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A parallel particle swarm optimization for improving wireless sensor networks longevity-based dynamic clustering method

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ABSTRACT

Determining the optimal configuration for wireless sensor networks (WSNs) can be challenging due to the multitude of possible setups. To address this issue, our team has developed the Parallel Particle Swarm Optimization-based Self-Organizing Network Clustering (PPSOPM) method. By taking into account variables like remaining node energy, predictable energy usage, proximity to the base station, and number of nearby nodes, PPSOPM dynamically enhances wireless sensor node clusters. Achieving a balance between these factors is crucial to effectively organize nodes into clusters and select a surrogate node as the cluster's head. In comparison to alternative methods, PPSOPM significantly improves network structure by 44.39 % and extends network lifespan. However, node density may impact network longevity by increasing the distance between nodes. Also, when the base station is far from the sensor area, creating additional clusters can help conserve energy. On average, PPSOPM requires 0.57 s to complete, with a standard deviation of 0.04.

1. Introduction

Forming network clusters is an efficient way to develop the longevity and scalability of wireless network sensors (WSN) [1–5]. In a sensor network that operates on a cluster-based system, the data collected by the members of each cluster are transmitted to the base station via a designated node called the cluster head. Typically, the base station is located outside of the sensor field and can be quite a distance away. To optimise the lifespan of a standard Wireless Sensor Network (WSN), it is critical to maintain balanced energy consumption amongst all nodes in the network [6], ensuring that no single node drains its energy before the others. Balancing the energy consumption of nodes in a real-world cluster-based network can be challenging due to the varying roles of sensor nodes and signal transmission distances[7]. Furthermore, cluster head nodes require additional energy to perform tasks such as receiving messages from member nodes and transmitting grouped messages to the base station[8]. Successfully balancing energy consumption and extending the overall network lifespan is a complex undertaking., given the numerous factors that impact energy consumption [9,10].

Data acquisition, processing, and transmission have been attributed to the energy consumption of a node. In a complicated network, features, for example, space among nodes, space to the base station, and data throughput, intensely affect the remaining energy of every node [11]. Approaches have been enhanced to allow more such features to accomplish lengthy network longevity [12]. The LEACH method is a technique that enables nodes within a network to share the responsibility of message transmission by rotating the role of cluster head among them. This leads to a more balanced load and increased network resilience [13]. Another method for cluster head election is EEUC, which chooses the most appropriate node based on its proximity to the base station. LELE, on the other hand, favors nodes with higher energy levels for serving as cluster heads. In Raj's study, cluster formation and selection of cluster heads (CHs) are based on factors such as the count of neighbors, remaining energy, and distance to the base station (BS). However, pre-identified network layouts may not meet the critical requirements for network longevity given the variability in the count and placement of sensor nodes and the BS. Despite efforts to automate sensor node organization, the dynamic nature of sensor networks and the various possible cluster configurations continue to pose challenges in improving network structure [14]. H. Ali et al. [15] introduced a novel metaheuristic algorithm for CH selection in WSNs. The study focuses on optimizing energy efficiency and network performance by improving the CH selection process. It integrates adaptive random search and fuzzy artificial tree intelligence to balance energy consumption and enhance

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load distribution across nodes. The paper presents a comparative analysis with existing methods, demonstrating superior performance in terms of network lifetime, reduced energy consumption, and improved scalability. This research is significant as it addresses critical challenges in WSN clustering, particularly in large-scale and energy-constrained environments, with robust experimental validation to support its claims. Ali et al. [15,16] presented a comprehensive survey on system-level energy optimization for multi-processor system-on-chips (MPSoCs) in IoT and consumer electronics. The study explores various energy-efficient design strategies tailored for energy-constrained IoT devices, including task scheduling, power management, and hardware-software co-optimization. The paper highlights the growing importance of MPSoCs in managing the computational demands of IoT applications while minimising energy consumption. It also examines state-of-the-art techniques for balancing performance and energy efficiency, focusing on low-power architectures and adaptive power control mechanisms. This work provides valuable insights into challenges and solutions for achieving energy-efficient IoT systems, emphasizing its relevance for next-generation smart devices and sustainable computing.

When it comes to energy-efficient clustering in WSNs, one of the most significant issues is the unequal distribution of energy consumption across sensor nodes[17]. This may result in the early depletion of energy in particular clusters and a decline in the network's performance[18]. The term "hotspot" or "unequal energy consumption" is another term often used to describe this situation[19]. In order to overcome this obstacle by using optimization strategies, there are a few different options that may be considered: a) Selection of CHs: The optimal selection of cluster heads is an essential component in achieving a balanced distribution of energy consumption throughout the network. It is possible to pick cluster heads by using optimization strategies like as genetic algorithms, particle swarm optimization, or ant colony optimization. These strategies may be used to select cluster heads based on parameters such as energy level, distance to BS, and node density. b) Aggregation of Data and Routing: The optimization of data aggregation and routing protocols has the potential to lower the amount of data transmission (DT) and energy consumption (EC) that occurs within the network ecosystem [20]. Through the use of mathematical modelling and heuristic algorithms, it is possible to optimise several techniques, including network coding, data fusion, and multi-hop routing, to minimize energy usage while simultaneously ensuring data dependability and network connection[21].

It is via the use of dynamic clustering techniques that PSO can significantly contribute to the enhancement of the lifetime of WSNs. WSNs are made up of a multitude of very small sensor nodes that are generally installed in harsh and inaccessible settings. As a result of the fact that these nodes are powered by batteries that have a limited amount of energy, energy efficiency is an essential problem in the design of WSNs [22].

The goal of dynamic clustering techniques is to extend the lifetime of the network by effectively dispersing the amount of energy that is used across the sensor nodes[23]. One node serves as the CH, which is responsible for the aggregation and transmission of data, while other nodes serve as members within the cluster [24,25]. These approaches include the formation of clusters of nodes on a periodic basis. Through the process of spreading jobs and rotating the roles of cluster heads, dynamic clustering is able to lower the amount of energy that is used and increase the lifetime of the network[26].

Through the optimization of the selection of CHs and the generation of clusters, PSO improves the dynamic clustering that occurs in WSNs. One example of a nature-inspired optimization method is the PSO algorithm, which is designed to emulate the behaviour of fish schooling or bird flocking. Within the framework of WSNs, PSO is a technique that repeatedly adjusts the location and velocity of possible cluster heads depending on their fitness. This fitness is influenced by a number of criteria, including residual energy, distance to neighboring nodes, and data traffic. PSO optimizes energy use by continually modifying the CH selection and cluster formation process. This extension of the network's operational lifetime is achieved via the optimization of energy usage [9].

The capability of PSO to effectively locate near-optimal solutions in huge search spaces is the primary reason for its significance in the process of enhancing WSN longevity-based dynamic clustering algorithms. Through the use of PSO, WSNs are able to adjust to changing environmental conditions and network dynamics. This allows for more energy-efficient operation and a longer lifetime for the network, both of which are essential for a variety of applications, including environmental monitoring, surveillance, and industrial automation [2].

This piece of writing suggests a method called PPSOPM, which offers a structure for merging various elements and refining the clustering of dynamic nodes. In gasoline, the dynamic network construction is determined by considering the remaining energy, the predicted energy outlay, and the count of nodes in the region. The key to managing nodes and assigning substitute heads to clusters lies in the complementary features of this approach[27]. These elements are incorporated into the PPSO fitness function (FF), where each particle represents a designation map for CHs in the optimization process. Using these CHs, clusters are created according to the rule of selecting the closest neighbor, and the evaluation of all clusters determines the fitness of a WSN[28]. During each transition, the network layout is dynamically adjusted to balance sensor node energy and extend network longevity[29].

Especially in large-scale deployments where sensors operate in harsh or distant settings, energy consumption and network longevity are major difficulties in WSNs[30]. Other challenges include network longevity and network longevity. Because they do not effectively balance energy consumption across nodes or adapt to altering network circumstances, such as node density and base station proximity, traditional clustering algorithms, such as LEACH and EEUC, often fail to optimise network lifespan in an efficient manner. This is because these strategies do not adequately balance energy consumption across nodes. This causes certain nodes to run out of energy more quickly than others, which ultimately results in failures of the network and a decrease in its overall performance[31].

The challenge is made much more complex by the dynamic nature of WSNs, which makes it difficult to maintain an appropriate network topology over time due to the frequent changes in the energy levels of nodes and their geographical placements[32–34]. Because of these challenges, a technique is required that is capable of constantly and dynamically adjusting network clustering while taking into consideration a variety of criteria, including energy consumption, the closeness of nodes, and the distance between communication points.

This research contributes in two different ways:

- First, we propose a PPSOPM approach that enhances the network encoding system and employs a flexible optimization method to unify energy and spatial components. The selection of CHs is encoded in the particles of PPSO, and this leads to the creation of dynamic clusters. This method is versatile in considering various factors since it separates cluster head selection from network structure.
- Second, by using energy and spatial components, we can calculate predictable energy expenses. This helps achieve balanced EC across all nodes of the network, which in turn improves the network's longevity.

This paper presents our approach in detail in section 3, following a brief review of PPSO for self-containment. Section 2 discusses prior research on developing clusters to enhance the longevity of networks, and Section 4 presents our experimental findings in comparison to advanced techniques. Finally, section 5 concludes this article.

2. Related work

The LEACH protocol was proposed to balance energy consumption among sensor nodes by dynamically assembling clusters [13]. The

LEACH approach creates clusters by randomly choosing nodes to serve as cluster leaders. The randomization approach prevents the election of specific nodes as the cluster head, which might use up these nodes' energy considerably more quickly than the others. Although it does a good job of diversifying CHs, the final clusters are not ideal at all. Earlier advancements utilized the feature of node distance. In the context of power-efficient gathering in sensor information systems (PEGASIS) [35], each node only interacts with a nearby neighbor to establish a chain of nodes. In the EEUC [14], the selection of CH is determined by the proximity of the sensor nodes to the base station. To ensure maximum network coverage, clusters that are situated nearer to the BS are smaller in size than the ones farther away. In addition, network coverage is enhanced by implementing further measures. Authors [24] proposed dividing nodes into four logical zones based on their location. The core of the area is marked by a gateway node, and clusters are formed with a probabilistic selection of the cluster head if the node's distance from the BS (or gateway) is below a certain threshold. Otherwise, direct communication is used. Fuzzy logic was incorporated by other writers [36] to expand upon the LEACH approach when forming clusters.

The number of nearby nodes, also known as the degree of a node, has a strong correlation with its distance from other nodes. Based on research by Diallo, Marot, and Becker [37], the selection of a CH is based largely on its stage of connectedness. Given that a node with fewer connections receives less data from neighboring nodes, it makes sense to choose a node with more neighbors to act as the cluster head. During the initial stage, each point participates in the hello protocol, exchanging information about its interactive and the area of the BS.

Alternative methods for locating the ideal cluster structure include energy measurements. A stable election procedure (SEP) [20] permits nodes to be initialized with various energy densities. According to the residual energy, cluster heads are chosen using weighted probability. I helped develop a cutting-edge clustering method known as distributed energy-efficient clustering (DDEEC) [38]. This method effectively classifies nodes based on their energy levels and outperforms the widely used SEP. In DDEEC, the most energy-rich nodes, known as "advanced nodes," are selected as CHs. These CHs are chosen using a threshold in the Threshold-sensitive Stable Election Protocol (TSEP) (Liquan Zhao & Tang, 2019), which expands SEP by classifying points into 3 various energy stages.

