A secure energy-efficient routing protocol for disease data transmission using IoMT

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ABSTRACT

The outlook of the World toward health infrastructure has drastically changed due to COVID-19 which created the need for the development of emerging technologies where interactions between the patients and the health workers can be minimized. Consequently, a secure and energy-efficient internet of medical things (IoMT) enabled wireless sensor network (WSN) is proposed for communicable infectious diseases that utilizes genetic algorithm. The proposed system makes use of movable sinks in IoT-enabled WSNs for healthcare called OptiGeA. The OptiGeA protocol is depicted for cluster heads (CHs) election by joining the factor of energy, density, distance, and heterogeneous node's capacity for fitness function. Additionally, a novel deployment technique and multiple mobile sink approaches are proposed to reduce transmission distance between sink and CH during system operation which mitigates hotspot issues. It is evident from the simulations that the OptiGeA protocol outflanks state-of-the-art protocols in terms of different performance measurements.

1. Introduction

In today's scenarios, robust healthcare infrastructure is an essential requirement for any country because of the evolution of various infectious and communicable diseases in the world. A strong healthcare system provides an optimal state of health for every human being in their home, workplace, etc. Additionally, healthcare infrastructure plays a significant role when any communicable infectious diseases like Ebola, MERS, SARS, COVID-19, etc., are evolved randomly. Most countries have limited doctors and healthcare infrastructures for managing such disasters. Thus, there is a dire need to incorporate emerging technologies in the existing healthcare infrastructures where patients can remotely connect to doctors. This can help the patient to get the treatment in the limited infrastructure and the limited number of doctors, which can be available for multiple human beings. Some additional infrastructures are required to implement such technology called the Internet of medical things (IoMT).

IoMT has dramatically impacted individual lives and the masses by connecting smart medical devices across the internet. The enhancement of IoMT infrastructure is possible by using a dense IoT-enabled wireless sensor network (WSN) structure [1]. The IoMT enables WSN is usually a spatially and geographically distributed network of battery-operated medical sensors such as airflow, oxygen, temperature, barcode sensing blood pressure, pulse oximetry, etc., placed at critical locations. Each sensor device is dedicated for
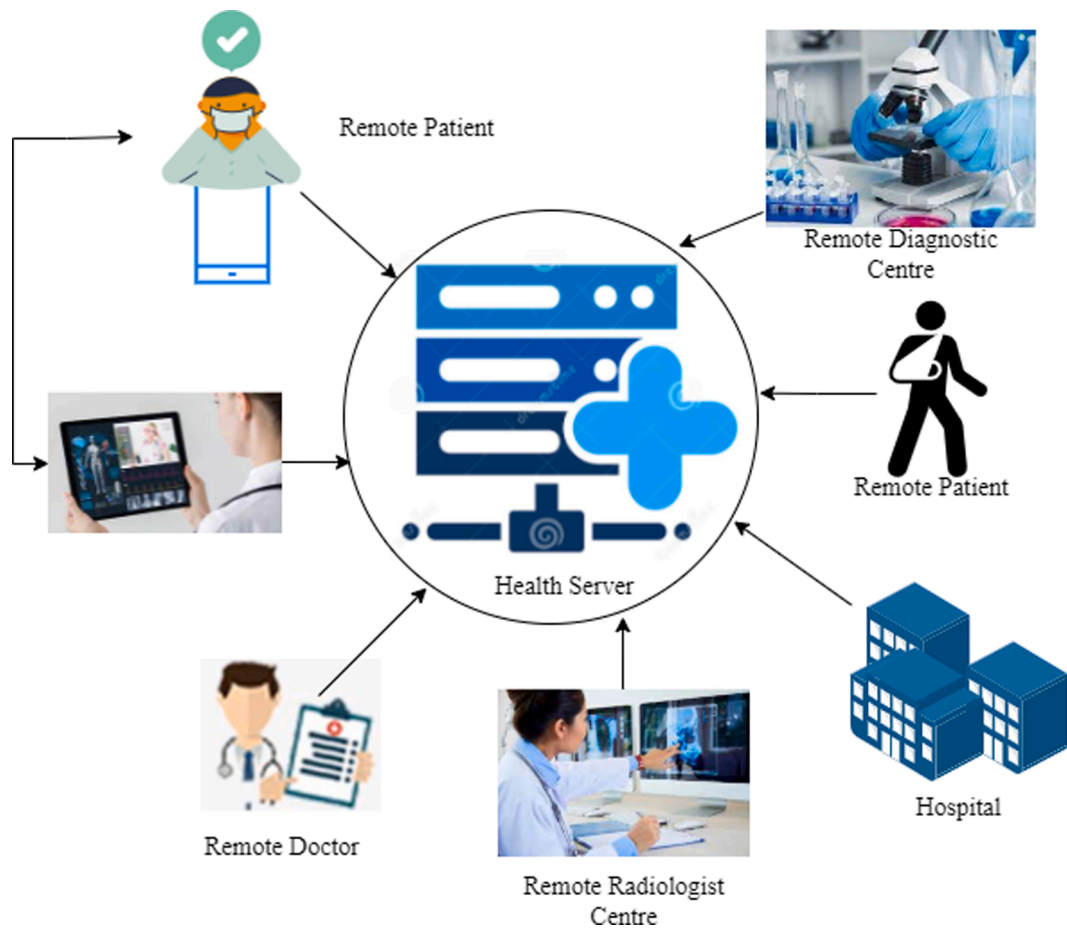

Fig.1. Remote IoMT enabled WSNs technology for communicable infectious diseases.

performing a specific task or a set of tasks. These devices (SNs) are equipped to monitor ambient changes such as airflow, oxygen, temperature, barcode sensing, blood pressure, pulse oximetry, ambient lighting, etc., which can be recorded and logged thoroughly. The required information is processed to a central location known as the sink.

The IoMT enabled WSN can be divided into various categories based on their operation methods and applications [2]. In Fig.1, a remote IoMT-enabled WSNs technology for communicable infectious diseases is shown where doctors and patients communicate with each other and get prescriptions during any treatment. This system also provides remote assistants and remote diagnostics for doctors and patients. This IoMT enabled WSN networks to also offer the ability to self-configure and re-configure themselves, enabling them to work unattended. This ability makes them greatly usable even in remote and hostile environments [3]. However, WSN systems have some limitations as follows. The most critical vulnerability of an IoMT-enabled WSN is the energy requirement of nodes. Each device node needs the energy to operate and the energy is usually present in the form of battery power. The energy is utilized in all the node activities, from data collection and monitoring to synchronizing and data transmission to the sink. As nodes operate on battery power, the SNs are limited by the battery's energy and are susceptible to energy depletion. It is impossible to replace the battery in a remote or hostile environment. Therefore, battery depletion can lead to SNs shutting down, ultimately leading to network-wide sensor failure. This failure can cause the entire IoMT-enabled WSN to shut down. It is observed that the duration of the lifetime of an IoT-enabled WSN is directly dependent on the rate of depletion of energy in SNs [3]. Therefore, to increase the lifetime of an IoMT-enabled WSN, energy depletion needs to be minimized and controlled. That is why much of the research work in an IoMT-enabled WSN focuses on energy efficiency and extending wireless sensor networks' lifetime.

Initial efforts to manage energy depletion were resolved by using the concept of clustering. Clustering is a method where multiple sensors are grouped into clusters and elect a single cluster head (CH) representative of each cluster. The clustering aims to delegate the data communication task to sink from each sensor to the cluster head. This clustering allows the rest of the nodes to save energy, while the cluster head utilizes its energy to communicate all the nodes' data in the cluster to the sink. One of the earliest clustering algorithms for IoT-enabled WSN is the low energy adaptive clustering hierarchy (LEACH) protocol [4]. A homogeneous IoT enabled WSN Network is a network in which each node is assumed to be similar in processing power and energy availability. However, perfect homogeneity in all the nodes across the cluster is not always possible in real-world situations. However, the clustering protocols need to consider the network's heterogeneity, particularly heterogeneity in terms of energy. The most crucial step in a clustering-based protocol is selecting

a cluster head. The cluster head is responsible for aggregating data, removing redundancy, and passing it on to the sink. One of the most energy-expensive operations is data transmission using wireless radio. It is to be noted that since the cluster head is doing the extra work of aggregation, processing, and receiving communications from all the nodes in the network, it is more susceptible to energy drainage as compared to other nodes. If a CH goes out of energy, the whole cluster and its functioning would be disturbed, which can decrease the network lifetime [4].

An optimized approach for selecting a CH is needed to handle the aforementioned issues, accounting for all these factors. Meta-heuristic approaches can be used to optimize CH selection. A CH selection is considered optimized if it minimizes energy consumption [4]. However, this is a non-deterministic polynomial-time hard problem that can be addressed using metaheuristic approaches and incorporating some critical features that can be used to generate and calculate a fitness function. Another very significant factor affecting energy usage during wireless transmission is the distance between communicating nodes [5].

Generally, the node transmission power decays as the distance of transmission increases. It means that as the distance increases, the power consumption for transmission is also increased. This factor can cause faster depletion in the nodes, especially those that are farther from the CH. Instead of using a long-distance single-hop transmission, multi-hop transmission can be used to tackle this issue. The node passes its signal to a close-by node, acting as a relay between the communicating nodes. However, this multi-hop transmission can gradually deplete relay nodes over the network's lifetime. This depletion can lead to a no connection zone called a hotspot. A hotspot in a WSN is an area where SNs are entirely exhausted. One approach to alleviate or diminish the hotspot problem is by incorporating mobile sinks to upgrade the distance factor of communication. These mobile sinks ensure that distance can be reduced and make it possible to prolong the network's lifetime.

GA-based strategies are reasonable for enormous IoT empowered WSN zones for information communication and plan energy productive clusters for information accumulation. In the first place, the protocol chooses CH arbitrarily from different types of sensor devices and afterward continuously moves to efficient solutions. Typically, a large portion of the Genetic calculation-based protocols do not exploit network heterogeneity. In some cases, a normal node is chosen as CH despite the cluster's other two types of nodes namely, intermediate and advanced. This is because of the heuristic nature of GA, as any mix of chromosomes can bring in the best fitness. If such a circumstance happens in the startup stage, it can affect the stability period frame; as a normal node won't have the option to hold the cluster for long [5]. In this manner, the proposed protocol considers energy and comparative abilities as a parameter (inclination/slant) for assessing and effectively determining the cluster head. Along these lines, the most impressive nodes are more likely to be chosen as cluster heads. For the network's lifespan, distance optimization is also taken into consideration.

