IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 6 January 2023, accepted 22 February 2023, date of publication 9 March 2023, date of current version 17 March 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3254594

RESEARCH ARTICLE

An Energy-Efficient Hybrid Clustering Technique (EEHCT) for IoT-Based Multilevel Heterogeneous Wireless Sensor Networks

SANDIP K. CHAURASIYA[1], SANTU MONDAL[2], ARINDAM BISWAS[3], ANAND NAYYAR[4], (Senior Member, IEEE), MOHD ASIF SHAH[5,6], AND RAJIB BANERJEE[7], (Member, IEEE)

[1]Department of Cybernetics, School of Computer Science, Energy Acres Building, University of Petroleum and Energy Studies (UPES), Bidholi, Dehradun, Uttarakhand 248007, India
[2]Department of Computer Science and Engineering, NSHM Knowledge Campus, Durgapur, West Bengal 700053, India
[3]Centre of IoT and AI Integration with Education-Industry-Agriculture and the School of Mines and Metallurgy, Kazi Nazrul University, Asansol, West Bengal 713340, India
[4]Graduate School, Faculty of Information Technology, Duy Tan University, Da Nang 550000, Vietnam
[5]Department of Economics, Bakhtar University, Kabul 1006, Afghanistan
[6]School of Business, Woxsen University, Hyderabad, Telangana, 502345, India
[7]Department of Electronics and Communication Engineering, Dr. B. C. Roy Engineering College Durgapur, Durgapur, West Bengal 713206, India

Corresponding authors: Arindam Biswas (mailarindambiswas@yahoo.co.in) and Mohd Asif Shah (ohaasif@bakhtar.edu.af)

This project is partially funded by the Department of Science & Technology-Association of Southeast Asian Nations (DST-ASEAN) (Grant No: CRD/20201000284) and Kazi Nazrul University, University Grant Commision-Scheme for Trans-disciplinary Research for India's Developing Economy (KNU UGC-STRIDE).

ABSTRACT Internet-of-Things (IoT)-based Heterogeneous Wireless Sensor Network (HWSN) has emerged as a prevalent technology that plays a significant role in developing various human-centric applications. Like in a wireless sensor network (WSN), energy is also the most crucial resource in IoT-based HWSN. The researchers have proposed many works to achieve energy-efficient network operations by minimizing energy usage. A vast proportion of these works emphasize using the clustering approach, which has proved its worth to a great extent. However, most schemes require the repeated formation of clusters incurring a significant amount of nodes' energy in the clustering process. The protocol design of such schemes also varies with the changing levels of heterogeneity. In this work, a hybrid clustering scheme-An Energy-Efficient Hybrid Clustering Technique (EEHCT) has been proposed for IoT-based HWSN that minimizes the energy consumption in clusters' formation and distributes the network load evenly irrespective of the heterogeneity level to prolong network lifetime. It appropriately utilizes dynamic and static clustering strategies to formulate the load-balanced clusters in the network. EEHCT establishes its supremacy over state-of-the-art schemes via an extensive set of simulations and experimentation in terms of multiple network performance metrics like stability, throughput, and network lifetime. Like, it achieves a gain up to 90.27% with respect to network lifetime over its peers in the standard operating conditions and under varying network configurations. In addition to quantitative analysis, a statistical analysis has also been provided to demonstrate the formation of energy-balanced clusters through the proposed scheme.

INDEX TERMS Clustering, energy-efficiency, heterogeneity, Internet-of-Things, network lifetime.

I. INTRODUCTION

With advancements in micro-electromechanical systems (MEMS) and wireless technology, the researchers are working on technologies such as IoT, Cloud Computing, and Big Data Analytics to solve various real-life problems. Amongst all these technologies, IoT has emerged as the most promising one due to its ability to connect things to the Internet enabling unprecedented computing capability. Since the inception of IoT, wireless sensor network has always been an integral part of IoT [1]. An IoT-based WSN comprises various specialized sensors participating in various applications like environment

The associate editor coordinating the review of this manuscript and approving it for publication was Liang-Bi Chen.

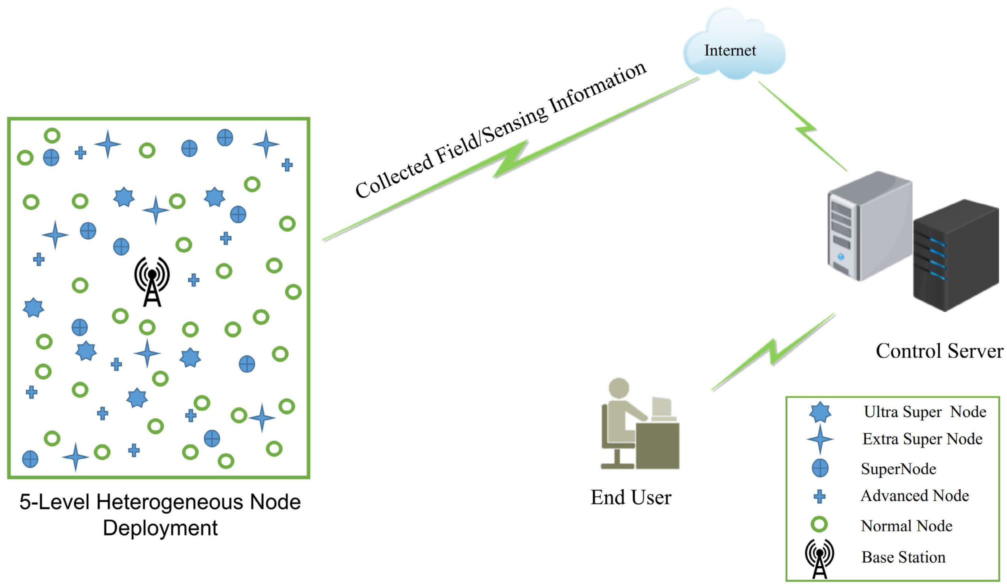


FIGURE 1. IoT-based multilevel heterogeneous wireless sensor network.

sensing, disaster prediction and management, habitat monitoring, intelligent transportation, military surveillance, and weapon control.

To add on more functionality, IoT-based WSN might contain sensor nodes with different abilities giving birth to a popular variant of its, IoT-based HWSN. An exemplary scenario of the IoT-based HWSN is portrayed in Fig. 1, wherein a 5-level network has been demonstrated. The base station (BS) collects the field information from the deployed sensors and stores them in a central repository. The end-users can access the data from such repository by providing an appropriate set of credentials.

An *m-level* IoT-based HWSN refers to an underlying wireless sensor network with *m* types of sensors with different functionality and ability [2]. Such wireless networks comprise nodes with different abilities and dissimilar functionalities. For example, it can be considered an application scenario where the WSN may contain nodes of different sensing ranges, sensing tasks, or computational abilities, etc [3].

It can be intuited that the deployment of sensor nodes with different functionality and/or ability might result in a network facilitating improved performance at lower cost. This is why the HWSN has emerged as a popular variant of the wireless sensor networks.

Based on node heterogeneity, HWSNs can be further categorized into the following three major categories- Energy heterogeneity based HWSN, Computation Heterogeneity based HWSN, and Link Heterogeneity based HWSN. In the energy heterogeneity based HWSN, the nodes are deployed with different initial energy. It also refers to the networks with replaceable battery-enabled sensors. In the computation heterogeneity, nodes might have different computational abilities. Like, some sensors might have powerful processing units along with larger storage capacity in comparison of others. Lastly, in the third type of link heterogeneity-based HWSN, the nodes might have long-distance and highly reliable communication links in comparison of other network nodes.

Energy heterogeneity is treated as the fundamental one and the other two (link and computation heterogeneity) are the functions of energy heterogeneity. The link and computation heterogeneity may negatively affect the network lifetime if not supported by energy heterogeneity. Thus, the energy heterogeneity is the main concern and has been addressed by many researchers.

This work focuses on achieving energy efficiency at the network layer by proposing a scheme that ensures the foremost requirements like self-organization and energy-efficient data transmission via clustering in an energy heterogeneous network.

Clustering refers to the process of identifying natural associations among the objects and grouping them [4], [5]. In this process, the entire set of nodes is partitioned into groups/clusters on the basis of node's attribute or required network parameters like the nodes' mutual distance, nodes' distance to and the BS (or equivalently sink), nodes' functionality, and nodes' energy level. In its taxonomy, sensors can be classified as member nodes and cluster heads. Inside a cluster, the members are required to produce the data packets and to connect only to the cluster head (CH) for data transmission. The CH executes tasks like application-specific processing and data aggregation. It conveys the cluster data to the BS using a direct or multihop approach. Thus, clustering ensures that only a few nodes (cluster heads here) suffer from the overhead of long-distance transmission. Thus, clustering lowers energy consumption and enhances the overall network lifetime. Moreover, it also enables data aggregation, saving the nodes' energy further.

Moreover, there are two strategic classes of the clustering techniques- static clustering [6], [7], [8], [9], [10] and dynamic clustering [11], [12], [13], [14], [15], [16], [17],

[18], [19]. In the static clustering technique, once formed, clusters remain constant for the rest of the network lifetime or until they are not resolved administratively. Contrary to this, clusters are reformed at the beginning of each round in dynamic clustering. Due to the repetitive formation of clusters in dynamic clustering, energy consumption is higher than in static clustering. With reference to static clustering, if the clusters are not designed appropriately, the network might suffer from energy inefficiency leading to a reduced network lifetime.

However, most of the works reported in the context of HWSN require the prior knowledge of deployed energy-heterogeneity. Moreover, they employ the dynamic clustering technique spending significant energy in the formation of clusters. Thus, a scheme that reduces energy consumption in successive cluster formation and performs equivalently well with possible energy heterogeneity levels might be sought as the solution to counter the challenges mentioned above.

In this present work, an Energy-Efficient Hybrid Clustering Technique (EEHCT) for IoT-based HSWN is proposed that accommodates any finite levels of energy heterogeneity and partitions the network into energy-balanced clusters. Here, the term hybrid clustering refers to the approach wherein both the dynamic and static clustering strategies are implemented. The scheme starts with dynamic clustering, but later on, upon determining the energy-balanced clusters, the clusters are declared static prohibiting any further change in the cluster formation.

The major objectives of this work are:

- A detailed analysis of the various existing clustering schemes or protocols aiming at improving the network lifetime in the heterogeneous wireless sensor networks.
- Development of an energy-efficient clustering solution which,
  - utilizes a mixture of dynamic and static clustering approaches.
  - ensures energy-balanced network partitioning.
  - is scalable to any desired level of energy heterogeneity so that the scheme's performance is not affected due to the varying levels of energy heterogeneity
- Performance comparison of the EEHCT with the existing schemes, like [11], [17], [18], [20], [21], and [22] with respect to the parameters- network lifetime and energy consumption.
- Stability and statistical analysis of the simulation results.
- Analysis of the EEHCT's performance under varying energy-heterogeneity levels and network configurations to confirm its scalability and adaptability.

A. ORGANIZATION OF PAPER

The work is further organized into five subsequent sections. Section II discusses the major existing works to identify the technical gaps yielding motivations for the design of EEHCT. Section III briefs the adopted models in the work. Section IV describes the proposed scheme- EEHCT along with the respective protocol architecture, operational phases, and algorithm. Section V discusses the simulation experimentation in-depth proving the supremacy and validity of EEHCT over the existing ones and its sustainability and scalability under the different network configurations. Section VI concludes the paper with future scope.

II. RELATED WORKS

Clustering has already established its importance and acceptability in traditional wireless sensor networks to a great extent, especially with regard to the features like scalability and energy efficiency. Many works, [8], [19], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], have already been done referring to clustering as the key to achieving the objectives like scalability and energy efficiency. Clustering has not only proved its significance in the traditional WSNs but also in the IoT-based HWSN to achieve energy efficiency. Many works have already been reported in this context, like [14], [15], [16], [17], [18], [20], [21], [22], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], and [62]. The schemes such as SEP (Stable Election Protocol) [14], DEEC (Distributed Energy Efficient Clustering) [15], D-DEEC (Developed Distributed Energy Efficient Clustering) [16], E-DEEC (Enhanced Distributed Energy Efficient Clustering) [17], ED-DEEC (Enhanced Developed Distributed Energy Efficient Clustering) [18], DRE-SEP (Distance-Based Residual Energy-Efficient SEP) [20], DARE-SEP (Distance Aware Residual Energy-Efficient SEP) [21], and DE-SEP (Distance and Energy Aware SEP) [22] have been proposed following the philosophy of LEACH [11]. Like LEACH, such schemes implement strategies like the randomized rotation of cluster heads (ensuring the load distribution), data aggregation (to lower the energy consumption), and localized coordination (to assure scalability and robustness in dealing with the dynamic networks) too.

In this section, a thorough review of the existing clustering schemes pertaining to HWSN has been carried out, identifying their respective themes and limitations.