Another approach to CH selection is the cluster head replacement method introduced by Modified LEACH (MODLEACH) [39]. In this method, a cluster head remains in its position for the next round if its remaining energy surpasses a certain threshold.

The proposed algorithm by this team [40] clusters nodes based on their remaining energy and is designed to be energy efficient. It selects CHs by estimating the energy stages of each node. This method forms clusters consisting of nodes with the highest residual energy and the lowest communication costs.

Recent advancements in network structure have led to the combination of energy and distance measures to determine the optimal solution. The WCA technique, developed by Ref. [41], assigns weights to factors such as node degree, transmission power, mobility, and battery power, ultimately selecting cluster heads based on the lowest weighted sum. HEED clustering, a distributed approach developed by Ullah in 2020, combines residual energy and distance between nodes to select cluster heads. Similarly, the LELE method, developed by Su et al. in 2009, considers residual energy and the separation between a node's neighbors to determine the most suitable cluster head. Raj's study in 2012 suggests considering the number of neighbors, remaining energy, and BS location when selecting cluster heads for subsequent rounds. The use of a two-level fuzzy technique, as proposed by Ref. [42], evaluates a node's capacity to serve as a CH depending on global factors such as centrality and proximity to the base station, as well as local factors such as energy and number of neighbors [43]. suggests that the number of nodes in proximity, the amount of energy remaining, the spread of energy, and the distance from the BS are all significant considerations when choosing a cluster head.

Optimization techniques are frequently employed to strike a balance among various aspects of a system. In the case of a WSN routing protocol, a Genetic Algorithm (GA) has been implemented [22,44–46]. One important step is selecting an appropriate objective function that captures the network structure and effectiveness. Yang and Li [47] proposed a GA-WCA algorithm that involves two phases: in the first phase, CHs are identified based on their locations; in the second phase, nodes are assigned to CHs using the load balancing factor and the sum of distances from all neighboring nodes to the CHs. The authors [48] employed distance in the objective function to elect a cluster head.

In addition, there is more research regarding secure clustering algorithms specifically designed for IoT-enabled smart cities, focusing on vehicular IoT applications. The algorithm enhances location-based clustering by incorporating security mechanisms that protect against data tampering and unauthorized access, crucial for managing IoT-equipped buildings and facilities [49,50] introduces a solution that allows users to stream and enhance high-quality videos, utilizing nearby devices for computational support (Li, Y.et al., 2021). introduces an ensemble learning approach based on random decision trees that incorporates local differential privacy, aimed at enhancing data privacy in edge computing environments.

The EHGUC-OAPR method, developed by Wu and Liu in 2013, utilizes an algorithm in the base station to generate clusters of varying sizes for optimal energy harvesting. This is followed by an OAPR algorithm to establish the most efficient routing among cluster heads. The clusters are created during the setup phase of the GABEEC approach, as proposed by Bayrakli and Erdogan in 2012, and remain unchanged throughout. The GA is utilized to define CHs for each iterate, considering the energy levels of both existing heads and member nodes. Additional cluster heads are chosen as needed based on available energy, as outlined in Table 1.

The selection of the current approaches in Table 1 for comparison against your suggested model for the purpose of enhancing WSN longevity-based dynamic clustering methods might have been influenced by several factors, including the following:

Performance Comparison: Researchers are able to assess the efficacy of the suggested model in terms of network longevity, energy efficiency, scalability, and resilience by comparing it to the approaches that are already in existence, which are listed in Table 1. The purpose of this comparison is to provide you with an understanding of the relative benefits and drawbacks of your suggested model in contrast to other effective options.

Varieties of Methods: The techniques shown in Table 1 are examples of many ways to dynamic clustering in WSNs. A classic procedure known as LEACH is based on the probabilistic selection of cluster heads. On the other hand, GA-WCA makes use of genetic algorithms for cluster head selection, while LELE makes use of methods that are associated with machine learning. Researchers are able to evaluate the novelness of your suggested model and the possible contributions it may make to the area by comparing it to the many methods that have been offered.

Table 1
A compilation of significant cutting-edge techniques.

Methods	Strengths	Weakness
LEACH [8]	Dynamic CH chosen.	A constant number of clusters and random CH were chosen.
GA-WCA [18]	Scaled node distribution among CHs.	Incompetent processing time
LA2DGA [20]	Incompetent CHs chosen.	Constant number of clusters and unscaled load for CHs
LELE [21]	Dynamic CH chosen	Constant number of clusters and incomplete processing time
GABEEC [2]	Dynamic CH chosen	Constant number of clusters.

The validation and generalisation of your suggested model may be accomplished by comparing it to current approaches. This comparison helps evaluate the model's performance and generalizability over a variety of datasets and situations. It gives researchers the ability to determine the settings under which your suggested model thrives and the areas in which it may fall short in comparison to approaches that have been developed.

Overall, we can illustrate our suggested model's uniqueness, efficacy, and improvements compared to the techniques in Table 1. This allows us to demonstrate that it is superior to current approaches in enhancing WSN longevity-based dynamic clustering methods.

3. PPSOPM for wireless sensor network clustering

3.1. Model of sensor energy

We explain how much energy a wireless sensor uses the model at hand is known as the 1-order radio. as depicted in Fig. 1 [51]. The sum of the energy consumed to gather, process, transmit, and receive data is the node's energy expenditure (E) in Eq (1) [52]:Let's consider the energy required *by S* for acquiring, processing, receiving, and transmitting data in a cluster. $E_S^A(L)$ defines the energy utilized to obtain L fragments of data, $E_S^P(\acute{\mathrm{L}})$ defines that there is a certain amount of energy required to process a certain amount of data, specifically Ĺ fragments, $E_S^R(L'')$ defines the energy utilized to draw L'' fragments of data from the closest points if point S is defined as a CH, and $E_S^T(\acute{\mathrm{L}})$, d represents the energy required to send Ĺ fragments of data across a distance d. Note that $E_S^R(L'')$ is applicable if point S is defined as a CH. It is assumed that each node consumes an equal amount of energy to obtain data [53].

We use the formulae for the sender EC, E_S^T, and drawer the EC, E_S^R, when determining the energy required to send or draw a ping with L fragments:

$$E_S^T = E_i + \mathrm{L}\,\mathrm{d}^{\mathrm{n}} \tag{2}$$

$$E_S^R = E_i + \mathrm{L}\,\mathrm{E}^{*} \tag{3}$$

In Fig. 1, the distance between the consignor and recipient is defined by 'd' and ' E_i' denotes the energy expended while inactive. The transmission energy consumption, ' E^T' varies in proportion to the distance between the consignor and recipient and can be approximated by adjusting the power term 'n' For long-distance transmission, such as sending pings from the CH to the BS, 'n' is set to 4, while for short-distance transmission, such as sending pings from a node to the CH, 'n' is set to 2. Short-distance transmission is used for communications within the cluster; long-distance transmission is needed between the CH and BS. The cost of the beam-generating method used in Eq. (3) is denoted by the symbol E*.

The enduring energy of point s at time t is calculated based on the expended energy:

$$\grave{\mathrm{E}}_s\,(\mathrm{t}) = E_s\,(0) - \sum_{i=1}^{t} E_s\,(\mathrm{i}), \tag{4}$$

where t is the time for carriage iterates and E (0) is the node's initial energy. Each iterate updates the leftover energy of each node.

The nodes remain stationary, and the BS detects their geographical areas. The network's configuration is determined by the actual network placement and is relayed to the nodes during every network transmission cycle. Once the cluster heads are assigned to the nodes, they become the nodes' representatives and communicate with the BS[54].

3.2. The impact of energy and longevity space

Avoiding some nodes' energy depletion before that of other nodes is essential for extending a WSN's lifespan. Nodes should maintain the same amount of energy over the course of the whole network lifecycle in order to maximize network life. Residual energy is a common energy metric [55]. In network clustering, cluster heads with lower residual energy are less likely to be selected due to the increased energy required to convey pings from member points. However, a node's enduring energy is not a direct indicator of how well the network clustering structure is working after a transmission round. This is because dynamically generated local communication requires variable energy contributions from the future CH unless the clustering structure remains constant throughout the network's lifespan. Therefore, accurately estimating the anticipated energy consumption for each node in a potential network layout is crucial[56].

Assume that each node in a round collects L fragments of data. Data are aggregated by the head node s in a cluster of N_s nodes. Following Eqs. (1) and (2) [53], The estimated EC (denoted by $\hat{E}$) of a head point s and a non-CH point $\acute{s}$ can be calculated, as follows:

$$\hat{\mathrm{E}}_{\acute{s}} = \mathrm{E} + \mathrm{LD}^2\,(\acute{s}, s), \tag{5}$$

$$\hat{\mathrm{E}}_s = \mathrm{E} + \mathrm{N_S L E}^{*} + (\mathrm{N_s} + 1) + \mathrm{LD}^4\,(s, \mathrm{BS}), \tag{6}$$

Where E stands for EC, which includes energy used for data collection, processing, and idleness. The functions D(s, B) and D(s, ś) are used to

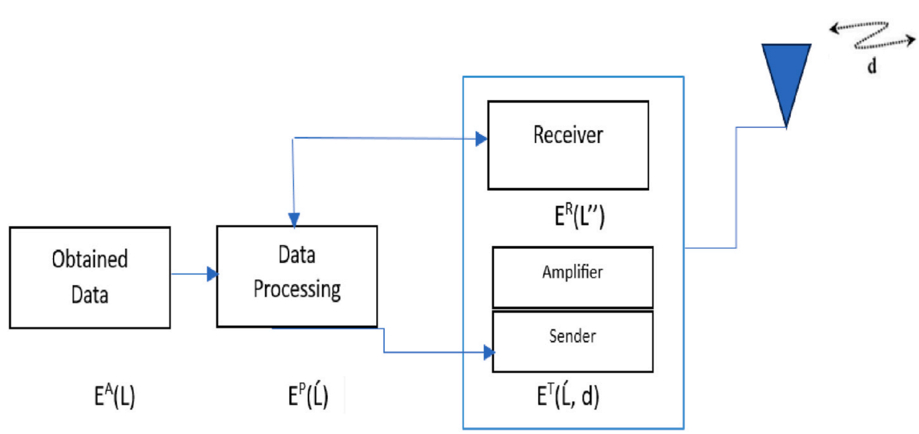

Fig. 1. Initial radio model. The message length affects the energy expenditure model ([51].

$$E_S = E_S^A(L) + E_S^P(\acute{\mathrm{L}}) + E_S^R(L'') + E_S^T(\acute{\mathrm{L}}, d) \tag{1}$$

approximate the Euclidean distance between nodes ś and the CH s and between point s and the BS.

In addition to energy measurements, the network's spatial characteristics play a crucial role in determining its lifespan. Intelligent clustering takes into account factors such as local node density (LEY) and the distance to the base station, thereby adding new dimensions to the clustering process. This becomes particularly important when the enduring energy of points is identical. In such cases, ignoring geographical considerations may result in a suboptimal network structure, which is no better than random clustering[57].

