A Heuristic Deep Feature System for Energy Management in Wireless Sensor Network

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Research Article

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A Heuristic Deep Feature System for Energy Management in Wireless Sensor Network

***Dr. Ambidi Naveena · Dr. Meeniga Vijaya Lakshmi**

Abstract The technology Wireless-Sensor-Network (WSN) has been employed in all digital applications for several purposes like sensing, storing, and sharing information. However, managing energy consumption is a more critical task because of the movable environment. So, the present research article aims to develop a novel Deep Belief Energy Management Framework (BDBEMF) for the WSN application. Initially, the required number of sensor nodes was created then a book BDBEMF was designed to monitor the high consumption nodes. In addition, the Low-energy adaptive-clustering-hierarchy (LEACH) protocol has been considered to make the communication process. Consequently, the cluster head has been selected based on less energy utilization and high-density hubs. The data rate of each node has been measured, and the high leaded data has been shared to work fewer nodes to balance the energy. Finally, the amount of alive and dead nodes was validated with few communication metrics. The presented model has gained the maximum throughput and less energy consumption and throughput.

Keywords Energy consumption and management · Wireless sensor network · Alive and dead nodes · Communication delay · Deep learning

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1 Introduction

The WSN comprised lots of tiny, low-cost hubs with sensing elements, energy, and memory constraints [1]. Multiple issues arise when learning each component in this specific type of network [2]. The Recent advancements in the WSN applications have facilitated the widespread adoption of low-power [3], low-cost, and multi-operational sensors with smaller diameters and short communication ranges. Cheap, intelligent sensors, networked via wireless networks and widely distributed [4], provide unprecedented levels of monitoring and management of homes, environments, and cities [5]. Additionally, network sensors are used in a broad range of defense applications, enabling unique innovations for observation and surveillance and various tactical uses [6]. The ability of WSN to self-localize can be a desirable characteristic [7]. Without knowledge about the data position in environmental monitoring applications such as agriculture, bus-fire management, and monitoring water quality, measurement info is worthless [8].

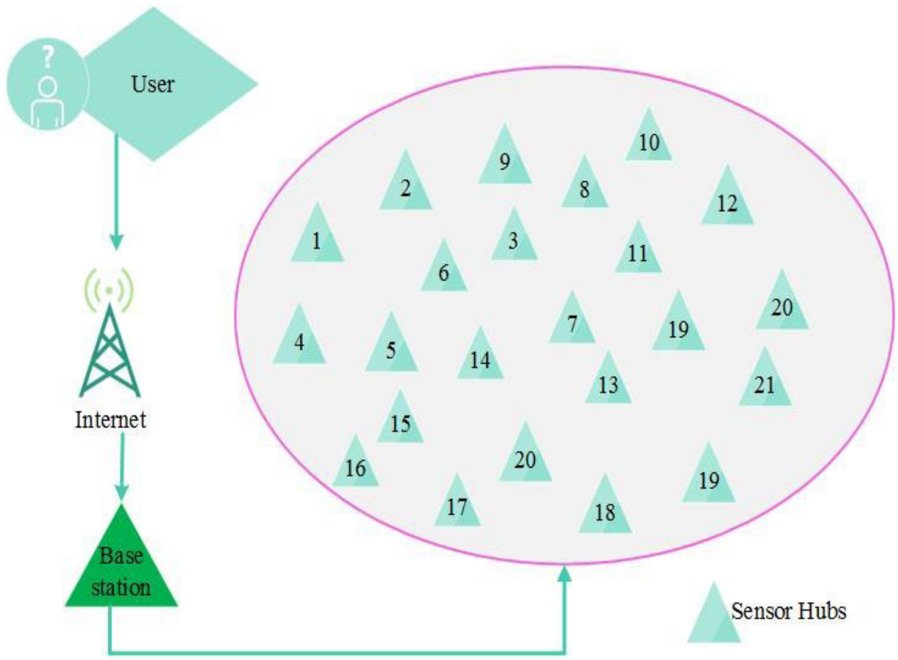

Fig.1 WSN communication

Additionally, position estimates can be used for various purposes [9], including inventory management, transportation, road traffic analysis, health monitoring, intrusion detection, and surveillance [10]. Moreover, the advancements in communication technologies and sensing have employed a large quantity of low-power and cost sensors that have been established [11]. Numerous small battery-powered sensor hubs are dispersed around a physical region in a WSN [12]. Furthermore, each sensing facility in the sensing environment has captured the data, such as temperature, radiation, vibration [13], and other environmental parameters [14]. Numerous energy management techniques have been presented in the past, in that more methods are based on the data assumption [15], data collecting, and processing function [16]. Hence, it consumes substantially less energy than transmission [17]. But, in today's world WSN is a practical application for the communication process in all digital fields [18]. So, the arranged sensor hubs in the WSN environment have to do multiple methods like target finding observation and sharing the data [19]. These various processes resulted in high energy consumption than the previous WSN [20].

Several works like the Data Dissemination model [21], block chain with key management process [22], etc., were designed to end these energy management issues, but those approaches resulted in other cases. Hence, the present article has aimed to develop a novel optimized deep feature strategy to manage the energy utilization in the WSN environment. Moreover, Low-Energy-Adaptive-Clustering-Hierarchy (LEACH) is an advanced protocol network in the WSN environment with a clustering model. So, a designed, optimized energy utilization system is planned to implement in the LEACH protocol.

The planned research design is organized as follows; recent related literature is described in the section.2, the problem in Leach protocol is described in the third section, the solution for the discussed issues is elaborated in the fourth section, the outcome of the proposed solution is described in the fifth section, and the research argument is concluded in section.6.

2 Related Works

Few recent works associated to this research works are described below

To control the energy usage in the WSN communication, Kuthadi et al [21] have designed the Data Dissemination model, which has incorporated the optimal energy constraints. In addition, for better communication, the adaptive protocol has been developed. Here, the data was shared from one point to multiple sources, and then the utilized energy resources were measured. Hence, the reduced energy consumption and wide data broadcasting rate have been recorded. But, it is not suitable for security.

Securing communication is an essential task in WSN. Hence, the blockchain with a critical management process has been framed by Jia et al. [22] in the WSN to manage energy usage and secure communication. This medium supports extensive cloud data and has gained the most delicate personal score. However, if the data size has crossed the average limit during the transmission, extra energy resources were required to proceed with the communication process.

