Prolonging WSNs lifetime in IoT applications based on consistent algorithm

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ABSTRACT

The rapid expansion in the use of internet of things (IoT) imposes the importance of developing its infrastructure. One of the most important components in IoT infrastructures is the wireless sensor networks. The development of these networks largely depends on how to extend their life. As one of the effective options adopted in this field is the use of cluster heads (CHs). This paper introduces an algorithm that efficiently determine the CHs by iteratively extracting an associative value for each node depending on two factors; node's residual energy, and geometrical distances between nodes and base station. In light of the extracted values, the nodes with the best associative values are elected as CHs based on adjustable threshold determined according to the network usage requirements. The algorithm has proven a significant increase in the lifetime of the network, as well as, it has proven its ability to maintain a high level of energy for long period of time. The proposed algorithm outperformed similar protocols like low energy adaptive clustering hierarchy (LEACH) and region based low energy adaptive clustering hierarchy (R-LEACH) by prolonging the network lifetime and increasing network stability, as well as enhances the throughput significantly.

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1. INTRODUCTION

The rapid development of communication systems and the spread of the use of 5G networks in the foreseeable future will revolutionize the internet of things technologies to cover most of the globe. According to this fact, internet of things (IoT) networks which relies on the use of a large number of devices, sensors, and actuators are expected to increase dramatically, as the international data corporation (IDC) estimated that by 2025, there will be about 84 billion connected devices which will generate and transmit information of about 186 Zettabytes [1]. This will undoubtedly lead to the need for large amounts of energy, which will directly affect the performance of devices and sensors used in networks, as well as, affect the longevity of networks, especially the wireless sensor networks. In wireless sensor networks (WSNs), replacing exhausted batteries in the deployed nodes may be unattainable or cost-prohibitive particularly in harsh environment. Hence the importance of developing an energy aware algorithm to prolong the lifetime of sensors in such networks [2].

Numerous researches and studies have been conducted in the field of reducing energy consumption in WSNs to extend their life [3]. One of the important research trends in this field is based on the choice of hierarchical cluster heads (CHs) to represent a group of nodes, and to balance the network energy. Each CH is responsible for collecting data, managing transmissions of the associated nodes, eliminating redundancies and compressed the data, and then transmitting the compressed data to a base station [4, 5]. Among these researches, the low energy adaptive clustering hierarchy (LEACH) protocol that is widely used in WSNs [6, 7]. The protocol tries to manage the energy load in the network using stochastic formula to select CHs in each round. Each CH allocates time division multiple access (TDMA) schedules to its related node members, in which each member node transmits its data in the corresponding time slot. In [8] a secure CH selection algorithm is presented to ensure that the CH is not a malicious one. The election of any CH depends on different metrics included behaviors of the nodes, waiting time, connectivity degree, and distances. A fuzzy logic technique is used as the base of selecting cluster heads in [9, 10], in which the centrality, nodes density, and the residual energy are considered as the main parameters. These techniques showed better performance in terms of lifetime comparing to some well-known approaches. A modified K-means algorithm is used in [11] to decide whether the node is suitable to be a CH or not, taking in consideration that the selected node should be with high energy.

The comparison simulation results showed that the proposed protocol outperform some existing clustering protocols in terms of energy consumption, network lifetime, and packet delivery. Clustering protocol using the ratio of node distance to residual energy as the base to the probability of electing CH in homogenous WSNs is proposed in [12]. The protocol achieves longer network lifetime and increases the effective messages. A self-organizing map neural network is used for energy clustering in [13]. Spatial coordinates and the energy of each node were used as training input data to form the clusters. As a result, each formed cluster consists of a high-energy node and a number of closest nodes with a lower energy. A combination of routing schema with clustering and sink mobility technique is presented in [14] in which a member weight is determined for each node to decide on the CHs. Three rules were used to calculate the member weights. The first one depends only on the residual energy of node, the second rule is depending on the ratio of the residual energy of each node to its distance to the sink, while the third rule is based on the ratio of the square of residual energy of each node to its distance to the sink. It is found that the third rule has a better performance in terms network lifetime.

