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Energy efficient cluster head selection using improved Sparrow Search Algorithm in Wireless Sensor Networks

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ABSTRACT

Wireless Sensor Networks include a substantial number of nodes with limited battery power that is used for gathering and sending the data to the Base station. Here most energy is consumed in data transfer. Hence a foremost problem is the maximization of network lifetime through minimization of energy consumption in the nodes. To resolve this issue, the clustering method is involved to achieve energy-efficient data transmission. A cluster head is elected which uses an energy distribution mechanism to conserve the remaining power, thereby extending network lifetime. Various present methodologies are employed but every algorithm had notable constraints individually. In this paper, a hybrid Sparrow Search Algorithm with Differential Evolution algorithm is intended to solve the energy efficiency issue by cluster head selection in Wireless Sensor Networks. The proposed algorithm uses the high-level search efficiency of the Sparrow Search Algorithm and the lively potential of Differential Evolution that enhances the lifetime of nodes. The performance of this hybrid model seems to be exploiting the count of alive nodes and dead nodes, throughput, and residual energy. The proposed Improved Sparrow search algorithm using the Differential evolution model for choosing the best possible cluster head shows a development in residual power and throughput than other compared algorithms.

1. Introduction

In the field of electronic and communication engineering, wireless communication has raced for technological growth in Wireless Sensor Network (WSN). This network consists of a collection of spatially distributed tiny nodes that transmit data with every other node in a wired or wireless medium forming an autonomous link. Each node has constrained power with actuators and sensors that work at low frequency devoid of any external means of network features. Finally, it becomes requisite to make use of existing energy efficiency in various applications to keep up the network in a normal operating state (Pitchaimanickam and Murugaboopathi, 2020). Hence the major challenge becomes the constraint of energy in nodes. So, to solve this issue and to reach better Quality of Service (QoS) in the network (Elshrkawey et al., 2018), numerous cluster-based protocols with various features were proposed in the literature. In the clustering technique, nodes are grouped to form a cluster as in Fig. 1 with members called Cluster Members (CM). Every cluster selects a Cluster Head (CH) that gathers data and then transfers it to the Base station (BS). Hence, the process of CH selection entails the right addressing to balance the energy consumption of CHs. If not, they might die quickly because of overload for the data gathering and sending process. Initially, for many algorithms, CHs are chosen randomly (Ahmad et al., 2019) and for very few application cases like a small area network CH are selected based on distance and residual energy. Each node is assigned with a unique address (ID) and the datum is sent to the determined destination with help of this address. In static clustering, the network is proactively divided into clusters, while in dynamic clustering, a cluster is set up reactively proximal to the event sensing nodes. Numerous authors have pointed out the retrospective review of cluster protocols (Sarkar and Senthil Murugan, 2019). Since it is wireless the nodes must require mobil-

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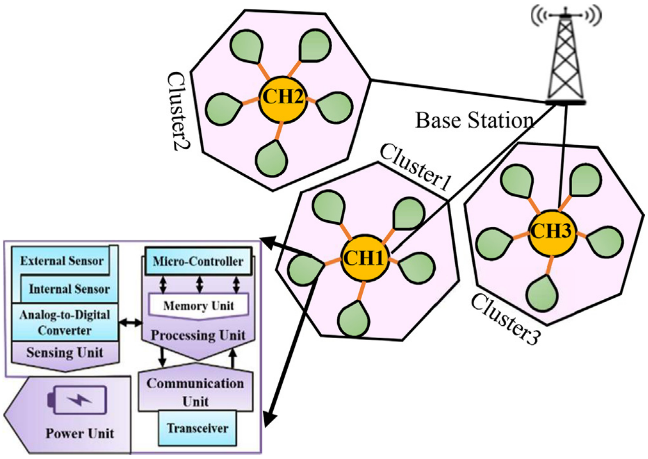

Fig. 1. Cluster formation Architecture.

ity within the search space. The nodes and BS can be either static (fixed) or (variable) mobile. The fixed nodes are stable (location and data), and they collect the data from the environment. The mobile node runs on a dynamic environment with unknown size and information. The static BS control the network and points out the direction. The mobile BS directs and controls the nodes. Major architectures like distributed (flat) and hierarchical (cluster-based) architecture can unravel the challenges raised.

