Research article

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Performance study and critical review on energy aware routing protocols in mobile sink based WSNs

https://doi.org/10.1515/ehs-2021-0007
Received May 27, 2021; accepted August 19, 2021;
published online October 6, 2021

Abstract: Wireless networks involve spatially extended independent sensor nodes, and it is associated with each other's to preserve and identify physical and environmental conditions of the particular application. The sensor nodes batteries are equipped with restricted energy for working with an energy source. Consequently, efficient energy consumption is themain important challenge in wireless networks, and it is outfitted witharestricted power storage capacity battery. Therefore, routing protocol with energy efficiency is essential in wireless sensor network (WSN) to offer data transmission and connectivity with less energy consumption. As a result, the routing scheme is the main factor for decreasing energy consumption and the network's lifetime. The energy-aware routing model is mainly devised for WSN with high network performance when transmitting data to a sink node. Hence, in this paper, the effectiveness of energy-aware routing protocols in mobile sink-based WSNs is analyzed and justified. Some energy-aware routing systems in mobile sink-based WSN techniques, such as optimizing low-energy adaptive clustering hierarchy (LEACH) clustering approach, hybrid model using fuzzy logic, and mobile sink. The fuzzy TOPSIS-based cluster head selection (CHS) technique, mobile sink-based energy-efficient CHS model, and hybrid Harris Hawk-Salp Swarm (HH-SS) optimization approach are taken for the simulation process. Additionally, the analytical study is executed using various conditions, like simulation, cluster size, nodes, mobile sink speed, and rounds. Moreover, the performance of existing methods is evaluated using various parameters, namely alive node, residual energy, delay, and packet delivery ratio (PDR).

Keywords: a sink node; cluster head; energy-aware; routing; wireless sensor network.

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Introduction

In the Internet of Things (IoT) system, wireless sensor network (WSN) is a significant task and involves connectivity, sensing, data processing, and data acquisition. Generally, WSN is composed of a huge number of sensors, and every sensor node has a non-refundable battery supply. Meanwhile, in WSN, minimum storage space, computational complexity, and energy-saving are essential. Besides, the sensor node is placed randomly without any preparation. In this circumstance, sensor nodes should be self-configurable for regulating them; therefore, the sensor node can communicate with the total network. Normally, the sensor node is located in the natural environment and disposed to harm (Mottaghi and Zahabi 2015). The sensors are small independent devices with various limitations, such as memory, communication range, computation capability, and battery power (Kaur and Kaur 2017). The disablement or accumulation of sensor nodes is responsible for various harms; thus, the network topology changes constantly. Moreover, the sensor node includes four elements: power element, sensing unit, communication element, and processing unit. The sensing element includes one or more sensors, and it has an analog to digital converter (Khan et al. 2014). Environmental parameters are sensed through various sensors, and it generates analog signals. Here, analog to digital converter changes the analog signals to digital signals and transmits them to processing elements. The microprocessor or microcontroller gathers the signals with a memory unit, and it is dependable for sensor node control (Kelotra and Pandey 2018). The communication element involves short-range radio, which is employed for receiving and transmitting data over radio channels. The power element consists of a battery supply for executing various tasks in which the global positioning system (GPS) component is also included for identifying sensor node position (Mottaghi and Zahabi 2015).

The WSN is a group of several micro sensor nodes, and the nodes are proficient in understanding the environment and collect the data from its surroundings. Then the data is forwarded to the sink node (Chauhan and Soni 2019; Yang, Lai, and Wang 2013). WSN has a broad range of applications, namely intrusion detection, agriculture, environmental monitoring, healthcare, industrial applications, military, and so on (Chauhan and Soni 2019; Pantazis, Nikolidakis, and Vergados 2012). Moreover, a node's energy is employed for performing various operations, like data aggregation, receiving data, and transmitting data in a network. Data aggregation is a process where various duplicates of common data are separated, and uncorrelated noise is also reduced (Chauhan and Soni 2019; Siavoshi, Kavian, and Sharif 2016). The WSN data is routed to the sink node by a path developed by nodes. Nodes can communicate with Base Station (BS) by multi-hop or single-hop traffic pattern (Nazir and Hasbullah 2010). The direct communication among BS and nodes is developed in single-hop communication, and obstinately communication takes place by intermediate nodes of multi-hop communication. Moreover, the nodes are gathered into groups, and it is mentioned as clusters, and every cluster has representative nodes, named CH. The sink location is dynamic or static, based on network necessity (Chauhan and Soni 2019; Pešović et al. 2010). In addition, the WSN is considered as a gadget system, which can be utilized for transferring the data. An entryway transfers the data with several hubs. WSN is a remote system, which includes BS and remote sensors (Wang et al. 2013). In addition, WSN consist of a huge amount of low-power sensor nodes from hundreds of thousands of sensor hubs. The sensor hub integrates radio handset based on battery source, electronic circuit interface, antenna, and microcontroller. Furthermore, total information collected through the sensor hub is transferred to the sink hub in WSN. Hence, the sink hub position highly influences the energy consumption and lifespan of WSN (Srinivas and Amgoth 2020).

Naturally, WSN involves many sensor nodes, and a BS is placed in the sampling environment. Sensor nodes can transfer the data to BS, which processes data. Moreover, the sink node transmits the command to the sensor node in critical situations. Every sensor node can transmit data to the sink by a single hop through long-distance transmission. In recent days, WSN is developed as a familiar research area because of its huge scale applications. Various techniques, such as cloud computing, are combined with WSN to improve their application (Kelotra and Pandey 2018). The information retrieval (Ghuge, Prakash, and Ruikar 2020b; 2021) using the regression methods (Ghuge, Prakash, and Ruikar 2018) is helpful to reduce the delay and hence the accuracy is enhanced (Ghuge, Prakash, and Ruikar 2020a). The clustering approach is one of the best solutions for decreasing energy consumption in WSN (Mottaghi and Zahabi 2015). The new method, named amend low-energy adaptive clustering hierarchy (A-LEACH) (Chauhan and Soni 2019; Vijayvargiya and Shrivastava 2012), was developed for selecting CH based on the weighted probability of nodes with remaining energy. In WSN, nodes are heterogeneous in which several nodes have high initial energy. This method offers optimal clustering, which enhances the lifetime of the network. Additionally, in (Chauhan and Soni 2019; Liu and Ravishankar 2011), a genetic algorithm (GA)-based LEACH system was devised to select CH. Here, the sink node gathers the information regarding nodes and estimated optimal probability for nodes to choose CH. Then, the sink node transfers a message in a network, including the optimal value of probability for producing clusters. Along with this, a chain-based routing protocol termed power-efficient gathering in sensor information (PEGASIS) was developed, where the chain was generated based on a greedy approach (Chauhan and Soni 2019; Lindsey, Raghavendra, and Sivalingam 2002).

Motivation

The WSN is used in several applications, like monitoring the environmental conditions like humidity, air quality accessing, temperature, pressure and so on. The challenges associated with the conventional WSN techniques are limited bandwidth, energy efficiency, cost requirement, delay and so on. Hence, in order to overcome those drawbacks, energy-aware routing protocols are devised in literature. In this paper, the analysis is performed to justify the effectiveness of energy-aware routing protocols in mobile sink-based WSNs. Here, optimizing LEACH clustering method, a hybrid approach using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS technique, mobile sink-based energy-efficient CHS method, and hybrid Harris Hawk-Salp Swarm (HH-SS) optimization approach are described and considered for evaluating the performance of mobile sink-based WSN.

The key contribution of the research article is detailed below:

The contribution of the proposed critical review on energy aware routing protocols in Mobile sink based WSNs is to analyze the conventional techniques like LEACH clustering method, a hybrid approach using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS technique, mobile sink-based energy-efficient CHS method, and hybrid HH-SS optimization.

The rest of the paper is arranged as follows: Section 2 explains motivation and literature review on energy-aware routing protocol in mobile sink-based WSN, and Section 3 illustrates the mobile sink-based WSN. Section 4 presents the explanation of review methods for energy-aware routing protocol in mobile sink-based WSN. Sections 5 describes the simulation setup, and the comparative analysis of various energy-aware routing protocols is depicted in Section 6. Finally, Section 7 concludes the paper.

Literature survey

This section illustrates about literature survey of various techniques developed for energy-aware routing protocol in mobile sink-based WSN, and the challenges present in existing methods are represented. Zhang and Li (2020) developed particle swarm optimization (PSO) approach for an energy-aware data gathering model in mobile sink-based WSN. At first, mathematical representation was generated based on delay and energy consumption limitations for the mobile sink data set. After that, optimal meeting points were selected for collecting data from source nodes by multi-hop relay. Consequently, an aggregation tree was also developed for the transmission of data. Moreover, a spanning tree was encoded to elements, and also the random model was devised for producing data collection spanning tree with tree height boundary restriction. Finally, the PSO model along with adaptive elite mutation was introduced for enhancing population diversity. This method has less processing time, but still, the network's life was affected by uneven node energy consumption. Jain et al. (2021) introduced delay-aware green routing protocol (DGRP) for mobile sink-based WSN. This method follows the virtual structure-based hierarchical routing system, which produces multiple rings in the sensor field for decreasing data delivery delay. The virtual structure node was physically near to rings, and it acts as high tier nodes to maintain information of sink position. Moreover, the ring maintenance technique was devised to avoid hotspot issues. This DGRP achieved less data delivery delay; hence, it was highly utilized for time-sensitive applications. However, this method has not implemented numerous mobile sinks to improve the communication overhead.

