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Optimized Energy – Efficient Path Planning Strategy in WSN With Multiple Mobile Sinks

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ABSTRACT Recently, wireless sensor networks (WSNs) were perceived as the foundation infrastructure that paved the way to the emergence of the Internet of Things (IoT). However, a challenging issue exists when WSNs are integrated into the IoT because of high energy consumption in their nodes and poor network lifespan. Therefore, the elementary discussions in WSN are energy scarcity in sensor nodes, sensors' data exchange, and routing protocols. To address the aforesaid shortcomings, this paper develops an optimized energy-efficient path planning strategy that prolongs the network lifetime and enhances its connectivity. The proposed approach has four successive procedures: initially, the sensing field is partitioned into equal regions depending on the number of deployed mobile sinks that eliminate the energy-hole problem. A new heuristic clustering approach called stable election algorithm (SEA) is introduced to minimize the message exchange between sensor nodes and prevent frequent cluster heads rotation. A sojourn location determination algorithm is proposed based on the minimum weighted vertex cover problem (MWVCP) to find the best position for the sinks to stop and collect the data from cluster heads. Finally, three optimization techniques are utilized to evaluate the optimized mobile sinks' trajectories using multi-objective evolutionary algorithms (MOEAs). Whilst the performance of the developed work was evaluated in terms of cluster heads number, network lifetime, the execution time of the sinks' sojourn locations determination algorithm, the convergence rate of optimization techniques, and data delivery. The simulation scenarios conducted in MATLAB and the obtained results showed that the introduced approach outperformed comparable existing schemes. It succeeded in prolonging the network lifetime up to 66% compared to existing routing protocols.

INDEX TERMS Ant colony optimization, clustering protocol, genetic algorithm, IoT, M2M, multiple mobile sinks, optimized path, routing protocol, simulated annealing, stable election algorithm, WSN.

I. INTRODUCTION

Wireless sensor network (WSN) is the preferred term adopted by the academic scholars to describe the ''wireless sensor and control network'' or ''wireless sensor and actuator network'' [1]. WSN is characterized by small-sized devices called sensor nodes which have the ability to sense the surrounding environment and send the sensory data to a centralized base station (sink node). The sensor nodes are battery-powered and randomly distributed in the area of interest for monitoring and relaying the data of the desired phenomenon wirelessly in a multi-hop communication [2]. WSNs consist of a tremendous number of sensor nodes that communicate with each other to form the network. The sensor network may be semi or fully connected because the sensor nodes are separated by a geographical distance when they are deployed over a wide geographical area [3], [4].

Autonomous wireless sensors serve as the gist of the WSNs, and therefore, WSNs can be identified as one of the Internet of things (IoT) pillars. The IoT is a recognized paradigm that exemplifies the interrelation of ubiquitous computing resources with diverse components in

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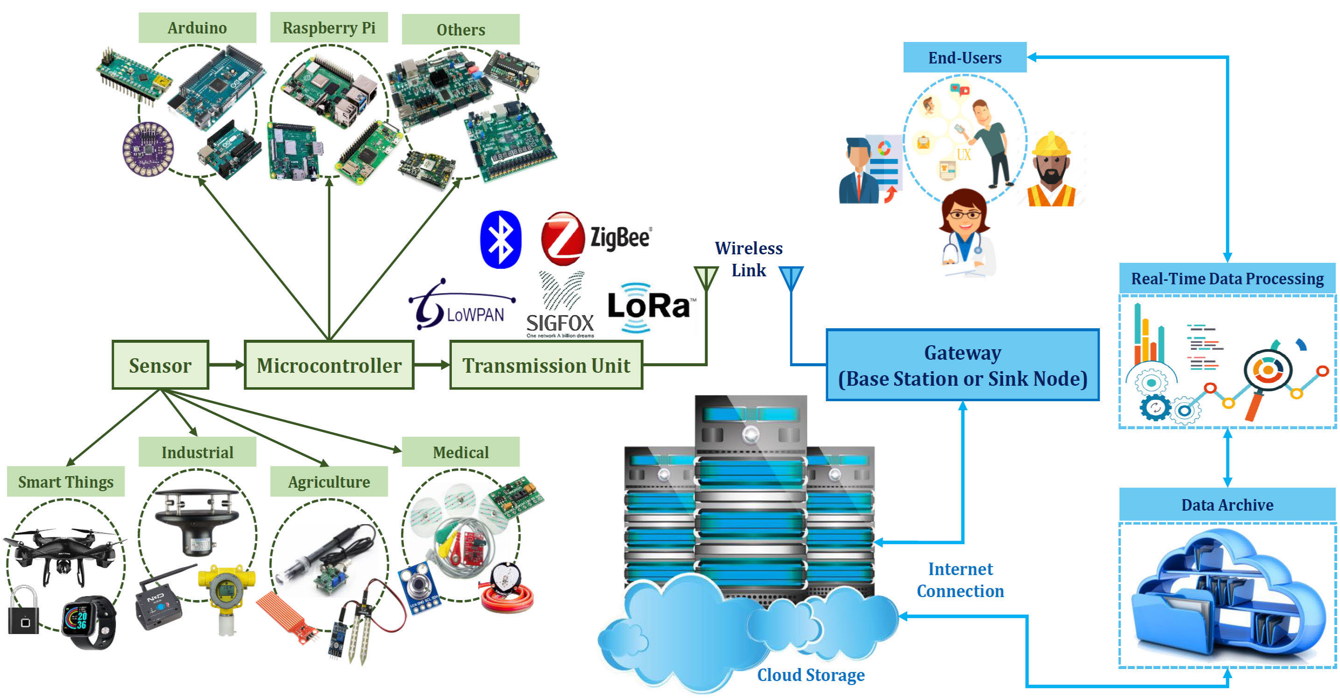


FIGURE 1. A simplified IoT system.

a dynamic environment. Different technologies can be utilized to implement assorted IoT applications such as (i) machine-to-machine (M2M) communication that enables two or more devices to communicate with each other without human intervention, (ii) context-aware computing that senses the surrounding environment and alters system behavior accordingly, and (iii) low power and low data rate wireless communication (e.g., radio frequency identification (RFID), Zigbee, etc.) that provides short-range communication at minimum power consumption. The common examples of IoT application including but not limited to wearable devices like a smartwatch for healthcare applications, a smart lock for smart home appliances, and drones or smart vehicles for domestic industrial automation [5], [6]. The international telecommunication union (ITU) depicted a comprehensive vision of IoT as the transformation from anytime connectivity for anyone at anywhere to the connectivity for anything [7].

Fig. 1 illustrates a simplified block diagram for IoT system. The sensors are used to amass the sensory data at particularized time intervals. The microcontroller formulates the data packets that include protocol stack control messages to proceed with medium access control operations. The transmission unit performs packet modulation and transmission over the wireless link. The gateway (base station or sink node) has two communication paths, the first is a low-power wireless link to communicate with the sensor nodes, and the second is an Internet connection to store and/or retrieve the data from the cloud. The gateway has an infinite energy source and may execute complex algorithms to curtail the number of data packets before being stored in the cloud. Finally, the sensory data will be transferred to the end-user for further data analysis where the reports are generated [8].

As stated earlier, the sensor nodes are battery-powered, and it is not feasible to regularly replace their batteries, especially for a large number of sensor nodes, while the gateway may be mains powered. The report of Ericsson mobility articulated that number of IoT-connected devices will increase from seven billion in 2017 to twenty billion in 2023 with 19% annual growth [9]. Therefore, significant efforts are required in order to replace and safely recycling this number of disposable batteries. Accordingly, the energy-efficient techniques are demanding in order to prolong the sensor node lifetime as the sensor nodes anticipate to operate for a long lifespan without human intervention and any maintenance.

The rest of the paper is formulated as follows: Section II elucidates the energy hole (hotspot) problems and the sink mobility types. While Section III scrutinizes the state-of-the-art researches that are available in the literature and are relevant to the introduced approach. In Section IV, a comprehensive demonstration of the proposed approach is illustrated. Section V presents a detailed discussion regarding the acquired results. Finally, Section VI suggests some future research directions and the paper is concluded in Section VII.

II. SINK NODE IN WIRELESS SENSOR NETWORKS

In general, the sensor nodes are deployed in a harsh environment that makes it difficult to recharge or replace the nodes' batteries when they are depleted during nodes operation. Several problems may exist when nodes are drained out of power, such as communication holes and coverage holes.

Therefore, several energy-efficient techniques have been conducted in order to maintain the battery power and prolong the node lifetime [10]. Duty-cycle scheduling is one of these techniques that enables the sensor node to perform sleep mode periodically without affecting the WSN operation [11]. Another technique is utilizing an energy-efficient routing mechanism that balances the energy consumption in every sensor node [12], [13]. While data aggregation mechanism is used to integrate similar or different multiple sensory data into a single packet, and hence a reduction in data transmission is achieved and node lifetime is extended as well [14]. The other energy-saving technique is to deploy mobile sensors that travel across the sensor field and change their locations depending on the energy level of the other nodes. A compromised approach is to adopt a mobile sink instead of a static sink or mobile sensor nodes. The mobile sink changes its location in the sensing area to gather the data from the sensor nodes and expand network lifespan. It is worth noting that most of the aforementioned energy-efficient techniques can exist together in the same sensing field [10], [15].

