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Effective autism spectrum disorder sensory and behavior data collection using internet of things

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ABSTRACT

Wireless body area networks (WBANs) connected with wearable internet of things (WIoT) offer useful features including sensory information collection, analysis, and transmission for continuous behavior monitoring of autism spectrum disorder (ASD) patients. Due to users' mobility and time-driven sensed data, data collection becomes very difficult. The current approach employs cluster-based multi-objective path-optimized data collection mechanisms that have experienced hotspot issues leading to loss of energy and coverage problems near the base stations. This work presents the high energy and reliable sensory and behavior data collection (HERSBDC) mechanism to address the research difficulties. To ensure network coverage, the HERSBDC initially provides a new uneven clustering mechanism. Next, multi-objective-based cluster head (CH) selection metrics are proposed. The final step is the creation of a multi-objective routing path to gather vital ASD data more reliably and energy-efficiently. Comparing the proposed HERSBDC algorithm to the low energy adaptive cluster-hierarchy (LEACH)-based, and distributed energy-efficient clustering and routing (DECR) methods, the simulation results demonstrate that the HERSBDC mechanism achieves a much better lifetime by 62.28% and 11.89%, the delivery ratio by 15.04% and 9.51%, with minimal delay by 52.65%, and 9.65%, and routing overhead by 32.05%, and 42.65%, respectively.

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1. INTRODUCTION

The wearable internet of things (WIoT) is currently attracting more attention from the research and business communities considering its wide applicability in different applications. The IoT opens up new possibilities for data transmission in wireless body area networks (WBANs), enhancing continuous surveillance of health and the remote healthcare infrastructure [1], [2]. IoT application-enabling WBNs are being examined in this work, where IoT devices equipped with sensors gather sensory and behavioral data related to autism spectrum disorder (ASD) and send it to a nearby IoT gateway for decision-support systems and services in the healthcare domain to enable effective management of ASD [3]. The sensory and behavior data bits cannot go directly to the IoT gateway server because IoT devices generally have restricted communication ranges and battery capacities. Instead, they must be routed through a few intermediate IoT devices to reach the IoT gateway server. This results in energy imbalance, delays, and increased communication expenses, among other issues. Thus, such issues are intolerable [4], when it comes to the implementation of applications in settings such as smart-city development [5], smart-healthcare [6], and home automation [7].

Clusters are used in the WBN-IoT environment [8], [9] to enhance comprehensive communication effectiveness and reduce energy consumption. Cluster heads (CHs) gather ASD patient sensory and behavior information from intra-cluster members in a clustering-based WBN-IoT system and carry out data aggregation to eliminate redundant information. The aggregated information are subsequently transmitted to the IoT gateway server via intermediary CHs. Unfortunately, most of the existing clustering-based techniques [10] did not solve the energy-hole problem (where CH closer to the sink uses energy more rapidly compared to farther away IoT devices), delivery ratio improvement, and latency reduction. Furthermore, the present approaches [11] were unable to reliably satisfy the quality of service (QoS) needed for modern healthcare applications.

The goal of the presented effort is to create a reliable, energy-efficient method of gathering sensory and behavioral information on ASD that also solves the energy-hole issue. Reliability and energy efficiency were combined in the creation of the reliable energy efficient routing (REER) protocol by [12], which used a clustering method based on various energy levels. Despite this, the energy-hole issues were not addressed. To address energy-hole issues, [13] created reliable and efficient routing (RER) by exploiting unequal clustering [14]. Route optimization techniques have been implemented to optimize energy and latency [15]. However, the existing approach was unable to meet the QoS [16] requirements of contemporary ASD healthcare applications. The proposed research project is motivated by the present challenges of ASD methods for gathering data in fulfilling specifications such as less delay, better energy efficiency, and greater data delivery for providing modern IoT-based healthcare assistance to ASD patients with QoS prerequisites motivates to introduce high energy and reliable sensory and behavior data collection (HERSBDC) mechanism for heterogeneous IoT-WBNs.

