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Research Article

A Secure and Stable Humanoid Healthcare Information Processing and Supervisory Method with IoT-Based Sensor Network

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Nowadays, the Internet of things- (IoT-) based emerging technologies are playing a very pervasive role in healthcare systems where information is required on a real-time basis. These systems may provide real-time alerts with continuous monitoring to the concern in the odd conditions. Thus, these systems help the elderly and ill person with a good quality life and reduce the number of caregiver persons. Based on the above facts, this paper proposes a secure, efficient, and stable humanoid healthcare information processing and supervisory method with an IoT-based sensor network. Here, five different parameters specifically network residual energy, node density, node average energy, number of neighbors surrounded of a node, and distance between the sensor node and sink are considered for effective utilization of the energy of the sensor nodes. This method also reduces the communication distance of the nodes which helps in proficient data collection from the human body. The performance of the proposed and the existing work is considered the stability period, number of alive and dead nodes, total energy consumption, number of packets send to cluster heads, and base station metrics with two different monitoring areas. Thus, the stability period of the proposed method is increased by 144.52% with respect to the existing method protocol.

1. Introduction

In the age of innovative distributed computing environment, the Internet of things- (IoT-) based sensor network plays a significant role in which various embedded sensor nodes and usually a single sink is used to supervise the monitoring region in this distributed environment [1]. Moreover, IoT-based wireless sensor networks (WSNs) are ordinarily used for sensing and observing physical and behavioral conditions of the human being, such as temperature, electrocardiogram, oximetry, electroencephalography, oxygen, and barcode sensing. Also, with the technology advancements in WSNs, these networks are highly accepted in various application areas such as other health sectors, natural disaster detection and control, forecasting and weather prediction, border security, and traffic control. But, a tiny sensor node with a limited energy source (like a battery) is responsible for providing the target region data as per the need of application and for performing for a long time; these sensor nodes require additional energy. Moreover, in hostile environments, it is complicated to replace the battery in IoT-based WSN or provide an external power source [2].

Various applications of healthcare where human body data is tracked and transferred on a real-time basis require very energy-efficient systems. In IoT-based WSN, it is essential to offer the maximum network lifetime we require to minimize the energy consumption rate at each sensor node during data communication among sensor nodes [3, 4].

Also, energy-efficient networks are essential to enhance the network performance in time-sensitive applications for fast and reliable data delivery [5]. However, continuous advancements in wireless technologies and various quick reposed-based monitoring applications are proposed, namely, human health monitoring on a real-time basis, industrial-sensor networks, volcano-monitoring networks, and habitat monitoring. But let us consider for human monitoring sensor network system. The entire network is worthless if the transmitted sensing data of the target monitoring area does not receive by the base station or sink at a particular time [6].

To overcome the above challenging issues, IoT-based heterogeneous WSNs are presented, with various sensor nodes with different sensing ranges to offer additional tractability in network task dissemination. Moreover, the IoT-constructed WSN may have a moveable and stationary sink [7, 8]. In comparison with static sink, the portable sink offers better coverage and energy-efficient data collection. This heterogeneous nature of IoT-based WSN is widely adapted in natural disasters such as landslides and forest fires. Therefore, we consider the mobile sink in order to perform sensing data collection instead of a static sink. Mobile sink deployments in IoT-based WSN provide a better security benefit, but the major issue with mobile ink is tracking the mobile sink's exact position [9].

To handle the sink mobility in the IoT-based WSN, several architectures are proposed in hierarchical routing protocols, such as a tree, cluster, ring, and grid. Instead of declaring the current position of the sink node to the entire network during movement, the mobile sink node updates its position only to the high-level sensor nodes. After that, the high-level nodes send the updated sink location to the requested low-level nodes in the network for smooth data transmission to the sink [10]. Thus, a multilevel hierarchy is provided by the IoT-based WSN among the nodes in the network to ensure efficient data delivery and enable less energy depletion through data communication in the network. The major contributions of the proposed technique are as follows:

(i) In the proposed work, a secure, efficient, and stable humanoid healthcare information processing and supervisory method with IoT-based sensor network is proposed

(ii) A three-level heterogeneity model is considered to categorize and define the role of each sensor

(iii) There are five different parameters considered to perform CH selection, namely, residual energy of the networks, node density, average energy of node, number of neighbors surrounded of a node, and distance between sensor node and sink. These parameters are deliberated for effective utilization of the energy of the sensor nodes which also helps in achieve heterogeneity benefits

(iv) In this work, a secure data collection and transmission method is also proposed which transforms the signal data using embedding algorithms before transmission

The remaining of this paper is organized as follows. Section 2 discusses the state of the art related to the proposed work. Section 3 discusses a secure and stable humanoid healthcare information processing and supervisory method with IoT-based sensor network method. Simulation and experimental study are presented using the MATLAB framework in Section 4. Finally, the paper is concluded in Section 5.

2. Related Works

In this section, some of the recently proposed works by the different authors in the domain of the information processing and supervisory method with IoT based sensor networks are discussed as follows.

Maheshwari et al. discuss a method for CH election using a butterfly optimization algorithm (BOA) [11]. This method considers residual energy, node degree, centrality, distance to the neighbor, and base stations for electing the optimum route. However, the average distance is not considered. Benelhouri et al. [12] proposed a gateway-based CH election using a genetic algorithm for single sink-based networks to perform data transmission effectively. The residual energy and average energy of the networks are considered for selecting the CH. Bangotra et al. discuss an intelligent opportunistic routing algorithm (IOP) for WSNs and its application towards e-healthcare using a machine learning technique that selects a relay node from the list of potential forwarder nodes to achieve energy efficiency and reliability in the network [13]. This method provides reliability by connecting several healthcare network devices in a better way that saves energy effectively. This technology also helps the remote patient to connect with healthcare services for a longer duration with the integration of IoT services. Rani et al. [14] suggested that distance-based enhanced threshold sensitive SEP for cluster head selection in heterogeneous WSN. This protocol considers node and network energy and distance among nodes and sinks for the CH choice. To maintain uniform energy consumption during data forwarding, a multiple hop manner was used among distant CHs and BS. Vishnuvarthan et al. [15] proposed an efficient way of data collection in strip-based WSNs. The analytical methodology helps for the same transmission range for effective data forwarding combined with mobile data collector which maintains an optimal speed for each cluster. Also, the transmission range was automatically attuned for exact information of energy consumption in the sensor nodes. Simulation results show significantly prolonged network lifespan in compression with the existing systems, but the energy hole problem was avoided.

Kumar et al. discuss a cardiac diagnostic feature and demographic identification (CDF-DI) method using IoT-enabled healthcare framework with machine learning [16]. This method gives a public key infrastructure (PKI) secured framework with significant models that recognize several cardiac disease features. This method is considered a statistical and machine learning technique to analyze the cardiac secondary dataset and recommended features that have possible effects on clinical practice. Furthermore, this method provides supportive aid to the existing medical support system to identify the possibility of the survival status of the heart patient. Latha et al. [17] proposed a trusted approach for energy-efficient data aggregation (TA-EEA) for data aggregation precision by keeping limited constraints in aggregation with reliability. Also, in the neighbor selection process, the duty cycle (DC) mechanism provides energy saving during data aggregation. The threefold process helps control congestion for smooth data transmission. These processes help to improve the network lifetime as well as reduce node overhead. Randhawa and Jain [18] proposed a methodology for cluster arrangement H-WSNs named CEC methodology. Hexagonal shape approach is used in CEC for cluster arrangement in the network. Dual factors, residual energy, and distance are considered in the CH selection phase. TDMA scheme is formulated to allocate time slots for data transmission. Experimental results prove that CEC performed better in comparison with existing techniques.