In [15] an algorithm called R-LEACH is introduced which is a modified version to LEACH protocol. In R-LEACH a CH selection scheme takes in its consideration the nodes residual energy. In addition, cluster head values were used to assign the post-group of CHs. The results showed that the proposed algorithm outperforms LEACH by enhancing WSN lifetime and residual energy by about 60-66%. A sampling-based spider monkey optimization method in conjunction with energy-efficiency is used in [16] to select cluster heads and to improve lifetime and stability of WSNs. The experimental results compared to similar protocols showed that the proposed technique improves the lifetime and the stability of the networks. Improving the CH election using neural networks and LEACH protocol introduced in [17], taking in consideration the node with highest energy level to be the CH. The simulation results of this approach perform better than LEACH. The Bellman-Ford algorithm is utilized in [18] to choose the cluster heads. This algorithm finds the shortest path from a single source in terms of distance/cost. The simulation results showed that this algorithm is better than the K-mediod clustering algorithm in network lifetime and energy consumption. An energy aware approaches introduced in [19, 20]. The clustering framework in these approaches are based on hybrid metaheuristic algorithms. Several parameters were used to evaluate the fitness function which include packet progress, energy, node density, cluster distance, and transmission delay. Results of comparison with similar protocols showed improvement in the performance of the proposed methods.

Some of the aforementioned approaches did not take into consideration the distance between the elected cluster head and the base station, and this may lead to energy loss in the event of choosing an edge node. Whereas, some approaches have adopted a random value to generate a threshold to be used in regarding the cluster heads, while other research relied on the link between this threshold value and the residual energy of the nodes. On the whole, these researches have succeeded in improving energy consumption and extending network lifetime, but this improvement was relatively small and did not meet the aspiration to achieve a significant increase in the longevity of the network.

In this work, a robust associative value is extracted based on a ratio combined two parameter vectors; nodes residual energy and distances from the nodes to the sink/base station respectively. The nodes with the best associative values will be elected to be cluster heads. After the end of each round, the associative values are recalculated, as the remaining energy of the nodes (CHs and non-CHs) have changed. In the remainder of this paper, section 2 introduces the adopted network and energy models. Section 3 explains the proposed algorithm and the details on how to extract the associative values. The simulation results and comparison with some classical protocols are presented and discussed in section 4, while section 5 presents the conclusions of this work.

2. NETWORK AND ENERGY MODELS

In this work the system model is assumed to adopt a wireless sensor network with static and homogeneous sensor nodes having identical sensing, processing, communication, and batteries power. These nodes are deployed randomly in the sensing field. The geographical locations of the nodes are known to each other through information exchange. The base station is stationary and mediates the sensitization field. The nodes have the ability to adjust the transmission power depending on how far is the destination to the target. Each node periodically sends its data at a specified time slot according to a schedule it will be notified. The network continues in its operation until all the nodes energy is exhausted. According to [21] the time period before the energy of the first node runs out is considered as the network stability, meanwhile the duration from the network start in its operation until the last node dies is the network lifetime. These two parameters can be described as (1) and (2), where T_{st}, T_{Nl} are the network stability and network lifetime respectively, and T_n is the lifetime of node n. In WSNs most of nodes energy is consumed due to its packets routing [22]. To calculate and evaluate the consumed energy in such networks the communication model implemented by [23] is considered as shown in Figure 1.