The novelty of proposed the HERSBDC is given. The hot-spot problem near the IoT gateway is addressed by introducing a novel unequal grouping algorithm. The work introduces an effective CH selection and Hop node selection strategy employing multi-objective functions (MOF) to improve energy efficiency. The work introduced multi-objective threshold parameters such as hop count, energy, and packet loss ratio for routing optimization during inter-cluster communication. In finding the optimal path the work uses the dragonfly algorithm (DFA); aiding in better performance in collecting ASD sensory and behavior information towards the IoT gateway server. The simulation results show the HERSBDC is very efficient in reducing delay, enhanced lifetime, and improved delivery ratio in comparison with the recent state-of-the-art routing mechanism.

The paper organization is as follows. Section 2, discusses various existing data routing its advantages, and its limitations. In section 3, the research methodology of the HERSBDC model is discussed. In section 4, the simulation result of HERSBDC with the existing routing model is shown. The last section discusses the significance of the HERSBDC model and future work is highlighted.

2. LITERATURE SURVEY

This section studies recent data collection protocols for WBNs and WBN-enabled IoTs for provisioning diverse healthcare time- and event-driven applications. The survey is focused on studying energy-efficient routing and reliable data collection protocols using IoT-enabled WBNs and identifies the benefits and limitations of current work. In the last few decades, there has been much development in wireless communication. Due to this development, IoT applications and IoT devices have come into the picture. One of the most successful healthcare IoT devices is the WBAN which consists of various sensors and actuators. To combat congestion in the network as well as extend the lifespan of dynamic WBAN, [2] suggested a data-centric load-aware routing (DCLAR) method. Key data-centric metrics that were considered in the design of this method included delivery time, dependability, throughput, as well as the lifespan of the network. Together, the link quality between nodes as well as node data was taken into account to guarantee the efficiency of data-centric metrics. In addition, because the movement of nodes greatly affects network traffic, the suggested protocol dispersed the load using a buffering management method. MT-MAC, presented in [6], is a method of effective cluster establishing for IoT-enabled WBAN. The researchers considered the node's handover method between virtualized clusters within the network to guarantee its security. Data from simulations shows that packet loss is significantly reduced using MT-MAC while nodes are moving around. Performance indicators such as loss of packets were studied in [4], which analyzed the effectiveness of body-to-body networks (BBNs). Throughout this study, all nodes are allowed to roam through the network environment freely. The presented approach includes new concepts-node entry likelihood as well as network entry probability which take into consideration the ability of individual nodes to move. In addition, they based node actions on a Markov chain approach. The efficiency associated with the presented method for mobile WBAN is demonstrated through simulation. A routing and clustering method for WBAN that utilizes ant colony optimization (ALO) was suggested in [8]. The ALO method was used to determine how many clusters were best. The outcome demonstrates the ALO algorithm's superiority over competing bio-inspired methods in several contexts. The fully connected energy-efficient clustering approach was introduced in [17]. It makes use of the electro-static discharge algorithm to build a completely associated system with the minimum connectivity between the sensor device and CH in a scenario including multiple hops. This will enable a better energy-efficient operation of the system. The model increases the lifetime of the system by facilitating complete interactions between the devices in a very energy-efficient way; thereby increasing the system's longevity by significantly lowering the number of devices that have failed. but was unable to maximize the QoS considering various locations. Alharbi *et al.* [18] discuss how region-based clustering, which depends on each device's connectivity inside a given area, may enhance data collection. The clustering approach uses CH to guarantee reliable routing and the most effective route is the one that combines with the least number of hops even though there are several options. An adaptable data collection methodology using hierarchical clustering for energy harvesting-WBNs was presented in [19] to ensure smooth transmission of data throughout the whole coverage region. First, a clustering hierarchy-based data collection model is being designed to achieve a more equitable share of device energy consumption. It is therefore advised to continually adjust the overall size of devices functioning throughout the energy-harvesting stage to provide uninterrupted coverage. Nevertheless, the system's congestion problems worsen primarily as a result of the duplicate data collecting. To mitigate the quantity of duplicate data, in [20] data collection is done employing a clustering mechanism using a static hub for WBNs. The multipath approach is also capable of improving the reliability of their model. The objective of their strategy is to lessen traffic management load to ensure the system can operate for extended periods. Nonetheless, the hotspot issue has a major impact on data collection energy overhead performances.