Cao et al. [19] discussed the machine learning approach to extract sensing data using BAT-ELM (Extreme Learning Machine) algorithm, and mobile HWSN is used for performing data collection mechanism. Also, ELM helps to minimize the data amount sent to the sink node with the help of a process for collecting and combining the sensor data was presented. Simulation outcomes proved that the BAT-ELM overcame the challenges associated with random weight and threshold generated during the input and hidden layers in HWSN. Anees et al. [20] proposed a data fusion and clustering scheme, HFECS (Hesitant Fuzzy Entropy-Clustering Scheme) for H-WSN. Also, it is designed to reduce energy consumption using OCRG (Opportunistic Connection Random Graph) theory for prolonging the network. The HFE (Hesitant Fuzzy Entropy) considers the weight coefficients and local information of sensor nodes in the process of CH election. Thus, this scheme shows better results than other clustering benchmarks regarding energy consumption, network lifetime, and PDR. Osamy et al. [21] designed an algorithm for EBCS (Entropy-Based Clustering Scheme) CH election formation in H-WSN. The main challenging task of CH selection is resolved by combining two approaches, namely, entropy weighted coefficient and weighted product model. After that, minimum communication cost is selected from each non-CH node in the CH election process. Finally, the collected data by CH is transmitted to the base station (BS). Dutt et al. [22] offered CREEP (CH-Restricted EEP) as a new approach to analyze the performances of stationary and mobile sink in H-WSN. Due to the small-scale network area, to enhance energy efficiency in the network. Simulation results show better performance of the proposed scheme in stationary and mobile H-WSNs by limiting the number of CHs. There are few methods which are considered various metaheuristics methods for electing the cluster ahead for increasing the lifetime of WSNs [23–26]. Dwivedi et al. discuss an energy enhancement in LEACH using fuzzy logic called EE-LEACH [27]. This method prolongs the lifespan of WSNs and also performs load balancing using equal energy dissipation. The election of CH and cluster formation are performed using rank using fuzzy inference systems. However, this work did not consider the various other parameters in CH election and formation such as average energy and number of neighbor's nodes.

3. System Model

In this section, system model of the proposed system and radio energy model are discussed. Here, before discussing the system model of the proposed system along with radio energy model. The basic network assumptions of the proposed networks are given below:

(i) Sensor nodes and sink are fixed in nature, connections are symmetric, and they are identified by their ID

(ii) Nodes are heterogeneous in nature which means three levels of heterogeneity in terms of their initial energy are considered before their random deployment

(iii) Each node follows the radio energy model rules for consuming the energy in data transmission, sensing, and receiving

(iv) Every sensing node has the capability of data aggregation and it can be fused by the CH if there is duplicity in the data

(v) The proposed routing architecture is for monitoring harsh environments where other interferences like radio and physical are not considered

Figure 1 shows an e-healthcare scenario where meaningful information is collected from the human body using various types of sensor nodes (like temperature, pulse oximeter, and heart rate sensor). This data is composed through the CH which collects data from their cluster members. Furthermore, data is processed to the e-healthcare system using Wi-Fi technology and the Internet. The e-healthcare system is connected with the healthcare database which contains all the information of patients. Whenever doctors want to access patient information they can access this information through the e-healthcare system and make decisions on real-time basis using IoT-based sensor system. The sensor nodes consume energy whenever they are transferring the information from one sensor to another sensor node [11].

The consumption of energy by the sensor nodes is for data transmission over the short distance is given as follows:

$$\epsilon_{txs} = L * \epsilon_{elec} + L * \epsilon_{fs} * d^2 \text{ if } d \leq d_0. \tag{1}$$

The consumption of energy by the sensor nodes is for data transmission over the long distance is given as follows:

$$\epsilon_{txl} = L * \epsilon_{elec} + L * \epsilon_{mp} * d^4 \text{ if } d > d_0. \tag{2}$$

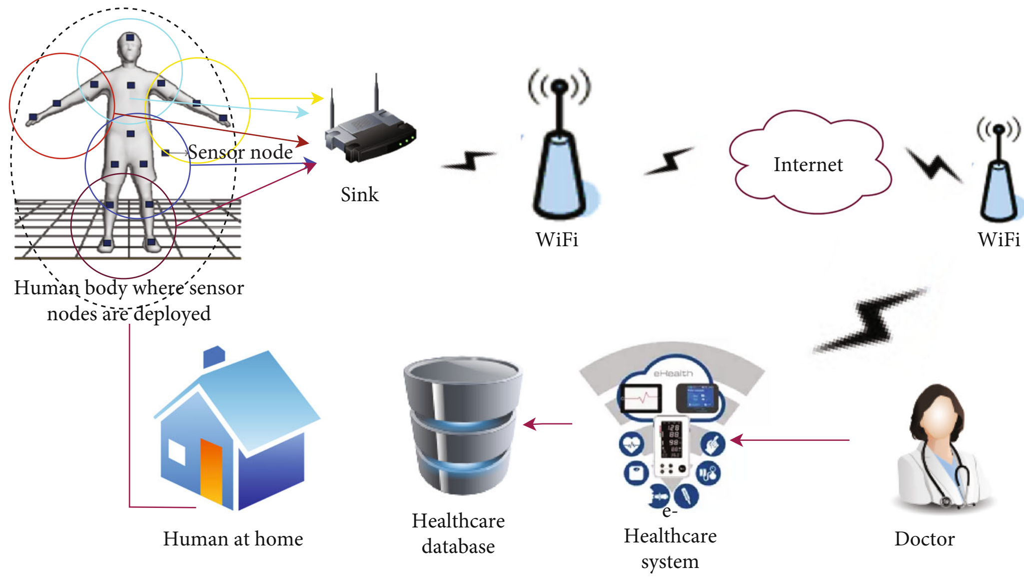

Figure 1: E-healthcare scenario where meaningful information is collected from the human body using various type of sensor nodes (like temperature, pulse oximeter, and heart rate sensor) and processed to the doctor on real-time basis using an IoT-based sensor system.

The consumption of energy by the nodes for data receiving is given as follows:

$$\epsilon_{rx} = L * \epsilon_{elec}. \tag{3}$$

The consumption of energy by the nodes for data sensing is given as follows:

$$\epsilon_{sx} = L * \epsilon_{elec}, \tag{4}$$

where ϵ_{elec}, ϵ_{fs}, and ϵ_{mp} are the consumption of energy in the electronic circuit, free, and multipath spaces, respectively, and d_0 is threshold distance is given below:

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}. \tag{5}$$

4. Proposed Method

In this section, the working of the proposed method is discussed by categorizing it into two different sections, namely, setup and steady-state phase. The setup phase comprises the network model and CH selection whereas data collection and transmission are related to the steady-state phase.

4.1. Setup Phase. In this subsection, the setup phase consists of the network model and CH selection. First of all, we will discuss the working operation of the proposed method which starts by developing the network model followed by the cluster head election method.