The sensor node depletes abundant energy to perform data sensing and data transmission towards the sink node. The sensor nodes closer to the sink node exhaust their residual energy faster than the farther nodes due to heavy data traffic while relaying the other sensors' data. Sensor node deaths around the sink node will cause topology disruption and lowering sensing coverage. This situation is called a hotspot problem and leads to isolating the sink node and hindering the aggregation of the sensory data across the network. A mobile sink is employed to alleviate the hotspot problem by visiting every sensor node in the sensor field during the data collection phase. However, the sink node traveling may be time-consuming, especially in large sensor fields, and hence some packets may be dropped by the sensor nodes due to finite buffer size. Therefore, effective delay-aware mechanisms are in demand to reduce packet losses and extend the network lifetime. Rendezvous points technique is one of the mobile sink scheduling techniques that reduces the data collection delay in WSNs. They are sensor nodes or specific locations in the sensor field in which the mobile sink visits while collecting sensor field data [16], [17]. The mobility patterns of the sink node depend on the application area where the WSN being deployed.

A good summary of the classification of sink mobility patterns has been provided in [3] and [18]:

1) Random mobility: it is the simplest form of mobility in WSN as the mobile sink does not need any network information. Unfortunately, this pattern does not provide optimal lifetime enhancement due to frequent update of sink position and route reconstruction accordingly;
2) Predictable mobility: it is also called deterministic mobility as the sensor nodes can predict the arrival time and position of the mobile sink because the mobile sink visits certain nodes periodically to collect the data;
3) Controlled mobility: it is also called optimized mobility as the data collection path of the sink node will be determined based on network parameters such as nodes residual energy, event location, and sink speed. In addition, the mobile sink visits certain nodes at a particular time interval and starts to collect the sensed data until the node's buffer becomes empty.

The existing challenges of the static sink in multi-hop and dense WSN led to utilize the mobile sink for collecting and disseminating sensory data. Accordingly, the main advantages of using mobile sinks in WSN include [19]:

- Improvement network reliability due to reducing the contention and collisions while accessing the wireless medium by collecting the nodes' data in single or finite hop transmissions;
- Improve the hotspot region by reducing the dependency on the relay nodes that are closer to the static sink, resulting in extending the network lifetime;
- Enhance network connectivity as the mobile sinks can collect the data from the isolated sensor nodes;
- Sporadic network architecture indicates lowered application cost because a limited number of nodes are required, and the mobile elements are available such as cars, trains, wildlife, etc.

III. RELATED WORKS

The available researches that were handling the hotspot (energy hole) problem can be assorted into two main categories based on the sink mobility: static (stationary) sink and mobile (movable) sink. The previous works are done in the mobile sink that solved the network performance degradation issues can be subdivided into the single mobile sink and multiple mobile sinks. Therefore, employing multiple mobile sinks in WSNs could improve network performance by sharing the network overhead among the deployed sinks. Over the past decades, the researchers proposed different approaches to extend the WSN lifespan. Among them, the most effective strategy is the determination of the mobile sink path to equalize the sensor nodes' energy depletion. Hence, the mobile sink path determination received considerable attention from academic scholars and researchers due to its importance in developing IoT-based real-world applications. In the recent literature, the sink mobility problem classified into two main categories: (1) optimized mobile sink path without clustering, and (2) optimized mobile sink path with clustering.

A. OPTIMIZED MOBILE SINK PATH WITHOUT CLUSTERING

Deng *et al.* [20] introduced an online algorithm that solved the issue of data gathering in sensor field with multiple mobile sinks by primal-dual approach. The main aim of their approach was to maximize the data transmitted by the sensor nodes. The online algorithm performed real-time decisions for the newly employed mobile sink based on the new sink data capacity and location.

Thomas and Mathew [21] presented an intelligent method to locate the best route for the mobile sink based on a modified travel salesman problem to gather the data from the sensor nodes. In their proposed approach, the mobile sink node traveled along the circle's chord that served as the maximum communication range of the sensor nodes. Their intelligent algorithm found out the optimal locations of the aforementioned chords along the mobile sink path.

Cheng *et al.* [22] developed a fast and efficient broadcast (FEB) protocol for asynchronous WSNs with mobile sink. The sink traveled along the sensing field in a predefined path depending on the coverage information that was shared with the sensor nodes before starting the transmission process. The authors argued that their proposed approach minimized the broadcast delay and reduced the energy consumption.

Sun *et al.* [23] presented hybrid positive and negative particle swarm optimization algorithm (HPNPSOA) to determine the optimal path for multiple mobile sinks and stop positions in hexagonal grids. The authors concluded that their proposed approach eliminated the energy hole problem, reduced network latency, and prolonged the network lifetime.

Gharaei *et al.* [24] developed energy-efficient mobile-sink sojourn location optimization (EMSLO) scheme for heterogeneous home network. Robovac is employed as a mobile sink, and the sojourn location was optimized to solve the energy hole and network coverage problems. The obtained results from their approach enhanced the coverage time and improved the network lifetime.

Kumar and Prasanth [25] proposed an optimized path selection technique for mobile sink based on weighted rendezvous planning (WRP). Their approach employed Q-learning-based adaptive zone partition method in order to partition the sensing field into small regions. The particle swarm optimization (PSO) algorithm was used to evaluate the optimum path from the rendezvous to the mobile sink. The authors argued that the network lifetime was extended because the energy consumption was reduced in multi-hop transmissions.

Byun [26] proposed a cost balancing algorithm for multiple mobile data collectors. His proposed algorithm aimed at achieving uniform delay while gathering the data from the stationary sensor nodes. The sensor field was partitioned into several grids where the mobile collectors traveled to collect the data. The mobile sinks' trajectories for the multiple mobile collectors were determined based on the traveling distance and the energy consumption of the nodes. The author argued that the network lifetime was extended by balancing the energy depletion in sensor nodes.

Zhong *et al.* [27] introduced a hyper-heuristic framework (HHF) that intelligently organized the mobile sink movements based on heuristic rules. Based on the prior knowledge of their networks, predefined low-level heuristics and training networks were designed and assigned as input to the genetic programming (GP) algorithm to automatically built-up high-level heuristics. As a result, the GP algorithm produced the heuristics with the highest fitness.

Wang *et al.* [28] introduced a trajectory scheduling method based on coverage rate for multiple mobile sinks (TSCR-M) that utilized particle swarm optimization (PSO) to find the optimal rendezvous points for the mobile sinks. TSCR-M integrated the genetic algorithm (GA) for scheduling the traveling trajectory of the multiple sinks. The authors argued that the network lifetime enhanced due to the reduction in node's energy consumption.

Jain *et al.* [29] proposed an event-based data transmission scheme called delay-aware green routing protocol (DGRP) that created virtual infrastructure by introducing multiple rings within the sensing field. The location information updates of the mobile sink in the DGRP scheme were limited to the sensor nodes that belonged to the designated ring only. The authors argued that the DGRP employed a single mobile sink and showed a remarkable improvement in terms of throughput and nodes' energy consumption.

Lin *et al.* [30] aimed at prolonging the network lifespan of heterogeneous WSN by adopting mobile sink. They introduced DDCF as a data collection mechanism that primarily comprised of two phases: data collection points and tree topology construction that were executed during each simulation round. The authors argued that the introduced mechanism improved the lifespan of the WSN.

B. OPTIMIZED MOBILE SINK PATH WITH CLUSTERING

Zhong and Ruan [31] proposed an energy-efficient routing technique for WSN utilizing multiple mobile sinks. The authors studied the effect of mobile sink numbers on network performance when the clustering method was used to group the sensor nodes across the erring field. The authors argued that the optimum number for mobile sinks was three, and there is no need to deploy more sinks as the sink node cost increased.

Koosheshi and Ebadi [32] presented multiple mobile sinks path determination strategy for WSN employed clustering technique. Their proposed approach divided the sensor nodes into unequal clusters based on fuzzy logic. The sensing field was divided into 16 equal regions, and the average residual energy was calculated in each region to determine the mobile sinks' optimum routes. The authors showed that their introduced approach decreased energy consumption and solved the energy holes that existed in WSNs.

Wen *et al.* [33] proposed cooperative data collection algorithm (CDCA) in order to extend the WSN lifetime. The CDCA algorithm consisted of three phases: network partition phase, collection points selection and path construction phase, and speed control phase. Their introduced algorithm began with splitting the sensor nodes into groups and appointed a mobile sink to each group. The authors argued that the energy consumption was minimized, and the network lifetime was extended accordingly.

Wang *et al.* [34] presented a routing scheme based on sink mobility with clustering approach. The proposed energy-efficient scheme divided the sensor field into sub-regions with equal sizes. Within each sub-region, the sensor nodes elected cluster heads and calculated the routing path based on the optimal consumed energy while transmitting the sensory data to the cluster heads using single-hop or multi-hop communication.

Sun *et al.* [35] proposed mobile intelligent computing based on compressive sensing data gathering (MIC-CSDG) algorithm. Their proposed approach was based on multi-hop data routing among sensor nodes. A clustering approach was adopted with compressive sensing data gathering mechanism to minimize the sampling data between cluster members.

Krishnan *et al.* [36] introduced a modified clustering technique based on low energy adaptive clustering hierarchy (LEACH) protocol for WSN utilizing multiple mobile sinks. The mobile sinks traveled along the sensing field to collect the data from the cluster heads, and their paths evaluated using the ant colony optimization (ACO) technique. The authors depicted that their developed approach eliminated data loss and improved the network lifetime.

Vijayashree and Dhas [37] proposed a data collection strategy for multiple mobile sinks with a clustering scheme. The cluster heads were selected based on nodes' residual energy, while the data collection path for the multiple mobile sinks evaluated using an artificial bee colony (ABC) algorithm. The obtained results from their proposed approach showed an effective reduction in redundant data transmission, conserved nodes' energy, and enhanced the network lifespan.