Smaragdakis et al. [14] proposed a LEACH-based clustering scheme, Stable Election Protocol (SEP), that deals with two levels of energy heterogeneity in the network. The sensors are categorized as normal and advanced nodes, where the advanced nodes are equipped with more initial energy than the normal nodes. SEP formulates the clusters similar to LEACH but with updated epochs designed separately for both types of nodes. SEP outperforms LEACH in dealing with energy heterogeneity present in the network; however, it requires repeated cluster formation in every network round and considers only two-level energy heterogeneity.

Qing et al. [15] proposed another LEACH-based scheme, DEEC. DEEC considers two-level heterogeneous networks. It attempts uniform load distribution by periodically rotating the energy-consuming CHs' role among the sensors. Moreover, to identify cluster heads for the dynamically formed clusters in every round, a probability-based selection is performed based on nodes' remaining energy and the average network energy. DEEC ensures the preferred selection of the higher energy nodes as CH over the lower energy nodes. However, the high-energy nodes, like advanced nodes, start getting penalized with the repeated assignment of cluster heads' roles, especially when their remaining energy comes into the range of those with low initial energy, that is normal nodes.

In another work, Elbhiri et al. [16] proposed Developed-DEEC for the HWSN to overcome the above-mentioned inefficiency. DDEEC modified the approach proposed in DEEC in such a way that in the starting rounds, advanced nodes are elected preferably as they always have higher residual energy than normal nodes. However, once their residual energy drops below a threshold residual energy, [16] fails to discriminate between the normal and advanced nodes. Moreover, the scheme deals only with level-2 energy heterogeneity.

Saini and Sharma [17] proposed E-DEEC, Enhanced-DEEC for the HWSNs, to deal with the three levels of energy heterogeneity compared to its ancestor schemes. The network is composed of normal, advanced, and super nodes. Moreover, the approach implemented in [17] for cluster heads' selection was similar to that in [15]. Hence, the scheme suffered from the same inefficiency as the nodes with higher initial energy got penalized repeatedly. The excessive load due to the cluster head's responsibilities quickly drains the energy of special nodes. As a result, special nodes' energy soon falls into a range that the scheme fails to discriminate between the normal and special nodes.

Javaid et al. [18] proposed a scheme called Enhanced Developed Distributed Energy-Efficient Clustering (ED-DEEC) for the HWSNs to compensate for the said inefficiency in the previously cited scheme by incorporating the solution proposed in [16]. More illustratively, [18] deals with three-level of energy heterogeneity like in [17]. A probability-based approach is applied for the CHs' selection, requiring the same set of parameters as in [15], [16], and [17], like the nodes' remaining energy and the average network energy. When the non-regular nodes' remaining energy drops to a certain threshold, all three types of nodes are treated equally for the cluster head selection. However, the scheme-EDDEEC, like its precursors [15], [16], [17], heavily depends upon the heterogeneity-specific probability-based solution for CHs' selection and considers only three-level heterogeneous networks.

Qureshi et al. [19] proposed an extension of [18] accommodating four types of sensor nodes. Like its parent schemes, [19] also uses uniquely defined probabilistic CH-selection equations pertaining to each class of sensor nodes. However, it starts treating the sensor nodes equally for the CH candidature once their residual energy drop below a certain threshold.

Mittal and Singh [20] proposed an improvement of SEP [14], DRE-SEP that entertains 3-level energy heterogeneity in the network. DRE-SEP was proposed mainly for the event-driven application. Like [11] and [14], DRE-SEP decides cluster heads based on the weighted probabilistic formula considering nodes' distance from the BS, initial energy, current energy, and type-based epochs as parameters. In addition to these parameters, [20] proposes the dual-hop communication between the CH and BS for further energy minimization.

Naeem et al. [21] proposed a variant of SEP [14] that considers the nodes' distance from the BS, initial and current energy in formulating the CHs in a 3-level HWSN. It calls for the multihop transmission between the CHs and the base station to minimize the long-distance energy consumption by the CHs. DARE-SEP utilizes two schematic constants, say w_1 & w_2 to prioritize the distance and energy factors in the probabilistic CH-selection process as per the application. However, the effect of the above-mentioned schematic contants are not thoroughly investigated in work.

Hossan and Choudhury [22] proposed another variant of SEP [14], titled Distance and Energy Aware SEP (DE-SEP). Like its predecessors, [22] considers BS-to-node distances and nodes' current energy in the formulation of CHs; however, it imposes a limit on the number of cluster heads allowed in the network to restrict excessive cluster formation.

Yu and Wang proposed [39] EDUC, an Energy-Driven Unequal Clustering protocol for HWSN, which formulates the unequal-sized clusters based on the nodes' distance from the BS. Reference [39] aims at balancing the energy consumption among the clusters. It also provisions the energy-driven cluster-head rotation within the cluster to balance energy consumption among the cluster's nodes. However, the unequal clustering led to inefficient and uneven load distribution.

Chand et al. [48] modified the scheme of Hybrid Energy Efficient Distributed (HEED) Clustering [13] for the application in heterogeneous sensor networks. Reference [48] applied the fuzzy logic in the process of CH selection. It considered three metrics- nodes' remaining energy, node-to-BS distance, and node density altogether for the suitable selection of the CHs; however, [48] loses the network data in case cluster heads failed to communicate with one another.

Singh et al. [50] proposed a scheme, Energy Efficient Protocol using Fuzzy Logic for HWSNs as the next version of [48] in which they further explored HEED [13] in the context of heterogeneous sensor networks along with the fuzzy logic. In addition to the parameters used in [48], like nodes' remaining energy, node-to-BS distance, & node density, nodes' average energy was also used in CH selection and formulating the clusters in turn. The scheme demonstrated its performance consistency in varying levels of energy heterogeneity concerning network lifetime. However, the scheme loses the data if the cluster heads fails to communicate with one another.

In another work, Singh et al. [51] proposed a scheme titled "Energy Efficient Heterogeneous DEEC Protocol for Enhancing Lifetime in WSNs". The scheme targets for the improvement of network lifetime and considers a level-3 heterogeneity model for the experimentations. Reference [51] formulated the clusters by selecting the cluster heads along with their cluster members on the basis of a threshold function and the weighted election probability. The scheme's success was demonstrated concerning network lifetime compared with that in [15]. However, the scheme is limited only to the three-level energy heterogeneity and depends on a heterogeneity-specific probability-based solution for selecting cluster heads.

Singh et al. [52] proposed Multi-Level HEED (ML-HEED) as an extension of their previous works [48], [50] for the HWSNs. In this work, [13] was further explored, accommodating any finite energy heterogeneity level. The performance of the ML-HEED was validated in respect of network lifetime and energy consumption under the varying levels of heterogeneity (up to 6-levels) in the network for both- fuzzy and non-fuzzy variants of HEED [13]. However, the scheme provisions repetitive cluster formation in the beginning of every round, incurring considerable network energy which if saved, could be used in executing other necessary network functionality.

Behera et al. [53] proposed a hybrid routing scheme for achieving energy efficiency in the sensor network comprising normal and advanced nodes. In this scheme, the entire network field is partitioned into smaller and manageable regions based on nodes' respective locations in the field, and an additional relay node is also provisioned to minimize the energy consumption in long-distance communication. Routing is manifested depending on the mode of communication, node to BS, node to CH, node to relay, and relay to BS. However, the structure proposed in the scheme confines the advanced nodes and the normal nodes within their predefined regional boundaries only, and no mixing of the nodes is allowed, limiting the scheme to be very application-specific. Also, the scheme considers only two levels of energy heterogeneity.

Priyadarshi et al. [54] proposed an energy-efficient routing scheme for three-level HWSN inspired by [11] and [15]. The scheme aims at efficient CH selection for the network operation based on the nodes' probability-dependent thresholds and residual energy. However, the performance of the scheme is limited to three level of energy-heterogeneity as the threshold functions used in the scheme are specific to the node-type similar to that in some of its predecessors [15], [16], [17], [18], [51]; and provisioning cluster-formation in every round also causes substantial amount of network energy.

Hassan et al. [55] proposed a dynamic clustering based scheme for 2-tier HWSN. In addition to the probabilistic CH-selection based on the type of nodes, [55] proposes no discrimination between the normal and advanced nodes once their residual energy levels fall below a certain threshold. Moreover, [55] implements the idea of direct transmission by the nodes if their distance from the respective CHs are greater than that from the sink to minimize the energy consumption further.

Masri et al. [56] proposed a novel Multi-Level Energy Efficient Clustering (MLEEC) protocol for 3-tier HWSN. The authors aimed to increase the network throughput along with the lifetime. Reference [56] determines the optimal count of clusters on the basis of the Poisson distribution of the nodes in the network. Reference [56] utilizes the aforesaid optimal cluster count in formulating the probabilistic CH selection equations. In the determination of the suitable cluster heads, nodes' remaining energy and their distance from the BS are used as the main parameters. Once the clusters are defined, the usual data collection and transmission rounds are called as in [11], etc.

Preethi et al. [57] proposed a clustering scheme that accommodates four types of nodes with different initial energy levels in the network like its predecessor [19]. In addition to the [19]-induced cluster heads determination, [57] select a sensor node as the overall cluster head while ensuring it is centrally located and high in energy. Thus selected, the overall CH manages the data transmission between all the clusters and BS.

Sharma et al. [58] proposed a static clustering scheme accommodating five levels of energy heterogeneity in the network. In their work [58], the authors have provisioned energy-harvested solar-enabled sensor nodes to act as cluster heads in the network. Reference [58] proposes two different modes of communication depending upon the nodes' distance to the base station. If it goes beyond a certain threshold, nodes communicate their data via the traditional clustering approach; however, if it is below the threshold, nodes can communicate their data directly to the BS.

Sahoo et al. [59] proposed another dynamic clustering-based technique for 2-tier HWSN. In [59], the authors have updated the probabilistic CH selection formule by incorporating the distance factor accordingly. Reference [59] considers the nodes' distance from the sink along with their residual energy to ensure that the nodes with the more remaining energy and nearer the sink are highly suitable for the CH-role. Like its predecessors, [59] follows the LEACH-based strategies for the rest of the network operations.

Gherbi et al. [60] proposed a clustering-based protocol for HWSN that partitions the network area based on the number of nodes deployed. Afterward, it utilizes only the nodes' residual energy criteria to determine the cluster heads among the nodes. The data exchange between the network and the base station is facilitated by allowing multihop routing among the CHs.

Kumar et al. [61] proposed another dynamic clustering-based scheme for the 3-tier HWSN under the title, THWSN: Enhanced Energy-Efficient Clustering Approach for Three-Tier HWSN. In [61], the authors have attempted to improve the network lifetime via careful selection of the cluster heads in the network. Reference [61] formulates three different probabilistic formulae to assist the nodes in their respective sensor classes- standard, intermediate, and advanced sensors in deciding upon the role of cluster heads. Moreover, in the formulation of type-based (based on nodes' type) threshold equations, nodes' remaining energy and their distances from the BS are the main selection criteria. After that, the

LEACH-based strategies are followed for the rest of the network operations.

The schemes mentioned above have two major limitations- heterogeneity-level specific solutions and dynamic clustering, causing substantial network energy. The network solution specific to a particular level of energy heterogeneity can not be treated as a generic one. Hence, it can not be applied for a network where the energy heterogeneity level is not known in advance. Like, a scheme defined for a 3-level energy heterogeneity may not work well for another level of heterogeneity. Besides, dynamic clustering requires forming clusters repeatedly at the beginning of every new round, which might result in considerable energy consumption as each network node is engaged in the process. In order to address the challenges described above, a novel scheme is proposed here. The scheme starts with dynamic clustering, but when energy-balanced clusters are obtained, clusters are declared static for the remaining operational time. A suitable mixing of dynamic and static clustering schemes (leading to the title- hybrid clustering) is approached to save the network energy spent in unnecessary and repetitive cluster formations. Moreover, unlike most existing schemes, EEHCT never defines the CH selection process on the basis of the type of nodes as in [14], [15], [16], [17], [18], [20], [21], [22], and [51]. Hence, It can deal with any level of energy heterogeneity in the network.

III. MODELS- NETWORK AND ENERGY

This section summarizes the network model and energy consumption model adopted in this work as follows:

A. NETWORK MODEL

EEHCT considers a heterogeneous sensor network with the characteristics listed below:

1) The deployed sensors have limited energy.
2) All the deployed sensors are static in the sense that the sensors are restricted from changing their locations.
3) The sensors can vary their transmission power-levels.
4) The sensors sense the environment on regular intervals.
5) Base station is static in the sense that it never changes its location.
   (It can be placed anywhere in the network suiting to the nature of the application; however, it is kept centrally located here to compare the scheme's performance with [17] and [18].)
6) The network may contain any number of nodes with different initial energies.

To further illustrate the idea of multilevel energy-heterogeneity, let the network has n-level of energy-heterogeneity, where $n > 0$ & $n \in Z^+$.