Osamy et al. [23] have designed a clustering strategy that relies on optimal head node selection for the clustering process. Hence, the created head node has collected the sources of their group node together from the base station and forwarded it to the particular hub. Simultaneously, the start of the cluster users has been collected by the cluster head and then sent to the target through the base station. However, if the cluster node gets injected, it degrades the communication process.

A protocol like genetic and LEACH has been developed for the WSN environment by Bhola et al [24]. Here to minimize the energy resources, the fitness process of the genetic model is utilized to identify the best route to share the data. Hence, if the shortest path has been selected correctly, it has reduced the execution and communication process. As a result, the usage of energy has been diminished. But, while preceding the communication through the shortest path, packet drop will happen if any node is disabled.

On the other hand, clustering algorithms were implemented by Israel Agbehadji et al. [25] for the energy optimization objective in the WSN environment. Moreover, this clustering algorithm has been designed based on heuristic models. Here, dual goals have been taken into consideration: maximizing the node lifetime and optimizing the energy usage. It has afforded the finest optimized energy usage results. But, it has taken more time to execute the process than the other models. The key strategy of the proposed model functions as follows.

- In the primary phase, the WSN environment has developed with the desired quantity of nodes.
- Consequently, the LEACH protocol has been developed to execute the communication process
- Moreover, a novel BDBEMF has been designed with required energy constraints modules.
- If the collision occurs during the transmission process, half the amount of data is shared with the other hubs that have tended to optimize the energy usage between the sensor nodes.
- Finally, the function of the proposed design is validated by calculating and comparing the key metrics with other models in terms of energy consumption, throughput, delay, packet drop, and packet transmission.

3 System Model And Problem Statement

The WSN has a lot of facilities and advancements to use in digital applications; considering those advantages, there are many issues such as pack drop, poor communication range, high energy consumption, less lifetime node, and so on. Considering all those issues, the high energy consumption is the primary cause of the met honed problems. Moreover, it is described that the wide range of energy utilizing hubs in the sensor environment might degrade the entire WSN communication system by reducing its lifetime. Hence, this reason has motivated this research to manage the energy consumption in the WSN environment.

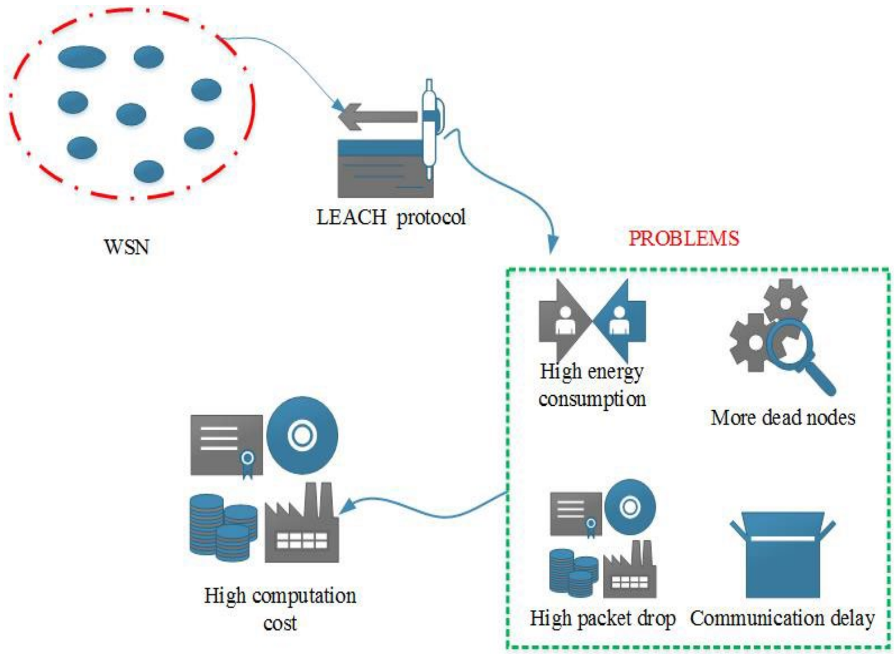

Fig.2 Problem in LEACH WSN

The reason for considering the LEACH in this present research work is high energy consumption. The problems that have occurred in conventional LEACH are described in fig.2. Usually, the LEACH model in WSN requires more energy to execute because the dead nodes have been increased while the iteration counts were increased. Hence, in the WSN, if the dead nodes are expanded, the other alive nodes need more energy for better data transmission. Considering these demerits, a novel optimized deep neural mechanism has been implemented to reduce the dead nodes by neglecting the high energy utilization nodes in earlier stages.

4 Proposed BDBEMF in WSN

The present work aims to design a novel Buffalo-based Deep Belief Energy Management Framework (BDBEMF) that has been planned and implemented for the WSN system. Hence, the robustness of the proposed model has been evaluated in the leach protocol. Finally, the key metrics have been measured and compared with other models. The proposed architecture is described in fig.3. Here, the optimal energy value is fixed in the buffalo fitness model. The iteration has been processed during the execution process until it reaches the fixed optimal energy constraints.

Hence, a load balancing strategy has been developed to reach optimal energy utilization status. This can avoid congestion during the data transmission process. Finally, the improvement score of the designed framework is validated by making a comparative analysis with other associated works.