Based on recent studies, the classification of clustering protocols can be listed under different genre as in Table 1. So far, vast clustering methods have been set up to optimize the CH selection to confirm the reliability of the network for data communication (Guhan et al., 2021). But every algorithm had prominent constraints. Hence by metaheuristics optimization algorithms provides a favourable result while overseeing exploration and exploitation.

For any metaheuristic algorithm to be competent, it should include the solution space with a globally optimal solution without getting stuck in local optima. For optimal results, there must be stability between exploration and exploitation (Subramanian et al., 2020). Notably, exploration for the best solution becomes complete, so we intend to pick a prominent meta-heuristic algorithm for the selection of CHs. This inspired us in combining the predominant Sparrow search algorithm (Xue and Shen, 2020) and Differential evolution (Storn and Price, 1997) explicitly.

The main contributions of this paper are detailed as follows:

1. We resolve the CH selection problems using an Energy-Efficient Cluster Head Selection by Improved Sparrow Search Algorithm using Differential Evolution (EECHS-ISSADE) model.
2. The foraging and antipredator nature of sparrows aids to effectively perform inter-cluster communication. The shortest path between CH to BS is identified using the SSA because the SSA can deliver rapid discovery of solutions in WSN. Here, the SSA is optimized with residual energy, and distance to overcome the limitation of the uncertain convergence time.
3. DE is used for selecting CH due to its high stability and less computational complexity. The proposed algorithm derives a Fitness Function (FF) for the clustering process based on numeral measures like residual energy, distance to the neighbors, distance to the BS.
4. Network lifetime is increased due to the energy-efficient CH selection. In addition, total packets received by BS are enhanced by limiting node energy consumption while transmitting the data packets.

Table 1
Protocol classification with the respective genre.

Protocols Genre	Protocols
Data-centric based	Sensor protocol for information via negotiation (SPIN), Directed Diffusion (DD), Energy-aware data-centric routing (EAD), Energy-aware Routing (EAR), Gradient-Based Routing (GBR), Rumor Routing (RR), Constrained anisotropic diffusion routing (CADR), ACtive Query forwarding In sensor nEtworks (ACQUIRE)
Hierarchical based	Low-energy adaptive clustering hierarchy (LEACH), Energy-aware routing for cluster-based sensor networks (EAR-CSN), Power-efficient gathering in sensor information systems (PEGASIS), Self-organizing protocol (SOP), Balanced-clustering energy-efficient hierarchical routing (BCEE), Threshold sensitive energy efficient sensor network (TEEN), Adaptive threshold sensitive energy efficient sensor network (APTEEN)
Location-based	Minimum energy communication network (MECN), Geographic energy-aware routing (GEAR), Energy-aware WSN geographic routing protocol (EAGRP), Trajectory-based forwarding (TBF), Small minimum energy communication network (SMECN)
Proactive (Table driven) based	Destination-Sequenced Distance Vector (DSDV), Optimized Link-State Routing (OLSR), Core-Extraction Distributed Ad hoc Routing (CEDAR), Topology-Based Reverse Path Forwarding (TBRPF)
Reactive based	Ad hoc QoS on-demand routing (AQOR), Temporally Ordered Routing Algorithm (TORA), Ad-hoc on-demand distance vector (AODV)
Mobility-based	Two Tier Data Dissemination (TTDD), Joint Mobility and Routing, Dynamic Proxy Tree-Base Data Dissemination
Multipath based	Sensor-Disjoint Multipath, N-to-1 Multipath Discovery, Distance Routing Effect Algorithm for Mobility (DREAM),
QoS-based	Sequential assignment routing (SAR), Maximum lifetime energy routing (MLER), Energy-aware QoS routing (EAQSR), Maximum lifetime data gathering (MLDG), Message-initiated constraint-based routing (MCBR),
Centralized	Power Efficient and Adaptive Clustering Hierarchy (PEACH), Base station Controlled Dynamic Clustering Protocol (BCDCP),
Distributed	Energy efficient hierarchical clustering (EEHC), Hybrid energy-efficient distributed clustering (HEED), Optimized Lifetime Enhancement (OLE)