$$T_{st} = min_{n\in N}(T_n) \quad (1)$$

$$T_{Nl} = max_{n\in N}(T_n) \quad (2)$$

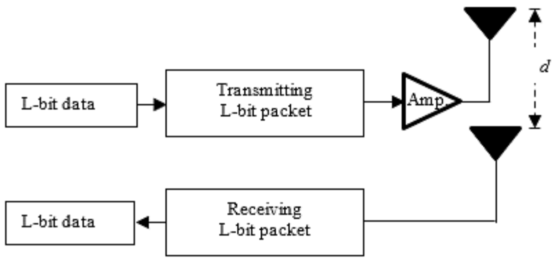

Figure 1. Energy communication model

In the transmission process, the consumed energy depends on the distance between the source and the destination. If this distance is greater than some threshold d_o, then the multi-path fading energy model is used, otherwise the free space energy model is considered [24]. The energy consumed in transmitting L-bit data packet to a destination node of d meters far is as illustrated in (3) and (4) [24].

$$E_{TX}(L,d) = L(E_{elec} + \varepsilon_{mp}\, d^4), \quad for\ d > d_o \quad (3)$$

$$E_{TX}(L,d) = L(E_{elec} + \varepsilon_{fs}\, d^2), \quad for\ d \le d_o \quad (4)$$

Where E_{elec} is the consumed energy per bit by transmitter or receiver, εmp and εfs are the transmission parameter of multi-path and free space respectively, and do is the threshold value of the transmission distance. Meanwhile the consumed energy to receive L-bit data can be calculated by [24]:

$$E_{RX}(L) = LE_{elec} \quad (5)$$

The threshold transmission distance is determined by as mentioned in (6) [25].

$$d_o = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}} \quad (6)$$

Knowing that, when the transmission distance d is greater than d_o then the energy model of (3) is used, otherwise, the energy model of (4) is applied.

3. EXTRACTING BEST ASSOCIATIVE VALUES

Selecting cluster heads randomly without considering the nodes' residual energy or how far are these nodes from the base station, as well as adopting un-sober relationship between the residual energy and these distances may not lead to a guarantee that the choice of CH is the best, as a result does not extend the life of the WSN appropriately. The novelty of this work lies in constructing a reliable function through which a value for each node can be extracted, this value reflects the possibility of electing the node as a cluster head or not. The work proposed a consistent relationship consolidates the residual energy and the distances between the nodes and BS. According to this relationship associative values (Av) between the nodes and the base station can be extracted. The nodes with the best associative values (BAV) then be chosen to work as CHs.

To calculate Av, a wireless sensor network with N nodes and a BS is considered. Each node i has initial energy E_i, where i =1, 2, .. , N. The Euclidean distance d_i between node i and the BS is calculated by;

$$d_i = \sqrt{(x_i - x_{BS})^2 + (y_i - y_{BS})^2 + (z_i - z_{BS})^2} \tag{7}$$

where (x_i, y_i, z_i) are the coordinates of node i, and (x_{BS}, y_{BS}, z_{BS}) are the coordinates of the BS. The values of the distances d differ from a few meters or less to several tens of meters or even more depending on the dimensions of the sensing field and the distance between node i and BS. In contrast, the values of nodes residual energies E are often fraction of the values of d. Therefore, a coherent Av based on both d and E can be achieved by normalizing the distance values. Appropriate normalization to d can be performed by subtracting the mean of d from each of the d's values and dividing the result by the standard deviation [26].

$$dn_i = (d_i - \bar{d})/d_{std} \tag{8}$$

where d_n is the normalized distance vector, $\bar{d}$ is the mean distance, and d_{std} is the standard deviation of the distance.

The formula of the associated values used in [27] is modified to accommodate the requirement of this work. The extracted associative value Av_i for i = 1, 2, …, N, is equal to the square of the product of (E_i and dn_i) normalized by the product of the sum of the squared residual energy vector E and the sum of the squared distances vector dn, that is;

$$Av_i = \frac{(E_i dn_i)^2}{\sum_{j=1}^{N} E_j^2 \sum_{j=1}^{N} dn_j^2} \tag{9}$$

