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An enhanced energy efficient protocol for large-scale IoT-based heterogeneous WSNs

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ABSTRACT

There is increasing attention, recently, to optimizing energy consumption in IoT-based large-scale networks. Extending the lifetime of battery-powered nodes is a key challenge in such systems and their various application scenarios. This paper proposes a new zone-based and event-driven protocol for saving energy in large-scale heterogeneous WSNs called TESEES (Threshold Enabled Scalable and Energy Efficient Scheme). The proposed protocol is designed to support network scenarios deploying higher levels of heterogeneity with more than three types of sensor nodes (i.e., four, five, and more). TESEES is a reactive version of the proactive SEES protocol, in which we leverage a novel state-of-the-art thresholding model on the zone-based hierarchical deployments of heterogeneous nodes to regulate the data reporting process, avoiding unnecessary frequent data transmission and reducing the amount of energy dissipation of the sensing nodes and the entire system. With this model, we present a general technique for formulating distinct thresholds for network nodes in each established zone. This mechanism allows for individually configuring the nodes with transmission settings tailored to their respective roles, independent of the heterogeneity levels, total node count, or initial energy. This approach ensures that each node operates optimally within the network. In addition, we present an improved hybrid TMCCT (Threshold-based Minimum Cost Cross-layer Transmission) algorithm that operates at the node level and ensures effective data transmission control by considering current sensor values, heterogeneous event thresholds, and previous data records. Instead of periodical data transmission, this hybridization mechanism, integrated with a grid of energy-harvesting relay nodes, keeps the zone member nodes in the energy-saving mode for maximum time and allows for reactive data transmission only when necessary. This results in a reduced data-reporting frequency, less traffic load, minimized energy consumption, and thus a greater extension of the network's lifetime. Moreover, unlike the traditional cluster-head

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election in the weighted probability-based protocols, TESEES relies on an efficient mechanism for zone aggregators' election that runs at the zone level in multiple stages and employs various static and dynamic parameters based on their generated weights of importance. This leads to selecting the best candidate nodes for the aggregation task and, hence, fairly rotating the role among the zones' alive nodes. The simulation results show significant improvements in the total energy saving, the lifetime extension, and the transmitted data reduction, reaching 29%, 68%, and 26% respectively, compared to the traditional SEES protocol. Also, the average energy consumption per single round has decreased by 36%.

Introduction

Recent advances in IoT technology have gained greater attention in various domains and industries, promising several advantages that permit a broad range of applications and intelligent systems [1–4]. Data collection or continuous monitoring, for example, is one of the IoT-based applications that is wildly used in different sectors such as manufacturing, healthcare, transportation, agriculture, education, construction, energy, retail, banking, etc. [5–12]. WSNs have been recognized as the main pillar of IoT-based systems, which have been rapidly improved in the past few years [13–16]. IoT-based WSNs paved the way for digital systems to see, hear, smell, and control different entities in the physical world, without the need for human intervention [17–19]. Related advancements in technologies, architectures, standards, and reference models have made this field a crucial research area that needs further study and investigations in various aspects and directions to meet the requirements of real-world applications. Especially those of large-scale deployment environments. In such scenarios, WSNs connect a large number of tiny heterogeneous sensing devices distributed in variable-sized areas to measure, monitor, track, and/or collect critical data of different types. One of the key requirements is to keep sensing systems in a continuous and accurate operational state for a longer working time, which makes energy consumption one of the key challenges in developing IoT-based monitoring systems and related applications [20–23]. The autonomous devices in such systems are usually equipped with limited-capacity and non-rechargeable batteries and are required to keep running continuously over an extended time, which may reach years [24,25]. Therefore, energy saving, management, and control are currently key concerns for IoT. The focus is on designing and developing energy-saving solutions and algorithms that can efficiently optimize the use of batteries and minimize the required energy dissipations of IoT-based sensing devices and systems; thus extending their lifetime [26–29]. In this context, several techniques have been proposed in the literature, following different approaches and mechanisms. At the highest level, energy-saving techniques for WSN, as discussed in [30–32], include energy-aware traffic routing, hierarchical clustering, resource management, duty cycling, transmitted data reduction, transceiver optimization, energy-efficient data acquisition, protocol overhead reduction, relay and sink node placement, energy-provision schemes, and voltage/current/and frequency control. Each of these categories comprises several efficient saving mechanisms that may, in turn, include further subcategories in the lower levels, which can be integrated and utilized in various manners. While the solutions introduced based on such methods show improvements in energy savings and other relevant metrics, none of them offer an optimal solution to address energy-related challenges in heterogeneous IoT networks that comprise different categories of sensing devices with varying energy levels. In such dense networks, a large volume of data is exchanged by battery-operated devices, leading to higher energy consumption and a shorter node lifespan. The premature expiration of nodes can lead to network instability and hinder the achievement of desired performance levels. Detecting failures, managing network nodes, and replacing batteries become challenging due to environmental constraints and large-scale deployment, particularly in inaccessible working areas. However, in zone-based proactive protocols, such as SEES, which are efficiently used in regularly clustered environments, the nodes report their data consistently in predefined time slots irrespective of related factors like fluctuations in sensed values or the actual need to transmit the most recent sensed data. While this proactive transmission strategy has its merits, it is not without limitations, particularly in time-critical applications. One drawback is the expenditure of energy by the heterogeneous nodes on unnecessary transmissions, even in cases when no changes are detected. This ultimately leads to shortening the network's lifetime. Therefore, efficient transmission control is imperative in such zone-based heterogeneous systems to reactively respond to the transmission triggers, save energy waste, and increase the system's lifetime. In this paper, we introduce a new energy-efficient reactive protocol for multilevel heterogeneous IoT-based WSNs to extend the network lifetime by avoiding unnecessary data transfer from the sensing devices and, hence, reducing frequent energy waste. In this proposed solution, we integrate a novel state-of-the-art event-thresholding model recently proposed in [33] with the proactive SEES protocol introduced in [34], in an efficient adapting way. The new reactive solution is called TESEES (Threshold Enabled Scalable and Energy Efficient Scheme), which addresses, in a different way from that of traditional cluster-based protocols, the energy efficiency of zone-based WSNs distributed in larger-scale IoT scenarios, covering wider sensing areas (e.g., agricultural fields, regular environments, etc.). The ultimate goal of TESEES is to optimize the energy consumption at the zone level by regulating the way data is transferred toward the upper layers while maintaining a scalable node distribution and a balanced energy load through all the created zones. With the state-of-the-art thresholding model adapted over the zonal deployment of the sensing nodes, TESEES reactively controls the process of data transmission from the sensing nodes in each zone upward to the sink nodes in the topmost layer. Based on this hybridized model, for each reporting interval, only the zone member nodes, whose sensed data meet the given requirements, are allowed to send their data to the base stations through relay nodes, while others remain off in energy conservation mode. For this, each node in every zone is configured in TESEES to consider different values of transmission thresholds (i.e., hard threshold and soft threshold), as well as values of its previously transmitted data within a defined sliding window, in order to decide whether to send its collected data or to remain asleep. Based on some given criteria, the threshold values can be configured for each zone member node in a way that enables the administrator to identify under which conditions each node can activate itself to send sensed data as well as to alter threshold values high and low within the nodes and/or zones. This helps in creating the desired level of redundancy when needed to ensure reading accuracy and overcome interference and changes in environmental conditions. In addition, TESEES adapts an efficient SEES-based mechanism for aggregator nodes' election differently from the weighted probability-based cluster-head election in traditional hierarchical clustering protocols. The election algorithm runs in multiple stages based on various static and dynamic parameters linked with their generated weights of importance, through which the best aggregator nodes are selected and the aggregation task is fairly rotated among the alive nodes in each zone. This mechanism supports considering several election parameters for the zone member nodes, regardless of the total count of the network nodes or the size of the working area. Moreover, TESEES is implemented to be a general zone-based thresholding-oriented protocol that can be applied in realistic multi-level heterogeneity scenarios that consider higher levels of nodes' heterogeneity (i.e., four, five, and more) and utilizes energy-harvesting nodes in a grid manner to relay data from the sensing layer to the base-station layer with less energy cost. Therefore, it is highly applicable to the time-driven IoT-based WSNs and applications deployed in large-scale regular environments. The major contributions of this paper are briefed as follows:

- TESEES, a reactive protocol for enhancing the Energy Efficiency of Large-Scale IoT-based Heterogeneous WSNs, efficiently adapts a state-of-the-art event-thresholding model to zonal-based solutions, as well as an improved data transmission model accordingly. This protocol addresses the limitations of traditional SEES [34], offering a flexible configuration and control of the data transmission process in multi-level heterogeneous networks, and hence, reduces redundant transmission and highly improves energy-saving.
- The event-thresholding model offers a novel and general mechanism for formulating heterogeneous thresholds of the network nodes in each created zone, enabling each sensor node to be configured with its own transmission settings based on its role, irrespective of the heterogeneity levels, the total number of nodes, or their initial energy. The heterogeneous thresholding process considers a combination of parameters including current sensed data, a window of previously reported data, the preferred boundary of sensed values, and the range within which data are considered significant.
- A hybridized TMCCT (Threshold-based Minimum Cost Cross-layer Transmission) algorithm, integrated with a grid of zone-cornered energy-harvesting relay nodes, for effective data transmission control based on generated heterogeneous thresholds, transmission distance, residual energy, current, and previously reported data. TMCCT runs at the node level and hence considers the local configuration of the node, and decides when it is necessary to send its date and which path is energy-efficient for transmission.
- Extensive simulation-based experiments and analysis through a custom program implemented, comparing TESEES to traditional SEES protocol through different network scenarios and thresholding model configurations. The results demonstrate the superiority of TESEES in regulating data transmission and accordingly performs well in terms of traffic load, network stability, energy-saving, and network lifetime

The rest of the paper is organized as follows. In "Related Work", we present related work. In "TESEES: The proposed protocol", we present TESEES, the proposed protocol with a detailed description of its working principles. "Experimental setup" presents the experimental setup and methodology, while "Simulation results analysis" covers the discussion and analysis of the simulation results. We conclude this work in "Conclusion".

Related work

Different techniques and strategies have been used in developing energy-saving algorithms and schemes for traditional WSNs and IoT-based systems as well. Custer-based solutions are among those efficient solutions that have been highly utilized and integrated with different approaches to optimize the energy demands of limited resources and low-power heterogeneous devices. In this section, we provide a brief literature review related to the protocol introduced in this paper. We start with a review of energy-efficient solutions for time-driven, so-called periodic sensor networks (PSN); secondly, we summarize the zone-based clustering protocols. Then, we present SEES, the existing traditional zonal protocol, briefing its aspects linked to the current solution, which we developed to address SEES limitations, specifically time-based data transmission models. Finally, we brief shortcomings of the reviewed solutions.

