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OPTIMISED ROTATING ENERGY-EFFICIENT CLUSTERING FOR WIRELESS SENSOR DEVICES BY SEWING TRAINING-BASED OPTIMISATION

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Abstract. Wireless sensor networks (WSNs) have become well-known as innovative, active, and robust technology accepted in many real-world applications. Due to the power supply restrictions and the power limitations of sensors that are typically known in WSN, using energy becomes a challenge in networks. These two restrictions are essential for achieving energy efficiency and raising the network's lifetime in WSN. Clustering develops multipath routing and scalability, performing optimisation, and making WSN naturally more reliable. This paper introduces an Optimised Rotating Energy Efficient Clustering for Heterogeneous Devices (OREECHD). OREECHD is a clustering technique for heterogeneous WSNs that presents a unique cluster head selection method based on node residual energy and node-induced work. OREECHD defines the term intra-traffic rate limit (ITRL). The document outlines communication restrictions for traffic inside a network with WSNs. ITRL could be applied to develop energy efficiency. We apply the Sewing Training-Based Optimization (STBO) algorithm to recognise the best ITRL in various WSN adjustments. The simulation results show that the proposed algorithm using clustering based on the best ITRL improves the energy consumption in the sensor network by 8.9 % over the REECHD. The simulation outcomes account for the number of dead nodes present in the OREECHD and REECHD networks during the 1 400 and 1 250 rounds, respectively. The network lifetime is significantly improved compared to REECHD, since OREECHD is a classic example of an unequal clustering algorithm. The network's lifetime is 1 200 rounds, which exceeds the REECHD lifetime of 800 rounds. The rate of residual energy at the average node decreases from 19.39 % to 15.41 %.

Keywords: Wireless sensor network, clustering, energy-efficient clustering, network life, low consumption algorithms.

1. Introduction

WSN refers to the collaborative infrastructure that includes multiple tiny, wireless, battery-powered nodes known as Sensor Nodes (SNs) and a powerful node(s) known as Base Station(s) (BS). SNs are resource-limited and restricted in the ability to process, battery, memory storage, and bandwidth [1].

The WSN system incorporates the gateway, allowing wireless connectivity to other systems and shared nodes. The wireless mechanism relies on the needs of different applications. Several accessible standards contain 2.4 GHz radio, given the IEEE 802.15.4/IEEE 802.11 (Wi-Fi) standards or proprietary radios that are commonly 900 MHz. WSN has applications in domains containing remote control, health care, and utilities. In healthcare, wireless devices are enabling less invasive monitoring of patients. To reduce energy consumption as well as data transmission time, the nodes of the sensor are classified into a lot of clusters [2].

Sensors can generate large amounts of data and have heterogeneous features, such as memory, communication abilities, and computational power. Whole nodes are comparable; for instance, they share the same technology and transmit data at a similar pace. WSNs are referred to as homogenous. Because the devices are powered by batteries, collecting data from WSN is vital to ensure that the method is energy efficient [3].

To decrease the expenditure of energy in such a network, the method of clustering is normally used. Here, the network is organised in clusters, with every cluster being controlled and combined with the elected node known as cluster head (CH). The remaining nodes in the cluster are the members of the cluster. Data measurement is sensed by members of the cluster, relayed to CH, which then gathers the data. CH transfers the last report to a node called the base station. Despite the clustering method, nodes transfer a lot of energy for data processing, transmission, and reception from one node to another or to a base station. Thus, work on cluster-based routing protocols has intensified in two homogeneous and heterogeneous WSNs, decreasing energy use in these processes [4].

The Rotating Energy Efficient Clustering for Heterogeneous Devices (REECHD) [3] clustering protocol produces clusters of different sizes. This is done for heterogeneous wireless sensor networks to balance the intra-cluster communication. The node's transmission rate and residual energy are considered during the CH selection. REECHD defines the intra-traffic rate limit (ITRL) term. It describes the restrictions on intra-traffic communication, which entire clusters of WSN should comply with. ITRL is an effective way of dealing with clusters' amounts in WSN. Lower ITRL values may result in more clusters than higher ITRL values. Increasing the number of clusters may result in reduced intra-traffic communication while increasing inter-traffic communication costs. This research aims to utilise Sewing Training-Based Optimization (STBO) [5] to determine the optimal ITRL for various configurations of WSN.