These values represent an indicator that governs and balances the relationship between the residual energies and the nodes distances. During data transmission, the residual energies of the nodes are decreased, as a result their Av will be changed, and this may cause some nodes to have a small associative value despite their proximity to the base station. An illustrative example of five nodes deployed randomly in a sensing field with a BS located in its center is shown in Figure 2 (a), in which, the center of the bubbles represents the locations of the nodes while the radius indicates the amount of the associative value of each node. The node that has the BAV is the one with the largest radius. After some while and due to data transmission, the nodes consumed unequal energies depending on how far the target is and whether the node takes the responsibility of acting as CH or not. As a result, the Av's of these nodes were changed, and the node with the BAV may also change as shown in Figure 2 (b).

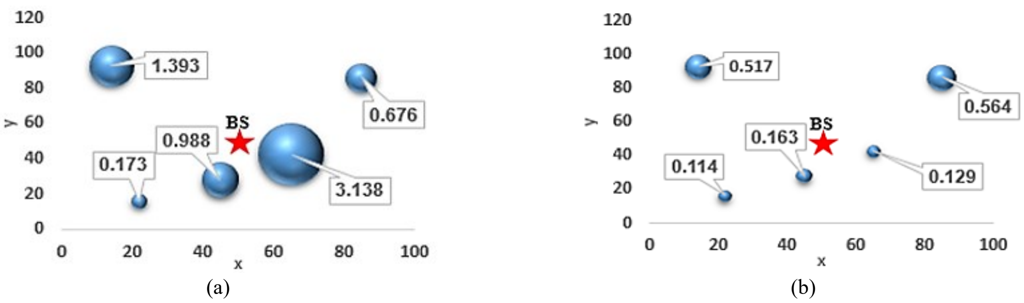

Figure 2. Nodes associative values; (a) equal energies, and (b) different energies

After deploying the nodes in the sensing field, it is assumed that the BS and all the nodes know the location of each other and their initial energies by sharing information. The first step in the proposed technique is to calculate the Av of the nodes. Among these values the nodes with the BAV are elected to be CHs. The decision on how to determine BAV is based on a threshold Av_o which depends mainly on the mean of Av, that is:

$$BAV = \{Av \geq Av_o | Av_o = k * mean(Av)\} \tag{10}$$

and

$$CH(BAV) = \{n|n \in N\} \tag{11}$$

where k is the threshold adjustment parameter, and $0 < k \leq 1$. Several values were adopted for Av_o and its impact on extending network lifetime was studied.

The proposed algorithm utilized iterative procedures, where in each iteration the nodes with the BAV are determined and elected to be CHs. Then a loop considers each elected CH individually to do the following: each CH inform the other nodes their time to transmit data, receive their data, and send the aggregated data to BS. After the end of each iteration, the associative values vector for all the nodes are recalculated based on their new residual energy and their distances to BS. These operations are repeated until all the nodes in the network deplete their energies. The detail steps of the proposed algorithm are as follows:

Step 1: Initialize the network parameters
Step 2: Deployed the nodes in the sensing field
Step 3: While number of dead nodes< total number of nodes, do step 4-11
Step 4: Calculate nodes' Av
Step 5: Determine the nodes with BAV: (Av>Avo), and store them in CH-List
Step 6: While CH-List not empty, do step 7-10
Step 7: Select CH node from CH-List
Step 8: Aggregate packets from non-CH nodes and transmit the data to BS
Step 9: Compute residual energy for all the nodes
Step 10: Remove the CH from CH-List
Step 11: Determine the dead nodes.

A flow chart illustrates the processes of electing cluster head using BAV algorithm is shown in Figure 3.