In this work, a three-level heterogeneity model is considered to categorize the different number of nodes deployed in the sensor network. The categorization depends on the residual energy of the nodes. The total number of nodes are n in the work which contains three different types of energy, i.e., ϵ_1, ϵ_2, and ϵ_3. The sensor nodes that have ϵ_1 energy are considered low energy nodes and ϵ_3 energy are considered higher energy nodes, and the nodes that have ϵ_2 energy are called middle-level nodes because they have energy between the ϵ_1 and ϵ_2 which satisfy the inequality $\epsilon_1 < \epsilon_2 < \epsilon_3$. The low level energy nodes (η_1) are more in number than the middle number of nodes (η_2) and a higher number of nodes (η_3) in the networks, whereas the higher energy nodes are minimum in numbers which satisfy the inequality $\eta_3 < \eta_2 < \eta_1$. The sum of network energy is deliberated as

$$\mathrm{Sum}_\epsilon = \iota \times n_n \times \epsilon_1 + \iota^2 \times n_n \times \epsilon_2 + \left(1 - \iota - \iota^2\right) \times n_n \times \epsilon_3, \tag{6}$$

where ι (Iota) is the model parameter and number of η_1, η_2, and η_3 nodes are $\iota \times n_n$, $\iota^2 \times n_n$, and $(n_n - (\iota * n_n + \iota^2 * n_n))$ with the ϵ_1, ϵ_2, and ϵ_3 energy, respectively.

If we are putting $\iota = 0$ in (1) it generates only 1 type of nodes with energy $\mathrm{Sum}_\epsilon = n_n * \epsilon_3$ in 1-level heterogeneity with higher nodes instead of low level nodes. It can be modified into low energy nodes by using the following condition:

$$\iota = \frac{\epsilon_3 - \epsilon}{\beta * f(\epsilon_2, \epsilon_3)}. \tag{7}$$

In equation (6), if we are putting $1 - \iota - \iota^2 = 0$, then it generated two types of nodes called low level energy nodes (η_1) and the middle number of nodes (η_2). It also generated two solutions $(\sqrt{5} - 1)/2$ and $(\sqrt{5} + 1)/2$ where the relation $(\sqrt{5} - 1)/2$ gives a value in the interval of $(0, 1)$ and can be considered for defining 2 levels of heterogeneity with two types of nodes.

Input: $n_n = 100$, $r_{\max}$ = maximum rounds
Output: n_{alive}, n_{dead}, n_{CH}, and *throughput*
Homogeneous and heterogeneous SNs are deployed in the monitoring area randomly
Set $n_{\text{CH}} = 0$ and $E_i = 0$, E_{res}
for $r = 1$ to $r_{\max}$ do
  Set $n_{\text{alive}=n_n}$, $n_{\text{dead}} = 0$
  for $i = 1$ to n_n do
    if $E_{\text{res}}(i) > 0$ then
      Apply CH election procedure using setup phase
      $n_{\text{CH}} = n_{\text{CH}} + 1$
      Perform steady phase for data collection
    else
      Update $E_{\text{res}}(i)$ node using radio energy model
    if $E_{\text{res}}(i) == 0$ then
      n_{dead}=n_{dead}+1
      if $n_{\text{dead}} == n_n$ then
        all SNs dead
        break
      else
        $n_{\text{alive}} = n_{\text{alive}} - n_{\text{dead}}$
      end if
    end for
  end for
Return I

Algorithm 1

The upper bond is signified as $\iota_{\text{upp\_b}}$ with the value $(\sqrt{5}-1)/2$ and consider the lower bound as $\iota_{\text{low\_b}}$ in case of 3 levels of heterogeneity. ι satisfy the inequality $\iota_{\text{low\_b}} < \iota < \iota_{\text{upp\_b}}$ and consider the function value f as $(\epsilon_3 - \epsilon_2)$ from (2). Thus, calculate $\iota_{\text{low\_b}}$ as below:

$$\iota_{\text{low\_b}} < \frac{\epsilon_3 - \epsilon_1}{\beta * (\epsilon_3 - \epsilon_2)} < \left(\sqrt{5} - 1\right)/2. \tag{8}$$

With the relation $\iota_{\text{low\_b}} < (\alpha_2 + \alpha_1)/\beta * \alpha_2$ and considering $\epsilon_2 = \alpha_1 + \epsilon_1$ and $\epsilon_3 = \alpha_2 + \epsilon_2$ gives the following

$$\frac{\alpha_2}{\alpha_1} < \frac{1}{\beta * \iota_{\text{low\_b}} - 1} = -\frac{\alpha_2}{\alpha_1} \geq \frac{1}{1 - \beta * \iota_{\text{low}_{\text{b}}}}. \tag{9}$$

If $-\alpha_2/\alpha_1 = 0$ in (4), we get the following relation:

$$1 - \beta * \iota_{\text{low\_b}} < 0 = \frac{1}{\beta} < \iota_{\text{low\_b}}. \tag{10}$$

By putting the value in (3) gives the following:

$$(\epsilon_3 - \epsilon_1) \leq \frac{\beta * \left(\sqrt{5} - 1\right)}{2} * (\epsilon_3 - \epsilon_2), \tag{11}$$

$$\beta * \left(\sqrt{5} - 1\right) * \epsilon_2 - 2 * \epsilon_1 \leq \left(\beta * \left(\sqrt{5} - 1\right) - 2\right) * \epsilon_3. \tag{12}$$

However, the energies of η_1, η_2, and η_3 nodes are fixed as ϵ_1, $\epsilon_2 = \epsilon_1 \times (1 + \omega)$, and $\epsilon_3 = \epsilon_1 \times (1 + \mu)$, respectively, where constants are as $\omega = 0.06$ and $\mu = 0.11$.

By using the above system model, the number of nodes for each level of heterogeneity as well as their initial energies is fixed and deployed in the decided monitoring area to the network setup. After that, the process of election of cluster heads has started. Initially, 5% of nodes are elected as cluster heads randomly by considering the condition of the proximity that the two cluster heads cannot be selected in the range of each other. Then, the remaining cluster heads are elected by considering the same constraint. After the selection of cluster heads, information of elected cluster heads is broadcast on the basis of RSSI. Based on that information, sensor nodes joined the respective clusters. The CH collects the data from the respective cluster members and then performs data aggregation and sends to the sink using multihop communication.

4.2. CH Selection. Initially, the process of selection of CH is based on the LEACH [8] protocol which is the very first protocol in WSNs. This process is based on probability which helps in electing in the cluster heads. Additionally, a threshold value is calculated for checking the eligibility for become the cluster head. This probability and threshold values of nodes depend on the various parameters which are given as follows:

(a) *Residual energy of the networks*: it refers to the ratio of the sum of the energy of each node to the total energy of the networks

$$\epsilon_{\text{res}} = \sum_{i=1}^{n_n} \epsilon_{\text{res}}(i)/\epsilon_t, \tag{13}$$

where $\epsilon_{\mathbf{res}}$ and ϵ_t are the residual and total energy of the networks.