The cluster head-to-sink communication separation is streamlined by introducing mobile sinks. The sink movement helps clusters to pick the nearest accessible sinks and transmit information to them, promoting the dissemination and balancing the request load onto sinks. Also, it is superfluous to shape clusters close to the base station prompting undesirable handing-off of data first to CH and afterward to the BS. The sensor node itself is sufficiently closed to communicate straightforwardly with the base station and send proper data packets to it. The direct information assortment by sinks lessens undesirable relaying of information and movement of information packets over a more extended distance to arrive at the base station and subsequently, altogether improve the sensor network lifetime. To address the above concerns, the foremost contribution of the paper is given as follows:

- This paper proposes an energy-efficient internet of medical things (IoMT) enabled WSNs for communicable infectious diseases using a genetic algorithm. This method considers the IoMT network and performs clustering by merging energy parameters, the density of nodes, distance, and heterogeneous node's capacity for patient data collection and also provide doctors suggestions for further assistance. GA being a heuristic strategy facilitates the psychological heap of settling on a multi-target choice by planning a solitary fitness function dependent on carefully choosen fitness parameters.
- For efficiently situating heterogeneous SNs an organization system has been proposed. Nodes are conveyed in the network as per a reasonable consistent structure. The sole point of strategic arrangement is to conserve and monitor energy during network activity. The network deployment strategy likewise deals with high-energy nodes' firmly bound organization.
- Both static and portable sinks are deployed in different use-cases of OptiGeA protocol outside and inside the system region to reduce the hot-spot issue. The single sink format is likewise proposed following the same parameters for CH determination as portrayed for multi-sinks.
- This work proposes a secure data collection and transmission method, which transforms the signal data using embedding algorithms before transmission.
- Sometimes, it is insignificant to form clusters close to the base station. This prompts undesirable transferring of information to CH first. Afterward to the BS, though, the node is sufficiently close to communicate straightforwardly with the base station and send suitable packets to it. The direct information assortment by sinks lessens the undesirable accumulation of information and movement of data packets over a wider distance to arrive at the base station and consequently, improves the lifetime of the sensors.

This research paper is presented as follows: Section 2 describes the literature on the recent techniques. Section 3 and 4 deliberate the system model and the proposed method, respectively. The simulation results are discussed in Section 5. The paper is concluded in Section 6, finally.

2. Literature review

The continuing improvements in IoT-enabled WSNs are concentrated on routing protocols, which have to handle the energy constraints. Several innovations in the field have been proposed. Clustering-based solutions are the best for load balancing and energy

management among SNs [5]. Clustering protocols for homogeneous WSNs have been the focus of a lot of research. Basically, the SNs should have similar levels of energy, transmission, and processing. However, because of the continual changes in the environment, homogeneity is not always the best choice, particularly in applications that operate in hazardous environments, such as fire detection in forest areas. Having a few more nodes with extra power is helpful in such applications to extend the network's lifespan. Similarly, various clustering-oriented approaches for enhancing network efficiency, lifetime, and stability have been proposed by several academics [4–25]. The most important objective in these types of protocols is to choose the cluster head (CH) with precision. As a result, the issue of energy drainage is transformed into the issue of CH selection. Moreover, if we consider homogeneous WSNs, each sensor node consists of equivalent energy and device capabilities, hence each node is treated equally for CH. As a result, the rotation of the CH is employed to balance the load in such networks. But heterogeneous sensor networks consist of a few nodes with stronger energy capacity than the others, and they are chosen as CHs because of their greater energy capacity. The remaining nodes function as standard SNs, which are used to collect the data from their surroundings.

Clusters-oriented functionality was incorporated into the SEP protocol [4]. This protocol's setup phase and steady-state phase are the two main parts of CH selection with precision. Based on random number generation, the nodes determine whether or not to become CH during the setup phase. Every node transmits the revealed information to its nearby CH during the steady-state phase. The collected information at CH is compiled and efficiently transferred to the sink node. One key downside of SEP is that it relies on a probabilistic approach to picking the CH, which may not necessarily result in flawless outcomes in all cases. Therefore, to achieve more precise non-homogeneous networks for the CH selection process. Qing et al. [5] proposed a novel approach for multi-tier heterogeneity i.e distributed energy-efficient clustering (DEEC) method in which CH selection is emphasized for nodes with high initial and remaining energies [10]. It is more common for high-energy nodes in DEEC to become CH, even if they have a relatively modest amount of energy when transmitting data. Higher energy nodes are penalized.

Elbhiri et al. [6] discussed developed-DEEC (DDEEC) another heterogeneous protocol, to normalize the DEEC problem by implementing an energy threshold for CH nodes. DEEC [5] and DDEEC [6], always operate at high energy levels, however, because they use single-hop communication for the data transmission process, due to this issue these protocols outperform in large area networks. The protocols stated above do not take into account the distance between transmitting nodes, resulting in significant energy usage. Kumar et al. [7] presented the EEHC scheme, which is an energy-efficient heterogeneous clustering scheme. The sensor node energy is not taken into account by EEHC in the CH selection approach but during the placement of nodes in networks, 3-levels of heterogeneity are considered. Enhanced DEEC (EDDEEC) [8], which uses another protocol for this purpose followed by the same approach as DDEEC [6]. In terms of energy heterogeneity, Qureshi et al. proposed another procedure termed BEENISH [9], which has four levels of heterogeneity. It also made use of more energy-efficient CH selection processes.

All of the protocols covered thus far aim to lengthen network lifetime by establishing and maintaining a long period of stability. P-SEP was proposed by Paola et al. [10], which uses a random selection technique for CH selection rather than giving higher energy nodes a greater priority. The above-mentioned clustering methods are intended for proactive applications. The protocols DRESEP [11], SEECP [12], and TEDRP [13] are introduced to control reactive applications such as dense forest activity detection and earthquake detection. However, due to the development of inactive zones in the network, the above-mentioned clustering protocols are vulnerable to hotspot problems. Even though the above-mentioned clustering algorithms take into account a variety of CH election parameters, the current performance is not up to date. As a result, establishing a metaheuristic method that considers all essential parameters to efficiently increase the CH selection process while also improving the network's performance is key to the domain's advancement.

A population-based optimization method is a genetic algorithm (GA). It converges on the population's fittest members, i.e., the fitness function helps to provide the best solution. Bari et al. [14] present GA-based approaches for large and dense area IoT-enabled WSNs that leverage single-hop transmission and identify the most energy-efficient clusters for sensing data collection. Because inter-cluster communication is limited, it chooses the CHs at random. They also compared and examined the suggested GA-based routing performance at various path loss component values. Another strategy for obtaining optimum states is presented by Norouzi et al. [15]. However, because of the single-hop communication method, it had an excellent transmission distance. Bhaskar [16] and Bayrakl et al. [17] offer a few alternative GA-based protocols, such as GABEEC and GDSDA for network lifetime and security, respectively. However, both of these protocols are not scalable and thus ineffective for large-area WSNs. Kumar et al. [18] suggested a GDFEC clustering protocol for heterogeneous WSNs based on GA and fuzzy inference systems. However, because this method ignores the distance parameter while picking CHs, it is ineffective if the distance between communicating nodes is significant.

Dehghani et al. [19] used GA to present an improved energy-oriented cluster-based routing protocol. However, it has some issues like a hotspot, complicated topology, and higher overhead. For dynamic deployment of SNs, Ragavan et al. [20] used GA-based methods and Tabu search to discover the best path. It can withstand hotspot issues and network instability, making it very appealing. A GA-based dynamic clustering strategy for increasing WSN lifetime is discussed by Yuan et al. [21]. For selecting the smaller number of CHs, this method considers the number of nodes in the area, remaining energy, estimated energy expenditure, and distance to the BS. In a heterogeneous WSN, Verma et al. propose an optimized process of CH selection using a genetic algorithm for single and multiple data sinks [22]. These methods use three parameters: remaining energy, node-to-sink distance, and node density. These three parameters are used to calculate the fitness function. This approach is handy in a variety of contexts since it can handle many data sinks.

Other researchers have also discussed various data collection techniques using IoT-based WSNs [23–25]. Singh et al. discuss secure and efficient GA-based data communication methods for IoT-based WSN [23]. However, this paper only considers signal security and does not consider the authentication process. Nandan et al. discuss an optimized GA for CH election based on adjustable sensing ranges and movable sinks for IoT-based WSNs. However, authentication in the connection of nodes and sinks has not been considered. The papers [24, 25] discuss an efficient data collection method for IoT-based WSN to apply disaster management. These methods use the
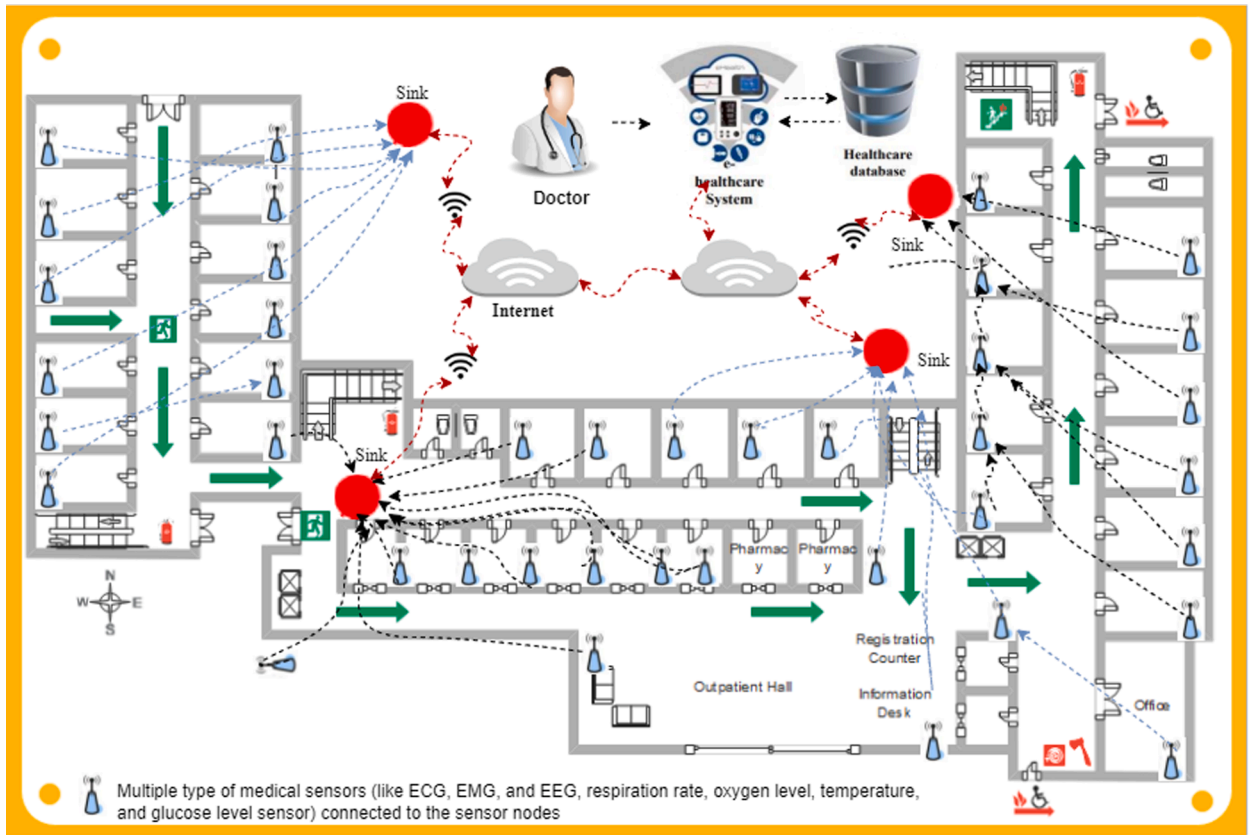
Fig. 2. A remote IoMT enabled WSNs based information processing system for doctors in hospital.