Time-driven based approaches

Time-driven or so-called periodic sensor networks (PSN) involve sensor nodes collecting and transmitting data at regular intervals. The intervals can be predetermined or dynamically adjusted based on system needs. While this approach finds applications in various domains, it can lead to higher energy consumption and shorter systems' lifetime [35,36]. To address these challenges, solutions have been developed to minimize energy demands, extend systems' lifespan, and maintain desired performance levels. In [37], DaT protocol is proposed for redundant data removal, utilizing an improved k-Nearest Neighbor algorithm. The protocol classifies and merges similar data classes. Then, the best representative readings from each class are sent to the sink. A DaT-based improved solution was introduced in [38], which uses both spatial and temporal redundancy based on the kNN algorithm. At the lower layer, DaT protocol is employed for redundancy removal, while at the aggregation layer, ETDTR protocol is implemented for further reduction through exploiting spatial correlations. Criteria such as lengths of vectors and Euclidian distance are used to decide, in several steps, on redundancy removal before transmitting data to the sink node. The authors of [39] incorporated two classes of the BM model, namely nearest neighbor distance and spherical contact for energy allocation and scheduling. The WSNs are divided into point-centered units within a rectangular area, with each unit containing a sensor, while the distance distribution is considered the most representative characteristic in their algorithm. EDiMoFA is proposed in [40], as a distributed solution, mainly focusing on coverage improvement for extending network lifetime. The protocol incorporates three techniques: virtual network partitioning based on the ddivide-and-conquer concept, dynamic selection of region heads, and FA optimization algorithm for scheduling. The protocol operates periodically in two phases: a steady-state phase for information exchange, partitioning and optimization, and a monitoring phase based on the best sensor device schedule produced. In [41], the authors presented EFoCoD protocol for energy-saving in fog computing applications. LiDaRE, a lightweight algorithm, is implemented at the node level to reduce redundancy based on the nodes temporal correlation. The reduced data is then compressed and sent to the fog gateway. The work in [42] integrates energy harvesting, unequal clustering, and graph theory to improve energy efficiency in mobile education settings. Factors such as node degrees, distance of nodes to the BS and to each other, and energy levels of cluster heads are considered when selecting message routes in order to achieve better energy balancing. In [43], DBSCAN protocol is introduced for IoT networks, which runs in a distributed manner at the node level to create network clusters. A new periodic cluster method is proposed for CH selection based on residual energy, neighbor nodes, and node distance within its group. Data transmission occurs in the steady state based on the active/idle status of nodes within the TDMA schedule. CH performs data aggregation and then transmits it to the BS. In [44], SeDeSCA algorithm is proposed with two working phases: clustering and device scheduling. DBSCAN algorithm is employed for clustering, while scheduling runs in three subphases: CH selection, coverage optimization for optimal scheduling through Cuckoo algorithm, and active/sleep-based periodic monitoring. The aim was to achieve a minimum number of active devices periodically. In [45], IEE-LEACH protocol is introduced, which adapts clustering and periodic data transmission. Factors such as residual energy, average energy, and proximity to the BS are considered when selecting cluster heads, which aggregate and compress data before transmitting to the BS. Also, it employs single-hop, multi-hop, and hybrid communications to optimize energy consumption. In [41], DaTOS is proposed for tactile Internet-based fog computing, which implements LiReDaR and DaSeRE algorithms. LiReDaR, a lightweight algorithm, is used to minimize data of sensor node before transmission to the gateway through compression, while DaSeRE algorithm, which relies on mini-batch k-Means, runs at the gateway to eliminate repetitive data sets resulting from spatial correlation before sending them to the server on the cloud. The authors of [46] presented DiPCoM for IoT networks, which employs ARIMA prediction model to determine data transmission to the gateway. If the predicted data are not similar to previously sent ones, they are processed by an efficient lossy compression approach that employs APCA, differential encoding, SAX, and LZW algorithms for redundancy removal and then sent to the network gateway. in [47], the authors introduced a fitness function that considers both Homogeneous and heterogeneous WSNs, allowing for the selection of an optimal CH and a balanced node distribution. This selection considers factors such as average energy, the distance to BS, the count of adjacent nodes, and the number of nodes per cluster. Accordingly, they developed a new hybrid protocol for cluster-based routing that also enhances QoS parameters, and redesigned TDMA scheduling based on RSS for balancing energy dissipation and enable nodes to turn into sleeping states once they transmit their data. In [48], EDaP energy-efficient protocol is introduced for edge-based IoT networks. The protocol operates at the node and gateway levels. At the node level, the data is reduced through either MRLE or Hufman encoding algorithms, then compressed and forwarded to the gateway. At the gateway level, k-means and agglomerative clustering techniques are utilized to optimize scheduling and monitoring tasks for the next period based on spatial correlation. The nodes are grouped depending on their data similarity, and only one node from each cluster sends its data to the gateway periodically. In [49], the authors introduced AREDaCoT for WBSNs, which runs in two-stage periods: redundancy removal and sampling rate adjustment. In the first phase, NEWS chart is employed to translate the collected data into its correlating score based on the patient's health condition, while an improved LED algorithm is used to remove redundant data measurements. This is done according to their calculated scores, where only the measurements with higher critical scores will be reported, where the patient's health may require emergent actions, and hence, all readings are significant. In the second phase, the level of risk to the patient is assessed, and then the sampling rate is calibrated for biosensors. For further reading on relevant solutions, the readers can refer to [50–58] .

Zone-based clustering approaches

The zone-based clustering approaches are considered hybrid solutions that integrate static and dynamic clustering techniques. The working area is divided at the time of nodes' deployment into smaller areas called zones. These zones are kept the same over the network's operation time. In each zone, one or more CH (or ZH) are elected dynamically in every transmission round based on the changing network conditions. Traditional WSNs are typically configured using dynamic protocols, whereas in IoT-related systems and large-scale constrained networks, hybrid and zone-based static clustering approaches are usually preferred, as they have less computational overhead [59,60]. The size can be the same for all the created zones or can be different from one to another, depending on some network characteristics such as density, connectivity, coverage, etc. Z-SEP [61] is one of the earliest SEP-based zonal protocols, which partitions the sensing area rectangularly into three subareas: one in the middle for normal sensing nodes, and the other two head zones are for advanced nodes that are equipped with extra energy. This solution enables nodes in the middle zone to communicate directly with the base station located in the center, while those in the other zones send their data through the cluster head, which should be chosen dynamically in each transmission round. ZET protocol [62] was proposed by Jaffri and Cai, in which they divided the working area into nine zones of the same size. The head of each zone is chosen according to its distance to both the base station and a reference point in the middle, as well as its residual energy. A node can send its data to ZH once it becomes bigger than a predefined threshold. ZH aggregates all the data from nodes and sends it, after compression, to the base station. ZBRP protocol [63], is another solution that organizes the targeted area in the form of hierarchical rings. It creates several smaller zones in each ring, where the data is sent in a multi-hop path down to the base station through the zone heads of the lower clusters, while the nodes in the first ring send their data directly to the base station. In [64] EEZBC algorithm is proposed recently for large-scale WSNs, where the sensing field is divided into some equal-sized zones based on the design preference, in which each node can accommodate different numbers of sensing nodes. A zone monitor (ZM), as well as a cluster head (CH) are selected for each zone. ZM plays different roles, including deciding the number of CHs, selecting CHs, and re-clustering. The other member nodes use the distributed fuzzy inference technique to join one of the selected cluster heads, which will receive data, aggregate it, and send it to the base station in multi-hop communication. In [65], TEZEM protocol is presented for next-generation WSNs, in which the sensing area is divided into multiple equal-sized zones with a single CH for each zone selected periodically based on the residual energy. The BS is located in the middle, to which the sensed data is sent in multi-hop through CHs once it reaches a predefined value. The number of CH remains fixed for all zones to achieve energy load balancing. IZ-SEP is a new heterogeneity-enabled protocol proposed for WSNs in [66], which supports two levels of heterogeneity and partitions the sensing field into two zones, the inner zone, and the outer zone according to the nodes' initial energy. IZ-SEP allows nodes to communicate in two different manners. The normal nodes communicate directly to the BS at the center, while advanced nodes communicate through cluster heads. For cluster-head selection, IZ-SEP considers two parameters: the neighbors' count within the cluster and the node's remaining energy. In [67], E-GLBR is proposed with better-optimized zone creation, communication mode, and CHs election compared with IS-ZEP. The sensing area is divided into four zones with different sizes and coordinates, based on which the nodes communicated to BS either directly, through a predefined gateway or through selected CHs. E-GLBR is designed based on the genetic algorithm and considers CH energy consumption, along with transmission distance, residual energy, and node density in the formulated fitness function to improve HCs selection. The optimized E-GLBR fitness function helps to improve energy-load balancing and minimize energy consumption. However, many more zone-based solutions for IoT-based WSNs have not been included in this paper due to the lack of space. Readers may refer to [68–77] for further details. In Table 1, we present a summary of zone-based clustering approaches.

SEES protocol

SEES [34] is a novel scalable and energy-efficient zone-based protocol that is designed for time-driven networks deployed in larger-scale accessible environments (e.g., agricultural fields, regular environments, etc.). SEES introduces three key algorithms: (i) a hybrid-placement scheme, (ii) a Multi-Stage Weighted Election heuristic (MWSE), and (iii) a Minimum Cost Cross-layer Transmission model (MCCT). It also utilizes energy-harvesting technology by considering some energy-harvesting intermediate nodes (EHs) in a way that saves a higher amount of energy, ensures fair load-balancing, and enables a long-lived network. Further, SEES considers multi-level heterogeneity by leveraging a new model that considers up to n types of sensing devices with n different levels of battery capacities (where n is a positive integer number). The hybrid-placement scheme in SEES is for dividing the targeted area into smaller equal-sized zones and deploying sensor, relay, and base station nodes. It first determines the number of zones (Z), the number of heterogeneous nodes in each zone (N^z), and the total number of relaying nodes for the sensing field (R) according to the Eqs. (1), (2), and (3) below, respectively.

$$Z = \left(\left\lceil \frac{\sqrt{N}}{\sqrt{F_s}} \right\rceil \right)^2 \tag{1}$$

$$N^z = \begin{cases} \left\lceil \frac{N}{Z} \right\rceil, & \text{if } z = 1 \\ \left\lceil \frac{N - \sum_{i=1}^{z-1} N^i}{Z - z + 1} \right\rceil, & \text{if } z > 1 \end{cases} \quad \text{for } z = 1, 2, \ldots, Z \tag{2}$$

$$R = (\sqrt{Z} + 1)^2 \tag{3}$$

where N is the total number of nodes and F_s is the scalability factor. Then, it uniformly deploys N^z heterogeneous nodes in each related zone in a random manner and deterministically places R energy-harvesting relay nodes at pre-known positions (i.e., a single EH node at each zone's corner). Also, it deployed the local base stations (LBS) nodes in predefined locations around the working field. MWSE heuristic in SEES selects some robust sensor nodes called Zone Aggregation Group (ZAG) as candidates to run the aggregation and transmission tasks for every created zone independently. The selection process considers m election parameters: p_1, p_2, p_3, …, p_m, associated with m weights of importance: w_1, w_2, w_3, …, w_m, and runs in m successive steps: s_1, s_2, s_3, …, s_m. In each stage, one of the election parameters is considered the dominant parameter, which is assigned the highest weight. The weights are generated by a new generation model according to the Eqs. (4) and (5) below, where μ is a predefined weighting factor and $w_1 + w_2 + w_3 + \ldots + w_m = 1$.

$$w_i = \mu \times w_{i-1}, \quad \begin{array}{l} \text{for } i = 2, 3, \ldots, m \\ \text{and} \quad 0 < \mu \le 1 \end{array} \tag{4}$$

$$w_1 = \frac{1}{1 + \mu + \mu^2 + \cdots + \mu^{m-1}} \tag{5}$$

After ZAGs' election, MWSE chooses N_{za}^z nodes from each ZAG as a subset called zone aggregators (ZAs) to take the role of data aggregation for the respective zone in the current transmission round according to the following equation:

$$N_{za}^z = \kappa\% \times N_{alv}^z \tag{6}$$

Table 1
A summary of zone-based clustering approaches.

Protocol	Main addressed issues	Zone creation	Heterogeneity support	Transmission type	Execution mode	CH election	Major limitations
Z-SEP [61]	Energy efficiency, Network stability	Three zones of different size	Two levels of heterogeneity	Proactive	Distributed	Probability-based	Low scalability, low heterogeneity support, redundant transmissions
ZET [62]	Energy efficiency, energy load, balancing, stability	Nine zones of the same size	Homogeneous nodes only	Reactive (fixed threshold)	Distributed	Deterministic	No heterogeneity support, redundant transmissions
ZBRP [63]	Energy efficiency, coverage, connectivity, load balancing	Hierarchical rings with zones in each ring	Homogeneous nodes only	Proactive	Distributed	Hybrid	Low scalability, no heterogeneity support, redundant transmissions
EEZBC [64]	Energy efficiency, scalability	Variable number of equal-sized zones	Homogeneous nodes only	Proactive	Distributed	Hybrid	No heterogeneity support, redundant transmissions
ZSEP-E [78]	Energy efficiency, energy-load balancing, stability	Three zones of different size	Three levels of heterogeneity	Proactive	Distributed	Probability-based	Low scalability, low heterogeneity support, redundant transmissions
ZDG [79]	Energy efficiency, energy-load balancing, throughput	Variable number of equal-sized squared zones	Homogeneous nodes only	Proactive	Distributed	Deterministic	No heterogeneity support, redundant transmissions
FZSEP-E [80]	Energy efficiency, stability, energy-load balancing,	Three zones of different size	Two levels of heterogeneity	Proactive	Centralized	Deterministic based on FL	Low scalability, redundant transmissions
ZDEC [81]	Energy efficiency, stability, energy-load balancing	Eight zones of the same size	Homogeneous nodes only	Proactive	Distributed	Deterministic	Low scalability, no heterogeneity support, redundant transmissions
TEZEM [65]	Energy efficiency, energy-load balancing, Stability	Variable number of equal-sized zones	Homogeneous nodes only	Reactive (fixed threshold)	Distributed	Deterministic	Low scalability, no heterogeneity support, redundant transmissions
IZ-SEP [66]	Energy efficiency, stability, throughput	Two zones, an inner and outer zones	Two levels of heterogeneity	Proactive	Distributed	Probability-based	Low scalability, low heterogeneity support, redundant transmissions
E-GLBR [67]	Energy efficiency, energy-load balancing, coverage, stability,	Four zones of different size	Two levels of heterogeneity	Proactive	Hybrid	Deterministic based on GA	Low heterogeneity support, redundant transmissions

where N^{z}_{alv} is the number of the active nodes in the respective zone, and $\kappa\%$ is defined in advance. MCCT in SEES is for deciding the minimum-energy communication path for transmitting data from the sensing layer to the topmost layer. It uses a cross-layer conception based on a hierarchical transmission model, which allows for selecting the best route that meets higher levels of energy conservation. In this model, the data gathered by the heterogeneous nodes can be transmitted to EH relay nodes either normally through ZA nodes (in a multi-hop path) or via a single-hop path directly (a cross-layer communication path), whichever has the minimum transmission distance. The data is subsequently aggregated by EH nodes and transmitted upwards to the LBSs in the top layer. These LBSs store the received data for future needs and/or send it to the MBS for additional analysis.