The remainder of this paper is structured as follows: The paper is divided into five sections. Section 1 provides an introduction, Section 2 discusses literature reviews, and Section 3 presents a detailed proposed mechanism. Section 4 presents the results and analysis of the proposed method. Section 5 presents the conclusion of the manuscript.

2. Related work

With the rapid improvement of the Internet of Things (IoT), WSNs have been used in different domains. The issue of energy in WSNs has attracted much more attention, and a lot of experts and investigators have conducted research on the efficiency of energy. Under sensor nodes' restricted energy situation, increasing network lifetime has become a significant subject in the present discussion. Various clustering algorithms have been created for WSNs. We provide a review of works that utilise metaheuristic techniques. We focus on the metaheuristic algorithm as the foundation of our suggested method.

In [6], the new term in clustering is defined as a multi-weight chicken genetic algorithm based on a swarm for energy-efficient clustering (MWCSGA). This includes six parts. They are the model of the system, the algorithm of genetics, CCSO-GA CH selection, inter-cluster and intra-cluster communication, chicken swarm optimisation, and the multi-weight clustering model. Such a protocol aids in raising the efficiency of energy in the communication process in the network.

In [7], a new routing protocol of energy-efficient clustering for WSNs based on the Yellow Saddle Goatfish Algorithm (YSGA) was presented. This technique recognises optimum network configuration for decreasing energy use in each round and extending the network's lifetime. The YSGA protocol automatically assigns CHs' numbers and chooses sensor nodes that play the roles of CHs in each round.

In [8], the CH selection is enhanced by utilising K-medoids with ASFO algorithms, clustering, and CMRP for efficient routing in WSNs. The K-ASFO approach could be used to optimally select CH from suitable nodes – present research clusters sensor nodes using the Adaptive Sailfish Optimisation (ASFO) method with K-medoids, while in [9], the selection of energy-efficient CH by applying the developed GWO algorithm version is presented, which takes into account the balancing factor, sink distance, intra-cluster distance, residual energy, and average-like parameters in CH selection. The presented protocol of EECHIGWO has multi-hop features and gives optimum values of a fitness function for developing a lifetime of WSN. The fitness function design for a selection of CH is given by the two residual energy and their Euclidean distance amount at SNs to BS. In addition, in [10], the routing protocol energy-efficient clustering algorithm for heterogeneous WSN was presented, given the algorithm of bamboo growth optimiser (BFGO). The primary reason is using the BFGO algorithm optimisation ability to perform CH selection, identify optimum CH node collection, ensure cluster allocation rationality, and increase the network's performance. Firstly, given the bamboo forest growth features, the algorithm of bionic intelligent optimisation is presented for the optimisation issue.

In [11], the routing protocol of energy-efficient clustering, using the hybrid Mayfly-Aquila optimisation (MFA-AOA) algorithm, was presented to solve such crucial challenges in WSNs. To ensure the stability of long-term energy, the incorporation of AOA into MFA helps to achieve a balance between exploration and exploitation in the process of CH selection. MFA and AOA Meta-heuristic properties are inherited in the clustering method, which is used to locate significant CHs and the optimal BS placement to enhance energy efficiency. While in [12], the energy-efficient algorithm for selecting CH, given the newly formulated fitness function and applying manta ray foraging optimisation (MRFO), is presented. The objective function for the presented formulation considers various parameters of a network, such as the average distance between CH and sensors in the cluster, the distance in CH balancing, CHs and base station (BS), and residual energy.

In [13], the authors focus on two strategies, namely a combination of the HBACS and HBACM optimisation algorithms, which stand for "Butterfly Optimisation" and "Ant Colony Optimisation", respectively, with static and mobile sink nodes. By minimising the energy usage and prolonging the network's lifetime, BOA allocates optimal CH, and ACO carries out energy-efficient routing.

