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A Teaching Learning Based Optimization Algorithm for Cluster Head Selection in Wireless Sensor Networks

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Abstract

In wireless sensor networks, clustering techniques are widely used for cluster heads selection and also to reduce power consumption. Therefore, these techniques are applied to increase network life time and optimum number of CHs. In this work, teaching learning based optimization (TLBO) algorithm is adopted for finding the optimum number of cluster heads in a sensor field. Another, objective of this algorithm is also to reduce power consumption and increase the network life time. The proposed algorithm is integrated with LEACH protocol, called LEACH-T and considers the residual energy for selecting the CHs. Simulation results show that the proposed algorithm enhances the network life time by reducing the power consumption during packets transmission. It is also observed that the proposed algorithm is an effective and efficient algorithm for CHs selection.

Keywords*: Clustering, LEACH, TLBO, WSNs*

1. Introduction

In recent years, wireless sensor networks (WSNs) has fascinated considerable attention from research community in terms of cluster heads (CHs) selection mechanism, reducing energy consumption, collaborative information processing, and communication [1]. WSN is a network of dense interconnected sensor nodes and process the information collaboratively. The nodes of the WSN are powered with small battery which is the main energy source for sensor nodes. The work of the sensor nodes collects the information from environment and process the collected information for decision making. As a result of this, power consumption of nodes increases and nodes become dead due to lack of power. Hence in WSNs, collaborative information processing and power consumption can be considered as key issues. Another key issue, in WSNs is type of communication between nodes to CHs and CHs to Base Station (BS), weather it is single hop or multi-hop. It is also found that residual energy is also considered as warm area of research in recent past. Many researchers give attention towards this area and consider the residual energy among with normal energy consumption of nodes in WSNs. Most of the cluster based routing protocol consider the residual energy as one of the important parameter for CHs selection.

The goal of this research work is to attain collaborative data processing and also increase the network life time by reducing energy consumption in WSNs. Thus to achieve the same, a new method is adopted to elect the optimum CHs in sensor field and this method is integrated into LEACH protocol. Another aspect of this work is to consider residual energy for selection of CHs among distributed sensor nodes in sensor field. Further, to prolong network life time and also to obtain optimum CHs, a new fitness function is also proposed for CHs selection algorithm. In this, single hop as well as multi-

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hop radio channel is adopted for transmission of data. Hence the contribution of this work is highlighted as below.

(i) Extensive study on different cluster based routing protocols in the domain of WSNs.

(ii) To propose an efficient optimization algorithm for the selection of optimum cluster heads.

(iii) To devise a new fitness function for cluster head selection algorithm and also adopts the concept of energy grading.

Rest of paper is organized as follows. Section 2 describes the recent work in the domain of CH selection and energy efficiency for WSNs. In section 3, teaching learning based optimization method is explained. Section 4 explains CHs selection protocol, radio energy model and newly proposed fitness function for efficient WSNs. Section 5 includes environment and various parameters for WSNs and also contains experimental results and discussion. The conclusion of the work is given in section 6.

2. Related Work

This section describes the related work in the domain of WSNs especially cluster head (CH) selection algorithms, evolutionary and swarm based algorithm for WSNs and variants of LEACH protocol. Heinzelman *et al*., have developed a clustering based protocol for WSNs, it is known as LEACH protocol. The LEACH was developed to select CHs randomly for transmission of the energy load from CHs to BS [2]. Simet *al*., [3] proposed an energy-efficient cluster head selection algorithm (ECS) which selects cluster head by utilizing only its information to extend network lifetime and minimize additional overheads in energy limited sensor networks. M. C. M. Thein and T. Thein [4] proposed a modification of the LEACH's stochastic cluster head selection algorithm by considering the additional parameters, the residual energy of a node relative to the residual energy of the network for adapting clusters, and rotating cluster head positions to evenly distribute the energy load among all the nodes. Attea and Khalil proposed a new evolutionary based routing protocol for clustered heterogeneous WSNs [5]. To select optimum number of cluster heads (CHs) among sensor nodes, Quiang *et al*., have developed an efficient cluster head selection algorithm by using collaborative data processing on CH nodes and named it CHSCDP [6]. The results show that CHSCDP gives better performance than the other algorithm being compared.Jain *et al*., have presented a cluster head selection algorithm to choose optimal CHs [7]. In this algorithm, weights and ranks are used to identify CHS. A node having higher value of weight is selected as cluster head among its neighbors. Deshmukh and Gawali have developed an improved version of LEACH protocol for enhancing the network life time [8]. A new mechanism is introduced in the LEACH protocol to choose CHs based on the stochastic geometry and remaining energy of sensor nodes. The experimental results are compared with LEACH, TEEN and PPT based protocols and it is found that the improved version of LEACH protocol extends the network life time significantly.

