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A Stable Energy Balancing Based Clustering Routing Protocol for IoUT using Meta-heuristic Technique

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Abstract- Energy consumption and network longevity are important factors in Internet of Underwater Things (IoUT) networks. In such networks, clustering approach enable to reduce the energy consumption in notable rate. In clustering based routing protocols, the cluster head (CH) must be carefully chosen. By avoiding premature energy exhaustion during certain underwater nodes (UNs) and CHs duration network operation, the energy balancing strategy approach is suitable to improve the network's stability and dependability. Accordingly, this paper provides an energy-balancing based on artificial bee colony (ABC) to select and replace an optimal CHs according to energy levels, UNs depth, and distance from the surface base station (SBS). The proposed method enable to optimization the IoUT energy efficiency by balancing strategy that uses the Q-learning algorithm to ensure more balanced distribution of tasks across UNs and CHs.. Q-learning is used to make tradeoff decision between the random and ABC fitness functions solutions. The simulation compares the ABC Stable Election Protocol (ABC-SE) to the Energy Balancing ABCSE (ABC-EBSE). The results indicate that the ABC-EBSE scheme outperforms the ABC-SE in term of energy and network efficiency

Keywords- IoUT, Energy Distribution, Clustering Approach, Meta-heuristic, Energy Balancing, ABC, Q-learning.

I. INTRODUCTION

Internet of Underwater Things (IoUT) networks have limited energy resources, and due to difficult underwater environment, an efficient energy-based routing protocol is necessary to provide energy-efficient operations [1]. The UNs in underwater environments makes battery maintenance and recharging more difficult. By incorporating clustering-based methods into routing protocols, the IoUT network lifetime and reduce efficiency can be improved [2]. Clustered UNs acting as cluster members (CMs) establish more efficient communication with their respective CHs, reducing overall energy demand in IoUT communications [3].

In the context of IoUT, there are significant differences in both the resources accessible to UNs and the network's structure. The primary focus is on the heterogeneous energy levels among UNs, which have a substantial impact on the stability of CH selection and intercommunication [4]. As a result, routing protocols optimized for these specific conditions, such as the Stable Election Protocol based on artificial bee colony (ABC) algorithm, can enhance energy utilization [5]. However, considerations of UNs energy levels, depths, and other underwater environment features must be taken into account in the construction of such protocols in order to optimize network throughput and extend its operational lifetime.

In this paper we develop ABC-EBSE routing protocol for heterogeneous nature of UNs' resources and IoUT network structures, aiming to improve network throughput and extend operational lifetime by considering energy levels, depths, and other underwater environment features. The major contributions of this paper are.

- CH Selection Stability: maximizes energy-efficient communication between UNs by stable CHs
- Energy Conservation: prolong the network's lifetime while minimizing consumption.

Accordingly, the goal is to develop a routing protocol based on the energy balancing approach, as it aims to take advantage of the strengths of the stable election protocol and ABC algorithm and align their different strategies with the possibility of energy balancing using the Q-learning approach. This approach aims to compromise that takes into account both stochastic fitness value of the stable protocol and deterministic fitness value of ABC using a Q-learning approach to make decision in electing and replacing the CHs, which ultimately aims at a more comprehensive and effective energy optimization strategy within the context of the IoUT.

The rest of the paper is organized as follows: section 2 reviewers the related works. In section 3, the proposed system model is provided. The simulation results and discussion are given in section 4. Finally the conclusion is reviewed in section 5.

II. RELATED WORKS

Energy consumption in IoUT influences numerous approaches and procedures. Most recent studies have concentrated on the clustering approach, which is the most appropriate technique for energy efficiency in IoUT [6]. However, CHs in the clustering strategy may lose energy early depending on their distribution and proximity to the SBS. Many studies have been undertaken in an attempt to optimize the

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process of CH selection and intercommunications during routing protocol by employing energy balancing and distribution techniques [7].

