third priority to play down the energy consumption and diminish the intra-cluster transmission distance respectively.
- ρ_5 and ρ_6 are the fifth priorities for respectively choosing a CH with the smallest degree of neighborhood and increasing the proximity between a CH and its CMs.

4. RESULTS AND DISCUSSION

The implementation and performance of the proposed method are discussed in this section. The conditions of the simulated algorithms are implemented in MATLAB. The performance is analyzed using the following different metrics: dead nodes, and the size of the total number of packets sent. The simulation parameters are listed in Table 1.

Table 1. Simulation Parameters

Parameters	Values
Area	100 m × 100 m
E	0.5 J
E_{elec}	50 n J
E_{fs}	10 pJ/bit/m^2
E_{mp}	16fJ/bit/m^2/m^4
k	4000 bits

In order to optimize the overall energy consumption of each node in the network. Therefore, FA will be used to facilitate the selection of cluster heads. The components considered by FA for way better CH determination are residual energy, consumed energy, distance between nodes and distance of the candidate CH to the sink node, node degree and node centrality. The FA parameters are summarized in Table 2.

Table 2. FA parameters

Parameters	Values
Dimension	6
Population Size	10
Absorption coeff.	0.01
Reduction factor	0.96

The FA parameters obtains from Table 2 are used to deploy sensor nodes in the network. The results are shown on the Figure 2. This proposed strategy is compared with few approaches such as LEACH, TEEN and DEEC which are by and large utilized to make strides the energy effectiveness of WSNs. The performance evaluation following the dead node and packet size is illustrated in Figure 3.