Donta *et al.* [38] proposed a hierarchical agglomerative clustering-based data collection (HACDC) algorithm. The HACDC approach determined the optimal rendezvous points using unsupervised machine learning for 3D WSNs. In addition, a novel statistical approach was used to find the optimal number of clusters in HAC and set the rendezvous points at the center of each cluster.

Pang *et al.* [39] proposed collaborative data collection scheme that utilized multiple mobile sinks. The authors introduced a path equalization algorithm (PEABR) to determine the optimal path for the mobile sinks when visiting the cluster heads. The network was divided into clusters, and the cluster heads were chosen based on their residual energy to collect the sensory data from cluster members. The authors argued that their proposed approach was feasible while balancing the path length of each mobile sink without increasing the additional path calculation cost.

Liu *et al.* [40] proposed iterative sensor node association and trajectory planning policy to reduce the age of information (AoI) of each ground sensor node. Dynamic programming was used by the trajectory planning algorithm to evaluate the optimum value of the maximum and average AoI for the unmanned ariel vehicle (UAV). Their proposed scheme had an optimized clustering weight that guaranteed a balance between the uploading time of the sensor node and the flight time of the UAV when different simulation scenarios were executed.

This paper was motivated by the recent IoT applications that implicitly needed sink mobility. For instance, the personal digital assistance (PDA) handled by a rescuer moving

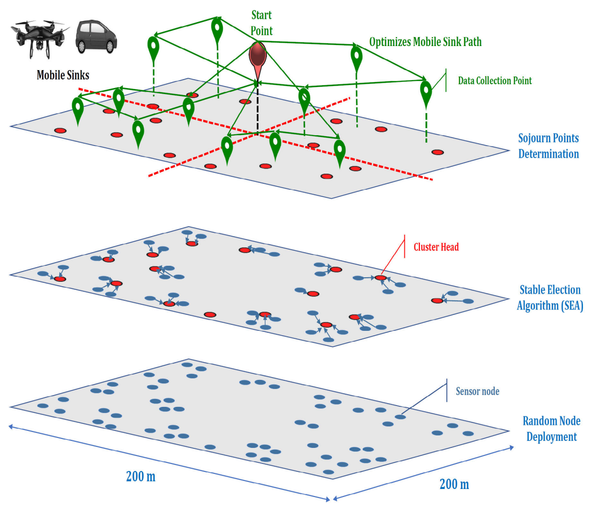


FIGURE 2. **The proposed approach scheme.**

across a disaster area to search for any survivors [41] and may other applications with similar scenarios surveyed in [42], [43]. While the sink mobility enhanced the network lifetime, it also incurred route adjustments overhead to the routing protocol. In a conventional way, there is only one stationary sink resided at the center of the sensing field to gather the sensory data through single-hop or multi-hop transmissions. Therefore, the energy consumption of the nodes nearer to the sink was high and caused energy holes in WSNs. While in cluster hierarchy, all the cluster members sent their data to the cluster head, and unbalance energy depletion existed due to the increased burden on these cluster heads. In order to address the aforementioned problems, this paper employed mobile sinks in order to reduce the number of hops during data transmissions, achieve uniform energy depletion among the sensor nodes, and thereby prolong the network lifespan. An optimized path determination strategy is proposed with clustering techniques for both homogeneous and heterogeneous sensor networks. Fig. 2 illustrates the hierarchical structure of the proposed approach and the major contributions are as follows:

1) Developing a stable election algorithm (SEA) that enables the sensor nodes to form clusters and the cluster heads are selected based on heuristic rules. The SEA is capable of preventing unnecessary frequent cluster head selection and/or rotation in homogeneous and heterogeneous WSNs;
2) Developing a cognitive sojourn location determination algorithm based on minimum weighted vertex cover problem (MWVCP). The introduced algorithm searches for the optimum minimum number of virtual vertices that cover the sensing field, while each virtual vertex must cover a maximum number of cluster heads within its vicinity. These sojourn locations represent the best locations for the mobile sinks to stop while traveling across the sensing field to collect cluster heads' data;

3) Developing an optimized mobile sink trajectory based on a multi-objective evolutionary algorithm (MOEA). The optimized mobile sinks' paths are calculated using the sojourn locations' coordinates in which four mobile sinks are deployed to gather the sensing field data. In addition, three optimization techniques are employed to determine the best technique that provides efficient data collection and faster convergence to the optimal solution.

IV. PROPOSED APPROACH

In this paper, we assume that the sensor field consists of 200 randomly deployed sensor nodes distributed over a geographical area (200 × 200 m^2). The sensor nodes are stationary and aware of their geographical locations only when certain sensor node is elected to be a cluster head. Multiple mobile sinks are employed to gather the sensory data. The sensor nodes are grouped together to form a cluster. The cluster head is responsible for collecting cluster members' data within the single-hop transmission. The sink nodes travel along the field freely (aerial or terrestrial movement without obstacle). their optimized moving paths are calculated when the cluster heads locations are received at the base station.

A. NETWORK MODEL

In this paper, three types of networks have been employed to provide comprehensive simulation scenarios of all available IoT-based WSN applications. The sensor nodes in the introduced models are assumed to be stationary, unaware of their geographical location except when the node becomes a cluster head, identical in terms of sensing facility and communication range. All the networks models have N sensor nodes and can be described as follows:

1) Homogeneous network (single-tier)
In this model, all the sensor nodes are similar in having the same initial energy when the simulation started. The sensor node with initial energy (e_0) is called the normal node. The total initial energy of the homogeneous sensor network can be expressed by:

$$E_{total\ 1-tier} = \sum_{i=1}^{N} e_0 \tag{1}$$

2) Two-tier heterogeneous network
In this model, the sensor nodes are classified into two main groups: normal and advanced nodes. The fraction of advanced nodes in the heterogeneous network is n. Therefore, the number of advanced nodes in the sensor field is nN, and the advanced node is equipped with α times more energy than the normal node. Hence, the total initial energy of a two-tier heterogeneous sensor network can be expressed by:

$$\begin{aligned} E_{total\ 2-tier} &= N(1-n)e_0 + nNe_0(1+\alpha) \\ &= Ne_0(1+\alpha n) \end{aligned} \tag{2}$$

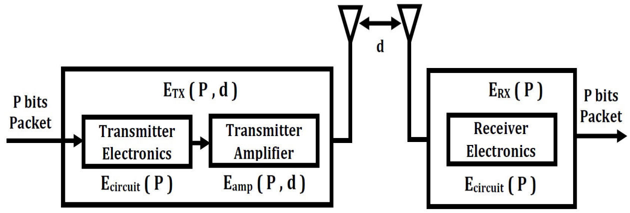


FIGURE 3. The first order radio model diagram.

3) Three-tier heterogeneous network
In this model, the sensor nodes are characterized into three main classes: normal, advanced, and supernodes. The fraction of advanced and supernodes in the heterogeneous network is n. Let n_0 is the percentage of supernodes from n, and $Nn(1-n_0)$ is the total number of advanced nodes whilst the remaining $N(1-n)$ is the number of normal nodes in the three-tier heterogeneous network. The supernode is equipped with β times more energy than the normal node. Accordingly, the total initial energy of a three-tier heterogeneous sensor network can be expressed by:

$$\begin{aligned} E_{total\ 3-tier} &= Nnn_0e_0(1+\beta) \\ &\quad + Nn(1-n_0)e_0(1+\alpha) \\ &\quad + N(1-n)e_0 \\ &= Ne_0(1+n(\alpha+n_0(\beta-\alpha))) \end{aligned} \tag{3}$$

B. ENERGY CONSUMPTION MODEL

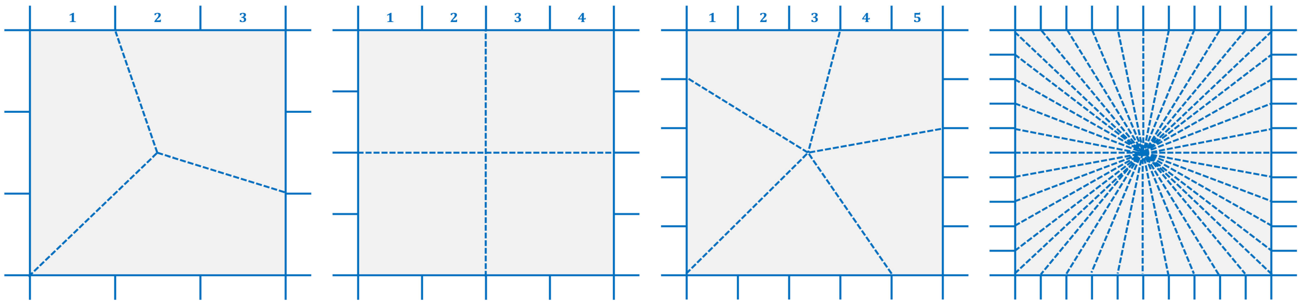
The first order radio model introduced by Heinzelman in [44] is employed in this paper for later energy consumption performance simulation. Fig. 3 depicts the block diagram of the adopted radio model whilst the mathematical representation is given in Eq. 4 and Eq. 5 for transmission and receiving energies, respectively.

$$\begin{aligned} E_{TX}(P,d) &= E_{circuit}(P) + E_{amp}(P,d) \\ &= E_{circuit} \times P + E_{amp} \times P * d^2 \end{aligned} \tag{4}$$

$$\begin{aligned} E_{RX}(P) &= E_{circuit}(P) \\ &= E_{circuit} \times P \end{aligned} \tag{5}$$

The E_{TX} is the energy dissipated during transmission of a packet, and E_{RX} is the energy consumed during receiving a packet. While P is the packet size and d is the geographical distance between the cluster head and its members and between the mobile sink and the cluster heads, which is assumed to be fixed in the introduced simulation scenarios. The $E_{circuit}$ is the depleted energy in the transmitter and receiver electronic circuits that is equal to 50 nJ/bit while the consumed energy in amplifier circuit E_{amp} is 100 $pJ/bit/m^2$ for attaining a specific level of signal-to-noise ratio (SNR).