In [14], the novel strategy of energy-efficient clustering using quantum-based bio-inspired optimisation such as Quantum Elite Grey Wolf Optimisation (QEGWO) is presented to improve the performance of IWSNs. Newly, the novel quantum operators, such as quantum rotation gate, quantum NOT gate, and quantum probability amplitude, are modelled in QEGWO to increase global search ability. While in [15], the authors presented a novel technique for routing based on clusters, which makes the routing process more efficient for increasing the network's lifetime. It is performed in two steps: choosing the optimum CH through a new Moth Levy adopted Artificial Electric Field Algorithm (ML-AEFA), and data transmission performed by the new algorithm of Customised Grey Wolf Optimisation (CGWO). In addition, in [16], the event-driven energy-efficient protocol considering the algorithm of genetic is presented, which applies different parameters, such as the left node energy, min nodes' distance to the base station, and node neighbourhood degree as values of the fitness function, assesses solutions in a heterogeneous WSN.

One beneficial tool for managing the number of clusters within the WSN is the ITLR. Low ITLR values can produce more clusters than high ITLR values. At the expense of increased inter-traffic communication, more clusters may result in decreased intra-traffic communication. The aggregation rate determines which ITLR is chosen. We stress that the ITLR works just as well when the distribution of nodes is not uniform, even though denser regions may get more clusters overall. The aim of this work is to balance the intra-cluster communication, which balances energy consumption and extends the lifetime of WSNs.

3. Proposed method

In this paper, we proposed the method of STBO-ITRL, integrating Sewing Training-Based Optimisation (STBO) and the intra-traffic rate limit (ITRL) aspect.

The rate each CH should apply when forming a cluster is referred to as the intra-traffic rate limit (ITRL). Specifically, every CH should guarantee that the total member node transmission rates never exceed ITRL. It is described by the equation below:

$$\sum_{i=1}^{|\text{member\_set}|} \text{sending\_rate}(n_i) < \text{ITRL}, \tag{1}$$

where

member_set includes whole nodes of the members that compose the cluster,

|member_set| refers to member_set cardinality,

n_i is the node which belongs to member_set,

sending_rate(n_i) is node n_i transmission rate.

We can describe the lower and upper bound for ITRL:

$$\left[0.\sum_{i=1}^{|\text{WSN\_nodes}|} \text{sending\_rate}(n_i)\right]. \tag{2}$$

That |WSN_nodes| is the WSN node number. We have flat routing (e.g. each WSN node is CH and has no member nodes) while ITRL is zero. We could have a unique cluster that contains the whole, while ITRL is the sum of the send rates of the nodes. ITRL is a useful means of controlling the number of clusters in a WSN. More clusters could be formed with lower ITRL values than with higher ones. More clusters may result in less intra-traffic communication, but at a higher cost. Denser locations could have higher cluster counts, therefore using ITRL is effective without distinctively using nodes. Reducing power consumption and increasing the WSN's lifespan enables balanced intra-cluster communication. We find the optimal ITRL under various WSN changes using a meta-heuristic approach. Here, the algorithm of STBO resulted in the best ITRL.

STBO is a metaheuristic algorithm that relies on a population of novice tailors and training teachers. Each STBO is a possible answer to an issue, displaying specified values for choice criteria. Thus, each member of STBO could be represented mathematically using a vector. An analysis of the STBO population could be performed with the help of a matrix. The matrix representation in Equation (3) is a defining characteristic of the STBO population:

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1.1} & \cdots & x_{1.j} & \cdots & x_{1.m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i.1} & \cdots & x_{i.j} & \cdots & x_{i.m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{N.1} & \cdots & x_{N.j} & \cdots & x_{N.m} \end{bmatrix}_{N\times m}, \tag{3}$$

where

X is the population matrix of STBO,

X_i is the i^{th} member of STBO,

N is the total number of members in the STBO population,

m is the number of criteria for the task.