The rest of the paper is organized as follows: Section 2 briefly discusses the related work. Section 3 introduces the proposed model for cluster head selection, Section 4 presents the simulation study, Section 5 validates the proposed model. Finally, section 6 discusses the conclusion and introduces the perspectives for future work.

2. Related works

The prime motto of the clustering protocols has been the discovery of parameters for CH selection. The first imprint of clustering was presented in LEACH (Low Energy Adaptive Clustering Hierarchy) (Heinzelman et al., 2002) is a hierarchical and probabilistic protocol. To be more precise, LEACH is a conventional clustering protocol postulated for the topology control feature. It mainly focuses on choosing CH chaotically in a cyclic manner, here the energy is evenly distributed between the nodes. This coordinates clustering for curtailing the energy utilization and boosting network lifetime. The energy efficiency is achieved by randomly choosing the cluster head. For obtaining maximum network lifetime, the nodes themselves self-organize in the form of clusters and re-cluster themselves for almost every cyclic round. The main obstacle is the arbitrary selection of CH that culminates in the imbalanced residual energy between nodes. While the selected

CH has less energy, then it can end in performance deprivation. Considering the probability value of nodes (p), if p is lower than a random value (r) generated by nodes, then the nodes convert themselves into CH. The value of p increases for each round until CH is elected. If CH is chosen, then the p value is reset. If the p value is equivalent to 1, then all nodes become CH in t_i time interval. The t_i value is built on the number of CH. Each CH operates Time Division Multiple Access (TDMA) to transmit data from BS and avoid unnecessary collisions so that minimum energy is used. Code Division Multiple Access (CDMA) is also used to reduce interference between clusters. As CH utilizes high energy than other nodes, the energy is evenly distributed among nodes. If a node has been CH, then it cannot be CH again after p rounds. The probability to become CH again is 1/p. LEACH has endured intense modification by researchers leading to different methods (Xiangning and Yulin, 2007) to enhance network performance since the metrics like node degree and energy were not considered in multi-hop data transfer between CHs. Several traditional algorithms (Al-Zubaidi et al., 2019) were identified, and to improve these issues, several metaheuristic algorithms were proposed. Table 2 depicts the summary of all metaheuristic approach-based clustering algorithms from the literature. Artificial Bee Colony (ABC) algorithm Fitness Function (FF) gets fixated on optimizing the parameters that played a vital role in Cluster Head Selection process called Energy-efficient CHS using ABC (EECHS-ABC) (Ahmad et al., 2019). This considers distance from BS, intra-cluster distance and residual energy for minimizing the energy consumption and to enhance network lifetime. EECHS -ABC simulation shows better performance and reduces packet loss ratio with increased energy efficiency in the network. An energy-efficient dynamic Cluster Head Selection with Particle Swarm Optimization algorithm (EEDCHS-PSO) (Guhan et al., 2021) resolves CH selection issue by balanced energy consumption during the formation of the cluster with greater coverage. It uses distance and residual energy parameters. CH helps in data transmission from cluster to CH of other clusters or to BS. The simulation results reveal better performance in energy competency and load balancing with low control overhead. Breeding Artificial Fish Swarm Algorithm (BAFSA) (Sengottuvelan and Prasath, 2017) for optimal CH selection using intra cluster distance and residual energy parameters to reduce energy consumption and to increase network lifetime. A hybrid Grasshopper Optimization Algorithm (GOA) and Crow Search Algorithm (CSA) based optimal CH Selection (HGWCSOA-OCHS) (Subramanian et al., 2020) enhances lifetime