A compact genetic algorithm is applied to minimize the energy depletion in WSNs [9]. The results of GA are compared with LEACH, LEACH-C and HEED protocols and it is found that the proposed protocol performs better in terms of avg. residual energy, live nodes, and packets sent. For the selection of CHs, a crossover operator based evolutionary algorithm is reported and named it HACH [10]. This protocol uses Boltzmann selection operator for the selection of inactive node and crossover operator to generate the high quality solution from different population. The authors claimed that the proposed protocol provides quality of solution in terms of network life time. To maximize the network lifetime and minimize the intra-cluster distance, a cuckoo search based energy efficient protocol is presented for WSNs [11]. The performance of the protocol is tested on several parameters like clustering capability, network lifetime and scalability and compared with

LEACH, PSO and LEACH-C. It is shown that cuckoo search based protocol gives better results using all parameters. A hierarchical cuckoo search routing protocol is also reported for WSNs [12]. In this protocol, cuckoo search method is adopted for the selection of CHs, data collection and aggregation. The authors claimed that the proposed protocol outperforms LEACH and M-GEAR protocols in terms of energy saving. Yadav *et al*., have developed a discrete particle swarm optimization algorithm for selection of CHs in WSNs [13]. This algorithm considers the residual energy and distance between sensor nodes for optimal clustering. The simulation results show that the PSO based protocol improves the network life time in comparison to other algorithms. To handle energy consumption issue of WSNs, an improved variant of Leach-C protocol is devised and called it EB-Leach-C [14]. In EB-Leach-C protocol, K-Means and SOM are adopted for CHs selection and a new cost function is also designed for choosing optimum relay node. Results show the existence of the EB-Leach-C protocol in the field of WSNs. To extend the network life time, a firefly based clustering protocol is developed for WSNs [15]. The aim of firefly algorithm is to elect the CHs in order to reduce energy consumption in each iteration. From the results, it is observed the adoption of firefly algorithm decreases the death rate of nodes. To determine optimum CHs in WSNs, Yazdani *et al*., have applied modified GSA algorithm for CHs selection [16]. To increase the life time of WSNs, Mishra *et al*., have introduced new method for CHs selection based on fuzzy concept [17]. In this work, residual energy, base station distance, concentration and local distance parameters are considered to elect the CHs among sensor nodes. For the above mentioned parameters, fuzzy fitness values are computed. To design low power scalable WSNs, Ari *et al*., have developed a new cluster based routing protocol, named it ABC-SD [18]. The proposed protocol is the combination of ABC algorithm and linear programming. In this work, a multi objective function is also derived for the election of CHs based on linear programing. Simulation results show that the ABC-SD algorithm considerably improve the performance of the WSNs in comparison to other existing algorithms. To deal with energy and CHs selection constraints of WSNs, Yadav *et al*., have developed an improved version of LEACH protocol using fuzzy logic concept [19]. This protocol considers energy level, distance from cluster head and crowdedness parameters to resolve the above mentioned issues and the values of these parameters are fuzzified in order to improve the performance of WSNs. The results show the effectiveness of the proposed protocol especially in terms of network life time. To overcome the disadvantage of LEACH protocol during the data transmission, lee *et al*., have applied a dual hop method (single hop and multi hop) for data transmission and claimed that the proposed amendment reduces the shortcoming of LEACH protocol [20]. To improve the energy efficiency of LEACH-C protocol, Ma *et al*., have developed another variant, called LEACH-CC based on the power constraint [21]. It is observed that LEACH-CC provides significant result in terms of energy consumption. A modified K-Means (MK-Means) algorithm is applied to find the suitable CHs in WSN [22]. In this work, three CHs are identified instead of single CH for transmission of data. But, out of these, only one cluster head active at a time and all CHs have a load sharing mechanism. The simulation results show that the proposed protocol works better than the existing algorithms.Gupta *et al*., have applied a modified ant colony optimization (MACO) for the selection of CHs using residual energy parameter and it is employed in LEACH protocol [23]. It is found that integration of MACO and LEACH enhances the performance of the LEACH protocol. To maximize the network life time and also the throughput, Singh *et al*., have proposed two amendments in LEACH protocol [24]. First amendment is directed to CHs selection policy and second amendment directed to transmission of data. For CHs selection, a cluster head replacement scheme is introduced, whereas a dual power transmission scheme is adopted for data transmission. To enhance energy efficiency and life time, Razaque *et al*., have presented a P-LEACH protocol [25]. This protocol is the combination of the PEGASIS and LEACH protocols. Results show that the P-LEACH protocol overcomes the