The cluster heads and cluster members can communicate directly; this type of communication is called intra-cluster communication. We assume that the mobile sink can reach



(a) No. of mobile sinks = 3 (b) No. of mobile sinks = 4 (c) No. of mobile sinks = 5 (d) No. of mobile sinks = ℕ

FIGURE 4. Sensing field segmentation based on the number of deployed mobile sinks.

each cluster head within the mobile sink's transmission range using a single-hop communication. The cluster members cannot send any data to the mobile sink directly. At the same time, a symmetric radio channel is employed during the simulation to ensure that the transmission energy between two nodes remains the same for a fixed SNR.

C. CLUSTER FORMATION

The number of sensing field partitions depends on the desired number of the deployed mobile sinks. The introduced segmentation procedure works for square sensing fields only. The division procedure targets to divide the field into multiple equal areas, and each area should have the same side length. Therefore, each side of the sensing field is divided into equal $\mathbb{N}$ congruent segments, where $\mathbb{N}$ is the number of deployed mobile sinks. Then, choosing a corner for an odd number of mobile sinks or the middle point of the field side for the even number of mobile sinks to start the sensing field division process. Once the starting point is identified, the total number of sides' segments is divided by the number of mobile sinks to determine how many segments each area should have. Finally, a line is drawn from the starting point of each segment to the center of the sensing field to determine the segment border. Fig. 4 illustrates how the sensing field is divided for 3, 4, 5, and $\mathbb{N}$ mobile sinks respectively.

The sensor field is portioned into four equal regions in order to achieve distributed cluster head selection that solved the scalability issues while prolonging the network lifetime by ultimately minimizing the energy depletion in sensor nodes. The topology of the sensor network is unexpected due to random node deployment in the sensing field. The random deployment of sensor nodes does not guarantee that each subregion of the sensing field will have all three types of nodes (normal, advanced, super). It could be possible that a certain region may not contain any advanced and/or super nodes when random node deployment is adopted. Therefore, the main goal of the introduced clustering algorithm is to reduce the overall energy depletion by utilizing a new heuristic mechanism that reduces the unnecessary re-clustering frequency.

The introduced stable election algorithm (SEA) conserves sensors' energies by eliminating cluster formation message exchange while providing stable distributed clusters. The SEA consists of three phases: cluster initiation, cluster head rotation, and data collection.

1) Cluster initiation phase starts once the sensor nodes were powered on after deployment. In the homogeneous network, all the nodes have a similar probability of becoming a cluster head because they have equal residual energy (e_0). The sensor nodes begin to broadcast "Hello" messages to their neighbors and receive acknowledgment messages from them. After the aforementioned message exchange is finished, each node constructs a neighbors table. The sensor node that has a maximum number of neighbor nodes will be elected as an initial cluster head among the neighbor nodes within its vicinity. While in a heterogeneous network, the initial cluster head is chosen based on the total number of neighbor nodes and the node's residual energy. In other words, the advanced and supernodes have a higher priority to become a cluster head than normal nodes because they have higher residual energy.
2) Cluster head rotation phase launches when the residual energy (E_r) of the current cluster head dropped below a certain predefined threshold (E_{Th}) value. After the initial cluster head selection procedure is finished, every sensor node in the sensor field consciously monitors its residual energy and evaluates the cluster head rotation index ($\mathbb{R}$) that is given in Eq. 6 during each simulation round. An advertisement message is broadcasted by the current cluster head to initiate the cluster head rotation procedure when its E_r reached a certain predefined value. The node with a high rotation index value will win the competition to be elected as the next cluster head for that cluster. The heuristic approach used in evaluating the rotation index will prevent the sensor nodes from generating multiple control messages for cluster head selection and rotation. In addition, the SEA eliminates the frequent cluster head rotations that deplete the node's energy without

performing useful functions.

$$\mathbb{R}_i = \left[\sqrt{\left| \frac{\gamma}{1 - \gamma (i \bmod (1/\gamma))} \right|} * E_r * \psi \right] * \eta \quad (6)$$

where γ is a random number between 0 and 1 that serves as a seed for later cluster head selection, i is the simulation round for the current scenario, ψ is the number of times that the current node became a cluster head so far, and η is the multiplication index ($\eta = 1$ when $E_r \geqslant E_{Th}$ and $\eta = 0$ when $E_r < E_{Th}$). The η blocks old cluster heads from being chosen in the future while allowing them to participate in the communication until they deplete their remaining energies.

3) The data collection phase begins upon the completion of cluster head selection and/or rotation. At the beginning of this phase, the selected cluster heads report their geographical locations to a centralized base station for computing the optimized route(s) of the mobile sink(s). Once the node is chosen to serve as a cluster head, it activates the global system for mobile communications (GSM) module to determine its location using the global positioning system (GPS) and send its location to the base station using short message service (SMS). Upon the completion of SMS transmission, the cluster head turns off the GSM module and never uses it again. The sensor nodes within the cluster start sending the sensory data to the cluster head in order to be aggregated before sending the received data to the mobile sink. The cluster head can reach the mobile sink in a single-hop within its transmission range. When the sink node arrives at the sojourn location, it broadcasts a notification message to inform the cluster heads within its transmission range to start sending the aggregated data. The sink node waits, and then it moves to the following sojourn location after the time out of no data received timer.

D. OPTIMIZED MOBILE SINK PATH DETERMINATION

In this paper, the sojourn point can be defined as the best point (location) in the sensor field where the mobile sink node can communicate with the maximum number of cluster heads that are covered by its transmission range. The introduced algorithm for sojourn point determination scans the received cluster heads' locations and searches for the best position that satisfied the sojourn point definition. Fig. 5 shows three cluster heads and their corresponding sojourn point.

After receiving the cluster heads' locations, the centralized base station assumes that the sensing field is an undirected weighted graph $G(V, E, w)$, where $v = \{1, 2, \ldots, a\}$ is the vertices set, $E = \{1, 2, \ldots, b\}$ is the edges set, and w is the weights. The vertices represent the cluster heads, while the edges represent the communication link between them. The introduced sojourn location determination algorithm is based on MWVCP. The weighted vertex cover problem aimed at finding a subsets of minimum number of virtual vertices (VV) where $VV \subseteq V$, such that $\forall (u, v) \in E$, either $u \subseteq VV$ or $v \subseteq VV$, and every vertex v linked to c weights, $w_1(v), w_2(v), \ldots, w_c(v)$. The proposed sojourn algorithm will search for a set of VV that minimizes the m objective functions $f_i(\mathbb{V}) = \sum_{\mathbb{V}[v]} w_i(v)$, where $i = 1, 2, \ldots, c$. Finally, the MWVCP of the sojourn location algorithm can be formulated as follows:

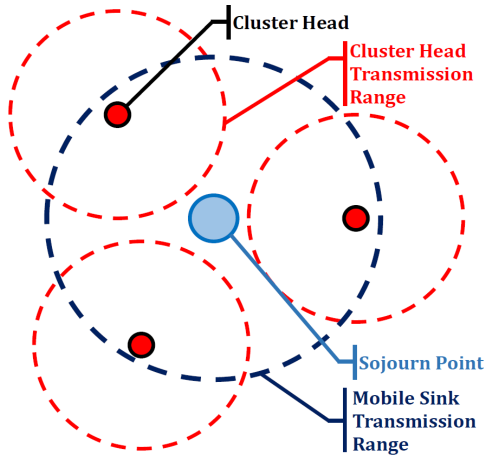


FIGURE 5. The sojourn location of a mobile sink node among three cluster heads.

$$Min\ F(\mathbb{V}) = (f_1(\mathbb{V}), f_2(\mathbb{V}), \ldots, f_m(\mathbb{V}))^T \quad (7)$$

where $\mathbb{V}$ is a binary vector that represents the optimal solution. When VV is the solution, then $\mathbb{V} = 1$; otherwise, $\mathbb{V} = 0$. In summary, the VV represents the minimum sojourn locations for the multiple mobile sinks, and each location covers the maximum number of cluster heads.

Two main scenarios are conducted: single mobile sink and multiple mobile sinks. For the single mobile sink, the centralized base station is located at one of the sensing field corners. Whilst in multiple mobile sinks scenarios, the centralized base station is positioned at the sensing field center. When employing multiple mobile sinks, the sensing field is portioned into four equal regions in order to extend the network lifetime and improve network delay.