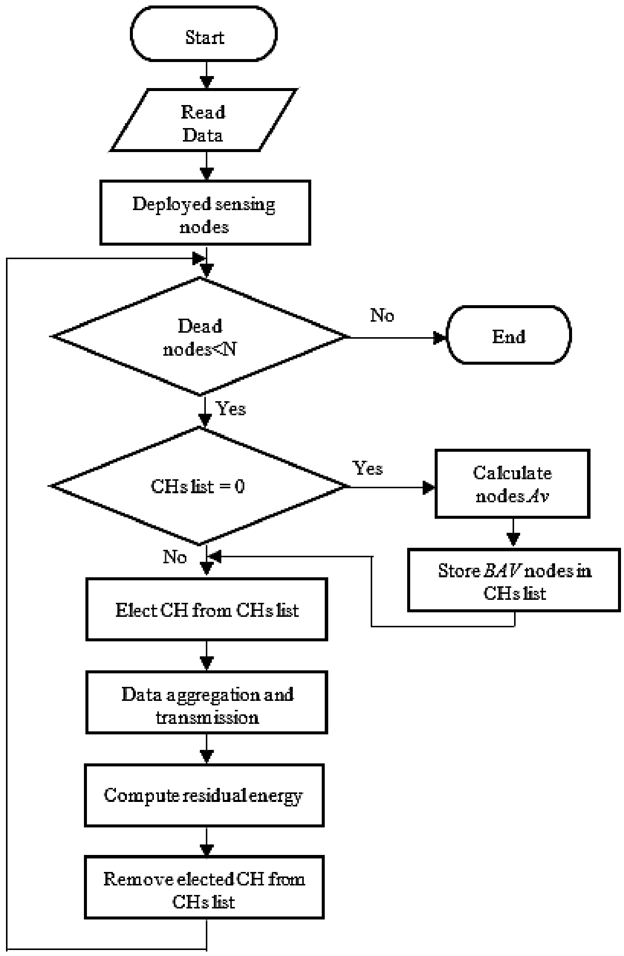

Figure 3. Flow chart illustrates CHs election based on BAV

4. SIMULATION RESULTS

The simulation is based on the assumption that a WSN with 100 static and homogeneous sensor nodes deployed randomly in a sensing field of dimensions 100*100 m and a stationary BS mediates the sensitization field. All the nodes have the same initial energy. The network model also assumes the parameter values shown in Table 1. Results are extracted using MATLAB (R2017b) as a simulation tool to characterize the network models.

Table 1. Parameter values of the network

Parameter	Value
Nodes initial energy	0.5 J
Multi-path transmission parameter (εmp)	$1.3*10^{-15}$ J/bit/m^4
Free space transmission parameter (εfs)	$0.1*10^{-12}$ J/bit/m^2
Consumed energy per bit (Eelec)	$50*10^{-9}$ J/bit
Energy of Data aggregation per bit (EDA)	$5*10^{-9}$ J/bit
Number of bits per packet (L)	4000 bit

4.1. Network analysis

As mentioned earlier, the decision on electing CHs in the proposed technique is determined by the nodes with *BAV* which depends on the value of Av_o. According to (10), Av_o can be adapted by changing the value of the threshold adjustment parameter *k*. The impact of considering different Av_o values on the network lifetime, number of transmitted packets from the nodes to CHs and from CHs to BS, and on the residual energy have been studied. Figure4 shows the effect of considering different values of *k* on the number of round (in average) required until the death of the first node (network stability), the death of half of the nodes, and the death of last node (network lifetime).

The smaller the value of k the more nodes with *BAV*. In other words, the number of nodes that will be elected as CHs will increase. Allowing a greater number of participations as CHs using a coherent criterion leads without any doubt to increase the stability of the network and extend its life, and this is what's reflected in the case shown in Figure 4.

The effects of considering different Av_o values on the number of packets sent from normal-nodes to CHs and from CHs to BS (throughput) are shown in Figure 5. The number of normal nodes increases as the value of Av_o increases. This will undoubtedly increase the number of packets from normal-nodes to CHs. By contrast, the number of CHs will decrease as Av_o increases, which will reduce the number of packets sent from CHs to BS. The network residual energy based on different Av_o values is shown in Figure 6. As it is noticed from the figure, the energy level of the nodes continues for a longer period as the value of k decreases, in other words, the more nodes that have *BAV*.