In [8], Muhammad et al. (2023) propose a routing method for UWSNs named Shifted Energy Efficiency and Priority. The goal of the research is to improve the efficiency of the energy balanced for UWSNs. The proposed protocol is based on the depth and energy of the UNs, as well as the average energy differential between the expected to UNs those will forwards the packets. The results reveal that proposed approach is outperforms in terms of energy efficiency.

In [9], Ahmad et al (2022), provide the cooperative energy-efficient routing protocol to extend network lifetime and ensure network reliability. The cooperative technique is used in the study to achieve network reliability. The suggested approach outperformed existing routing protocols in terms of packet delivery ratio, energy consumption, transmission loss, and end-to-end delay, according to simulation results.

In [10], Lilhore et al. (2022) present a depth regulated with energy-balanced routing protocol, which allows to modify the depth of lower energy UNs and exchange with higher energy UNs. The upgraded genetic algorithm and data fusion technique are the foundation of the suggested protocol. The suggested model outperforms both energy-efficient depth-based routing techniques and current depth-based routing techniques in terms of energy consumption for UWSN, according to the results.

In [11], Kapileswar et al (2022), proposed a routing protocol based on bald eagle search algorithm. In the proposed scheme, the location and sector are identified by UNs in the proposed routing algorithm during the initialization process, along with the neighbor UN selection and the identification of the energy-efficient path. UNs that have a high residual energy in the route after broadcasting are chosen by comparing them to the network's average residual energy. The results of the simulation validate that the BES algorithm performs better in terms of network lifetime and energy usage.

The related research that were previously addressed offer several strategies for minimizing energy usage that are based on the energy balancing technique. Nevertheless, some of them make the assumption that UNs are homogeneous, while others neglect to account for all aspects of the underwater network environment, including UN depths, distance from the SBS, and residual/average energies. A static CH election approach is also used by others. Due to the specific variety of IoUT, which includes varying energy levels, changing depths, and distances, these issues are seen as relatively major gaps in the IoUT network, which will have an impact on the network's lifetime and performance. By using an energy balancing technique with ABC based stable election routing protocol, the method allows the network to deploy resources more efficiently, eliminating energy imbalances and enhancing overall performance by trading off between the ABC and stable election fitness probability solutions for the CH selection and route stability during communications.

III. PROPOSED SYSTEM MODEL

The proposed ABC-EBSE routing protocol performance results are presented in this section compared with ABC-SE. To measuring IoUT network efficiency, the performance of the proposed routing protocol is assessed using several performance metrics, including the network lifetime, throughput, residual energy, and CH overhead. Our proposed methods are based on the IoUT network Model shown in figure 1.

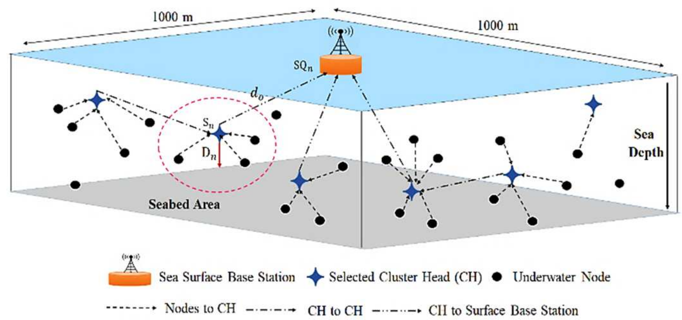

Figure 1. IoUT Network model

In the proposed model, the UNs depth, average and residual energies, and distances from the SBS influence the CH election process are considered. The defining of the 3D underwater environment space is provided by the coordinate system (x, y, d). UNs are dispersed at random inside this precise underwater area. To reduce energy consumption and extend the network's lifetime, our suggested routing protocol, which utilizes the IoUT network stable clustering technique, must effectively choose the ideal number of CHs and distribute energy among them appropriately. The proposed methodology intends to improve data transmission efficiency and minimize energy consumption in the context of the IoUT inside demanding underwater conditions by implementing ABC with stable election protocol and balancing approach based on Q-learning in the given IoUT network architecture.