(b) *Node density*: it refers to the number of nodes in the range of the cluster head. This factor also helps in the CH selection of the dense area where more number of nodes are deployed

$$n_{nD} = \sum_{i=1}^{n_n} D_{(n_n(i)-n_{nNS}(i))}/n_n \times \frac{1}{D_{(n_n(i)-f\_\mathrm{SNs})}}, \quad (14)$$

where n_{nD} is the node density, f_SNs is the farthest sensor node, $D_{(n_n(i)-\mathrm{Sink})}$ is the Euclidean distance from ith node and sink, $D_{\mathrm{avg}(n_n(i)-\mathrm{Sink})}$ is the average distance at the center of ith node and sink, and $D_{(n_n(i)-f\_\mathrm{SNs})}$ is the Euclidean distance from ith node and the farthest SNs

(c) ϵ_{avg} *average energy of node*: it refers to the ratio of the sum of the energy of each node to the total number of nodes in the networks

$$\epsilon_{\mathrm{avg}} = \frac{1}{n_n}\sum_{i=1}^{n_n} \epsilon_i. \quad (15)$$

(d) n_{nNS} *is the number of neighbors surrounded of a node*: this parameter indicates the number of sensor nodes in the surrounding of other sensor nodes

$$n_{nNS} = \frac{\sum_{i=1,j=1}^{n_n(\mathrm{CH})} D_{n_n(i)-n_n(j)}}{n_n(\mathrm{CH})}, \quad (16)$$

where $D_{n_n(i)-n_n(j)}$ is the distance among the ith and j th nodes in the cluster and $n_n(\mathrm{CH})$ is the total number of SNs in the cluster.

(e) *Distance between sensor node and sink*: it refers to the distance between the sensor nodes and sink. It helps in reducing the communication distance

$$D_{\mathrm{SNs-sinks}} = \sum_{i=1}^{n_n} D_{(n_n(i)-\mathrm{Sink})}/D_{\mathrm{avg}(f\_\mathrm{SNs-Sink})} \times \frac{1}{\sum_{i=1}^{n_n} D_{(n_n(i)-\mathrm{Sink})}/n_n}. \quad (17)$$

The sum of network energy (Sum_ϵ) can be calculated using equation (6) as follows:

$$\begin{aligned}\mathrm{Sum}_\epsilon &= \iota \times n_n \times \epsilon_1 + \iota^2 \times n_n \times \epsilon_2 + \left(1-\iota-\iota^2\right) \times n_n \times \epsilon_3 \\ &= n_n \times \left(\iota \times \epsilon_1 + \iota^2 \times \epsilon_2 + \left(1-\iota-\iota^2\right) \times \epsilon_3\right),\end{aligned} \quad (18)$$

$$\mathrm{Sum}_\epsilon = \epsilon_1 \times n_n \times \left(\iota + \iota^2 \times \epsilon_2/\epsilon_1 + \left(1-\iota-\iota^2\right) \times \epsilon_3/\epsilon_1\right), \quad (19)$$

where ϵ_1 is the node initial energy and $\epsilon_1 \times n_n$ is network total energy. $(\iota + \iota^2 \times \epsilon_2/\epsilon_1 + (1-\iota-\iota^2) \times \epsilon_3/\epsilon_1)$ is the expression expressing the incremental factor for the heterogeneous network which has $(\iota + \iota^2 \times \epsilon_2/\epsilon_1 + (1-\iota-\iota^2) \times \epsilon_3/\epsilon_1)$ times more energy than homogeneous nodes. Noncluster head sensor nodes can be converted into the CH after $1/p_i \times (\iota + \iota^2 \times \epsilon_2/\epsilon_1 + (1-\iota-\iota^2) \times \epsilon_3/\epsilon_1)$ rounds. The average probability for converting node into CH for the heterogeneous system is as $n_n \times 1/p_i \times (\iota + \iota^2 \times \epsilon_2/\epsilon_1 + (1-\iota-\iota^2) \times \epsilon_3/\epsilon_1)$. The weighted probability for electing the cluster heads for η_1, η_2, and η_3 nodes is denoted by p_{η_1}, p_{η_2}, and p_{η_3}. The probability value $p(i)$ for η_1, η_2, and η_3 nodes is computed as follows:

$$p_{\eta_1} = \frac{p_i \times \epsilon_{res} \times n_{nD}}{(\iota + \iota^2 \times \epsilon_2/\epsilon_1 + (1-\iota-\iota^2) \times \epsilon_3/\epsilon_1) \times \epsilon_{\mathrm{avg}} \times D_{\mathrm{SNs-sinks}} \times n_{nNS}}, \quad (20)$$

$$p_{\eta_2} = \frac{p_i \times \epsilon_{\mathrm{res}} \times (1+\omega) \times n_{nD}}{(\iota + \iota^2 \times \epsilon_2/\epsilon_1 + (1-\iota-\iota^2) \times \epsilon_3/\epsilon_1) \times \epsilon_{\mathrm{avg}} \times D_{\mathrm{SNs-sinks}} \times n_{nNS}}, \quad (21)$$

$$p_{\eta_3} = \frac{p_i \times \epsilon_{\mathrm{res}} \times (1+\mu) \times n_{nD}}{(\iota + \iota^2 \times \epsilon_2/\epsilon_1 + (1-\iota-\iota^2) \times \epsilon_3/\epsilon_1) \times \epsilon_{\mathrm{avg}} \times D_{\mathrm{SNs-sinks}} \times n_{nNS}}. \quad (22)$$

The probability of η_1, η_2, and η_3 nodes satisfies the relation $\epsilon_{\mathrm{res}} > 0$. The value of the threshold $T(i)$ can be computed for η_1, η_2, and η_3 as follows:

$$T(\eta_{1i}) = \frac{p_{\eta_{1i}}}{1 - p_{\eta_{1i}}\left[r \bmod \left(1/p_{\eta_{1i}}\right)\right]} \times \frac{n_{nNS}}{D_{\mathrm{SNs-sinks}}} \times \left[\left(r \operatorname{div}\left(\frac{1}{p_{\eta_{1i}}}\right)\right) \times \left(1 - \frac{\epsilon_{\mathrm{res}}}{\epsilon_{\mathrm{int}}}\right)\right], \quad (23)$$

$$T(\eta_{2i}) = \frac{p_{\eta_{2i}}}{1 - p_{\eta_{2i}}\left[r \bmod \left(1/p_{\eta_{2i}}\right)\right]} \times \frac{n_{nNS}}{D_{\mathrm{SNs-sinks}}} \times \left[\left(r \operatorname{div}\left(\frac{1}{p_{\eta_{2i}}}\right)\right) \times \left(1 - \frac{\epsilon_{\mathrm{res}}}{\epsilon_{\mathrm{int}}}\right)\right], \quad (24)$$

$$T(\eta_{3i}) = \frac{p_{\eta_{3i}}}{1 - p_{\eta_{3i}}\left[r \bmod \left(1/p_{\eta_{3i}}\right)\right]} \times \frac{n_{nNS}}{D_{\mathrm{SNs-sinks}}} \times \left[\left(r \operatorname{div}\left(\frac{1}{p_{\eta_{3i}}}\right)\right) \times \left(1 - \frac{\epsilon_{\mathrm{res}}}{\epsilon_{\mathrm{int}}}\right)\right]. \quad (25)$$

The threshold functions for η_1, η_2, and η_3 are denoted as $T(n_{\eta_1})$, $T(n_{\eta_2})$, and $T(n_{\eta_3})$, respectively. This threshold value helps in electing the cluster heads efficiently. The complete process of the proposed algorithm is described in the following steps.