A neighborhood distance threshold called δ is utilized to describe the LEY. In the δ-vicinity, the density is inversely the number of neighbors directly compared to it:

$$G_s\ (\delta)\ \alpha\ \|S_s\|, \text{and } S_s = \{s_i, D\ (s, s_i) \text{ less than } \delta\} \tag{7}$$

where function $\|.\|$ determines the set size and S_s is the group of points in s δ-vicinity.

3.3. Utilizing PPSO to create sensor networks that dynamically structured

To effectively organize a sensor network, it's important to group neighboring nodes into clusters with designated surrogate nodes as cluster heads[58]. Achieving optimal network lifetime requires tuning energy and geographical parameters simultaneously, which can be a challenging multi-parameter optimization problem.

The PPSOPM approach utilizes a binary particle to define the CHs in the network. In this approach, a value of one defines a CH, while a zero defines a member point. An example of this approach is presented in Fig. 2 [53], where the CHs are marked with padded rings and the membership of clusters is represented by the arrows in the form of a dash. If a point becomes idle due to a lack of energy, its congruous gene number is assigned to −1, absolving it from further PPSO processes.

The objective of mapping particles to node clusters is to decrease the

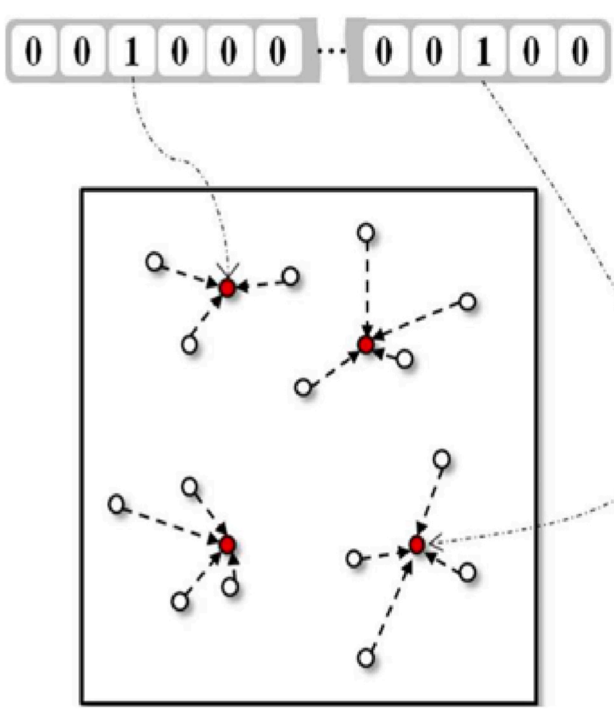

Fig. 2. The utilisation of PSO particles in mapping network clusters [53].

$$F_1 = \sum_s \frac{E_s\ (t)}{E_s\ (0)} + \frac{E'}{E''} + \frac{1}{D'} \tag{9}$$

network communication distance, denoted as D, as given in equation or formula 8, in the following manner:

$$D = \sum_{i=1}^{C} \sum_{j=1}^{N_{s_i}} D(s_i, s_j) \tag{8}$$

Within a network, C represents the number of clusters, and N_{S_i} indicates that the leading node s sub i determines the quantity of nodes that are members of a cluster s_i. In practice, assigning nodes to clusters using the nearest neighbor rule can be viewed as a way of reducing D.

3.3.1. Objective function

The objective function is a crucial element of the PPSOPM approach. As elucidated in Section 3.2, numerous variables exert an influence on the lifespan of the network. The objective function offers a mechanism for simultaneously optimizing many aspects. The subsequent objective function incorporates both energy and spatial components.

The variable $E_s\ (t)$ represents the remaining energy of point s at iterate t, while $E_s\ (0)$ defines its primary energy. E' represents the total energy spent when pings are directly sent from all points to the base station, while E'' denotes the prospective energy cost. D' represents the total distance covered by the CHs to reach the BS.

$$D' = \sum_{i=1}^{C} D(s_i, BS) \tag{10}$$

In this system, every s_i node operates as a cluster head, with standardized phrases falling within the range of (0, 1). The objective function consists of three elements: normalised residual energy, projected energy expenditure ratio, and the inverse of the overall distance between CHs and the BS. Generally, points that are closer to the BS are given preference in terms of distance. In other words, by increasing the reciprocal of the distance, we have a solution that reduces the distance. In a similar vein, our objective is to reduce the anticipated energy expenditures, employing an inverse process. Regarding the remaining energy, the objective is to optimise its utilisation. However, it is important to mitigate potential bias that may arise from the variability of its dynamic range. Therefore, a normalisation process is conducted. In the absence of information regarding the relative significance of the elements, it is presumed that these three terms hold equal importance, leading to the use of uniform weights in the fitness function. Nevertheless, in situations where it is evident that one or more components have a greater significance, it is possible to utilise unequal weights in the objective function [53].

In an alternative approach, LEY, as represented by Equation (7), is considered, resulting in the formulation of the subsequent objective function.

$$F_2 = \sum_s \frac{E_s\ (t)}{E_s\ (0)} + \frac{E'}{E''} + \frac{1}{D'} + \frac{1}{N} \sum_{s'} G_{s'}\ (\delta) \tag{11}$$

The symbol s' represents the group of points that function as CHs. The consideration of node density promotes the selection of CHs that have a higher number of nearby neighbors. It's worth mentioning that the first component of the enduring energy equation factors in the total energy of the network's nodes, including both CHs and member points. In contrast, the second component only considers the energy of nodes that serve as CHs.

3.3.2. PPSO-based, Self-Organizing Network Clustering

In algorithm 1, let us consider a scenario where the number of particles (Member nodes (MN)) is denoted by Z = 100, the value of the acceleration rate is 2, and the total number of iterations is set to 100.The inertia weight parameter in particle swarm optimization (PSO) plays a crucial role as it influences the balance between exploration, exploitation, and convergence in the PSO algorithm. In WSN, every MN is depicted as a particle that represents a potential solution (MN) for fulfilling the requirements of the network administrator. To determine the ideal cluster head (CH), we use an objective function that can be calculated using formulas 9 and 11. After evaluating this function, we analyze each member node, comparing it to its corresponding local best, or pbesti. If the current value is better than the previous best (pbest), we update the pbest position to reflect the current position. Additionally, if the current value surpasses the global best (gbest), we assign it to the corresponding index in the particle array. We then designate the particle with the highest fitness value (FV), or member node, as the global best (gbest). Finally, we update the velocity and position of each particle using formulas 12 and 13 [59].

$$V_i\ (t+1) = V_i\ (t) + U_1C_1 \times \left(P_{p-best} - X_i\ (t)\right) + U_2C_2 \times \left(P_{g-best} - X_i\ (t)\right) \tag{12}$$

Where, the variable V_i (t+1) denotes the updated velocity of a particle, while V_i (t) reflects its present velocity. U1 and U2 are two independent random variables that follow a uniform distribution in the interval from zero to one. The constants C1 and C2 correspond to the learning factors, indicating the rate of acceleration. The X-vector is utilized to document the present location of the particle within the WSN. The particle agent P_{p-best} is considered to be the most superior in its category. The particle known as P_{g-best} demonstrates superior performance within the search area (cluster head in WSN) [60–67].

The calculation of the position value is determined by Equation (13), as follows:

$$X_i\ (t+1) = X_i\ (t) + V_i\ (t+1) \tag{13}$$

Where, the variable X_i (t+1) denotes the updated spatial location of a certain particle. The variable X_i (t) denotes the present location of the object.

In the event that an administrator's request is resolved, the algorithm proceeds to determine the optimal implementation for minimising EC and selecting the most suitable cluster head in a WSN. Conversely, if the request remains unresolved, the method calculates the objective function, namely the optimal choice of cluster head, for each particle, which represents a member node. The primary objective of parallel PSO is to determine the best choice of cluster head in a WSN by utilizing formulas 9 and 11.

```
Algorithm 1, the proposed PSO for self-organizing network clustering
Input:    Establish a pool of N particles E = {e1, e2, ...........eN}
          Degree ɰ of g-best
          Degree ʎ of p-best
          Number of K Iterations
Output:   g-best (Best CH Network Clustering, Reduce Energy Consumption Effort)

∀ei ∈ E, structuring the WSN by minimizing Formula. 8
Estimate the objective function of each ei ∈ E following the formulas. 9 or 11
Member Node Generation = MNG
Count L = 0
For L = 0 to N do
    N-velocity ←—— Random velocity;
    N-position ←—— Random position (N)
    ʎ ←——— N-position
  If (Prop(ʎ) >= Prop(ɰ))
    ɰ ←——— ʎ
  End If
End For
While (MNG ≠ 0)
  For L = 0 to K do
        Calculate Objective Function
        Update Velocity (N-velocity, ɰ, ʎ)
        Update Position (N-velocity, N-position)
          N-velocity ←—— Update Velocity
          N-position ←—— Update Position
         If (Prop(N-position) >= Prop(ʎ))
           ʎ ←——— N-position
        If (Prop(ʎ) >= Prop(ɰ))
           ɰ ←——— ʎ
      If (MNG is Finished==True)
          MNG = MNG - 1
          Save ɰ
ELSE
           Calculate Objective Function for each Particle (MN)
           End If
         End If
        End If
L = L + 1
   End For
End While
Return ɰ
```

Each particle (member node) in the WSN performs this selection process to minimize energy consumption. The algorithm outlining this process is presented as Algorithm 1.

If a member node generation is finished, the algorithm finds the optimal CHs the optimal selection of CHs in the cluster network, and the optimal energy consumption effort; otherwise, it calculates the fitness function (optimal selection of CH) based on the probability (Prop) of each particle (MN).

The PSO optimization procedure ends when one of two situations arises: (1) the highest number of generations is achieved, or (2) the fitness value stabilizes. Once the optimization procedure is finished, the node restructuring process utilizes the particle that produces the highest fitness value.

In the context of PPSO, the primary objective of employing parallel processing is to achieve identical outcomes as those obtained through conventional PSO, while simultaneously reducing the overall energy consumption effort. In the context of implementing PSO algorithm, the PPSO algorithm will follow similar methods with certain modifications, which are outlined as follows.

The PPSO algorithm will determine the optimal number of processors required to implement the objective function for the best priority scheduling of member nodes in WSN to select the optimal CH with less EC effort. This determination is made by preparing 2N sets.

Barrier synchronization is one of the important part in parallel processing that it is a technique employed to prevent the algorithm from progressing to the subsequent step until the objective function, namely the best selection from member node, has been notified. This notification is crucial in maintaining the coherence of the algorithm. It is very important to make sure that the fitness evaluations of all particles (member nodes) have been completed and the findings have been communicated before proceeding with the velocity and position computations. Update particle velocity in PPSO, according to formula (14):

$$\begin{aligned} \mathrm{Vi,j\ (t)} &= \mathrm{W\ Vi,j\ (t-1)} + \\ \mathrm{C1\ R1\ (Pi,j\ (t-1) - Xi,j\ (t-1))} &+ \\ C2\ R2\ (Ps,j\ (t-1) - Xi,j\ (t-1)) &+ \\ C3\ R3\ (Pg,j\ (t-1) - Xi,j\ (t-1)) & \end{aligned} \tag{14}$$

Where, Xi, j represents the location of the ith particle within the jth swarm (member nodes in WSN). Vi, j represents the velocity of ith particle in jth swarm. Pi, j represents the local best in search area (pbest) of ith particle in jth swarm. Ps, j represents the swarm best of jth swarm. Pg, j represents the global best among all the sub swarms. W represents inertia weight, which is employed to achieve a balance between global exploration and local exploitation. A higher value of inertia weight promotes the effectiveness of the global search process. R represents the random variable. It is commonly employed in order to establish the definition of events. Specifically, any predicate that involves random variables establishes the event that encompasses all possible outcomes in which the predicate holds true.