Mehta and Saxena (2020) devised a multi-objective cluster head-based energy-aware optimized routing (MCH-EOR) scheme for WSN. Initially, this method employed the Sail Fish Optimizer (SFO) model and multi-objective optimization approach for providing the solution for developed issues while expanding the lifespan of WSN. After that, a multi-objective clustering approach was adopted by efficient fitness function for choosing robust CH. The CH for all clusters was selected using various objectives, such as coverage, residual energy, communication cost, and proximity. In addition, the SFO technique was employed for choosing the optimal path during the routing process. At last, route alternation was applied for selecting another route and rejecting route failure during data transmission. This model obtained a high packet delivery ratio and throughput, but this method failed to enhance the lifespan of WSN. Chauhan and Soni (2019) modeled the mobile sink-based energy-aware clustering (MSEAC) model for WSN. This method was mainly developed for improving network lifetime and solving energy hole problems. At first, the network was separated into several rectangular portions, and every portion includes one CH. Moreover, firefly optimization algorithm (FFA) was employed to select suitable CH. Some essential parameters like distance from the node to sink, average node to node distance, and residual energy, were also considered for processing. This method attained good energy efficiency and communication efficiency in WSN, but this method was not efficient for load balancing. Roy, Mazumdar, and Pamula (2020) developed an energy and coverage sensitive, an aware hierarchical routing protocol for mobile sink-based WSN. In this method, the mobile sink nodes were limited to decreasing the energy hole problem. This model mainly includes four stages: prepare stage, set up segment, routing part, and steady stage. Initially, the mobile sink was moved to every sojourn position and transferred a beacon message of the sensor node in the preparation phase. After that, distributed clustering approach was employed for evenly separating the entire network into the number of clusters. In addition, the CH selection was performed based on two parameters, like distance and residual energy in the setup stage. Consequently, in the routing tree phase, the optimal loop-free routing path was generated in which cluster data was transmitted to the mobile sink. Finally, the data was gathered using the steady state phase. This model highly decreased end-to-end delay, but this method is still not identified for the optimal sojourn position for the routing process.

Wen et al. (2020) introduced a joint Density-aware and Energy limited path construction approach termed DEDC for Data Collection in mobile sink-based WSN. Originally, this method estimated the grid dimension using path length limitation. Furthermore, monitoring areas were separated into various grids and determined the unbalanced and balanced grids in the path construction stage. Here, the constrained path length was separated into two kinds: irregular path length and regular path length. Then, this model created a regular path and the regulated path sections for unbalanced grids. The path adjustment and regular path construction helped create a path to balance network lifetime and forwarding loads. This method was effectively decreased high energy consumption, but this method failed to select the appropriate path for data transmission. Dahiya and Singh (2018) devised mobile sink-based coverage optimization and link-stability estimation routing protocol named MSCOLER for optimal coverage restoration and link stability calculation in WSN. This model mainly includes two stages: grid-based firefly simulated annealing (GFSA) and link stability estimation routing (LSER). Initially, the GFSA model contains grid-based network coverage for solving optimization problems. Finally, a link quality-based routing process was applied to determine relay nodes for improving the network's lifetime. This method highly improved the network lifetime even though this method failed to reduce the computational time. Christopher and Jasper (2020) modeled Dynamic Hexagonal Grid Routing Protocol (DHGRP) model for WSN. Initially, this method separated a network through various hexagonal virtual grids to share the sink's current location between nodes. Here, the network was separated into square grids for a huge area coverage communication process. After that, the dynamic path was selected to avoid data delivery delay, while the sink node was shifted to a new position. This method was also included various sharing rules for avoiding congestion and follows random silk mobility samples. This method achieved minimum delay and maintained a high lifetime of the network—however, this method has not solved various security problems due to data transmission. The literature review of the existing methods is depicted in Table 1 given below:

Challenges

The challenges faced by the existing energy-aware routing protocol in mobile-based WSN techniques are illustrated below.

- The PSO approach (Zhang and Li 2020) was developed for an energy-aware data gathering method in mobile sink-based WSN. However, this method failed to

Table 1: Literature review of existing and proposed method.

Author	Technique	Advantages	Drawback
Chauhan and Soni (2019)	Developed mobile sink-based energy-aware clustering (MSEAC) model for WSN	Achieved better energy efficiency and communication efficiency	Not applicable for efficient load balancing.
Zhang and Li (2020)	Developed Particle swarm optimization (PSO) approach for an energy-aware data gathering model in mobile sink-based WSN	Achieved low processing time	Due to uneven node energy consumption, network life time is reduced.
Jain et al. (2021)	Developed delay-aware green routing protocol (DGRP) for mobile sink-based WSN	Obtained less data delivery delay	It failed to implement numerous mobile sinks to improve the communication overhead
Mehta and Saxena (2020)	Developed multi-objective cluster head-based energy-aware optimized routing (MCH-EOR) scheme for WSN	Achieved better packet delivery ratio and throughput	Failed to improve the lifespan of WSN
Roy, Mazumdar, and Pamula (2020)	Developed an energy and coverage sensitive, an aware hierarchical routing protocol for mobile sink-based WSN	Achieved reduced end-to-end delay	It failed to identify the optimal sojourn position for the routing proces
Wen et al. (2020)	Developed a joint density-aware and energy limited path construction approach termed DEDC for data collection in mobile sink-based WSN	Obtained better energy consumption	Failed to select the appropriate path for data transmission
Dahiya and Singh (2018)	Developed mobile sink-based coverage optimization and link-stability estimation routing protocol named MSCOLER for optimal coverage restoration and link stability calculation in WSN	Obtained better network lifetime	Failed to reduce the computational time
Christopher and Jasper (2020)	Developed dynamic hexagonal grid routing protocol (DHGRP)model for WSN	Obtained less delay and achieved a high lifetime of the network	Failed to solve the security problems.

control high computational complexity and network preservation rate.

- In (Jain et al. 2021), DGRP was devised for mobile sink-based WSN, but this technique has not sustained various mobile sinks to enhance data delivery performance.
- The MSEAC model (Chauhan and Soni 2019) was introduced in WSN for improving the lifespan of a network. Although, this technique was not much effective for load balancing and congestion control.
- Energy and the coverage-sensitive process were modeled in (Roy, Mazumdar, and Pamula 2020) for mobile sink-based WSN. However, this method does not incorporate buffer and energy-constrained mobile sink for solving developing problems in several applications, such as smart environment, IoT, Internet of Nano Things (IoNT), etc.
- DHGRP was developed in (Christopher and Jasper 2020) for mobile sink-based WSN, but this method failed to handle various security problems during data transmission.

Mobile sink-based WSN

In general, WSN has one BS A_s with n number of sensor nodes. Wireless link specifies direct communication between sensor nodes in particular radio range. Every sensor node is uniformly distributed in magnitudes, indicated in meters with the highest communication radio range. In addition, every sensor node includes distinctive identification, and it is gathered as cluster. The BS is located in the position of $\{0.5F_u, 0.5G_v\}$, and it is encoded with the near-optimal solution for obtaining data symbols from nodes. Coordinate values of F_z and estimate the sensor node position G_z. Then, the data is transformed to BS from every sensor node, and a CH-based routing technique performs it. The number of sensor nodes are indicated as S_c, and it is considered as a CH, T_o. S_c^g represents the group of sensor nodes in a cluster set, S_c means sensor network and it is divided into s_c number of clusters also the number of standard nodes are similar to $g – S_c$. Then, data packets are transmitted to every nodes P to its subsequent CH T_o, and also CH gathers every data packet. Subsequently, data packets are transmitted to BS A_s. The entire sensor node is installed to locate and distance among yth normal node to Cth CH is specified as, $f_{y,C}$ as well as distance among Cth CH to BS is denoted as V_C (Kumar and Kumar 2015). The network model of WSN is portrayed in Figure 1.