shortcomings of both the protocols. To enhance the performance of LEACH protocol, Tasi *et al*., have developed a quantum inspired evolutionary algorithm (QEA) [26]. The results show that QEA is an effective and efficient protocol for WSNs. To maximize the energy, network coverage and transmission reliability, Elhabyan and Yagoubhave developed a PSO based clustering protocol for WSNs [27]. The results confirm the existence of the protocol in terms packet delivery rate and scalability.

3. Teaching Learning Based Optimization (TLBO) Algorithm

Rao *et al*., have developed teaching learning based optimization (TLBO) algorithm based on the concept of classroom teaching [28]. In short span of time, this algorithm became popular in research community. A lot of optimization problems have been solved by using TLBO algorithm and provides better results in comparison to existing algorithm [29-32]. As far as our knowledge is concerned, the TLBO algorithm is not applied in the field of WSNs. TLBO algorithm consists of two phases- teacher phase and learner phase. The description of these phases is given below.

Teacher Phase: The objective of teacher phase is to improve the knowledge of students so that result of class significantly improves and improved results can increase the mean result of class. But in general, a teacher can enhance the result of class up to some extent, because there are several constraints in terms of teacher and learners *i.e.* students. Consider, M denotes the mean of the knowledge of learners and T denotes any teacher in iteration. The teacher wants to enhance the current mean knowledge of learners and it may be possible by dragging M towards T and this can be expressed using equation 1.

$$\mathrm{DifferenceMean} = \mathrm{r} \times (\mathrm{T_{mean}} - \mathrm{T_f} \times \mathrm{M_i}) \quad (1)$$

In equation 1, $\mathrm{M_i}$ and $\mathrm{T_{mean}}$ represent the mean of the knowledge of learner and teacher in i^{th} iteration, $\mathrm{T_f}$ denotes the teaching factor, and r is a random number in the range of 0 and 1.

$$\mathrm{T_f} = \mathrm{round}\big(1 + \mathrm{rand}(0,1)\big) \quad (2)$$

The new mean of the knowledge is updated using equation 3 which is described as below.

$$\mathrm{X_{i,new}} = \mathrm{X_{i,old}} + \mathrm{DifferenceMean_i} \quad (3)$$

Learner Phase: The aim of the learner phase is to enhance the knowledge of learner from others. So, to improve his or her learning ability, a learner can interact with other learners randomly. In learner phase of the TLBO algorithm, learners learn knowledge from others. This learning capability of learners can be expressed as follows.

If i^{th} learner wants to interact with the kth learner and the fitness of the kth learner is higher than i^{th} learner, then the position of ith learner will be updated otherwise k^{th} learner. This can be summarized in equations 4-5.

$$\mathrm{X_{i,new}} = \mathrm{X_{i,old}} + \mathrm{r_i} \times (\mathrm{X_k} - \mathrm{X_i}) \quad (4)$$

Else

$$\mathrm{X_{i,new}} = \mathrm{X_{i,old}} + \mathrm{r_i} \times (\mathrm{X_i} - \mathrm{X_k}) \quad (5)$$

If the fitness of new position of ith learner is better than old position, then new position takes over the old one otherwise not.