Table I
The energies dissemination of for 3-TiHet, 2-TiHet, and 1-TiHet nodes.

Degree of heterogeneity	SNs type	No. of nodes	The initial energy of SNs	The total energy of SNs
Dgr-3-Het	Advanced	$n*q$	$E_i*(1+\rho)$	$E_i*(1+\rho)*q*n$
	Intermediate	$n*q_o$	$E_i*(1+\tau)$	$E_i*(1+\tau)*q_o*n$
	Normal	$n*(1-q-q_o)$	E_i	$E_i*(1-q-q_o)*n$

Total network energy for Dgr-3-Het: $Energy_{adv} + Energy_{int} + Energy_{nrm} = E_i*(1+\rho)*q*n + E_i*(1+\tau)*q_o*n + E_i*(1-q-q_o)*n = E_i*n*(1+\tau*q_o+q*\rho)$.

GA process for electing the CH. However, most of the parameters are related to optimizing the energy only.

3. System model

A secure and sustainable IoMT-enabled WSNs-based information processing protocol in the healthcare scenario is discussed in Fig. 2. In this scenario, multiple types of sensors (like ECG, EMG, EEG, respiration rate, oxygen level, temperature, glucose level sensor, etc.,) are connected to the SNs. Here, doctors with their assistants and the patient are connected with the healthcare system and they can make possible communication whenever it is needed. The proposed situation for the sensor network is set for the heterogeneous condition with a predefined measure of energy stock. In this work, a 3° heterogeneity (dgr-3-Het network) is considered with all systems comprising of *n* number of positioned SNs. These SNs are deployed in the patient wards of the hospital along with the outpatient department areas of the hospital. The sensors continuously monitor the patients and send that information to the sinks nodes with the help of SNs. Here, multiple sink nodes are considered for collecting the data efficiently from the various deployed SNs. Furthermore, these sinks forward the collected data to the controlling server of the healthcare system. This healthcare system is also connected to healthcare databases. After getting the information from the healthcare system, doctors can analyze the collected information and then suggest prescriptions on the available information.

In this scenario, the energy of the SNs where various types of sensors are deployed and optimized using GA algorithm. Additionally, a secure data transmission signal is forwarded by applying compression and encryption at the SNs. As the slant of heterogeneity increases new SNs with higher energy are added to the network. The dgr-3-Het network comprises a wide range of characterized nodes
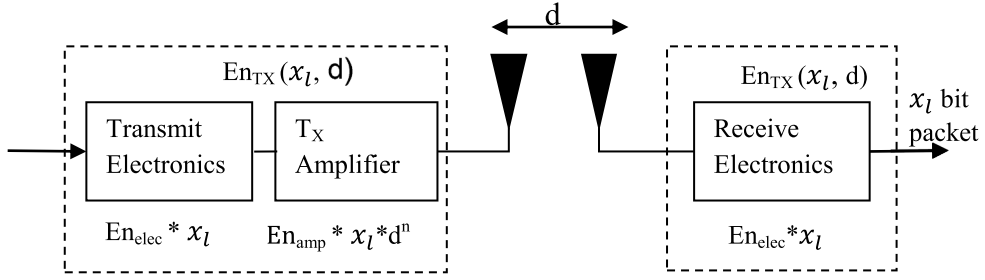
Fig. 3. Radio energy dissipation model.

for example normal, intermediate, and advanced SNs as communicated in Table I. *Energy$_{nrm}$, Energy$_{int}$,* and *Energy$_{adv}$* establish the energy of normal, intermediate, and advanced SNs in the system. The energy thought fulfills the disparity *Energy$_{nrm}$ < Energy$_{int}$ < Energy$_{adv}$*. Advanced nodes have more introductory energy than intermediate nodes which further have higher beginning energy than normal nodes. The total number of normal, advanced, and intermediate nodes are spoken to by N_{nrm}, N_{adv}, and N_{adv} individually and calculated using Eqs. (1)–(3). The extent of normal nodes in the system is most noteworthy with advanced nodes having the least proportion. The number of nodes fulfills the accompanying disparity $N_{nrm} > N_{int} > N_{adv}$. E_i characterizes the underlying initial energy of the sensor hubs. E_t defines the all-out energy of the system. More energy proficient nodes of intermediate & normal assume a noteworthy job of aggregating information from other cluster nodes using GA calculation. The underlying energy, total energy, and node appropriation for all the degrees are exhibited in Table I.

Dgr-3-Het: In degree 3 heterogeneity, three distinct types of SNs i.e. normal, intermediate and advanced are deployed in the network field. The fraction of energy for the middle and advanced SNs is τ and ρ times higher energy than normal nodes. τ and ρ portray the energy proportion of intermediate and advanced nodes respectively. The q and q_o depict the extent of advanced and middle nodes, as expressed in Table I.

$$n_{advanced} = n * q \tag{1}$$

$$n_{intermediate} = n * q_o \tag{2}$$

$$n_{normal} = n * (1 - q - q_o) \tag{3}$$

The energies of the *Energy$_{adv}$, Energy$_{int}$,* and *Energy$_{nrm}$* are as $E_i*(1 + \rho)*N_{adv}$, $E_{init}*(1 + \tau)*N_{int}$, and E_i*N_{nrm}. The total energy of the Dgr-3-Het is $E_t = Energy_{adv} + Energy_{int} + Energy_{nrm}$ where $E_t = E_i*n*(1 + \tau*q_o + q*\rho)$.

In the proposed system, a radio energy model [6] comprises digital signal processing (DSP) frameworks, a radio receiver, and analog to digital converters, as appeared in Fig. 3. The radio receiver devours the highest energy in information transmission. In this way, the foremost objective is to diminish the consumption of energy when information is transmitted from the different stages over different distances.

The consumption of the energy for the SNs to transfer a data packet at a distance d of x_l bits is given in Eq. (4) by $En_{Tx}(x_l,d)$ as below:

$$En_{Tx}(x_l, \ d) = \begin{cases} x_l * \left(En_{ele} + \ En_{efs} * \ d^2 \right) \ if \ d \ \leq \ d_o \\ x_l * \left(En_{ele} + \ En_{amp} * \ d^4 \right) \ if \ d \ > \ d_o \end{cases} \tag{4}$$

where d, En_{ele}, En_{efs}, and En_{amp} are denotes the distance between sending and receiving nodes, energy Eq. (5)consumption by the transmitter, energy consumption by the transmitter in the case of free space, energy consumption by the multipath space, respectively. d_o signifies threshold distance where it is computed in Eq. (5) as follows:

$$d_0 = \sqrt{\frac{En_{efs}}{En_{amp}}} \tag{5}$$

For receiving the data from any other SNs the consumption of energy is given in Eq. (6) by $En_{rec}(x_l)$ as below:

$$En_{rec}(x_l) = \ x_l * \ En_{ele} \tag{6}$$

The CH consumes energy in data aggregation as given in Eq. (7) by $En_{agg}(x_l)$ as below:

$$En_{agg}(x_l) = t * x_l * \ En_{da} \tag{7}$$

where En_{da} is the energy required in data aggregate with t be the number of packets.

4. Proposed work

The proposed work is discussed in the various sections like SNs deployment strategy, movable sink concept, data collection process,
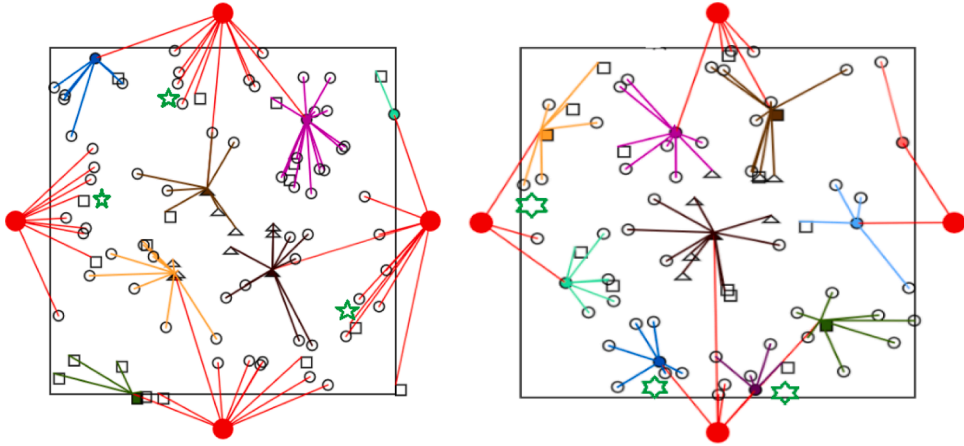
Fig. 4. Instances of data collection by sinks from the nearby SNs and cluster heads directly.

clustering parameters with the complete proposed algorithm, and security strategy which are given as follows:

4.1. SNs Deployment strategy

The three sorts of nodes are circulated at various areas in the event of Dgr-3-Het of heterogeneity in a discretionary manner. The roundabout segment, for the most part, comprises energy bountiful nodes, for example, the higher energy nodes called advanced nodes, whereas other sorts of nodes are put outside the round section. This guarantees a relationship among normal and intermediate nodes and maintains a strategic distance from the excess firmly bound arrangement of intermediate nodes. The advanced nodes ($D\_N_{advanced}$) density is defined as follows for SNs deployment strategy:

$$D\_N_{advanced} = \frac{Number\ of\ advanced\ nodes}{Circular\ subsection\ area}$$

The intermediate nodes ($D\_N_{intermediate}$) density as per the SNs deployment strategy is given as below:

$$D\_N_{intermediate} = \frac{Number\ of\ intermediate\ nodes}{Sensor\ field\ area - Circular\ subsection\ area}$$

The normal nodes (D_N_{normal}) density as per the SNs deployment strategy is given as below:

$$D\_N_{normal} = \frac{Number\ of\ normal\ nodes}{Sensor\ field\ area - Circular\ subsection\ area}$$

4.2. Movable multiple sink strategies

There are four base stations which are deployed in outdoor network zone at a pointed separation of 90^0 particulars to contiguous base stations for multi sink situations as shown in Fig. 3. In a single static base station condition, the area the of sink is fixed in arranged locale, though multiple base stations situation deploys base stations in various regions of interest for compelling data assortment. The developed movement strategy is plotted circularly since the arbitrary movement of sinks won't be reasonable for data gathering as in most cynical situations, it might place sinks in a scanty zone very away from thick SNs regions.