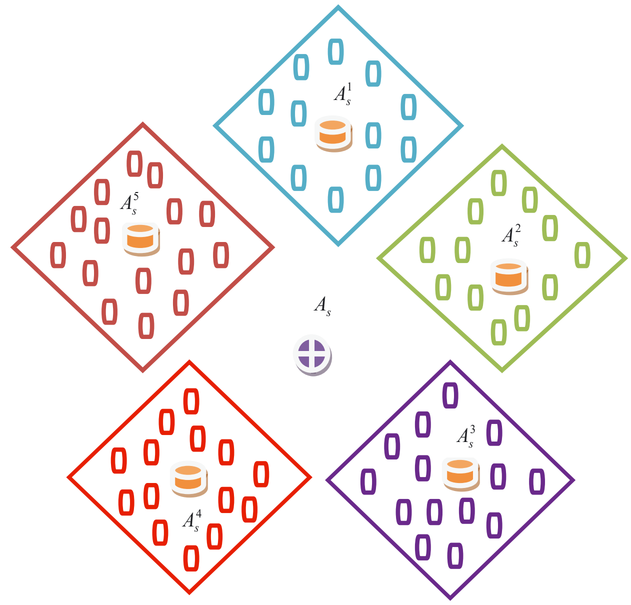

Figure 1: Network representation of mobile sink-based WSN.

Methods taken for review

In this section, various techniques, such as optimizing LEACH clustering model (Mottaghi and Zahabi 2015), the hybrid method based on fuzzy logic and mobile sink (Kaur and Kaur 2017), Fuzzy TOPSIS-based CHS approach (Khan, Bilal, and Young 2018), mobile sink-based energy-efficient CHS model (Chauhan and Soni 2019) and Hybrid HH-SS optimization technique (Srinivas and Amgoth 2020) are some of the methods considered for review. It is explained in the below section.

Optimizing LEACH clustering technique

Here, the system is composed of a fixed number of nodes, and it is located randomly in the sampling area. Every node has initial energy, equivalent to I_0 and mobile sink that moves through the center of the sampling area. This optimizing LEACH clustering approach (Mottaghi and Zahabi 2015) was separated into various rounds, same as the LEACH technique. Here, every node produces the data at a similar rate and transfers them one time in all round. In this model, all rounds initiated with setup stage and carried out with steady-state phase and set up stage includes three main stages. The initial stage of the setup phase is Task Ordination (TO), in which Rendezvous Node (RN) and CH were selected. After that, the cluster setup stage was employed for developing clusters, and finally scheduling stage was applied, where CH transmits the schedule to every member for arranging node transmission period. Moreover, node data is broadcasted to the mobile sink in the steady-state stage, and it involves a single stage, named data transmission. Moreover, the basic energy model was utilized to compute energy consumption while receiving or transmitting the data. Here, energy consumed for transmitting b bits of the message to position p meters in the distance is given by,

$$I_{\mathrm{re}} = I_{\mathrm{re-Elec}(b)} + I_{\mathrm{re-amp}(b,p)} = \begin{cases} b \times I_{\mathrm{re}} + b \times p^2 \,;\, p < p_0 \\ b \times I_{\mathrm{re}} + b \times p^4 \,;\, p \geq p_0 \end{cases} \quad (1)$$

$$p_0 = \sqrt{\frac{I_{\mathrm{pa}}}{I_{\mathrm{pm}}}} \quad (2)$$

where, I_{re} represents the energy consumed by electronic radio circuit for 1 bit transmission, I_{pa} denotes energy consumed by power amplifier on free space model. The term I_{pm} signifies energy consumed by power amplifiers in the multipath model.

In this technique, high energy consumption is necessary for data transmission from CH to the mobile sink. However, high energy consumption must be decreased for better efficiency. The CH transfers the collected data to the mobile sink or nearby existing RN base on the mobile sink position. In addition, if the distance between the mobile sink and CH is less than p_0, then the collected data directly broadcast the mobile sink. Meanwhile, if the distance is higher than p_0, then the data is transferred to RN to store the data until it transfers to the mobile sink. Similarly, if the transmission distance is less than p_0, then the consumed energy is proportional to the square of p. Moreover, if the transmission distance is greater than p_0, then the energy consumption is proportional to the fourth power of p. Thus, the total energy consumed for broadcasting and receiving data is given below.

$$I_{\mathrm{tot}} = I_{\mathrm{re}}(b, p) + I_{\mathrm{rm}}(b) \quad (3)$$

where, I_{rm} denotes the energy consumed through a node in receiving node. Therefore, this method reduces energy consumption more than conventional LEACH in WSN, while a huge network is employed.

Hybrid model using the mobile sink and fuzzy logic method

In this technique, fuzzy logic and mobile sink are combined for the region-based clustering process in WSN (Kaur and Kaur 2017). The procedure of this hybrid method is elaborated as follows: At first, the network area is considered with $l \times l$ meters. After that, the network region is separated into small segments with similar dimensions. In this system, every node transmits its position and energy level information to the sink node. Besides, sensor nodes are arranged randomly in every pre-defined sub-region. Thus, all area has its region head, and numerous member nodes and member nodes transmit a data to the region head. Furthermore, a distributed method is developed for selecting the region head. The selection process depends on fuzzy variables, such as average energy consumption, large amount of neighbors, and high residual energy. In this scheme, every region head generates Time Division Multiple Access (TDMA) schedule in member nodes for transferring data. Here, the sink node is changeable with borderline, and it is not energy-constrained, which means it has the appropriate amount of energy to receive data from the region head.

Besides, regions heads are separated into two groups: boundary region head and non-boundary region head. The boundary region head transfers the data to the sink node, while the sink node presents in its area. Therefore, the boundary region head has an adequate duration for transmitting data to the sink node once the sink node is available in its borderline. Additionally, other nodes do not transmit the data to a particular boundary region head when the region head transmits data to the sink node. Similarly, the non-boundary region head computes a high bound limit and less bound limit of both x and y axis for estimating the next relay node. Meanwhile, the non-boundary region decides a relay node in which the sink node is placed directly, decreasing data packet size and transmission delay.

Moreover, in a fuzzy rule base system, various parameters are utilized for electing the region head. Then, the residual energy, amount of neighbors, and distance to sink node are estimated for all nodes in a particular area for the election model. Finally, the assessment of region head selection is based on various conditions, and the possible cases are denoted in below Table 2.

Hence, this model is employed before the cluster technique for enhancing the clustering technique performance without influencing the performance of sensor nodes. Here, the cluster head selection (CHS) is processed with less computational complexity.

Fuzzy TOPSIS-based CHS model

The Fuzzy-TOPSIS approach is devised using multi-criteria decision-making for effectively selecting CH and improving the lifespan of WSN. Here, the sink node takes the decisions according to ranking index values through various

Table 2: Fuzzy rule-based system.

S. No	Amount of neighbor	Residual energy	Base station distance	Possibility to choose region head
1.	High	Low	Far	Less
2.	Low	High	Far	Less
3.	High	High	Far	Medium
4.	Low	Low	Near	Less
5.	High	Low	Near	Medium
6.	Low	High	Near	Medium
7.	High	Low	Near	High

measures. First, the selected CH transmits an advert to its nearby node inside its transmission range. After that, the residual sensor node receives various adverts from dissimilar CH in their transmission range, and it decides to connect with minimum distance CH. This approach ensures that the CH is not altered in each round for decreasing overheads in the setup stage. In addition, the alternations of CH are based on several threshold values. If the chosen CH threshold value is less than other nearby nodes, re-clustering is executed.

The cluster selection method is separated into six stages, random exploitation of sensor node, neighbor node detection, CH selection, CH creation, intra-cluster, inter-cluster multi-hop communication model, and sink mobility with conventional octagonal and random trajectories. The exhaustive process of this model is represented as below.

At first, every sensor node was arranged randomly in WSN for an easy and low-cost exploitation scheme. Once exploitation is completed, the sink node transmits a data control packet in a network, and it includes position information in stage 1.

In stage 2, the neighbor node identification is performed where every sensor node transmits a data control packet in their transmission range based on Carrier Sense Multiple Access (CSMA) approaches. The data control packet involves significant information, like node position and ID information, distance from BS, the average distance among node and nearby node, node density, node energy consumption rate, and residual energy. Normally, there is no information related to its nearby nodes; thus, node density and sink node distance are reserved as vacant in the data control packet. After that, every sensor node updates its neighborhood table and receives the data control packet from nearby nodes.

Consequently, CH selection is executed in stage 3 based on the Fuzzy-TOPSIS approach. The values present in the nearby table are not similar, so the values are normalized to the same range for selecting CH. Afterward, a weighted decision matrix is created through criteria weight assignment to all values of the normalized matrix in which minimum and maximum values are computed. Once the decision matrix is normalized, every value is restored based on rank value and transformed to fuzzy membership functions. The sequence is processed because it is not a simple process for allocating the precise value of the sensor node for every fuzzy membership function. Moreover, separation measures are estimated by n-dimensional Euclidean distance of all alternatives based on Fuzzy Positive Ideal Solution (FPLS) and Fuzzy Negative Ideal Solution (FNIS). At last, the node with a high-rank index in its transmission range is selected as CH, for that rank index is estimated by below equation,

$$R_i = \frac{\mathrm{A}^-}{\mathrm{A}^+ + \mathrm{A}^-} \tag{4}$$

Clustering is formulated in stage 4 in which CH declared itself as CH in its transmission range, and another node present in that area is linked with CH through transmitting join request. Afterward, CH generates TDMA scheduling based on the number of node numbers connected with it. Normally, CH is not altered in each round for minimizing overhead, and the CH changes id depends on the threshold value. Once the selected CH threshold is lesser than other nearby nodes then, re-clustering is executed.