4. Cluster Head Selection Using TLBO

This section describes the working of proposed TLBO based CHs selection algorithm in detail. It is considered that Base Station (BS) is located inside sensor field and is also aware about the location of sensor nodes.

4.1. Modification in TLBO Algorithm

Prior to apply TLBO algorithm for CHs selection, two modifications are made in TLBO algorithm for enhancing its searching mechanism and also to improve convergence rate. As a result of this, genetic crossover and mutation operators are integrated in TLBO

algorithm. The genetic mutation operator is applied in teaching phase, whereas, genetic crossover operator is applied in learning phase of TLBO algorithm. These modifications are mentioned in Algorithm 1 and Algorithm 2.

Algorithm 1: Teacher Phase of TLBO algorithm

For i =1 to K (for each learner *i.e.* no. of CHs)
For j =1 to D (dimensions)
$\text{DifferenceMean} = r(T_{mean} - T_f \times M_i)$
$T_f = \text{round}(1 + \text{rand}(0,1))$
IF (DifferenceMean $< rand()$)
Apply genetic mutation operator on T_{mean} and M_i
Compute Difference Mean and generate the new mean of knowledge
($X_{i,new}$) using equation 3.
Else
$X_{i,new} = X_{i,old} + \text{DifferenceMean}_i$
End
End
Accept $X_{i,new}$ if $f(X_{i,new})$ is better than $f(X_{i,old})$
End

The proposed genetic crossover operator in TLBO algorithm generates the CHs which are dispersed in sensing field and aim to select a node with higher energy. It is also taken into consideration that two nodes within the same cluster region is not allowed. Each CH is associated with an array which contains the nodes with decreasing residual energy. For the crossover operation, two nodes of higher energy are selected and position of CH is computed individually, denoted by CH1, CH2 and so on. Each subsequent CHs position in the CH_{all} is compared with the CH_{new} array set in order to ensure decisions based on distance between the CHs and their residual energy.

Algorithm 2: Learner Phase of TLBO algorithm

For i =1 to K (for each learner *i.e.* no. of CHs)
Randomly pick two learners X_i and X_k such that $i \neq j$
IF $(F(X_i) < F(X_k))$
IF $(\text{Threshold Probabilty of } X_k < rand())$
Apply genetic crossover operator on X_i and X_k and generate the new
position of learner X_k.
End IF
$X_{i,new} = X_{i,old} + r_i \times (X_k - X_i)$
Else
$X_{i,new} = X_{i,old} + r_i \times (X_i - X_k)$
End
Accept $X_{i,new}$ if $f(X_{i,new})$ is better than $f(X_{i,old})$
End

4.2. Radio Energy Channel

In this work, an efficient and effective radio and energy dissipation channel is taken for experiment which is described in [3]. It is necessary to consider free space and multipath fading channels for effective energy dissipation model. In this work, we consider both of

channels. Hence to determine the consumption of the energy for transmitting M bits over distance d is computed using equation 6.

$$E_{TX}(M,D) = \begin{cases} M.E_{elect} + M.\varepsilon_{fs}.d^2 & \text{if } d \le d_0 \\ M.E_{elect} + M.\varepsilon_{mp}.d^4 & \text{if } d > d_0 \end{cases} \quad (6)$$

Where, E_{elect}denotes residual energy, ε_{fs} and ε_{mp}denote energy consumption of free space and multipath fading channels respectively and d denotes the distance between sensor nodes and CH. d_0 can be measured using $d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}$. The radio expansion for receiving M bits data can be measured using equation 7.