In this paper, the optimized mobile sink path is one of the NP-hard optimization problems that required the evaluation of a closed shortest path with minimum cost and delay. The optimized path should pass through a predefined set of sojourn points where each sojourn point can be visited only once. The multi-objective evolutionary algorithms (MOEAs) may be deemed as an optimum solution for multiple-criteria decision-making (MCDM) problems because MOEAs evaluation encompasses many metrics. The developed algorithm aimed at minimizing simultaneously the cost, distance, and delay of the mobile sink path. Let ξ is a sojourn point and $\mathbb{S}$ is a set of ξ $(i, j = 1, 2, \ldots, m)$, $C_{i,j}$ is the cost of moving from ξ_i to ξ_j, $d_{i,j}$ is the distance from ξ_i to ξ_j, and $\tau_{i,j}$ is the traveling delay from ξ_i to ξ_j. The decision variable Γ is given in Eq. 8. While the objective functions for minimizing the cost, distance and delay are given in Eq. 9, Eq. 10, and Eq. 11 respectively.

$$\Gamma_{i,j} = \begin{cases} 1 & \text{if } \xi_j \text{ is visited from } \xi_i \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

$$\mathbb{C} : Min \sum_{i}^{m} \sum_{j}^{m} C_{i,j}\, \Gamma_{i,j} \tag{9}$$

$$\mathbb{D} : Min \sum_{i}^{m} \sum_{j}^{m} d_{i,j}\, \Gamma_{i,j} \tag{10}$$

$$\mathbb{T} : Min \sum_{i}^{m} \sum_{j}^{m} \tau_{i,j}\, \Gamma_{i,j} \tag{11}$$

While the optimization constraints are: $\sum_{i}^{m} \Gamma_{i,j} = 1$ for all i and j, the evaluated route must not be chosen more than once ($\Gamma_{i,j} + \Gamma_{j,i} \leqslant 1$) and $\Gamma_{i,j} \geqslant 1$.

The evolutionary algorithm (EAs) received considerable attention from industrial researchers and academic scholars in different fields because of the robust and effective merits that exist while finding a set of trade-off solutions. Three EAs are utilized in the optimized mobile sink path determination algorithm: ant colony optimization (ACO), genetic algorithm (GA), and simulated annealing (SA). These optimization techniques have been employed in the simulation scenarios for single mobile and multiple mobile sinks. There are many similarities between the aforementioned EAs. However, each intelligent heuristic algorithm possesses unique characteristics primarily in its strategy for seeking the optimum solution. The three EAs are employed in this work to solve the same multi-objective optimization problem (optimized mobile sink path).

TABLE 1. The parameters of simulation scenarios.

Parameter	Value
Sensing field dimensions	$200 \times 200\ m^2$
Number of sensor nodes (N)	200
Deployment type	Random
Sensor node's initial energy (e_0)	$0.5\ J$
Packet size	$127\ bytes$
Amplifier energy (E_{amp})	$100\ pJ/bit/m^2$
Energy consumption in idle state ($E_{circuit}$)	$50\ nJ/bit$
Consumed energy during data aggregation	$5\ nJ/bit$
Number of mobile sinks	1 and 4
Simulation rounds	9000

V. RESULTS AND DISCUSSIONS

In this work, the simulation scenarios were conducted using MATLAB 2020a running on a Windows 10 operated PC with Intel Core i5 CPU and 4 GB of RAM. In addition, all the results were evaluated when the sensor network had the maximum number of clusters. Table 1 shows the detailed parameters' values for the conducted simulation scenarios.

The developed SEA approach was compared among four well-known cluster-based routing protocols in terms of network lifetime and cluster heads' count. Low energy adaptive clustering hierarchy (LEACH) is a pioneer cluster-based hierarchical routing protocol that is employed in WSNs to extend the network lifetime. The sensor nodes in LEACH managed themselves in groups called clusters, and only one node in each group is nominated to be a cluster head. Every node executed a stochastic algorithm during each simulation round to decide if it would be a cluster head or not during this round. The cluster head rotation carried out in a random fashion, or the node that had the highest energy level was chosen to be a cluster head for the current simulation round [45].

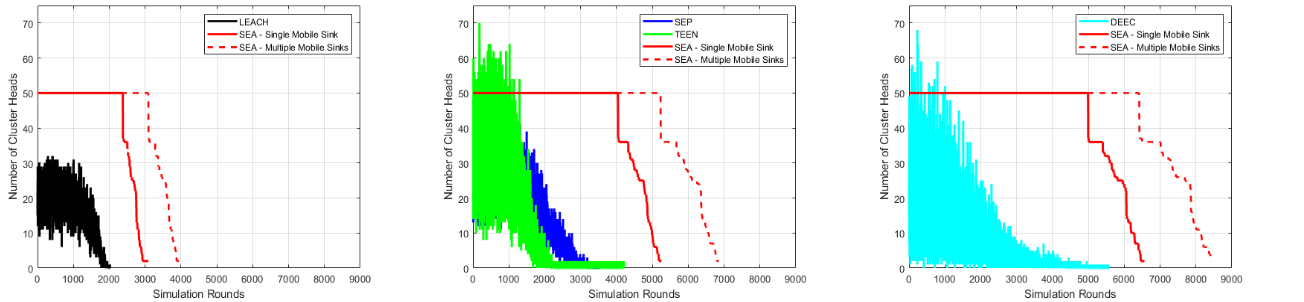
Stable election protocol (SEP) is a two-level heterogeneous cluster-based protocol. The SEP protocol guaranteed that the advanced node had a higher priority to be selected frequently as a cluster head. Therefore, the clustering mechanism resulted in random cluster heads selection that was distributed based on their respective energy [46].

Threshold sensitive energy-efficient sensor network (TEEN) is a cluster-based routing protocol with a hierarchical multi-hop feature that is used broadly in time-critical applications. The TEEN protocol was designed for reactive networks that interacted with unexpected variations in the surrounding environment. The TEEN protocol was employed in two-tier heterogeneous networks with two attributes: soft and hard thresholds value. The cluster heads selection criteria in TEEN were similar to LEACH [47], [48].

Distributed energy-efficient clustering (DEEC) protocol is a significant three-tier heterogeneous routing protocol in which selection of cluster heads carried on the ratio between the remaining energy of each node and the average of network's energy. Thus, the sensor nodes that were equipped with high initial and remaining energies possessed more opportunities to be selected as cluster heads than the low energy nodes [49], [50].

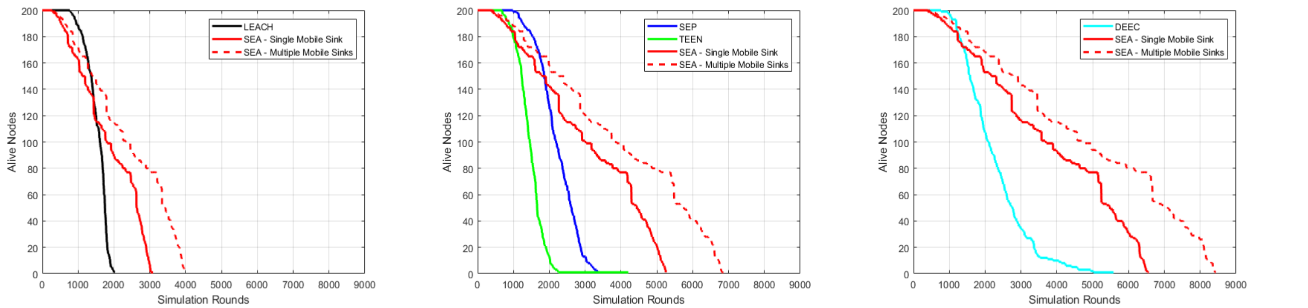
Fig. 6 shows the number of cluster heads versus simulation rounds for the proposed SEA approach and the four well-known routing protocols. The SEA approach was employed in both homogeneous and heterogeneous sensor networks, and it is clear that the developed algorithm for cluster head selection exhibited a stable behavior due to the heuristic nature. The SEA approach did not fluctuate during cluster head selection and rotation compared to LEACH, SEP, TEEN, and DEEC protocols. The clusters were formed according to the formula presented in Eq. 6 that prevented cluster head rotation from occurring in each simulation round.

Many diverse definitions for sensor network lifetime and stability period existed in the literature. For simplicity, this work adopted the definitions introduced by Mak in [51] and Abo-Zahhad in [52]. The term "network lifetime" stands for the time interval between the instant the sensor network starts operating to the death of the last alive sensor node. Whilst the term "stability period" stands for the time interval between the instant the sensor network starts operating to the death of the first alive sensor node. These definitions also support



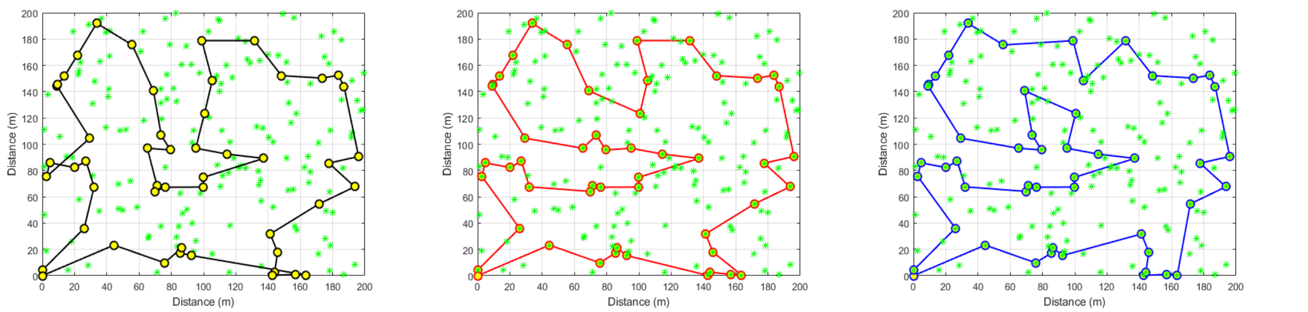
(a) Homogeneous network (Single Tier) (b) Hetrogeneous network (2-Tier) (c) Hetrogeneous network (3-Tier)

FIGURE 6. **The number of cluster heads versus simulation rounds.**



(a) Homogeneous network (Single Tier) (b) Hetrogeneous network (2-Tier) (c) Hetrogeneous network (3-Tier)