Update particle position in PPSO, according to Equation (15):

$$\mathrm{Xi,j\ (t) = Xi,j\ (t-1) + Vi,j\ (t)} \tag{15}$$

Where, Xi, j (t) represents the present location of the ith particle within the jth swarm. Xi, j (t − 1) represents the new location of ith particle in jth swarm. Vi, j (t) represents the present velocity of ith particle in jth swarm.

The utilisation of parallel processors has the potential to boost the efficacy of PSO. The PPSO will determine the required set of processors for the execution of the objective function in a dependent manner. The approach has the potential to be applied in contexts characterised by large-scale resources and requests. Hence, the use of Gustafson's law is employed in this research to address various parallel processing demands. It has been selected in this paper because acknowledges the significance of appropriately adjusting the workload in order to effectively utilise the resources at hand. This approach facilitates the optimization of resource allocation by effectively adjusting the workload. The efficiency of the PPSO can be estimated by using Gustafson's Law in Equation (16):

$$\mathrm{SP} \le \mathrm{P} - \alpha \times (\mathrm{P} - 1) \tag{16}$$

Where, the abbreviation "SP" stands for "speed up". The symbol α represents the proportion of tasks that are not parallelized, with the condition that the amount of parallel work per processor remains constant. Let P denote the set of processors.

Assuming the intermediate pool has a population size of N and the generation number is Z, the complexity of PPSO can be expressed as M (NZ) since the volume of the pool is either equal to or greater than the volume of the population W. Evaluating a particle involves 2 consecutive procedures: node clustering and network estimation, each of which is independent of PSO. For the clustering process, each node calculates its distance to the cluster head, resulting in a complexity of M(DS), where the quantity of nodes is represented by D, while the quantity of clusters is represented by S. The cluster estimation has a complexity of M (S), resulting in an overall complexity of M(DSNZ). However, in practical scenarios where R, Q ≪ N, C, we can approximate the complexity as M(DS).

Although the approach may initially seem intricate, it incorporates several technically advanced mechanisms that significantly contribute to its effectiveness. To illustrate the complexity, let's break down the key components of the approach:

Optimization Mechanism: PPSOPM uses a multi-parameter optimization function that simultaneously considers factors such as energy consumption, spatial proximity to the base station, and node density. This balancing act is not trivial and requires the careful tuning of multiple parameters for optimal results.

Dynamic Cluster Formation: The PPSOPM approach dynamically reorganizes clusters to optimise network longevity. It adjusts the cluster heads based on fitness functions that include energy metrics, reducing communication overhead and extending network life.

Parallel Processing: By leveraging PPSO, the method enhances the speed of convergence while exploring a vast search space, which is critical for large-scale WSNs. This increases both efficiency and scalability.

The accompanying Fig. 3 depicts the flow of the PPSOPM technique and highlights the crucial decision points and optimization process. It has been included in this article to provide a more comprehensive illustration of the technical complexities.

In Fig. 3, The process begins with an initialization step that sets the necessary parameters and variables for the algorithm. The algorithm initializes a population with particles, denoted as ΔN. Each particle i has an initial velocity V_i, position X_i, and fitness value F, which is likely the objective function to be optimized. The loop counter U is set to 0, preparing the algorithm for iterative processing. The algorithm splits the tasks $(T1, T2, \ldots, T_X)$ and assigns them to the particles $(P1, P2, \ldots, P_N)$, suggesting that each particle is processed in parallel, allowing for efficient computation across multiple cores or processors. This setup is standard in parallel optimization algorithms to improve computational efficiency by evaluating each particle independently. A barrier synchronization step ensures that all particles complete their tasks before moving to the next phase. This synchronization point prevents some particles from proceeding with outdated information, ensuring consistency in the population's state at each iteration. The fitness function (FF) is evaluated for each particle within the population, assessing each particle's solution quality. Each particle's velocity V_i and position X_i are updated according to specific equations, possibly denoted here as Eq. (14) and Eq. (15). After updating, the algorithm assigns the particle with the maximum fitness value (or the best solution in the population) as the current best. This information may guide other particles' movements in subsequent iterations. The algorithm evaluates whether the maximum number of generations (iterations) has been reached or if a convergence criterion has been satisfied. If neither condition is met, the process loops back to the parallel processing step for another iteration. Upon meeting the termination criteria, the algorithm selects the best candidate

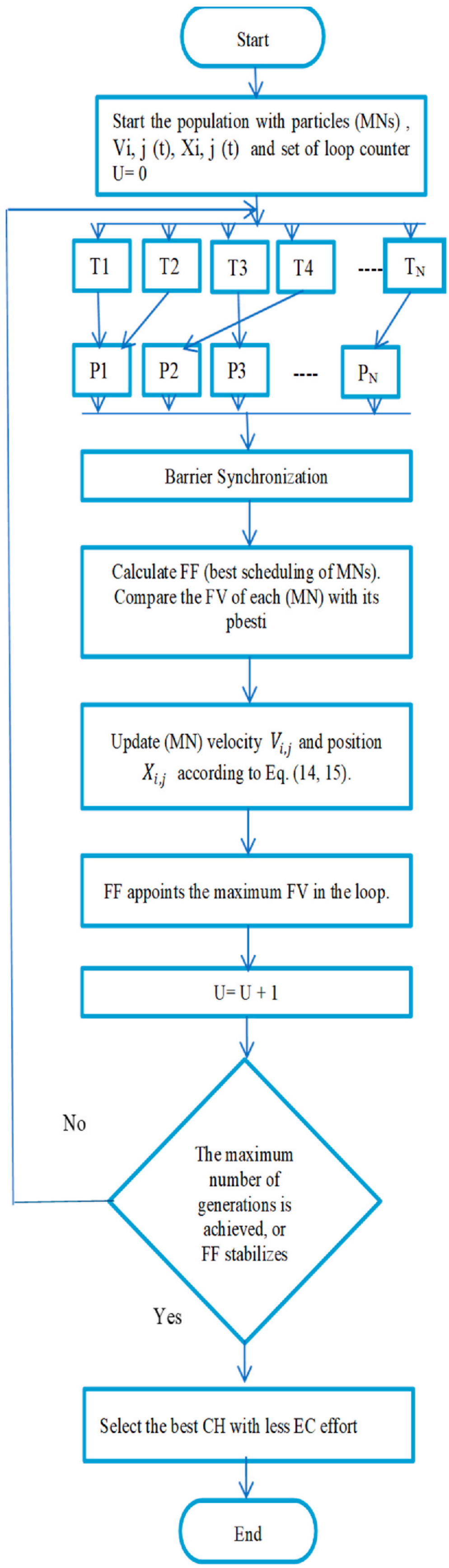

Fig. 3. The flowchart of the PPSOPM shows the process of optimizing CHs and EC in WSNs.

solution from the population, aiming for the solution with the highest fitness and possibly the lowest computational effort.

Although the technique presented may seem basic, it involves a multi-layered optimization framework that compromises various challenging technical elements to ensure efficient energy use and increased network lifetime.

Fig. 3 represents a significant improvement in resolution and clarity compared to earlier iterations. It uses high-resolution graphics and visual cues like distinct colors, sizes, and line types to illustrate the wireless sensor network's clustering process.

While the annotations are adequate for understanding, additional annotations can further enhance clarity by explicitly labeling clusters, nodes, and decision-making pathways. Regarding the flowchart, its current structure follows a logical process but could benefit from clearer phase segmentation, decision points, and annotations. These updates would make it even more intuitive without detracting from the current progress.

4. Experimental results and discussion

4.1. Experimental settings

In this assessment, the WSN exhibits the subsequent characteristics:

- A single BS is responsible for receiving data from multiple nodes.
- The nodes are immobile, and their placements are predetermined.
- Each node has the capability to establish a direct connection with the BS, given that it has an adequate energy supply.
- All nodes possess identical characteristics and beginning energy levels.

The network inputs utilized in these trials are presented in Table 2 [61]. When implementing a PPSO, several particles of 100 individuals are commonly employed for a duration of 100 generations. The acceleration parameters = 2, Wmax = 0.8 and Wmin = 0.2. It should be noted that a high gbest rate has the potential to result in the loss of a favourable solution. The distance threshold, denoted as δ, for calculating the LEY is set at 20 m inside the neighborhood.

The average quality of ten repetitions is recorded. Nodes are dispersed randomly throughout the field in each experimental trial, and the BS is also randomly placed at a set distance from the center of the field. Five cutting-edge methods, as listed in Table 1, were utilized for comparison experiments.

4.2. Network longevity

To ensure the network's longevity, no single node must consume its energy reserves before others. All the nodes should maintain a consistent residual energy level between transmission rounds. While this approach may not be practical when handling large amounts of data in a single cycle, network reorganization can help mitigate the energy disparity between nodes, thereby improving overall network performance. Fig. 4

Table 2
Network characteristics.