Shortcomings

As we discussed above, different literature works show that high efforts were made and various techniques have been introduced to save energy and improve the lifetime of WSNs in IoT environments. Even though these methods demonstrate improved performance in terms of different metrics such as data reduction, data compression, coverage enhancement, scheduling, optimal CH election, hierarchical, zone-based routing, relay node placement, etc., which, in turn, lead to saving considerable energy, none of them could ensure an optimal solution that perfectly solves the addressed energy-related issue while keeping the preferred level of other related factors such as accuracy, reliability, availability, security, etc. However, this becomes more challenging in ever-growing IoT-based heterogeneous WSNs, in which a huge amount of data is transmitted and exchanged by battery-operated heterogeneous devices, thus shortening their lifetime. In addition, some of the proposed solutions have complex implementations and higher computations that require a high level of energy to be executed within the resource-constrained devices, whether at the node level or CH level. Thus, they contribute to increasing energy consumption. Also, the mode of working matters in large-scale, heterogeneous, and dense deployments. Distributed algorithms are preferred but lack global information, while centralized algorithms are more suitable but more costly in terms of communication time and energy. In this scenario, hybridization and tradeoffs can help produce a better solution and improvement. Furthermore, the given solutions did not consider high level of heterogeneity scenarios, in which the networks include several categories of sensing devices (i.e., four, five, six, …, etc.), each has its own level of energy and may need special considerations and working configurations. Therefore, it is imperative to propose a contemporary solution that addresses inherited limitations and takes into account the considerations of heterogeneous IoT-based sensing networks. Even though SEES protocol considers heterogeneous deployment in zone-based scenarios, its method of data transmission produces a higher network load and, leads to higher energy consumption. This procedure runs periodically in every transmission round for each node to send its data proactively toward base stations, regardless of the measured values that may be similar to already reported data in previous rounds. This results in high data redundancy and unnecessary consumption of energy dissipated by the member nodes for data transmission as well as by zone aggregators and relay nodes for data receiving, processing, and forwarding. This raises the need for an efficient reduction of the frequent data transmission times, unless it is required. This can be achieved by utilizing some type of regulation and control for data reporting frequency that should lead to optimizing energy consumption and maximizing the overall network lifetime. We address these limitations in our proposed solution, as detailed in the next section.

TESEES: The proposed protocol

TESEES is an event-driven reactive protocol that is assumed to be used in zone-based IoT large-scale WSNs. By this, we mean a massive number of wireless objects/devices deployed in a large working area with different levels of battery capacities. Such heterogeneous networks usually include a large variety of sensor types (each has its own role and range of values to be measured based on various factors, including the type of the sensor itself). In addition, these sensors are resource-constrained in many ways, such as storage resources, computing resources, energy resources, etc. Thus, robust clustering protocols are required to control the data transmission process of such zone-based heterogeneous networks to achieve higher energy utilization and maintain a long network lifetime. For this, TESEES is developed to regulate data transmission at the zone level through a general event-thresholding model. This model decides when a node must report the collected data based on its generated threshold and a sliding window formulated. Unlike the traditional zonal solutions, this protocol supports multi-level thresholding heterogeneity of sensor nodes and can be used for any large-scale deployment regardless of the number of nodes' categories and levels of their initial energies. This enables the network administrator to alter the value at which he/she will receive sensed data for a specific sensor at a specific time. In addition, as in the improved version of SEES, the adapted structure of the sensing field provides a flexible zone design that can be employed in various IoT-based applications independently of the working area's size. This is due to the fact that the zonal creation of the subareas is based on a scalability factor that varies the number of zones according to desired network performance. Thus, this hybrid formulation approach of heterogeneous thresholds in zone-based environments and the enhanced distributed transmission algorithm make TESEES a novel solution that addresses the limitations of proactive SEES and similar zonal protocols In the following subsections, we present TESEES as a new improved version of SEES protocol and discuss its different aspects, including its system framework, the adapted thresholding model, and its operation. The aim is to minimize transmission energy and extend the overall system lifetime of large-scale heterogeneous WSNs, regardless of the number of deployed nodes, or the size of the sensing area. In Table 2, we describe the notations, parameters, and quantities used in this paper.

System model description

The network model of TESEES, generally, consists of N heterogeneous sensing nodes (HNs), R energy-harvesting-enabled relay nodes (EHs), B local sink nodes (LBSs), and a single master sink node (MBS). These different types of nodes are arranged in a hierarchical framework that consists of four layers: the data collection layer, the aggregation/processing layer, the relaying/intermediate layer, and the sinks/convergence layer, as shown in Fig. 1. The network's heterogeneous nodes in the first layer are determined

Table 2
Descriptions of notations and parameters used.

Notation/Parameter	Description	Notation/Parameter	Description
HNs, EHs, $LBSs$	Heterogeneous Nodes, Energy-Harvesting Nodes, and Local Base Stations	N, R, B, Z	No. of HNs, EHs, LBS, and Created Zones
HT, TS	Hard Threshold, Soft Threshold	TH_i^{min}, TH_i^{max}	Min. and Max. Threshold for Category i
VS, VR_i, VC^j, VP^j	Sensed Value, Reported Value, Current Value, and Previous Value	VS^{min}, VS^{max},	Minimum and maximum Sensed Values i
TH_L^{min}, TH_L^{max}	Minimum and Maximum Limits of Thresholding model	WS^j, DA^j	Sliding Window, and Average Difference of Node j
n, m	No. of Heterogeneity Levels and Election Parameters	N_s^i, E_s^i	No. of Nodes and Energy Level of Category i
A, F_s	Deployment Area, and Scaling Factor	μ, ϑ, κ, φ	Election Parameters
$p_{1\ldots n}$, $w_{1\ldots n}$, $s_{1\ldots n}$,	Parameters Set, Weights, and Election Stages	β, γ, Θ, α	Heterogeneity Parameters and Constants
N^z, N_{alv}^z	No. of Total Nodes and Alive Nodes in a Zone z	N_{za}^z, N_{na}^z,	No. of Aggregator and Non-Aggregator Nodes in Zone z
P_r, E_h, η_c	Received Power, Harvested Energy, and Conversion Efficiency	R_{min}^h, R_{max}^h,	Maximum and Minimum Harvesting Rate
E_r^j, C_{nt}^j, N_{sc}^j	Residual Energy, Centrality, and Election Score of a Node j	d_{za}^j, d_{rn}^j, $d_{sn_k}^j$	The distance of node j to nearest ZA, Nearest Relay, and a Sensing Node k
E_{Tx}, E_{Rx}	Energy Cost for Transmission and Receiving Processes	$E_{Tx-elec}$, $E_{Rx-elec}$	Energy Dissipation of Transmitter and Receiver Circuits
E_{fs}, E_{mp}	Energies Dissipations for Free-Space amp., and Multipath amp.	l_b, d_0	Size of Transmitted Data, and Transmission Distance Threshold
E_{sn}^j, E_{za}^k, E_{rn}^c	Energy Dissipations of Sensing Node j, Aggregator Node k, and Relay Node c	EH_{cap}, E_{tot}	Max. Energy of EH nodes, and Total Energy of all Network Nodes

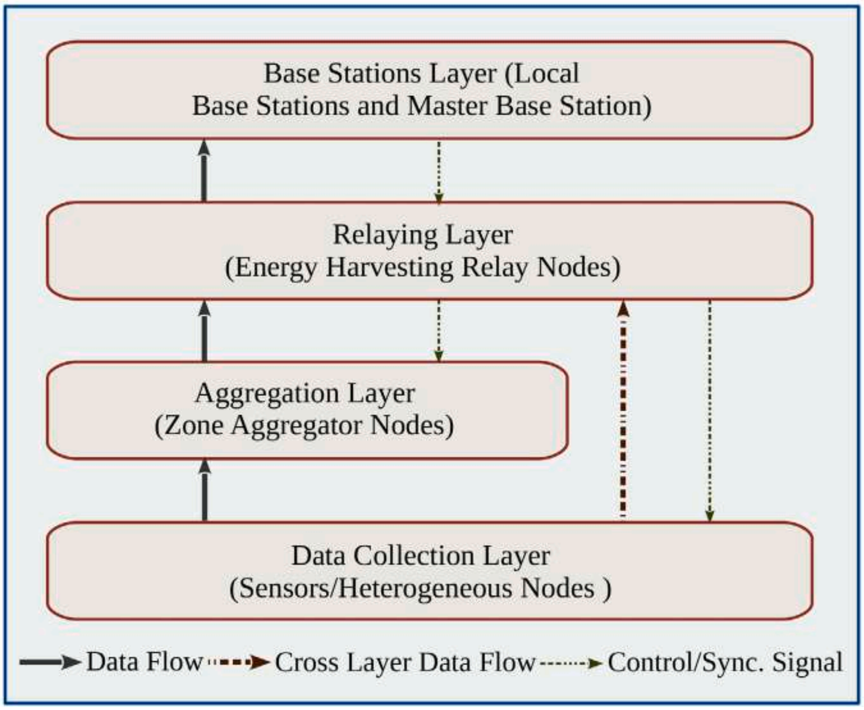

Fig. 1. Network model architecture.

according to a multi-level heterogeneity model [15,82] that supports up to n types of nodes (n is a positive integer number). The number of nodes for each category (N_s^i), and their respective initial energies (E_s^i) are defined as per Eqs. (7) and (8) respectively:

$$N_s^i = N \times (\beta - \gamma_1) \times (\beta - \gamma_2) \times (\beta - \gamma_3) \times \cdots \times (\beta - \gamma_i) \tag{7}$$

$$E_s^i = E_s^1 \times (1 + (i-1) \times \alpha) \tag{8}$$

γ_i in the above equation is equal to:

$$\gamma_i = \gamma_{i-1} - 2 \times \Theta \tag{9}$$

where β and γ_i are the heterogeneity parameters in the used model, Θ is a constant value, and α is the extra energy factor that indicates how much E_s^i+1 is more than E_s^i. γ_1 and E_1^i are predetermined by the administrator.

The energy-harvesting nodes (EHs) in the second layer are deployed in a grid manner, predesigned based on the number of zones, and used as intermediate nodes relaying data from the sensing nodes in the lower layer to the sink nodes in the top layer. These nodes can draw their energy from ambient power sources simultaneously while transmitting and receiving information. The net amount of the derived energy, Eh, harvested by a relay node is given by:

$$E_h = \eta_c \times P_r \tag{10}$$

where η_c is the energy conversion efficiency, and P_r is the amount of the received power. The rate of energy-harvesting, R^h, is assumed to vary, due to the environmental effects, from R^h_{min} to R^h_{max}, i.e., $R^h \in [R^h_{min}, R^h_{max}]$ These intermediates relaying nodes are added in order to optimize the energy consumption of the non-harvesting sensor nodes in different zones, thus elevating the network lifetime. The local sink nodes (LBS) in the third layer are deployed around the working field of the network to receive the aggregated data from relaying nodes and send it to the master BS node (MBS). The aim is to reduce the energy load and computation overheads on the HN nodes as well as on the EH relay nodes and, hence, minimize their energy dissipation.