Uses an unequal clustering technique in [21] to lower energy usage of IoT devices with short battery lifespan. Furthermore, a novel two-stage priority-based load optimization technique is modeled to significantly reduce transmission delay. Utilized the type-2 fuzzy rule [22] and its modification [23] in [14] to carry out the uneven cluster construction. Yet, given the varied quality needs of contemporary IoT healthcare services, the use of the present data collection system was severely constrained by quality optimization and dependability to ensure reliability [12], [13]. To accomplish data collection employing clustered-based routing assuring energy minimization, an upper triangular matrix was constructed utilizing a hypergraph in [24]. In this case, CHs have been chosen with the least amount of hypergraph transverse by representing the IoT node as a hypergraph and its edges as the clusters. Next, by constructing an upper triangular matrix using the best intermediate nodes for data communication, data collection improvement has been finished. The goal of [5] is to provide innovative data collection methods, when combined with the requirement that sensory data arrive at the base station (BS) according to a predetermined likelihood, maximize power balance, and prolong the lifetime of WBNs by introducing an innovative two-hop and multi-hop data collection techniques. However, poor synchronization between nodes impacts the performance of data collection as stated in [25]. Thus, Sah *et al.* [25] select CHs according to active nodes and harvesting node numbers to enhance throughput with energy efficiency.

Ding *et al.* [26] designed a topology control strategy to enhance the energy efficiency of software-defined WBNs. First, the network is a cluster, and software-defined relays are designed to mitigate interference during communication by optimizing the power and bandwidth rate. The Markov model is used for packet queue and energy tradeoff optimization considering different link state probabilities. However, fault tolerance cannot be guaranteed as obtaining exact channel information is difficult. A multi-objective fault tolerance mechanism is introduced by employing deep reinforcement learning (DRL)-based algorithm in IoT-WBNs in [27]. The primary goal is to identify problematic devices with high precision and minimal computational time to provide reliable communication. Lastly, energy-efficient sensory information collection via a mobile sink greatly extends the lifetime of IoT-WBNs. For IoT-WBNS, an intelligent fault detection strategy with minimal energy consumption is presented in [28] that greatly improves failure detection rates and lowers the misclassification rate. IoT device component problems are found using a unique 3-tier failure identification mechanism. Moreover, a deep learning process that has been refined is employed to identify different faults, consequently preventing IoT devices from dying too soon. A multi-schedule graph that incorporates multiple schedules is produced in [29] by the meta-scheduler, which uses particle swarm optimization [30] technique for robust job distribution to resolve scheduling issues associated with every adaption context in IoT-WBNs. A new meta-scheduler that accounts for the frequent connection failures in IoT-WBNs is presented in the present study. During the initial stage of system layout, a graph representing all possible plans is created, considering multi-point failure occurrences. Three essential requirements are met by the routing algorithm in [31]: it is reliability, energy efficiency, and environmental awareness. As a result, several factors are taken into consideration when data collection decisions are taken. These characteristics comprise connectivity, deadlines, and energy awareness for balancing the energy usage between IoT nodes and IoT gateway servers considering the operating environment. For an ideal outcome, the problem is formulated in integer linear programming [9]. The survey demonstrates that the existing data collection approaches are unable to reliably balance energy-delay tradeoffs with less packet loss addressing the hotspot issues considering healthcare applications. The following section presents a high energy efficiency and reliable sensory and behavior data collection methodology that combines all these aspects.

3. PROPOSED METHOD

This work presents a high-energy and reliable sensory and behavior data collection (HERSBDC) mechanism for individuals with ASD using IoTs and edge-cloud platforms. The work adopts an unequal clustering of WBAN for collecting sensory data of individuals with ASD. The adoption of unequal clustering will aid the proposed model in solving the hotspot problems. The work further introduces an effective CH selection and Hop node selection strategy employing multi-objective metrics to improve the energy efficiency and reliability of WBAN. Finally, the work introduces multipath based routing using an evolutionary computing model to assure high energy and reliable sensory data collection mechanism employing IoTs and edge-cloud platform.