At the beginning of the STBO implementation, all individuals in the population are randomly initialised using equation:

$$x_{i.j} = \text{lb}_j + r \cdot (\text{ub}_j - \text{lb}_j)\,.i = 1.2.\cdots.N.j = 1.2.\cdots.m, \tag{4}$$

where

$x_{i.j}$ represents the j^{th} variable value assigned by the i^{th} member X_i of STBO,

r is a random number between 0 and 1,

lb_j and ub_j are the lower and upper bounds of the j^{th} issue variable, respectively.

Every member of STBO shows a candidate solution to the provided issue. Thus, the objective function of the issue can be assessed, given the values specialised to every candidate solution. Given the candidate solution placement in the problem's criteria, values computed for an objective function could be modelled by applying the vector by equation:

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times m} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times m}, \tag{5}$$

where

F is used to symbolise a vector of the objective function,

F_i is used to indicate the value of the objective function regarding the i^{th} candidate solution.

The numerical values of the objective function are the primary candidate solution variables used for the comparison. Based on the best candidate solution or the X_{best} member of the population, the optimal solution for the objective function is determined. During each iteration of the algorithm, the population is modified, which results in the discovery of new values for the objective function. The best candidate solution must be updated after each iteration. The design of an algorithm ensures that the optimal response at the end of each iteration is the best solution among all of the other iterations that came before it. There are three steps involved in updating the candidate solutions in STBO. These stages are training, imitation of the instructor's skills, and practice opportunities.

Step 1 Training for exploration. The initial step for upgrading STBO members is selecting training instructors and helping beginner tailors develop sewing skills. Each member of STBO who is a novice tailor receives training from other members who have a superior value for the objective function. Each potential member selected as a feasible training instructor for every member X_i of the STBO group, where i ranges from 1 to N, is defined using the following identity:

$$\mathrm{CSI}_i = \{X_k | F_k < F_i.k \in \{1.2. \cdots .N\} \cup \{X_{best}\}\}, \tag{6}$$

where CSI_i represents the whole collection of viable candidate training instructors for the i^{th} member of STBO. The only suitable instructor for training candidates on X_i is X_{best}, described as $\mathrm{CSI}_i = \{X_{\text{best}}\}$. For each i in the set $\{1, 2, \cdots, N\}$, a member from the set CSI_i is randomly selected as the i^{th} member training instructor, denoted as SI_i. Instructor SI_i instructs STBO members in sewing skills. Directing individuals under teachers' supervision enables the STBO population to explore different regions of space to identify prime locations. STBO updates the step illustrating the presented exploration capability of the given strategy in the global search. First, the new position for each member of the population is created by applying Equation (7) to update the members of the population given the STBO step:

$$x^{\mathrm{PI}}_{i.j} = x_{i.j} + r_{i.j} \cdot (\mathrm{SI}_{i.j} - I_{i.j} \cdot x_{i.j}), \tag{7}$$

where

$x^{\mathrm{P1}}_{i.j}$ is its d^{th} dimension,

F^{P1}_i is the value of the objective function,

$I_{i.j}$ are the numbers which are randomly chosen from set $\{1, 2\}$,

$r_{i.j}$ are random numbers from intervals $[0, 1]$.

Next, when the new position develops the value of the objective function that replaces the last position population member, the update condition is designed by applying equation:

$$X_i = \begin{cases} X^{\mathrm{PI}}_i & F^{\mathrm{PI}}_i < F_i, \\ X_i & \text{else}, \end{cases} \tag{8}$$

where X^{P1}_i refers to the new STBO member position given in the first STBO step.

Step 2 Teacher's abilities in exploring and imitating. The second step in upgrading STBO members involves mimicking novice tailors trying to imitate teachers' skills. The STBO design model assumes that a novice tailor will make every effort to improve their sewing skills to the extent that they are comparable to those of an instructor. Each member of STBO is represented as a vector with a dimension of m, and each element of the vector represents a difference between two possible outcomes. At this point in the STBO process, every decision criterion is presumed to correspond to a distinctive sewing ability. Every single member of the STBO executes a selection of m_s selected instructor skills, $1 \leq m_s \leq m$. Because of this process, the algorithm population is moved to various spaces and areas during the search, demonstrating the capability of STBO exploration. The criteria that each member of the STBO follows, such as the specialised skill set of the training teacher, are centred on equation:

$$\mathrm{SD}_i = \{d_1.d_2. \cdots .d_m\}. \tag{9}$$

That SD_i is the set $\{1, 2, \cdots, m\}m_s$ – integration that shows decision variables set indexes such as skills recognised to mimic the i^{th} member from the instructor and $m_s = 1 + \frac{t}{2T}m$ is the number of skills chosen to mimic, t represents the iteration count, and T is the total number of iterations. The following formula is used to determine the new position for each member of the STBO. This is accomplished through the use of a simulation that mimics the skills of the instructor:

$$x^{\mathrm{P2}}_{i.j} = \begin{cases} \mathrm{SI}_{i.j} & j \in \mathrm{SD}_i, \\ X_{i.j} & \text{else}, \end{cases} \tag{10}$$

where

X^{P2}_i is a recently established role for the i^{th} member of the STBO given the second STBO stage,

$x_{i.j}^{P2}$ is the d^{th} dimension of X_i^{P2}.

The new position replaces the last related member position when it develops objective function value:

$$X_i = \begin{cases} X_i^{\text{P2}} & F_i^{\text{P2}} < F_i, \\ X_i & \text{else}, \end{cases} \tag{11}$$

where F_i^{P2} is X_i^{P2} objective function value.

Step 3 Exploitation (practice). Step three in keeping STBO members up-to-date is to practice sewing by mimicking the actions of a beginner tailor. Indeed, as part of the STBO design process, we look for the most practical solutions close to potential candidates by conducting a local search. This STBO phase demonstrates the local search capability of the provided algorithm. A new position around each STBO member is initially constructed using Equation (12). This will allow us to mathematically represent this STBO step, ensuring that recently calculated members of the population remain only in the given search space.

$$x_{i.j}^{\text{P2}} = \begin{cases} \text{lb}_j & x_{i.j}^* < \text{lb}_j, \\ x_{i.j}^* & x_{i.j}^* \in [\text{lb}_j.\text{ub}_j], \\ \text{ub}_j & x_{i.j}^* > \text{ub}_j, \end{cases} \tag{12}$$

where

$x_{i.j}^* = x_{i.j} + (\text{lb}_j + \frac{r_{i.j}(\text{ub}_j - \text{lb}_j)}{t})$,

$r_{i.j}$ is a random number from interval $[0, 1]$.

Next, when the objective function value develops, it replaces the last STBO member position based on equation:

$$X_i = \begin{cases} X_i^{\text{P3}} & F_i^{\text{P3}} < F_i, \\ X_i & \text{else}, \end{cases} \tag{13}$$

where

X_i^{P3} denotes the newly-created role for STBO's i^{th} member, as determined by the STBO's second stage,

$x_{i.j}^{\text{P3}}$ is its d^{th} dimension,

F_i^{P3} is the value of the objective function.

4. Evaluation

For evaluating the proposed clustering method's (OREECHD) performance, the proposed method is performed and compared with the base method model (REECHD) [3]. To analyse the performance of the proposed method (OREECHD) and base method (REECHD), they were implemented and tested in MATLAB under various network scenarios with different sensor node numbers randomly placed in the network.

After the network placement, clusters are shaped based on the strategy of clustering, sense of sensor nodes, and send the sensed data to CH. After gathering the data using CH, they are transferred to the base station.

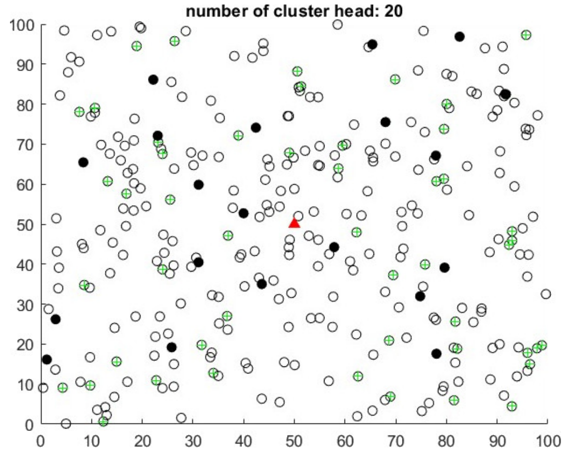


Figure 1. Work environment of the first scenario.