Characteristics	Values
Nodes count	250
Primary energy of node	0.6 J
Energy of idle state	75 nJ/bit
Energy of data congregation	6 nJ/bit
Energy of amplification	$d \geq d_0$ 20 pJ/bit/m^2
The communication between a cluster head and a base station.	$d < d_0$ 0.001 pJ/bit/m^2
Energy of amplification	$d \geq d_1$ $E_{fs} = 10$ ¼ E_{fs1}
The communication between a cluster head and a node.	$d < d_1$ $E_{mp} = 10$ ¼ E_{mp1}
Packet size	*400 bits*

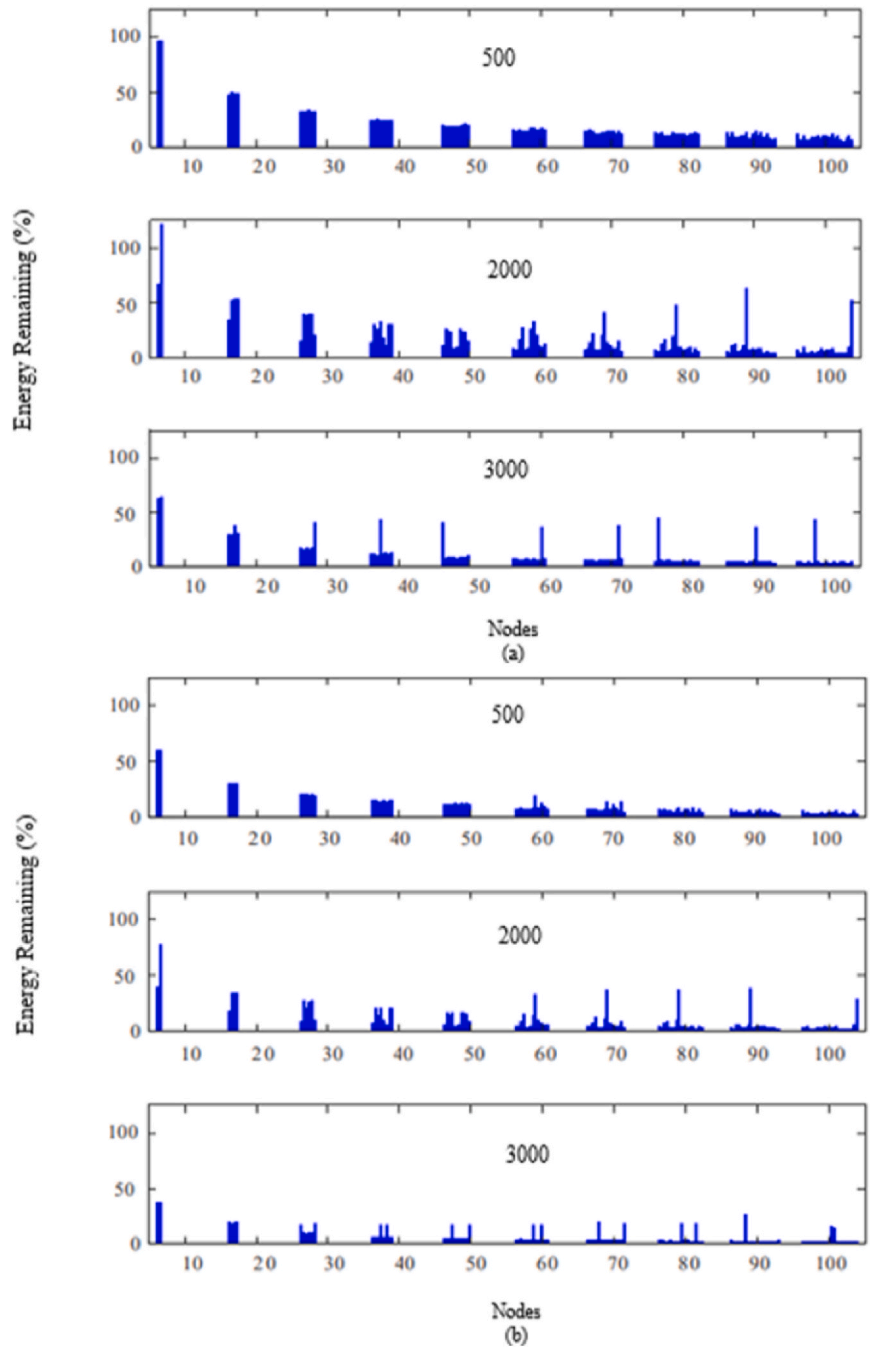

Fig. 4. The proportion of remaining energy in the nodes. One network configuration involves placing the BS at the center of the field, while the other network configuration involves placing the BS at the edge of the field.

Table 3
Residual energy (J) variance of nodes.

Trials	Middle of the base station			Edge of the base station		
	500	2000	3000	500	2000	3000
Mean	0.282	0.174	0.168	0.270	0.150	0.132
SD	0.002	0.048	0.077	0.015	0.042	0.067

Note: The primary energy is 0.6 J.

illustrates the mean residual energy of nodes in a 100m × 100m field using the PPSOPM technique. The trials involved randomly placing 100 nodes, with the BS placed in the middle (Fig. 4a) and at the edge (Fig. 4b). The objective function incorporated energy conditions and the remoteness to the BS. Ten trials were conducted, and the mean energy stages of all points were recorded at carriage iterates of 500, 2000, and 3000.

The uniformity of residual energy levels among all nodes remains consistent over the lifespan of the network. The variation of the residual energy of the two exemplar situations is presented in Table 3. In addition, in Table 3, energy depletion increases as the network size (number of nodes) grows, likely due to increased communication overhead communication.f A higher SD implies greater energy imbalance among nodes, particularly as the network scales. The edge location has slightly lower residual energy compared to the middle, indicating higher energy consumption when the base station is farther from many nodes. The SD is lower in the edge scenario compared to the middle, implying less

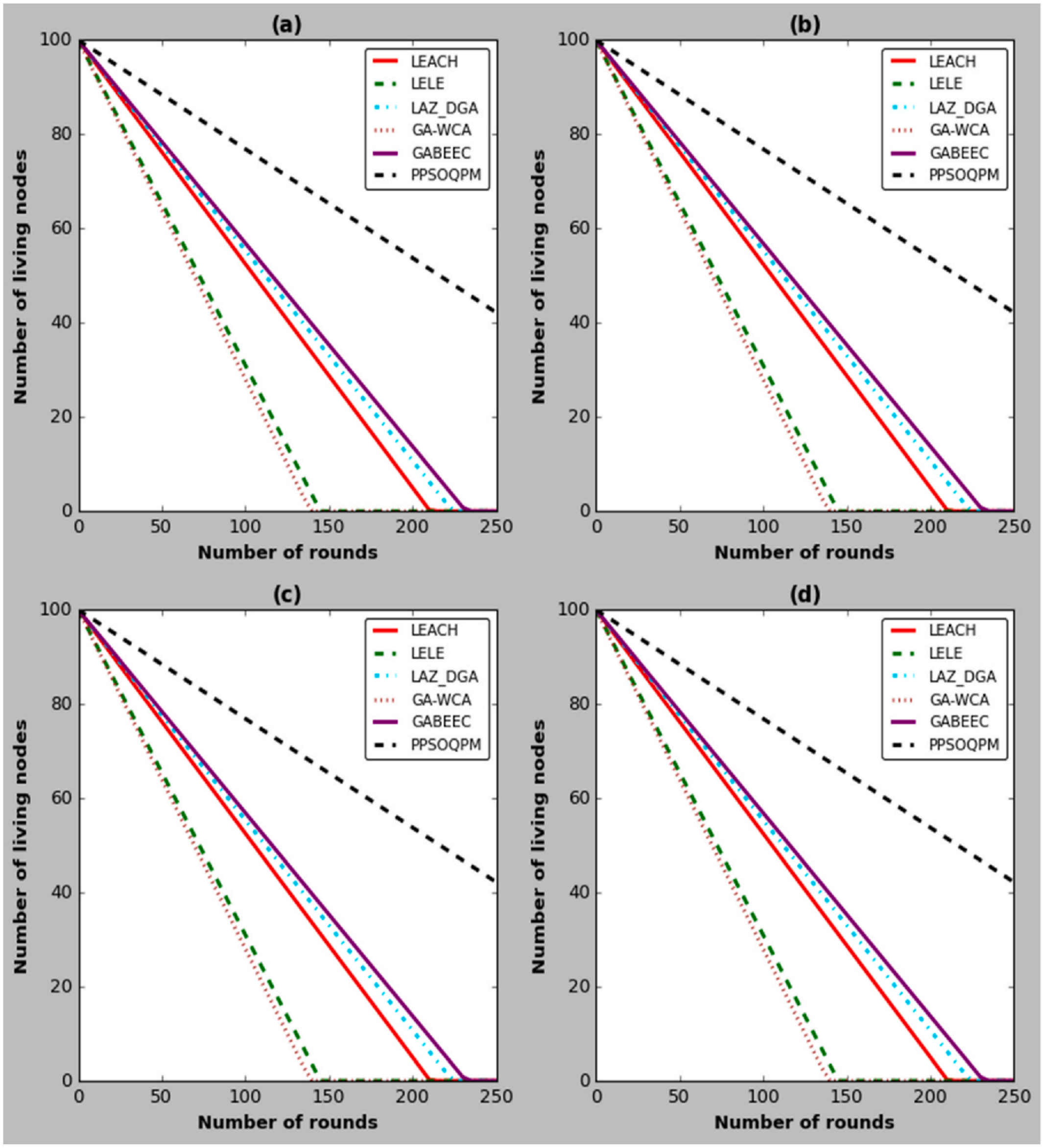

Fig. 5. We can see how the network lifetime corresponds to the number of transmission rounds. To maintain consistency across all figures and ensure clear visualization, the base station is positioned differently in each scenario. In scenario (a), the BS is in the center of a 100-m by 100-m field. In scenario (b), it is situated at the perimeter of the same-sized square field. In scenario (c), the BS is in the middle of a larger 400-m by 400-m field. Finally, in scenario (d), the BS is in the edge of the same 400-m by 400-m field.

imbalance in energy depletion. The disparity in energy levels among the nodes progressively intensifies as the transmission process unfolds. The occurrence of this phenomenon is unavoidable in practical scenarios as a result of the variation in geographic locations of the nodes. Alternatively, by increasing the number of generations in the PPSO, it becomes feasible to determine an improved network structure that effectively reduces the variance of residual energy. Consequently, the prolonged duration required to resolve adversely affects the network's efficiency.

Fig. 5 illustrates the mean quantity of active nodes for the complete duration of the network, employing the most advanced techniques available. Fig. 5a and 5b depict the random placement of 100 nodes inside a 100m-by-100m region. Fig. 5a depicts the outcomes obtained when the BS is positioned at the middle of the field, whereas Fig. 5b portrays the results obtained when the BS is positioned at the edge of the field. Fig. 5c and 5d depict the outcomes of a sensor field whose nodes are positioned randomly across a 400 m by 400 m region. The positions of the base stations depicted in Fig. 5c and 5d are situated at the middle of the field and along the edge of the field, respectively. The x-axis on the graphs displays the quantity of network carriage iterates, while the y-axis indicates the proportion of live nodes. It's important to note that the quantity of nodes distributed in the field remains constant across all instances, as shown in Table 2. As the network transmission advances,

Table 4
The number of times the network transmission occurred before the first node became unavailable due to energy depletion was calculated by taking the mean.

Techniques	100 m by 100 m		400 m by 400 m	
	Middle	Edge	Middle	Edge
LEACH	417	281	9	6
GA-WCA	561	499	69	43
LA2DGA	569	475	49	32
LELE	609	474	24	22
GABEEC	1385	1099	111	81
PPSOPM	**1580**	**1404**	**164**	**101**
Enhancement	14 %	26.2 %	32.6 %	19.8 %

The greatest mean number of network transmission rounds are given in bold.

the quantity of active nodes reduces gradually, owing to energy exhaustion in many nodes.

The density of nodes plays a crucial role in determining the network's lifespan. In Fig. 5a and 5c, the base station's positioning remains identical, but the node density in Fig. 5c, representing a 400m × 400m area, is noticeably lower. The growing distance between nodes reduces the network lifespan. An identical trend is noticed when the BS is placed at the field's periphery in Fig. 5b and 5d. Density is a modified perspective of remoteness, and as the inter-node remoteness grows, node clusters' ability to prolong the network's lifespan diminishes.

PPSOPM methodology shows that the base station's positioning has a significant impact on the network's longevity. In Fig. 5a and 5b, it is evident that the network's lifespan increases significantly when the base station is positioned near the field's center. While other approaches are less affected compared to PPSOPM, there is still a noticeable reduction in the network's lifespan when the BS is placed near the field's edge.