3.1. Unequal clustering

To make the IoT gateway server (GWS) determine the clustering strategy and perform layering, each node calculates the distance length of each layer. The distance length d_L can be calculated as in (1),

$$d_L = \frac{(d_{max} - d_{min})}{4} \tag{1}$$

where d_{min} and d_{max} define the closest and farthest of the IoT device from the IoT GWS. The clustering process is carried out independently at each level, using (1) to aid in enhancing the overall lifetime of the network with steadiness. In our work, the IoT gateway server is placed outside the sensing region to validate lifetime performance. The unequal clustering is done for designing the data collection mechanism in WBAN. The IoT gateway server uses updated radius R as defined in (2), if $R > R_{max}$, then the node location will probably be outside level 1. The complete process of unequal clustering is given in Algorithm 1. Steps 2 to 4 describe the broadcasting information between IoT devices and the GWS. Step 5 computes the distance D_L and step 6 computes the level with the IoT gateway server. Step 7 to 16, all the IoT devices validate the level based on minimum and maximum distance with the IoT GWS through (2).

$$R_c(i) = \left[1 - a\left(\frac{(D_{max} - d_{i,BS})}{d_{max}}\right) - b\left(1 - \frac{(E_{rem}(i,r))}{E_{max}}\right)\right] RL_{max} \tag{2}$$

Algorithm 1. Propsoed unequal clustering

1. **Input** (IoTDevice(i), d_{min}, d_{max}, GWS
2. **Output** (IoTDevice(i)$.levels$
3. GWS comunicates information to all IoT devices
4. IoT devices obtain the information from GWS
5. IoT devices communicates the conditional information to GWS
6. Computes the distance using (1)
7. ∀ IoT devices, GWS **do**
8.   **If** the distance IOT device (i) to $GWS < d_{min} + d_L$ **then**
9.   IoTDevice(i).level=L1;
10.   **Else If** the distance IOT device (i) to $GWS > d_{min} + d_L$ && distance IOT device (i) to $GWS < d_{min} + (L2 \times d_L)$ **then**
11.   IoTDevice(i).level=L2;
12.   **Else if** the distance IOT device (i) to $GWS > d_{min} + (L_2 \times d_L)$ && distance IOT device (i) to $GWS < d_{min} + (L3 \times d_L)$ **then**
13.   IoTDevice(i).level=L3;
14.   **Else**
15.   IoTDevice(i).level=L4;
16.   **End**
17. **End**

3.2. Cluster head and hop node selection

The nodes K are placed randomly across the WBAN and are divided into k clusters of unequal size where the cluster closer to the base station has a lesser radius with a lesser number of nodes and nodes far away from the base station have a higher number of nodes. From K devices, $\mathcal{D}$ devices are elected as CHs and $\mathcal{D}$ is represented as (3).

$$\mathcal{D} = \{\mathcal{D}_1, \mathcal{D}_2, \mathcal{D}_3, \dots, \mathcal{D}_y, \dots, \mathcal{D}_k\} \quad (3)$$

Thus, $\widetilde{\mathcal{D}}$ defines member nodes that are not the CH. The selection of CH is very important for effective sensory data collection in the healthcare domain. In this work a multi-objective parameter such as energy remaining, and location (connectivity) of nodes have been considered for CH selection as defined in (4),

$$O_{\mathcal{D}} = \gamma * T_h^{\mathcal{D}} + (1-\gamma) * T_m^{\mathcal{D}} \quad (4)$$

where γ defines the optimization parameter of CH selection, $T_h^{\mathcal{D}}$ defines the ratio between the average energy remaining of CH $\vec{L}_{\mathcal{D}}$ and member node $\vec{L}_{\widetilde{\mathcal{D}}}$ as defined in (5).

$$T_h^{\mathcal{D}} = \vec{L}_{\mathcal{D}} / \vec{L}_{\widetilde{\mathcal{D}}} \quad (5)$$