4.3. Steady Phase. The steady phase helps in the data collection and transfer data between the sensor nodes to CHs and the cluster heads to the sink. The data aggregation is also performed at the various CHs after collecting the data from the sensor nodes and other CHs. Time Division Multiple Access (TDMA) technique is used for collecting the data from the sensor nodes to the CHs where dedicated time slots are given for each sensor node for transferring the data. The transmission of the data from the sensor nodes to CH and CH to sink depends on the threshold value of the each level nodes $T(n_{\eta_1})$, $T(n_{\eta_2})$, and $T(n_{\eta_3})$. The energy consumption in transmission, receiving, data aggregation, and sensing is calculated according to the radio energy model. In this process, the energy of each node is cheeked; if the energy of node is higher than 0, then the node will be alive; otherwise, it will be considered dead node and that will be removed from the list. If all the nodes are dead, then networks fail. Furthermore, if the sensor energy is not equal to zero then the sensor can be participant in the CH election for the next round. All the cluster heads forward the data to the nearest cluster heads/sinks using the single-hop communication, and then, further data is forwarded to the next nearer CH/sink. This approach helps in reducing energy consumption as well as avoids the hotspot problem of the WSNs.

4.4. Signal Compression and Encryption Method. During the transmission of information signal can be transmit using the predictor, namely, gradient edge detection (GED), and the signal size may be reduced by removing the prediction error ($E_{p_{p,q}}$)

$$E_{p_{p,q}} = \alpha_{p,q} - \beta_{p,q}, \tag{26}$$

where the predicted and original vales are $\beta_{p,q}$ and $\alpha_{p,q}$, respectively. The Huffman coding technique is used for predicting the error where it encodes each and every symbol. The values of the signal like ($V_0, V_1, V_2, \dots V_N$) are encoded into ($\gamma_0, \gamma_1, \gamma_2, \dots \gamma_N$) encoded bit stream on the basis of the occurrences. The elements of $\alpha_{p,q}$ are decoded into the binary stream of the 8-bit sequence. After that, a matrix is prepared by considering the encryption process. A $r_{p,q}$ size matrix is also required which is generated by the pseudorandom numbers. Conversion process of the matrix is given as follows:

$$\alpha^t_{p,q} = \lfloor \alpha_{p,q}/2^{t-1} \rfloor \bmod 2, t = (1, 2 \cdots 8). \tag{27}$$

The encryption process is performed as follows:

$$\alpha e^t_{p,q} = \alpha^t_{p,q} \oplus r^t_{p,q}. \tag{28}$$

After that, the obtained value $\alpha e^t_{\mathrm{p,q}}$ is converted into the decimal as given in the formula below:

$$\alpha e_{p,q} = \sum_{t=1}^{8} \alpha e^t_{p,q} \times 2^{t-1}. \tag{29}$$

Thus, using the above complete process, the signal is in the secure and compressed form. The reverse process is performed at the receiver for recovering the original data.

5. Simulation Results and Discussion

In this method, an e-healthcare scenario is proposed where meaningful information is collected from the human body using various types of sensor nodes (like temperature, pulse oximeter, and heart rate sensor) and processed to the doctor real-time basis using IoT-based sensor system. The information is gathered by the various sensors and processed through the multihop communication. The sensor nodes collect the information and send it to the server with the help of the other and as well as with the help of the cluster heads. This process consumes a lot of energy that can be optimized by the proposed scenario as we considered in Figure 1. In this section, a detailed description of the simulations environment of the existing method EE-LEACH [27] and proposed protocol with different performance are explained. In this simulation environment, sensor nodes are deployed on the body of the human being. The performance metrics considered in this work are stability period, number of alive nodes, number of dead nodes, total energy consumption, and number of packets sent to cluster heads and base station. Two different scenarios are considered for deploying the sensor nodes, i.e., $100\,\mathrm{m} \times 100\,\mathrm{m}$ area with sink position $(50, 50)$ and $200\,\mathrm{m} \times 200\,\mathrm{m}$ area with sink position $(100, 100)$, respectively. The implementations of the proposed and existing work are performed in the MATLAB with i7 processor, Windows 10 OS with 8 Gb RAM. The data sink is placed in the middle of the area. There are three type of nodes in the deployed networks for defined three levels of heterogeneity. The energy of the heterogeneous nodes in 3 levels of heterogeneity for normal, advance, and super are 0.2 J, 0.5 J, and 1.25 J, respectively, and the number of heterogeneous nodes in 3 levels of heterogeneity is 50, 30, and 20, respectively. There are 25 simulations performed by considering the same parameters for each metrics and then taken average to calculate the final results which are shown in the figures. All the radio energy parameters are considered same as considered in the existing method EE-LEACH [27]. The simulation parameters utilized in this paper are given in Table 1 as follows.

5.1. Simulation Results for Scenario 1. In scenario 1, the sensor nodes are deployed in the $100\,\mathrm{m} \times 100\,\mathrm{m}$ area and sink position is situated in the middle of the area at $(50, 50)$. In the performance analysis of the existing method EE-LEACH [27] and proposed protocol 3-level heterogeneity is considered. The comparative study analysis of the existing method EE-LEACH [27] and proposed protocol with different metrics are discussed as follows.

5.1.1. Stability Period. The stability of the networks can be calculated by the number of rounds completed before the first node dead in the network. Thus, it defines the constancy to the network. It is observed from Figure 2 that the first node dead of existing method EE-LEACH [27] in 795

Table 1: Simulation parameters and their respective values.

Simulation parameters	Values
Network area	100 m × 100 m and 200 m × 200 m
Number of data sink	1
Initial energy of the nodes	0.2 J
Type of heterogeneity	3-level heterogeneity
Energy fraction between advanced and intermediate nodes	$\omega = 0.06$ and $\mu = 0.11$.
Energy consumed by the transmitter and receiver	50 nj/bit
Threshold distance (d_0)	87 m
Energy required by the amplifier over a shortened distance (E_{efs})	10 nj/bit/m^2
Energy required by the amplifier over a larger distance (E_{mp})	0.0013 nj/bit/m^4
Energy consumption in data aggregation (E_{da})	5 nj/bit/signal
Data packet size	2000 bits
Number of simulation runs	25

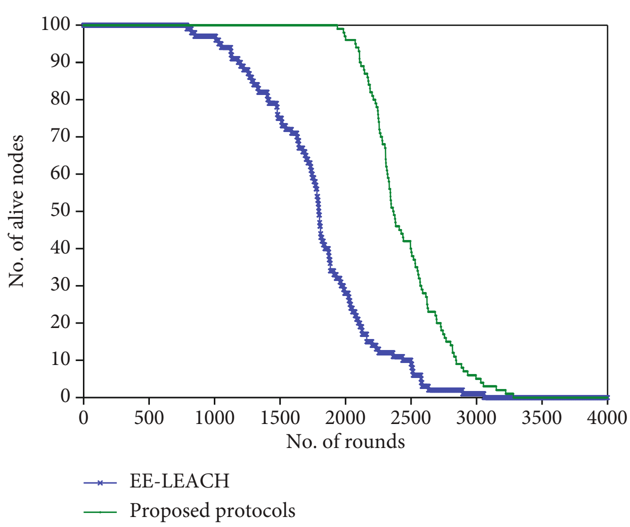

Figure 2: Alive nodes vs. rounds.

rounds and first node of the proposed protocol is surviving up to 1944 rounds. Thus, the stability period of the proposed method is increased by 144.52% with respect to the existing method EE-LEACH [27] protocol. The main reason behind this improvement is the election of clustering parameters with the existence of heterogeneity. The distance and energy parameters are directly cutting the energy uses and improving the preservation for the nodes. The node density is decreasing the communication cost during intracluster communication. Finally, it is observed the proposed method effectively elects the cluster head and improves the stability period.