Let N refers to the number of sensors in the network and $\zeta_1, \zeta_2, \zeta_3, \ldots, \zeta_n$ refer to the proportional factors of the deployed sensors of type-1, 2, 3, . . ., n such that

$$\zeta_1 + \zeta_2 + \zeta_3 + \ldots + \zeta_n = 1 \tag{1}$$

Hereby,

$$\begin{aligned}(\zeta_1 + \zeta_2 + \zeta_3 + \ldots + \zeta_n).N &= 1.N\\ \zeta_1.N + \zeta_2.N + \zeta_3.N + \ldots + \zeta_n.N &= N\\ \sum_{i=1}^{n} \zeta_i.N &= N\end{aligned} \tag{2}$$

Let m_i denotes the number of sensors of type-i, like

$$m_i = \zeta_i.N \tag{3}$$

Then, (2) can be written as follows:

$$\sum_{i=1}^{n} m_i = N \tag{4}$$

Similarly, let $\beta_1, \beta_2, \beta_3 \ldots$ be the energy-multipliers for the nodes of type-1, 2, 3, . . ., such that

$$\beta_1 < \beta_2 < \beta_3 < \beta_4 < \ldots \tag{5}$$

where $\beta_1 = 0$, referring to the nodes of type-1 (the normal nodes).

Then, the initial energy of a jth type node say E^j can be defined as follows:

$$E^j = (E_0 + \beta_j.E_0) \tag{6}$$

where, E_0 is the initial energy of the normal nodes known a priori.

Therefore, total network energy, $E_{network}$ can be defined as follows:

$$\begin{aligned}E_{network} &= \sum_{1}^{n} m_i.E^i\\ &= m_1.E^1 + m_2.E^2 + \ldots + m_n.E^n\\ &= m_1.(E_0 + \beta_1.E_0) + m_2.(E_0 + \beta_2.E_0)\\ &\quad + m_3.(E_0 + \beta_3.E_0) + \ldots + m_n.(E_0 + \beta_n.E_0)\\ &= m_1.E_0 + m_2(E_0 + \beta_2.E_0) + m_3.(E_0 + \beta_3.E_0)\\ &\quad + \ \ldots + m_n.(E_0 + \beta_n.E_0) \quad (since\ \beta_1 = 0)\\ &= E_0.(m_1 + m_2(1 + \beta_2) + m_3.(1 + \beta_3)\\ &\quad + \ \ldots + m_n.(1 + \beta_n)\\ &= E_0.(m_1 + m_2 + m_3 + \ \ldots m_n + m_2.\beta_2 + m_3.\beta_3\\ &\quad + m_4.\beta_4 + \ \ldots + m_n.\beta_n)\\ &= E_0.(N + m_2.\beta_2 + m_3.\beta_3 + m_4.\beta_4 + \ldots + m_n.\beta_n)\\ &\qquad \textit{from}\ (4)\\ &= E_0.(N + N.\zeta_2.\beta_2 + N.\zeta_3.\beta_3 + N.\zeta_4.\beta_4\\ &\quad + \ \ldots + N.\zeta_n.\beta_n) \qquad \textit{from}\ (3)\\ &= N.E_0.(1 + \zeta_2.\beta_2 + \zeta_3.\beta_3 + \ldots + \zeta_n.\beta_n)\end{aligned}$$

Equations (1) - (6) can be used to extend the idea to any definite level of energy-heterogeneity accordingly.

B. ENERGY CONSUMPTION MODEL

The widely adopted Radio Energy Dissipation Model as in [20], [21], [22], [60], [61], [62], [63], and [64] is used in this work for the computation of energy consumptions in the activities like data transmission, reception, and aggregation by the nodes. The adopted model can be described as follows in (7)-(11):

$$E_T(s, d) = s * E_{elec} + s * \varepsilon_{amp}(d) \tag{7}$$

$$\varepsilon_{amp}(d) = \begin{cases} \varepsilon_{fs} * d^2, d \leq d_0 \\ \varepsilon_{mp} * d^4, d > d_0 \end{cases} \tag{8}$$

$$E_R(s) = s * E_{elec} \tag{9}$$

$$E_D(s) = s * \varepsilon_{da} \tag{10}$$

where $E_T(s, d)$ refers to the energy required for the transmission of s-bits over the distance d meters; $E_R(s)$ refers to the energy required for receiving s-bits message; and $E_D(s)$ denotes the energy required for aggregating s-bits message. $E_{elec}(= 50\, nj/bit)$ is the energy required to run the electronic circuitry. ε_{amp} is the per bit energy required to run the amplification circuitry, which can be further described either as $\varepsilon_{fs}(= 10\, pj/bit/m^2)$ or $\varepsilon_{mp}(= 0.0013\, pJ/bit/m^4)$ referring to the free-space and multipath fading models used respectively. $\varepsilon_{da}(= 5\ nJ/bit/signal)$ is the energy requirement for per bit data aggregation. d_0 denotes the threshold distance as follows:

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \tag{11}$$

IV. PROPOSED SCHEME- ENERGY-EFFICIENT HYBRID CLUSTERING TECHNIQUE (EEHCT)

EEHCT aims at achieving an energy-efficient clustering solution for the HWSN which is not restricted by the levels of energy heterogeneity as in its ascendant schemes such as [17], [18], [20], [21], and [22].

EEHCT can accommodate every energy heterogeneity level in accordance to the application deployed. With the obtainment of energy-balanced clusters (the clusters with approximately the same energy level), clusters are fixed for the rest of the network operations. Thus saved energy can be further utilized in other essential network operations.

A. ARCHITECTURE AND WORKING

EEHCT divides the network operations into network rounds. A network round comprises two phases- setup and steady-state phases, respectively. The network is partitioned into clusters in the setup phase, and the actual data transfer happens in the steady-state phase.

The scheme starts with the traditional Received Signal Strength Indicator (RSSI)-based dynamic clustering (as in LEACH [11]) irrespective of the present energy heterogeneity. However, later on, once the base station concludes energy-balanced clusters based on information received from the cluster heads, it declares clusters to remain unchanged for the rest of the operations, hence static. Here, energy-balanced clusters are the clusters with almost equal average residual energy. Such clusters ensure that the network is partitioned in a more balanced way leading to even load distribution among the sensor nodes. Fig.2 briefs the idea of hybrid clustering adopted in EEHCT. Immediately after the nodes' random deployment, as in Fig. 2(a), EEHCT results in initial random clusters (Fig. 2(b)) with dissimilar energy levels due to the RSSI-based dynamic clustering. After a few rounds, when the base station determines clusters with almost the same energy levels (Fig. 2(c)) based on the inputs of cluster heads, it immediately declares the clusters static for the rest of the network rounds.

EEHCT follows the philosophy of LEACH [11] like the randomized rotation of CHs' role to ensure even load distribution among the network nodes before it obtains the energy-balanced clusters. With the obtainment of energy-balanced clusters, EEHCT introduces the temporary cluster heads (*TCHs*) to decide the cluster heads for the next rounds as in [7] and [8]. The detailed working of EEHCT has been explained in subsequent sections.

1) PHASES OF OPERATION

As stated earlier at the beginning of this section, the overall network operation is divided into rounds where a round consists of two different phases, namely, *setup phase* and the *steady-state phase*. The setup phase segregates the network into a finite number of clusters, and the steady-state phase actuates the data transmission in the network.

The setup phase is executed in two different modes-dynamic clustering and static clustering. The switching between the modes depends upon the beacon messages-**static=FALSE** or **static=TRUE** issued by the base station. Here, each of the beacons is issued only once. The network operation starts with the beacon message, **static=FALSE**, indicating to proceed with the traditional RSSI-based dynamic clustering. As soon as the base station determines the formation of energy-balanced clusters based on the inputs by the cluster-heads, it immediately issues the beacon, **static=TRUE** indicating to freeze the current clusters' formation for the remaining network lifetime. The phases are described subsequently as follows:

(i) **Setup Phase**

- **static=FALSE (Dynamic Clustering):** In this mode of setup phase, network nodes with the willingness to serve as cluster-heads (*CHs*) advertise throughout the network. The decision to serve as a *CH* is taken in accordance to the theory suggested by [11]. Here, every node generates a random number, say $R \in (0, 1)$, and if $R < T_r$, the node declares itself as *CH*. T_r being round-specific threshold can be defined as follows:

$$T_r = \begin{cases} \dfrac{P_o}{1 - P_o * (r.mod(\frac{1}{P_o}))} & \text{if } n \in G \\ 0 & \text{Otherwise} \end{cases} \tag{12}$$

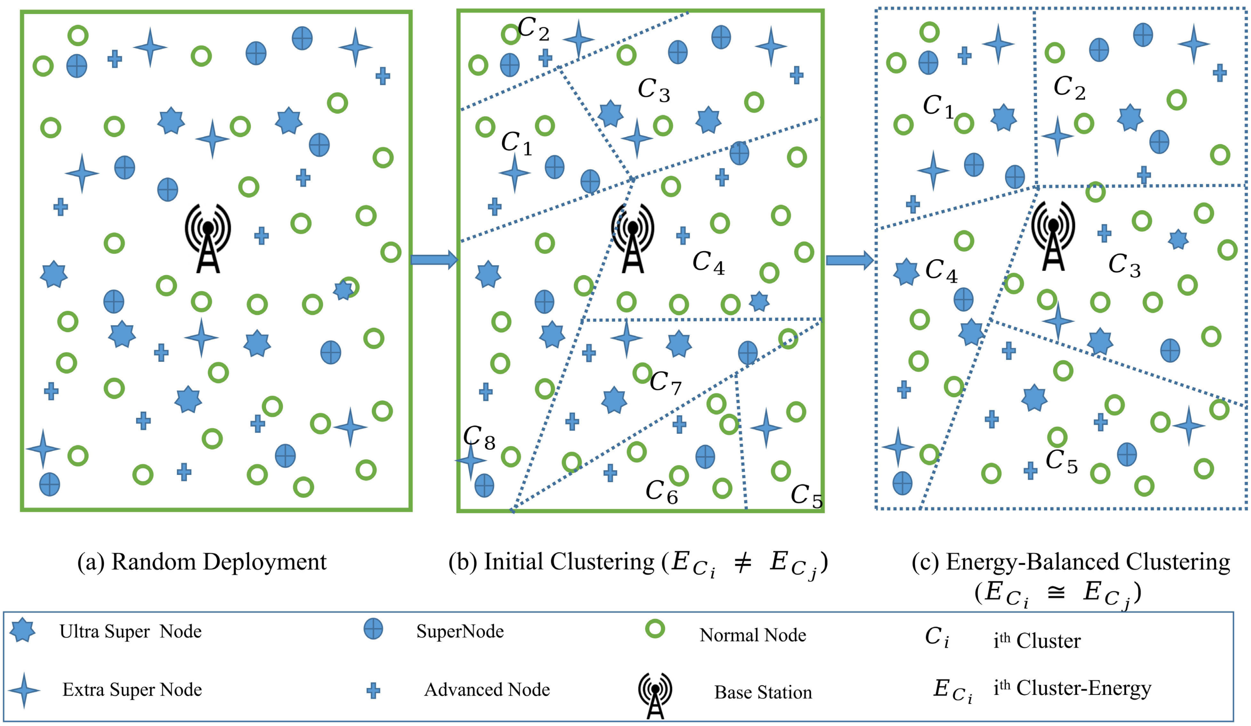


FIGURE 2. **Clustering in EEHCT.**

where P_o refers to the user-defined optimal percentage of CHs (like P_o = 0.1), r refers to the current round and G refers to set of the nodes which have not been cluster heads for the last (1/P) rounds [11]. Upon hearing these advertisements by the respective *CHs*, non-CH nodes decide whom to join based on received signal strength. After finalizing the decision, nodes inform to their chosen *CHs* with the respective information using CSMA. At last, *CHs* acknowledge and send the TDMA slots for the transmissions to their respective cluster members; and thereafter, network nodes transit directly to the steady-state phase.

- **static=TRUE** (**Static Clustering):** This mode of setup phase is called if the BS broadcasts the beacon, **static=TRUE** indicating the fixing of the most recent clusters' formation for the rest of the network operation. Along with the beacon broadcast, **static=TRUE**, there also come the identities of Temporary Cluster Heads (*TCHs*) for the respective clusters (as explained in the subsequent steady-state phase) for assisting in cluster heads' selection process for the ongoing rounds. *TCHs* appointed by the base station now ask their member nodes to send residual energy information in order to finalize the *CHs* (for the current round) and *TCHs* (for the next round). Say for a $Cluster_i$, the member nodes send the required information to their TCH_i. TCH_i then declare the sensor with the highest remaining energy as CH_i and the sensor with minimal remaining energy as TCH_i. The process is executed in each of the clusters formed. Here, the policy of having separate CH and TCH for every cluster has been proposed to ensure further even load distribution and to avoid a single node suffering from all the computational and transmission overhead.