Zones' formation and ZAG election

As an enhanced protocol, TESEES adapts similar procedures to divide the sensing area into several zones, distribute different types of nodes, and elect ZAG and ZA nodes as in SEES protocol we described in "TESEES: The proposed protocol". The process starts by running the hybrid-placement scheme, which includes three major functions: (i) static zoning of the targeted area; (ii) random deployment of the heterogeneous nodes at the zone level; and (iii) deterministic placement of the energy-harvesting relay nodes. The number of zones, the number of nodes in each zone, and the number of relaying nodes are calculated according to Eqs. (1), (2), and (3), respectively, as presented in "TESEES: The proposed protocol". A scalability factor (F_s) is used to define the maximum number of HN nodes that can be deployed in a single zone, which helps in maintaining a certain level of network scalability and energy load balancing as required by the application. The optimal value of N^z is achieved when N is a multiple of $(Z \times F_s)$. In this case, all the zones accommodate the same number of HN nodes, which is, at maximum, equal to F_s. For a squared working area, A ($L \times L\ m^2$), the resulting zones are also squared with a dimension length equal to $\frac{L}{\sqrt{Z}}$. The origin of the zone $z_{i,j}$ is given as follows:

$$z_{i,j}(x,y) = (i \times \frac{L}{\sqrt{Z}} + A_x, j \times \frac{L}{\sqrt{Z}} + A_y), \qquad \forall i,j \in [0, \sqrt{Z} - 1] \tag{11}$$

Where (A_x, A_y) is the origin point of the main sensing area. In deploying EH nodes, every squared zone is surrounded, at maximum, by four EH relay nodes (one at each corner). This helps in ensuring higher levels of network connectivity and fault tolerance, where communication can be made with any of the other three relay nodes in the case of any failure of the current one. The LBS nodes in TESEES, which are non-constrained in terms of energy, represent the convergence point, at which they are distributed around the sensing area in predefined places. The aim is to reduce the load and computation overheads on the HN nodes as well as on the EH relay nodes and, hence, minimize their energy dissipation. LBSs are usually connected to the MBS, the single supernode, which is placed at a relatively distant location from the network field and is generally linked through the Internet to a central application system. The logical view of the sensing field, as adapted from SEES protocol, is shown in Fig. 2. However, this placement scheme ensures effective connectivity and maintains high network scalability.

Once the network is formed, MSWE heuristic is run in two procedures: (i) ZAG election and (ii) ZAs assignment. This algorithm runs the nodes' election in a novel way that differs from the traditional methods such as LEACH [83], SEP [84], TEMSEP [33], or other protocols that use the same concepts. The ZAG election process is executed in multiple stages based on multiple weighted parameters, similar to what is indicated in "TESEES: The proposed protocol". It focuses on considering both the dynamic and static parameters according to the importance of their level in each stage in order to determine the robustness of different network nodes. Then, to make decisions on which nodes are the best candidates for the aggregation task, thus enabling a fair balance between all the considered parameters. A general weights' generation model is employed based on a weighting factor (u) that is used as a control knob to fine-tune the different weights of importance and thus get the preferred balance between various election parameters. The different election weights are generated as indicated in Eqs. (4) and (5) mentioned above. In this election, the concept of Weighted Linear Combination (WLC) is used, by which all the parameters of a node are standardized into a common value range and then summed up according to the weighted average scheme. Thus, each node j will get its final score (N^j_{sc}) by multiplying the scaled values for each of its criteria/parameters (P^j_i) by their respective weights (w_i) and then adding the resulting values of all these products as in the equation below:

$$N^j_{sc} = \sum_{i=1}^{m} \mathcal{P}^j_i \times w_i \tag{12}$$

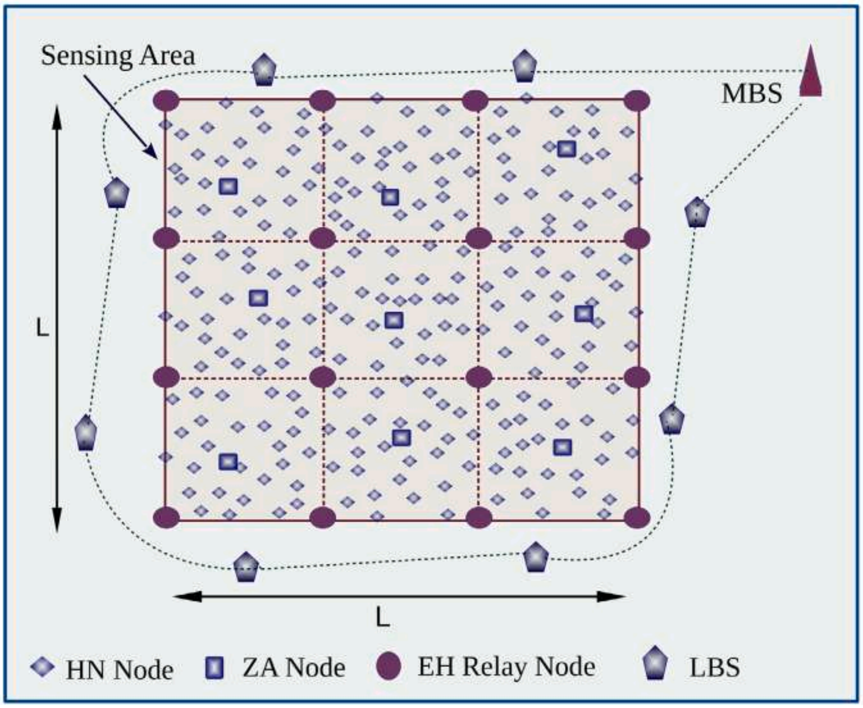

Fig. 2. A logical view of the sensing field structure.

This is repeated for all election stages; in each stage, one parameter is given the highest weight, and only the top $\vartheta\%$ nodes from each stage are considered as the input nodes of the next stage ($\vartheta\%$ is predetermined constant). The top $\vartheta\%$ nodes of the final stage are, then, taken as the ZAG member nodes for the respective zone. These nodes remain the same, performing their task several transmission rounds before reelection, while ZAs assignment procedure runs repeatedly in every transmission round to choose a subset of nodes (N_{za}) alternately from these elected ZAGs as indicated in Eq. (6) according to their remaining energy. These chosen nodes take on the role of data aggregation (i.e., zone aggregators) for the current transmission round. However, N_{za} decreases as more nodes deplete their energy over time and becomes 0 when all the nodes in the zone have died.

Event-thresholding model

To overcome the problem of frequent transmissions as the major limitation of the traditional proactive SEES protocol, TESEES considers a state-of-the-art event-thresholding model that was recently proposed in TEMSEP [33], the weighted probability-based dynamic clustering protocol. We efficiently adapt this model to provide a new reactive data transmission mechanism for zone-based clustering schemes that minimizes the number of times in which the nodes are required to report their sensed data. This is achieved by taking into account the heterogeneous thresholds as well as the current and previous measured values. This consideration enables identifying which nodes must turn their transmitters on and send their data toward LBSs, and which nodes must keep them off in energy-saving mode till they meet event-reporting requirements, thus maximizing the energy savings. In the adapted model, two types of transmission thresholds are defined: a hard transmission threshold (TH) and a soft transmission threshold (TS). In addition, a sliding window (WS) is defined as the values of already transmitted data for a node in the previous transmission rounds. TH is the primary threshold based on which the nodes are enabled and gain the possibility of reporting their measured data, while TS is the second threshold that is used in combination with WS to make the final decision about turning the transmitter on and sending these data values or not.

The new approach for generating thresholds here is designed to correspond with the higher levels of heterogeneity model that is used in TESEES. For this, each different category of nodes has its own set of TH and TS (i.e., category-i has different TH_i– and TS_i from other groups of nodes). TH_i for any category represents a range of values within given limits TH_i^{min}, and TH_i^{max}, by which each j node gets its own TH_i^j threshold within its category, while TS_i of each category remains the same for all the nodes within the respective category. TH_i^{mini} and TH_i^{max} for all nodes' categories are predefined according to some criteria given by the owner such as the number of nodes, the type of sensors, and the nature of the network, where $TH_1^{min} = TH_L^{min}$ and $TH_1^{max} = TH_L^{max}$ (TH_L^{min} and TH_L^{max}, here, represent the upper and lower limits of the thresholds that can be generated by the thresholding model at the lowest level and the highest level of heterogeneity, respectively. In defining such threshold limits for each level of heterogeneity, it is considered that the nodes with the least amount of energy in the lower levels should report their data less than those having an extra amount of energy in the higher levels. However, these limits of thresholds of different categories (i.e., TH_i^{min} and TH_i^{max}) should be selected within the ranges of sensing values (VS) that can be measured by the nodes in the respective category, i.e., TH_i^{min} should be higher than VS_i^{min} and TH_i^{max} should be less than VS_i^{max}. The relationship between threshold values, threshold ranges, and sensing values' ranges can be represented as follows:

$$
\begin{aligned}
&TH_1^j \in \left[TH_1^{min}, TH_1^{max}\right] \subset \left[VS_2^{min}, VS_2^{max}\right] \quad \text{(1st level)}\\
&TH_2^j \in \left[TH_2^{min}, TH_2^{max}\right] \subset \left[VS_2^{min}, VS_2^{max}\right] \quad \downarrow\\
&TH_3^j \in \left[TH_3^{min}, TH_3^{max}\right] \subset \left[VS_3^{min}, VS_3^{max}\right] \quad \downarrow\\
&\vdots \qquad\qquad \vdots\\
&TH_n^j \in \left[TH_n^{min}, TH_n^{max}\right] \subset \left[VS_n^{min}, VS_n^{max}\right] \quad (n\text{th level})
\end{aligned}
$$

The sliding window in this model is defined as the values that are already reported (VR) in the last S transmission rounds (i.e., $WS = [VR_1, VR_2, VR3, \ldots, VR_S]$). To include WS of a node in making the transmission decision with its generated thresholds, the average of differences (DA) between the current measured value of the nodes and all the previous values (VP) in the WS should be calculated using the following equation:

$$DA_i^j = \frac{\sum_{k=1}^{S} \sqrt{(VC_i^j - VP_{i_k}^j)^2}}{S} \tag{13}$$

To decide whether to send the current data or not, the nodes have to involve their TH, TS, and DA. A node j first examines its current value (VC_i^j). If it is found to be larger than or equal to TH_i^j, then the node enables itself for possible transmission and then checks its DA_i^j. If it is found to be larger than or equal to TS_i, the node then activates its transmitter, sends its current data upward to the LBS through the intermediate layer, and turns off its transmitter again. This process of making the decision is executed in every transmission round to avoid transmitting the same data in consecutive reporting cycles, which generally leads to consuming a higher amount of energy unnecessarily. This procedure is shown in Algorithm 1 (lines 1–6 and 19–21).

Threshold-based MCCT

TMCCT (Threshold-based Minimum Cost Cross-layer Transmission) algorithm in TESEES is provided based on the event-thresholding model we discussed above as its main component. TMCCT plays a significant role in reducing the number of reported data points and, hence, improving energy savings by keeping nodes' transmitters in sleep mode when there is no significant change in the measured values, in addition to selecting the minimum energy-cost transmission path. In TMCCT, each node starts making its own independent decision on whether to send its current data or not, as per the event-thresholding model. If the decision is not to send the data, the node does nothing and keeps its radio transmitter off. Otherwise, the data communication process starts according to the pre-defined policies and rules of operation of TESEES. The node activates its transmitter, calculates its distances to the surrounded EHs and ZAs, and joins the nearest one. The EH and ZA nodes, then, make a TDMA-based schedule including all the associated non-ZA nodes, in which every node is assigned a single time slot independently. After getting the TDMA time slot, the node starts sending its available data to the associated EH/ZA node and then goes into sleep mode for the remaining slots. According to this procedure, the nodes have the ability to send their data to an EH node through the path that has the least transmission distance based on the calculation, i.e., either (i) directly in a single-hop transmission (a cross-layer communication path) or (ii) through their zone aggregator (ZA) in a multi-hop transmission (the default communication path). Furthermore, in this TMCCT, the intra-communication among regular HN nodes or ZA nodes within the zones is not enabled to save energy. The communication between any two ZA or non-ZA nodes must be done through the relaying layer. Regular HN nodes can communicate only with ZAs/EHs in the same zone for data transmission, and similarly, ZAs can communicate only with the EH relay nodes around the same zone. Also, inter-cluster communication can be achieved only through EH nodes in the relaying layer, which can communicate with all ZAs and non-ZAs located in neighboring zones at a single-hop distance; however, EHs also can communicate with any LBS node in the topmost layer that falls within their communication range. The TMCCT procedure based on the new event-thresholding model is shown in Algorithm 1.