In the depicted effort, direction movement is predefined and gets consistently refreshed with no topological knowledge of the position of SNs. It is accepted that deployed SNs recognize the area coordinates of moving base stations by utilizing some service. The base stations move outdoor the scheme terrain in roundabout style, making a virtual circle whose inside is situated at a point ($cent_x$, $cent_y$) of the system. The radius *rad* of this simulated sphere is also kept sufficient to retain base stations neither nearby nor excessively far away from the network area. Throughout the installation period of system boundaries and variables, base stations create their coordinates and arrange their trajectory direction according to the accompanying condition:

$$p\_x = rad * \cos(\sigma) + \ cent_x$$

$$p\_y = rad * \sin(\sigma) + \ cent_y$$

Where σ ranges from $0 \leq \sigma \leq \pi/2$, $0 \leq \sigma \leq \pi$, and $0 \leq \sigma \leq 2\pi$ for single quadrant pivot, 180^0 (2 quadrants) turn and complete round revolution, respectively. The points $cent_x$ *and* $cent_y$ put the hover at the mid-point of the system area. The above conditions make a series of roundabout positions by progressively changing σ values.

4.3. Data collection by the base station from the nearby SNs and CHs directly

Sometimes, it is completely irrelevant to form clusters nearby the base station (BS) in the clustering scenarios. It leads to unwanted conveying of data between the nodes to CH and then to the BS, whereas the node itself is closed enough to directly communicate with the BS, which can transmit data packets directly to the BS. The direct data collection (DDC) by base stations decreases unwanted data aggregation and reduces data packet movement over a lengthier distance to reach the base station. So, the clustering process decides on construction CHs and carefully considers that no CH is formulated in regions nearer to the base station to promote the DDC concept.

The nodes near BS up to a predefined range are eligible for direct data collection. From the other nodes, only sparsely located nodes in some regions can directly send data to the nearest BS, as shown in Fig. 4. There are green color five-pointed stars where the star symbol in Fig. 4 indicates that nodes in the constituency can be cluster nodes with an assigned CH, but are independent sensors elected for DDC. The number of active nodes depletes their energy during the network operations and a time could come when a suitable, efficient solution would be to make a cluster near the BS. At the time, the algorithm considers that route and makes clusters near the base station shown with a six-pointed star in Fig. 4. The nodes are close enough to BS to be regarded as independent nodes but are still chosen as cluster heads or common nodes as this points to a much more efficient solution. Hence, this concept of direct data collection reduces unwanted packet movement to a great extent.

4.4. Optimized genetic algorithm for CH selection (OptiGeA)

4.4.1. Fitness parameters
There are four distinctive fitness evaluation parameters are analyzed for CH political race:

a) **Node's energy factor**

The CH dissipates its network energy at a different rate as various sensors communicate information to it for additional handling. It carefully allows the re-organizing procedure of network construction progressively alive SNs hold the clusters, along these lines, adding to the life span of network activity. The energy parameter is given in Eq. (8) as follows:

$$P_1 = \sum_{t=1}^{n} \frac{Energy_{Res}(t)}{Energy_{Max}(t)} \tag{8}$$

where $Energy_{Res}$ represents outstanding the energy of t'th node and $Energy_{Max}$ presents the initial most extreme energy of the node when the system began its activity. The estimation of j fluctuates from 1 to n thinking about all the active nodes for interest. In heterogeneous conditions, the estimation of $Energy_{Max}$ differs for nodes according to their characterized capacities. The parameter is the whole portion of remaining energy to their greatest introductory energies. A higher estimation of P_1 adds to superior fitness esteem.

a) **Node-sink distance**

The distance between the sending and receiving node is considered higher than it considers the energy consumption in the network. The information transmission over distance is the most energy-devouring part therefore, the plotting factor of distance is significant for design the fitness function. It guarantees that the cluster head has least correspondence distance with its nearest accessible sink, subsequently, promising energy preservation. The transmission distance improvement fitness parameter is expressed as follows:

$$Dist_{AVG(n-S)} = \frac{\sum_{k=1}^{N} Dist_{(n-S)}(k)}{n} \tag{9}$$

$$P_2 = \sum_{t=1}^{N} \left(\frac{Dist_{(n-S)}(t)}{Dist_{F(n-S)}} + \frac{1}{Dist_{AVG(n-S)}} \right) \tag{10}$$

Transmission distance factor P_2 is a collection of distance cost actuated by separation for t'th hub where t varieties from 1 to add up to n. In Eq. (10), Euclidean separation among t'th node and the nearest base station is presented by $Dist_{(n-S)}$ though the parting among the farthest node and base station is represented by $Dist_{(n-S)}$. $Dist_{AVG(n-S)}$ focuses on the average separation distance of all the active nodes from their individual nearest sinks and is calculated as given in Eq. (9). The average distance factor $Dist_{AVG(n-S)}$ is comprised to coordinate the choice of CH closer to the base station and advancing cluster head election inside a distance scope of $Dist_{AVG(n-S)}$. It is very evident that the more the assessment of P_2 more it favors the choice of a CH which builds up the least communication parting distance between CH and its relating base station.

a) **Node density**

The higher node density helps the CH protect and possess the remaining energy supply of cluster nodes that otherwise would be gulped broadly. In this way, a trademark node is chosen as CH that is encircled by the huge number of firmly related SNs in contrast with other nodes in the same cluster. This fitness parameter identified with the density of the clusters is depicted as follows:

$$P_3 = \left(\frac{\sum_{t=1}^{n_C} Dist_{(n-NN)}(t)}{n_C} * \frac{1}{Dist_{(n-FN)}(t)} \right) \qquad (11)$$

In Eq. (11) t runs from 1 to n_C i.e. number of nodes in the defined cluster. $Dist_{(n-NN)}(t)$ and $Dist_{(n-FN)}(t)$ process the distance among t'th SN and neighboring nodes and the Euclidean among i'th SN and farthest SN inside the same cluster. The parameter is figuring the actual separation distance between neighboring nodes inside a cluster. This distance ought to be as little as conceivable promoting CH determination of a node, which in any event is good for neighboring nodes. At least, $Dist_{(n-FN)}(t)$ought to be expected under the circumstances. The denominator $Dist_{(n-FN)}(t)$ ought to be as little as conceivable to amplify the P_3 factor preferring the negligible distance of intra-cluster communication to safeguard energy utilization.

a) **Comparative slant**

Regardless of the nearness of an advanced or intermediate node in the cluster, here and there, occasionally a normal node is chosen as CH. This can be legitimately identified with the way that any combination of chromosomes can prompt a superior fitness value. On the off chance that such a condition happens in the starting stage, it legitimately influences the stability period frame as an ordinary node cannot hold common nodes for long. Consequently, an unequivocal comparative slant similar to a drift factor is added to stay away from this risk by preferring the choice of extraordinary energy and proficient nodes to lower energy CH. The comparative slant does not change the individual capacity decision of the SNs and it is only measured at the time of initialization. The value of P_4 is deciphered as given in Eq. (12) as follows:

$$P_4 = \begin{cases} 1 - \dfrac{N_{adv}}{n} \text{ for advanced node} \\[2mm] 1 - \dfrac{N_{int}}{n} \text{ for intermediate node} \\[2mm] 1 - \dfrac{N_{nrm}}{n} \text{ for normal node} \end{cases} \qquad (12)$$

P_4 helps the determination of top energy SNs for group heads as the factor is relatively identified with the energy measure supplied in sensors toward the early phase. The parameter is less positive for normal nodes as their extent in sensor populace is high and is higher for advanced nodes because they are least in extent. In like manner, the intermediate energy SNs get more significance than normal energy SNs during the CH choice procedure.

With the mentioned fitness boundaries, fitness capacity can be concocted by absorbing the parameters of fitness with some weightage factors into a solitary articulation. This fitness work grasps command on the structure as a solitary amount of legitimacy as in what way the given cluster organization closed is to accomplish the predefined aim. The system execution metric is given by Eq. (13) to the extent that GA fitness functions for the proposed method:

$$F = \frac{1}{\alpha * P_1 + \beta * P_2 + \gamma * P_3 + P_4} \qquad (13)$$

where α, β, and γ are loads of the fitness parameters remaining energy, distance streamlining, and density of node, individually. P_4 has not related any weight coefficient because it added inclination to stay away from vitality thriving traps. To guarantee the equivalent commitment of individual factors where the weights are assigned to the coefficients equally. Any fitness parameter, state P_2 can be featured by expanding its relating weight coefficient esteem somewhat higher than other coefficient esteems, making it applicable according to the necessity of various zone networks. All the coefficient esteems summarize unity according to the accompanying condition given in Eq. (14).

$$\alpha + \beta + \gamma = 1 \qquad (14)$$

The proposed algorithm is coordinated to minimize fitness value F over the developmental procedure of network chromosomes focusing on ideal system execution for looking through conceivably effective cluster structure arrangement.