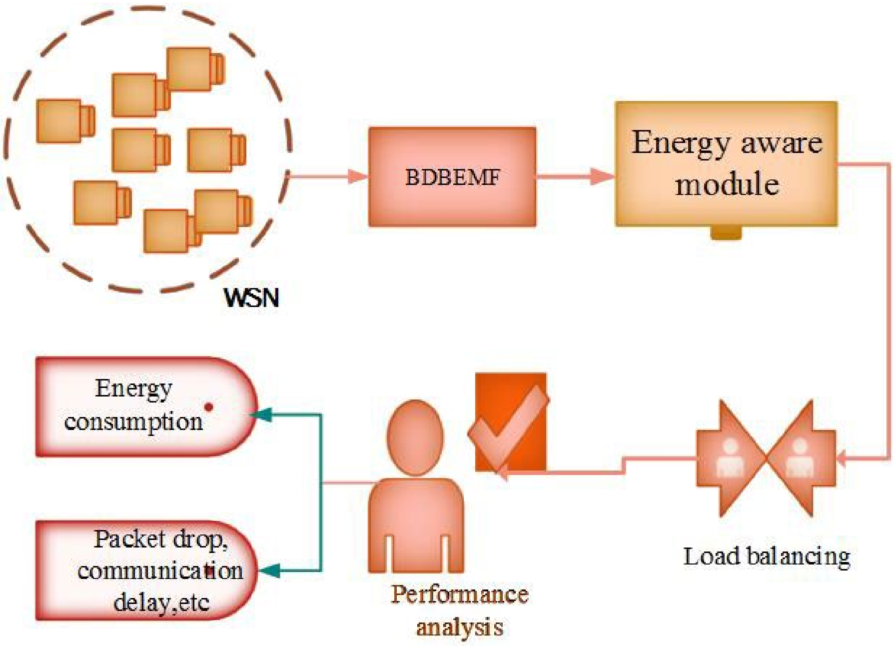

Fig.3 Proposed architecture

4.1 Node formation

The routing protocol that has been considered in this research work is LEACH. Usually, the LEACH contains the clustering scheme to manage the energy utilization for the communication functions. Hence, the LEACH model is taken; however, data overloading might disturb the WSN system and has tended to come with more energy. Therefore, a novel monitoring mechanism and load balancing model have been implemented in this research. Moreover, the planned technique is named BDBEMF, which functions in the principle of buffalo optimization [28] and the deep belief neural model [29]. The creation of number of sensor nodes is processed by Eqn. (1). The node initialization variable is determined as $f(s_n)$ and the sensor hubs are determined as s_n

$$f(s_n) = s_n\{1,2,34......n) \tag{1}$$

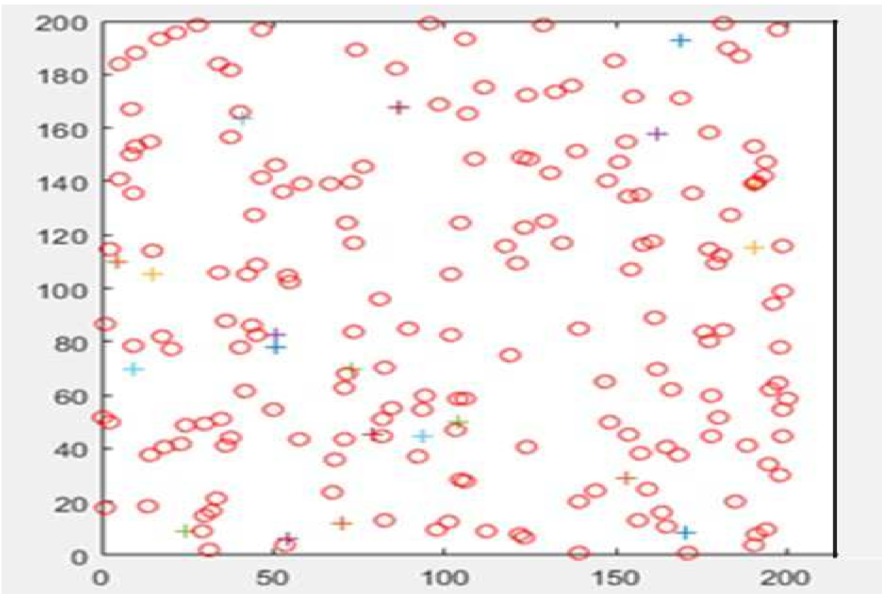

Fig.4 Node formation (200x200 m^2)

To avoid the packet flow rate, the active status of the users has to be estimated before initiating the data transmission process.

$$s_n(t=1) = \beta\left(T_s + \sum_{i=1}^{n} s_{ni}, s_{nj}\right) \tag{2}$$

Here, β is the monitoring variable, which is taken from the buffalo algorithm, s_{ni} is the source sensor node and s_{nj} is the receiver node. Moreover, the status activation evaluation variable is described as T_s, the iteration of sensor nodes generation is represented as $s_n(t=1)$. Node formation in the MATLAB environment is detailed in fig.4, 200 hubs were generated with several cluster nodes.

4.2 **C**luster head selection

Consequently, the cluster head was selected by analyzing the density of the node and energy consumption. Hence, the eligibility of the cluster head hubs is elected by Eqn. (3). Here, 0.5 is the fixed range attained from the buffalo model. Furthermore, n_d is node density and n_e is the energy utilization percentage of each node. Moreover, the cluster-head is denoted as C_h and the E_c is the energy utilization variable. Hence, the measure of energy utilization is validated by Eqn.(3).

$$E_c = \frac{n_d + n_e}{0.5} \tag{3}$$

$$C_h = \begin{cases} if(E_c \le 1 & Head\_node \\ else & search \quad other \end{cases} \tag{4}$$

If the measured energy usage rate is less than or equal to 1, it is elected as a cluster head equated in Eqn. (4). But, if it is not matched, then another node has to be estimated. Hence, the process is iterated continuously till the condition is met.

4.3 Load Balancing

In addition, the balancing module has been processed by Eqn. 5(), the variable L_b is the load balancing parameter, n_d is the node density and R_d denotes the data rate. To find the collision occurrences, the maximum data rate has been checked then the data rate of the each node is subtracted from the maximum data rate. From this calculation, if the results are greater than 0.6 then it indicates the occurrences of collisions. Here, the data sharing parameter is determined as D_s.

$$L_b(s_n) = n_d + \beta(\max R_d - S_n(R_d)) \tag{5}$$

$$D_s = \begin{cases} if(L_b(s_n(load > 0.6)) & congestion \\ else & normal \end{cases} \tag{6}$$

The load balancing analysis has met the condition, then the half amount of data is shared with the freehubs in the developed WSN. Here, the beta is the monitoring parameter in the buffalo model, that is, head buffalo, which is utilized to find the safe location. The data migration or sharing has been executed using Eqn. (6).

$$\beta(R_d) = R_d(s_n) < 0.5 \tag{7}$$

Consequently, freehubs have to be identified to reduce the congestion rate. Hence, the free statues node is estimated by Eqn. (7). If any node in the connected WSN has less than 0.5Mbps data rate, that hub is said to be freehubs. Moreover, half of the data from the high-loaded node is shared with the freehubs. Hence, the loads in the WSN system were balanced, and the energy utilization rate was in the optimal status.