TESEES operation

The execution of TESEES starts with the offline deployment of nodes and is followed by the online transmission phase. In the deployment phase, the hybrid-placement scheme is run to create the sensing network by dividing the area into several zones, determining the number of nodes in each zone, and deploying the HNs, EHs, and LBSs. It also includes placing the MBS node and defining the various heterogeneous thresholds and the size of WS. The transmission phase includes two subphases: the initialization phase, which runs for one time only, and the data reporting phase, which runs repeatedly till the end of the network operation. In the initialization phase, some types of messages are generated and exchanged by different types of nodes, as indicated in Table 3. These messages are used for the initial configuration of the network, so each node will know the operation parameters, heterogeneous thresholds, transmission policies, IDs, functions of its neighbors, transmission distance, etc. In the data reporting phase, both the

Algorithm 1 : Threshold Based MCCT

Input: $ZAs,\ EHs,\ TH_i^j,\ ST_i,\ Z$

$VC_i^j \leftarrow$ Update $current\_sensed\_value$
if $VC_i^j \geq TH_i^j$ **then**
  $TRANS_i^j$.Enabled = 1
  $DA_i^j = \frac{\sum_{k=1}^{S} \sqrt{(VC_i^j - VP_{i_k}^j)^2}}{S}$
  if $DA_i^j \geq ST_i$ **then**
    $TRANS_i^j$.Activated = 1
    $NxtHop_i^j \leftarrow My\_nearest\_relay$
    $Dmin_i^j = NxtHop_i^j.distance$
    $MyZA_i^j \leftarrow My\_nearest\_ZA$
    $MyZA_i^j.Relay \leftarrow MyZA_i^j.nearest\_relay$
    $d_{za} = MyZA_i^j.distance$
    $d_{rn} = MyZA_i^j.Relay.distance$
    if $((d_{za}^2 + d_{rn}^2) < {Dmin_i^j}^2)$ **then**
      $NxtHop_i^j = MyZA_i^j$
      $Dmin_i^j = d_{za}$
    end if
    send $JOIN$ message to $NxtHop_i^j$
    wait until receiving $TDMA$ schedule
    send VC_i^j to $NxtHop_i^j$
    $TRANS_i^j$.Enabled = 0
    $TRANS_i^j$.Activated = 0
  end if
end if

Output: "Transmission Decision: Wake-up and Send or Remain Asleep"

Table 3
Types of messages in the initialization phase.

SN	Message	Description
1	INFO	Includes the node information. Broadcasted by all the HN nodes to the relaying layer and then to $LBSs$ and MBS layer
2	SET	Includes information such as which zones are served by which LBS node. Sent by MBS to the deployed $LBSs$
3	INIT	Includes all the necessary information concerning the main functionality of the nodes, transmission policies, operation parameters, etc. Sent by $LBSs$ to EHs of their zones

algorithms MSWE and TMCCT are executed. This phase is further subdivided into many repeated transmission intervals (called rounds). These intervals are defined in a way that allows all the HN nodes at the sensing layer to transmit their data to LBS nodes at the highest layer via EH/ZA nodes. MSWE is run here at the top layer by LBS nodes (i.e., every several intervals) to perform ZAG/ZAs selection as discussed earlier. Once the ZAs nodes are identified by MSWE and announced, the TMCCT algorithm starts running at the node level (at every node in the lower layer), as we explained above. In this algorithm, which runs every transmission round, all the HN nodes take their appropriate action independently, either to send their current data based on TDMA created by ZA/EH nodes or to keep themselves in energy-saving mode. Here, all selected ZAs also similarly join the closest EHs and get allocated TDMA slots by their respective EH nodes. The ZA nodes that receive current data from non-ZAs, then, aggregate and send it to its associated EH node in the intermediate layer, which, in turn, performs an additional aggregation task on the data received from non-ZAs of the neighboring zones and does other necessary operations like compression, etc. The data is then forwarded upward to the LBSs in the highest layer using a randomly selected CDMA code and via a single-hop communication path. The LBSs, then, use this data for analysis/further actions and/or forward it to the distant MBS node, which is generally linked through the Internet to a central application system. Fig. 3 shows the general flowchart of the main procedure of TESEES protocol.

TESEES complexity

We verify the computational complexity of TESEES in terms of running steps. As indicated in "TESEES Operation" and Fig. 3, the online transmission phase starts after the static deployment and zone creation phase, in which two subphases run as indicated.

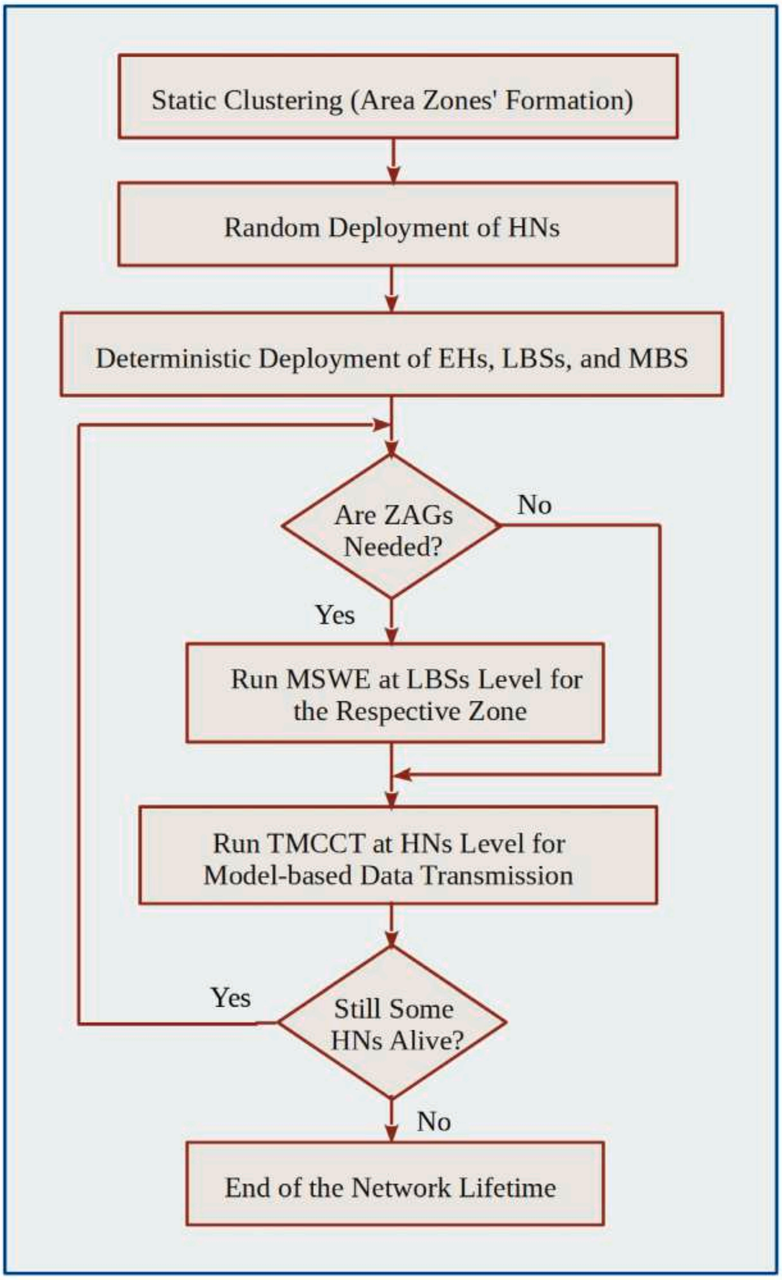

Fig. 3. A general flowchart for the main procedure of the proposed TESEES protocol.

The initialization phase, which runs only once, results in a complexity of $\mathcal{O}(n)$ as the configuration messages and other information are changed and sent by HNs, LBS, and MBS. Here, generating the heterogeneous thresholds and calculating the distance of NHs to the four corners' relay nodes occur only once, and do not affect the complexity. In the data reporting phase, for each episode, MSWE, which runs at LBSs level, results in a complexity of $\mathcal{O}(n^2)$ as getting C^j_{nt} of each node requires calculating the distance to all other nodes in the zone. The other parameters p_i, m_i, and s_i are in nature made constants as input by the administrator. TMCCT, which runs at the node level, results in $\mathcal{O}(n)$. Here, distances are already known for each node, and applying the thresholding model always takes linear steps; thus, there is no additional computation overhead; only direct comparison may be needed. Therefore, the total complexity of the proposed protocol is equal to $\mathcal{O}(n) + \mathcal{O}(n^2) + \mathcal{O}(n) = \mathcal{O}(n^2)$, which is a quadratic complexity that depends on the total number of nodes as the main input to the protocol algorithm. However, the number of episodes for data reporting and the actual running time depend on the transmission activities of the nodes and machine capability. Even though TESEES integrates the new thresholding models and improves the transmission procedure, its complexity remains at acceptable level, similar to that of traditional SEES.

End-to-end delay

In WSNs, the End-to-End delay refers to the time it takes for a packet to travel from the sensor node that generates it to the destination node that receives it. In the data reporting phase of TESEES protocol, the MSWE algorithm runs at the LBS level every several rounds, offloading election processing overhead from the sensor and relay nodes to LBSs. During this execution, only the announcements of newly elected ZAG are broadcasted downwards by the LBSs, without affecting the upward packet transmission by the sensor nodes. TMCCT, which manages data transmission, operates at the node level, where a sensor node selects the transmission path based on information acquired from previous steps, including the distance to its ZAs and EH relay nodes. Then, the data transmission occurs within the allocated time slot for each node, directed toward the chosen next hop. The ZAs and relay nodes perform standard data aggregation on the received packets without incurring additional processing overhead, such as data redundancy processing or similar tasks, which are beyond the scope of our current study. In addition, the presence of multiple ZAs and relay nodes results in reduced aggregation time, as the sent packets are distributed among different ZAs and EH relay nodes closer to the source node. Moreover, the utilization of multiple LBSs enables the ZAs and relay nodes to transmit packets over shorter distances to the nearest LBS. Consequently, TMCCT minimizes end-to-end delay by eliminating the need for complex computations during transmission, in contrast to existing multi-hop protocols. Compared to traditional SEES which we addressed in this paper, TESEES decreases the frequency of node-level transmissions through an event-thresholding model. This reduction leads to a decreased number of packets received and aggregated at any given time by the ZAs and EH relay nodes, resulting in optimized processing time and thus, improved end-to-end delay. Furthermore, the incorporation of cross-layer communication mechanisms further reduces the total transmission time. Sensor nodes can directly communicate with EH relay nodes when the distance is shorter, instead of transmitting to ZAs. Similarly, ZA nodes are allowed to communicate directly with LBSs if they are in close proximity instead of multi-hop communication through relay nodes. However, it is important to note that the transmission time may increase in larger sensing areas, where the distance from EH relay nodes in the inner zones to the LBSs is greater, while the transmission of the relay nodes in the border zones' remain the same. This phenomenon represents the primary cause of higher latency of TESEES if used in situations with wider working areas. Nevertheless, the communication time for packets generated by the sensor nodes remains unaffected. This can be attributed to our efficient scalable deployment algorithm, which dynamically adapts the number of zones and relay nodes in accordance with the total nodes' count and the size of the area. This adjustment process is formulated using Eq. (1) and Eq. (2), enabling optimal distribution and resource utilization.

Experimental setup

For evaluation, we have used Matlab software to carry out the simulation experiments and compared the performance of the proposed solution with that of the traditional SEES protocol using different network scenarios and configurations. Each simulation was run 10 times, and the average of them has been taken as the evaluation results. In this section, we present the simulation setup, parameters, and energy dissipation model.