$$E_{RX} = M.E_{elect} \quad (7)$$

4.3. Fitness Function

In WSNs, success of the CHs selection algorithm depends on the fitness function designed to choose the nodes as CHs. In this work, a new fitness function is designed for CHs selection. This function comprises of two important aspect of WSNs *i.e.* first, the energy consumption between CH and sensor nodes; second, the amount of energy consumption for aggregating the data at CHs level plus transmitting the information to BS. The energy consumption between sensor nodes and CHs is computed using equations 8-10.

$$E_1(j) = \sum_{k=1}^{K} \sum_{\forall n_{k_j} \in C_k} \left\{ \frac{E_{k_j} - f(k_j, C_k)}{E_{max} - E_{min}} \right\} \times k_j \qquad \text{where } j = 1,2, \dots \dots . n \quad (8)$$

$$f(k_j, C_k) = \begin{cases} s^2(k_j, C_k) & \text{if } s\,(k_j, C_k) \le d_0 \\ s^4(k_j, C_k) & \text{if } s\,(k_j, C_k) > d_0 \end{cases} \quad (9)$$

$$s(C_k, k_j) = \min(k_j, C_k) \qquad \forall\, k = 1, 2, 3, \dots, K \quad (10)$$

The notations denoted in equations 8-10 are summarized as.E_{k_j} denotes the energy of jth node of kth cluster; $f(k_j, C_k)$ is a function used to compute the energy consumption between sensor nodes and CHs; E_{max} and E_{min} denote the maximum and minimum energy of decay in WSN; C_k represents the kth cluster; s is a function which computes the minimum of jth node and k^{th} cluster; the value of $k_j = 1$, it is the jth node of kth cluster, otherwise = 0 and d_0 denotes the threshold distance.

The energy consumption between CHs and BS is computed using equations 11 and 12.

$$E_2(j) = \sum_{k=1}^{K} \left\{ \frac{E_{C_k} - g(C_k, BS)}{E_{max} - E_{min}} \right\} \times C_k \quad (11)$$

$$g(C_k, BS) = \begin{cases} d^2{}_{(C_k,BS)} & \text{if } d^2{}_{(C_k,BS)} \le d_0 \\ d^4{}_{(C_k,BS)} & \text{if } d^2{}_{(C_k,BS)} > d_0 \end{cases} \quad (12)$$

The description of notations defined in equations 11 and 12 are given as E_{C_k} denotes the energy of kth cluster; $g(C_k, BS)$ is a function used to compute the energy consumption between CHs and BS; E_{max} and E_{min} denote the maximum and minimum energy of decay in WSN; C_k represents the kth cluster; the value of $C_k = 1$, it represents the kth cluster, otherwise 0 and d_0 denotes the threshold distance.

The total energy consumed to transmit the M bit data from sensor nodes to BS is measured using equation 13.

$$F(j) = E_1(j) + \mu\, E_2(j) \quad (13)$$

4.4 Proposed Approach

This subsection describes the implementation steps of proposed TLBO based CHs selection algorithm. The main objective of the algorithm is to elect the optimum CHs in each iteration for reducing the energy consumption and also increasing the network life

time. The clustering mechanism of the proposed algorithm is based on the LEACH considering the residual energy for selecting CHs. Assume that n is the total number of nodes deployed randomly in the monitoring zone. For K number of clusters the cluster head selection algorithm is implemented as below:

Algorithm 3: Proposed TLBO Based Approach for CHs Selection

Initialize the network size m× n, no. of sensor nodes; initial population of learners *i.e.*
clusters (K), E_{elec}, E_{fs}, E_{amp}, E_0, and maximum number of iterations.
While (iteration< maximum number of iterations)
For Learner=1 to K // No. of clusters
For d = 1 to D // dimensions
Compute the initial position of learners *i.e.* CHs
Evaluate the value fitness function$F(X_i)$ using equation 13.
End for
End for
Identify the position of teacher among learners using minimized value of fitness function.
Apply the teacher phase of TLBO algorithm (Algorithm 1).
Apply the Learner phase of TLBO algorithm (Algorithm 2).
Compute the new CHs and stored into list M_{itr}.
Repeat step 2 to 6 until maximum iteration reached; iteration+ +
End while

5. Experimental Results

This section demonstrates the results of the proposed protocol.