Algorithm: 1 BDBEMF

Start
{
Node initialization ()
{
$int\ S_n = 1,2,3,..n;$
// initializing required number of nodes
$fixing \rightarrow sender, receiver$
}
Cluster head selection ()
{
$int\ C_h, E_c, n_e, n_d$
// initializing CH selection parameters
$if\ (E_c \leq 1)$
{
Head_node *// cluster head node*
}***else (search other)***
Load balancing ()
{
$int\ L_b, R_d, D_s$
//initializing load balancing parameter
$if\ (data\_rate > 0.6)$
{
Congestion possibility
}***Else (normal)***
Data sharing () *// data has been shared successfully*
{
$if\ (s_n(data) < 0.5)$
{
Low load (L_l) *node*
Migrate high $R_d \rightarrow L_l$
} ***else (search other node)***
}
Successful data Transmission
}
Stop

The designed mathematical formulation is described in the form of pseudo-code, which is defined in the algorithm. One, and the working procedure of the novel BDBEMF is given in fig.5. Here, the energy utilization rate has been optimized by enabling the load balancing model and clustering approach.

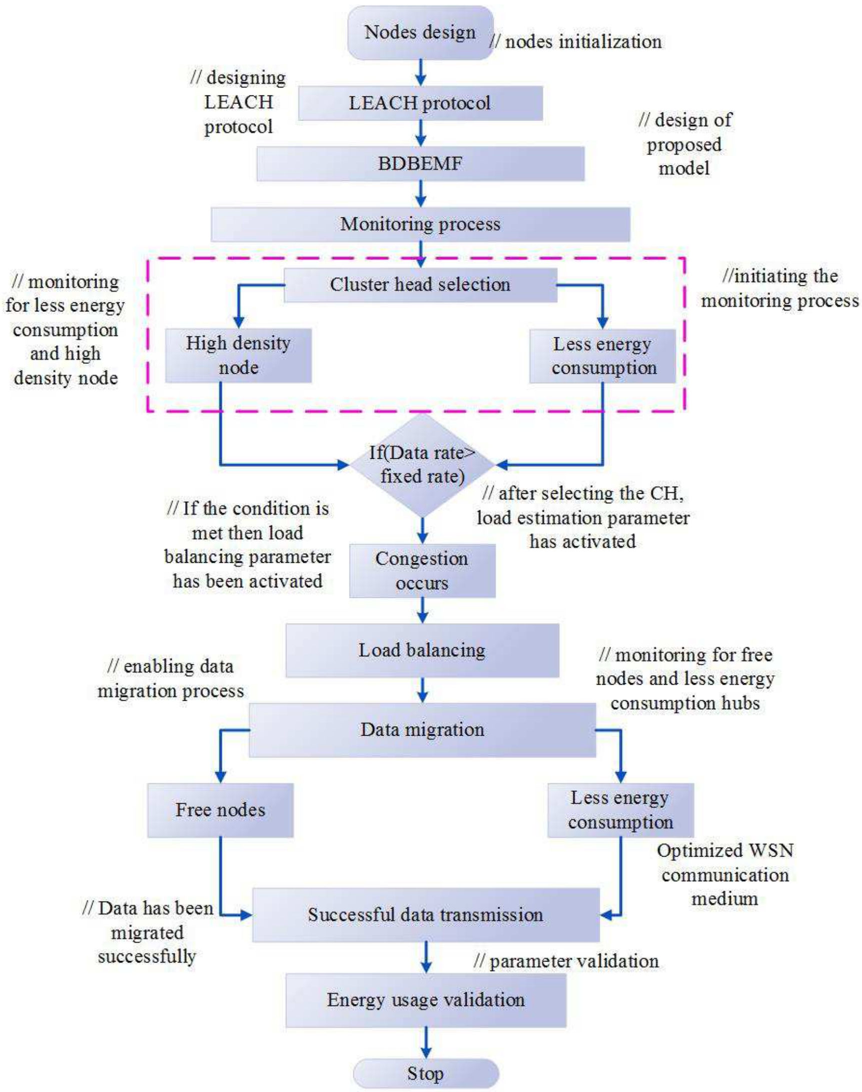

Fig.5 Proposed BDBEMF work flow

5 Results and discussion

The planned design is checked in the MATLAB environment running on the Windows ten platform. The required sensor nodes have been developed, and a novel BDBEMF has been modeled with several features such as load balancing, energy optimization, congestion control, and high data delivery. The execution parameters and their specification is detailed in table1.

Table 1 Execution parameters details

Parameter specification	
Operating system	Windows 10
platform	MATLAB
version	R2020a
nodes	200
Node status	moving
Network type	WSN
Objective	Energy management
Network parameters	
Network size	200x200 m^2
Number of nodes	200

Packet size	3500, 6000 bits
Initial energy, E_o	0.1 J/node
Transmitter-energy , E_{TX}	50nJ/bit
Receiver-energy , E_{RX}	50nJ/bit
short distance Amplification energy, E_{fs}	10pJ/bit/ m^2
long distance Amplification energy, E_{mp}	0.0013 pJ/bit/ m^2
Energy for Data aggregation, E_{da}	5 nJ/bit
CH probability, p	0.2
Maximum iterations count	200

5.1 Case study

To check the improvement score of the proposed technique in the leaching environment, normal Leach and BDBEMF-based Leach has been validated. Also, the parameters are validated in dual phases

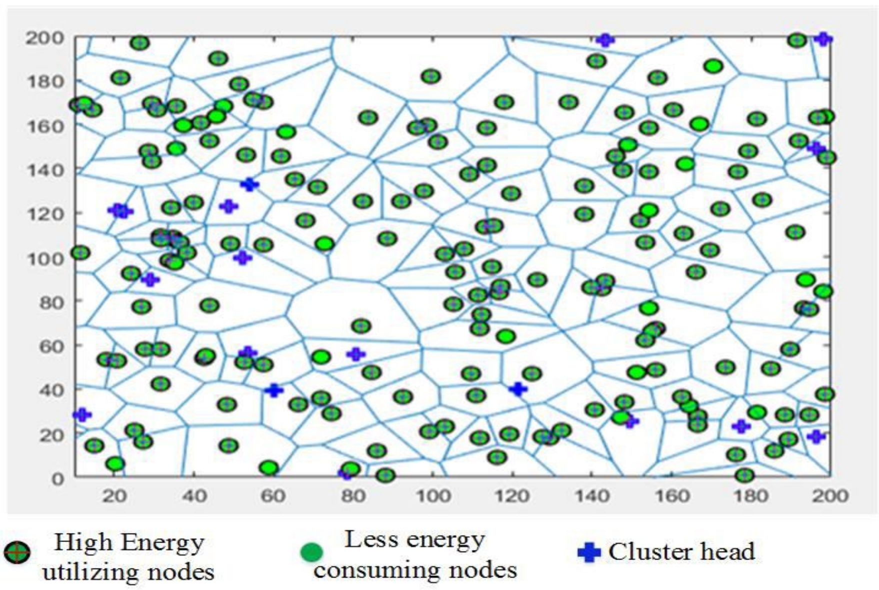

Fig.6 Node formation With CH

before and after applying the buffalo fitness.