(ii) **Steady State Phase:** Similar to its ascendant schemes, cluster members send their information to the respective cluster heads in the allocated TDMA slots. Then the *CHs* forward the data to the *BS* after performing data aggregation. In addition to the aggregated data, EEHCT requires each *CH* to send the average residual energy of its cluster, say *AvgClusterEnergy* to the *BS* based on which it decides when to declare the clusters static.
After receiving each cluster's average residual energy, the BS compares them. If it finds the clusters with an approximately similar level of average residual energy, the BS concludes that the energy-balanced clusters have been achieved. The process can be illustrated further below.
Let $AvgClusterEnergy_i$ refers to the average energy of the i^{th} cluster as in (13).

$$AvgClusterEnergy_i = \frac{1}{m}.\sum_{j=1}^{m} ResidualEnergy_j^i \quad (13)$$

where m denotes the size of the i^{th} cluster and $ResidualEnergy_j^i$ denotes the residual energy of the j^{th} node in i^{th} cluster.
Then the BS declares the clusters to be energy-balanced if the difference between any two clusters' average energy is negligible as follows:

$$\forall_{i \neq j \leq k}\ diff(AvgClusterEnergy_i, AvgClusterEnergy_j) \approx 0 \tag{14}$$

The base station immediately broadcasts the beacon message, **static=TRUE** at the beginning of the next network round, indicating that the clusters thus formed won't be changing for the remaining network operations. Along with this broadcast, it also conveys the sensor nodes in the network their Temporary Cluster Heads (*TCHs*) meant to assist in the CH selection process for the upcoming rounds of network operation. Here, the TCH-ids are nothing but the current cluster-head Ids of the frozen cluster formation. More illustratively, once the BS determines that the clusters executing the most recent data transmission are energy-balanced, it announces them (the clusters' current configuration) to be static and declares the CHs in their respective clusters to serve now as the TCHs. Alike any clustering scheme, the radio of non-CH nodes is kept off until their turns come to transmit according to already communicated TDMA slots, whereas that of cluster heads are always kept on to receive the data from respective member nodes accordingly.

2) ALGORITHM-EEHCT

Input:
- N : Number of randomly deployed nodes
- E_i : Initial energy of the $i^{th}node$

Output:
- k: Number of energy-balanced clusters deduced in the network operation

1) BEGIN
2) static=FALSE
   /*Beacon message by the base station to start with traditional dynamic clustering*/
3) Repeat the following until all the nodes are not dead
   /* SETUP PHASE */
4) if static ==FALSE
5) [Cluster[k]] = *SetupPhase_DynamicClustering( )*
   /* k → Number of clusters formed */
6) else
7) [Cluster[k]] = *SetupPhase_StaticClustering(k, TCH[ ])*
8) end if
   /* STEADY STATE PHASE */
9) for $i \leftarrow 1 : k$
10) for j ← 1 : m
    /* m → No. of cluster-members */
11) DataTransmission($m_j \rightarrow CH_i$)
12) end for
13) $CH_i \rightarrow BS$
    /* Aggregated Data Transmission along with $AvgClusterEnergy_i$ (defined in (13)) */
14) end for
    /* Followings are to be executed by the base station */
15) if *AvgClusterEnergy* for each of the cluster is approximately equal
    /* as per (14) */
16) static = TRUE
    /* Beacon message by the base station to switch to static clustering (Only Once) */
17) for $i \leftarrow 1 : k$
18) $TCH_i = CH_i$
    /* Along with the beacon message */
19) end for
20) end if
21) END

SetupPhase_DynamicClustering( ):

1) BEGIN
2) $T_r = \frac{P_o}{1-(r\ mod\ (\frac{1}{P_o}))}$
   /* T_r →Cluster-Specific Threshold as defined in [11] */
   /* r → Current round number */
   /* P_o → User-defined optimal percentage of cluster-heads */
3) for $i \leftarrow 1 : N$
   a) if $R_i \leq T_r$
      /* R_i → Random number generated within the i^{th} node */
   b) $Node_i$ declares itself a cluster-head (CH)
   c) end if
4) end for
5) for $i \leftarrow 1 : N$
   /* ∀ nodes */
   a) if $Node_i \notin \{Cluster - Heads\}$
   b) $Node_i$ joins an appropriate cluster
   c) end if
6) end for
7) return Cluster[k]
   /* i.e. specifications of k-clusters formed during the process */
8) END

SetupPhase_StaticClustering(k, TCH[ ])):

BEGIN
for $i \leftarrow 1 : k$
    for $j \leftarrow 1 : m$
        ResidualEnergy($m_j \rightarrow TCH_i$)
    end for
CH_i= Node with max($ResidualEnergy^i{}_j$)
TCH_i = Node with min ($ResidualEnergy^i{}_j$)
return Cluster[k]
END

Moreover, the entire network operation can also be summarized in the flowchart attached herewith as Fig. 3.

V. PERFORMANCE ANALYSIS

A. SIMULATION & EXPERIMENTATION

This section discusses and analyzes a large set of experimentations performed to:

1) ***Establish the efficacy of EEHCT in formulizing the energy-balanced clusters over state-of-the-art schemes- [11], [17], [18], [20], [21], [22]:***
A statistical analysis has been performed in this first set of experiments to demonstrate that the proposed scheme, EEHCT, results in more energy-balanced clusters than its counterparts. The standard deviation has been used to demonstrate the efficacy of EEHCT in establishing energy-balanced clusters.
2) ***Exhibit the efficiency of EEHCT over state-of-the-art schemes- [11], [17], [18], [20], [21], [22]:***
In this set of experiments, EEHCT is compared to LEACH [11], E-DEEC [17], ED-DEEC [18], DRE-SEP [20], DARE-SEP [21], and DE-SEP [22] with respect to various network performance metrics- *network lifetime*, *network energy consumption*, *average residual energy per node*, etc.
As in [17], [18], [20], [21], and [22], a 3-level energy-heterogeneity model is adopted here to establish and peruse the performance of the EEHCT. In the adopted 3-level energy-heterogeneity, three different types of sensors- normal (N), advanced(A), and super nodes (S) with different initial energies are deployed as in Fig. 4(a).
Let N indicates the total number of sensors deployed, and ζ_2, ζ_3 refer to the fraction of advanced and super nodes. Likewise, if normal nodes have initial energy equal to E_0 and β_2 and β_3 are the energy multiplier for the advanced and super nodes, respectively, then the total network energy at the time of deployment can be found as (from subsection III-A):
$$E_{network} = N.E_0.(1 + \zeta_2.\beta_2 + \zeta_3.\beta_3) \tag{15}$$
In other words, the total energy in such heterogeneous network can be obtained by multiplying $(\mathbf{1}\ \mathcal{C}\ \boldsymbol{\zeta_2.\beta_2}\ \mathcal{C}\ \boldsymbol{\zeta_3.\beta_3})$ to the total energy of its homogeneous counterpart with the intial energy E_0.
Fig. 4 demonstrates the working of EEHCT for a 3-level HWSN. It represents how immediately after the nodes' random deployment (Fig. 4(a)), EEHCT results in initial random clustering (Fig. 4(b)), which are then converted into energy-balanced clusters (Fig. 4(c)).
In addition, the consistency in the performance of EEHCT over the existing ones has also been demonstrated through different network configurations caused by varying the proportion factors of advanced and super nodes in the 3-level heterogeneous network.
3) ***Exhibit the consistent performance of EEHCT in the presence of finite levels of energy heterogeneity:***
In this set of experiments, EEHCT has been evaluated against the varying levels of energy-heterogeneity viz. level-1, 2, 3, 4, & 5. However, it can accommodate every energy heterogeneity level without any generality-loss. The level-1 network consists of the nodes with the same power and functionality, termed the traditional homogeneous network; the level-2 heterogeneous network refers to the nodes with two different initial energy; similarly, level-3 energy heterogeneity indicates the nodes with three different initial energies, and so on. The performance of EEHCT under the aforementioned heterogeneous networks is analyzed in terms of *network lifetime*, *energy-consumption*, and *packet-delivery* at the BS to substantiate the fact that EEHCT performs well with every level of energy heterogeneity.

TABLE 1. Simulation parameters.

Parameter	Parameter's Value
Dimension of the Sensing Field	100 x 100 m^2
Location of Base Station	$(50m, 50m)$
Number of Sensors in the Sensing Field	$\{100, 150, 200, 250, 300\}$
Normal Nodes' Initial Energy	$0.5J$
Advanced Nodes' Energy Multiplier	1.5
Super Nodes' Energy Multiplier	2.0
Proportional Factors for Advanced & Super Nodes (ζ_2, ζ_3)	{(0.3, 0.2), (0.3, 0.2), (0.24, 0.36), (0.28, 0.42)}
Message Length	$4000bits$

B. SIMULATION ENVIRONMENT & ASSUMPTIONS

MATLAB is used here as the simulation tool to simulate the working of EEHCT and the existing schemes. The network model and adopted energy consumption model for the network operation have already been explained in subsections- III(A) and III(B).

It is assumed that a total of N sensors are deployed using uniform random distribution across a sensing field of the dimension $M \times M$ m^2. Further, the deployed network follows the continuous data flow model.

C. SIMULATION PARAMETERS

In order to compare the performance of the EEHCT against that of the existing ones- [11], [17], [18], [20], [21], [22]

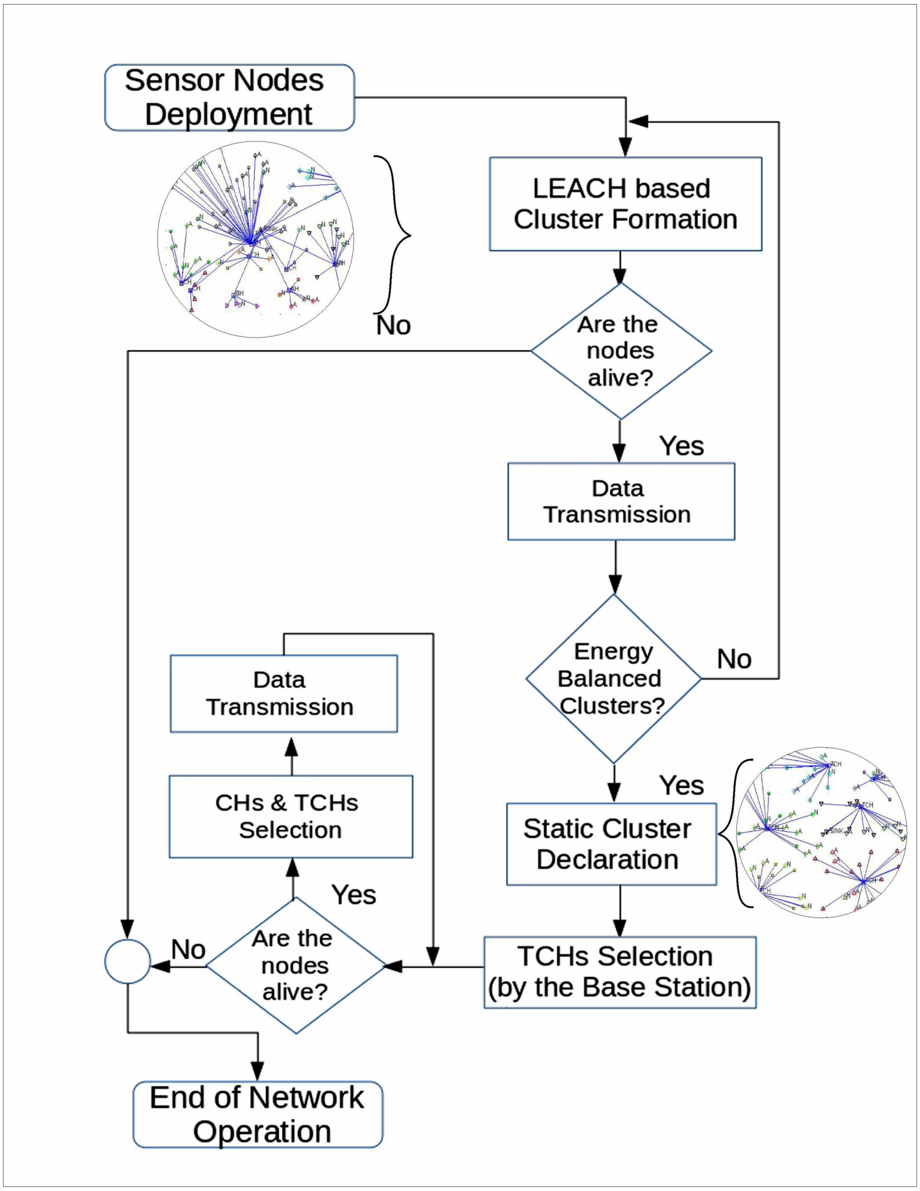


FIGURE 3. EEHCT-flowchart.

with respect to the 3-level energy-heterogeneity, the set of simulation parameters used in the simulation has been listed in Table 1. 100 nodes are deployed across the 100 × 100 m^2 following the random uniform distribution. Moreover, the following performance metrics are used:

- Network lifetime- As in [7], [8], [11], [13], [17], [18], [20], [21], and [22], it is measured as the time when the last node dies in the network .
- Network Stability- It is intuited that the network with less energy consumption per round and with more average residual energy per node per round bring more stability and durablity in the network operations. Hence, the network stability is measured in terms of energy consumption and average residual energy per node.