of the network by minimization of delay, distance amid nodes and energy stabilization It also resolves the premature convergence issue that avoids it from exploring the search space in an effective way. Simulation tests shows reduced energy consumption, enhanced network lifetime by assessing the percentage of alive and dead sensor nodes in the network. Firefly algorithm (FA) with cyclic randomization algorithm (FCR) (Sarkar and Senthil Murugan, 2019) selects CH and preserves energy efficiency. Here the distance among the nodes is low, and a possible number of alive nodes were terminated. FA is expanded for protracting the energy efficiency and network lifetime. Incorporating Artificial Neural Network (ANN) with enhanced LEACH (Kovendan et al., 2018) helps to attain energy efficiency in network guaranteeing effective use of existing energy for CH selection. The distance-based ANN determines the distance for electing CH and utilize its effectiveness of faster computation without negotiating the computational cost. A hybrid DragonFly Algorithm (DFA) and FA (FPU-DFA) (Alghamdi, 2020) considers metrics like energy, delay, and distance for selecting CH that make the network service prompt. FA position is updated and replaced with DFA. FPU-DFA is compared in terms of the number of alive nodes, network energy, and delay. Genetic algorithm (GA) based Optimized Clustering (GAOC) (Verma et al., 2019) protocol optimizes CH selection by assimilating the parameters like residual energy, distance to the BS, and node density in its formulated fitness function. To pioneer promptly with the Hot-Spot problem, and to shorten the communicating distance from the nodes to BS, Multiple data Sink based GAOC(MS-GAOC) is also put forward that outperform the benchmark functions of different performance metrics. A hybrid FA with PSO (HFAPSO) (Pitchaimanickam and Murugaboopathi, 2020) improves the global search of fireflies using PSO resulting in optimal CH positioning in LEACH-C. HFAPSO results in extending network lifetime, increasing the alive nodes, and reducing the energy utilization. Energy efficient Cluster Head Selection algorithm based on PSO (PSO-ECHS) (Rao et al., 2017) is evaluated using the BS distance, intra cluster distance and residual energy. PSO-ECHS saves energy and extends the network lifetime but does not consider fault tolerance and energy balancing. To overcome this a hybrid PSO algorithm with Harmony Search Algorithm (HSA-PSO) (Shankar et al., 2016) is put forth for optimal selection of CH using HSA search capability. This confirmed its predominance with respect to throughput, residual energy, the number of dead and alive nodes. Hybrid PSO and Tabu Search (TS) (TabuPSO) (Vijayalakshmi and Anandan, 2019) based CH selection enhances the network lifetime with balanced energy consumption. TabuPSO CH selection was assessed to be noteworthy in CH selection for the objective of enhancing network lifetime. The method uses the advantages of TS for resolving the issue of local optima in PSO-based CH selection. Cat Swarm Optimization (CSO) (Chandirasekaran and Jayabarathi, 2019) for clustering is instigated considering RSS, residual energy and intra cluster distance for real time WSN scenario. CSO simulation results indicate a superior performance in energy consumptions, throughput, overhead, and network lifetime. Hybrid Artificial Bee Colony and Monarchy Butterfly Optimization Algorithm (HABC-MBOA) (Rambabu et al., 2019) based CH selection substitutes ABC worker bee with MBOA butterfly adjusting operator to avoid getting stuck into the local optimal solution. HABC-MBOA eradicates CH getting loaded with maximum number of nodes. Few of these hybrid metaheuristics algorithms have been used extensively, due to complex computation and energy inefficient nature, the residual energy assured by them are not sufficient in enhancing the network lifetime.

This paper deliberates the existing clustering algorithms drawbacks and proposes a hybrid metaheuristics optimization algorithm for cluster head selection to solve the energy efficiency issue.