As a result, it can be said that if the application for the network requires a large number of transmissions from the nodes and needs high network stability, then the value of k must be small. But if the application focuses on increasing the life of the network as much as possible through the durability of the remaining energy then the value of k must be high.

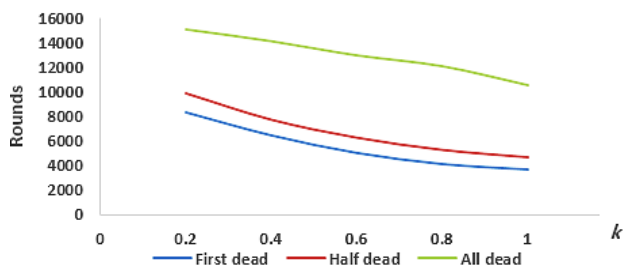

Figure 4. Effect of different Av_o values on the network stability and lifetime

4.2. Comparative results

To check the performance of the BAV algorithm, the threshold adjustment parameter *k* is set to 0.5 which returns the mediate value of Av_o, i.e. the obtained results are based on Av_o = 0.5*mean(Av). These results are compared with LEACH and R-LEACH protocols. The comparison considers the same initial data as well as the same coordinates of the random nodes' deployment in each session for the three approaches. All the obtained results represent the average counts for several iterations.

The results of the residual energy is as shown in Figure 7, in which its values in both LEACH and R-LEACH are almost close to each other and deplete in about round 1500, whereas *BAV* can conserve energy for a much longer period as it continues to more than round 8500. This constitutes about 450% increasing in network lifetime compared to both LEACH and R-LEACH. This is due to the high capability of BAV algorithm in balancing the load and uniformly consumed the energy.

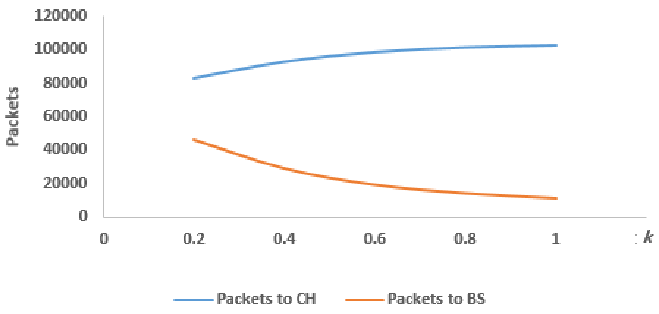

Figure 5. Effect of different Av_o values on the number of transmitted packets from nodes to CHs and from CHs to BS