A. IoUT Stable Election Protocol

In IoUT stable election protocol two energy levels are used to represent the UNs heterogeneity, the normal and advanced UNs which are used in the process of CHs selection [12]. The selection probability is based on residual energy Ei and UNs depth di, given by the equations (1) and (2) as follows.

$$p_n(IoUT) = \frac{p\, E_i(r)}{(1+\alpha\ \mathrm{m})\, \overline{E_i(r)}\, d_i} \quad (1)$$

$$p_a(IoUT) = \frac{p\ (1+\alpha)\ E_i(r)}{(1+\alpha\ \mathrm{m})\ \overline{E_i(r)} d_i} \quad (2)$$

Where, and $E_i(r)$ denotes the residual energy of nodes i in round r. And d_i is the depth impact between the SBS and UNs. $\overline{E_i(r)}$ denotes the r[th] average energy of nodes at round r.

The initial probability of both normal and advanced UNs for stable election IoUT is based on random number (RN) between 0 and 1 that generated by each UNs. If the RN falls below a set threshold, the UNs will assume to act as a CH [13]. The threshold for each UNs as either an advanced T_a or a normal T_n can be determined in the following equations (3) and (4).

$$T_n = \begin{cases} \frac{Pn}{1-Pn\left(r \bmod \frac{1}{pn}\right)} & ;\ if\ thre\ \in G' \\ 0 & otherwise \end{cases} \quad (3)$$

$$T_a = \begin{cases} \frac{Pa}{1-Pa\left(r \bmod \frac{1}{pa}\right)} & if\ thre\ \in G'' \\ 0 & otherwise \end{cases} \quad (4)$$

Where G' and G" are the sets of normal and advanced UNs that have not been elected as CHs in the last $\frac{1}{pn}$ and $\frac{1}{pa}$ rounds, respectively.

B. Proposed Solutions

In the IoUT stable election protocol, CHs are chosen using a random number with a predefined thresholds T_n and T_a in equations (3) and (4). These thresholds might not adjust well to altering IoUT network conditions or different UN energy levels, which could result unstable routing protocol and weak selected CHs [14]. ABC will greatly improve the IoUT stable election protocol in terms of energy efficiency, adaptability to dynamic environments, and improved CH selection based on various relevant UNs characteristics, such as average energies, depths, distances between the UNs and CHs, CHs and SBS, in order to ensure IoUT network energy optimization and adaptability [15].

Furthermore, the IoUT Stable Election Protocol's utilization of energy balancing through a trade-off between random number fitness and ABC fitness offers a more reliable and flexible CHs selection procedure in IoUT networks. Through the combination of random number fitness's and ABC's optimization abilities, this method improves more the routing stability and energy efficiency [16]. Its enable to create thresholds that are adaptively controlled by both random and optimal fitness criteria helps to balance energy consumption among UNs and CHs, reducing overhead and extending network lifetime.

- *ABC Stable Election Protocol (ABC-SE)*

In the proposed ABC-SE routing protocol, the fitness evaluation is used in the CH selection process by the ABC algorithm to assess a particular CH configuration's performance in relation to predefined parameters. The specific parameters of the fitness function may vary depending on the objectives and goals of the IoUT network [17]. For example, a fitness function may be created to maximize network coverage and minimize energy consumption while balancing these factors. The ABC fitness function can be calculated by the following equation.

$$f(i) = k\{Re(i) + N_D\} + \{1-k\} \times \{\frac{1}{Eu(i,b)}\} \quad (5)$$

Where the scaling factor is denoted by k. Re (i) of the UNs residual energies. N_D represents the number of nodes connecting to a specific UN within its transmission range is known as the UN degree. Eu is the distance in Euclid between UN I and the SBS. The influence of undersea conditions on energy consumption is the basis for the Re (i).