FIGURE 7. **The number of alive sensor nodes versus simulation rounds.**



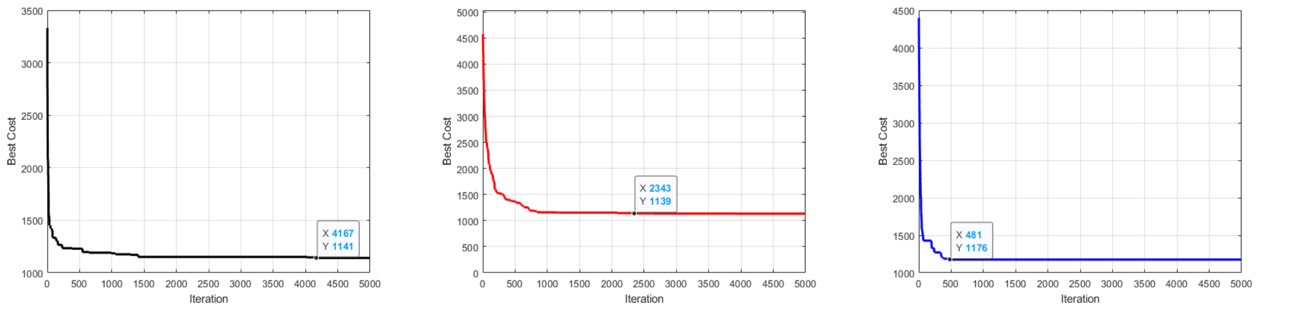
(a) ACO (b) GA (c) SA

FIGURE 8. **Optimized energy-efficient path for single mobile sink.**

a fairer basis for similar sensor network protocol performance comparisons among the proposed approach.

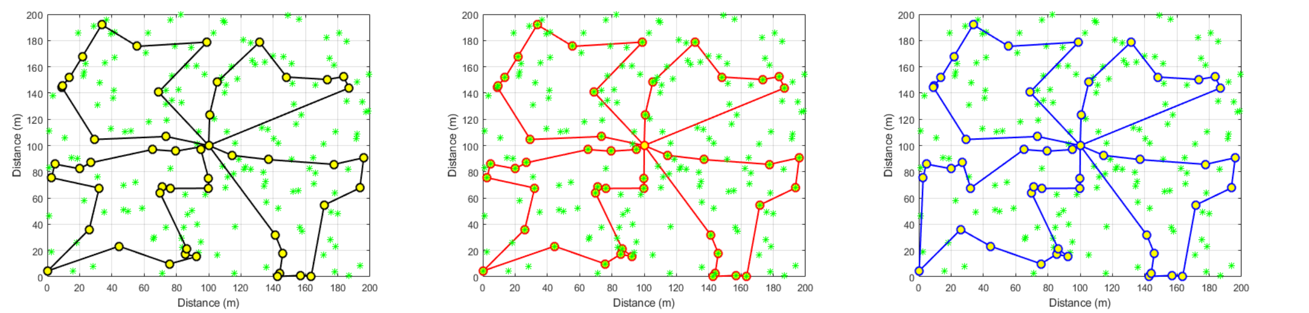
Fig. 7 depicts the network lifetime in terms of the number of alive nodes versus the simulation rounds. The SEA approach conserved the node's energy by eliminating unnecessary message exchange during cluster formation, and hence, the node's lifetime increased. The network lifespan for sensor network adopted optimized single mobile sink with SEA approach can be extended by 41%, 39.5%, 22%, and 16% compared to LEACH, SEP, TEEN, and DEEC respectively. Whilst for the sensor network that employed multiple mobile sinks with SEA approach can extend the network lifespan by 66%, 64%, 48% and 41% compared to LEACH, SEP, TEEN, and DEEC, respectively.

Without any doubt, with a more considerable stability period, the reliability of the sensor network clustering process will be better. On the other hand, there should be a trade-off between sensor network lifetime and its reliability since the failure of a single sensor node does not block the other sensor nodes from transmitting their data due to the self-organized feature of WSN and the redundancy nature of the deployed sensor nodes in the sensor field. Hence, the



(a) ACO (b) GA (c) SA

FIGURE 9. Best cost of optimization objective function for single mobile sink.



(a) ACO (b) GA (c) SA

FIGURE 10. Optimized energy-efficient paths for multiple mobile sinks.

proposed approach has a short stability period compared to other approaches while it has a longer network lifetime.

Fig. 8 shows the optimized sink path when utilizing a single mobile sink that traveled across the sensing field and stopped at the determined sojourn locations. The optimized path was calculated using ACO, GA, and SA techniques, and Fig. 9 depicts their corresponding convergence to the optimum solution. Different paths were calculated based on the optimization technique being used. The obtained results showed that SA determined the optimized sink path with 88.5% and 79.5% faster than ACO and GA, respectively.

Fig. 10 shows the optimized paths that were calculated for each mobile sink when four mobile sinks were employed in the sensing field. Three optimization techniques were utilized (ACO, GA, and SA) in order to study the effectiveness of the best technique. The determined paths by different techniques were similar in some regions because of the limited number of sojourn locations that made the objective function converged to the same path. The multiple mobile sinks succeeded in prolonging the network lifetime by shortening the communication path between the cluster heads and mobile sinks. Therefore, the hotspot problem or energy holes around the sink was eliminated when an optimized path was adopted when the mobile sink(s) traveled across the sensing field.

Fig. 11 depicts a comprehensive run for optimized path determination when four mobile sinks were employed.

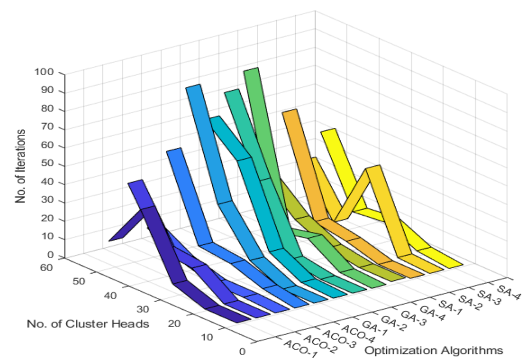


FIGURE 11. The simulation result for multiple mobile sinks scenario.

The sensing field was partitioned into four regions, and the number beside the optimization techniques represents the region's index. The obtained simulation results showed that for a different number of cluster heads, the SA calculated the optimum path faster than the ACO and GA by 19.6% and 49%, respectively.

Fig. 12 shows the execution time of sojourn points determination algorithm versus cluster heads number. This algorithm is adopted for both single mobile and multiple mobile sinks as there is no change in the clustering algorithm. The algorithm's execution time increases as the number of cluster

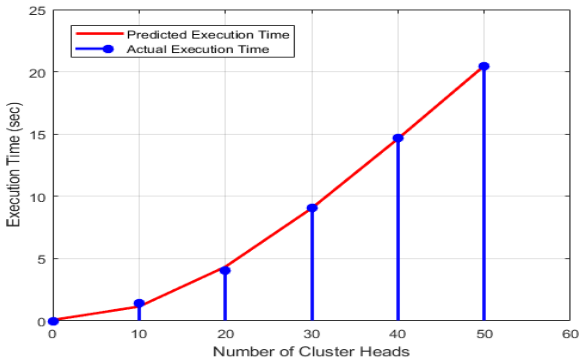


FIGURE 12. The execution time for the proposed sojourn algorithm.

heads increases because the search space of virtual vertices for the developed algorithm became large. The relationship between the algorithm execution time ($\mathbb{E}_s$) and the number of cluster heads (ν) is obtained after performing curve fitting to the sampled data that was shown in Fig. 12. Eq. 12 depicted the obtained formula of evaluating the execution time when a particular number of clusters exited in the sensor network.

$$\mathbb{E}_s = -0.0001\nu^3 + 0.0137\nu^2 - 0.0186\nu + 0.0722 \quad (12)$$

The sensor nodes rely on their accumulated energy in the attached battery to perform sensing and data transmission tasks during their lifetime. One of the important metrics that affect the network lifespan is packet delivery, especially when energy-constrained devices are deployed.

Fig. 13 depicts the network remaining energy versus the simulation rounds. In LEACH, TEEN, SEP, and DEEC, the sensor nodes depleted their energy much quicker than the proposed SEA approach. Due to the heuristic scheme in cluster head selection and rotation, the introduced SEA scheme had a smooth slope compared to the aforementioned routing protocols. While Fig. 13(d) illustrated the comparison between the proposed approach and the work presented by Krishnan [36]. Krishnan's approach adopted multiple mobile sinks with ACO to determine the mobile sink trajectory. However, his work is suitable only for homogeneous networks and is limited to three mobile sinks only. It is clear that the proposed SEA scheme exhibited the same behavior when it is deployed in homogeneous or heterogeneous networks by utilizing fair load balancing techniques.

Table 2 shows a numerical comparison between the work presented in this paper and the work introduced by Pang [39] in terms of the number of lost packets. In Pang's work, when the distance between the mobile sinks and the cluster heads increased, the number of lost packets increased until the mobile sinks became unable to receive any packet because they were out of the transmission range of the cluster heads. While in the presented work, this situation is not possible because the developed sojourn location determination algorithm takes into account that the sojourn locations should be within the transmission range of the cluster heads, and therefore very few packets will be lost.

TABLE 2. The data delivery comparison.