There are a total of 200 nodes. In those nodes, few hubs are CH, some are less energy utilization nodes, and some are full energy-consuming nodes. These node frames have been generated before

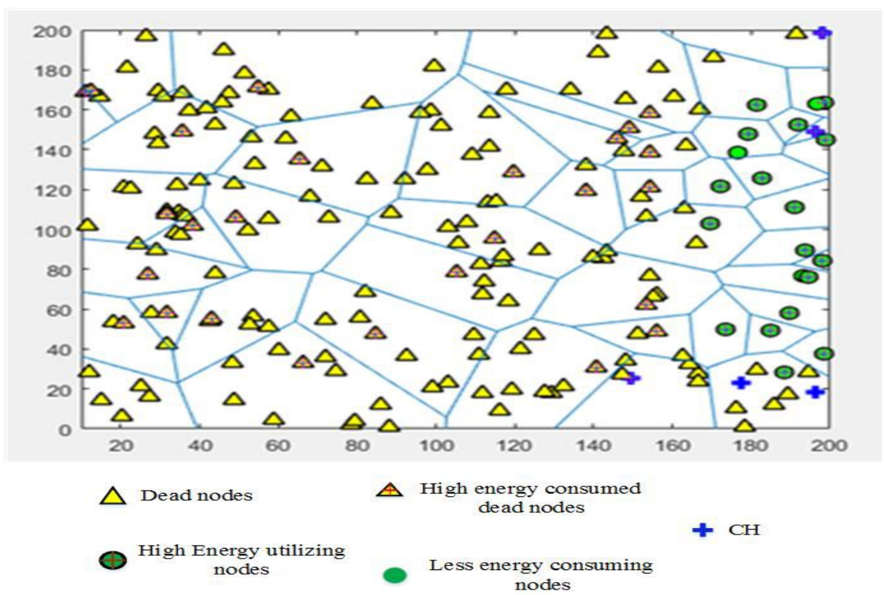

Fig.7 Dead and alive nodes after completing the iteration (B.O)

applying the chimp optimization model. Node design with the elected CH is described in fig.6.

The amount of alive and dead hubs was calculated in dual phases before incorporating the buffalo fitness and after including the buffalo fitness solutions. Moreover, B.O, the number of nodes killed was increased, which indicates the more number of the yellow triangle presented in fig.7 and the graphical represented in fig.8. In addition, the dead nodes, which have consumed more energy, are described as a yellow triangle with a plus symbol. Also, the green nodes have been determined as live nodes; the green circle with red color plus indicates the widest energy utilization node, and the only green circle

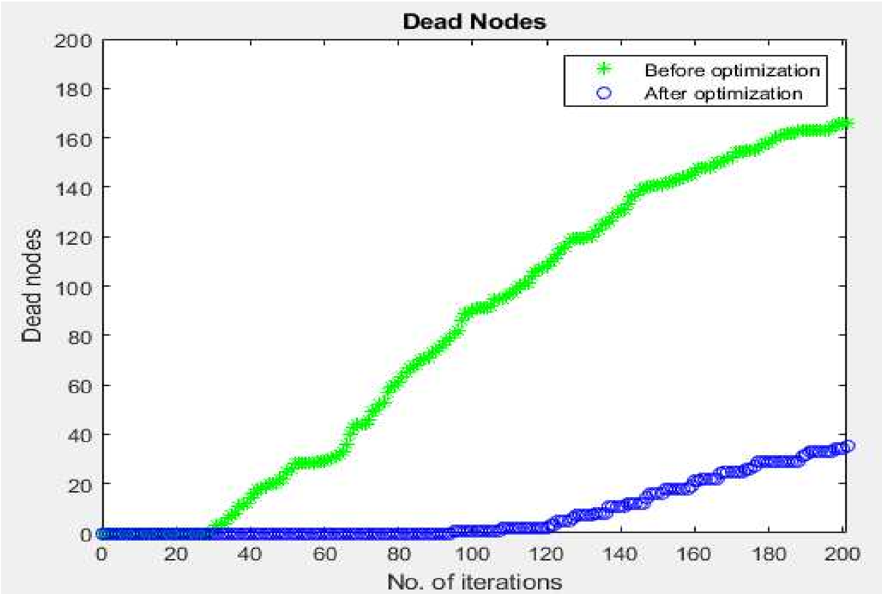

Fig.8 Dead nodes assessment

indicates the less energy consumption nodes.

Moreover, the CH is represented as a blue plus symbol. Before applying the buffalo fitness, the

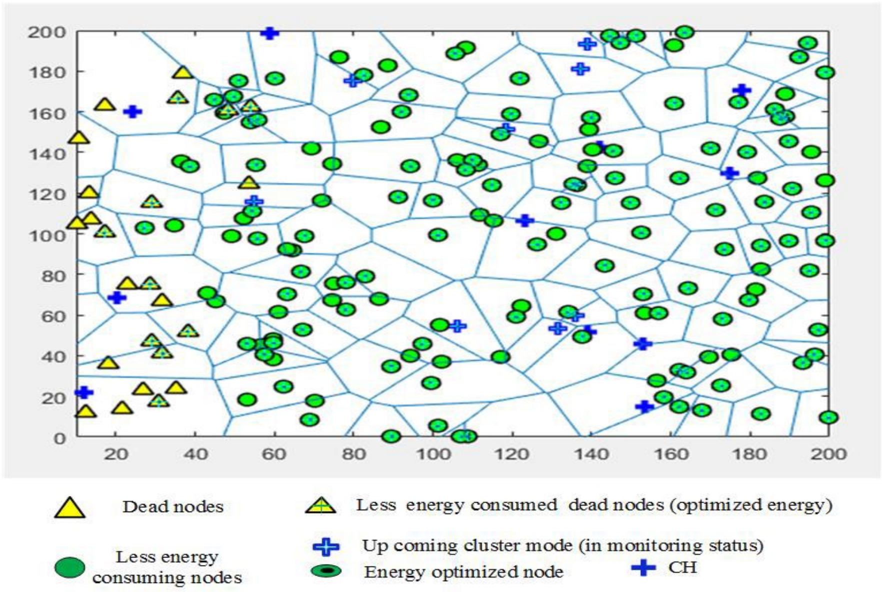

Fig.9 Optimized WSN

dead nodes are in maximum counts, leading to record high energy wastage outcomes.