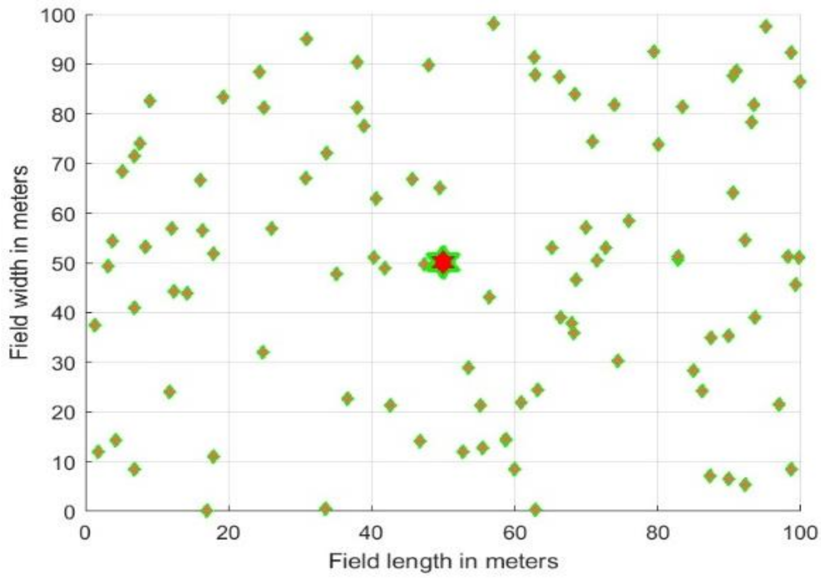


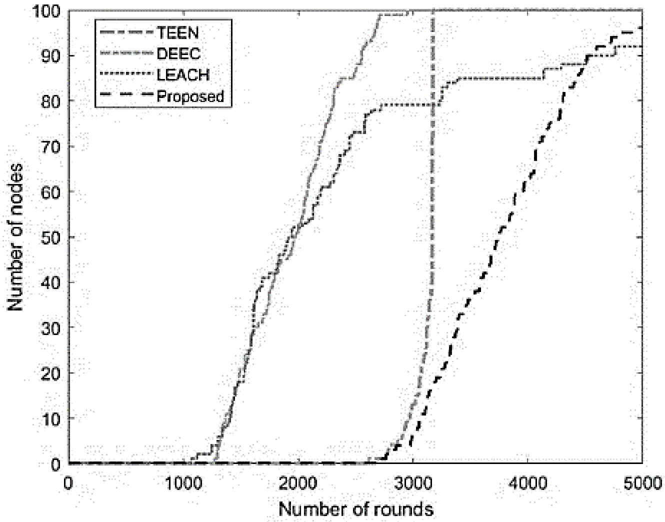
Figure 2. Node deployment

4.1. Performance in terms of dead node

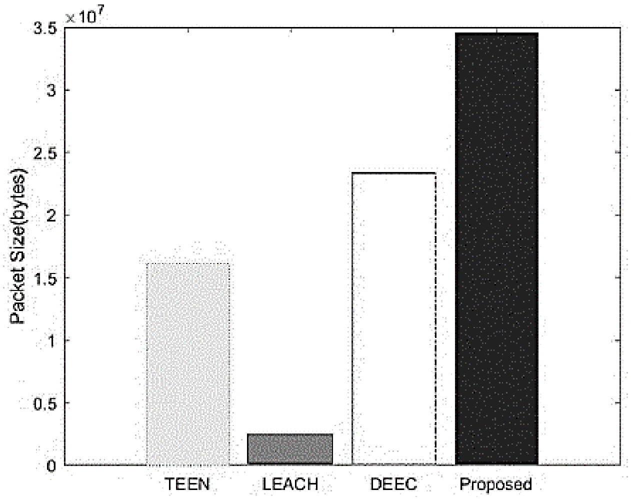
The performance of dead nodes in the proposed methodology is tested with existing algorithms such as LEAC, DEEC and TEEN. The cluster upkeep stage of the proposed strategy is utilized to preserve the network without any dead nodes up to 2721 rounds while LEACH, DEEC and TEEN are maintained up to 1067, 1292 and 2610 respectively. Thereafter, the node with the highest residual energy is considered to select the CH from the group of sensor nodes. The reason why nodes pass on quicker in LEACH and DEEC is the he single jump information transmission. This leads to consuming more energy via WSN. While TEEN selects a CH based on the amount of residual energy of the nodes while limiting the number of packets transmitted per transmission round. Subsequently, this dead node examination appears that the proposed has moved forward the performance of the node in terms of energy gain compared to LEACH, DEEC and TEEN. This performance is illustrated in Figure 3(a).

4.2. Performance in terms of packet size

The total packets number transmitted to the sink node is evaluated in this section. This is an important metric because it is related to the lifetime of a network. The packet size metric increases when the network lifetime is longer. The proposed method improves the WSN lifetime more than LEACH, DEEC and TEEN. The performance evaluation of transmitted packets at sink node of the proposed methodology, LEACH, DEEC and TEEN algorithms is shown in Figure 3(b). It appears that the proposed strategy accomplishes more gotten packets at sink node compared to LEACH, DEEC and TEEN. The reason for getting higher information bundles at sink node is the effectiveness of the FA fitness functions of the proposed technique. These fitness functions are considered to preserve the residual energy of the nodes to maximize the number of active nodes across the WSN which leads to increase the lifetime of the network. As a result, the number of data packets transmitted to the sink node increases. In addition, these fitness functions are utilized to choose only the node with sufficient energy to transmit data packets to the sink node. This avoids packet loss in the data transmission phase to the sink node.



(a)



(b)

Figure 3. Performance evaluation (a) by dead node and (b) by packet size

5. CONCLUSION

In this paper an optimal selection of CHs in WSN has been developed to optimize the energy consumption in order to increase the network lifetime. Clarifications provided on the use of the firefly algorithm (FA) for CH selection are provided. This approach is different from the previous research work based on LEACH, DEEC, and TEEN methods. The comparison between the proposed approach and the previous one shows a higher number of transmitted packets and a lower number of dead nodes and therefore a higher network lifetime. The preliminary steps for implementing this solution are illustrated. Though the achieved results show good performances. So, it would be interesting to apply this approach to a real case taken from field data.

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