D. RESULT AND DISCUSSION

1) As stated in the point 1 of subsection V-A, this first set of experiments establishes that EEHCT partitions the network in more energy-balanced clusters with respect to the schemes- [11], [17], [18], [20], [21], and [22]. Since the network comprises nodes with different initial energy, clusters with similar energy-levels (termed energy-balanced clusters) might result into better network performance. In order to establish this, standard deviation of the clusters' energy (σ_{CE}) is taken into consideration as in the (16).

$$\sigma_{CE} = \sqrt{\frac{\sum_{i=1}^{k}(ClusterEnergy_i - \mu_{CE})^2}{k}} \tag{16}$$

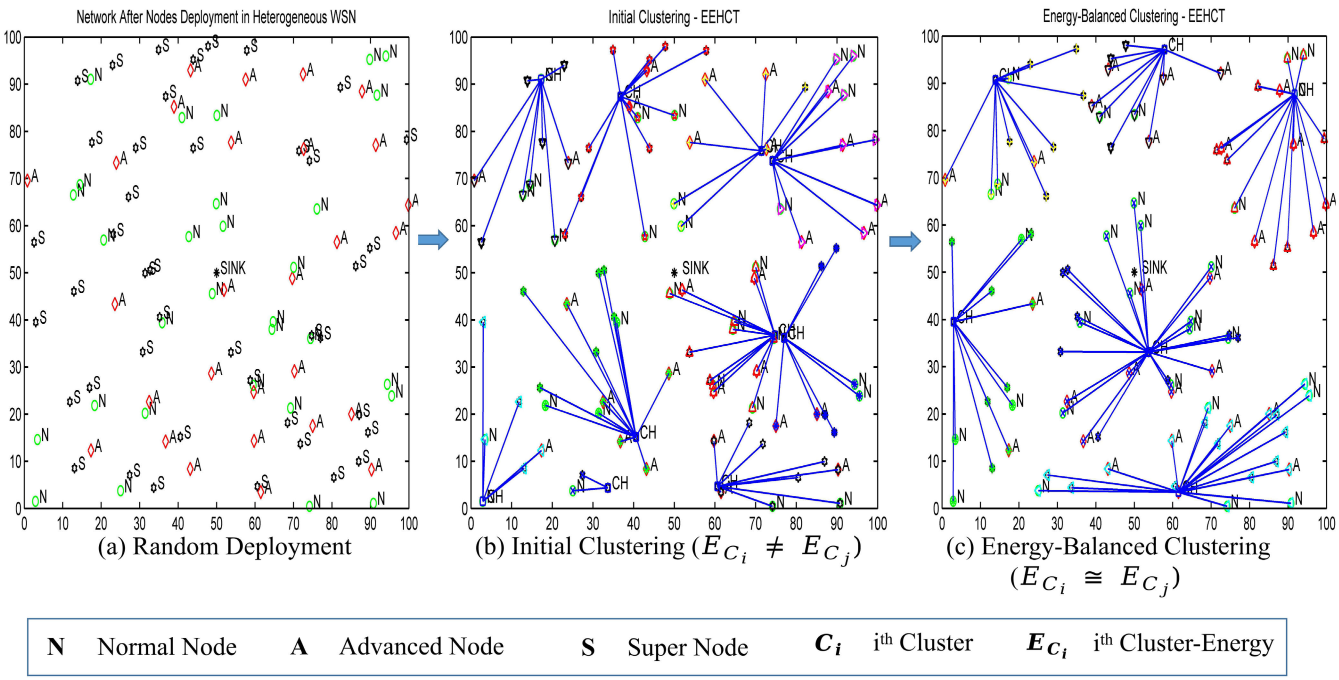


FIGURE 4. Simulation interface for a 3-level HWSN.

where, k indicates the number of clusters formed and $ClusterEnergy_i$ implies to the energy of the i^{th} cluster. μ_{CE} is defined as follows in (17):

$$\mu_{CE} = \frac{1}{k}\sum_{i=1}^{k} ClusterEnergy_i \tag{17}$$

Fig. 5(a) - 5(g) demonstrate the efficacy of EEHCT in forming the energy-balanced clusters with respect to [11], [17], [18], [20], [21], and [22].

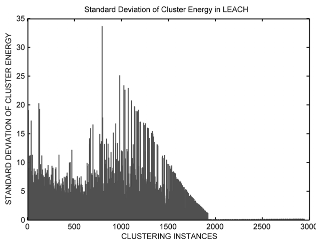
It can be easily observed from the following figures that the standard deviation of clusters' energy is much less in EEHCT than in LEACH [11], E-DEEC [17], ED-DEEC [18], DRE-SEP [20], DARE-SEP [21], and DE-SEP [22]. The respective bar graphs of LEACH, E-DEEC, ED-DEEC, DRE-SEP, DARE-SEP, and DE-SEP (Fig, 5(a) - 5(f)) demonstrate high variations in cluster energy implying energy-imbalanced clusters in the network. Contrary to that, Fig. 5(g) exhibit a smooth plane with lower height referring to the formation of energy-balanced clusters via EEHCT in the network.

2) In the next set of experiments, the relative performance of LEACH [11], E-DEEC [17], ED-DEEC [18], DRE-SEP [20], DARE-SEP [21], DE-SEP [22], and EEHCT has been discussed with respect to the above-mentioned performance metrics- network lifetime, and network stability.

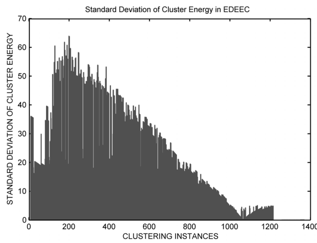
The EEHCT has been evaluated against the state-of-the-art schemes under different network configurations too, like by varying the proportion of advanced nodes (ζ_2) and super nodes (ζ_3). Table 2 lists the chosen values of ζ_2 and ζ_3 as (ζ_2, ζ_3). This is to reiterate that 3-level heterogeneous model is adopted here for the performance comparison of EEHCT with that of the [11], [17], [18], [20], [21], and [22].

Fig. 6 - Fig. 8 brief the performance of all the schemes- LEACH, E-DEEC, ED-DEEC, DRE-SEP, DARE-SEP, DE-SEP, and EEHCT with respect to the performance metrics- network lifetime, network energy consumption, and average residual energy per node respectively. Table 2 summarizes the performance of EEHCT with respect to that of LEACH, E-DEEC, ED-DEEC, DRE-SEP, DARE-SEP, and DE-SEP in terms of network lifetime under varying proportion of participating nodes in 3-level HWSN. It is apparent from the Fig. 6 that EEHCT outperforms [11], [17], [18], [20], [21], [22] in each of the network configurations adopted. More illustratively, for a network with 100 nodes, when (ζ_2, ζ_3) = (0.2, 0.3), EEHCT succeeds with a gain of 94.65%, 40.97%, 49.54%, 53.56%, 72.66%, & 62.98% in terms of network lifetime over LEACH, E-DEEC, ED-DEEC, DRE-SEP, DARE-SEP, & DE-SEP. Similarly, when the network assumes (0.3, 0.2), (0.24, 0.36), and (0.28, 0.42) as values for (ζ_2, ζ_3), EEHCT outperforms (LEACH, E-DEEC, ED-DEEC, DRE-SEP, DARE-SEP, DE-SEP) with (99.64%, 50.31%, 53.51%, 73.32%, 80.64%, 80.87%), (87.4%, 37.86%, 16.32%, 78.18%, 76.95%, 35.67%), and (83.28%, 37.90%, 12.43%, 74.93%, 73.84%, 39.79%) gains respectively in terms of network lifetime.

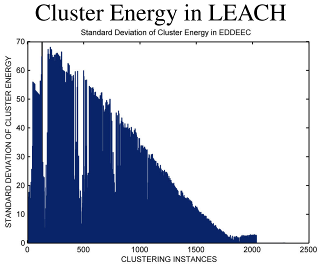
Fig. 7 and Fig. 8 demonstrate the improved network stability in EEHCT when compared to the schemes- LEACH, E-DEEC, ED-DEEC, DRE-SEP, DARE-SEP, and DE-SEP with respect to the metrics- network energy



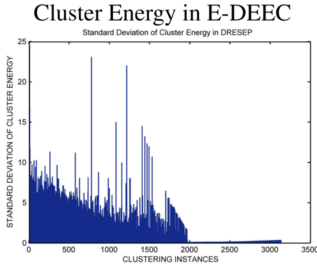
(a) Standard Deviation of Cluster Energy in LEACH



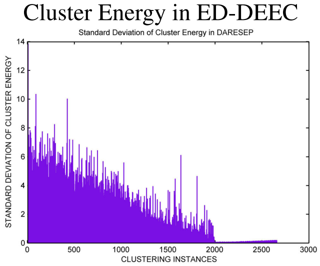
(b) Standard Deviation of Cluster Energy in E-DEEC



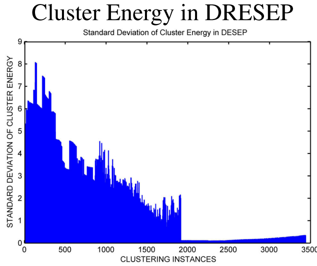
(c) Standard Deviation of Cluster Energy in ED-DEEC



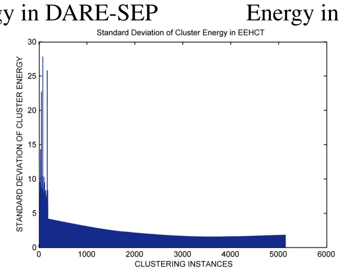
(d) Standard Deviation of Cluster Energy in DRESEP



(e) Standard Deviation of Cluster Energy in DARE-SEP



(f) Standard Deviation of Cluster Energy in DE-SEP



(g) Standard Deviation of Cluster Energy in EEHCT

FIGURE 5. Standard deviation of cluster energy in LEACH, EDEEC, EDDEEC, DRESEP, DARE-SEP, DE-SEP, & EEHCT in 3-level HWSN.

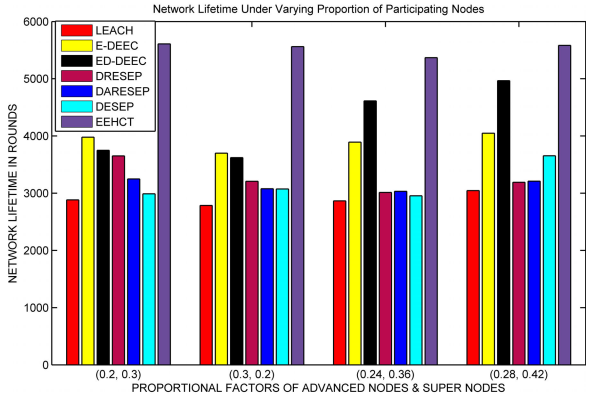
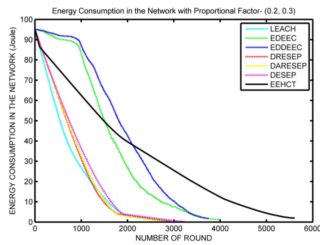
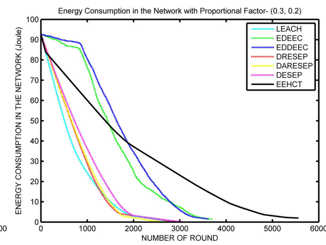


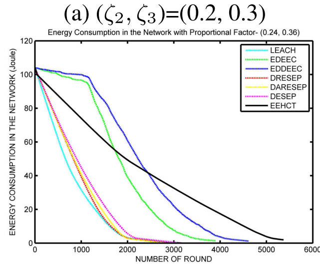
FIGURE 6. Network lifetime under varying proportion of participating nodes.



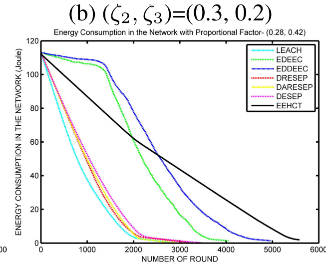
(a) (ζ_2, ζ_3)=(0.2, 0.3)



(b) (ζ_2, ζ_3)=(0.3, 0.2)



(c) (ζ_2, ζ_3)=(0.24, 0.36)



(d) (ζ_2, ζ_3)=(0.28, 0.42)

FIGURE 7. Network energy consumption under varying proportion factors in LEACH, EDEEC, EDDEEC, DRESEP, DARE-SEP, DE-SEP, & EEHCT in 3-level HWSN.

TABLE 2. Tabular comparison of network lifetime under varying proportion of heterogeneous nodes in 3-level HWSN.