Similarly, the $T_m^{\mathcal{D}}$ defines the ratio of the distance of CH $\vec{E}_{\mathcal{D}}$ and member node $\vec{E}_{\widetilde{\mathcal{D}}}$ as defined in (6).

$$T_m^{\mathcal{D}} = \vec{E}_{\widetilde{\mathcal{D}}} / \vec{E}_{\mathcal{D}} \quad (6)$$

In reducing the load and enhancing system energy efficiency in this work hop nodes are elected. The job of the hop node is to just transmit the aggregated packet from CHs to the IoT GWS. The hop-nodes can be represented as (7).

$$\mathbb{D} = \{\mathbb{D}_1, \mathbb{D}_2, \mathbb{D}_3, \dots, \mathbb{D}_u, \dots, \mathbb{D}_v\} \quad (7)$$

However, to reduce control channel overhead the neighboring CH is selected as hop-nodes (HN) using a multi-objective parameter defined in (8),

$$O_{\mathbb{D}} = \varphi * T_h^{\mathbb{D}} + (1-\varphi) * T_m^{\mathbb{D}} \quad (8)$$

where φ defines the optimization parameter of hop-nodes selection, $\mathbb{S}$ defines the member nodes, $T_h^{\mathbb{D}}$ defines the ratio between the average energy remaining of hop-nodes $\vec{L}_{\mathbb{D}}$ and member node $\vec{L}_{\mathbb{S}}$ as defined in (9).

$$T_h^{\mathbb{D}} = \vec{L}_{\mathbb{D}} / \vec{L}_{\mathbb{S}} \quad (9)$$

Similarly, the $T_m^{\mathbb{D}}$ defines the ratio of the distance of hop nodes $\vec{Z}_{\mathbb{D}}$ and member node $\vec{Z}_{\mathbb{S}}$ as defined in (10).

$$T_m^{\mathbb{D}} = \vec{Z}_{\mathbb{S}} / \vec{Z}_{\mathbb{D}} \quad (10)$$

3.3. Routing path construction and optimization:

Once the CH and hop nodes are elected, a multi-objective routing path $L_{\mathcal{M}}$ is constructed to assure high reliability and energy efficiency (11),

$$L_{\mathcal{M}} = (\mathcal{E}_v) + (\mathcal{H}_l) + \mathcal{PL}_{,}^{p}) \quad (11)$$

where $\mathcal{E}_v$ represents the remaining energy, $\mathcal{G}_l$ represents the number of inter-cluster hop-nodes needed and is measured using (12),

$$\mathcal{H}_l = \sum_{t \in l} \mathcal{SD}(t) * \mathcal{DS}(t) \quad (12)$$

where $\mathcal{PL}_{,}^{p}$ defines the packet loss (PL) [10] in certain link l and is measured using (13),

$$\mathcal{PL}_{,}^{p} = 1 - (1 - L_{,}^{b})^{B}. \quad (13)$$

where $L_{,}^{b}$ represents the average bit error rate considering packet size B. In identifying the best path, the DFA [32], [33] is used for the optimization of the MOF (14),

$$MOF = min\left[weight_1(\mathcal{E}_v) + weight_2(\mathcal{H}_l) + weight_3\left(\mathcal{PL}_{\prime}^{p}\right)\right] \tag{14}$$

where $weight_1$, $weight_2$, $and\ weight_3$ define the application-specific performance weight customization for parameters like energy, hop count, and packet loss, respectively. The adoption of DFA aids in identifying a better path with high energy efficiency and reliability which is shown in a simulation study.

3.4. Energy consumption study

The work assumes every sensor node sends and transmits $\mathscr{b}_o$ bits of data to CH. The total aggregated data $\mathcal{B}_{\mathscr{h}}$ by CHs is measured using (15).

$$\mathcal{B}_{\mathscr{h}} = \sum_{o=1}^{\mathscr{h}} \mathscr{b}_o \tag{15}$$

where $\mathscr{h}$ defines the size of members within the cluster. The total energy consumption depends on sensing, transmission, receiving, and putting the node to sleep-awake process as defined in (16) and (17).