As illustrated in figure 2, the use of ABC with IoUT stable election process can reduce energy consumption by optimizing the fitness function of chosen CHs. Prior to the CH selection threshold check operation, the UNs energy levels r(e), depth D(n), and distance d(o) from the SBS are determined and used to optimise the initial probability of selection based on the calculated fitness function. The ABC determined the maximum fitness value to be selected for the CH selection process and scheduled the computed fitness function. The best CHs will be chosen in accordance with these specifications and criteria. In response, CHs transmit the base station and itself an ACK to indicate that they are CHs.

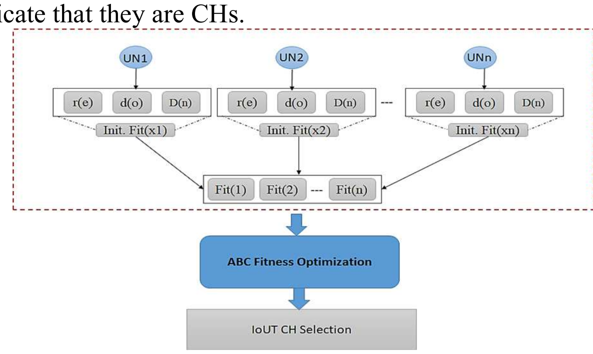

Figure 2. ABC Fitness Function Calculation Process

The scheduler's ABC technique initially took into account the population of UNs with calibrated fitness function sets, which may be utilized in the CH selection procedure [18]. For every UNs that may be a CH candidate, there are numerous sets of fitness, which can be thought of as a set of potential solutions.

- *Energy Balancing based ABCSE (ABC-EBSE)*

In the proposed ABC-EBSE routing protocol, to find optimal cluster set solution, the initial cluster set consists of the chosen initial clusters. IoUT stable election algorithm randomly turns each cluster in the current optimal cluster set to create a new cluster. After calculating the fitness function of randomly chosen clusters, ABC methods are used to choose the best new cluster set solutions [19]. By creating a trade-off scheme between the best fitness of random stable election process and ABC algorithms, the objective function value of the new cluster set is determined based on UNs energies inside each cluster.

The Q-learning approach is used to finds the tradeoff between random fitness values and ABC fitness values. The calculated fitness probability will be employed in the CHs election procedure following the tradeoff strategy. During the CH selection and routing operations, the energy used by UNs inside the clusters will be balanced by the UNs' reliance on each other during the tradeoff scheme process [20]. The fitness value determined by the following equation represents the Q-learning reward.

$$fit_{(reward)} = w_{(ABC)} \times Pr_{(CH)} + (1 - w_{(ABC)}) \times rand \quad (6)$$

Where; $w_{(ABC)}$ represents the Initial weight for ABC probability. The $Pr_{(CH)}$ represents the update CH probability based on ABC fitness value given by the following equation.

$$Pr_{(CH)} = \frac{(Pr_{(ABC)} - \min(Pr_{(ABC)}))}{(\max(Pr_{(ABC)}) - \min(Pr_{(ABC)}))} \quad (7)$$

Where $Pr_{(ABC)}$ is a calculated probability of fitness value by ABC algorithm given by the following.

$$\Pr_{(\mathrm{ABC})} = \frac{\mathrm{fit\ (CH)}}{\sum \mathrm{fit\ (CH)}} \tag{8}$$

The which fit (CH) calculation is based on two factors, the CH probability $\Pr_{(\mathrm{CH})}$ and the weight of ABC probability $w_{(\mathrm{ABC})}$ .The selection of ABC weights probabilities as an action for Q-learning is based on the following calculations.

$$\mathrm{QL}_{\mathrm{W\ (ABC)}} = \begin{cases} \min(1,\ w_{(ABC)} + \alpha)\ ; & \gg ABC\ probalility \\ \max\big(0,\ w_{(ABC)} - \alpha\big); & \ll\ ABC\ probalility \end{cases} \tag{9}$$