After the successful CH selection and formation, the communication system is performed in stage-5. Here, the threshold-based inter-cluster and intra-cluster communication systems are introduced for permitting a more sensible method. For example, if the node distance from CH is higher than "5 m", another appropriate node is chosen to send data with less energy. Likewise, if the CH distance is higher than "15 m" from BS, another appropriate CH is selected to transmit data with minimal energy.

Finally, the sink node alters its location based on predictable mobility with an octagonal trajectory. Similarly, sink node and CH also randomly shift their locations after every round. Therefore, this model increases the connectivity, reliability, and data rate; as a result, it enables ad-hoc WSN. Moreover, it is employed inconsistent and safety-critical circumstances without performing any maintenance for a particular duration.

Mobile sink-based energy-efficient CHS approach

In this system, a MSEAC system is devised to enhance network lifespan and avoid energy hole issues. This developed model mainly considers below three factors:

every sensor node except the sink node are inactive, mobility of sink node depends on centroid value, and the last one is network needs the same amount of energy to transmit data packets from one node to another node requires semantic channel for communication. The mobility of the sink node is computed through the centroid of CH in this model. Here, a network is considered with a certain number of sensor nodes, distributed randomly. Thus, the network has a particular amount of clusters, and every cluster has the same number of nodes.

Moreover, this method is developed using three stages: preparation stage, setup stage, and steady-state phase. The network involves a predetermined amount of nodes, and it is evenly distributed in the preparation stage. The sink node defines network parameters, like the amount of area for region separation, initial energy nodes, size of observing area, and the number of nodes. At first, every sensor node is allocated with the same quantity of energy. This model separates the sensing region into similar size areas; consequently, nodes are placed randomly in all areas. The network is divided into 4 equal rectangular areas and 8 equal rectangular areas in this scheme. After that, the setup stage is performed in which CH selection, cluster generation, and next-hop selection procedure are processed. Once the network is initialized, the sink is located in the middle position in the monitoring area. Here, the CH location is randomly chosen to produce the initial population in the optimization technique. Afterward, the fitness function is computed, and the best fitness function is considered for choosing efficient CH. Then, the firefly approach is employed for optimizing for identifying nodes with maximum fitness function. The firefly optimization technique is the meta-heuristic model, and the main intent of utilizing the meta-heuristic technique is to offer the best solution with high computational speed. Finally, the steady-state phase is employed in which data transmission is performed. The CH transfers its position to the sink node after placing CH in a network for computing an efficient position. Afterward, the communication process is initiated by transferring sensed data from a cluster member to CH. Moreover, in this structure, CH is dependable for sending data to the sink node. The cluster member utilizes the amount of energy for forwarding data to CH during the communication process. CH consumes energy during collection of received data, obtains the data packet from cluster member, and broadcast the collected data packet to sink node. Every CH communicates with the sink node in two ways, namely CH is communicating to the mobile sink by another CH, and CH can directly transfer data packets to the mobile sink. As a result, multipath fading and free space systems are employed in this technique for avoiding extreme energy consumption.

Hence, the developed MSEAC model performs effectively concerning packet delay, packet delivery ratio (PDR), and network lifespan.

Hybrid HH-SS optimization technique

The Energy Efficient WSN with mobile sink policy based on hybrid Harris Hawk Salp Swarm optimization scheme, termed EE-hHHSS, was developed for energy-efficient routing. This model mainly involves the following three processes: cluster creation, CH selection, and mobile sink movement. Here, energy-efficient scheduling is employed to improve the lifetime of WSN and cluster-based routing for reducing energy consumption. BS is considered a mobile sink in this technique, and the network is classified into various clusters based on the K-medoid approach. Mainly the effective CH is chosen using hybrid Harris Hawk Optimization (HHO) and Salp Swarm Optimization (SSO) model. Energy efficiency is obtained through the identification of optimal mobility trajectory for the mobile sink. Besides, Adaptive Ant Colony Optimization (AACO) scheme-based sink moving policy is devised to find optimal traversal path. In addition, the AACO method utilizes a mobile sink considering CH distance, and because of the short transmission range between CH and mobile sink, consumption of energy is decreased. This AACO technique also decreases the distance between sink nodes and CH and the movable mobile sink model.

In the beginning, cluster generation is obtained by separating the total sensor region into various segments, and the entire amount of sectors are determined by CH. The K-medoid clustering approach is employed for separating the data set into various groups of clusters. Once the cluster is formed, then CH is selected for transmission of data. Every cluster has one CH, and it can be chosen by hybrid harris hawk and salp swarm optimization approach. The hybrid HHO and SSO methods are devised by energy and distance of sensor node in the cluster. Moreover, CH is selected using weight function, and it is established through distance and residual energy between CH and the source hub. Here, residual energy is considered as a member node, and the nodes can broadcast the data to CH. However, CH is selected effectively based on residual energy and cluster center distance (Jagtap and Gomathi 2019).

The Harris Hawks Optimization (HHO) approach is a technically advanced swarm-based approach for global optimization. Mainly, HHO is stimulated through cooperative characteristics and the chasing model of Harris Hawks (HHs), which is called surprise pounce. These hawks attack the prey jointly from different directions in an attempt to make shock to prey. The various chasing models are observed from HH based on the prey escaping prototype and dynamic character. Hence, this technique mathematically imitates patterns and behaviors for devising an optimization approach. Meanwhile, the HHO model includes two stages, namely exploration, and exploitation. HHs are renowned as the greatest or other solutions in the exploration stage, whereas hawks execute surprise jumps to exploit planned prey in the exploitation stage. Here, HHO algorithm parameters are optimized based on Salp Swarm Algorithm (SSA), enhancing convergence rate and reducing complexity for minimizing computational duration. SSA is an optimization approach, which is based on population, and it replicates salp swarm activities. Normally, salps are organisms in the sea with an apparent barrel-shaped body formation. They survive in deep oceans and shift by force of water to find their food, which is ordered as swarms, named salp chains. After that, the mobile sink shifted in the monitored area through multi-hop communication and gathered the data. Furthermore, the moving method for the sensor network is employed for decreasing hot spot issues.

Simulation setup

The execution of this performance study is performed using MATLAB tool with 4 GB RAM, Windows 8 OS with Intel core i-3 processor.

The simulation parameters, evaluation metrics, simulation results, comparative analysis, and comparative discussions are described below.

Simulation parameters

Here, the simulation area, mobile sink speed, cluster size, number of rounds, and number of nodes are considered simulation parameters.

Evaluation metrics

Number of alive nodes

The term alive node is termed several nodes and transmits data to BS after combining data. Moreover, alive nodes are used for computing weights of random numbers.

Delay

Delay is considered through node quality, and it is computed from time consumed by application request for responding.

Energy

Residual energy is defined as the energy summation of every hop, and it specifies remained energy in the nodes. The residual energy must be high, and it is expressed as,

$$B = \frac{1}{h} \sum_{j=1}^{h} E(Z_j) \tag{5}$$

where, h is the number of hops and $E(Z_j)$ is the energy of jth hop.

PDR

PDR is termed as the ratio of the received data packet and the transmitted data packet, and it is used for computing routing efficiency.

$$\mathrm{PDR} = \frac{\text{Received data packet}}{\text{Sent data packet}} \tag{6}$$

Simulation result

The simulation output of mobile sink-based WSN is portrayed in Figure 2. Here, the black stared line represents the BS, the black line with the red circle specified CH, and the red circle indicates nodes.

Comparative review

In this section, the comparative review of various methods, like optimizing LEACH clustering model (Mottaghi and Zahabi 2015), the hybrid method using fuzzy logic and mobile sink (Kaur and Kaur 2017), Fuzzy TOPSIS-based CHS technique (Khan, Bilal, and Young 2018), mobile sink-based energy-efficient CHS system (Chauhan and Soni 2019), and Hybrid HH-SS optimization scheme (Srinivas and Amgoth 2020) are included. The comparative review is carried out using various nodes, simulation area, sink speed, cluster size, and several rounds.