5.1.2. Number of Alive Nodes. This metric defined the survival period of the networks in terms of the number of

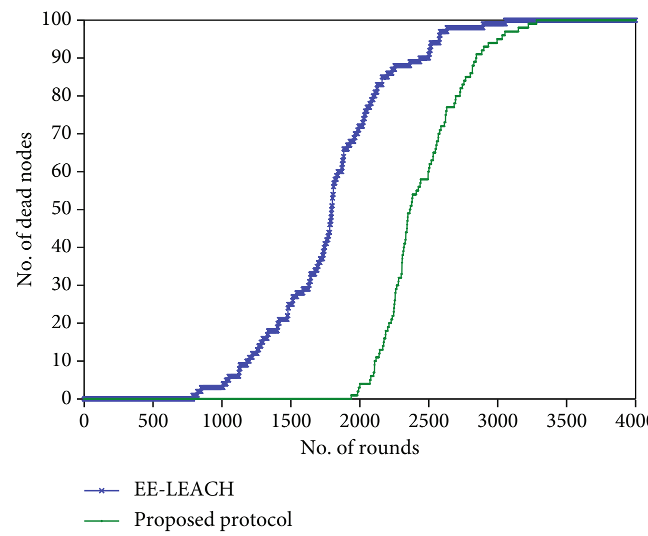

Figure 3: Dead nodes vs. rounds.

rounds covered till one of the nodes is alive in the networks. Figure 2 shows the number of alive nodes for the existing method EE-LEACH [27] and proposed protocols with respect to number of rounds. The first, half, and last node dead of the existing method EE-LEACH [27] and proposed protocol is in 795, 1789, and 2888 rounds and 1944, 2376, and 3284 rounds, respectively. The whole network runs more for the proposed method with respect to rounds as compared to the existing methods. This gigantic improvement in the results indicates due to a reduction in the distance between the sink and cluster heads as well as number of cluster heads. This improvement in prolonging the network lifetime is due to the reduction in the energy expenditure during the election of cluster heads and data communication from the sensor nodes to sink.

5.1.3. Number of Dead Nodes. The number of dead nodes in the networks can be calculated as the dead nodes in the networks against the rounds. With all the nodes dead, then the network is considered as fail. The number of dead nodes with respect to the rounds is shown in Figure 3. The first node dead of the existing method EE-LEACH [27] and proposed protocol is in 795 rounds and 1944 rounds, respectively. The half node dead for EE-LEACH [27] method is 1789 rounds whereas 2376 rounds in case of proposed protocol. The improvement in the dead of the last node for the proposed method is 2888 rounds where as it is observed for the EE-LEACH [27] method is 3284 rounds. It is concluded from the analysis that the proposed method covers more number of rounds as the EE-LEACH [27] method. This improvement in the prolonging the rounds is due to the reduction in the energy expenditure during election of cluster heads and data communication from the sensor nodes to sink.

5.1.4. Total Energy Consumption. The total energy consumption is the another significant factor which calculates the sum of the total remaining energy of the networks per round which indicates the efficient consumption of the network

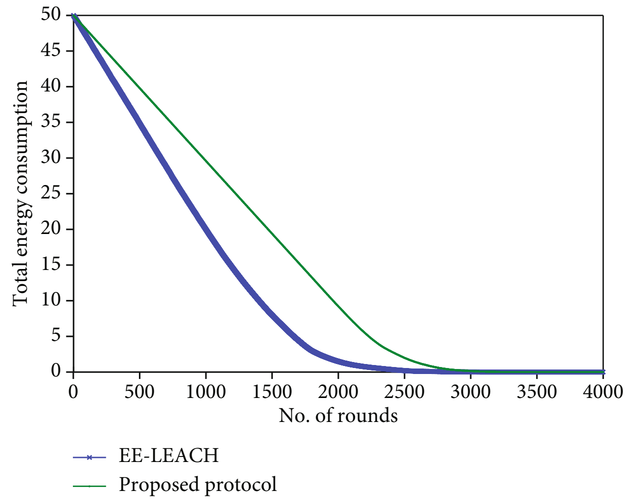

Figure 4: Energy consumption vs. rounds.

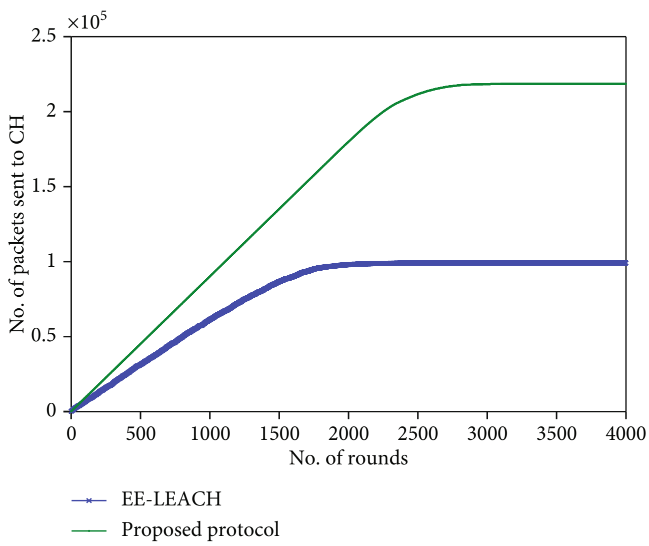

Figure 5: Packet sent to CH vs. rounds.

energy. The total energy consumption with respect to the rounds is shown in Figure 4. During the data transmission process, the reduction in the network energy starts. In the proposed method, the remaining energy is saved as compared to the existing method because of the reduction in the number of hop count for transferring the data from the sensor node to sink via cluster heads. The proposed method covers more number of rounds as compared to the existing EE-LEACH [27] method. It can be evident from Figure 4 that the total remaining network energy is higher in the proposed method than in the existing EE-LEACH [27] method. Moreover, the communication within the cluster also helps in preserving the energy of the networks in an efficient manner.

5.1.5. Number of Packets Sent to Cluster Heads. It defines as the number of data packets transmitted successfully to the cluster head per unit times. The number of packets sent to the cluster heads with respect to the rounds is shown in

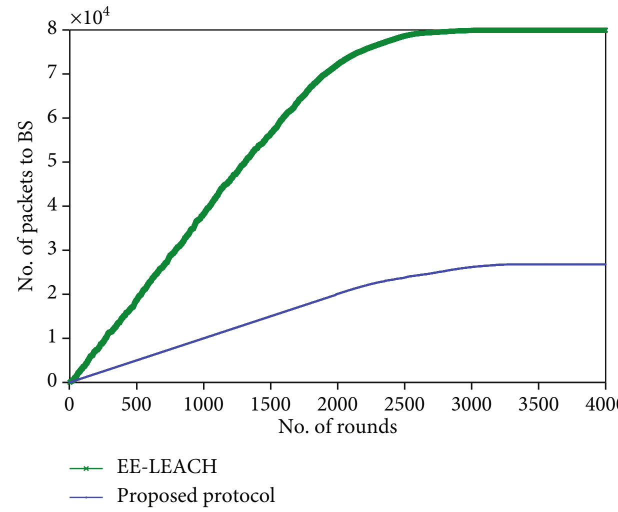

Figure 6: Packet sent to BS vs. rounds.