$$\mathcal{E}_{\mathbb{S}} = \left(1 - l_{sleep}\right)[\mathcal{E}_{src}(\mathbb{q}, \mathbb{e}) + \mathcal{E}_{dst}(\mathbb{q})] + l_{sleep}\mathcal{E}_{sleep} \tag{16}$$

$$\mathcal{E}_{\mathbb{S}} = \left(1 - l_{sleep}\right)\left(\mathbb{q}\mathcal{E}_{elec} + \mathbb{q}\mathcal{E}_{\mathbb{F}} * \frac{\mathbb{A}^2}{2n\pi} + \mathbb{q}\mathcal{E}_{elec}\right) + \ l_{sleep}\mathcal{E}_{sleep} \tag{17}$$

Where l_{sleep} defines the probability that nodes go to sleep mode, $and\ \mathcal{E}_{sleep}$ defines the energy needed during the sleep schedule. The aggregated information from CHs is then transmitted to the hop node. As the hop-node is placed closer to CHs the free space model is used for computing the energy consumption of CH as defined in (18) and (19).

$$\mathcal{E}_{\mathcal{D}} = \mathcal{E}_{src}(\mathbb{q}, \mathbb{e}) + \left(\frac{\mathbb{H}}{\mathbb{h}} - 2\right)\mathcal{E}_{dst}(\mathbb{q}) + \frac{\mathbb{H}}{\mathbb{h}}\mathbb{q}\mathcal{B}_{\mathscr{h}} \tag{18}$$

$$\mathcal{E}_{\mathcal{D}} = \mathbb{q}\mathcal{E}_{elec} + \mathbb{q}\mathcal{E}_{\mathbb{F}}\frac{\mathbb{A}^2}{2n\pi} + \left(\frac{\mathbb{H}}{n} - 2\right)\mathbb{q}E_{elec} + \frac{\mathbb{H}}{n}\mathbb{q}\mathcal{B}_{\mathscr{h}} \tag{19}$$

The hop nodes are placed far away from base station; therefore, a multipath propagation model is used and the energy consumption of the hop node is measured using (20) and (21).

$$\mathcal{E}_{\mathbb{D}} = \left(1 - l_{sleep}\right)[\mathcal{E}_{src}(\mathbb{q}, \mathbb{e}) + \mathcal{E}_{dst}(\mathbb{q})] + l_{sleep}\mathcal{E}_{sleep} \tag{20}$$

$$\mathcal{E}_{\mathbb{D}} = \left(1 - l_{sleep}\right)(\mathbb{q}L_{elec} + \mathbb{q}\mathcal{E}_{\mathbb{M}}\mathbb{e}_{\mathcal{S}}^{4} + \mathbb{q}L_{elec}) + \ l_{sleep}\mathcal{E}_{sleep} \tag{21}$$

Where $\mathbb{e}_{\mathcal{S}}^{4}$ is a parameter to measure the distance between hop nodes and the IoT GWS. Thus, using the above energy consumption considering both intra and inter-cluster communication is measured using (22).

$$\mathcal{E}_{\mathbb{T}} = \mathcal{E}_{\mathcal{D}} + \mathcal{E}_{\mathbb{D}} + \left(\frac{\mathbb{H}}{\mathbb{h}} - 2\right)\mathcal{E}_{\mathbb{S}}. \tag{22}$$

The overall energy relies on number of IoT nodes, topology size, and position of the IoT GWS and is measured using (23).

$$\mathcal{E}_{\mathcal{T}} = \mathbb{h}\mathcal{E}_{\mathbb{T}}. \tag{23}$$

The proposed HERSBDC mechanism adopting unequal clustering, enhanced CH and hop node selection, and multi-objective routing optimization aid in improving network lifetime and delivery ratio with minimal delay, routing, and computational overhead in comparison with current state-of-art data collection mechanism which is shown in simulation study below.