4.4.2. Cluster formation process of the proposed technique

GA technique utilizes hereditary tasks to develop network structure for ideal cluster development. The CH data can be held by the chromosomes of the network and these chromosomes do not give any improvement in the network structure by incorporating direct duplicating. The development of ideal clusters for valuable transformative certain genetic operations (crossover and mutation) is essential. Moreover, the paramount cluster arrangement till now is preserved by duplicating it straightforwardly to up and approaching group of the populace called as elitism approach for saving finest competitor candidate solution until now and the chromosome stays qualified to take part in the process of selection for the emergence of coming generations.

a) **Genotype & phenotype encoding information:**

The arrangement of the network information stored by chromosome is known as genotype. It is genuine computerized data/hereditary enigma relating to which an SN is trapped as a common node or CH. According to the proposed development framework, all chromosome signifies that "which SNs are CHs" and "which SNs are common nodes". Genotype encoding for a chromosome is depicted
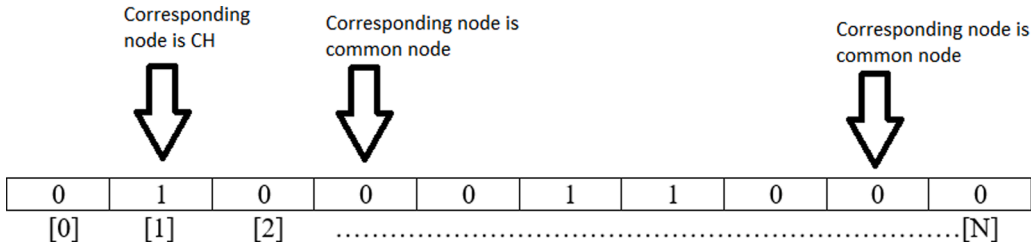
Fig. 5. Genotype encoding for a chromosome.

in Fig. 5. An array is constructed for an equal number of nodes deployed in the networks that contain the value either 0 or 1. In this array, 0 indicates that the corresponding node is related to the common node whereas 1 is indicating the corresponding node belongs two the CH. In the proposed system, the structure of the genotype characterizes the granular degree whereas the phenotype conforming to the genotype is visually described as a chromosome. Thus, the representation of genotype information is called the phenotype. Here, the digital data are placed into integer variables and indicated by the shades. When the digital information is 1 means it is a CH indication then a hub loaded up with color is formed and 0 indicates the worth makes an unfilled node.

a) **Crossover**

It is a genomic process activity to associate two chromosomes with creating another offspring. It works on two-parent components and is binary. This guarantees genotype data of the cluster structures is conveyed for coming generations. In the 1-point crossover, a censored point is chosen that as a rule is the chromosome's gene mid-point. The offspring stream of bits contains semi-digital information from the first and semi from the second parent. Also, it is very conceivable that produced offspring from crossover activity may comprehend at least two CH's within the vicinity of each other. Such offspring are dismissed as they fail the approval criteria. Then, the crossover probability is calculated as the crossover ought to occur or passes to the cohort's parent chromosome. C_x^{Pop} and C_y^{Pop} denote the chromosomes of the parent used in the crossover operation to define that all the genotypes are always equal in length.

1 The procedure starts by picking an arbitrary cut-point for crossover operation over C_x^{Pop} and C_y^{Pop}. Let CP_X be that variable
2 *Set $CP_X = random(0, len(C_x^{Pop}))$*
3 let *child$_{Chromosome}$ = Array(len(C_x^{Pop}))*
4 Combine digital data of i'th and j'th parent chromosomes.

Repeat for set K = 0 to len(C_x^{Pop})
If SNPopulation(k) is not dead
If K < CPX:
childChromosome[k] = C_x^{Pop} (k)
Else childChromosome[k] = C_y^{Pop} (k)
Else childChromosome[k] = *0*

1 **If** *Valid(child$_{Chromosome}$):*

Return *child$_{Chromosome}$*

1 **ELSE Return** null

a) **Mutation**

Likewise, as indicated by the principle of variety, the evolving procedure ought not to stall at the local solution; it should continue scanning elective cluster structures for the network. It needs to be satisfied by a transformation process that introduces assorted diversity. A mutation pace of 2% suggests that it is a 2% chance to change a digital value. In our use-case, transformation activity flips the bit either from 0 to 1 or 1 to 0 for example shifting as a common node to CH and the other way around. In the wake of changing a common node to CH, it is conceivable, that this new CH was added in the region of previously current CH. In this way, unacceptable chromosome are dismissed. This function obtains kth chromosome C_k^{Pop} and effective function authorizations for validation progression.

1 For each chromosome gene value J in chromosome C_k^{Pop}, where

$J = 1,2,3....len(C_k^{Pop})$ **Repeat**

1 **If** *random(1)* $\leq M^{Rate}$:
2 C_k^{Pop} $(J) = !\ C_k^{Pop}$ (J)
3 **If not** *Valid(C_k^{Pop})* **then** CH takes place in the range of another CH
4 **Discard mutation**

4.3. The Working Process of the Proposed Technique: In this section, the proposed work process is described in detail

Mating Pool algorithm:

1 CPop = chromosome population for creating selection pool and initialize sum = 0.
2 sum = $\sum_{k=1}^{len(C^{Pop})} C_k^{Pop}.fitness$
3 Let PDF = [] be probability distribution array.
4 For x = 1 to len(CPop) add the probability of the fitness value of a separate chromosome to the PDF array i.e.
5 PDF.push((CxPop.fitness / sum) * 100)
6 Let selection_set = [] be the empty choice pool array storing chromosome.
7 For y= 1 to len(CPop) repeat
8 m = ceil(PDF[y] * CyPop.fitness)
9 for j = 1 to m do
10 sel*ection_set.push(y)*

Proposed Technique:

1 Initialize N = number of SNs, size = chromosomes population size, CRate = Crossover rate, MRate = Mutation rate, α-β-γ = fitness coefficients and generationCount keep track of current generation.
2 Let SNPopulation = {X = 1,2,3.........N} be sensor nodes array.
3 Let CPop = current chromosome population array (genotype population). Every chromosome is checked for its legitimacy and afterward pushed to CPop.
4 For y = 1 to size do
5 CtPop ← generate_chromosome(N)
6 Let sinks = array holding sinks for the network.
7 For each chromosome t, calculate the fitness of the tth chromosome
8 For y = 1 to len(CPop) do
9 CyPop.fitness = Fitness(CyPop) using following equation-

$$F(k) = \frac{1}{\alpha * \text{P1} + \beta * \text{P2} + \gamma * \text{P3} + \text{P4}}$$

10 **While** *termination criteria not met* **do**

Increment generationCount
Comparing chromosomes of current generation-
fitchrom = for each Fitness(CiPop) > Fitness(CjPop) where i is not equal to j and $1 \leq i, j \leq$ size
Normalize chromosome population's fitness values fit_value = fitchrom.fitness
For j = 1 to len(CPop)
CjPop.fitness = CjPop.fitness / fit_value
selection_pool ← mating_pool_procedure(CPop).
Initialize offspringPop = [] holding child population and set offset ← 1.
IF elitism is true then
offspringPop.push(fitchrom)
Create a child population by incorporating genetic operations over the current generation of population.
While len(offspringPop) < size repeat steps b & c
If random(1) < CRate then:

- PFirst = CPop[selection_pool[random(0, len(selection_pool))]]

- PSecond = CPop[selection_pool[random(0, len(selection_pool))]]
- childch = Crossover(PFirst, PSecond)
- childch =Mutation(childch)
- offspringPop.push(childch)

   Else parent directly added to next generation

- offspringPop.push(CPop[offset])
- offset = offset + 1

   C^Pop = offspringPop
   Evaluate fitness of the newly generated population
   For n = 1 to len(CPop) do
   $Cn^{Pop}.fitness = Fitness(C_n^{Pop})$

1 **endWhile**

Genetic algorithm boundaries are set; the size of the populace, number of SNs in the network, rate of crossover C^{Rate}, rate of mutation M^{Rate}, and generation tally. Furthermore, the weight quantities for the boundaries of fitness α, β, and γ are specified explicit measures. The SNs are either positioned arbitrarily or dependent on an organization's methodology. The chromosome genes are formed randomly and created after validation procedure and fixed to chromosome populace C^{Pop} array. The fitness function is computed by calculating fitness parameters P_1, P_2, P_3, and P_4, evaluating network performance. Develop the current population of chromosomes to make offspring populace utilizing genetic approach. Chromosomes are placed into a rank depending on their fitness esteems and the high fit nodes have increasingly coincidental for a determination as a parent during evolution. Hold the fittest network structure through elitism technique to abstain from losing the best competitor solution up until this point and continue adding child chromosomes to *offspring^{Pop}* array. The 1-point crossover is pragmatic to interchange genotype for chromosomes new generation i.e. (r`x, r`y) by a merging chromosome of the parent with stable crossover rate (C^{Rate}) i.e., Crossover(rx, ry|C^{Rate}) => r`x, r`y. The off-springs crossover operation (r`x, r`y) that are generated newly added to the population diversity for choosing a new cluster structure which applied over mutation operator with mutation rate M^{Rate} i.e., Mutation(rx|M^{Rate}) = `rx, Mutation(ry|$M_{rate}$) = `ry

The proposed protocol works in two distinct stages: setup and steady stage. In the setup phase, the statement of the network development and CH determination technique is examined. The network arrangement parameters and system factors are organized in the formulation. The algorithm begins with the deployment of nodes. If mobile sinks occur, the direction of movement of the sink is chosen, and all the coordinates are fixed for base station movement. For OptiGACHE-MoMS-Outside, sinks are found relative to one another at an angular separation of 90^0 and for OptiGACHE-MoMS-In&Out precise separation is 180^0. Whenever CHs are chosen then data transmission starts under the steady phase and all the steps are given as follows:

Step 1: After cluster head determination, information dissipation starts from cluster nodes dependent on edge/threshold rules. The data transmission from cluster nodes is contingent on the subsequent limitation. CHs nodes transmit data if the value of the contemporary detection (T(V)) is higher than the effectively fixed threshold esteem (J(V)). Otherwise, there is no transmission of data executed.
Step 2: As the CH assembles information from its cluster nodes, aggregating the information and sending it straightforwardly to the base station, it looks through the closest base station progressively by assessing Euclidean separation among sinks and CH.
Step 3: SNs energy is measured after each dispersal of communication. On the off chance that it happens, its leftover energy is equivalent to or under zero, the SN is thought to be dead and is spoken to by setting the DN_i banner as true.
Step 4: Moreover, the sum of the dead node (DN) is expanded by 1 and the CH determination procedure continues for subsequent SN choice. If the tally of the DN is smaller than the complete number of sensor hubs (N). On the off chance that none of the hubs is active, protocol stops to continue.