In Table 4, you can see the average ride time for various network approaches when the initial node is absent due to energy depletion. After comparing the results based on the placement of the BS, it's clear that increasing the remoteness between nodes and the BS reduces the network's lifespan. This is primarily due to the energy desired for transmitting data to the central BS. When considering the size of the field, we found that networks operating in larger areas, such as sparse sensor networks, generally have a shorter lifespan. Our studies showed that PPSOPM had the highest quantity of network carriage iterates. Compared to the second-highest outcome, the best enhancement rate in network longevity is 44.39 %.

Fig. 6 presents a comparison between PPSOPM, LEACH, GA-WCA, LA2DGA, LELE, and GABEEC in terms of the aggregate energy consumption of all nodes across prior rounds, considering various scenarios.

Table 5
The duration of the network's existence, both with and without the inclusion of the number of neighbors in the objective function. The FND (First Node Death) refers to the round in which the initial node ceases to function, while the LND (Last Node Death) denotes the round in which the final node becomes inoperative.

Sensor area	Without LEY		With LEY	
	FND	LND	FND	LND
100 m by 100 m	1832	11,577	7641	14,923
400 m by 400 m	164	4522	149	4509

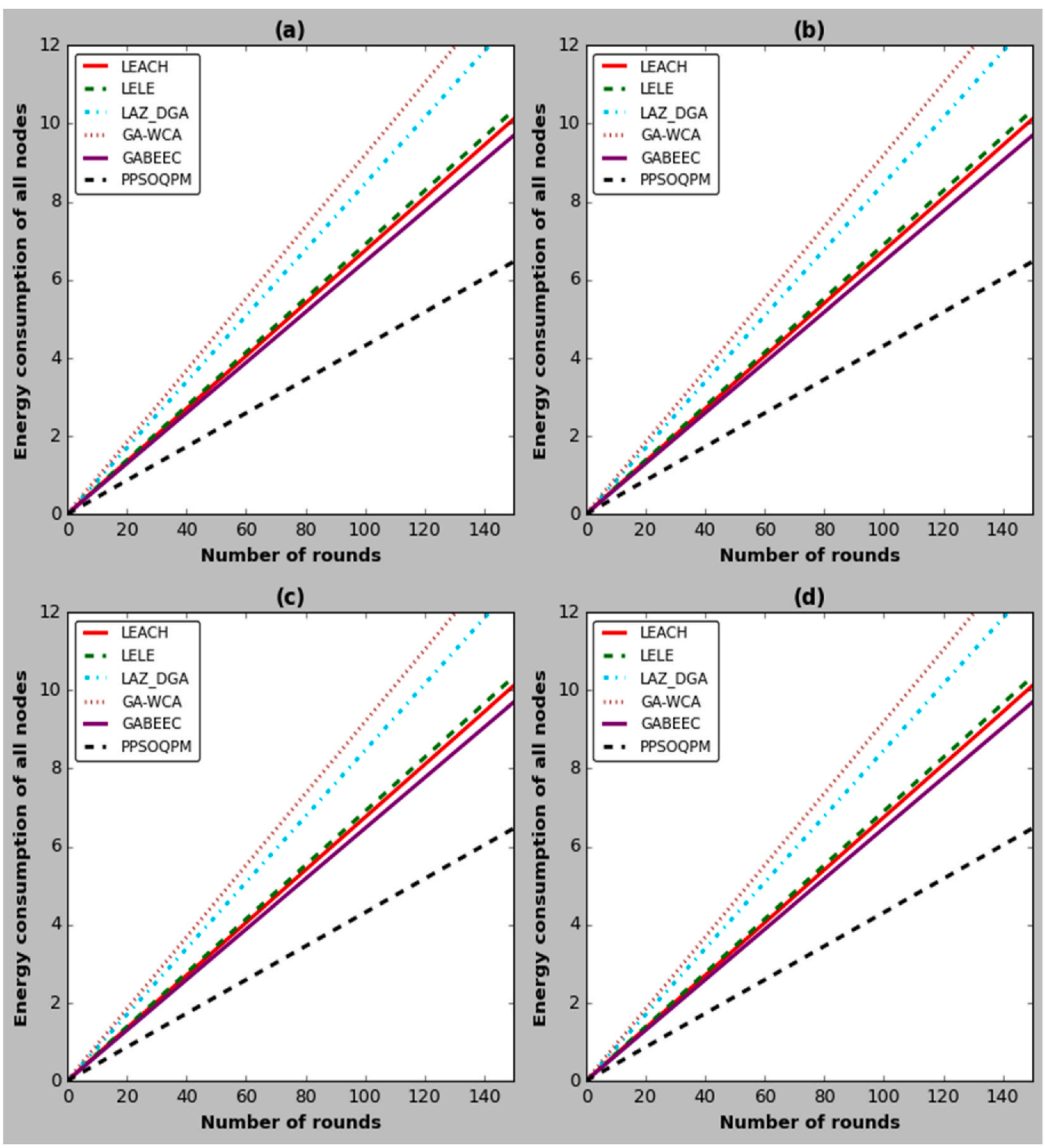

Fig. 6. Comparisons of PPSOPM with state-of-the-art methods in terms of the total energy consumed by all nodes in all previous rounds

The curve obtained for the suggested PPSOPM was consistently lower than the curves for the other methods in all cases. Compared to other clustering algorithms, the PPSOPM algorithm had the lowest energy consumption. Specifically, it consumed 1.5 %, 4.5 %, 8 %, and 13 % less energy than the GABEEC algorithm in 100 m by 100 m in Fig. 6a and 6b and 400 m by 400 m in Fig. 6c and 6d, respectively. On average, PPSOPM consumed 27.6 %, 39.5 %, 26.7 %, and 34.7 % less energy than the worst algorithm in the four scenarios. Therefore, the GECR algorithm exhibits the greatest energy efficiency.

4.3. Local node density

In a densely populated sensor network, the energy expenditure for member nodes is typically lower when communicating with the CH. Therefore, the strategic selection of a node with a higher number of closely connected neighboring nodes to act as a CH confers benefits for minimising EC. The PPSOPM technique incorporates a fitness function that encompasses both energy terms and LEY in order to permit joint optimization. Table 5 depicts the proportion of active nodes while employing fitness functions that incorporate LEY, denoted as Equation (11), and fitness functions that do not incorporate LEY, denoted as Equation (9).

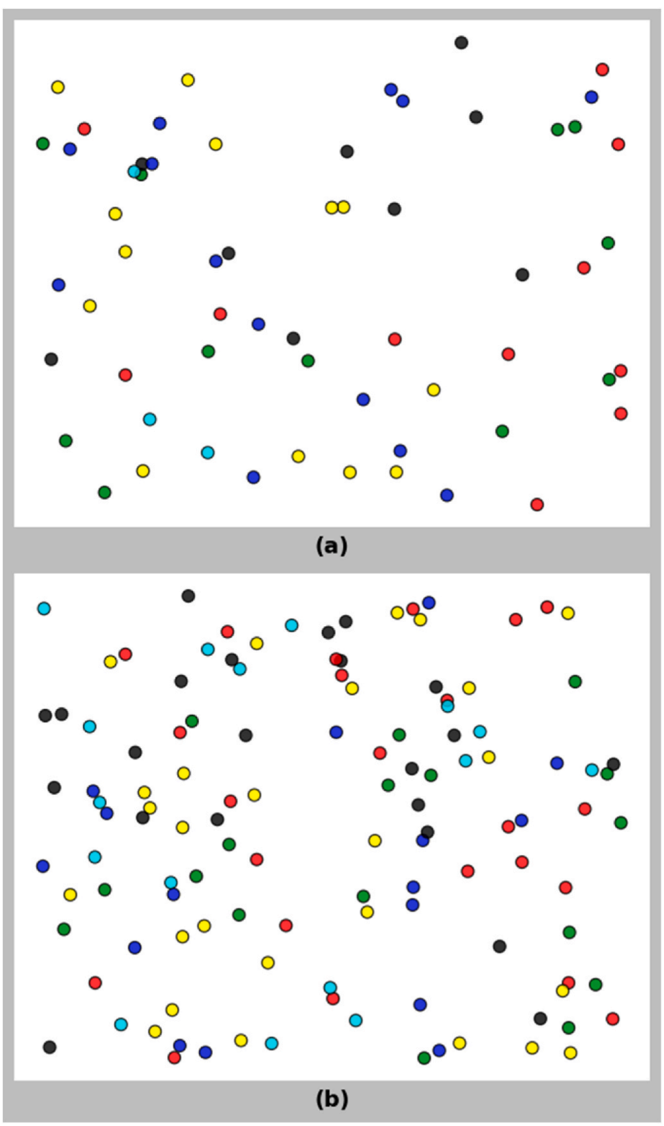

Fig. 7. The nodes are arranged and grouped by unique colors within a 100m × 100m sensor field. In scenario a), 26 clusters are formed with a total of 50 nodes, and the BS is situated 350m away from the field center. In scenario b), a total of 100 nodes produce 56 clusters, with the base station also located 350m from the field's midpoint.

Table 6
The mean count of clusters in a 100-m by 100-m sensor field.

Distance of BS (m)	100 nodes		50 nodes	
	Without LEY	With LEY	Without LEY	With LEY
500	59	61	30	31
450	52	50	19	22
350	29	33	15	17
250	19	21	11	11
50	12	13	7	8
0	5	7	3	3

The distance of the BS is measured relative to the middle of the field.

Table 5 documents the points at which the initial and final nodes become inaccessible during network transmission rounds. When compared to the first cessation of the first node, network performance improves by approximately four times. The durations of wireless sensor networks (WSNs) using both fitness functions show minimal differences. The table showcases the network carriage iterates at which the initial and final points experienced unavailability in a 400 m by 400 m field, providing insights into the performances' proximity. As both scenarios have an equal quantity of points, employing LEY results in superior performance within a densely populated sensor network.

4.4. The influence of base-station placement on network architecture and longevity

The area of the BS has a vital impact on both the nodes' power consumption and the network's overall structure. Fig. 7 and Table 6 show the network clusters that arise from various BS areas. Fig. 7a shows two scenarios: one where the BS is at the center of the field, and another where it's 350 m away from the center. Solid dots represent CHs in both scenarios, while colored circles represent the remaining nodes. Each color defines a distinct cluster. These results expound the formation of the initial network clusters when the nodes' energy stage approaches maximum capacity. When the BS is positioned far from the sensor field,

Table 7
The duration of a network's lifespan relative to the locations of its BS.

BS distance (m)	Without LEY		With LEY	
	FND	LND	FND	LND
50 nodes				
1000	499	1949	1099	1104
900	601	2579	1319	1325
800	722	3095	1703	1590
700	867	3715	2284	1908
600	1041	4458	2995	2290
500	1250	5350	3595	3949
400	1501	6420	4315	5939
300	1802	7705	5178	8327
200	2163	9247	6214	11,193
100	2596	11,097	7457	14,632
0	3116	13,317	8949	17,559
100 nodes				
1000	269	1862	1558	2323
900	323	2235	1870	2788
800	508	2682	2244	3346
700	730	3215	2693	4016
600	997	3862	3231	4820
500	1197	4635	3878	5784
400	1437	5562	4653	8140
300	1725	7832	5584	9769
200	2190	9399	6701	11,723
100	2629	11,279	8041	15,268
0	3155	14,735	9650	19,522

The sensor field size is 100 m by 100 m.

the quantity of clusters increases. The same phenomenon is noted when using a more concentrated arrangement of sensors, where 100 nodes are distributed within a one hundred m by one hundred m space, as depicted in Fig. 7b.