4. RESULTS AND DISCUSSIONS

This section studies the performance of HERSBDC with baseline low-energy adaptive cluster-hierarchy (LEACH) and other recent routing protocols such as LEACH-based [5], and distributed energy-efficient clustering and routing (DECR) [9]. The sensoria simulator [34] has been used for conducting simulation studies. The simulation parameters used for the comparative study are as follows, network area is fixed with 100 m×100 m with one GWS. The IoT devices are varied from 200, 400, 600, 800, and 1,000. The sensing and transmission range is 5 meters and 10 meters, respectively. The first-order energy consumption model is used. The network lifetime, delivery ratio, delay, and routing overhead are diverse metrics used for studying the performance of different routing methodologies.

4.1. Network lifetime vs device density

The following section examines HERSBDC's lifetime efficiency using standard LEACH as well as other currently used data collection strategies like DECR and LEACH-based. Figure 1 shows a pictorial representation of the lifetime efficiency of various data collection methods for device sizes ranging from 200 to 1200. The outcome demonstrates that the LEACH performs poorly over its lifetime. Finally, the suggested HERSBDC mechanism produces far superior lifetime efficiency compared to various data collection mechanisms considering variations in device densities. The DEEC method produces a far superior lifetime than the LEACH-based. Compared to LEACH-based, and DECR, the HERSBDC increases lifetime efficiency by 62.28%, and 11.89%, respectively. The significant lifetime improvement is because of the usage of new unequal cluster formation defined in Algorithm 1, CH selection using (4), and multi-objective optimization of (14) using DFA.

4.2. Routing overhead vs device density

The following section examines HERSBDC's routing overhead outcomes using standard LEACH as well as other currently used data collection strategies like DECR and LEACH-based. The routing overhead is measured in terms of a number of hops needed to carry out data collection towards the IoT GWS; less value indicates enhanced performance. Figure 2 shows a pictorial representation of the routing overhead outcomes of various data collection methods for device sizes ranging from 200 to 1,200. The outcome demonstrates that the LEACH performs poorly over its routing overhead performance. Finally, the suggested HERSBDC mechanism produces far less routing overhead compared to various data collection mechanisms considering variations in device densities. The DEEC method produces far less routing overhead than the LEACH-based. Compared to LEACH-based, and DECR, the HERSBDC reduces routing overhead by 32.05%, and 42.65%, respectively. The significant communication overhead reduction is because of the usage of (14) optimization using DFA to obtain optimal path; thereby aiding in reducing retransmission overhead.

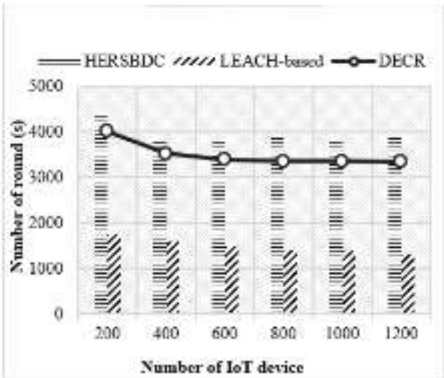

Figure 1. Network lifetime under different IoT devices

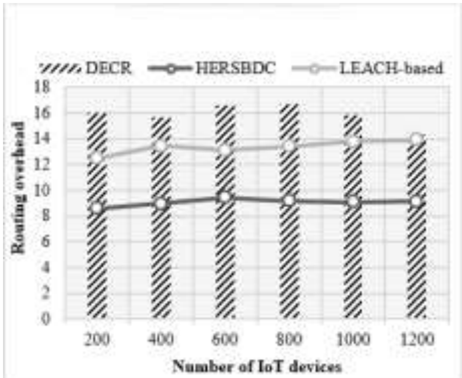

Figure 2. Routing overhead under different IoT devices

4.3. Delay vs device density

The following section examines HERSBDC's delay outcomes using standard LEACH as well as other currently used data collection strategies like DECR and LEACH-based. The delay is measured in terms of time taken to carry out data collection towards the IoT GWS; less value indicates enhanced performance. Figure 3 shows a pictorial representation of the delay outcomes of various data collection methods for device sizes ranging from 200 to 1,200. The outcome demonstrates that the LEACH performs poorly over its delay performance. Finally, the suggested HERSBDC mechanism produces far less delay compared to various data collection mechanisms considering variations in device densities. The DEEC method produces far less delay than the LEACH-based. Compared to LEACH-based, and DECR, the HERSBDC reduces delay by 52.65%, and 9.65%, respectively. The significant delay reduction is because of the usage of multi-objective weighted routing using (14).