Simulation parameters

Table 4 shows the total number of nodes, the total amount of energy, the number of heterogeneity levels, and the size of the area in the two scenarios we used in the experimental simulation, The broken down number of nodes and the amount of energy in each category of nodes for both scenarios are depicted in Figs. 4(a), 4(b), 5(a), and 5(b). The values of different parameters we configured are given in Table 5 (i.e., deployment, heterogeneity, multi-stage election, energy harvesting, event-thresholding, and communication energy parameters). For valid and robust evaluation and comparison, we used the same values of parameters as used in SEES [34,82,85] protocols for heterogeneity parameters, MSWE election parameters, transmission parameters, and relay nodes' capacities. For deployment, the locations of LBS nodes have been uniformly deployed in the range of 20 to 50 meters around the targeted area; while the MBS node, has been located at a distance of 150 meters from the sensing area. For the heterogeneity model, based on the related settings used, the number of nodes and the initial energy for each level were the same values for both the simulated protocols in the different scenarios. For the energy-harvesting setting, as the transmission interval is set to be 0.1 h, it results in a random harvesting rate in the range of [0.00036, 0.027] joules, standard values of the solar power that can be derived by a cell with a volume equal to 1 mm located indoors or outdoors, respectively, as used in [34,86]. For ZAG election, we considered three parameters ($m = 3$): (i) the node residual energy (E_r), (ii) the node centrality (C_{nt}), and (ii) the node distance to the nearest relay node (d_{rn}), and thus, three weights of importance are generated as per Eqs. (4) and (5). The centrality of a node C_{nt}^{j} is defined, here, as the inverse of the node's averaged distances to all other heterogeneous nodes:

$$C_{nt}^{j} = \frac{N^{z} - 1}{\sum_{k=1}^{N^{z}} d_{sn}^{j\to k}}, \qquad k \neq j \tag{14}$$

where $d_{sn}^{j\to k}$ is the distance of the node j to the node k. In addition, the value of μ was set to 0.5. By this, the weight generated for each level is, approximately, equal to two times that in the lower level (i.e., the generated values of w_1, w_2, and w_3 have been given as 0.57, 0.29, 0.14 respectively). In the event-thresholding model we adapted in TESEES, we used a similar setting as given in

Table 4
TESEES evaluation scenarios.

Scenario	N	A (m^2)	E_{tot} (J)	n
1	4000	400 × 400	5450	4
2	5000	500 × 500	7588	5

Table 5
Values of simulation parameters.

Parameter	Value	Parameter	Value	Parameter	Value
N, A, E_{tot}, n	as per scenario (Table 4)	$E_{Tx-elec}$	50 nJ/bit	VS^{min}	20, 30, 40, 50, 60
F_s	40	$E_{Rc-elec}$	50 nJ/bit	VS^{max}	100, 150,200, 250, 300
B	12	E_{da}	5 nJ/bit/signal	R_h^{max}	0.027
n	4, 5	E_{fs}	10 pJ/bit/m^2	R_h^{min}	0.0036
α, γ, Θ	2, 0.4, 0.025	E_{mp}	0.0013 pJ/bit/m^4	EH_{cap}	0.5 J
μ, m	0.5, 3	φ	0.2	l_b	4000 bits
ϑ	0.7	κ	0.1	E_t^1	0.5 J

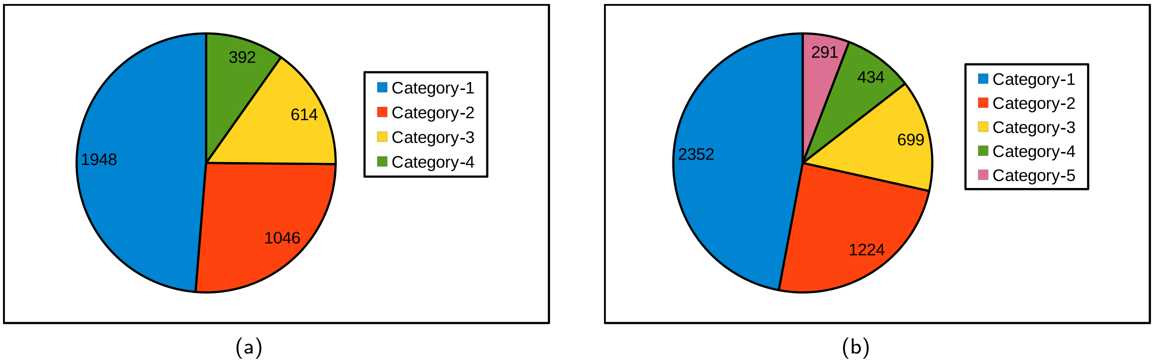

Fig. 4. The total number of nodes for each heterogeneity level: (a) Scenario-1 and (b) Scenario-2.

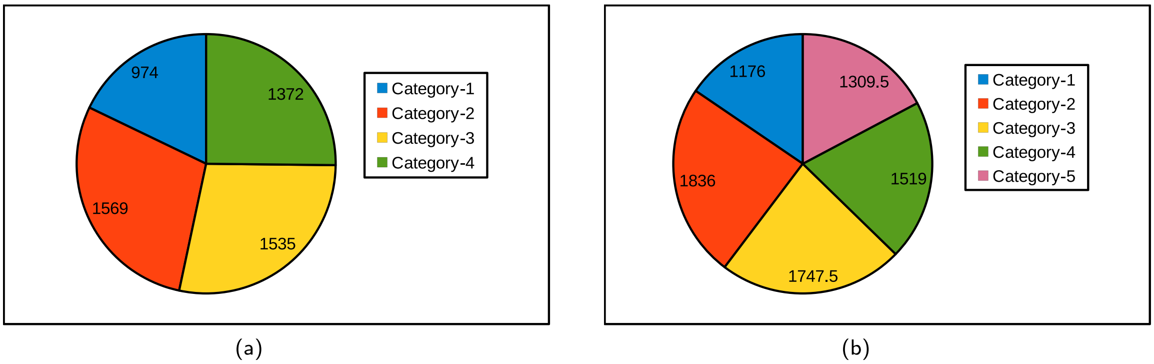

Fig. 5. The total amount of energy (in joul) for each heterogeneity level: (a) Scenario-1 and (b) Scenario-2.

the TEMSEP protocol. We defined two different settings for the TH, while a single setting is used for ST, as shown in Table 6. The TH limits for each heterogeneity level (i.e., TH_i^{imin} and TH_i^{max}) are calculated depending on the limits of the nodes' sensed values (i.e., VS_i^{min} and VS_i^{max}) with different percentages in each configuration. For this, VS_i^{min} and VS_i^{max} for each category are set as (20, 100), (30, 150), (40, 200), (50, 250), and (60, 300) for the first, second, third, fourth, and fifth heterogeneity levels respectively. Table 6 shows the simulation settings of TH_i and ST_i, where i is the level of heterogeneity and α is the energy-increasing factor. "α/i" is used to control the value of ST_i in order to meet the heterogeneity model requirement for achieving a fair balancing of energy load, which assumes that the nodes in higher levels are used more frequently in data reporting than those in lower levels.

For the evaluation process, we have considered the same metrics used in SEES and TEMSEP protocols. This includes the first and last node dead, half nodes dead, number of alive nodes, lifetime gain, the average number of transmissions, energy gain, dissipated energy, node energy cost, data energy cost, network throughput, throughput gain, and average round data sent.

Table 6
Simulation settings of TH_i and TS_i.

Threshold	Configuration I (c1)	Configuration II (c2)
TH_i^{min}	$VS_i^{min} + 10\% \times VS_i^{max}$	$VS_i^{min} + 20\% \times VS_i^{max}$
TH_i^{max}	$VS_i^{min} + 20\% \times VS_i^{max}$	$VS_i^{min} + 30\% \times VS_i^{max}$
TS_i	$(VS_i^{max}/TH_i^{min}) \times 2.\alpha/i$	$(VS_i^{max}/TH_i^{min}) \times 2.\alpha/i$

Energy dissipation model

We use the first-order energy dissipation model as it has been utilized in existing literature [84,87,88]). The energy consumption of the radio transmitter (E_{Tx}) and receiver (E_{Rx}) according to this model are given as follows:

$$E_{Tx} = \begin{cases} l_b \times (E_{Tx-elec} + E_{mp} \times d^4), & \text{if } d > d_0 \\ l_b \times (E_{Tx-elec} + E_{fs} \times d^2), & \text{otherwise} \end{cases} \tag{15}$$

$$E_{Rx} = l_b \times E_{Rx-elec} \tag{16}$$

where l_b is the length of transmitted data, d is the transmitted distance, $E_{Tx-elec}$ is the transmitter energy, $E_{Rx-elec}$ is the receiver energy, E_{mp} is the multi-path amplifier energy, and E_{fs} is free space amplifier, and energy d_0 is equal to:

$$d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{17}$$

To calculate the total energy dissipated by the network in a single round, we need to know the consumed energy of all non-ZA and ZA nodes at the zone level, as well as all EH nodes at the network level. At the zone level, the energy consumptions of a non-ZA node j and a ZA node k are given by Eqs. (18) and (19), respectively:

$$E_{na}^j = l_b \times (E_{Tx-elec} + E_{fs} \times {d_{za}^j}^2) \tag{18}$$

$$\begin{aligned} E_{za}^k = l_b \times \Big[& E_{Rx-elec} \times N_{na\to za}^k + E_{da} \times (N_{na\to za}^k + 1) \\ & + E_{Tx-elec} + E_{fs} \times {d_{rn}^k}^2 \Big] \end{aligned} \tag{19}$$

Where d_{za}^j and d_{rn}^k, are their distances to their nearest next-hops, respectively, which are assumed to be less than or equal to d_0 in these equations. $N_{na\to za}^k$ is the number of non-ZA nodes that have been associated with the ZA node k, and E_{da} is the energy consumption of data processing (aggregation). The energy consumed per round by an EH node c (E_{rn}^c), when its distance d_{bs}^c to an LBS node is less than or equal to d_0 is given by:

$$\begin{aligned} E_{rn}^c = l_b \times \Big[& E_{Rx-elec} \times (N_{na\to rn}^c + N_{za\to rn}^c) + E_{da} \times \\ & N_{na\to rn}^c + E_{Tx-elec} + E_{fs} \times {d_{bs}^c}^2 \Big] \end{aligned} \tag{20}$$

where $N_{na\to rn}^c$ and $N_{za\to rn}^c$ are the number of non-ZA and ZA nodes that have joined the intermediate node c, respectively.

However, the total energy consumed by the total network (E_{tot}) can be calculated as follows:

$$E_{tot} = \sum_{z=1}^{Z} \sum_{j=1}^{N_{na}^z} E_{na}^j + \sum_{z=1}^{Z} \sum_{k=1}^{N_{za}^z} E_{za}^k + \sum_{c=1}^{R} E_{rn}^c \tag{21}$$

Where Z, R, N_{na}^z, and N_{za}^z are the number of zones in the network, the number of relay nodes, the number of non-ZA, and the number of ZA nodes in every zone, respectively.

Simulation results analysis

In Tables 4, 5, and 6, we showed the scenarios as well as the parameters and threshold configurations, respectively, that we used in simulation experiments. In this section, we analyze the obtained results and discuss the performance of reactive TESEES for both configurations of event thresholds in comparison with the performance of the traditional proactive SEES protocol. For clarity of the presented results, we use two different notations: TESEES-c1, and TESEES-c2 for the first and second configurations of the event-thresholding model, respectively. We present the results of both scenarios simultaneously for each evaluation metric, briefing the discussion and highlighting any significant difference between the performance of the two scenarios, which may indicate additional inferences. In general, we observed that the results show higher improvements in the TESEES performance with both configurations in all scenarios over SEES protocol for all the parameters considered. Also, both protocols are seen to have the same behavior in the second scenario, similar to that in the first scenario, for almost all the parameters. Clear improvements for both protocols are

Table 7
Different measures of the system lifetime at different percentages of alive nodes for both scenarios.

Percentages of alive nodes	(a) Scenario-1			(b) Scenario-2		
	SEES	TESEES-c1	TESEES-c2	SEES	TESEES-c1	TESEES-c2
100%-1 (FND)	2250	2851	3206	2265	2876	3080
80%	2401	3303	3717	2364	3269	3678
60%	2465	3637	4124	2463	3628	4101
40%	7137	8776	10354	7052	8741	10325
20%	9162	13258	15347	10163	13802	16194
0% (LND)	15155	19878	23651	18314	24023	28416

Table 8
Percentages of the lifetime improvements achieved by TESEES over SEES protocol at different points of its operation time for both scenarios.