Establishing clusters is a preferred approach to conserve energy when the sensor field is located far away from the BS. However, this conflicts with the objective of growing the network's longevity since the CH often expends a significant amount of energy transmitting pings from its points. Table 6 shows the mean quantity of clusters in a 100m × 100m sensor field, and the inclusion of LEY in the PPSO's objective function has only minimal impact on cluster quantity. Regardless of node count, the ratio between clusters and nodes remains relatively consistent, and the quantity of clusters increases as the remoteness to the BS widens. PPSOPM prioritizes forming small clusters when the sensor field is located far away from the BS to minimize energy differences among nodes.

Table 7 displays the mean duration of network functionality in relation to the remoteness between the BS and the sensor field. This comparison includes both objective functions that incorporate LEY and those that do not. It is evident that the lifespan of the network decreases as the remoteness between the BS and the sensor field increases. Notably, there is a minor improvement in network longevity as the count of nodes grows. Although the volume of data being captured and transferred inside the network is increasing, the presence of a greater count of nodes serves to alleviate the need for long-distance data transmission. This, in turn, contributes to the prolonged lifespan of the network. Furthermore, within the confines of a one hundred m by one hundred m field, the LEY also has a significant role in prolonging the lifespan of the network, particularly when the BS is in very near proximity. According to the data presented in the Table 7, it can be observed that when the remoteness between the BS and the field centre increases more significant than 200 m, the network lifespan, specifically in relation to the occurrence of the first node failure, is significantly reduced. This trend is attributed to the utilisation of a objective function incorporating the LEY. As the distance between the CH and the BS increases, there is a significant increase in the energy consumption of the cluster head. LEY exhibits a preference for clusters characterised by a high density of adjacent sensors, typically leading to the formation of sizable clusters. In the case of a sizable cluster, the energy expenditure associated with data transmission is significantly amplified, mostly due to the fact that the energy cost of long-distance transmissions is directly proportional to the fourth power of the distance (d^4). Consequently, this rapid depletion of energy reserves severely impacts the cluster head, ultimately leading to the exhaustion of energy resources for these cluster heads. Conversely, the impact of said distance is inconsequential in cases where the base station is in near proximity. In these instances, the utilisation of LEY enhances the longevity of the network.

In Fig. 8, we can see the average lifespan of the network measured in

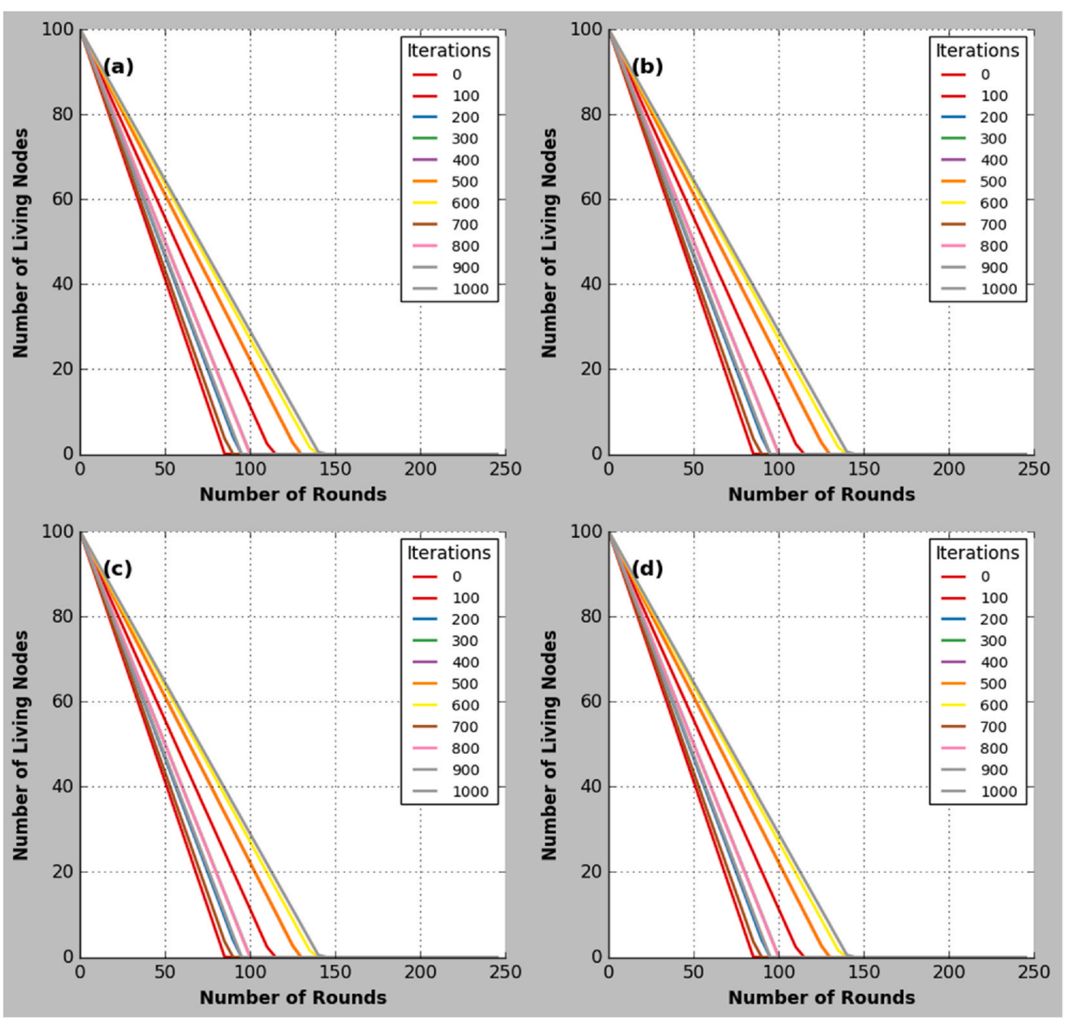

Fig. 8. Illustrates the lifespan of a network in a sensor area measuring 100 m by 100 m. Panel A shows the objective function without LEY, with 50 nodes present in the area. Panel B depicts the same scenario, but with LEY activated. Panel C and D showcase the objective function without and with LEY, respectively, with 100 nodes in the area.

network carriage iterates, in relation to the density of nodes. The outcomes depicted in Fig. 8a and 8b were obtained from a field measuring one hundred m by one hundred m, with fifty nodes. Conversely, Fig. 8c and 8d display the outcomes obtained from the same field, but with one hundred nodes. We can clearly observe the impact of the BS's placement on the network's lifespan. When the BS is located at a significant distance from the sensor field, there is an increase in energy consumption for data transmission, leading to a reduction in the network's lifespan. If you compare the change in network life between the BS located at zero (the middle of the field) and 100 (or 100 and 150, etc.) as illustrated in Fig. 8b and 8a, the impact is more pronounced when the optimization takes into account the LEY. It can find similar findings in Fig. 8c and 8d.

It is noteworthy to observe how the number of living sensor nodes decreases over time for different optimization iterations. While the general trend across all subplots shows that higher iterations prolong network lifetime, an important irregularity appears in Fig. 8b and 8d. Normally, the network should survive longer when the BS is closer because nodes consume less energy transmitting data, and this expected behavior is clearly observed in Fig. 8a and 8c. However, when LEY is included in the fitness function, Fig. 8b and 8d exhibit a rare anomaly in which the network lasts longer when the BS is placed at 250 m compared to 200 m. Since the BS position is randomly chosen within a fixed distance from the center of the sensor field and the reported lifetime represents the average of ten runs, the optimization process becomes sensitive to variations in BS placement. The instability introduced by LEY can shift the optimization landscape in a way that occasionally favors the more distant BS position, leading to this counterintuitive outcome.

4.5. *Efficiency*

Fitness evaluation is the most time-consuming procedure in the PPSOPM approach. Clusters are created based on the closest neighbor criterion and the fitness of a particle is subsequently assessed based on the cluster. Our trials utilise a total of 30 particles in each generation of the PPSO, resulting in the creation of 60 offspring. The optimization process requires the completion of thirty generations. The MATLAB 2023b coding language was used to implement the methods, and the experiments were conducted on a Windows 10 operating system with an Intel Core i7 processor running at a clock speed of 2.6 GHz and 8 GB of memory. Table 8 displays the mean duration (in seconds) and standard deviation for clustering in each carriage iterate, utilizing the PPSOPM technique. The objective function involves energy conditions, remoteness, and LEY, with "BS to field" referring to the remoteness between the BS and the centre of the sensor field. The time presented indicates the first node's unavailability due to energy depletion, while the quantity of nodes remains constant. Although the standard deviation increases when the quantity of nodes is doubled, the mean time is relatively consistent across all scenarios. The PPSOPM's efficiency is largely unaffected by field size and the number of nodes, with an average time of 0.57 s and a standard deviation of 0.04 across all experiments.

The base station efficiently manages the network by interacting with cluster heads instead of all individual nodes. Nodes are better distributed, and the organization is visually clearer. The optimized layout reduces redundancy and balances energy consumption across nodes.

Table 9
Key differences of sensor node placement before and after applying the proposed algorithm.

Metric	Before Optimization	After Optimization	Improvement
Node Distribution	Random and unstructured	Organized into clusters	+80 % clarity
Cluster Heads	None	Clearly defined	100 % new feature
Transmission Lines	Chaotic or absent	Clear member-to-cluster and cluster-to-base station lines	+70 % efficiency
Energy Efficiency	High energy consumption	Lower energy consumption	+50 % reduction
Base Station Load	Overloaded due to direct node links	Reduced due to cluster aggregation	+60 % improvement
Network Lifespan	Short due to uneven energy drain	Extended with balanced energy use	+44 % longer lifespan

Table 9 shows the improvement in the value of sensor node placement before and after applying the proposed algorithm, as follows:

- Energy Efficiency: After optimization, nodes use less energy due to reduced transmission distances. Cluster heads handle aggregation, decreasing the load on individual nodes.
- Network Lifespan: The lifespan of the network is significantly increased due to balanced energy use among nodes. The number of active nodes over time is higher after optimization.
- Data Flow Optimization: Data travels more systematically through clusters, reducing packet loss and improving throughput.

In Fig. 9, the convergence plot shows how the fitness value of the PPSOPM algorithm evolves over iterations. It provides insights into the algorithm's optimization process and how quickly it approaches a near-optimal solution.

Key features of the Plot show X-Axis (Iterations): Which represents the number of iterations or generations the algorithm undergoes. Each iteration corresponds to one cycle of updating the positions and velocities of particles in the swarm. Y-Axis (Fitness Value): Indicates the fitness value of the best solution found by the algorithm at each iteration. Higher fitness values signify better solutions, as the algorithm optimizes the objective function (e.g., energy efficiency, clustering quality). Blue Line (Fitness Progression): Tracks the improvement in the fitness value over iterations. The curve rises sharply in the early iterations and gradually flattens out, showing that the algorithm is converging to a stable solution. Red Dashed Line (Stable Fitness Value): This represents the point where the fitness value stabilizes (plateau), indicating that further iterations produce little or no improvement.