Where α represents the learning rate of Q-learning approach. Based on the selected action, the Q-learning algorithm will update the optimized weights of ABC. The Q-learning will raise the fitness probability of the ABC algorithm if the action is 1, and it will lower the fitness probability if the action is less than 1. Based on the estimated CH residual energy calculations made during the ABC process, the ABC fitness probability is incremented and decremented [21]. By allowing the Q-learning to trade off the ABC vs. rand fitness probability, this method will enable it to balance the energy between the chosen CHs. The Q-learning equation can be computed in the following equation.

$$\mathrm{Q\ (next)} = \mathrm{Q\ (current)} + \mathrm{alpha} \times (\mathrm{reward} + \mathrm{gamma} \times \max\ (\mathrm{Q}) - \mathrm{Q\ (action)}) \tag{10}$$

In equation (10), the reward represent the fitness values fit (reward) calculated from equation (1). After Q-learning, the final values of fitness probability based on ABC weight and random weight can be calculated by the following;

$$\mathrm{Fit\ CH}_{\mathrm{(prob)}} = \mathrm{QL}_{\mathrm{w\ (ABC)}} \times \Pr_{(\mathrm{CH})} + (1 - \mathrm{QL}_{\mathrm{w\ (ABC)}}) \times \mathrm{rand} \tag{11}$$

Algorithm 1. ABC-EBSE Routing Procedure

Initialize *Network Area, Clusters, Acoustic Communication Parameters*
Initialize *UNs Residual Energies, Depth, Euclidean Distances*
1: **find** each of the remaining UN decides to join its nearest CH according to distance
2: **set** current cluster set= initial cluster set
3: **calculate** the UNs energy probabilities
4: **find** the objective function value
5: **calculate** the objective function value by random value *by IoUT stable election process*
6: **for** number of current optimal clusters = 1 to max **do**
7: **implement** the ABC algorithm to select the CHs in each current optimal cluster
8: **repeat** step (5) *by ABC process*
9: **end** for
10: **For** each calculated objective function value **do**
11: **implement** the tradeoff process and energy balancing algorithm by Q-learning approach
12: **Calculate** fitness value of Q-learning reward
13: **find** the fitness (CH) probability fit (prob) by ***equation (11)***
14: **if** (fit (prob) > IoUT Stable election threshold) **then**
15: Current optimal CH= new CH
16: updates the fitness probability
17: **else**
18: Current optimal CH= Previous CH
19: updates the fitness probability
20: **end if**
21: **end for**

The proposed ABC-EBSE routing protocol procedure is depicted in algorithm 1. In order to choose the best CHs, the protocol process compares the final Fit (prob) with the IoUT stable election protocol threshold. The new cluster set is recognized as the current optimum cluster set if the value of the objective function of the existing optimal cluster set is higher than that of the new one. If not, a probabilistic process recognizes the new cluster set as the current optimal cluster set. The optimum cluster set is generated at the conclusion of the iteration. A lower value of the objective function indicates the CH set is optimal in relation to the entire network, the CH is optimal in the cluster, and the CH selection is more reasonable.

IV. Simulation and Results Discussion

The IoUT network has been developed using a MATLAB-based simulation model in order to evaluate the performance of the proposed algorithms. The 500 m × 500 m underwater network region contains 50 different UNs with a single SBS. The seabed's maximum depth is 50 meters. Table 1 displays the network parameters used in the simulation model. The UNs are dispersed at random throughout the underwater space in the simulation model. Another assumption is that the UNs must use the CHs to establish a direct connection to the SBS.