Percentages of alive nodes	(a) Scenario-1		(b) Scenario-2	
	TESEES-c1	TESEES-c2	TESEES-c1	TESEES-c2
100%-1 (FND)	27%	42%	27	36%
80%	38%	55%	38%	56%
60%	48%	67%	47%	67%
40%	23%	45%	24%	46%
20%	45%	68%	36%	59%
0% (LND)	31%	56%	31%	55%

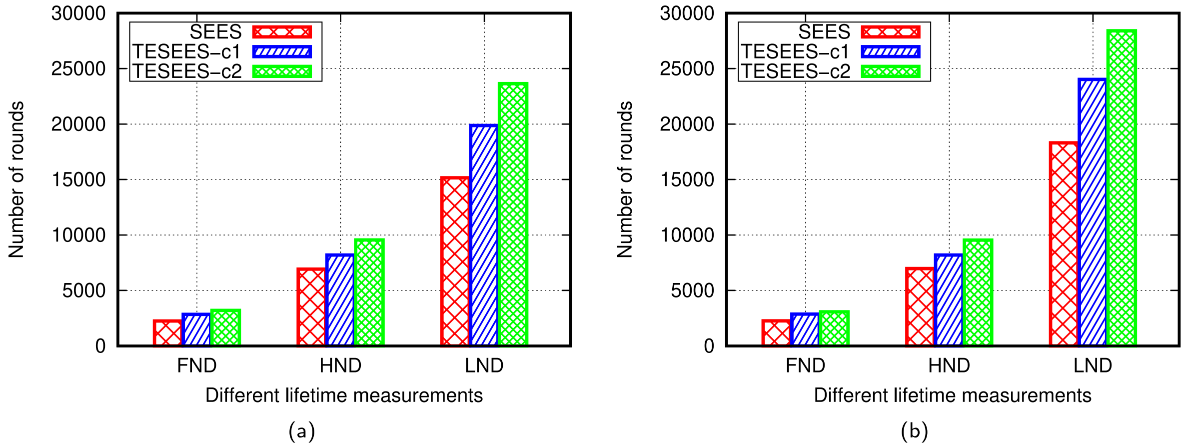

Fig. 6. Different lifetime measurements (FND, HND, and LND): (a) Scenario-1 and (b) Scenario-2.

observed in the second scenario due to including additional levels of heterogeneous nodes. TESEES shows better improvements than SEES protocol when we make a comparison between its performances in the two scenarios we simulated.

Figs. 6(a), 6(b), 7(a), and 7(a) show lifetime measures (i.e., FND, HND, and LND) and the number of alive nodes over simulation time for both protocols, respectively. It is obvious that TESEES greatly better than SEES protocol. FND has the values 2250, 2851, 3206, and 2265, 2876, 3080 for TESEES-c1, TESEES-c2, and SEES, respectively, in both scenarios, which shows a clear extended stable period in TESEES over SEES protocol. LND also has a similar increase with values 15155, 19878, 23651, and 18314, 24023, 28416, for the same protocols in both scenarios, respectively. For HND, as well, TESEES shows higher values. This is because TESEES protocol reduces the number of data transmissions through the implementation of the event-thresholding model. Hence, keeping the nodes in energy-saving modes most of the time and consequently increasing their lifetimes. It is also clear that the nodes in SEES protocol expire faster than those in TESEES as indicated in Figs. 7(a), and 7(b) as a result of the higher energy consumption for unnecessary frequent transmissions. Table 7 show the numerical values of lifetime measures for both protocols, while Table 8 presents the percentages of the lifetime improvement achieved by TESEES over SEES for both scenarios.

Figs. 8(a), 8(b), and 9 indicate the total energy consumption over the simulation time and the average energy consumption per a single transmission round for both protocols. It is clear that TESEES consumes less energy than SEES in both scenarios. The average energy dissipated for SEES, is equal to 360 mj and 414 mj, while for TESEES it is equal to 274 mj, 230mj, and 316 mj, 267mj, respectively for the first and second configurations in both scenarios. The percentage of energy saved by TESEES over the SEES protocol in a single round is equal to 24%, 36% for both the first and second configurations, respectively, which are the same in the two scenarios. In Figs. 10(a) and 10(b), we present the amount of energy consumed at selected points of the simulation rounds

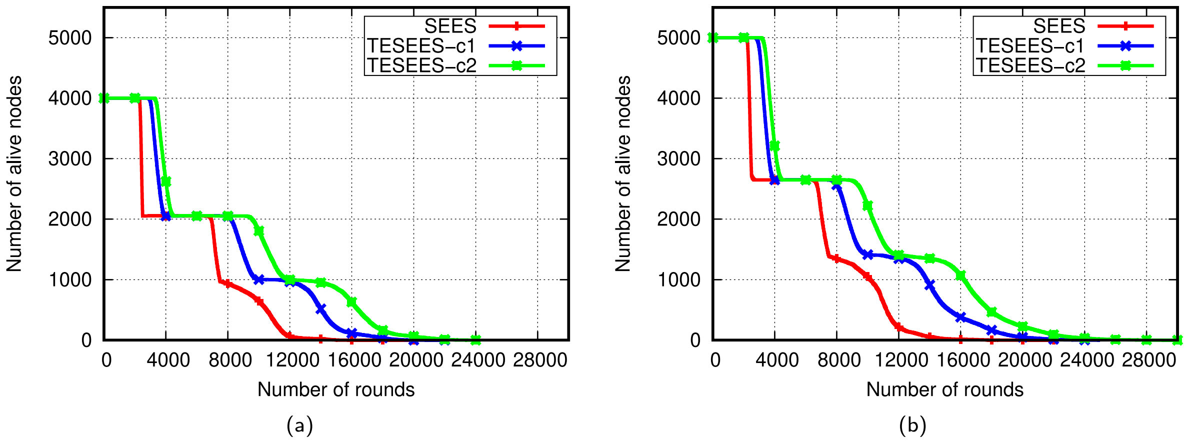

Fig. 7. The number of active nodes over the simulation time: (a) Scenario-1 and (b) Scenario-2.

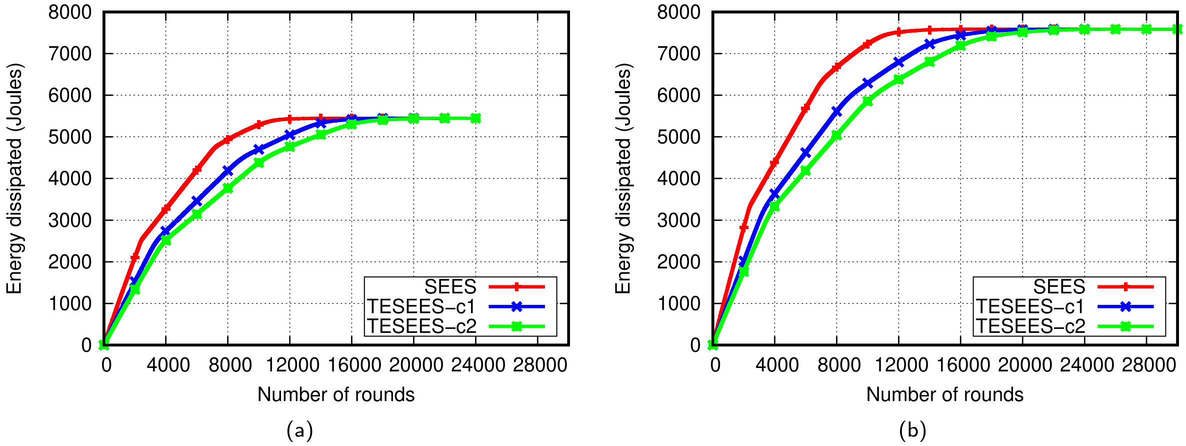

Fig. 8. The energy dissipated over the simulation time: (a) Scenario-1 and (b) Scenario-2.

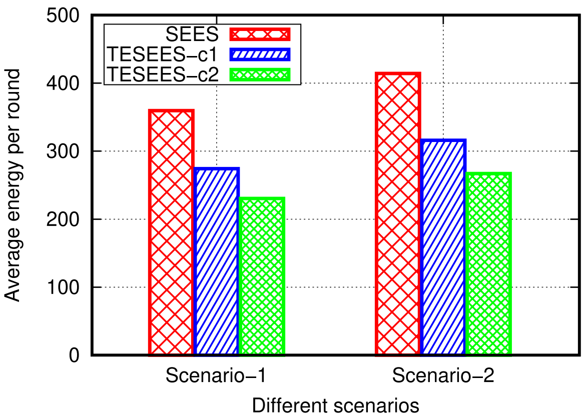

Fig. 9. The average energy consumed for a single transmission round in both scenarios.

for both protocols in the two scenarios, respectively, while in Table 9, we show the percentages of energy saved by TESEES over SEES protocol versus different percentages of its simulation rounds.

The results also indicate that both TESEES and SEES fairly balance the energy load among all the network nodes. We observed that a large number of nodes expire, approximately, at the same round for each protocol. This is, generally, shown in the curves

Table 9
Percentages of the energy saving achieved by TESEES over SEES protocol at different points of its operation time for both scenarios.

Percentages of SEES lifetime	(a) Scenario-1		(b) Scenario-2	
	TESEES-c1	TESEES-c2	TESEES-c1	TESEES-c2
20%	20%	29%	17%	25%
40%	18%	25%	18%	26%
60%	12%	20%	12%	17%
80%	7%	12%	4%	9%

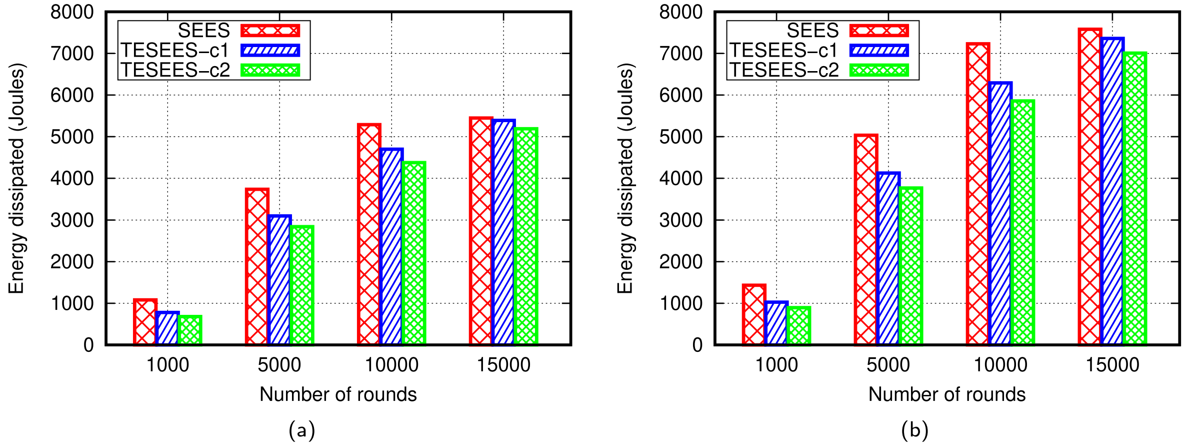

Fig. 10. The amount of energy consumed at some points of simulation rounds: (a) Scenario-1 and (b) Scenario-2.