Figure 5. The cluster formation reduces the distance between the sensor nodes and their respective cluster heads which helps in increasing the lifetime of sensor nodes. The total packet sent by the cluster heads is 1.0×10^5 and 2.14×10^5 per round. The improvement in the cluster head election is done by the defined clustering parameters which reduce the data communication distance and optimize the process of cluster head election. The proposed protocol preserves energy for future communication, and a lot of energy is saved by all independent nodes as no unnecessary traffic is generated near the base station and also removes the hotspot problem at the sink.

5.1.6. Number of Packets Sent to Base Station. It determines the throughput of the networks and also ensures the quality of service and reliability of the networks. The throughput of the networks is the number of data packets transmitted successfully to the base station per unit times. The number of packets sent to the base station with respect to the rounds for the proposed and existing networks is shown in Figure 6. Reducing the cluster formation for the closer nodes to the sink and optimizing communication distance factor increase the network's quality of service. The clustering parameters for cluster head selection promote lifespan expectancy and throughput. Communicating more data packets is only possible if nodes live for a longer time in the network. In the case of the proposed method, throughput is amplified inclusively with lifetime by transmitting 2.73×10^4 packets whereas the existing method transferred 8.0×10^4 packets to the sinks. Such an enhancement can be perceived due to the distance optimization between the sink and nodes and preserving energy for future communication. Also, a lot of energy is saved by independent nodes as no unnecessary traffic is generated near the base station. This energy appears back in the form of throughput.

5.2. Simulation Results for Scenario 2. In the section, scenario 2 is considered where the sensor nodes are deployed in the 200 m × 200 m area and the sink position is situated in the

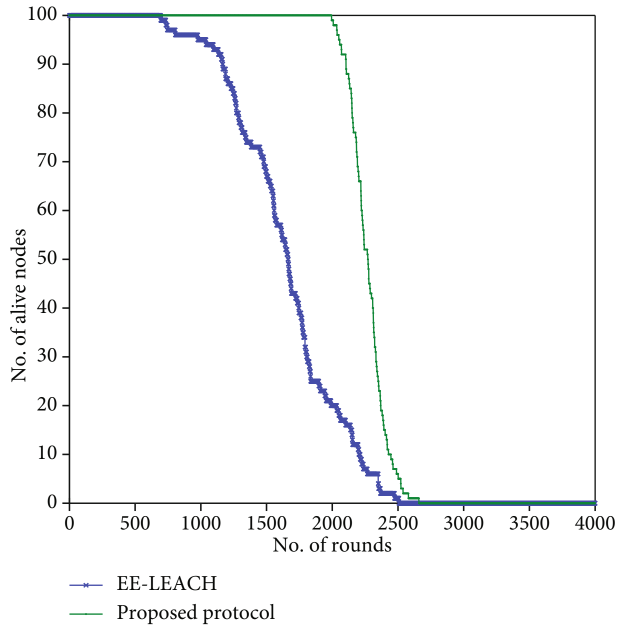

Figure 7: Alive nodes vs. rounds.

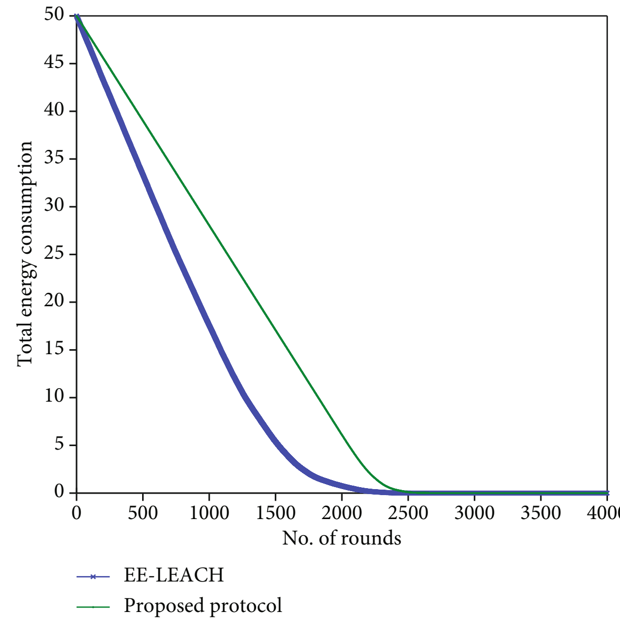

Figure 9: Energy consumption vs. rounds.

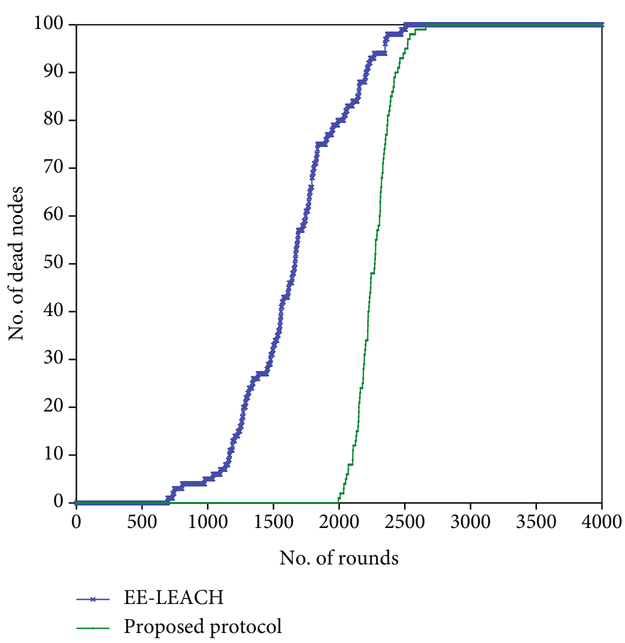

Figure 8: Dead nodes vs. rounds.

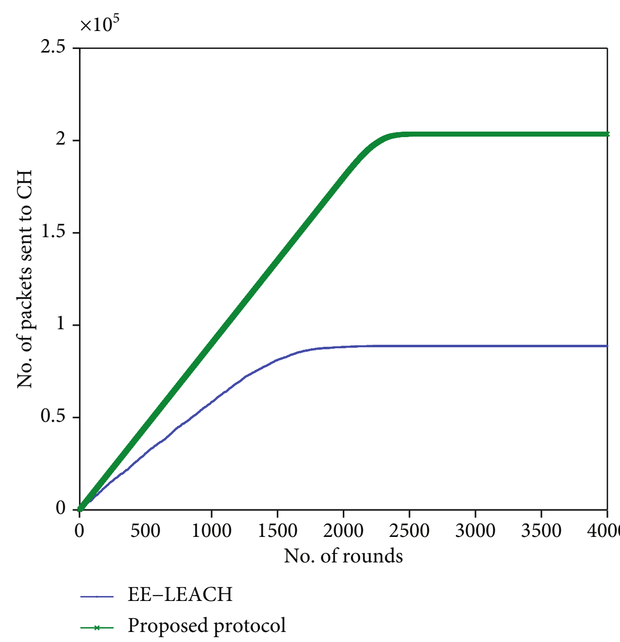

Figure 10: Packet sent to CH vs. rounds.

middle of the area at (100,100). In the performance analysis of the existing method EE-LEACH [27] and proposed protocol, 3-level heterogeneity is considered. The comparative study analysis of the existing method EE-LEACH [27] and proposed protocol with different metrics is discussed as follows.