Hence, to design the energy-optimized WSN, a novel BDBEMF has been developed in the present work. The performance of the BDBEMF after applying the buffalo fitness is explained in fig.9. Measuring the energy wastage based on iteration count is much more important to check the robustness of the designed model in the LEACH concept. Hence, the metrics of energy dissipation are validated in dual cases the before and after applying the buffalo fitness. The presented novel BDBEMF model has scored the reduced energy dissipation rate in double instances. This desirable outcome is gained because of the monitoring model process in the initial layer. So, in the starting phase itself, the high energy utilization hubs were removed, resulting in fewer dead nodes.

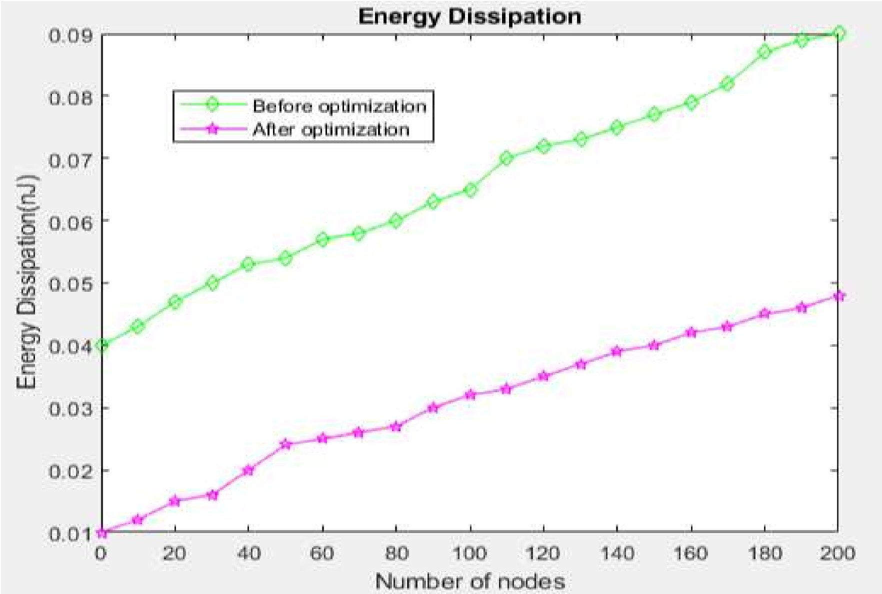

Fig.10 Energy Dissipation

Hence, the energy dissipation score has been calculated in nJ, which is in the negligible state only; it has verified the robustness of the presented model. Also, considering the before Optimization (B.O), after applying the buffalo optimization has helped to earn the finest outcome for 200 iterations, the recorded energy dissipation score is 0.05nJ. In addition, before using the buffalo process, the recorded energy dissipation score was 0.15 nJ. These statistics are analyzed in fig.10.

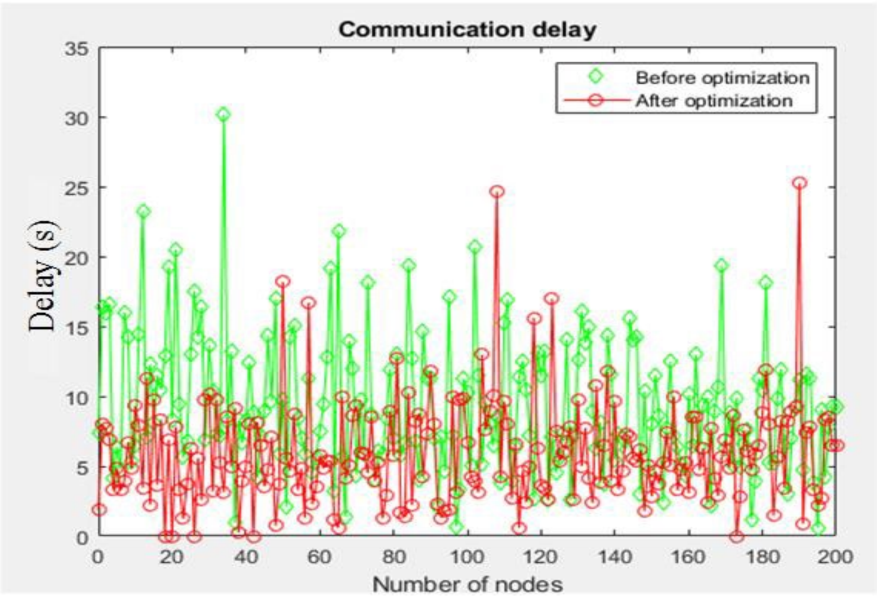

Fig.11 Communication Delay

The communication delay has been validated based on seconds; after incorporating the buffalo fitness, the communication delay has been considerably reduced, which is described in fig. Here, the red line indicates after optimization, and the green line represents B.O. the recorded delay measure is detailed in fig.11. The overall outcome for the 200 rounds iteration is tabulated in table.2.