2.1. Sparrow search algorithm (SSA)

Sparrow Search Algorithm (SSA) was put forward by Jiankai Xue and Bo Shen (Xue and Shen, 2020) inspired by the foraging and anti-predating behaviors of sparrows. The sparrows are friendly, omnivorous species that are circulated in every part of the world as two kinds namely the producer and the scrounger. They are creative, have strong memory power, and are interested to survive near humans. The producers are virile and vigorously look for the food, whereas the scroungers acquire foodstuff from the producers. Moreover, the proof exhibit that the birds generally utilize behavioral tactic and switch amid producer and scrounger. Every sparrow is a producer when it explores food sources, however, the ratio of producers and scroungers remains the same. Sparrows that have maximum power are treated as the producers. Energy reserves might have a vital task when the bird selects their foraging strategy. The birds with low energy scrounge more. Various starving scroungers prefer to migrate from place to place to find food and conserve maximum energy. Scroungers obey producers which offers an optimal food source. The principles are composed of maximum energy levels which preserve and offer foraging regions for all scroungers. Hence, energy level is based on the fitness values estimations. It is also useful for discovering enriched

Table 2
Summary of various metaheuristic approach-based clustering algorithms in wireless sensor networks.

Algorithm	Objective	Parameters	Network type	Compared with	Future
(Shankar et al., 2016)	To obtain a global search with faster convergence for energy-efficient CH selection	Distance, Energy	Heterogenous	LEACH DT HAS PSO	–
(Rao et al., 2017)	To conserve the energy of nodes for prolonging the lifetime of the network	Intra-cluster distance, Residual energy	Homogeneous	E-LEACH LEACH-C PSO-C LDC	To develop a routing algorithm using a metaheuristic approach
(Sengottuvelan and Prasath, 2017)	To reduce overall energy consumption and increase network lifetime	Packet loss rate, Distance	Homogeneous	LEACH GA BFSA	–
(Kovendan et al., 2018)	To improve the lifetime of nodes and increase energy efficiency	Throughput, Energy, Packet delivery ratio	Homogeneous	LEACH LEACH-C	-To incorporate the cloud computing and priority queues
(Ahmad et al., 2019)	To increase energy efficiency and node lifetime	Residual energy, Intracluster distance	Homogeneous	LEACH E-LEACH PSO-C	-A new cluster-based algorithm
(Vijayalakshmi and Anandan, 2019)	To improve network lifespan, network's energy efficiency	End-to-end delay, Packet loss, Alive nodes	Homogeneous	Multi-Hop LEACH PSO	-A hybrid model by firefly techniques with TS.
(Sarkar and Senthil Murugan, 2019)	To improve energy efficiency and node lifetime	Distance, Number of CH	Heterogenous	ABC GA GSO	-A new cluster-based Algorithm
(Verma et al., 2019)	To shorten communicating distance from the nodes to the sink	Dead nodes, Node density, Throughput, Remaining energy	Homogeneous	DCH-GA TEDRP GADA-LEACH	To propose a model for achieving better performance by moving sink scenario
(Chandirasekaran and Jayabarathi, 2019)	To minimize intra-cluster and to optimize energy balance in CHs	Intra-cluster distance, Residual energy	Homogeneous	LEACH PSO	To analyze the feasibility of fetching the large data for cloud computing application
(Rambabu et al., 2019)	To extend network lifetime with guaranteed QoS	Distance, Energy	Homogeneous	FFCG-CH SS FFOCR-CHSS HAS-PSO CHSS	-Hybrid Artificial Bee Colony and Bacterial Foraging Algorithm
(Pitchaimanickam and Murugaboopathi, 2020)	To increase network lifetime and decrease energy consumption	Alive nodes, Residual energy, Throughput	Homogeneous	LEACH-C FA	-Hybrid model to improve network lifetime. - Large-scale Real-time application
(Subramanian et al., 2020)	To balance alive and dead nodes, improve network lifetime	Alive nodes, Residual energy	Heterogenous	SFA-CHA ABC-CHS FCGWO-CHS	-To formulate Elephant Herd Optimization-based clustering algorithm
(Alghamdi, 2020)	To improve network performance	Alive nodes, Delay Network energy,	Homogeneous	GA PSO GWO WOA	-To propose computational cost model
(Guhan et al., 2021)	To resolve CH selection coverage and balanced energy consumption	Residual energy, Distance	Homogeneous	LEACH SEECH	-Implement on real time applications
Proposed EECHS-ISSADE	To improve network performance by minimizing energy consumption.	Distance, Residual Energy	Homogeneous	EECHS-ABC LEACH TABU-PSO	-Implement on large-scale real-time application