4.4. Delivery ratio vs device density

The following section examines how well HERSBDC performs in terms of delivery ratio when compared to data collection protocols like DECR and LEACH-based. Figure 4 is a pictorial representation of the delivery ratio outcomes for various data collection protocols under varying device sizes of 200 to 1,200 devices. The DEEC model accomplishes a significantly more effective delivery ratio than LEACH-based with 90.49%. Finally, the proposed HERSBDC mechanism achieves a much better delivery ratio outcome with 95.98% compared to various data collection mechanisms considering various device densities. The significant delivery ratio enhancement is because of data collection using CH using (4) and relay using (8) employing multi-objective data collection using (14) and optimization using DFA.

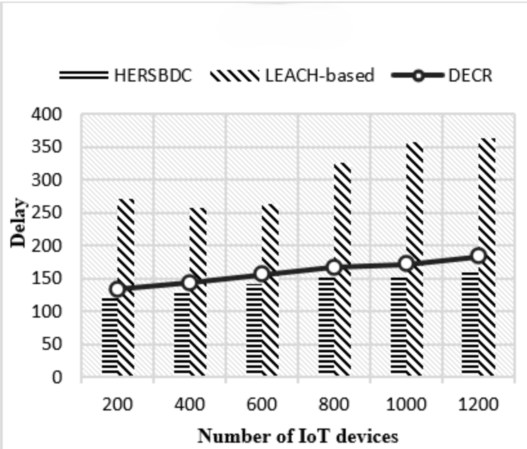

Figure 3. Delay under different IoT devices

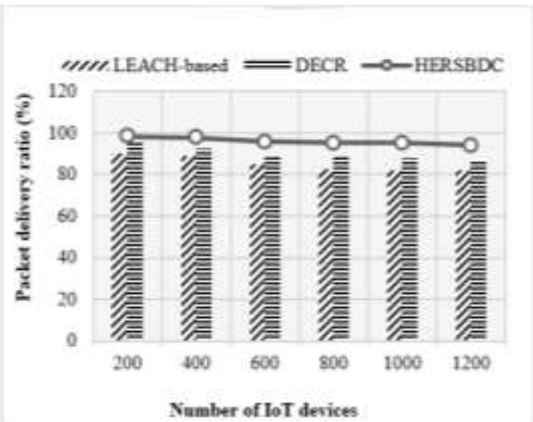

Figure 4. Delivery ratio under different IoT

5. CONCLUSION

Several fault-tolerant, reliable, and energy-efficient data collection mechanisms for IoT-WBANs have been examined in the present study. According to the investigation, present techniques do not offer every necessary component needed to provide the quality-of-service needs of contemporary IoT ASD applications. To ful-fill the investigation's specifications, this study presented the HERSBDC data collection method. Deployment, uneven cluster construction, CH selection, and multi-objective path optimization by the HERSBDC. The network can support the energy and reliability of ASD applications in IoT-WBAN using HERSBDC's mechanism. The adoption of DFA with weight optimization parameters allows dynamic optimization as per healthcare application needs. The simulation results of the study demonstrate that HERSBDC outperforms LEACH-based and DECR in terms of delivery ratio, with improvements of 15.04% and 9.51%, respectively. In comparison with LEACH-based, and DECR, respectively, HERSBDC increases network lifespan by 62.28%, and 11.89%; lowers routing overhead by 32.05%, and 42.65%; and lowers delay by 52.65%, and 9.65%, respectively. Future research will examine the use of multiple IoT gateway servers linked to the edge-cloud environment, in addition to considering a wider range of healthcare analytical applications in federated learning platforms.

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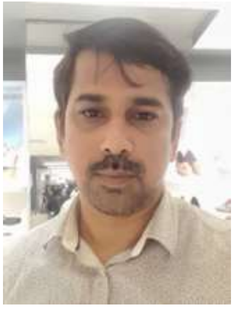

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