Analysis using nodes

The analysis using a various number of nodes with regards to alive nodes, delay, PDR, and residual energy is

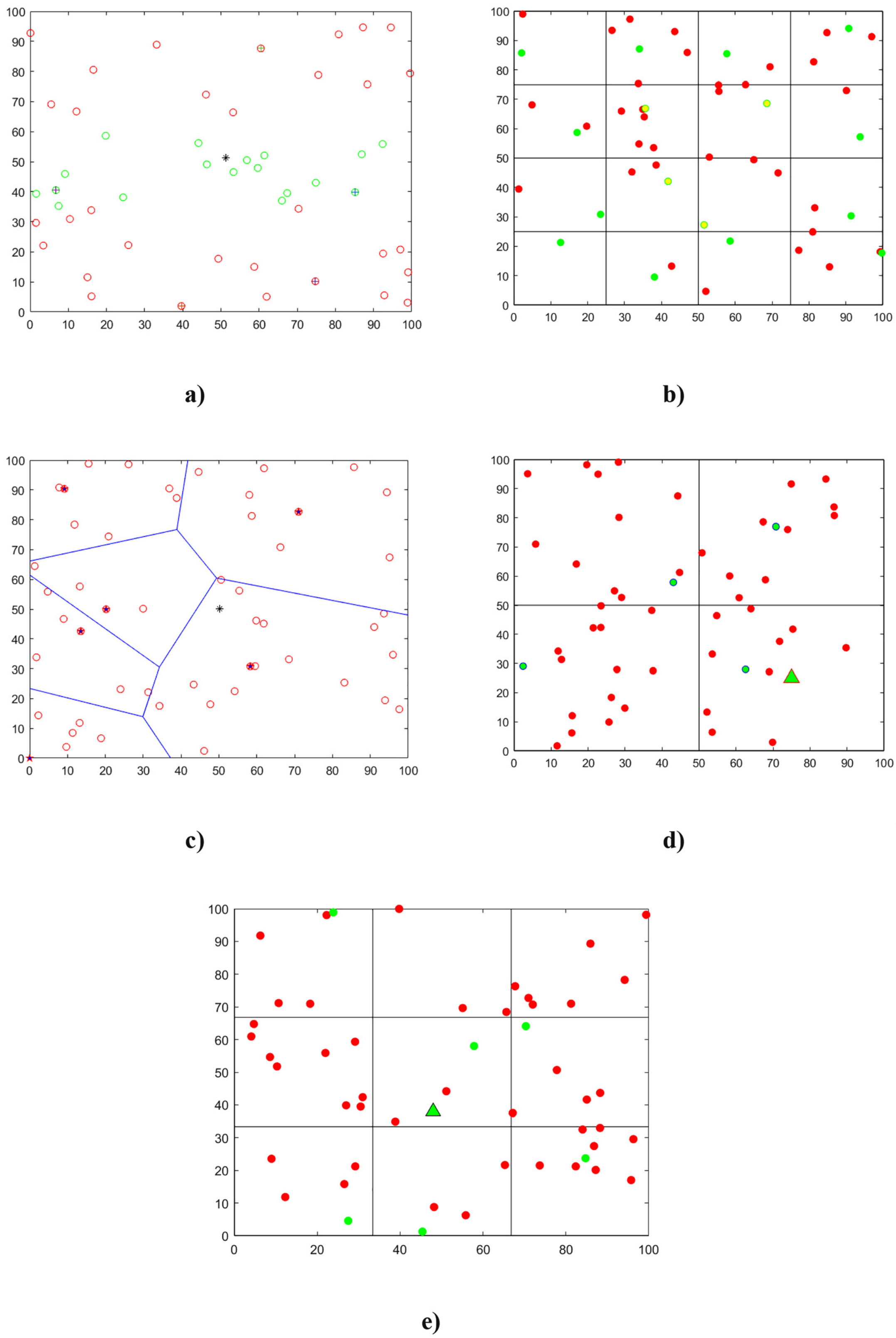

Figure 2: Simulation results of a) LEACH clustering model, b) hybrid method using fuzzy logic and mobile sink, c) Fuzzy TOPSIS-based CHS technique, d) mobile sink-based energy efficient CHS system, e) Hybrid HH-SS optimization scheme

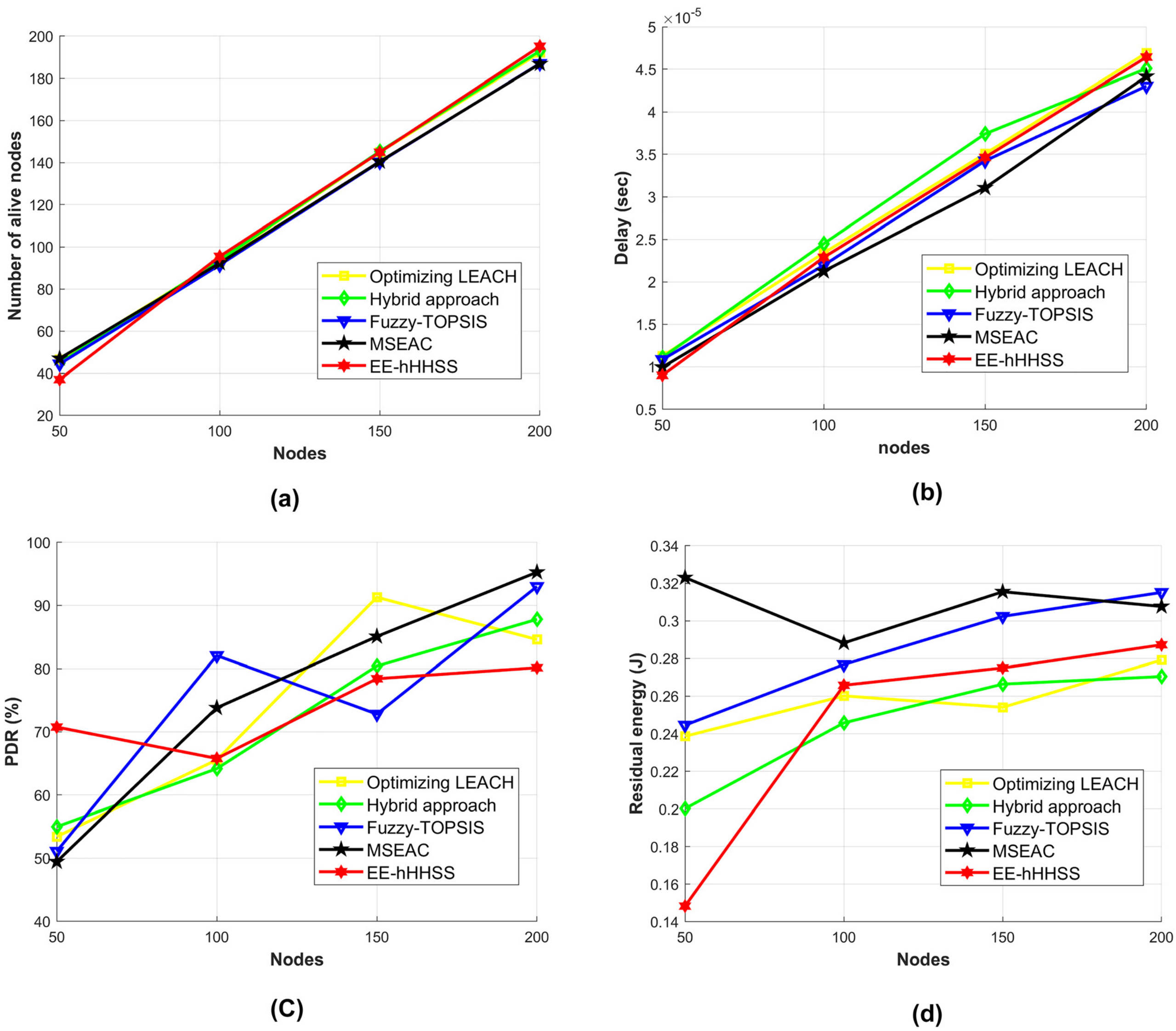

Figure 3: Analysis based on number of nodes concerning (a) alive nodes, (b) delay, (c) PDR, and (d) residual energy.

represented in Figure 3. The analysis using alive nodes by varying number of nodes is displayed in Figure 3a. The number of alive nodes computed by various optimizing LEACH clustering, the hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization techniques are 93.27, 93.69, 91.44, 92.31, and 95.50 for 100th node. The analysis of delay term using various numbers of nodes is shown in Figure 3b. The delay value is estimated by various methods, such as optimizing LEACH clustering approach is 2.33×10^{-5} s, hybrid method using fuzzy logic and mobile sink is $2.44 \times 10{-}5$ s, Fuzzy TOPSIS-based CHS method is $2.19 \times 10{-}5$ s, mobile sink-based energy-efficient CHS model is $2.12 \times 10{-}5$ s, and hybrid HH-SS optimization approach is $2.28 \times 10{-}5$ s in 100th node. Furthermore, the analysis regarding PDR through changing the number of nodes is presented in Figure 3c. At node 100, PDR values calculated by optimizing LEACH clustering, the hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization approaches are 65.57, 64.17, 82.06, 73.81, and 65.78%. Similarly, analysis-based residual energy concerning various nodes is portrayed in Figure 3d. At the 100th node, residual energy obtained by various schemes, like optimizing LEACH clustering approach is 0.260J, the hybrid method using fuzzy logic and mobile sink is 0.245J, Fuzzy TOPSIS-based CHS method is 0.276J, mobile sink-based energy-efficient CHS model is 0.288J, and hybrid HH-SS optimization approach is 0.265J.