Table 1. Simulation Parameters

Parameters	**Values**
IoUT network area	500 ×50 m
UNs	50
Depth	50 m
E_{elec}	55 nJ/bits
E_{mp}	0.0015 pJ/bit/ m^4
E_{DA}	6 nJ/bit/signal
E_{fs}	12 nJ/bit/m^2
d_o	10 m
Packet Size (k)	512 bytes
Q-learning rate	0.1
Q-learning discount factor	0.9
CH selection criteria's	r (e) , d (o), and D (n)
Fraction of the advanced nodes	m = 0.5
Times more energy than normal nodes	α=1.5
Max Iterations	10000

A. Network Lifetime

Figure 3 illustrates how the proposed algorithms perform in terms of network lifetime based on the total number of dead UNs across iterations. It shows that ABC-SE increases the number of dead UNs consistently over the duration of the iterations. This growing pattern indicates a concerning deterioration in the lifetime and dependability of the network over time. An increase in inactive UNs could indicate a number of issues, including ineffective resource management and lack of flexibility in response to changing network conditions, which might affect network performance.

On the other hand, ABC-EBES provides an acceptable results. At the lower iterations, there is initially a slight increase from zero to very low dead UNs. notably, the number then levels off and remains at a constant, quite low number of dead UNs for the next few iterations. The steady number of inactive UNs indicates the energy balancing strategy enabled by Q-learning has brought about stability. In comparison with ABC-SE, ABC-EBES shows an ability to reduce UN inactivity, which helps to prolong the lifetime of the network.

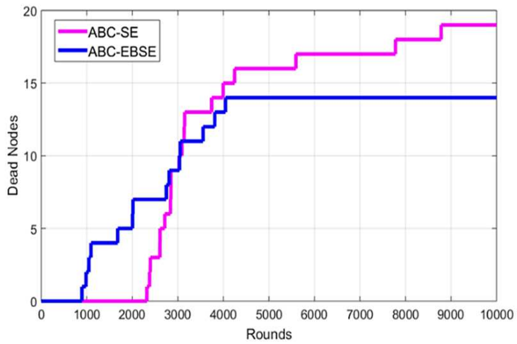

Figure 3. Number of Dead UNs during 10000 Iterations

The gradual rise in dead UNs seen in ABC-SE indicates a serious degradation of the network's lifetime. Due to the increasing inaction of UNs, this trend may result in reduced network efficiency, increased packet loss, and possible loss of service. On the other hand, ABC-EBES has a far more stable network lifetime. Its usefulness in maintaining network stability over an extended period is demonstrated by its ability to maintain a consistent count of dead UNs, particularly after an initial phase of adjustment.

The comparison that is based on the amount of dead UNs highlights how much longer the network lifetime of ABC-EBES is than that of ABC-SE. The ability of ABC-EBES to maintain a consistent and comparatively low number of inactive UNs during the iterations highlights its potential to guarantee long-term network performance and dependability. The incorporation of energy balancing mechanism by Q-learning shows an essential factor in enhancing network stability.

B. Average Residual Energy

The average residual energy values for ABC-SE and ABC-EBES across iterations are shown in Figure 4. The results show that average residual energy of ABC-SE continuously decreases during the duration of the iterations. By the max iteration, the rate of decrease gradually reduced from its initial value of 2 joules to 1.25 joules. This represents a gradual reduction over time in the average energy levels among the UNs. Although the energy decrease might indicate difficulties maintaining energy levels, which might accelerate resource depletion of UNs.

In ABC-EBES the residual energy starts at 2 joules, as the same like ABC-SE in low first iteration, and remains at that energy level higher than ABC-SE during high iterations. Unlike ABC-SE, ABC-EBES starts to stabilize at 1.5 joules after the 4,000 iteration cycle, indicating a more stable energy gradual decrease. This mean that the ABC-EBES stabilization indicates to a more controlled decrease in energy levels and maybe more successful energy management techniques.