4.1. The evaluation criteria

During implementation, we measure the parameters of a network, such as the use of energy and transmission distance, and analyse the efficiency of the network. The proposed method efficiency is evaluated in several assessment parameters below:

- Network lifetime,
- number of dead nodes each turn,
- the first dead node,
- half of the dead nodes,
- the last dead node,
- total energy consumed,
- average residual node energy.

4.2. Discussion

In this section, we compare the performance of the proposed method (OREECHD) and the base method (REECHD) on several dead nodes, network lifetime, average remaining energy rate, and consumed energy. If the first node goes down, that's the end of the network's lifetime. First, we consider the default network environment and compare the lifetimes of the two algorithms.

4.2.1. First scenario

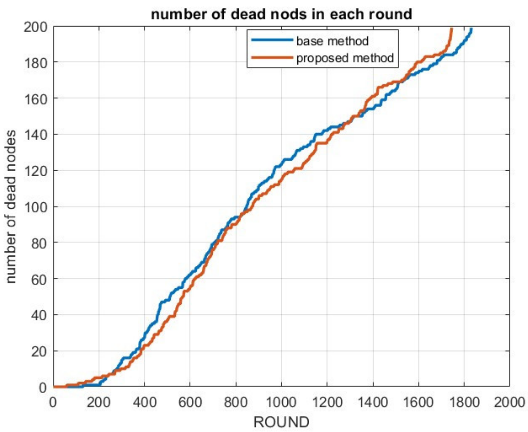
In this scenario, the network size was 100×100 square metres (see Figure 1). 200 nodes with a primary energy of 0.5 J are randomly shared in the area. The primary station is placed outside the work area with coordinates (50 and 50) based on Figure 1; it is assigned in red triangle form. Scenario simulation parameters can be observed in Table 1 and STBO algorithm simulation parameters are in Table 2. These study results are illustrated in Figure 2. Figure 2a shows the number of dead nodes of OREECHD and REECHD in 1 400 and 1 250 rounds, respectively. The single-hop routing method OREECHD achieves the fastest network lifespan at 50 rounds, as shown in Figure 2b. The network lifetime increases significantly when using OREECHD instead of REECHD because it is

#	Parameters	Values
1	Network Size	100×100 m
2	Base station coordinates	(50 and 100)
3	Nodes number	200 or 300
4	Data package size	1 000 bits
5	Initial energy per node	0.5 J
6	Tx Rx and Energy of	5×10^{-8} nJ bit^{-1}
7	Amplifier of εfs	10^{-11} pJ bit^{-1} m^{-2}
8	Amplifier energy of εmp	0.0013 pJ/bit/m4
9	Control message size	100 bits
10	Simulation time limit	10 000 s

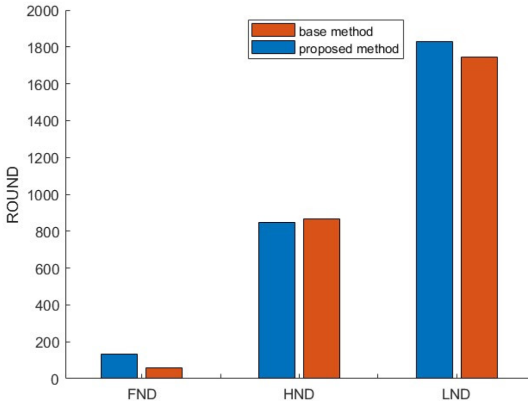
TABLE 1. Parameter used in the simulation of the first and second scenarios.