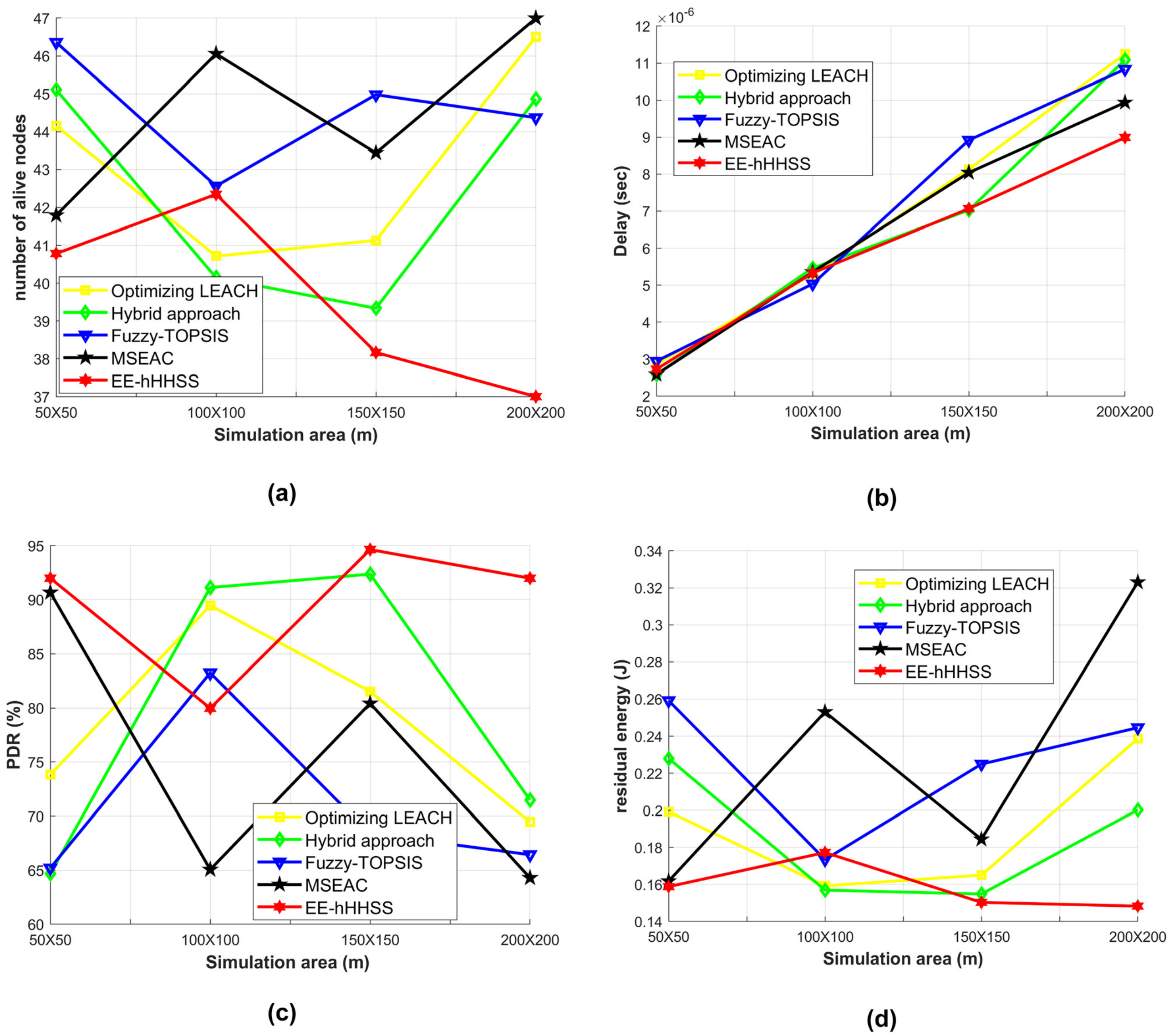

Figure 4: Analysis using various simulation areas in terms of (a) alive nodes, (b) delay, (c) PDR, and (d) residual energy.

Analysis using simulation area

The analysis based on simulation area in terms of alive nodes, delay, PDR and residual energy is presented in Figure 4. The analysis using alive nodes through changing simulation area is portrayed in Figure 4a. At 150×150 size, alive node value attained by different methods, like optimizing LEACH clustering approach is 41.13, hybrid method using fuzzy logic and mobile sink is 39.33, Fuzzy TOPSIS-based CHS method is 44.98, mobile sink-based energy efficient CHS model is 43.44 and hybrid HH-SS optimization approach is 38.16. Moreover, the analysis with respect to delay using various simulation areas is denoted in Figure 4b). In 150×150 size, delay values computed by optimizing LEACH clustering, hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization approaches are 8.13×10^{-5} s, 7.02×10^{-5} s, 8.92×10^{-5} s, 8.04×10^{-5} s, and 7.06×10^{-5} s. The analysis of PDR using various simulation areas is shown in Figure 4c. The PDR value calculated by several models, like optimizing LEACH clustering approach is 81.52%, a hybrid method using fuzzy logic and mobile sink is 92.36%, Fuzzy TOPSIS-based CHS method is 68.38%, mobile sink-based energy-efficient CHS model is 80.42%, and hybrid HH-SS optimization approach is 94.64% in 150×150 dimension. Likewise, the analysis using residual energy by changing sizes of simulation area is displayed in

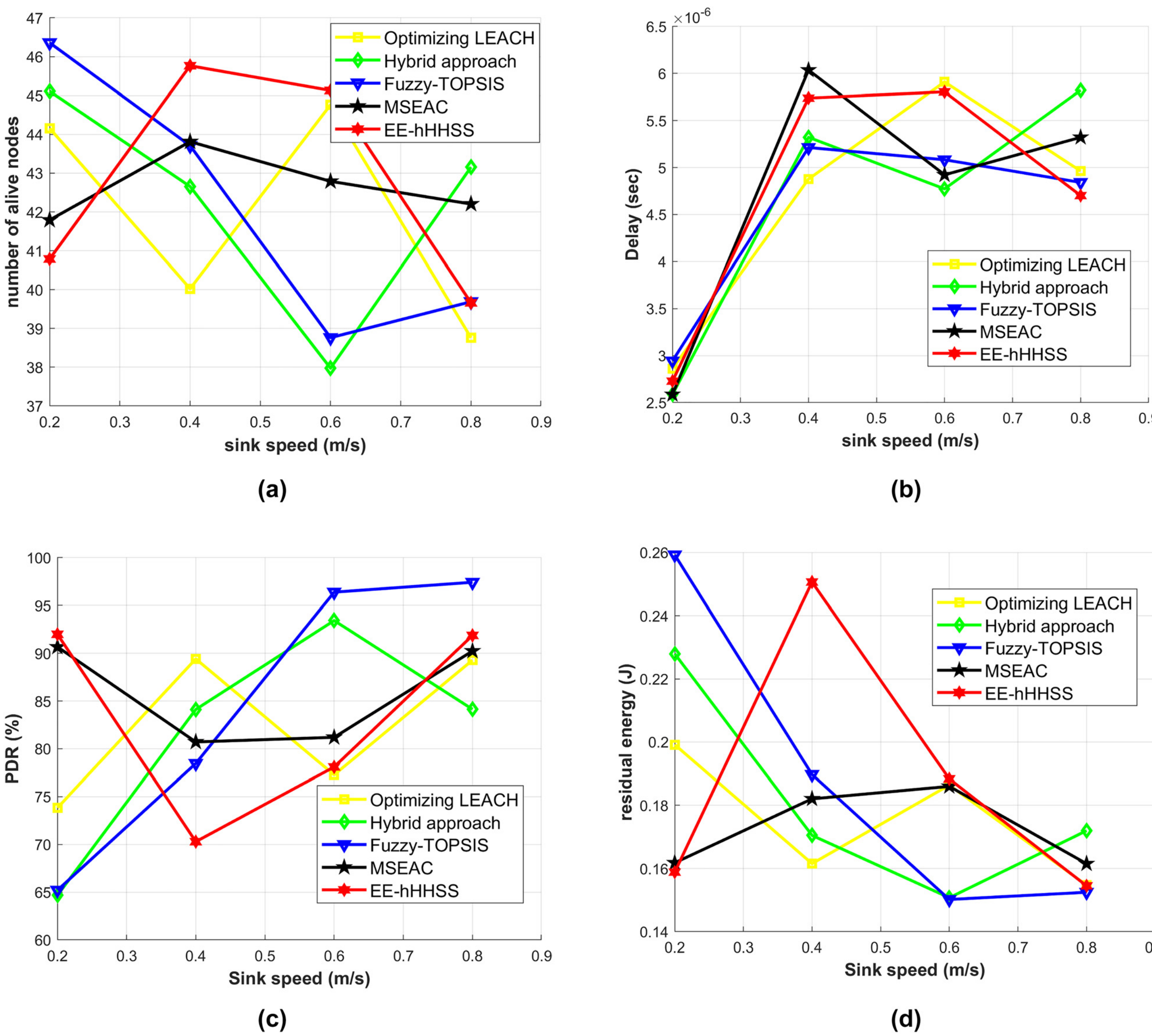

Figure 5: Analysis using sink speed with respect to (a) alive nodes, (b) delay, (c) PDR and (d) residual energy.