Distance	Sent Packets	Lost Packets	
		Pang [39]	Proposed Approach
10	1000	0	0
15	1000	0	0
20	1000	1	0
25	1000	23	5
30	1000	101	12
35	1000	382	N/A
40	1000	1000	N/A

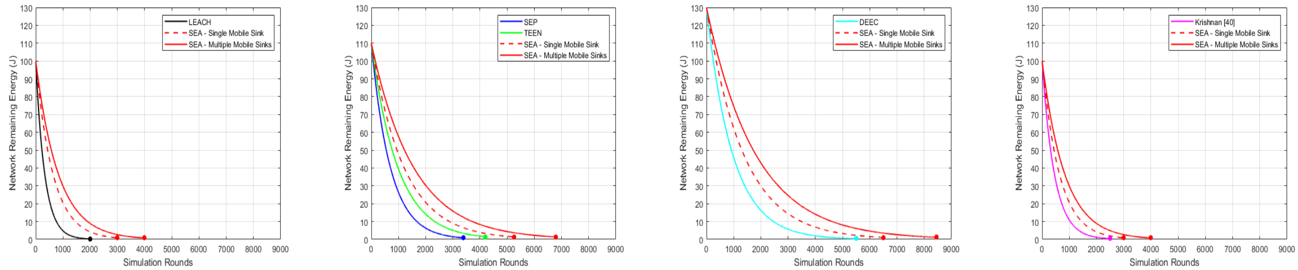
TABLE 3. The multiple mobile sinks trajectory comparison.

No. of CHs	Algorithm	Mobile Sinks Labels			
		#1	#2	#3	#4
10	Krishnan [36]	540	540	545	N/A
	SEA + ACO	286	233	179	198
	SEA + GA	260	275	230	269
	SEA + SA	243	164	170	225
20	Krishnan [36]	840	846	853	N/A
	SEA + ACO	287	295	207	298
	SEA + GA	277	304	270	239
	SEA + SA	230	319	308	319
30	Krishnan [36]	988	996	997	N/A
	SEA + ACO	337	308	323	307
	SEA + GA	318	331	304	344
	SEA + SA	350	326	265	313

Table 3 depicts the length of mobile sink trajectory for multiple mobile sinks approaches. In this paper, multiple scenarios were conducted in order to study the effectiveness of the proposed approach. The work presented by Krishnan [36] is used in the comparison, and it was based on ACO when calculating the mobile sink path trajectory and his work is limited to three mobile sinks that collected the sensory data from cluster heads. Whilst the multiple mobile sinks in the SEA scheme with ACO, GA, and SA visited sojourn locations to collect the sensory data from multiple cluster heads. The obtained results showed that the proposed approach outperformed Krishnan's work by providing a shorter traveling tour when the mobile sinks visited the sojourn locations. The developed optimized path algorithm shortens the traveling path by introducing virtual vertices covering the maximum number of cluster heads within its vicinity.

VI. OPEN RESEARCH DIRECTIONS

Most of the previous and ongoing researches that focused on sink mobility issues heavily depend on simulation scenarios. At the same time, hardware testbeds are necessary for laboratory researches in order to transfer and deploy the confirmed results in WSN-based real-world systems. The following factors are essential in designing WSN testbed in general and sink mobility in particular.



(a) LEACH (b) SEP and TEEN (c) DEEC (d) Krishnan [36]

FIGURE 13. The remaining network energy versus simulation rounds.

- Cost: robots are considered as mobile objects that explore the sensing field and collect the sensed data. However, these mobile robots are expensive as they are designed for commercial purposes. Hence, the testbed cost needs to be monitored when deploying mobile sinks in real-world WSN-based applications.
- Energy consumption: the sensor nodes and mobile sinks deplete their stored energy during sensing, processing, and communication tasks. Batteries are the common approach in powering the sensor nodes but a power cable may be considered as the best choice if the system is deployed in an indoor environment.
- Stability: testbed steadiness-related concerns are worth research attention. The hardware and software malfunctions could be managed and fixed promptly in small-scale WSN testbeds. Large-scale WSN testbeds should have diverse stable mobility management schemes as they are deployed in real-world applications.

VII. CONCLUSION

This paper presents an optimized path planning strategy based on the SEA scheme that formed clusters based on heuristic information from the sensor nodes. The proposed scheme can be employed in both homogeneous and heterogeneous sensor networks with variable sensor nodes that are distributed indiscriminately in a predefined monitoring area. A comprehensive review has been done in order to address the challenges of adopting single and multiple mobile sinks in WSNs. Hence, the surveyed recent research led to classify the existing routing protocols and identify their advantages and drawbacks that could be used to enhance the performance requirements of the developed approach.

Uneven energy depletion among the deployed sensor nodes participates in the generation of hotspots or energy holes. The network lifetime extension is affected by these energy holes, and therefore mobile sinks were utilized to enhance the current WSN architecture performance. In this work, four mobile sinks were adopted to gather the sensed data from the distributed cluster heads. The sinks' sojourn locations were evaluated based on the minimum weighted vertex cover problem (MWVCP). Whilst the optimized sink path should pass through all the sojourn locations and it is calculated through multi-objective EAs that are aimed at minimizing the traveling distance and time.

Four well-known routing protocols were used in the evaluation of the proposed approach: LEACH, SEP, TEEN, and DEEC. While ACO, GA, and SA techniques were employed to find the optimum path for mobile sinks. The simulation results showed that the network lifespan for sensor network adopted optimized single mobile sink with SEA approach can be extended by 41%, 39.5%, 22% and 16% compared to LEACH, SEP, TEEN, and DEEC, respectively. Whilst for the sensor network that employed multiple mobile sinks with SEA approach can extend the network lifespan by 66%, 64%, 48% and 41% compared to LEACH, SEP, TEEN, and DEEC, respectively. In addition, The simulation results showed that SA determined the single optimized sink path with 88.5% and 79.5% faster than ACO and GA, respectively. While for the multiple mobile sinks, the SA calculated the optimum path faster than the ACO and GA by 19.6% and 49%, respectively.

REFERENCES

[1] S. Yang, "Wireless sensor networks: Principles, design and applications," in *Signals and Communication Technology*. London, U.K.: Springer, 2013.

[2] G. Han, H. Wang, X. Miao, L. Liu, J. Jiang, and Y. Peng, "A dynamic multipath scheme for protecting source-location privacy using multiple sinks in WSNs intended for IIoT," *IEEE Trans. Ind. Informat.*, vol. 16, no. 8, pp. 5527–5538, Aug. 2020.

[3] Y.-C. Wang and K.-C. Chen, "Efficient path planning for a mobile sink to reliably gather data from sensors with diverse sensing rates and limited buffers," *IEEE Trans. Mobile Comput.*, vol. 18, no. 7, pp. 1527–1540, Jul. 2019.

[4] M. Matin, Ed., *Wireless Sensor Networks—Technology and Protocols*. Rijeka, Croatia: InTech, Sep. 2012.

[5] M. Stoyanova, Y. Nikoloudakis, S. Panagiotakis, E. Pallis, and E. K. Markakis, "A survey on the Internet of Things (IoT) forensics: Challenges, approaches, and open issues," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 2, pp. 1191–1221, 2nd Quart., 2020.

[6] A. Thiruchelvi and N. Karthikeyan, "Pair-based sink relocation and route adjustment in mobile sink WSN integrated IoT," *IET Commun.*, vol. 14, no. 3, pp. 365–375, Feb. 2020.

[7] G. Aceto, V. Persico, and A. Pescape, "A survey on information and communication technologies for industry 4.0: State-of-the-art, taxonomies, perspectives, and challenges," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 4, pp. 3467–3501, 4th Quart., 2019.