#	Parameters	Values
1	VarMin	0.1
2	VarMax	1
3	nVar	1
4	Number population	50
5	Max Iteration	100

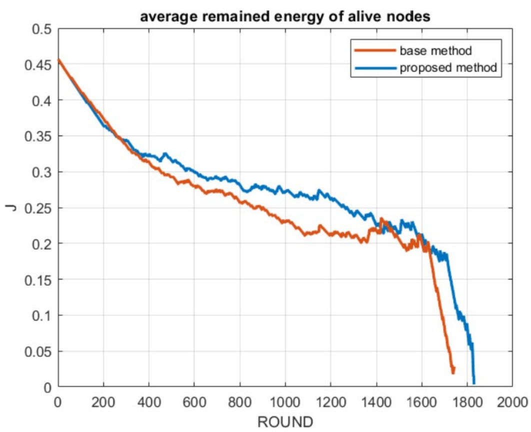
TABLE 2. Parameter used in the simulation of the STBO.



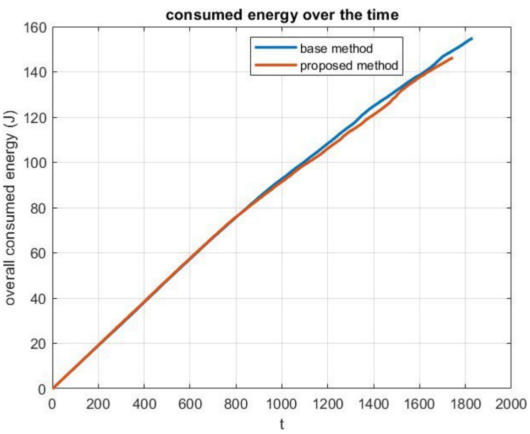
(A). Number of dead nodes.



(B). Network life.

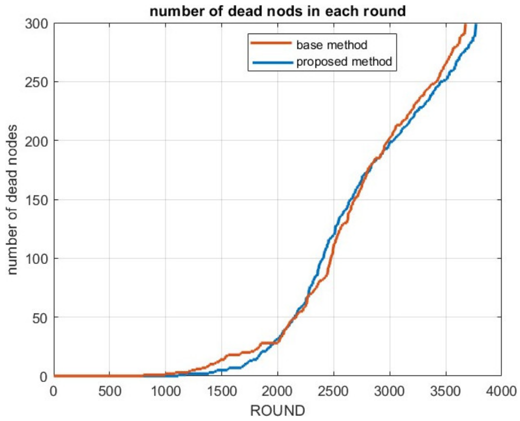


(C). Average energy remaining.

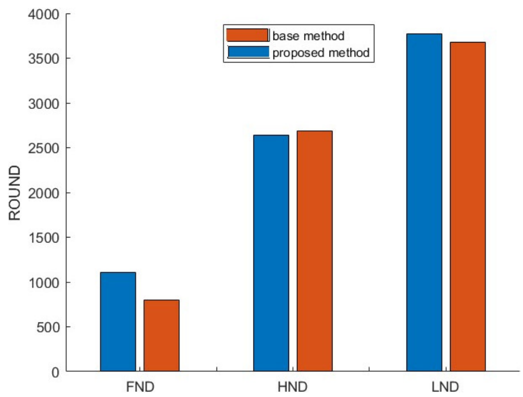


(D). Energy consumption.

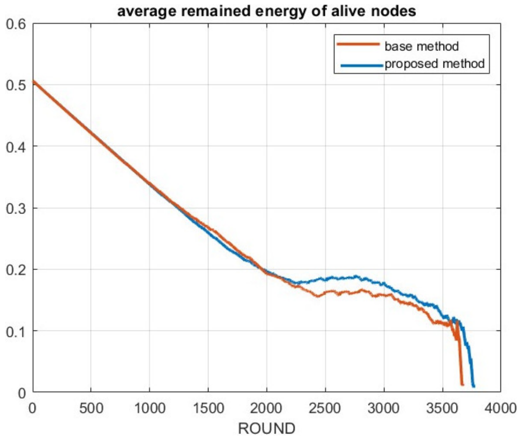
FIGURE 2. Results of the first scenario.