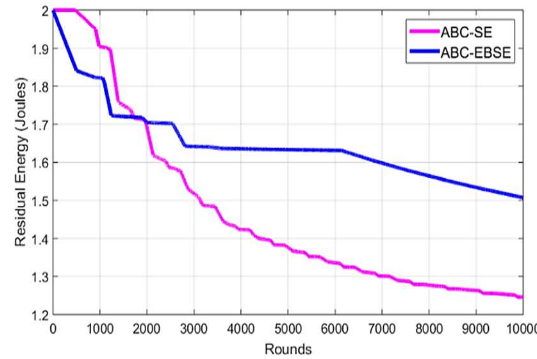

Figure 4. Average Residual Energy during 10000 Iterations

The ability of ABC-EBES to sustain a more stable average residual energy across iterations to better sustainability and more effective energy use, which may prolong network lifetime and improve UNs communication performance. By comparing ABC-EBES to ABC-SE, the energy balancing techniques used by the ABC-EBES may be more successful in maximizing energy utilization and distributing energy among UNs, which could result in higher energy reduction and enhanced network sustainability.

C. CHs and Network Efficiency

Table 2 compares the packets transmitted to CHs and SBS, the number of selected CHs, and the overall network efficiency between ABC-EBSE and ABC-SE. Based on the given results, it can be concluded that the ABC-SE and ABC-EBSE protocols initialize an equivalent number of Cluster Heads, indicating a comparable basis for CH establishment in the network. ABC-SE shows an ability to transmit fewer packets directly to the SBS given by 88733 bytes and a greater amount of packets towards the CHs by 78096 bytes. This distribution may indicate a greater emphasis on intra-CH node communication, which could result in enhanced data flow within clusters.

On the other hand, ABC-EBSE transmits significantly less data given by 52620 bytes to the CHs but more data given by 94147 bytes directly to the SBS, indicating a preference for direct communication with the SBS and maybe avoiding CHs more frequently for data transfer. This possibly because of its integrated energy balancing schemes and optimized routing algorithms, since ABC-EBSE would send less packets to CHs. It could attempt to reduce energy consumption inside clusters by minimizing data transfer to CHs, since CHs usually execute aggregation and forwarding operations, which need more energy. This approach might include avoiding CHs, communicating with the SBS directly, and possibly avoiding energy-intensive routing through multiple intermediate UNs.

TABLE 2. CH and Network Efficiency during 10000 Iterations

Protocols	Performance Results			
	Created CHs	Packets to SBS (bytes)	Packets to CH (bytes)	Network Efficiency (%)
ABC-SE	9	88733	78096	68.3108
ABC-EBSE	9	94147	52620	83.3219

The network efficiency given results provides additional insight into how effectively data is delivered and transmitted throughout the network. ABC-SE shows a moderate level of efficiency in transmitting data, as indicated by its network efficiency of 68%. Although it communicates with CHs in specific ways, its efficiency indicates that data delivery process optimization can still be enhanced. However, ABC-EBSE outperforms ABC-SE by a wide amount with a significantly better network efficiency of 83%. In comparison to ABC-SE, ABC-EBSE achieves considerably higher efficiency, indicating more efficient data transmission and possibly more optimized routing algorithms, even though it transmits more data directly to the SBS.

V. CONCLUSION

The basic approach of the study is to provide a dynamic and adaptable way to handle energy imbalances among UNs and CHs in IoUT scenarios by incorporate ABC into energy balancing for clustering methodologies. The study found from the experimental results that ABC-SE shows stability with respect to the number of formed CHs while providing stability with respect to the network lifetime and the number of alive UNs. But the average residual energy decreases more quickly, which suggests that maintaining energy levels throughout the network may be more difficult given its energy management. Its moderate performance in terms of network efficiency also indicates that there is potential for development in terms of data transmission strategy optimization. However, ABC-EBSE shows a more flexible and balanced strategy. It stabilizes with a more controlled fall in average residual energy, regardless of an initial phase of possibly higher CH overhead and energy reduction. This stability indicates longer network lifetimes and more efficient energy management. Furthermore, ABC-EBSE shows better network efficiency, sending more data to the SBS while keeping a higher level of efficiency, emphasizing better data transmission efficacy and optimized routing techniques.

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