[8] C. Siu and K. Iniewski, *IoT and Low-Power Wireless*, C. Siu, Ed. Boca Raton, FL, USA: CRC Press, Jun. 2018.
[9] *Ericsson Mobility Report*, Ericsson, Stockholm, Sweden, Nov. 2017. Accessed: Apr. 2020.
[10] C.-F. Wang, J.-D. Shih, B.-H. Pan, and T.-Y. Wu, "A network lifetime enhancement method for sink relocation and its analysis in wireless sensor networks," *IEEE Sensors J.*, vol. 14, no. 6, pp. 1932–1943, Jun. 2014.
[11] B. R. Al-Kaseem and H. S. Al-Raweshidy, "Energy efficient MAC protocol with smart sleep scheduling for cluster-based M2M networks," in *Proc. 6th Int. Conf. Inf. Commun. Manage. (ICICM)*, Oct. 2016, pp. 227–232.
[12] L.-L. Hung, F.-Y. Leu, K.-L. Tsai, and C.-Y. Ko, "Energy-efficient cooperative routing scheme for heterogeneous wireless sensor networks," *IEEE Access*, vol. 8, pp. 56321–56332, 2020.
[13] B. R. Al-Kaseem and H. S. Al-Raweshidy, "Scalable M2M routing protocol for energy efficient IoT wireless applications," in *Proc. 8th Comput. Sci. Electron. Eng. (CEEC)*, Sep. 2016, pp. 30–35.
[14] M. A. Al-Jarrah, M. A. Yaseen, A. Al-Dweik, O. A. Dobre, and E. Alsusa, "Decision fusion for IoT-based wireless sensor networks," *IEEE Internet Things J.*, vol. 7, no. 2, pp. 1313–1326, Feb. 2020.
[15] C. Tunca, S. Isik, M. Y. Donmez, and C. Ersoy, "Distributed mobile sink routing for wireless sensor networks: A survey," *IEEE Commun. Surveys Tuts.*, vol. 16, no. 2, pp. 877–897, 2nd Quart., 2014.
[16] N. Sharmin, A. Karmaker, W. L. Lambert, M. S. Alam, and M. S. A. Shawkat, "Minimizing the energy hole problem in wireless sensor networks: A wedge merging approach," *Sensors*, vol. 20, no. 1, p. 277, Jan. 2020.
[17] R. Anwit, A. Tomar, and P. K. Jana, "Scheme for tour planning of mobile sink in wireless sensor networks," *IET Commun.*, vol. 14, no. 3, pp. 430–439, Feb. 2020.
[18] M. I. Khan, W. N. Gansterer, and G. Haring, "Static vs. Mobile sink: The influence of basic parameters on energy efficiency in wireless sensor networks," *Comput. Commun.*, vol. 36, no. 9, pp. 965–978, May 2013.
[19] A. Khan, A. Abdullah, M. Anisi, and J. Bangash, "A comprehensive study of data collection schemes using mobile sinks in wireless sensor networks," *Sensors*, vol. 14, no. 2, pp. 2510–2548, Feb. 2014.
[20] R. Deng, S. He, and J. Chen, "An online algorithm for data collection by multiple sinks in wireless-sensor networks," *IEEE Trans. Control Netw. Syst.*, vol. 5, no. 1, pp. 93–104, Mar. 2018.
[21] S. Thomas and T. Mathew, "Intelligent path discovery for a mobile sink in wireless sensor network," *Procedia Comput. Science*, vol. 143, pp. 749–756, Jan. 2018.
[22] H. Cheng, L. Tao, and X. Zhang, "A fast and efficient broadcast protocol with a mobile sink node in asynchronous wireless sensor networks," *IEEE Access*, vol. 7, pp. 92813–92824, 2019.
[23] S. Sun, J. Zhao, X. Feng, J. Zhang, and J. Luo, "Mobile multi-sink nodes path planning algorithm concerned with energy balance in wireless sensor networks," *IEEE Access*, vol. 7, pp. 96942–96952, 2019.
[24] N. Gharaei, S. J. Malebary, K. A. Bakar, S. Z. M. Hashim, S. A. Butt, and G. Sahar, "Energy-efficient mobile-sink sojourn location optimization scheme for consumer home networks," *IEEE Access*, vol. 7, pp. 112079–112086, 2019.
[25] V. Senthil Kumar and K. Prasanth, "Weighted rendezvous planning on Q-learning based adaptive zone partition with PSO based optimal path selection," *Wireless Pers. Commun.*, vol. 110, no. 1, pp. 153–167, Aug. 2019.
[26] H. Byun, "Mobile collector-based cost balancing scheme for uniform data gathering delay and energy consumption in wireless sensor actuator networking systems," *IEEE Sensors J.*, vol. 20, no. 8, pp. 4260–4268, Apr. 2020.
[27] J. Zhong, Z. Huang, L. Feng, W. Du, and Y. Li, "A hyper-heuristic framework for lifetime maximization in wireless sensor networks with a mobile sink," *IEEE/CAA J. Automatica Sinica*, vol. 7, no. 1, pp. 223–236, Jan. 2020.
[28] J. Wang, Y. Gao, C. Zhou, R. S. Sherratt, and L. Wang, "Optimal coverage multi-path scheduling scheme with multiple mobile sinks for WSNs," *Comput., Mater. Continua*, vol. 62, no. 2, pp. 695–711, 2020.
[29] S. Jain, K. K. Pattanaik, R. Kumar Verma, S. Bharti, and A. Shukla, "Delay-aware green routing for mobile-sink-based wireless sensor networks," *IEEE Internet Things J.*, vol. 8, no. 6, pp. 4882–4892, Mar. 2020.
[30] Z. Lin, H.-C. Keh, R. Wu, and D. S. Roy, "Joint data collection and fusion using mobile sink in heterogeneous wireless sensor networks," *IEEE Sensors J.*, vol. 21, no. 2, pp. 2364–2376, Jan. 2021.
[31] P. Zhong and F. Ruan, "An energy efficient multiple mobile sinks based routing algorithm for wireless sensor networks," *IOP Conf. Ser., Mater. Sci. Eng.*, vol. 323, Mar. 2018, Art. no. 012029.
[32] K. Koosheshi and S. Ebadi, "Optimization energy consumption with multiple mobile sinks using fuzzy logic in wireless sensor networks," *Wireless Netw.*, vol. 25, no. 3, pp. 1215–1234, Jun. 2018.
[33] W. Wen, C.-Y. Chang, S. Zhao, and C. Shang, "Cooperative data collection mechanism using multiple mobile sinks in wireless sensor networks," *Sensors*, vol. 18, no. 8, p. 2627, Aug. 2018.
[34] J. Wang, Y. Gao, W. Liu, A. K. Sangaiah, and H.-J. Kim, "Energy efficient routing algorithm with mobile sink support for wireless sensor networks," *Sensors*, vol. 19, no. 7, p. 1494, Mar. 2019.
[35] Z. Sun, X. Xing, B. Song, Y. Nie, and H. Shao, "Mobile intelligent computing in Internet of Things: An optimized data gathering method based on compressive sensing," *IEEE Access*, vol. 7, pp. 66110–66122, 2019.
[36] M. Krishnan, S. Yun, and Y. M. Jung, "Enhanced clustering and ACO-based multiple mobile sinks for efficiency improvement of wireless sensor networks," *Comput. Netw.*, vol. 160, pp. 33–40, Sep. 2019.
[37] R. Vijayashree and C. S. G. Dhas, "Energy efficient data collection with multiple mobile sink using artificial bee colony algorithm in large-scale WSN," *Automatika*, vol. 60, no. 5, pp. 555–563, Nov. 2019.
[38] P. K. Donta, B. S. P. Rao, T. Amgoth, C. S. R. Annavarapu, and S. Swain, "Data collection and path determination strategies for mobile sink in 3D WSNs," *IEEE Sensors J.*, vol. 20, no. 4, pp. 2224–2233, Feb. 2020.
[39] A. Pang, F. Chao, H. Zhou, and J. Zhang, "The method of data collection based on multiple mobile nodes for wireless sensor network," *IEEE Access*, vol. 8, pp. 14704–14713, 2020.
[40] J. Liu, P. Tong, X. Wang, B. Bai, and H. Dai, "UAV-aided data collection for information freshness in wireless sensor networks," *IEEE Trans. Wireless Commun.*, vol. 20, no. 4, pp. 2368–2382, Apr. 2021.
[41] F. Yu, S. Park, E. Lee, and S. Kim, "Elastic routing: A novel geographic routing for mobile sinks in wireless sensor networks," *IET Commun.*, vol. 4, no. 6, pp. 716–727, Apr. 2010.
[42] E. S. Oliveira, J. P. J. Peixoto, D. G. Costa, and P. Portugal, "Multiple mobile sinks in event-based wireless sensor networks exploiting traffic conditions in smart city applications," in *Proc. IEEE 16th Int. Conf. Ind. Inform. (INDIN)*, Jul. 2018, pp. 502–507.
[43] Y. A. Qadri, A. Nauman, Y. B. Zikria, A. V. Vasilakos, and S. W. Kim, "The future of healthcare Internet of Things: A survey of emerging technologies," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 2, pp. 1121–1167, 2nd Quart., 2020.
[44] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan, "Energy-efficient communication protocol for wireless microsensor networks," in *Proc. 33rd Annu. Hawaii Int. Conf. Syst. Sci.*, Jan. 2000, p. 10.
[45] A. O. A. Salem and N. Shudifat, "Enhanced LEACH protocol for increasing a lifetime of WSNs," *Pers. Ubiquitous Comput.*, vol. 23, nos. 5–6, pp. 901–907, Feb. 2019.
[46] T. Jinpa and B. V. R. Reddy, "M-SEP: A variant of SEP for WSN," in *Advances in Intelligent Systems and Computing*. Cham, Switzerland: Springer, Aug. 2015, pp. 45–56.
[47] Y. Ge, S. Wang, and J. Ma, "Optimization on TEEN routing protocol in cognitive wireless sensor network," *EURASIP J. Wireless Commun. Netw.*, vol. 2018, no. 1, pp. 1–9, Feb. 2018.
[48] A. R. Khan, N. Rakesh, A. Bansal, and D. K. Chaudhary, "Comparative study of WSN protocols (LEACH, PEGASIS and TEEN)," in *Proc. 3rd Int. Conf. Image Inf. Process. (ICIIP)*, Dec. 2015, pp. 422–427.
[49] S. Singh, A. Malik, and R. Kumar, "Energy efficient heterogeneous DEEC protocol for enhancing lifetime in WSNs," *Eng. Sci. Technol., Int. J.*, vol. 20, no. 1, pp. 345–353, Feb. 2017.
[50] L. Qing, Q. Zhu, and M. Wang, "Design of a distributed energy-efficient clustering algorithm for heterogeneous wireless sensor networks," *Comput. Commun.*, vol. 29, no. 12, pp. 2230–2237, Aug. 2006.
[51] N. H. Mak and W. K. G. Seah, "How long is the lifetime of a wireless sensor network?" in *Proc. Int. Conf. Adv. Inf. Netw. Appl.*, 2009, pp. 763–770.
[52] M. Abo-Zahhad, S. M. Ahmed, N. Sabor, and S. Sasaki, "Mobile sink-based adaptive immune energy-efficient clustering protocol for improving the lifetime and stability period of wireless sensor networks," *IEEE Sensors J.*, vol. 15, no. 8, pp. 4576–4586, Aug. 2015.

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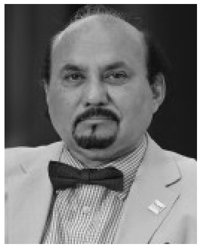

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