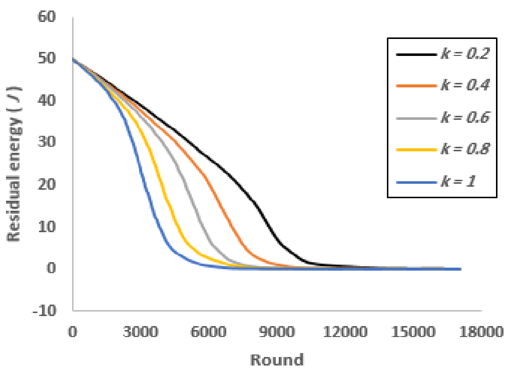

Figure 6. Effect of different Av_o values on the residual energy

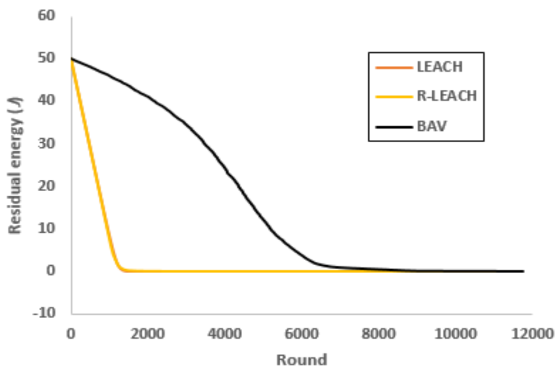

Figure 7. Residual energy

Figure 8 shows the network lifetime, in which the death of first node recorded at about round 900 and 1000 in LEACH and R-LEACH respectively, whereas in BAV the first node dies out in average at round 5800. Meanwhile, the death of the last node is in average at round 2000, 8000, and 13000 for LEACH, R-LEACH, and BAV respectively. The reason behind this difference is that in LEACH the selection of CHs depends on a threshold extracted from random value which make this selection not so efficient, where as in R-LEACH this threshold is modified by inserting the residual energy as an additional parameter to the LEACH threshold selection formula, in contrast, in BAV the selection of CHs is based on iteratively combining the parameter vectors of the residual energy and the distance for overall of the deployed nodes to extract the nodes with best associative values.

Throughput is an important metric that expresses the ratio of the packets actually received by BS to the number of sent packets. As BAV algorithm keeps the residual energy for a long period which leads to prolong the network lifetime, as well as it allows the exchange of roles and responsibilities between the nodes to work as a CH or as a non-CH, which makes the throughput high compared to both LEACH and R-LEACH. The average through put are about 12000, 8600, and 23000 for LEACH, R-LEACH, and BAV respectively as shown in Figure 9.

The significant improvement in network longevity, stability and throughput comes from the ability of the proposed algorithm in achieving high balancing in load distribution due to the robust selection of CHs, as well as allowing exchange the roles between nodes depending on the associative values. In contrast, the increase in the number of packets sent from CHs to the BS in BAV algorithm leads to a decrease in the number of packets transmitted from normal nodes to CHs, in addition, the summation of the total number of transmitted packets (packets from nodes to CHs + packets from CHs to BS) is less than the case in the comparative protocols.

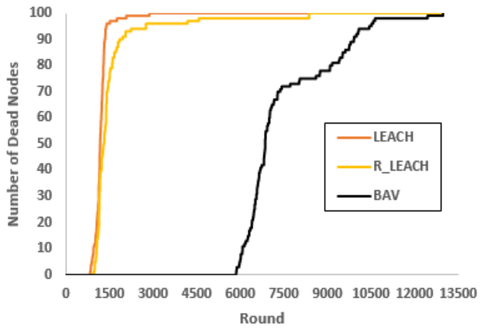

Figure 8. Network lifetime

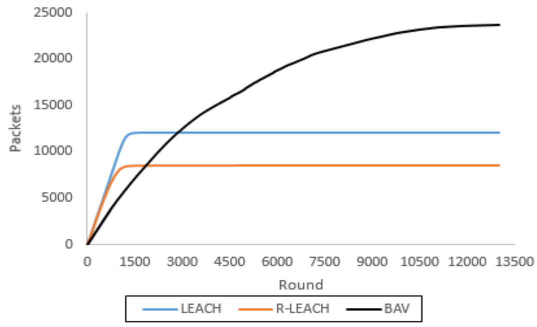

Figure 9. Network throughput

5. CONCLUSION

This work suggested a robust technique to elect CHs by extracting associative value to each node. Among these values, the nodes with BAV (based on calculated threshold) are elected as CHs. Permitting large number of nodes as CHs using a rigid criterion increases the stability of the network and prolongs its lifetime, as well as increases the network throughput, in other words, increasing the number of nodes covered in BAV reflected on maintaining the nodes energy level for a longer time. This is strongly motivated the use of BAV algorithm in the IoT applications. In addition, the capability of the proposed algorithm in managing and distributing the load uniformly made it significantly superior to similar protocols such as LEACH and R-LEACH, especially in the area of network stability and lifespan. Since the proposed algorithm iteratively calculates the nodes associative values depending on the residual energy and the distances to BS, therefore it can be easily adapted to be utilized in mobile sink.

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