4.4. Proposed encryption and compression method for signal

In the proposed work, sensor nodes collect the data and perform an encryption and compression process then forward the data to the other CHs or sinks. First of all, the prediction error of the signal is calculated to reduce the size. A prediction error ($\in_{a,b}$) of the signal can be measured to reduce the size of the signals whenever signals are transmitted from the sensor nodes using a gradient edge detection (GED) predictor as given in Eq. (15).

$$\in_{a,b} = x_{a,b} - p_{a,b} \tag{15}$$

where $x_{a,b}$, and $p_{a,b}$ are the original signal value and predicted signal value, respectively. The prediction error is encoded using the standard Huffman coding technique when coding each input symbol. The signal values ($< ct > Š < ot >_0$, $< ct > Š < ot >_1$, $< ct > Š < ot >_2,... < ct > Š < ot >_N$) are encoded into the binary stream as ($\delta_0, \delta_1, \delta_2,...\delta_N$) by considering in their the occurrence of their frequency. The GED predictor is not able to predict the first two borderline rows and columns. Each element of $x_{a,b}$ is generally

Table II

Simulation parameters used for the GAOC [22], MS-GAOC [22] protocols, and the OptiGeA, OptiGeA-MoMS-Outside, OptiGeA-MoMS-In&Out, OptiGeA-DDC, OptiGeA-MoMS-Outside-DDC and OptiGeA-MoMS-In&Out-DDC proposed protocols.

Network Model and Genetic parameters	Values
Size of Network	$100 \times 100 m^2$
Total Nodes in the Network	100
Sink Scenario: Multiple moveable	4
SNs Initial energy (E_{init})	0.5
Nodes Heterogeneity ($3°$)	advanced, intermediate and normal nodes
Energy fraction of nodes	Degree 3: $\rho = 2$, $\tau = 1$
Number of nodes fraction	Degree 3: $q = 0.2$, $q_0 = 0.3$
Transmitter and receiver energy consumption (En_{ele})	50nJ/bit
Threshold distance parameter (d_0)	87 m
Amplification energy consumption for $d \leq d_0$ (En_{efs})	$10 pJ/bit/m^2$
Amplification energy consumption for $d > d_0$ (En_{amp})	$0.0013 pJ/bit/m^4$
Data aggregation energy consumption (En_{da}:)	$5 nJ/bit/signal$
Packet size	2000 bits
Population size (size)	30
Crossover Rate (C^{Rate})	0.5
Mutation Rate (M^{Rate})	0.006
Crossover type	One-point crossover
Population selection method	Rank selection method
Chromosome count (depends on p_size)	30
Total generations	30-50

converted into the 8-bit binary sequence and then a Matrix of $M \times M$ size is generated using the encryption process. A pseudo-random matrix of $r_{a,b}$ size is also considered. Each element of the matric is converted into the 8-bit binary sequence using the following process as in Eq. (16):

$$x_{a,b}^k = \lfloor x_{a,b} / 2^{k-1} \rfloor mod \ 2, \ k = (1, 2...8) \tag{16}$$

To perform the encryption process on each element the communication original signaland the pseudo-random matrix is bitwise exclusive-OR as given in Eq. (17) follows:

$$xe_{a,b}^k = x_{a,b}^k \oplus r_{a,b}^k \tag{17}$$

After the XOR function, an 8-bit binary encrypted sequence $xe_{a,b}^k$ is obtained as in Eq. (18), and then it is converted into the decimal form to get the final encrypted value as follows:

$$xe_{a,b} = \sum_{k=1}^8 xe_{a,b}^k \times 2^{k-1} \tag{18}$$

Hence, the current communicational signal is compressed and secure. The receiver can recover this signal through the reverse process of the discussed method. Thus, the end-user device can get the original value of the communication signal.

5. Simulation setup and result discussions

In this work, various kinds of SNs like airflow, oxygen, temperature, barcode sensing, blood pressure, pulse oximetry, ambient lighting, etc., are deployed in a hospital scenario to monitor ambient changes where doctors get the patient information and prescribe the treatment accordingly. Remote treatment is necessitated in the case of communicable diseases for the safety of the health workers. Here, an IoMT-based technology evolved for accessing patient information called OptiGeA, and its simulation results are discussed and compared with the existing techniques like GAOC (genetic algorithm optimized clustering) and MS-GAOC (GAOC with multiple sinks) [22]. There are several metrics such as lifespan of networks, energy consumption, total clusters, and the number of packets sent to CH used to analyze the algorithms' performance. In this scenario, multiple types of sensors (like ECG, EMG, EEG, respiration rate, oxygen level, temperature, glucose level sensor, etc.,) are connected to the sensor nodes. Here, six different variants of the proposed work are discussed, namely: OptiGeA (Optimized GA), OptiGeA-MoMS-Outside (multiple movable sinks outside of the network for Optimized GA), OptiGeA-MoMS-In&Out (multiple movable sinks inside and outside of network with Optimized GA), OptiGeA-DDC (direct data collection with Optimized GA), OptiGeA-MoMS-Outside-DDC (multiple movable sinks outside network and direct data collection with Optimized GA), and OptiGeA-MoMS-In&Out-DDC (movable multiple sinks inside & outside network and direct data collection with Optimized GA).

The proposed method is compared with the GAOC and MS-GAOC [22]. The IoMT-enabled sensor networks for the OptiGeA and existing methods are deployed in the hospital healthcare system $100 \times 100 m^2$ area using 70 Joules energy. The networks are simulated on the i7 processor with 2.4 GHz and Windows 10 using 8GB RAM using MATLAB. The energies and number of the nodes in the network are 0.5 J, 1.0 J, & 1.5 J, and 50, 30, & 20, for normal, intermediate, and advanced nodes, respectively. The sinks coordinates
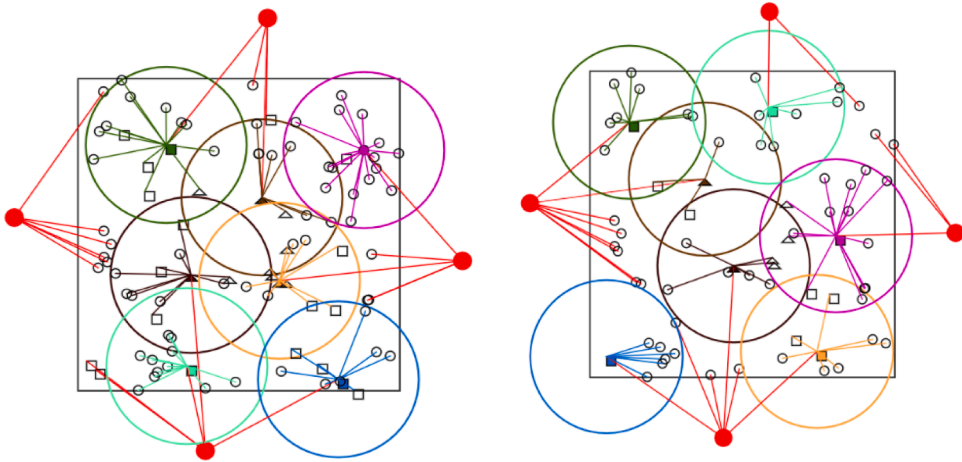
Fig. 6. Construction of network model by considering movable sinks outside the monitoring region and direct data collection process (i.e., OptiGeA-MoMS-Outside-DDC) for Dgr-3-Het.
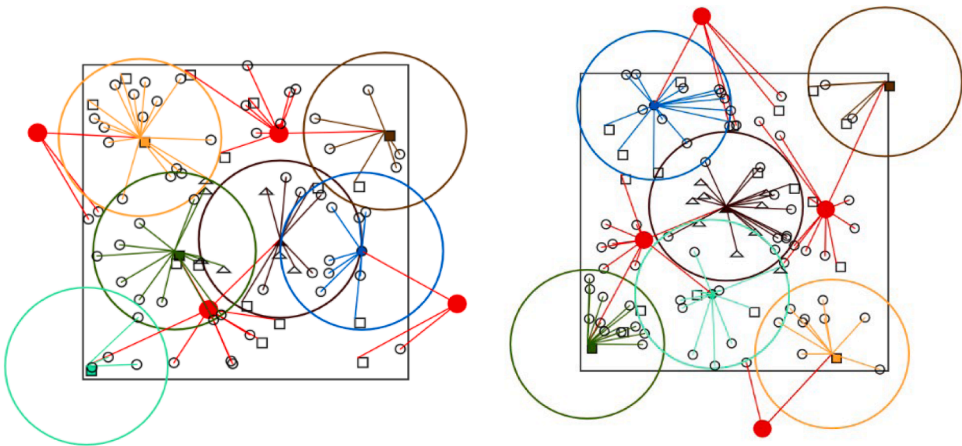
Fig. 7. Construction of network model by considering movable sinks inside & outside the monitoring region and direct data collection process (i.e., OptiGeA-MoMS-In&Out-DDC) for Dgr-3-Het.

are(110, 50), (− 10, 50), (50, − 10), and(50, 110) and the radius is 70m for the mobility of the sinks outside the networks and inside the network is 40m. The advanced, intermediate, and normal nodes are denoted by the triangle, square, and circle. Table II shows the simulation parameters which are used in simulations. The sink or base station is denoted by the red bubble, as shown in Figs. 6 & 7.

5.1. Stability period and network lifetime for Dgr-3-Het

The quantity of active nodes with the quantity of rounds for GAOC, MS-GAOC, OptiGeA, OptiGeA-MoMS-Outside, OptiGeA-MoMS-In&Out, OptiGeA-DDC, OptiGeA-MoMS-Outside-DDC, and OptiGeA-MoMS-In&Out-DDC for Dgr-3-Het is shown in Fig. 8. The Opti-GeA-MoMS-In&Out-DDC improves a lifetime by 66.95% in contrast with MS-GAOC. The percentage increment in the network lifetime is 30.82, 17.83, 27.07, 47.07 and 45.50 for OptiGeA, OptiGeA-MoMS-Outside, OptiGeA-MoMS-In&Out, OptiGeA-DDC and OptiGeA-MoMS-Outside-DDC by using 70 J total network energy. The stability period of OptiGeA is 13.91 % more than the GAOC whereas, OptiGeA-MoMS-Outside, OptiGeA-MoMS-In&Out, OptiGeA-DDC, OptiGeA-MoMS-Outside-DDC and OptiGeA-MoMS-In&Out-DDC is 13.91%, 4.31%, 6.73%, 2.25%, 4.94% and 10.53 % higher than that of the MS-GAOC for Dgr-3-Het.