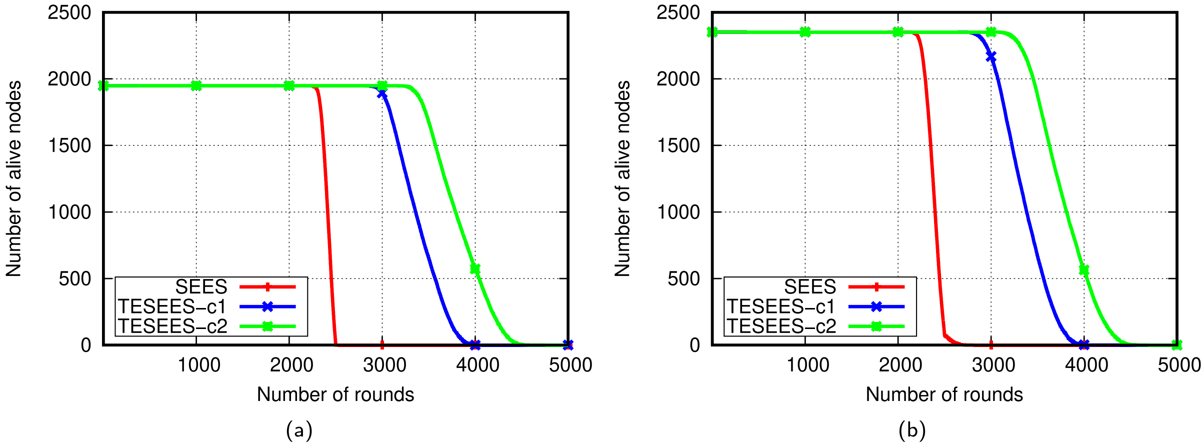

Fig. 11. Number of alive nodes in category-1 over the simulation rounds: (a) Scenario-1 and (b) Scenario-2.

of Figs. 7(a) and 7(b), in which approximately more than 50 of the network nodes run out of their energy in a very short period in both scenarios. However, the majority of these dead nodes in this short time are of category-1 (i.e. first level of heterogeneity), which are, generally, equipped with the lowest level of initial energies. The other nodes that remain active are mostly of the higher categories which keep performing their tasks for an extended time. This is also repeated for the nodes in category-2, category -3, category -4, and category –5 as shown in the same Figure. The nodes in higher levels (i.e., category-4 in scenario-1, and category-5 in scenario-2) live for the longest periods than all others, providing better energy-load balancing as they are mostly taking the role of data aggregation tasks. The number of alive nodes in the lowest and highest levels of heterogeneity over the simulation rounds as shown in Figs. 11(a), 11(b), 12(a) and 12(b) respectively, for both scenarios. We present these results to show how TESEES further extends the lifetime with different levels of node heterogeneity while keeping a fair energy load balance. Here, in scenario-1 we have only four categories of nodes, while in scenario-2, there are five types of nodes. The first and highest levels consist of 1948, 2352, and 392, 291 nodes for the two scenarios, respectively.

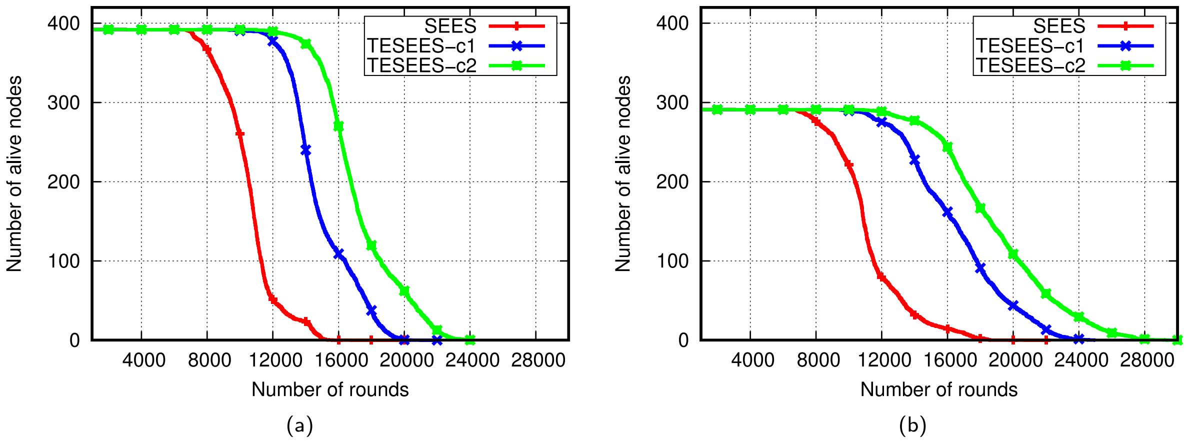

Fig. 12. Number of alive nodes in category-n over the simulation rounds: (a) Scenario-1 and (b) Scenario-2.

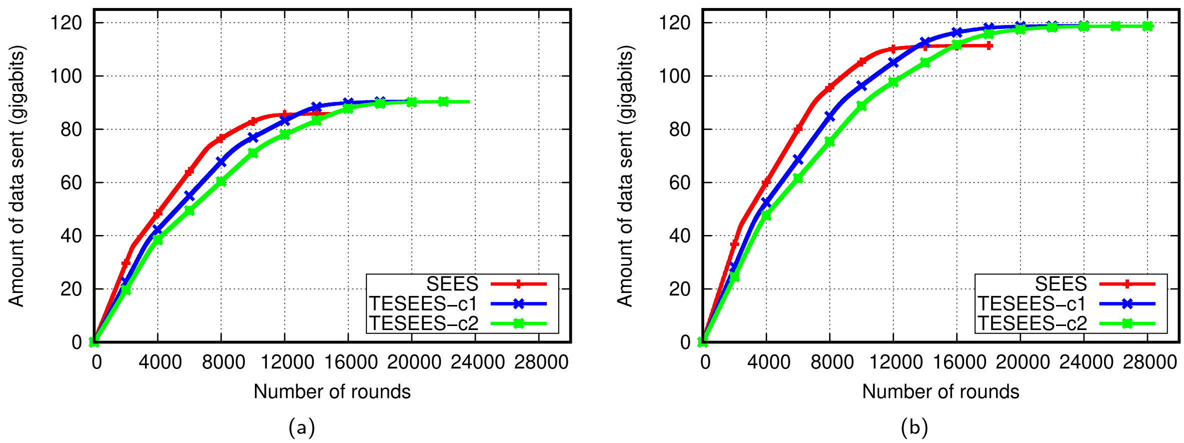

Fig. 13. The total amount of data sent over the simulation rounds: (a) Scenario-1 and (b) Scenario-2.

Table 10
Total amount of data sent (number of packets) in both scenarios.

Percentages of lifetime	(a) Scenario-1			(b) Scenario-2		
	SEES ($\times 10^3$)	TESEES-c1 ($\times 10^3$)	TESEES-c2 ($\times 10^3$)	SEES ($\times 10^3$)	TESEES-c1 ($\times 10^3$)	TESEES-c2 ($\times 10^3$)
20%	2.812	2.267	1.987	4.168	3.462	3.138
40%	4.236	3.484	3.167	6.450	5.280	4.754
60%	5.145	4.524	4.109	7.427	6.546	6.148
80%	5.432	4.783	5.069	7.579	7.321	6.938
100	5.450	5.211	5.396	7.588	7.548	7.433

In Figs. 13(a) and 13(b), we present the aggregated amount of data sent by HN nodes in the sensing area toward LBS nodes in the topmost layer (in gigabits) over the simulation rounds. This indicates that TESEES achieves a significant reduction in the data transmission rate (the amount of data reported by sensing nodes). This is due to the efficient regulation and control of data transmission achieved by implementing the adapted thresholding model, which enables the nodes to avoid turning their radio transmitters on unnecessarily. This does not only save the energy of non-ZA nodes but also the energy of ZA and EH nodes (i.e., for receiving and aggregation energy). Figs. 14(a) and 14(b) show the total energy dissipated versus the total amount of data sent, which indicate that SEES requires higher levels of energy demand per unit of data than that required in TESEES protocol, which behaves similarly in both configurations of the two scenarios. In Table 10, we present the number of packets transmitted versus various percentages of the simulation time for both protocols, while in Table 11, we show the total improvement of the network throughput (i.e., throughput gain) achieved by TESEES over SEES protocol.

Table 11
Percentages of reduction in the transmitted data achieved by TESEES over SEES protocol for both scenarios.

Percentages of alive nodes	(a) Scenario-1		(b) Scenario-2	
	TESEES-c1	TESEES-c2	TESEES-c1	TESEES-c2
20%	19.4%	29.3%	17%	25%
40%	18%	25%	18%	26%
60%	12%	20%	13%	17%
80%	12%	7%	3.4%	8.4%
100	4.4%	01%	0.5%	2.0%

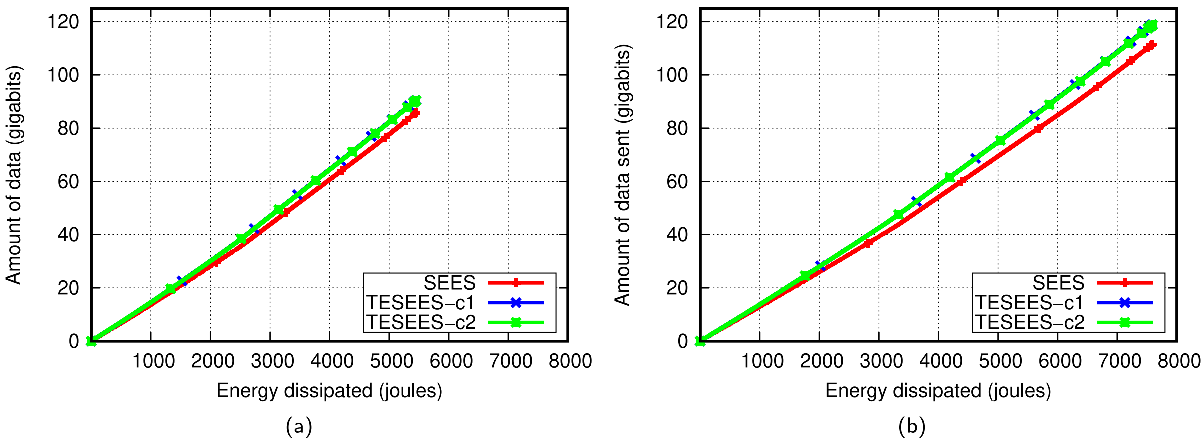

Fig. 14. Total dissipated energy for the total amount of data sent : (a) Scenario-1 and (b) Scenario-2.

Conclusion

In this paper, we have proposed TESEES protocol that addresses energy savings in large-scale IoT-based WSNs. TESEES is a reactive version that improves the traditional proactive SEES protocol by implementing a state-of-the-art event-thresholding model. This model controls the data transmission process of the sensor nodes through a novel mechanism that determines two types of heterogeneous thresholds utilized to avoid unnecessary frequent data reporting, based on the current and previous values measured. The nodes keep themselves in energy-saving mode unless there is a need to send the new sensed values. This helps in greatly reducing energy consumption and prolonging the overall lifetime of networks deployed through zone-based clustering techniques. We explained, in detail, the major components of TESEES and presented the new TMCCT (Threshold based Minimum Cost Cross-layer Transmission) model that selects preferred paths required for sending data from the sensing layer to the base station layer based on the new event-thresholding model. In addition, TESEES is a multilevel heterogeneous protocol that supports up to n levels of nodes' categories and is the first zone-based reactive protocol that uses more than three types of nodes (i.e., four and five levels of heterogeneity). Further, it selects zone aggregators through an efficient multi-stage mechanism that uses multiple election parameters as adapted from SEES, linked with an importance weight defined for each stage. These aggregators are then connected with a grid of energy-harvesting relay nodes to forward data toward the convergence layer with minimum energy consumption. We evaluate TESEES using different scenarios and threshold configurations. The experimental results of the simulation showed that TESEES protocol enhances energy savings, network lifetime, and traffic load reduction by 29%, 68%, and 26% respectively. Further, it can improve the overall system lifetime and network throughput by considering higher levels of heterogeneity. However, we conclude that TESEES is highly applicable to IoT-based WSNs and large-scale systems. Future work can be directed toward enhancing the TESEES protocol by comprehensively addressing various aspects of network settings, encompassing small-scale, medium-scale, and large-scale deployments. Noteworthy research directions include exploring various strategies for determining dominant parameters, both through random and dynamic approaches and conducting experimental analyses to assess the impact of end-to-end delay on the performance, thereby offering promising ways for enhancing energy conservation and optimizing network performance within the TESEES protocol.

CRediT authorship contribution statement

Antar Shaddad Hamed Abdul-Qawy: Conceptualization, Methodology, Software, Writing – original draft, Data curation, Investigation. **Nayef Abdulwahab Mohammed Alduais:** Conceptualization, Writing – review & editing. **Abdul-Malik H.Y. Saad:** Conceptualization, Reviewing. **Murad Ahmed Ali Taher:** Conceptualization, Validation. **Abdullah B. Nasser:** Conceptualization, Reviewing. **Sami Abdulla Mohsen Saleh:** Conceptualization, Validation. **Narendra Khatri:** Reviewing, Validation.

Declaration of competing interest

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

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