Table 2 Simulation performance Assessment

Rounds	dead nodes (B.O)	Dead nodes (A.O)	Alive node (B.O)	Alive node (A.O)	Energy utilization (J) (B.O)	Energy utilization (J) (A.O)
10	0	0	200	200	0.03	0.0
20	0	0	200	200	0.01	0.0
30	1	0	199	200	0.02	0.0
40	14	0	186	200	0.06	0.0
50	25	0	175	200	0.04	0.0
60	29	0	171	200	0.09	0.0
70	44	0	156	200	0.03	0.01
80	61	0	139	200	0.05	0.01
90	74	0	126	200	0.03	0.01
100	90	1	110	199	0.09	0.01
110	97	2	103	198	0.06	0.02
120	108	2	92	198	0.04	0.02
130	119	7	81	193	0.08	0.02
140	131	11	69	189	0.07	0.03
150	141	16	59	184	0.06	0.03
160	146	21	54	179	0.07	0.04
170	152	25	48	175	0.08	0.05
180	158	29	42	171	0.07	0.05
190	163	32	37	168	0.08	0.06
200	166	34	34	166	0.09	0.07

5.2 Comparative analysis

To measure the improvement score of the presented model, some recent related works have been considered, such as LEACH, Genetic optimization Leach (GOLEACH) [26], clustering LEACH [27], and EERP [27].

5.2.1 Energy Consumption

To calculate the energy consumption rate depreciation, this comparative analysis has been performed. Hence, the energy usage is validated by Eqn. (8).

$$Energy\_Consumption = \sum_{j=1}^{node} E_t + E_r + E_w \tag{8}$$

Here, E_t is the recorded total energy consumption for the data transmission, E_r is the consumed energy during data receiving process, and the waiting state energy utilization rate is determined as E_w

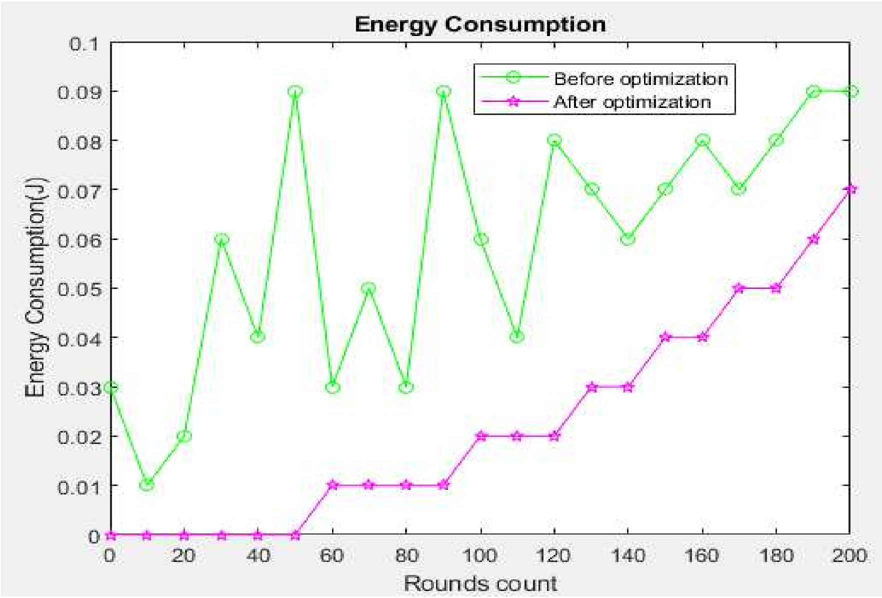

Fig.12 Energy consumption validation

Hence, by taking the energy utilization rate of each process, the total energy utilization rate was measured.

The parameter energy utilization has been measured in dual phases before and after applying the buffalo fitness. Hence, after 200 rounds, the recorded energy usage is 0.07J for optimized LEACH and 0.09 without using the buffalo functions, as shown in fig.12.

5.2.2 *Throughput ratio and Communication delay*

By measuring the time utilization of each process, the average communication delay was recorded. Here, T_t denotes the total time for packet transmission,

$$Delay = \sum_{j=1}^{node} T_t + T_r + T_w \tag{9}$$

Here, T_t denoted entire time for the communication broadcasting process, T_r represents the time utilization for the data receiving process, T_w and determines the time for the waiting process. Hence, the delay is measured by Eqn. (9).

The communication range of the WSN medium has been determined by Throughput validation. Moreover, the parameter throughput is measured by initializing the data sharing functions. In addition, the throughput metric was measured using Eqn. (10).

$$Throughput = \frac{delivered \quad packets \times packet \quad size}{Time\, of \quad packet \quad sent} \tag{10}$$

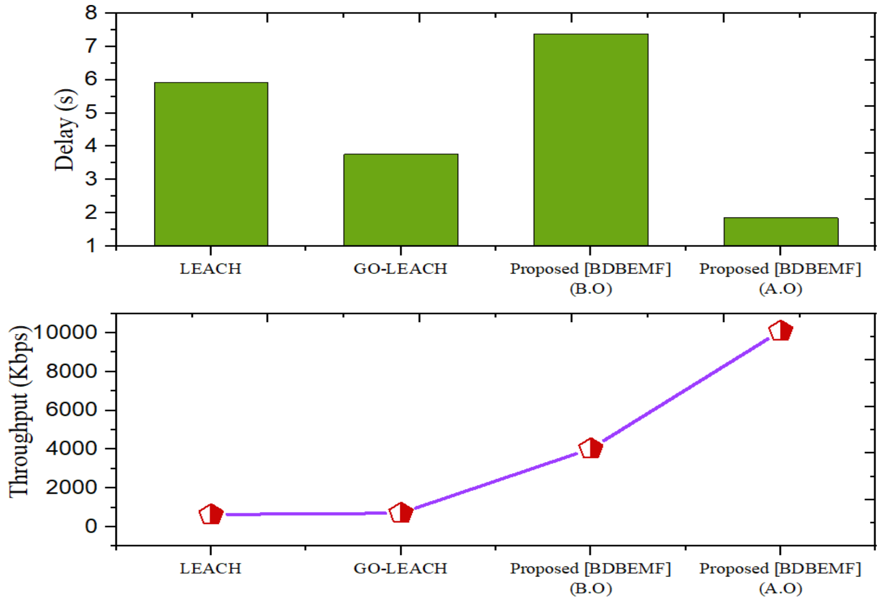

Fig.13 Assessment of Throughput and delay

The model that gained the most acceptable range of throughput score will have the finest data transmission rate. Hence, the presented model has earned the throughput measure as 10100Kbps after applying the buffalo fitness and 4037 Kbps recorded before incorporating the Buffalo fitness. Also, for the BDBEMF (A.O) recorded delay is 1.84s, and for BDBEMF (B.O), the gained delay is 7.3s. These statistics are structured in fig.13.