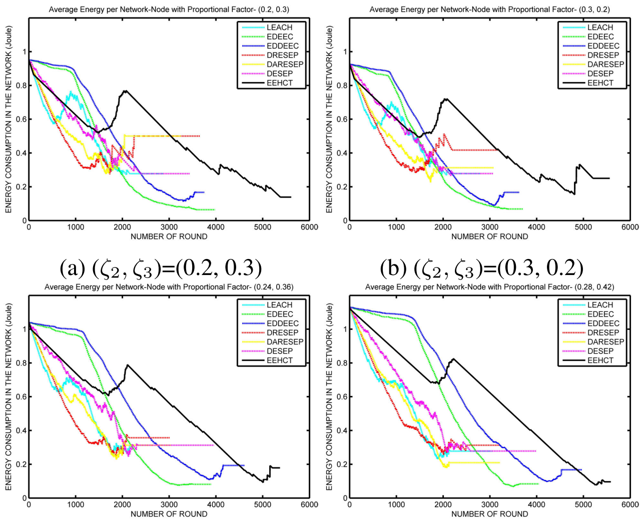
Scheme	Proportion Factors of Advanced & Super Nodes			
	(0.2, 0.3)	(0.3, 0.2)	(0.24, 0.36)	(0.28, 0.42)
LEACH	2881	2785	2864	3044
EDEEC	3978	3699	3893	4048
EDDEEC	3750	3622	4614	4965
DRESEP	3652	3208	3012	3191
DARESEP	3248	3078	3033	3211
DESEP	3441	3074	3956	3993
EEHCT	5608	5560	5367	5582

consumption and average remaining energy per node per round. It is evident from the Fig. 7 that the average energy dissipation rate is lower in EEHCT than its counterparts in every chosen network configurations. Similarly, Fig. 8 depicts the average remaining energy per node per round is better in EEHCT than in the existing ones for each of the above-mentioned network configurations.

Thus, it can be concluded from Fig. 6 - Fig. 8 and Table 2 that EEHCT performs consistently well in all possible network configurations compared to [11], [17], [18], [20], [21], and [22].

3) This last set of experiments examines the performance of EEHCT in varying levels of energy heterogeneity to demonstrate the consistent performance of the scheme in every possible level of energy heterogeneity. In order to ensure simulation simplicity, it has been assumed that the different categories of sensors have different initial energies but as explained in (5), like, type-1 nodes are of the least initial energy and type-5 nodes are equipped with the maximum initial energy.

Table 3 and Table 4 demonstrate an instance of nodes' count and their respective initial energy for network deployment of 100 nodes under different heterogeneity levels. This is to note that the nodes, along with



(a) (ζ_2, ζ_3)=(0.2, 0.3)
(b) (ζ_2, ζ_3)=(0.3, 0.2)
(c) (ζ_2, ζ_3)=(0.24, 0.36)
(d) (ζ_2, ζ_3)=(0.28, 0.42)

FIGURE 8. Average residual energy/node under varying proportion factors in LEACH, EDEEC, EDDEEC, DRESEP, DARE-SEP, DE-SEP, & EEHCT in 3-level HWSN.

TABLE 3. An instance of participating nodes in the multilevel HWSN with 100 nodes.

Node Type	Level-1	Level-2	Level-3	Level-4	Level-5
Normal Node (O) or Type-1 Node	100	20	30	20	15
Advanced Node (A) or Type-2 Node	X	80	14	10	15
Super Node (S) or Type-3 Node	X	X	56	10	10
Ultra Super Node (US) or Type-4 Node	X	X	X	60	10
Ultra High Super Node (UHS) or Type-5 Node	X	X	X	X	50

their initial energy to form a heterogeneous network of interest are chosen randomly. Like, heterogeneous nodes with proportional factors- $\zeta_1, \zeta_2, \zeta_3 \ldots$ along with energy multipliers- β_1, β_2, β_3, etc. (as in (1) - (6)) are chosen randomly to support the fact that the network is purely an application-specific network where nodes can be deployed as per the need of the application.

In addition to varying heterogeneity-levels, EEHCT has been examined in various node-density- 100 nodes, 150 nodes, 200 nodes, 250 nodes, and 300 nodes too to further strengthen its efficacy.

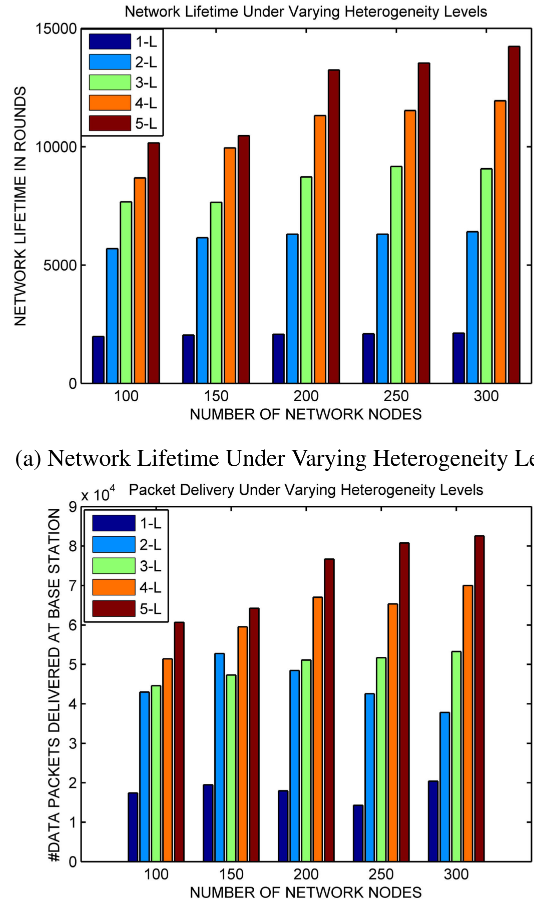
Fig. 9 along with the Table 5 summarizes the performance of EEHCT in varying levels of energy-heterogeneity with respect to network lifetime, and data packet delivery to the base station as follows:

Network Lifetime:

As defined already, network lifetime refers to the time when all the network nodes are dead. It is pretty evident from Fig. 9(a) that despite varying heterogeneity

TABLE 4. Initial energy of the participating nodes in the multilevel network with 100 nodes.

Node Type	Energy Multiplier (β)	Level -1	Level -2	Level -3	Level -4	Level -5
Normal Node (O) or Type-1 Node	(β_1=) 0	0.5 J	0.5 J	0.5 J	0.5 J	0.5 J
Advanced Node (A) or Type-2 Node	(β_2=) 2	X	1.5 J	1.5 J	1.5 J	1.5 J
Super Node (S) or Type-3 Node	(β_3=) 3.5	X	X	2.25 J	2.25 J	2.25 J
Ultra Super Node (US) or Type-4 Node	(β_4=) 4.5	X	X	X	2.75 J	2.75 J
Ultra High Super Node (UHS) or Type-5 Node	(β_5=) 5.5	X	X	X	X	3.25 J



(a) Network Lifetime Under Varying Heterogeneity Levels

(b) Data Packet Delivery Under Varying Heterogeneity Levels

FIGURE 9. EEHCT under varying heterogeneity levels.

levels, EEHCT continues to exhibit its smooth performance under every possible network configuration. For example, for a deployment of 100 nodes, the network lasts up to 1983, 5690, 7669, 8679, & 10157 network rounds, respectively, in level-1, 2, 3, 4, and 5 HWSNs.

TABLE 5. Performance of EEHCT with varying number of nodes deployed in a sensing area of 100m × 100m for level-1, 2, 3, 4, & 5.

No. of Nodes	Network Parameters	Level-1	Level-2	Level-3	Level-4	Level-5
100	Network Energy	50 J	130 J	162 J	212.5 J	242.5 J
	Network Lifetime	1983	5690	7669	8679	10157
	Packet Delivery	17399	42985	44598	51412	60652
	% Gain in Network Lifetime	X	186.93	286.73	337.67	412.20
	% Gain in Packet Delivery	X	147.05	156.32	195.49	248.59
150	Network Energy	75 J	195 J	249 J	350 J	405 J
	Network Lifetime	2038	6152	9033	10688	13083
	Packet Delivery	19469	52750	47299	59507	64244
	% Gain in Network Lifetime	X	201.86	342.22	424.43	541.95
	% Gain in Packet Delivery	X	170.94	142.95	205.65	229.98
200	Network Energy	100 J	260 J	332 J	487.5 J	567.5 J
	Network Lifetime	2068	6246	9063	11111	13448
	Packet Delivery	17959	48430	51111	66992	76675
	% Gain in Network Lifetime	X	202.03	339.7	437.29	550.29
	% Gain in Packet Delivery	X	169.67	184.60	273.03	326.94
250	Network Energy	125 J	325 J	415 J	625 J	730 J
	Network Lifetime	2092	6299	9238	11518	13845
	Packet Delivery	14291	42571	51684	65326	80751
	% Gain in Network Lifetime	X	201.04	341.58	450.57	561.81
	% Gain in Packet Delivery	X	197.89	261.65	357.11	465.05
300	Network Energy	150 J	390 J	498 J	762.5 J	892.5 J
	Network Lifetime	2100	6487	9298	11837	14188
	Packet Delivery	20377	37626	52325	67848	79232
	% Gain in Network Lifetime	X	208.9	342.77	463.67	575.6
	% Gain in Packet Delivery	X	84.65	156.78	232.96	288.83

The successive improvements in the network lifetime are because with more energy-heterogeneity, the network becomes enriched with more network energy. Network lifetimes for other node deployments under different heterogeneity levels have been tabulated in Table 5.

Data Packet Delivery to BS:

The amount of successfully delivered data packets indicates the success or failure of routing in the network. The higher the number of packets (delivered to BS), the greater the success of routing. It is a direct measure of success in collecting the information from the network and transferring it to the BS for further action. Fig. 9(b) describes this measure per network round. The number of successfully delivered data packets to the BS are 60652, 51412, 44598, 42985, & 17399 in the level-5, 4, 3, 2, & 1 HWSNs, respectively, for a deployment of 100 nodes. Table 5 describes the other figures of packet delivery for rest of the node deployment.

Thus, Fig. 9 and Table 5 confirm that EEHCT performs invariably well even under the varying energy-heterogeneity levels. In other words, the performance of EEHCT is not restricted to a particular heterogeneity level, but can be easily extended to any desired level as per the nature of the intended application.

Moreover, to further consolidate the performance of EEHCT, an extra set of simulations has been conducted to measure the network lifetime in different dimensions of sensing area like (100m × 100m), (200m × 200m), & (300m × 300m) for all the levels of energy-heterogeneity- 1,2,3,4,& 5. In each of these simulations, the sink is stationed at the center of the sensing area.

The statistics of this experiment is detailed in Table 6 as follows: Table 6 describes that the network lifetime increases with the increase in energy heterogeneity. This observation is due to the fact that the change in the energy heterogeneity level brings equivalent changes in the overall network energy. The aggregate energy in the network increases by adding higher degree of energy heterogeneity, and it decreases by neutralizing the energy heterogeneity in the network. However, widening the sensing area decreases the network lifetime because of higher communication costs due to the widened separation amongst the network nodes.

TABLE 6. Performance of EEHCT with 100 nodes in different network dimensions under varying heterogeneity-level.

Sensing Field	Network Parameters	Level-1 (50J)	Level-2 (130J)	Level-3 (162J)	Level-4 (212.5J)	Level-5 (242.5J)
100x100	Network Lifetime	1983	5690	7669	8679	10157
	% Gain in Network Lifetime	X	186.93	286.73	337.67	412.2
200x200	Network Lifetime	1703	4881	7287	7412	7826
	% Gain in Network Lifetime	X	186.61	327.89	335.25	359.54
300x300	Network Lifetime	1519	4765	6589	6914	7085
	% Gain in Network Lifetime	X	213.69	333.77	355.16	366.43

Based on the results of various simulations demonstrated in Fig. 5 - Fig. 9 and Table 2 - Table 6, EEHCT proves its worth in a heterogeneous network environment. Not only EEHCT outperforms LEACH [11], E-DEEC [17], ED-DEEC [18], DRE-SEP [20], DARE-SEP [21], and DE-SEP [22] but also ensures a consistent network performance without taking any specific level of energy heterogeneity into account. Hence, the scheme is scalable to any desired level of energy heterogeneity.

VI. CONCLUSION & FUTURE SCOPE

In this work, an energy-efficient hybrid clustering technique for the IoT-based HWSNs, EEHCT has been proposed. EEHCT achieves its primary goals of improving network lifetime and network stability without requiring the network to be characterized with any specific level of heterogeneity. It works well even in the n-level energy-heterogeneous network. Besides, the hybrid clustering (an appropriate amalgamation of dynamic and static clustering) technique is used to formulate energy-balanced clusters. EEHCT proceeds with dynamic clustering for the first few rounds, and later on, with the obtainment of energy-balanced clusters, it declares them static throughout network operations. Provisioning the static clusters allows energy consumed in the successive cluster formations to be saved and utilized in other necessary network operations. EEHCT not only outperforms the existing schemes such as LEACH, E-DEEC, ED-DEEC, DRE-SEP, DARE-SEP, and DE-SEP in terms of network lifetime but also exhibits improved network stability. Moreover, being a heterogeneity-independent scheme, it leads to a highly scalable network solution.