In the proposed OptiGeA protocol, the improvement in the network's lifetime is because of the effective election of higher energy capable nodes as CH out of all types of heterogeneity. The comparative slant clustering parameter encourages the advanced nodes to participate in the election of CH, and the advanced nodes takes advantage of its higher remaining energy and is elected as CH before the existing intermediate nodes, which further increases the network's sustainability. Furthermore, the proposed deployment concept, and movement of the sink with the adjustable range of sensor nodes, decreases the communication range by adding the concept of density which collectively reduces the energy consumption and also removes the hot spot problem. Moreover, a combination of the proposed concept gives a longer lifetime and stability period. The proposed methods remove the hotspot problem of the networks by
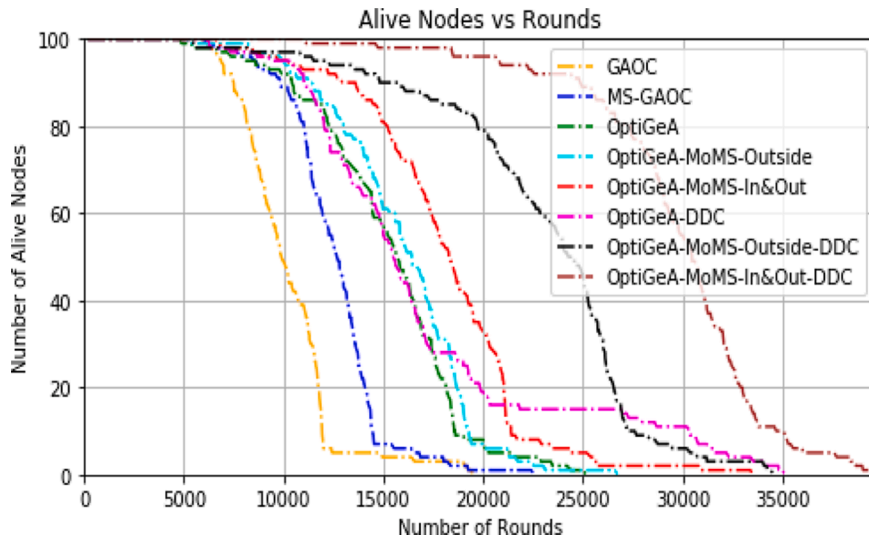
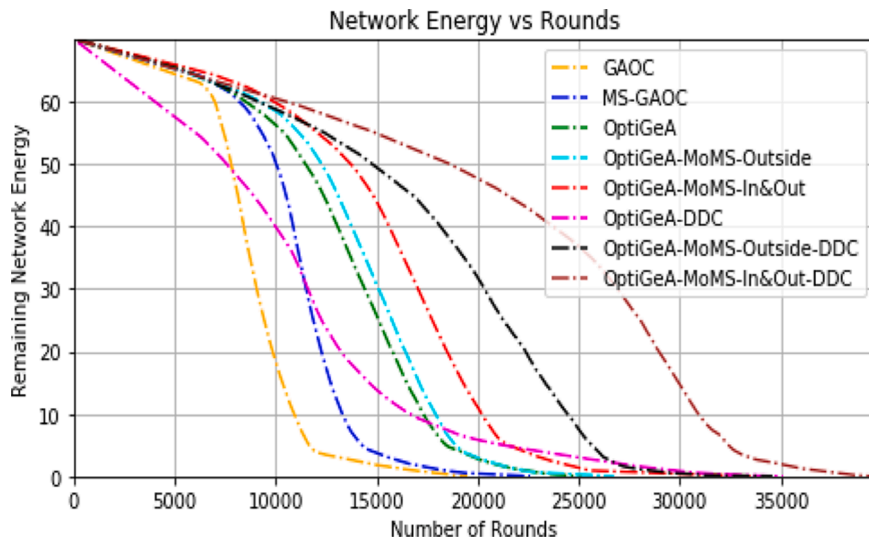**Fig. 8.** alive nodes vs rounds for Dgr-3-Het.

Fig. 9. remaining network energy vs rounds for Dgr-3-Het.

decreasing the range of the sensor nodes which are deployed near the sinks, whereas the existing methods have not considered the concept of adjustable sensing range.

5.2. Remaining network energy for Dgr-3-Het

The exhaustion of the system remaining's energy for conventions for static, movable, and DDC situations is portrayed in Fig. 9. The OptiGeA protocol works for a larger number of rounds transmitting a higher number of information packets. The OptiGeA, OptiGeA-MoMS-Outside, OptiGeA-MoMS-In&Out, OptiGeA-DDC, OptiGeA-MoMS-Outside-DDC and OptiGeA-MoMS-In&Out-DDC beat lifetime in contrast with GAOC and MS-GAOC. Ideal energy utilization with a fuse of the mobile sink and dynamic cluster size is reflected in arranged execution. The balanced sensing range improved cluster size and diminished packet movement first to CH and then to sink to convey data packets to individual base stations.

Similarly, the deployment of sinks set an accelerative decrease in communication energy and jump check adding to leftover energy preservation. Also, the nodes with the high energy are placed in the focal point of the system in Dgr-3 with the imminent of functioning extensive sufficient for communicating data to the nearest base station accessible. In addition, including two sinks inside the system region profoundly diminishes the CH to sink separation, subsequently protecting remaining energy and expanding alive rounds to 39678 rounds for OptiGeA-MoMS-In&Out-DDC. The severe decrement in the energy consumption is directly dependent on the
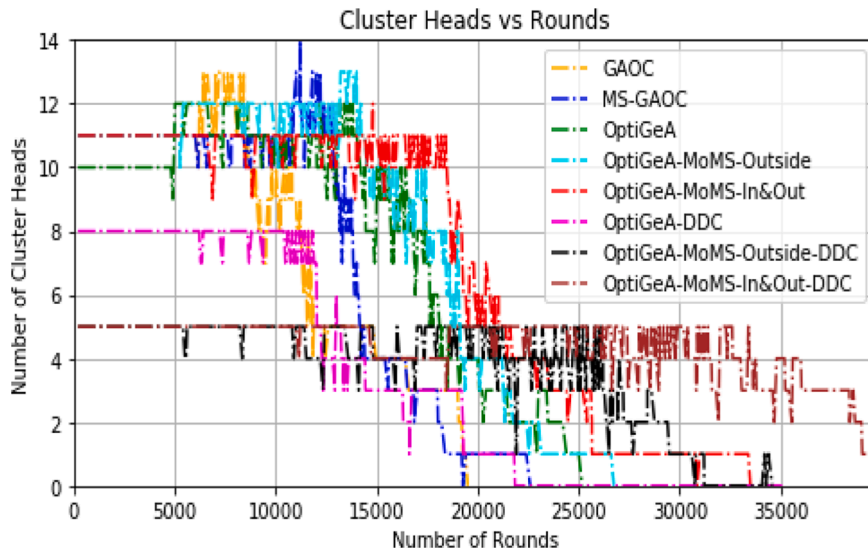
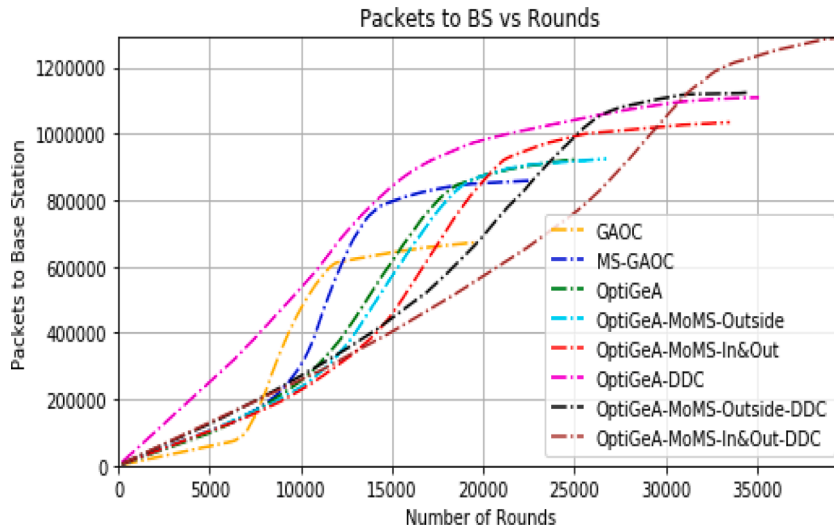**Fig. 10.** cluster heads vs rounds for Dgr-3-Het.

Fig. 11. packets sent to BS vs rounds for Dgr-3-Het.

movement of the sink with the adjustable range of sensor nodes which decreases the communication range of the DDC. If the communication range during the data collection process is less, then the consumption of the energy decrease.

5.3. Number of clusters formed for Dgr-3-Het

Fig. 10 shows the CH count per adjust of rounds for the Dgr-3-Het situation. The hereditary practice endures by looking through better cluster structure by adjusting CH positions over nodes to accomplish better fitness. The nearer SNs to the base station forthrightly forwarded bundles of data to it, inferring no CH development in that defined area which reduces energy drainage. Thus, a decline in CH is understood in conventions combined with DDC. The protocol instantiates with an arbitrary number of CHs picked lastly and moves towards an ideal arrangement structure. In the first place, OptiGeA-DDC, OptiGeA-MoMS-Outside-DDC, and OptiGeA-MoMS-In&Out-DDC have CH tally between 5 to 7 though, whereas different OptiGeA conventions bunch CH between 10 to 14. The self-determining sensors in DDC communicate legitimately with the base station are reduce the dissipation of energy in information accumulation and traffic handing-off. By means the system continues, the count of CHs continues to reduce. In the proposed methods, the formed number of CHs is in the constant range, which maintains a constant energy consumption rate during the steady phase.

Table III

performance of the existing and proposed protocols with different metrics.

| 3° Heterogeneous Network Protocols | | | | | | | |
Protocols	Network energy	Stability period	Half node dead	Last node dead	Throughput	% increment in lifetime	% increment in throughput
GAOC	70	5621	9886	19493	671313	-	-
MS-GAOC	70	6316	16360	23767	858715	-	-
OptiGeA	70	6403	16697	25500	912622	30.82	35.95
OptiGeA-MoMS-Outside	70	6588	20895	28028	946160	17.93	10.18
OptiGeA-MoMS-In&Out	70	6741	21771	30200	998426	27.07	16.27
OptiGeA-DDC	70	6458	22865	35107	1124352	47.71	30.93
OptiGeA-MoMS-Outside-DDC	70	6628	22655	34581	1109117	45.5	29.16
OptiGeA-MoMS-In&Out-DDC	70	6981	28471	39678	1290428	66.95	50.27

5.4. Throughput for Dgr-3-Het

Fig. 11 demonstrates the data packets sent to the sink according to adjustments completed for Dgr-3-Het. Essentially, many data packets are transmitted to the sink means the longer the network system works. The throughput greatly improves by 50.27% for OptiGeA-MoMS-In&Out-DDC outflanking MS- GAOC by an enormous edge. The data packets transmitted is 912622, 946160, 998426, 1124352 and 1109117 giving an addition of 135.95%, 10.18%, 16.27%, 30.93% and 29.16% if there should arise an occurrence of OptiGeA, OptiGeA-MoMS-Outside, OptiGeA-MoMS-In&Out, OptiGeA-DDC and OptiGeA-MoMS-Outside-DDC, respectively. This performance of the networks has increased due to choosing the effective clustering parameters for the fitness function, which perform the genetic task effectively. The sensor node works longer time in the deployed system with its remaining energy. The dynamic change of cluster size concerning the nearest accessible sink advantage in the data transmission by lessening hop-count that spares a considerable amount of energy for comparing the CH. The CH recaptures its rule once when the sink travels away from that accommodating packets from its sensor members. The lifetime of the proposed method is high means the network is collecting data for a long duration. Thus, the method sent additional packets to the sinks. This improvement is because of the decrease in the sensing range during the data collection and transmission process.