5.1 Parameters Settings and Experimental Environment

This subsection describes the various parameters and experimental environment of the proposed protocol. A 100 x 100-dimension field is taken for conducting the experiment. All sensor nodes are uniformly dispersed in above mentioned sensor field and it is supposed that the BS is located inside the sensor field. The proposed protocol is implemented in Matlab 2013 environment. The parameter settings of the wireless sensor network are as described in Table 1. Fig. 1 demonstrates the sensor field and distribution of nodes used for experiment.

Table 1. Parameters Setting of Proposed LEACH-T Protocol

Parameter	Value	Parameter	Value
Network field	100m x 100m	E_{DA}	5 nJ/ bit/ Message
Number of nodes	100	E_{mp}	0.00013pJ/bit
E_{TX}	50 nJ/bit	Message Size	4000 bits
E_{fs}	10 pJ/bit	P_0	0.1
E_{RX}	50 nJ/bit	Maximum No. of Iteration	4000
E_0	0.5 J		

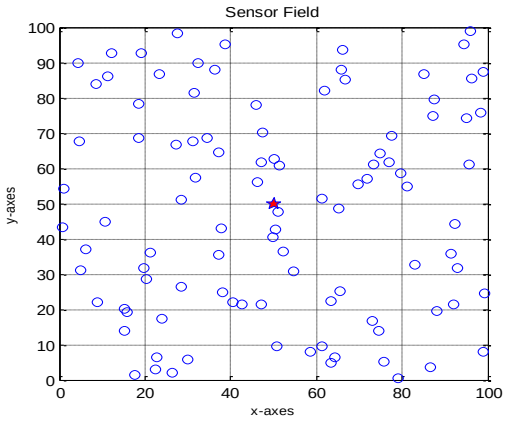

Figure 1. Sensor Field used for Experiment

5.2. Results and Discussion

The subsection describes the results of proposed LEACH-T protocol. To validate the proposed algorithm, network life time and packets sent to BS are chosen as performance parameters in this study. The network lifetime parameter is defined in terms of number of live and dead nodes. The result of the proposed protocol is also compared with LEACH protocol. The results are taken on the average of 30 independent runs and in each run have 4000 rounds. Table 2 shows the statistics of the network life time parameter. From this table, it is concluded that in LEACH protocol, first node become dead after 1100 rounds as all of its energy consumed during the data collection and transmission, half of sensor nodes die up to 1265 rounds and after 3625 rounds, no live node is present in the sensor field. Whereas, in LEACH-T protocol, first node become dead after 1550 rounds, half of nodes die up to 2080 and the last node dies in 2280 rounds. After 2280 rounds, still there are live nodes in LEACH-T protocol. Hence, it is said that incorporation of the TLBO algorithm in Leach increases the life time of the network and also reduced the power consumption of nodes.

Table 2. Life Time of Network in Terms of Dead Nodes for LEACH and LEACH-T Protocols

Algorithm	First Node Die	Half of Node Die	Last Node Die
LEACH	1100	1265	3625
LEACH-T	1550	2080	2280

Fig. 2 and 3 shows the comparison of live and dead nodes in each round for LEACH and LEACH-T protocols. From these, it is clearly shown that there is significant difference between the performance of the LEACH and LEACH-T protocols. In LEACH protocol, all nodes die after 3625 round, whereas LEACH-T protocol has live nodes after 4000 rounds. It is also observed that significant difference occurs between the nodes death rate. In LEACH protocol, nodes start die after 1100 rounds, whereas nodes become dead after 1550 rounds in LEACH-T protocol.