Figure 4d. The residual energy estimated by various optimizing LEACH clustering, the hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization techniques are 0.165J, 0.154J, 0.224J, 0.184J, and 0.150J for 150 × 150 size of simulation area.

Analysis using sink speed

The analysis using various sink speeds in terms of alive nodes, delay, PDR, and residual energy is represented in Figure 5. The analysis based on alive nodes by varying sink speed is displayed in Figure 5a. The number of alive nodes computed by various optimizing LEACH clustering, the hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization techniques are 44.15, 45.10, 46.35, 41.79, and 40.78 for sink speed of 0.6. The analysis of delay term by varying sink speed is showed in Figure 5b. The delay value is estimated by various methods, such as optimizing LEACH clustering approach is 5.91×10^{-5} s, the hybrid method using fuzzy logic and mobile sink is 4.77×10^{-5} s, Fuzzy TOPSIS-based CHS method is 5.08×10^{-5} s, mobile sink-based energy-efficient CHS model is 4.92×10^{-5} s, and hybrid HH-SS optimization approach is 5.80×10^{-5} s at 0.6 sink speed. Furthermore, the analysis with regards to

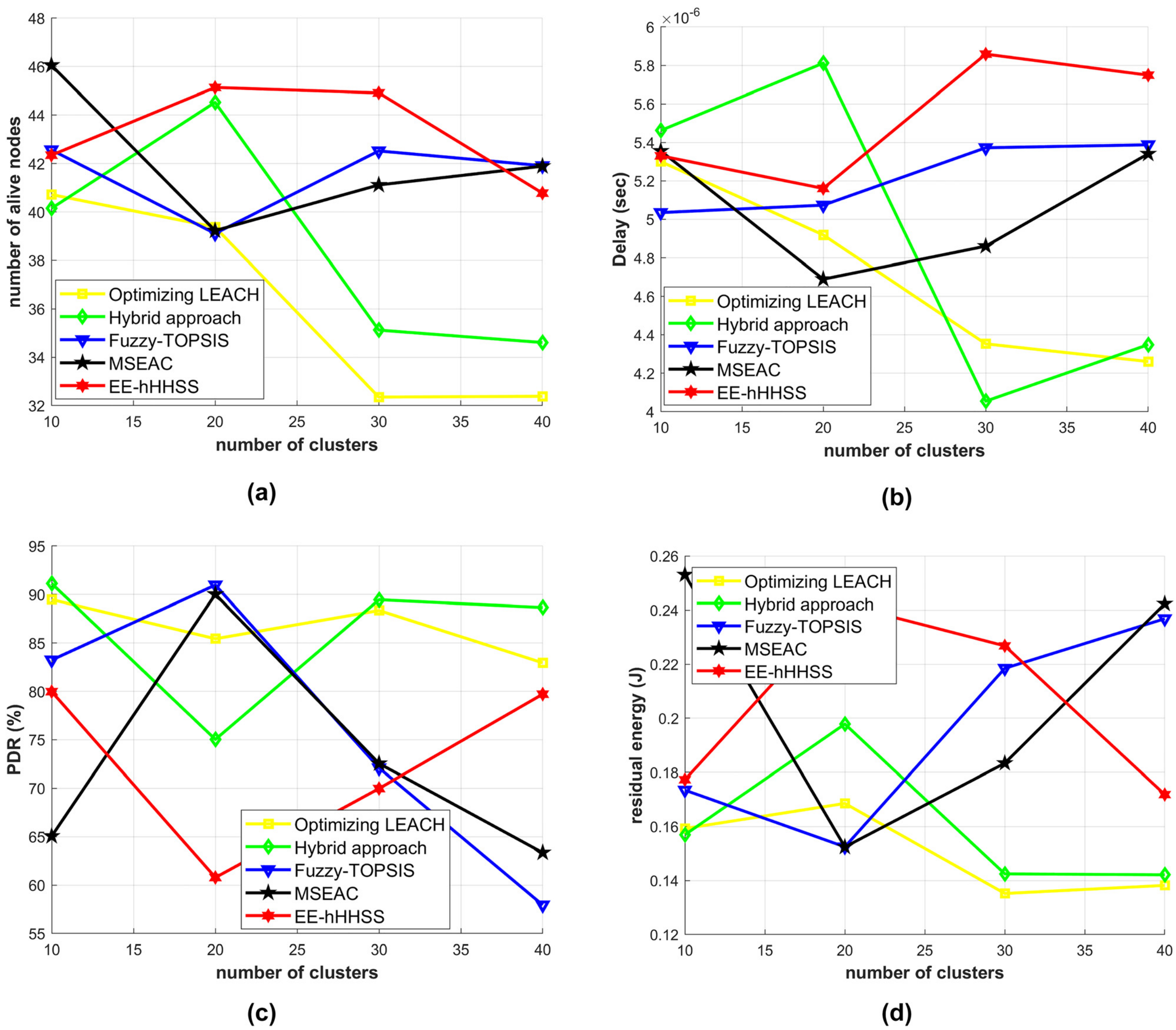

Figure 6: Analysis based on cluster size in terms of (a) alive nodes, (b) delay, (c) PDR and (d) residual energy.

PDR by changing the speed of the sink is presented in Figure 5c. At sink speed of 0.6, the PDR values calculated by optimizing LEACH clustering, the hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization approaches are 77.27, 93.43, 96.38, 81.19, and 78.10%. Similarly, analysis-based residual energy concerning various sink speeds is portrayed in Figure 5d. In 0.6 sink speed, residual energy obtained by various schemes, like optimizing the LEACH clustering approach, is 0.186J. The hybrid method using fuzzy logic and mobile sink is 0.150J, Fuzzy TOPSIS-based CHS method is 0.150J, mobile sink-based energy-efficient CHS model is 0.186J, and hybrid HH-SS optimization approach is 0.188J.

Analysis using cluster size

The analysis based on various cluster sizes in terms of alive nodes, delay, PDR, and residual energy is presented in Figure 6. The analysis using alive nodes by changing cluster size is portrayed in Figure 6a. At 40th cluster size, alive node attained by different methods, like optimizing LEACH clustering approach is 32.38, the hybrid method using fuzzy logic and mobile sink is 34.60, Fuzzy TOPSIS-based CHS method is 41.91, mobile sink-based energy-efficient CHS model is 41.89, and hybrid HH-SS optimization approach is 40.77. Moreover, the analysis concerning delay using various cluster sizes is denoted in Figure 6b. When the cluster size is 40, delay values are computed by optimizing LEACH clustering, the hybrid