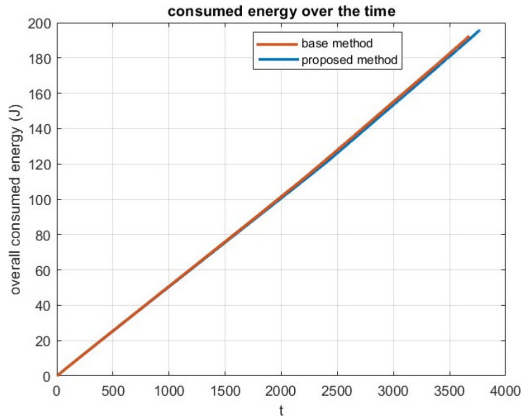
(a). Number of dead nodes.



(b). Network life.



(c). Average energy remaining.



(d). Energy consumption.

Figure 3. Results of the second scenario.

a typical unequal clustering algorithm. The suggested solution optimises inter-cluster routing using timing broadcasts and decreases communication energy usage during the CH competition stage. Compared to REECHD's 50 rounds, the network lifetime is 150. The average rates of node remaining energy at first node death for the two methods are shown in Figure 2c. A moderate decrease from 19.39 % to 15.41 % in node residual energy rate is observed. This finding provides more evidence that the ITRL optimisation mechanism can optimise the utilisation of node energy by balancing their energy consumption in a heterogeneous network. The proposed algorithm makes use of clustering to determine the best ITRL for a sensor network to ensure minimal energy usage. Based on the outcomes, the proposed algorithm generates FND, HND, and LND values. The number of dead nodes in the first scenario, the use of energy in the first scenario, and the average residual energy in Figure 2 illustrate the proposed technique's efficiency compared to the standard technique.

4.2.2. Second scenario

In this scenario, an area of work with dimensions of 100×100 meters is considered. 300 nodes with a primary energy of 0.5 J are randomly shared in the area, and the primary station is placed in the middle of an area of work with coordinates $(50, 50)$. The outcome of this study is illustrated in Figure 3. Figure 3a shows the number of dead nodes in each round. The single-hop routing method OREECHD achieves the fastest network life time as shown in Figure 3b. The average rates of node remaining energy at first node death for the two methods are shown in Figure 3c. While the energy consumption is shown in Figure 3d. In the proposed algorithm, clustering, given the best ITRL, develops sensor network energy use. The proposed algorithm makes use of clustering to determine the best ITRL for a sensor network to ensure minimal energy usage. The number of dead nodes, average residual energy, and energy usage in the second scenario values, as shown in Figure 3, confirm the proposed method's efficiency compared to the standard technique.

5. Conclusion

One way to save energy is by clustering sensor nodes. Clustering techniques allow data to be transferred with less energy. CH selection techniques are one of the factors that influence the sum energy level. REECHD, a clustering protocol for heterogeneous WSNs, is proposed to define a new selection protocol, which considers node residual energy and work carried out by the node. It is assumed that the rate of node transfer is applied. REECHD defines the ITRL term. It describes the limitation of in-traffic communications, which entire clusters of WSN should pursue. ITRL is a helpful way of controlling the number of clusters in WSN. Low values of ITRL can generate more clusters than high values of ITRL. More clusters can cause decreased intra-traffic communications at a higher inter-traffic communications cost. Here, we aim to apply the Sewing Training-Based Optimization (STBO) algorithm to recognise the best ITRL with various WSN adjustments. The proposed method was compared with the base method by running simulations and the results of the simulations illustrate that the proposed method applying clustering is the best ITRL to control the use of energy in a network of sensors. Based on the results, the proposed method generates average residual energy, provides method efficiency, network lifetime, number of dead nodes, energy consumption, and FND, HND, and LND values are better than for other techniques. The suggested strategy minimises communication energy usage during the CH competition phase by utilising timing broadcasts and enhancing inter-cluster routing. The network's lifespan is 150 rounds, which exceeds the 50 rounds of REECHD. In the future, we will improve the cluster-head selection strategy by incorporating characteristics such as the geometry of the target region. A new approach to fault localisation clustering and scalability will be explored.

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