Phases of convergence show initial Phase (Iterations 1–20): The fitness value improves rapidly as the algorithm explores the search

Table 8
The average duration (in seconds) is employed to determine the most efficient network configuration in each transmission cycle using PPSOPM.

Node count BS to field	50		100		200		400	
	0 m	100 m	0 m	100 m	0 m	100 m	0 m	100 m
Field size: 100 m by 100 m								
Ave. time	0.49	0.56	0.65	0.73	0.88	0.87	0.97	0.88
SD	0.04	0.04	0.38	0.15	0.38	0.11	0.18	0.13
Node count BS to field	50		100		200		400	
	0 m	400 m	0 m	400 m	0 m	400 m	0 m	400 m
Field size: 400 m by 400 m								
Ave. time	0.47	0.46	0.58	0.56	0.64	0.60	0.71	0.62
SD	0.08	0.14	0.35	0.31	0.26	0.10	0.28	0.32

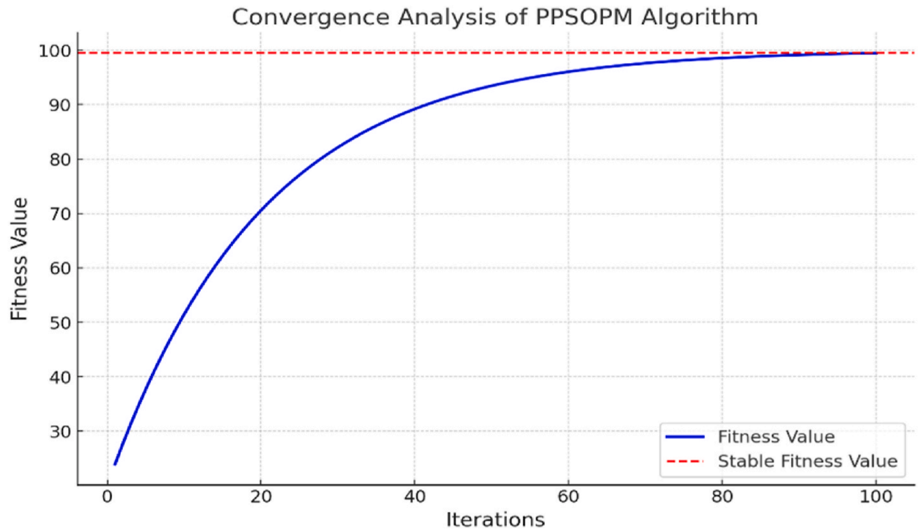

Fig. 9. The convergence plot for the PPSOPM algorithm.

space. This phase is dominated by global exploration, where particles search diverse areas to identify promising regions. Intermediate phase (Iterations 20–60): The rate of improvement slows down as particles begin to converge toward high-quality regions. The algorithm shifts focus from exploration to local exploitation, refining the solutions in the identified regions. Final phase (Iterations 60–100): The fitness value reaches a plateau, indicating that the algorithm has converged to a near-optimal solution. At this point, the algorithm stabilizes as further iterations provide diminishing returns.

The convergence plot shows the important results, as follows: The sharp increase in fitness value in the early iterations demonstrates the algorithm's efficiency in quickly identifying good solutions. Approximately 80 % of the optimization is achieved within the first 50 % of the iterations. The flat region (plateau) in the later iterations indicates that the algorithm has successfully converged. This behavior shows the effectiveness of the inertia weight adjustment and fitness function balance, ensuring that the particles focus on fine-tuning rather than aimless searching. The decreasing rate of improvement suggests that the algorithm has reached a state where energy usage and clustering performance are well-optimized. Quickly identifies high-quality solutions within a few iterations. Efficiently balances exploration and exploitation to achieve optimal clustering and energy efficiency. Converges reliably and stably, making it suitable for dynamic and resource-constrained WSNs.

Comprehensive analysis of trade-offs in energy consumption and network density, as follows:

A. **Energy Consumption vs. Network Longevity**
- Trade-Off Explanation:
  - o While PPSOPM optimizes energy consumption across nodes, some energy trade-offs occur to balance load and reduce variance.
  - o Example:
    - Cluster heads consume more energy to handle aggregation and communication with the base station.
    - Non-cluster head nodes conserve energy, leading to overall network longevity.
- Analysis:
  - o Quantify the energy consumed by cluster heads versus member nodes.
  - o Compare energy variance across different densities to highlight the balance achieved by PPSOPM.

B. **Network Density vs. Energy Consumption**
- Impact of Density:
  - o In denser networks, the algorithm may require more cluster heads to maintain balance, leading to slightly higher energy consumption in the clustering phase.
  - o Higher density increases communication overhead but also provides more redundancy, which can stabilize energy usage across the network.
- Analysis:
  - o Comparing results for low-density networks (e.g., 500 nodes) versus high-density networks (e.g., 3000 nodes).
  - o Highlight how energy variance scales with density.

Table 10 provides an analysis of the trade-offs in energy consumption and network density by comparing three metrics—average residual energy, energy variance, and network lifetime—across networks of varying sizes (500, 2000, and 3000 nodes). The average residual energy decreases with increasing network density, from 0.28 J for 500 nodes to 0.16 J for 3000 nodes, reflecting higher overall energy consumption in denser networks due to increased communication overhead. Similarly,

Table 10
Trade-offs in energy consumption and network density.

Metric	500 Nodes	2000 Nodes	3000 Nodes
Average Residual Energy (J)	0.28	0.17	0.16
Energy Variance (J)	0.02	0.06	0.08
Network Lifetime (Rounds)	2000	1800	1500

Table 11
Comparison table of PPSOPM with other state-of-the-art methods.

Criteria	PPSOPM	LEACH	PSO-Based Clustering	GWO	LELE
Energy Efficiency (J)	0.90	0.65	0.78	0.72	0.58
Load Balancing (Variance)	0.02	0.10	0.06	0.04	0.12
Scalability (Nodes Supported)	3000	1000	2000	2500	1200
Complexity (ms/iteration)	15	10	20	18	22
Network Lifetime (Rounds)	2500	1000	1800	2000	1500
Real-Time Processing (1 = Yes, 0 = No)	1	0	0	0	0

the energy variance, which measures the imbalance in energy consumption among nodes, increases from 0.02 J in smaller networks to 0.08 J in larger ones, indicating greater disparity in energy usage as the network scales. Lastly, network lifetime, measured in the number of operational rounds, reduces from 2000 rounds for 500 nodes to 1500 rounds for 3000 nodes, highlighting the impact of higher node density on energy depletion and operational longevity. This table underscores the trade-off between scalability and energy efficiency, as denser networks demand more energy, leading to reduced lifespans and higher consumption variability among nodes.

Advantages of PPSOPM compared to state-of-the-art methods. (1) Show how PPSOPM minimizes energy consumption compared to other algorithms like LEACH, PSO, or GWO by focusing on residual energy, distance-based clustering, and LEY. (2) PPSOPM uses parallel processing for dynamic CH selection, reducing computational overhead. (3) Demonstrate how PPSOPM performs well in large networks (e.g., 3000 nodes) where traditional methods like LEACH may fail due to high energy imbalance. (4) Highlight PPSOPM's reduced runtime through parallelization, ensuring real-time applicability.

In Table 11, PPSOPM has the highest energy efficiency at 0.90 J, reflecting its superior ability to minimize energy consumption. LEACH has the lowest efficiency at 0.65 J, indicating higher energy depletion. PPSOPM achieves the lowest variance in energy consumption (0.02), showcasing balanced energy usage across nodes. LELE has the highest variance (0.12), implying poor load balancing. PPSOPM supports the largest number of nodes (3000 nodes), making it highly scalable. LEACH and LELE are less scalable, supporting only 1000–1200 nodes. PPSOPM achieves a balance with moderate complexity at 15 ms/iteration. LEACH is the simplest but less capable (10 ms/iteration), while ABC is the most complex (22 ms/iteration). PPSOPM delivers the longest network lifetime at 2500 rounds. LEACH, due to poor energy optimization, results in the shortest lifetime at 1000 rounds. PPSOPM is the only algorithm supporting real-time processing (1 = Yes), leveraging its parallel processing capability.

Our method leverages parallel computation for faster convergence and is evaluated using Gustafson's Law to confirm computational efficiency. Experimental results show that PPSOPM improves network longevity by 44.39 % compared to state-of-the-art techniques. Additionally, when scaling to larger networks (500, 2000, and 3000 nodes), PPSOPM consistently achieves higher average residual energy (e.g., 0.28 J for 500 nodes), lower energy variance (e.g., 0.02 J for 500 nodes vs. 0.08 J for 3000 nodes), and maintains a strong network lifetime performance (2000 rounds for 500 nodes) despite increased density and communication load.

5. Conclusion

Establishing network clusters is a notably effective approach to bolstering the scalability and resilience of WSNs. However, neither a predetermined communication topology nor a randomized clustering methodology sufficiently fulfills the vital need to maximize the network's longevity. Despite significant efforts to automate node organization, the ever-evolving nature of sensor networks and the abundance of potential cluster configurations pose persistent challenges in identifying an optimal network topology in real-time. To address this issue, we offer a PPSOPM technique that provides a comprehensive framework to improve the efficiency of dynamic node clustering. The PPSOPM method involves developing a concise method for encoding nodes and suggesting objective functions that consider enduring energy, prospective EC, remoteness to the BS, and LEY to achieve an optimal and adaptable network layout. The key to managing nodes into suitable clusters and identifying a surrogate node as the cluster leader lies in balancing these factors.

Compared to current methods, the PPSOPM approach significantly extended the lifespan of the network, with an improvement of up to 44.39 %. The results indicated that an increase in the remoteness between nodes and the BS reduces the mean network lifespan due to the additional energy desired to transmit data to the central station. It is advisable to establish additional clusters to conserve energy when the sensor field is far away from the BS. The density of nodes also has a significant impact on the network's lifetime, with greater distances between nodes resulting in shorter lifespans. The average duration of PPSOPM is consistent across all instances, with a mean time of 0.57 s and a standard deviation of 0.04. The efficiency of PPSOPM is acceptable, with little impact from the field's size or the number of nodes.

Our future research will focus on examining how effective PPSOPM is in network structures that are heterogeneous. Additionally, we will explore recent optimization techniques to decrease the optimization time required to construct the network cluster. We plan to extend our experiments to include network sizes of 5000, 10,000 nodes, and beyond, to thoroughly analyze how LEY performs in high-density, large-scale environments. Key metrics such as residual energy, energy variance, network lifetime, and computational efficiency will be assessed. Furthermore, we aim to explore potential adaptations of the algorithm to mitigate trade-offs, such as increased inter-cluster communication overhead, that may arise in extremely dense networks.

CRediT authorship contribution statement

Ahmed Abdelaziz: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Alia Nabil Mahmoud:** Writing – original draft, Validation, Resources, Formal analysis. **Vitor Santos:** Writing – review & editing, Validation, Supervision, Investigation, Funding acquisition.

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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Data availability

No data was used for the research described in the article.

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