5.5. Analysis of the stability period, remaining energy, and network throughput for Degree -3 Heterogeneous Network Protocols

In this section, the percentage increment of GAOC [22], MS-GAOC [22], OptiGeA, OptiGeA-MoMS-Outside, OptiGeA--MoMS-In&Out, OptiGeA-DDC, OptiGeA-MoMS-Outside-DDC, and OptiGeA-MoMS-In&Out-DDC using network energy network lifetime, and throughput for Dgr-3-Het is depicted in Table III. The stability period for OptiGeA with static sinks is 13.91% viz a viz GAOC whereas OptiGeA-MoMS-Outside, OptiGeA-MoMS-In&Out, OptiGeA-MoMS-Outside-DDC, and OptiGeA-MoMS-In&Out-DDC for multiple sinks is 4.31, 6.78, 4.94, and 10.53% viz a viz MS-GAOC, respectively.

The OptiGeA-DDC performs 2.25% better in the stability period using a single sink viz a viz the MS-GAOC. The network lifetime increment of the OptiGeA is 30.82% viz a viz the GAOC, whereas the enhancement in the increment of the OptiGeA-MoMS-Outside, OptiGeA-MoMS-In&Out, OptiGeA-DDC, OptiGeA-MoMS-Outside-DDC, and OptiGeA-MoMS-In&Out-DDC is 17.93, 27.03, 47.71, 45.50, and 66.95%, viz a viz MS-GAOC, respectively. Additionally, the throughput of the OptiGeA is 35.95% viz a viz the GAOC whereas increment of the OptiGeA-MoMS-Outside, OptiGeA-MoMS-In&Out, OptiGeA-DDC, OptiGeA-MoMS-Outside-DDC, and Opti-GeA-MoMS-In&Out-DDC is 10.18, 16.27, 30.93, 29.16, and 50.27%, viz a viz MS-GAOC, respectively. The main reasons for such improvements are the selection of higher energy nodes as CHs using the effectiveness of the fitness function. Direct data collection also helps improve the performance of the networks because it reduces the data communication distance.

5.6. Analysis of sinks loads

This segment examines sink load concerning several rounds of the sinks in the networks. The information packets communicated from the CHs should be distributed between the numerous sinks located throughout the network. The CHs transfer packets to the nearest agreeable sink which can be determined by using the clustering parameters from a large number of shifting sinks. In a static sink state, the distance between CHs and sinks remains constant; however, in a mobile sink condition, the distance between CHs and sinks is evaluated continually before CHs select to transfer information to the next accessible sink. The load balancing measure is useful in determining the number of data packets transmitted to sinks by current cluster heads and how well they are distributed. As illustrated in Fig. 12, drains receive approximately the same number of packets as source sinks under dynamic sink conditions. Fig. 12 displays the total number of information packets being gathered by the equipped sinks. The sink movement of the OptiGeA protocol guarantees that sinks are getting equivalent burdens from sparse and dense node areas. Then again, a static condition system can veer off from load adjusting if, under the direst outcome, nodes are not consistently dispersed in the network territory.

The versatile sink topology expands the life expectancy of a system without upsetting the load, adjusting the proportion of the sinks. The SNs in the concentrated region put an extra burden on the nearest accessible sink and vice-versa. This situation is eased by sink
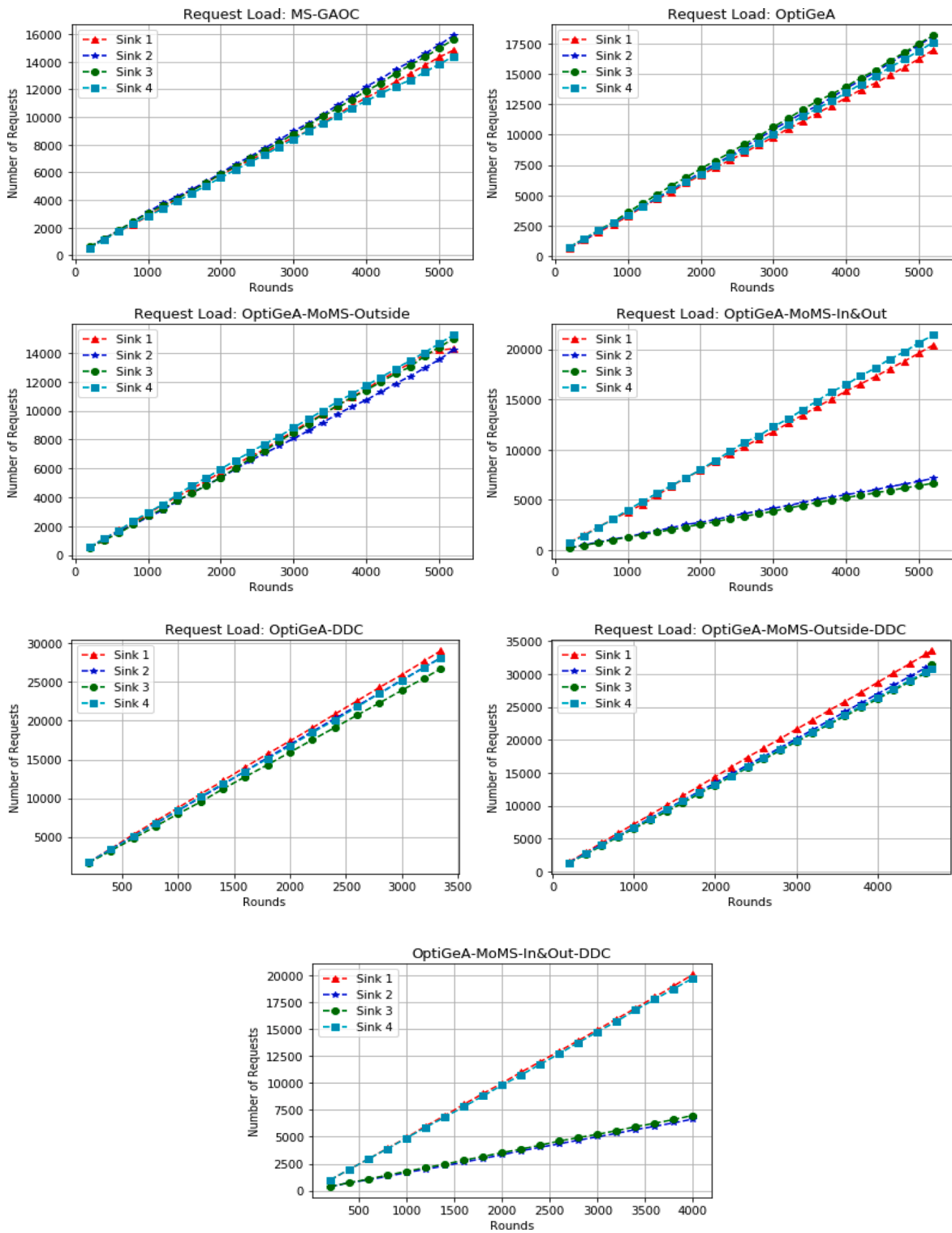
Fig. 12. Number of requests per rounds comparison of the MS-GAOC [22], OptiGeA, OptiGeA-MoMS-Outside, OptiGeA-MoMS-In&Out, OptiGeA-DDC, OptiGeA-MoMS-Outside-DDC, OptiGeA-MoMS-In&Out-DDC by for multiple sinks.

movement back and forth and gathering information from both scanty and dense network regions alongside guaranteeing the optimization of communication distance. In OptiGeA-MoMS-In&Out protocols, two sinks are inside and the other two are outside the network territory. In this manner, inside sinks accumulate a greater number of data than external sinks as they are a lot nearer to SNs.

The external sinks for the most part gather data packets from nodes at the boundaries of the network. Also, the consideration of the idea of direct information assortment does not upset the load request on relating sinks. Since the sinks are continuously moving, SNs continue changing their inclination between cluster head, common node, and independent node. Moving sinks continue gathering information from intently accessible sinks, henceforth, equally circulating sink load. Thus, the proposed strategy valuably distributes the load of the requests among the different sinks helping in improving the WSN's nature of administration.

6. Conclusion and future scope

In this paper, a secure and energy-efficient routing protocol using IoMT for patient and doctor communication using movable sinks and direct data collection for degree-3 heterogeneity is discussed. The OptiGeA variant achieves a 30.82 % increment viz a viz the GAOC for a single sink, while OptiGeA variants perform 17.93, 27.07, 47.71, 45.5, and 66.95% improvement in the network lifetime viz a viz the MS-GAOC for multiple sinks in case of Drg-3-Het. Several factors may contribute to this massive increase in network longevity. Firstly, using a fitness function, the highest capable node is selected as CH, where the parameter comparative bias favors the choice of more significant energy nodes as CH despite having less processing power. Secondly, the movability of sinks inside and outside of the network zone depletes remaining energy slower than the static sink environment, resulting in better results in contrast to the static sink environment. Thirdly, direct data collection minimizes the number of hops required for packets to be delivered to their appropriate sinks. Finally, a new deployment approach for positioning heterogeneous SNs in a well-organized manner is proposed to conserve energy during network operation as the primary goal. The technique also prevents the deployment of high-energy nodes that are too closely coupled. The suggested OptiGeA protocols maintain adequate load balancing while also easing the hot spot problem, which demonstrates the effectiveness of the protocols. For future research, the development of fault-tolerant systems, secure data transmission capabilities, the elimination of redundant data, and sensor node authentication procedures can be studied. Additionally, the work can be extended by incorporating edge computing and cloud computing methods for processing a large number of instructions such as videos.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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