Nowadays, varieties of IoT-based sensor network applications are incorporating mobile nodes, which may not result in always-on connectivity; hence, data exchange among the nodes is becoming more challenging. Therefore, a mobility-enabled IoT-based HWSN will be investigated in future to facilitate the data exchange among the nodes while tackling the intrinsic intermittent connectivity constraint in an effective and energy-efficient way.

REFERENCES

[1] A. Shahraki, A. Taherkordi, O. Haugen, and F. Eliassen, "A survey and future directions on clustering: From WSNs to IoT and modern networking paradigms," *IEEE Trans. Netw. Service Manage.*, vol. 18, no. 2, pp. 2242–2274, Jun. 2021, doi: 10.1109/TNSM.2020.3035315.

[2] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Commun. Mag.*, vol. 40, no. 8, pp. 393–422, Aug. 2002, doi: 10.1109/MCOM.2002.1024422.

[3] X. B. Wang, "Heterogeneous architecture for ad hoc networks," *Adv. Mater. Res.*, vols. 756–759, pp. 1059–1062, Sep. 2013, doi: 10.4028/www.scientific.net/amr.756-759.1059.

[4] S. Ghiasi, A. Srivastava, X. Yang, and M. Sarrafzadeh, "Optimal energy aware clustering in sensor networks," *Sensors*, vol. 2, no. 7, pp. 258–269, Jul. 2002, doi: 10.3390/s20700258.

[5] A. A. Abbasi and M. Younis, "A survey on clustering algorithms for wireless sensor networks," *Comput. Commun.*, vol. 30, nos. 14–15, pp. 2826–2841, Oct. 2007, doi: 10.1016/j.comcom.2007.05.024.

[6] A. S. Zahmati, B. Abolhassani, A. B. Ali Shirazi, and A. S. Bahitiari, "An energy-efficient protocol with static clustering for wireless sensor networks," *Int. J. Electron., Circuits Syst.*, vol. 1, no. 2, pp. 135–138, May 2007, doi: 10.5281/zenodo.1329188.

[7] S. K. Chaurasiya, T. Pal, and S. Das Bit, "An enhanced energy-efficient protocol with static clustering for WSN," in *Proc. Int. Conf. Inf. Netw. (ICOIN)*, Kuala Lumpur, Malaysia, Jan. 2011, pp. 58–63, doi: 10.1109/ICOIN.2011.5723134.

[8] S. K. Chaurasiya, J. Sen, S. Chaterjee, and S. D. Bit, "An energy-balanced lifetime enhancing clustering for WSN (EBLEC)," in *Proc. 14th Int. Conf. Adv. Commun. Technol. (ICACT)*, Feb. 2012, pp. 189–194.

[9] F. Bajaber and I. Awan, "Dynamic/static clustering protocol for wireless sensor network," in *Proc. 2nd UKSIM Eur. Symp. Comput. Modeling Simulation*, Sep. 2008, pp. 524–529, doi: 10.1109/EMS.2008.22.

[10] M. A. Wahdan, M. F. Al-Mistarihi, and M. Shurman, "Static cluster and dynamic cluster head (SCDCH) adaptive prediction-based algorithm for target tracking in wireless sensor networks," in *Proc. 38th Int. Conv. Inf. Commun. Technol., Electron. Microelectron. (MIPRO)*, May 2015, pp. 596–600, doi: 10.1109/MIPRO.2015.7160342.

[11] 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.*, vol. 2, Aug. 2000, pp. 1–10, doi: 10.1109/HICSS.2000.926982.

[12] W. R. A. Heinzelman Chandrakasan and H. Balkrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Trans. Wireless Commun.*, vol. 1, no. 4, pp. 660–670, Oct. 2002, doi: 10.1109/TWC.2002.804190.

[13] O. Younis and S. Fahmy, "HEED: A hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks," *IEEE Trans. Mobile Comput.*, vol. 3, no. 4, pp. 366–379, Oct./Dec. 2004, doi: 10.1109/TMC.2004.41.

[14] G. Smaragdakis, I. Matta, and A. Bestavros, "SEP: A stable election protocol for clustered heterogeneous wireless sensor networks," in *Proc. 2nd Int. Workshop Sensor Actor Netw. Protocols Appl. (SANPA)*, Boston, MA, USA, 2004, pp. 1–11.

[15] Q. Li, 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, doi: 10.1016/j.comcom.2006.02.017.

[16] B. Elbhiri, R. Saadane, S. El Fldhi, and D. Aboutajdine, "Developed distributed energy-efficient clustering (DDEEC) for heterogeneous wireless sensor networks," in *Proc. 5th Int. Symp. I/V Commun. Mobile Netw.*, Sep. 2010, pp. 1–4, doi: 10.1109/ISVC.2010.5656252.

[17] P. Saini and A. K. Sharma, "E-DEEC- enhanced distributed energy efficient clustering scheme for heterogeneous WSN," in *Proc. 1st Int. Conf. Parallel, Distrib. Grid Comput. (PDGC)*, Oct. 2010, pp. 205–210, doi: 10.1109/PDGC.2010.5679898.

[18] N. Javaid, T. N. Qureshi, A. H. Khan, A. Iqbal, E. Akhtar, and M. Ishfaq, "EDDEEC: Enhanced developed distributed energy-efficient clustering for heterogeneous wireless sensor networks," *Proc. Comput. Sci.*, vol. 19, pp. 914–919, Jan. 2013, doi: 10.1016/j.procs.2013.06.125.

[19] T. N. Qureshi, N. Javaid, A. H. Khan, A. Iqbal, E. Akhtar, and M. Ishfaq, "BEENISH: Balanced energy efficient network integrated super heterogeneous protocol for wireless sensor networks," *Proc. Comput. Sci.*, vol. 19, pp. 920–925, Jan. 2013, doi: 10.1016/j.procs.2013.06.126.

[20] N. Mittal and U. Singh, "Distance-based residual energy-efficient stable election protocol for WSNs," *Arabian J. Sci. Eng.*, vol. 40, no. 6, pp. 1637–1646, Jun. 2015, doi: 10.1007/s13369-015-1641-x.

[21] A. Naeem, A. R. Javed, M. Rizwan, S. Abbas, J. C.-W. Lin, and T. R. Gadekallu, "DARE-SEP: A hybrid approach of distance aware residual energy-efficient SEP for WSN," *IEEE Trans. Green Commun. Netw.*, vol. 5, no. 2, pp. 611–621, Jun. 2021, doi: 10.1109/TGCN.2021.3067885.

[22] A. Hossan and P. K. Choudhury, "DE-SEP: Distance and energy aware stable election routing protocol for heterogeneous wireless sensor network," *IEEE Access*, vol. 10, pp. 55726–55738, 2022, doi: 10.1109/ACCESS.2022.3177190.

[23] S. K. Singh, P. Kumar, and J. P. Singh, "A survey on successors of LEACH protocol," *IEEE Access*, vol. 5, pp. 4298–4328, 2017, doi: 10.1109/ACCESS.2017.2666082.

[24] L. Xu, R. Collier, and G. M. P. O'Hare, "A survey of clustering techniques in WSNs and consideration of the challenges of applying such to 5G IoT scenarios," *IEEE Internet Things J.*, vol. 4, no. 5, pp. 1229–1249, Oct. 2017, doi: 10.1109/JIOT.2017.2726014.

[25] H. Le, D. Hoang, and R. Poliah, "S-web: An efficient and self-organizing wireless sensor network model," in *Network-Based Information Systems(NBiS)* (Lecture Notes in Computer Science), vol. 5186, M. Takizawa, L. Barolli, and T. Enokido, Eds. Berlin, Germany: Springer, 2008, pp. 179–188, doi: 10.1007/978-3-540-85693-1_20.

[26] D. Jia, H. Zhu, S. Zou, and P. Hu, "Dynamic cluster head selection method for wireless sensor network," *IEEE Sensors J.*, vol. 16, no. 8, pp. 2746–2754, Apr. 2015, doi: 10.1109/JSEN.2015.2512322.

[27] S. Banerjee and S. Khuller, "A clustering scheme for hierarchical control in multi-hop wireless networks," in *Proc. IEEE Conf. Comput. Commun. 20th Annu. Joint Conf. IEEE Comput. Commun. Soc. (INFOCOM)*, vol. 2, 2001, pp. 1028–1037, doi: 10.1109/INFCOM.2001.916296.

[28] S. Lindsey, C. Raghavendra, and K. M. Sivalingam, "Data gathering algorithms in sensor networks using energy metrics," *IEEE Trans. Parallel Distrib. Syst.*, vol. 13, no. 9, pp. 924–935, Sep. 2002, doi: 10.1109/TPDS.2002.1036066.

[29] V. Loscri, G. Morabito, and S. Marano, "A two-levels hierarchy for low-energy adaptive clustering hierarchy (TL-LEACH)," in *Proc. IEEE 62nd Veh. Technol. Conf. (VTC-Fall)*, Sep. 2005, pp. 1809–1813, doi: 10.1109/VETECF.2005.1558418.

[30] B. Aoun and R. Boutaba, "Clustering in WSN with latency and energy consumption constraints," *J. Netw. Syst. Manage.*, vol. 14, no. 3, pp. 415–439, Sep. 2006, doi: 10.1007/s10922-006-9039-4.

[31] Y. Tian, E. Ekici, and F. Özgüner, "Cluster-based information processing in wireless sensor networks: An energy-aware approach," *Wireless Commun. Mobile Comput.*, vol. 7, no. 7, pp. 893–907, Sep. 2007, doi: 10.1002/wcm.502.

[32] J. Yuea, W. Zhang, W. Xiao, D. Tang, and J. Tang, "Energy efficient and balanced cluster-based data aggregation algorithm for wireless sensor networks," *Proc. Eng.*, vol. 29, pp. 2009–2015, Jan. 2012, doi: 10.1016/j.proeng.2012.01.253.

[33] T. Liu, Q. Li, and P. Liang, "An energy-balancing clustering approach for gradient-based routing in wireless sensor networks," *Comput. Commun.*, vol. 35, no. 17, pp. 2150–2161, Oct. 2012, doi: 10.1016/j.comcom.2012.06.013.

[34] D. Mahmood, N. Javaid, S. Mahmood, S. Qureshi, A. M. Memon, and T. Zaman, "MODLEACH: A variant of LEACH for WSNs," in *Proc. 8th Int. Conf. Broadband Wireless Comput., Commun. Appl.*, Oct. 2013, pp. 158–163, doi: 10.1109/BWCCA.2013.34.

[35] A. Nasrin, K. Jaber, and S. Farid, "HCTE: Hierarchical clustering based routing algorithm with applying the two cluster heads in each cluster for energy balancing in WSN," *IJCSI Int. J. Comput. Sci.*, vol. 9, no. 1, pp. 57–61, 2012.

[36] A. Mehmood, S. Khan, B. Shams, and J. Lloret, "Energy-efficient multi-level and distance-aware clustering mechanism for WSNs," *Int. J. Commun. Syst.*, vol. 28, no. 5, pp. 972–989, 2015, doi: https://doi.org/10.1002/dac.2720.

[37] C.-H. Lee and D. Y. Eun, "Exploiting heterogeneity to prolong the lifetime of large-scale wireless sensor networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2011, pp. 1–5, doi: 10.1109/ICC.2011.5963081.

[38] S. Halder and S. Das Bit, "Enhancement of wireless sensor network lifetime by deploying heterogeneous nodes," *J. Netw. Comput. Appl.*, vol. 38, pp. 106–124, Feb. 2014, doi: 10.1016/j.jnca.2013.03.008.

[39] J. Yu, Y. Qi, and G. Wang, "An energy-driven unequal clustering protocol for heterogeneous wireless sensor networks," *J. Control Theory Appl.*, vol. 9, no. 1, pp. 133–139, Feb. 2011, doi: 10.1007/s11768-011-0232-y.

[40] K. Xu and M. Gerla, "A heterogeneous routing Protocol based on a new stable clustering scheme," in *Proc. Military Commun. Conf. (MILCOM)*, vol. 2, Oct. 2010, pp. 838–843, doi: 10.1109/MILCOM.2002.1179583.

[41] D. Kumar, C. Trilok Aseri, and R. B. Patel, "EEHC: Energy efficient heterogeneous clustered scheme for wireless sensor networks," *Comput. Commun.*, vol. 32, pp. 662–667, Mar. 2009, doi: 10.1016/j.comcom.2008.11.025.

[42] D. Kumar, C. Trilok Aseri, and R. B. Patel, "Prolonging network lifetime and data accumulation in heterogeneous sensor networks," *Int. Arab J. Inf. Technol.*, vol. 7, no. 3, pp. 302–309, 2010.

[43] D. Kumar, T. C. Aseri, and R. B. Patel, "EECDA: Energy efficient clustering and data aggregation protocol for heterogeneous wireless sensor networks," *Int. J. Comput. Commun. Control*, vol. 6, no. 1, p. 113, Mar. 2011, doi: 10.15837/ijccc.2011.1.2206.