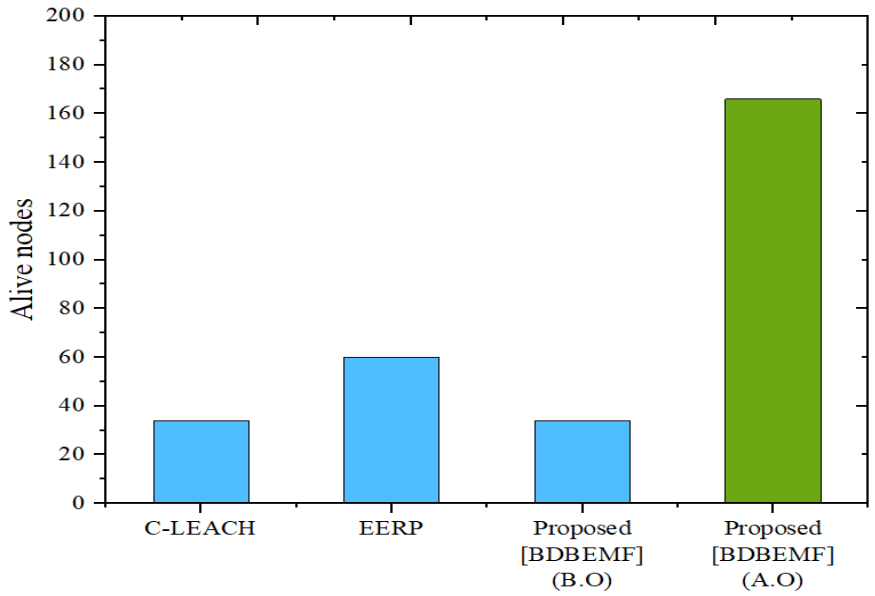

Fig.14 Validation measure of alive nodes

To measure the successive score of the designed model, the alive nodes count has been validated. Here, the presented novel BDBEMF has recorded the full live node as 166 after completing the 200 rounds. And Before applying the buffalo fitness, the registered alive nodes are 34 for 200 games. In addition, the existing scheme C-LEACH has gained the actual node count of 24 for 200 rounds, and the model EERP has attained the 60 actual nodes. Considering these approaches, the proposed model contains more alive nodes after complete iteration rounds, around 166. The comparison assessment is exposed in fig.14.

5.3 Discussion

The novel BDBEMF has earned the finest outcome in all performance assessments that have verified the presented model's robustness. The key merits of this designed model are dead node reduction. The proposed model has considerably reduced the dead nodes and maximized the actual nodes rate. This procedure has helped to minimize the packet flow rate and diminished energy usage. Hence, the pack drop measures are figured in fig.15. Moreover, the overall outcome of the implemented approach is tabulated in the table. Thus, the performance results have proved the robustness score of the presented model, and it is suitable for WSN applications to optimize energy utilization.

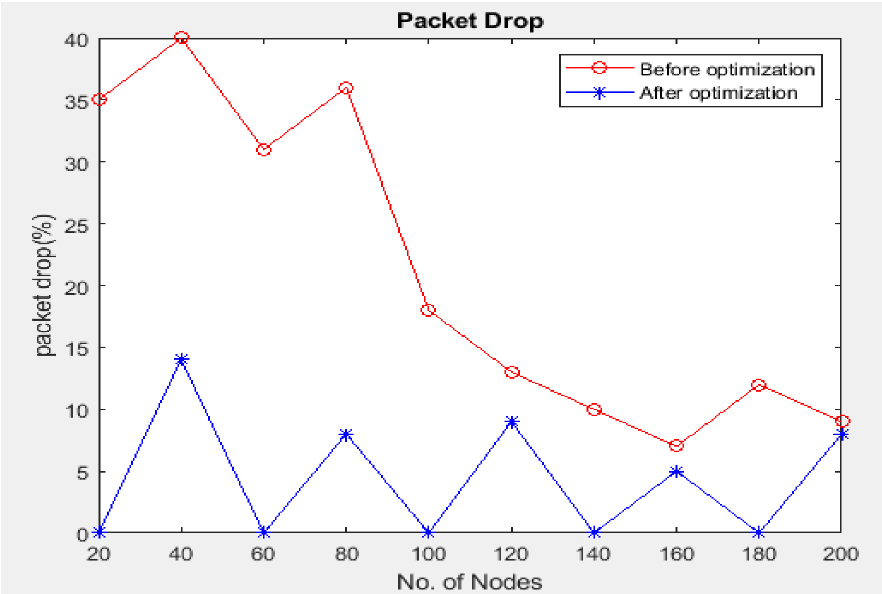

Fig.15 Packet drop assessment

Table 3 Overall performance

Execution metrics	Outcome
Throughput (kbps)	10100
Delay (s)	1.84
Packet drop (%)	6
Energy consumption (J)	0.07
Total nodes/alive nodes	200/166
Energy dissipation (nJ)	0.05

The overall finest outcome of the designed scheme is tabulated in table 3. Significantly, the recorded energy dissipation rate is meager, which is 0.05nJ, in a negligible state. So, it has more residual energy, which is about 8J after the completion of 200 rounds.

6 Conclusion

A novel BDBEMF has been designed for the WSN application form to manage the energy utilization rate. In addition, the LEACH protocol is taken into consideration to enable the communication process. Finally, the planned model is tested in the MATLAB platform. The efficiency rate has been validated regarding dead and alive nodes, throughput, packet drop, energy consumption, and wastage. Compared to other models, the novel BDBEMF has earned a high throughput score of 10100Kbps. It has improved the throughput rate up to 30%. Moreover, the reduced delay score yielded by the designed model is 1.84s. Compared to other models, it was minimized the delay rate by 3s. In addition, the recorded energy consumption score by the developed model is 0.07J; compared to normal LEACH, it has reduced the energy usage rate by 2%. Hence, the presented model is appropriate for the WSN application for the energy management process.

Acknowledgement
None

Compliance with Ethical Standards

1. Disclosure of Potential Conflict of Interest:

   The authors declare that they have no potential conflict of interest.

2. Statement of Human and Animal Rights

   i. *Ethical Approval*

   All applicable institutional and/or national guidelines for the care and use of animals were followed.

   ii. *Informed Consent*

   For this type of study formal consent is not required.

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