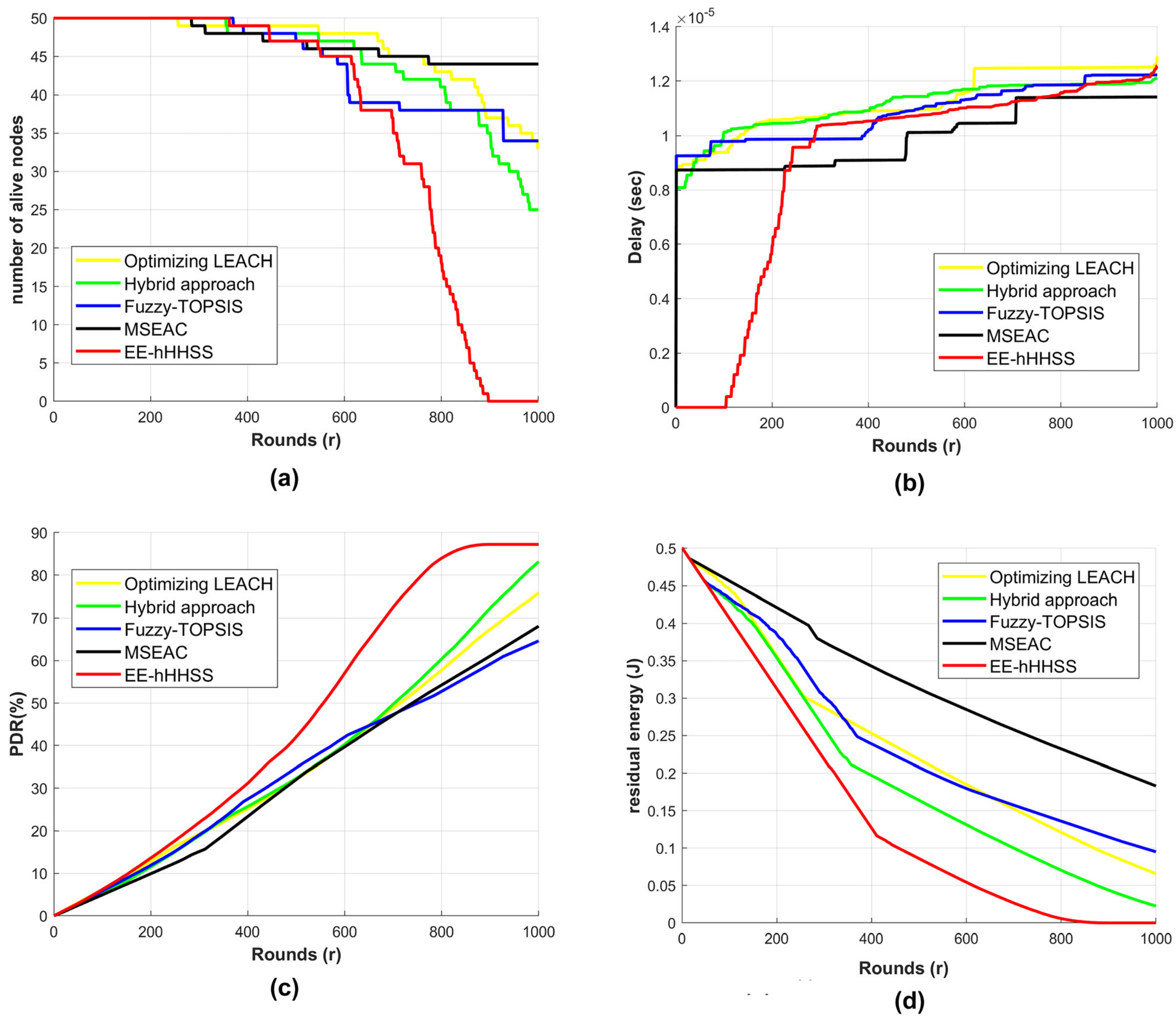

Figure 7: Analysis using various rounds concerning (a) alive nodes, (b) delay, (c) PDR, and (d) residual energy.

method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization approaches are 4.26×10^{-5} s, 4.35×10^{-5} s, 5.39×10^{-5} s, 5.34×10^{-5} s, and 5.75×10^{-5} s. The analysis of PDR using cluster size is shown in Figure 6c. The PDR value calculated by several models, like optimizing LEACH clustering approach is 82.95%, the hybrid method using fuzzy logic and mobile sink is 98.65%, Fuzzy TOPSIS-based CHS method is 57.94%, mobile sink-based energy-efficient CHS model is 63.35%, and hybrid HH-SS optimization approach is 79.91% for cluster size is 40. Likewise, the analysis using residual energy by changing the cluster sizes is displayed in Figure 6d. The residual energy estimated by various optimizing LEACH clustering, the hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization techniques are 0.138J, 0.142J, 0.236J, 0.242J, and 0.171J for 40th cluster size.

Analysis using rounds

The analysis using different amount of rounds in terms of alive nodes, delay, PDR and residual energy is represented in Figure 7. The analysis based on alive nodes by varying number of rounds is displayed in Figure 7a. The number of alive node computed by various optimizing LEACH clustering, the hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization techniques are 49, 48, 47, 47, and 47 at 500th round. The analysis of

Table 3: Comparative analysis.

	Metrics/Methods	Optimizing LEACH	Hybrid approach	Fuzzy TOPSIS	MSEAC	EE-hHHSS
Nodes	Alive nodes	192.10	192.96	187	186.85	195.17
	Delay (s)	4.69×10^{-5}	4.50×10^{-5}	4.30×10^{-5}	4.41×10^{-5}	4.64×10^{-5}
	PDR (%)	84.60	87.80	93	95.27	80.14
	Residual energy (J)	0.279	0.270	0.315	0.307	0.287
Simulation area	Alive nodes	192.10	192.96	187	186.85	195.17
	Delay (s)	1.12×10^{-5}	1.10×10^{-5}	1.08×10^{-5}	9.93×10^{-5}	8.99×10^{-5}
	PDR (%)	84.60	87.80	93	95.27	80.14
	Residual energy (J)	0.279	0.270	0.315	0.307	0.287
Sink speed	Alive nodes	38.75	43.15	39.68	42.20	39.66
	Delay (s)	4.96×10^{-5}	5.82×10^{-5}	4.84×10^{-5}	5.32×10^{-5}	4.70×10^{-5}
	PDR (%)	89.28	84.13	97.41	90.24	91.87
	Residual energy (J)	0.154	0.171	0.152	0.161	0.154
Cluster size	Alive nodes	32.38	34.60	41.91	41.89	40.77
	Delay (s)	4.26×10^{-5}	4.34×10^{-5}	5.3×10^{-5}	5.34×10^{-5}	5.74×10^{-5}
	PDR (%)	82.95	88.65	57.94	63.35	79.71
	Residual energy (J)	0.138	0.142	0.236	0.242	0.171
Rounds	Alive nodes	43	41	38	44	18
	Delay (s)	1.24×10^{-5}	1.18×10^{-5}	1.18×10^{-5}	1.14×10^{-5}	1.16×10^{-5}
	PDR (%)	57.74	60.36	52.74	54.23	84
	Residual energy (J)	0.121	0.070	0.136	0.232	0.005

delay term using different numbers of rounds is showed in Figure 7b. The delay value is estimated by various methods, such as optimizing LEACH clustering approach is 1.09×10^{-5} s, the hybrid method using fuzzy logic and mobile sink is 1.14×10^{-5} s, Fuzzy TOPSIS-based CHS method is 1.10×10^{-5} s, mobile sink-based energy-efficient CHS model is 1.01×10^{-5} s, and hybrid HH-SS optimization approach is 1.07×10^{-5} s at 500th round. Furthermore, the analysis regarding PDR by varying number of rounds is presented in Figure 7c. At the 500th round, the PDR values were calculated by optimizing LEACH clustering, the hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization approaches are 32.08, 32.33, 34.80, 32.06, and 42.03%. Similarly, analysis based on residual energy with respect to the various number of rounds is portrayed in Figure 7d. When the round is 500, residual energy obtained by various schemes, like optimizing LEACH clustering approach is 0.218J, the hybrid method using fuzzy logic and mobile sink is 0.163J, Fuzzy TOPSIS-based CHS method is 0.207J, mobile sink-based energy efficient CHS model is 0.312J and hybrid HH-SS optimization approach is 0.085J.

Comparative discussion

Table 3 represents the comparative discussion of various techniques based on the alive node, delay, PDR, and residual energy by changing nodes, simulation area, sink speed, cluster size, and rounds. The analysis using sink speed for various techniques concerning alive nodes, delay, PDR, and residual energy is explained as follows. The alive node obtained by various methods, such as optimizing LEACH clustering, the hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization approaches are 38.75, 43.15, 39.68, 42.20, and 39.66 for sink speed of 0.8. In addition, the delay value attained by various schemes, like optimizing LEACH clustering approach is 4.96×10^{-5} s, the hybrid method using fuzzy logic and mobile sink is 5.82×10^{-5} s, Fuzzy TOPSIS-based CHS method is 4.84×10^{-5} s, mobile sink-based energy-efficient CHS model is 5.32×10^{-5} s, and hybrid HH-SS optimization approach is 4.70×10^{-5} s in 0.8 sink speed. Moreover, PDR values obtained by various techniques, such as optimizing LEACH clustering, the hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS, mobile sink-based energy-efficient CHS, and hybrid HH-SS optimization approaches are 89.28, 84.13, 97.4, 90.24 and 91.87% in 0.8 sink speed. Similarly, residual energy obtained by various schemes, like optimizing LEACH clustering approach is 0.154J, a hybrid technique based on fuzzy logic and mobile sink is 0.171J, Fuzzy TOPSIS-based CHS scheme is 0.152J, mobile sink-based energy-efficient CHS technique is 0.161J, and hybrid HH-SS optimization model is 0.154J in 0.8 sink speed. Thus, from the below table, it is well cleared that EE-hHHSS approach achieves high alive node, EE-hHHSS model has less delay, the Fuzzy TOPSIS scheme obtains high PDR rate, and the hybrid approach based on fuzzy logic, and mobile sink achieves high residual energy.

Conclusion

In this paper, performance and effectiveness energy-aware routing protocols in mobile sink-based WSN are analyzed and reviewed. This research is performed to analyze and justify the effectiveness of energy-aware routing protocols in mobile sink-based WSNs. The mobile sink-based WSN methods should achieve less energy consumption and improve network lifetime. Here, the mobile sink-based WSN methods, such as optimizing LEACH clustering model, the hybrid method using fuzzy logic and mobile sink, Fuzzy TOPSIS-based CHS scheme, mobile sink-based energy-efficient CHS technique, and hybrid HH-SS optimization approach are considered for simulation. Along with this, these five methods are elaborated separately and estimated the performance analysis. The performance analysis is performed based on various parameters, like residual energy, alive nodes, PDR, and delay. In addition, the analytical study is performed using the number of nodes, simulation area, mobile sink speed, cluster size, rounds of experimentation. From this analysis and review, the EE-hHHSS model obtains a high alive node.

Author contributions: All the authors have accepted responsibility for the entire content of this submitted manuscript and approved submission.

Research funding: None declared.

Conflict of interest statement: The authors declare no conflicts of interest regarding this article.

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