It is illustrated from Figure 7 that the stability of the existing method EE-LEACH [27] in 712 rounds whereas the stability of the proposed protocol is 1902 rounds. Thus, the stability period of the proposed method is increased by 170.94% with respect to the existing method EE-LEACH [27] protocol. It is observed that the proposed method covers more rounds as compared to the existing method EE-LEACH [27] protocol. It is due to the improvement in the election of clustering parameters in heterogeneity, which shortens the communication distance. The distance and energy parameters directly cut the energy uses and improve the nodes' preservation. The node density is decreasing the communication cost during intracluster communication. Finally, it is observed that the proposed method effectively elects the cluster head and improves the stability period.

The number of alive nodes for the existing method EE-LEACH [27] and proposed protocols with respect to the number of rounds is shown in Figure 7. The first, half, and

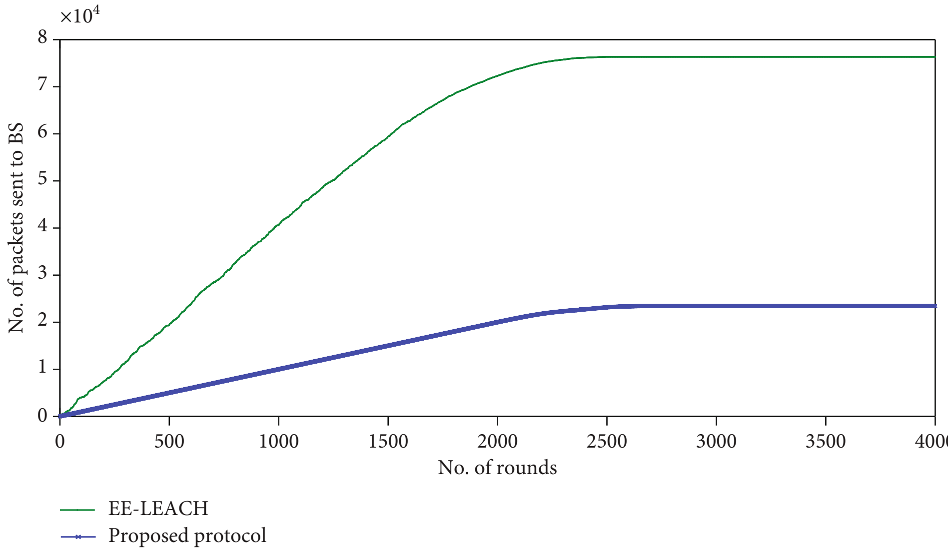

FIGURE 11: Packet sent to BS vs. rounds.

last node dead of the existing method EE-LEACH [27] and proposed protocol is in 712, 1667, and 2567 rounds and 1902, 2272, and 2677 rounds, respectively. The whole network runs more for the proposed method with respect to rounds than the existing methods. This gigantic improvement in the results indicates a reduction in the distance between the sink and cluster heads and the number of cluster heads. This improvement in prolonging the network lifetime is due to the decrease in the energy expenditure during the election of cluster heads and data communication from the sensor nodes to sink. Moreover, hotspot mitigation also helps in reducing energy consumption and achieving higher lifetime.

Figure 8 illustrates the number of dead nodes with respect to the rounds. The first node dead of the existing method EE-LEACH [27] and proposed protocol is in 712 rounds and 1902 rounds, respectively. The half node dead for EE-LEACH [27] method is 1667 rounds whereas 2272 rounds in case of proposed protocol. The improvement in the dead of the last node for the proposed method is 2517 rounds where as it is observed for the EE-LEACH [27] method is 2677 rounds. The performance of the proposed method is more as compared to the EE-LEACH [27] method in terms of the number of rounds. It is concluded from the analysis that the proposed method covers more rounds than the EE-LEACH [27] method. This improvement in prolonging the rounds is due to the reduction in the energy expenditure during the election of cluster heads and data communication from the sensor nodes to sink. It is also illustrated from Figure 8 that the proposed method covers more rounds at multiple stages of the dead nodes because of the reduction in the energy consumption using clustering parameters.

Figure 9 illustrates the total energy consumption with respect to the rounds. During the data transmission process, the reduction in the network energy starts. In the proposed method, the remaining energy is saved as compared to the existing method because of the reduction in the number of hop count for transferring the data from the sensor node to sink via cluster heads. Furthermore, node energy is preserved due to optimal selection of the cluster head nodes and reduction in the distance between cluster heads and sink. The proposed method covers more number of rounds as compared to the existing EE-LEACH [27] method. It can be evident from Figure 9 that the total remaining network energy is higher in the proposed method than in the existing EE-LEACH [27] method. Moreover, the communication within the cluster also helps in preserving the energy of the networks in an efficient manner.

Figure 10 displays the number of packets sent to the cluster heads with respect to the rounds. The cluster formation reduces the distance between the sensor nodes and their respective cluster heads, which helps in increasing the lifetime of sensor nodes. The total packet sent by the cluster heads is 1.91×10^5 and 2.07×10^5 per rounds. The improvement in the cluster heads election is done by the defined clustering parameters which reduce the data communication distance and optimizing the process of cluster head election. The proposed protocol preserves energy for future communication, and a lot of energy is saved by independent nodes as no unnecessary traffic is generated near the base station.

Figure 11 shows the number of packets sent to the base station with respect to the rounds for the proposed and existing networks. Reducing the cluster formation for the closer nodes to the sink and optimizing the communication distance factor increase the network's quality of service. The clustering parameters for cluster head selection promote lifespan expectancy and throughput. Communicating more data packets is only possible if nodes live for a longer time in the network. In case of proposed method, throughput is amplified inclusively with lifetime by transmitting 2.31×10^4 packets, whereas existing method transferred 7.70×10^4 packets to the sinks. Such an enhancement can be perceived due to the distance optimization between the sink and nodes and preserving energy for future communication. Also, a lot of energy is saved by independent nodes as no unnecessary traffic is generated near the base station. This energy appears back in the form of throughput. Moreover, this improvement is due to the longevity of the network in the proposed method which transmits a more number of packets to the sink as compared to the existing method.

6. Conclusion

This paper proposes a secure and stable humanoid healthcare information processing and supervisory method with an IoT-based sensor network. This method considers five parameters for electing the CH: residual energy, node density, average energy, number of neighbor's node, and distance between sensor and sink. The proposed method outperforms then the existing method EE-LEACH [27]. The first, half, and last node dead of the existing method EE-LEACH [27] and proposed protocol is in 712, 1667, and 2567 rounds and 1902, 2272, and 2677 rounds, respectively. It is also evident from the results the increment in the network lifetime is 167.13%, 36.29%, and 4.28% for the proposed model in case of first, half, and last node dead. There is improvement in the election of clustering parameters in the existence of the heterogeneity which shortens the communication distance. The distance and energy parameters are directly cutting the energy uses and improving the preservation for the nodes. The node density is decreasing the communication cost during intracluster communication. This improvement in prolonging the network lifetime is due to the reduction in the energy expenditure during election of cluster heads and data communication from the sensor nodes to sink. Moreover, the hotspot mitigation also helps in reducing the energy consumption and achieving higher lifetime. This work can be extended to incorporate the dynamic sensing range in the nodes and clusters, mobility in the sensor nodes, detecting the faults in the nodes, improving the node security, etc.

Data Availability

No hidden information in the paper.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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