[44] B. Elbhiri, R. Saadane, and D. Aboutajdine, "Stochastic and equitable distributed energy-efficient clustering (SEDEEC) for heterogeneous wireless sensor networks," *Int. J. Ad Hoc Ubiquitous Comput.*, vol. 7, no. 1, p. 4, 2011, doi: 10.1504/IJAHUC.2011.037849.

[45] C. Duan and H. Fan, "A distributed energy balance clustering protocol for heterogeneous wireless sensor networks," in *Proc. Int. Conf. Wireless Commun., Netw. Mobile Comput.*, Sep. 2007, pp. 2469–2473, doi: 10.1109/WICOM.2007.615.

[46] F. Farouk, R. Rizk, and F. W. Zaki, "Multi-level stable and energy-efficient clustering protocol in heterogeneous wireless sensor networks," *IET Wireless Sensor Syst.*, 4, no. 4, 2014, pp. 159–169, doi: 10.1049/iet-wss.2014.0051.

[47] V. Gupta and R. Pandey, "An improved energy aware distributed unequal clustering protocol for heterogeneous wireless sensor networks," *Eng. Sci. Technol., Int. J.*, vol. 19, no. 2, pp. 1050–1058, Jun. 2016, doi: 10.1016/j.jestch.2015.12.015.

[48] S. Chand, S. Singh, and B. Kumar, "Heterogeneous HEED protocol for wireless sensor networks," *Wireless Pers. Commun.*, vol. 77, no. 3, pp. 2117–2139, Aug. 2014, doi: 10.1007/s11277-014-1629-y.

[49] S. Chand, S. Singh, and B. Kumar, "3-level heterogeneity model for wireless sensor networks," *Int. J. Comput. Netw. Inf. Secur.*, vol. 5, no. 4, pp. 40–47, Apr. 2013, doi: 10.5815/ijcnis.2013.04.06.

[50] S. Singh, S. Chand, and B. Kumar, "Energy efficient clustering protocol using fuzzy logic for heterogeneous WSNs," *Wireless Personal Commun.*, vol. 86, no. 2, pp. 451–475, 2015, doi: 10.1007/s11277-015-2939-4.

[51] 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, doi: 10.1016/j.jestch.2016.08.009.

[52] S. Singh, "Energy efficient multilevel network model for heterogeneous WSNs," *Eng. Sci. Technol., Int. J.*, vol. 20, no. 1, pp. 105–115, Feb. 2017, doi: 10.1016/j.jestch.2016.09.008.

[53] T. M. Behera, S. K. Mohapatra, U. C. Samal, and M. S. Khan, "Hybrid heterogeneous routing scheme for improved network performance in WSNs for animal tracking," *Internet Things*, vol. 6, Jun. 2019, Art. no. 100047, doi: 10.1016/j.iot.2019.03.001.

[54] P. Rahul, R. Piyush, N. Vijay, A. Bibhudendra, and N. Shylashree, "Three level heterogeneous clustering protocol for wireless sensor network," *Microsyst. Technol.*, vol. 26, pp. 3855–3864, May 2020, doi: 10.1007/s00542-020-04874-x.

[55] S. Hassan, M. S. Nisar, and H. Jiang, "DTRE-SEP: A direct transmission and residual energy based stable election protocol for clustering techniques in HWSN," in *Proc. IEEE Int. Conf. Commun. Softw. Netw. (ICCSN)*, Jun. 2015, pp. 266–271, doi: 10.1109/ICCSN.2015.7296167.

[56] A. A. Masri, G. Y. Delisle, and N. Hakem, "Hierarchical routing protocol for multi-level heterogeneous sensor network," in *Proc. 16th Medit. Microw. Symp. (MMS)*, Nov. 2016, pp. 1–4, doi: 10.1109/MMS.2016.7803853.

[57] A. Preethi, E. Pravin, and D. Sangeetha, "Modified balanced energy efficient network integrated super heterogeneous protocol," in *Proc. Int. Conf. Recent Trends Inf. Technol. (ICRTIT)*, Apr. 2016, pp. 1–6, doi: 10.1109/ICRTIT.2016.7569562.

[58] A. Sharma, K. Goel, A. Bindal, and A. K. Bindal, "Static energy efficient clustering scheme for heterogeneous wireless sensor networks (S EECS)," in *Proc. 9th Int. Conf. Contemp. Comput. (IC3)*, Aug. 2016, pp. 1–6, doi: 10.1109/IC3.2016.7880193.

[59] B. M. Sahoo, A. D. Gupta, S. A. Yadav, and S. Gupta, "ESRA: Enhanced stable routing algorithm for heterogeneous wireless sensor networks," in *Proc. Int. Conf. Autom., Comput. Technol. Manage. (ICACTM)*, Apr. 2019, pp. 148–152, doi: 10.1109/ICACTM.2019.8776740.

[60] C. Gherbi, R. Doudou, and Z. Aliouat, "Energy dissipation and load balancing in self-organized heterogeneous WSN for e-applications," in *Proc. Int. Conf. Inf. Syst. Adv. Technol. (ICISAT)*, Dec. 2021, pp. 1–4, doi: 10.1109/ICISAT54145.2021.9678437.

[61] N. Kumar, P. Rani, V. Kumar, S. V. Athawale, and D. Koundal, "THWSN: Enhanced energy-efficient clustering approach for three-tier heterogeneous wireless sensor networks," *IEEE Sensors J.*, vol. 22, no. 20, pp. 20053–20062, Oct. 2022, doi: 10.1109/JSEN.2022.3200597.

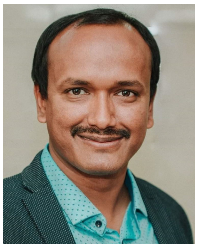
[62] M. G. Ri, Y. S. Han, J. Pak, S. G. Hwang, and C. M. Pong, "An improved equal hierarchical cluster-based routing protocol for EH-WSNs to enhance balanced utilization of harvested energy," *IEEE Access*, vol. 10, pp. 67081–67095, 2022, doi: 10.1109/ACCESS.2022.3183792.

[63] M. Gamal, N. E. Mekky, H. H. Soliman, and N. A. Hikal, "Enhancing the lifetime of wireless sensor networks using fuzzy logic LEACH technique-based particle swarm optimization," *IEEE Access*, vol. 10, pp. 36935–36948, 2022, doi: 10.1109/ACCESS.2022.3163254.

[64] A. S. Nandan, S. Singh, R. Kumar, and N. Kumar, "An optimized genetic algorithm for cluster head election based on movable sinks and adjustable sensing ranges in IoT-based HWSNs," *IEEE Internet Things J.*, vol. 9, no. 7, pp. 5027–5039, Apr. 2022, doi: 10.1109/JIOT.2021.3107295.

SANDIP K. CHAURASIYA received the M.E. degree in computer science and technology from the Indian Institute of Engineering Science and Technology, Shibpur, Howrah, West Bengal, India, in June 2010. He is working as an Assistant Professor with the University of Petroleum and Energy Studies, Dehradun, Uttarakhand, India. He has published many research articles in peer-reviewed journals and conferences. He has authored two books on wireless sensor networks. His research interests include mobile computing, wireless sensor networks, and the Internet of Things. He has reviewed a number of research articles in several reputed international conferences/journals. He is an active member of the Institution of Electronics and Communication Engineers (India), New Delhi.

SANTU MONDAL received the B.Tech. and M.Tech. degrees from the West Bengal University of Technology, India. He is currently pursuing the Ph.D. degree in AI, ML, and DL. He has six years of experience in teaching, research, and administration. He is currently working as an Assistant Professor with the Department of CSE, NSHM Knowledge Campus, Durgapur.



ARINDAM BISWAS received the M.Tech. degree in radio physics and electronics from the University of Calcutta, India, in 2010, and the Ph.D. degree from NIT Durgapur, in 2013. He was a Postdoctoral Researcher with Pusan National University, South Korea, with the prestigious BK21PLUS Fellowship, South Korea. He was a DST-JSPS Invitation Fellow with RIE, Japan; DST-ASEAN Invitation Fellow with Duy Tan University, Vietnam and Taylors University, Malaysia; Visiting Fellow with the Department of Electrical and Computer Engineering, National University Singapore. He has worked as a specially appointed Associate Professor (Visiting) with the Research Institute of Electronics, Shizuoka University, Japan. He is currently an Associate Professor with the School of Mines and Metallurgy, Kazi Nazrul University, West Bengal, India, where he has been actively engaged in teaching, research, and administration. He has 53 technical articles in different journals and 55 conference proceedings, eight authored books, 18 edited volumes, and ten book chapters of international repute. He has received research grants from different funding agencies, namely, SERB, DST-ASEAN, DST-JSPS, and UGC. He has also received international research grant from the Centre of Biomedical Engineering, Tokyo Medical and Dental University in association with RIE, Shizuoka University, Japan, for four consecutive years, from 2019 to 2023. He has supervised six Ph.D. students till date. His research interests include carrier transport in low dimensional system and electronic devices, nonlinear optical communication, THz semiconductor source, the IoT, and optimization. He is a Life Member of the Institute of Engineers (India), MGMI, and a Regular Fellow of the Optical Society of India. He was a reviewer for reputed journals. He has been selected for the IE (I) Young Engineer Award (2019–2020), the KNU Best Researcher Award (Engineering and Technology) 2021, the KNU Best Faculty Award 2022 (Faculty of Science and Technology), and the Best Paper Award in different international conferences. He has organized and chaired different international conferences in India and abroad.

ANAND NAYYAR (Senior Member, IEEE) received the Ph.D. degree in computer science from Desh Bhagat University, in 2017, in the area of wireless sensor networks, swarm intelligence, and network simulation. He is currently working with the School of Computer Science-Duy Tan University, Da Nang, Vietnam, as an Assistant Professor, a Scientist, the Vice-Chairperson (Research), and the Director of the IoT and Intelligent Systems Laboratory. He is a Certified Professional with more than 100 Professional certificates from CISCO, Microsoft, Amazon, EC-Council, Oracle, Google, Beingcert, EXIN, GAQM, and Cyberoam. He has published more than 140 research articles in various high-quality ISI-SCI/SCIE/SSCI impact factor journals cum Scopus/ESCI indexed journals, more than 70 papers in international conferences indexed with Springer, IEEE, and ACM Digital Library, and more than 40 book chapters in various Scopus/Web of Science indexed books with Springer, CRC Press, Wiley, IET, and Elsevier, with more than 8600 citations, H-index: 50 and I-index: 170. He has authored/coauthored and edited more than 40 books in computer science. He has 18 Australian patents, four German patents, one Japanese patent, 11 Indian Design cum Utility patents, three Indian copyrights, and two Canadian copyrights to his credit in the area of wireless communications, artificial intelligence, cloud computing, the IoT, and image processing. His current research interests include wireless sensor networks, the Internet of Things, swarm intelligence, cloud computing, artificial intelligence, drones, blockchain, cyber security, network simulation, big data, and wireless communications. He is member of more than 60 associations, such as Senior member and Life Member, including IEEE and ACM. He has associated with more than 500 international conferences as a program committee/chair/advisory board/review board member. He was the recipient of 35 awards for Teaching and Research—Young Scientist, Best Scientist, the Young Researcher Award, the Outstanding Researcher Award, Excellence in Teaching, and many more. He is listed in the world's Top 2% scientists as per Stanford University, in 2020 and 2021. He has reviewed more than 2000 articles for diverse Web of Science and Scopus indexed journals. He is an Associate Editor of *Wireless Networks* (Springer), *Computer Communications* (Elsevier), *International Journal of Sensor Networks* (IJSNET) (Inderscience), *Frontiers of Computer Science*, *PeerJ Computer Science*, *Human-Centric Computing and Information Sciences* (HCIS), *IET Quantum Communication*, *IET Wireless Sensor Systems*, *IET Networks*, *IJDST*, *IJISP*, *IJCINI*, and *IJGC*. He is the Editor-in-Chief of IGI-Global, USA journal titled *International Journal of Smart Vehicles and Smart Transportation* (IJSVST).

MOHD ASIF SHAH is currently an Associate Professor with Bakhtar University, Kabul, Afghanistan. He was earlier working as an Assistant Professor of economics with the Forbes Business School, India, and LPU, India. He has served as a Lecturer for the JCE, Jammu and Kashmir, India, and also supported his department with teaching assistance during the Ph.D. He has published more than 20 research articles (SCI/WOS/UGC indexed) with more than 30 citations.

RAJIB BANERJEE (Member, IEEE) received the M.Tech. degree in electronics and communication engineering and the Ph.D. degree in engineering from the Indian Institute of Engineering Science and Technology, Shibpur, West Bengal, India. He is currently an Assistant Professor with the Department of Electronics and Communication Engineering, Dr. B. C. Roy Engineering College, Durgapur, West Bengal. He has published many articles in SCI journals, patents, and peer-reviewed IEEE conferences. His research interests include wireless sensor networks, wireless multimedia sensor networks, low-power multimedia processing, the Internet of Things, and bioengineering. He is an IEEE Student Branch Counselor. He has organized many IEEE events and has also served as the organizing chair for IEEE conferences.