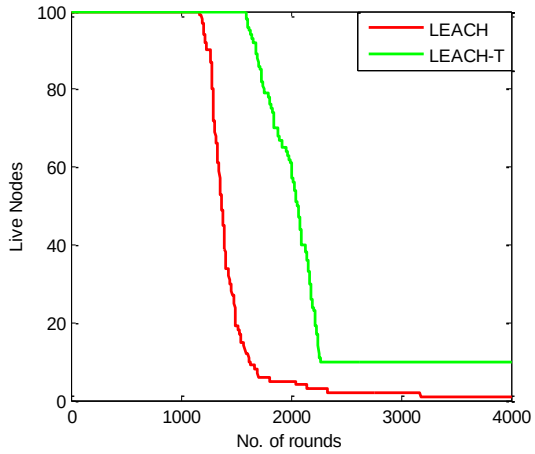

Figure 2. Comparison of Live Nodes in Each Round

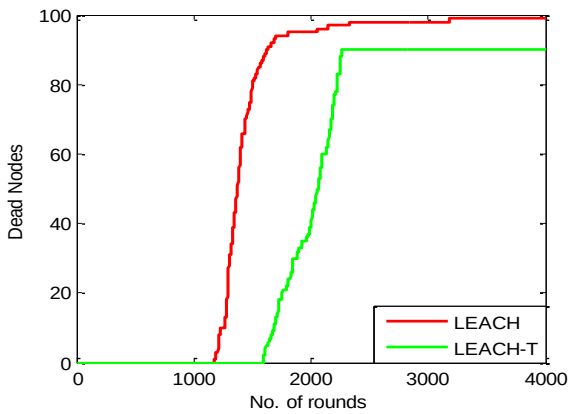

Figure 3. Comparison of Dead Nodes in Each Round

Table 3 shows the statistics of packets sent to the CHs to the BS of LEACH and LEACH-T protocols after 500, 1500, 2500, 3500 and 4000 rounds. It is observed that number of packets sent through LEACH protocol is 20000, whereas LEACH-T protocol sends 223300 packets. It seems that there is gradual increment in packets sent parameter after integration of TLBO algorithm in LEACH protocol. Fig. 4 shows the comparison of packets sent to BS for LEACH and LEACH-T protocol for each round and it's indicate that the performance of the LEACH protocol gradually enhanced.

Table 3. Packets sent to Base Station (In LEACH-T 10 Nodes remaining after 5000 rounds)

Algorithm	500	1500	2500	3500	4000
LEACH	5000	15000	17600	19800	20000
LEACH-T	50000	145000	203800	214300	223300

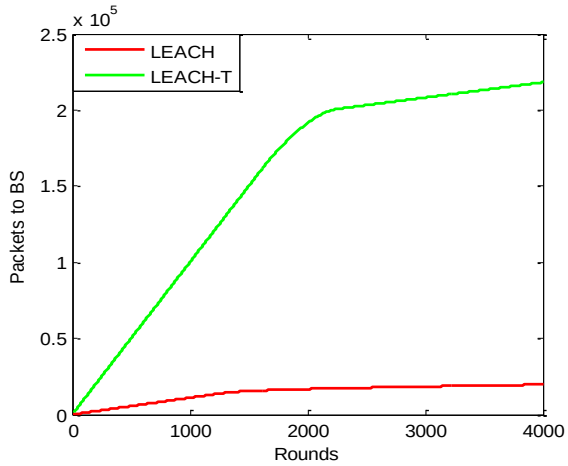

Figure 4. Comparison of Packets Sent to CHs to BS in Each Round

Finally, it can be stated that the energy consumption of nodes of proposed LEACH-T protocol is less than LEACH protocol and it is directly related to extending network lifetime. The number of packets sent to BS is also gradually increases which also confirm the impact of proposed CHs selection algorithm.

6. Conclusion

In this work, an efficient and effective cluster head selection algorithm is proposed to strengthen the LEACH protocol. The proposed CHs selection algorithm is based on the teaching learning based optimization method. In spite of this, a new fitness function is also designed to recognize the CHs among sensor nodes. Both of these are integrated into the LEACH protocol for enhancing its performance and also to find optimum CHs. The results show that both of improvements made in the LEACH protocol is more effective and also enhance its performance considerably in comparison to other algorithm being compared. It is also observed that performance of the algorithm enhances in terms of live nodes during each iteration and packets sent to BS. . In the future, the objective is to propose TLBO based routing protocol for WSNs and also to employ state of art meta-heuristics algorithm to enhance the performance of WSNs.

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