food source regions. The birds located on the periphery of the population are more likely to be attacked by predators and they constantly try to get a better position. At the same time the attackers in the group fight for the food with maximum intakes and need to raise its own predation time. The sparrow which is placed on the middle might travel towards their neighbours to reduce the risk of danger. Once the sparrow detects the predator, it begins to chirp and invokes an alert signal. If the Alarm Value (AV) is higher than required Safety Threshold (ST), then producers must move to safer zones for saving the life of other sparrows. Simultaneously, few scroungers often observe the producers and contend for food to enhance predation value. Sparrows in the border fly immediately to the safer zone and protect themselves from a danger. Whereas the sparrows in intermediate position of a group move in a random manner and reach the edge. Finally, the virtual sparrows are utilized for identifying the better food sources. The sparrow's position 'P' is given in equation (1) (Xue and Shen, 2020), wherein n is count of sparrows and d is the direction of variables that is to be optimized. Compared to scroungers, the producers discover food and assist the whole population.

$$P = \begin{bmatrix} P_{1,1} & P_{1,2} & \cdots & \cdots & P_{1,d} \\ P_{2,1} & P_{2,2} & \cdots & \cdots & P_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ P_{n,1} & P_{n,2} & \cdots & \cdots & P_{n,d} \end{bmatrix} \tag{1}$$

Using equation (2) (Xue and Shen, 2020), the sparrow population is selected randomly using randomization within the limitation of upper and lower bound in d dimension

$$P_{i,j} = LB_j + (UB_j - LB_j) * random(1,d) \tag{2}$$

As in equation (3) (Xue and Shen, 2020), the new position of a producer uses $\left(P_{i,j}^{t}\right)$ exiting position. Here $j = 1, 2, \ldots, d^{th}$ dimension of ith sparrow for maximum iteration I_{max} using an arbitrary value $\alpha \in [0, 1]$. Q is a random simple distribution value and L is a matrix of $1 \times d$ for all elements within 1. If $AV < ST$, then no predators exist, and producer launches into wider search. If $AV \geqslant ST$, then few sparrows have found the predator, and it is essential to safeguard them by flying to safer regions($AV \in [0, 1], ST \in [0.5, 1.0]$)

$$P_{i,j}^{(t+1)} = \begin{cases} P_{i,j}^{t} \cdot \exp\left(\frac{-i}{\alpha \cdot I_{max}}\right) & \text{if } AV < ST \\ P_{i,j}^{t} + Q \cdot L & \text{if } AV \geqslant ST \end{cases} \tag{3}$$

As in equation (4) (Xue and Shen, 2020), the scrounger position is updated. The scroungers' trail producers prominently. If the producers find the best food, then it leaves the place to compete for food. If the race is successful, then food from the producer is obtained. Where P_{Best}, and P_{Worst} are best and global worst position of producer, $A \in [-1, 1]$ is a matrix of $1 \times d$ and $A^{+} = A^{T}\left(AA^{T}\right)^{-1}$.If $i > n/2$, it approves that ith scrounger with ineffective fitness is more starving. As a result, the sparrows are away from risk would have an extra lifetime

$$P_{i,j}^{(t+1)} = \begin{cases} Q.\ \exp\left(\frac{P_{Worst}^{t} - P_{i,j}^{t_i}}{j^2}\right) & \text{if } i > \frac{n}{2} \\ P_{Best}^{(t+1)} + \left|P_{j,j}^{t} - P_{Best}^{(t+1)}\right| \cdot A^{+} \cdot L & \text{otherwise} \end{cases} \tag{4}$$

The primary position of the sparrow is given in equation (5) (Xue and Shen, 2020), where P_{GBest} is current global optimal location, random measure $K \in [-1, 1]$,β is a step size control parameter with random normal distribution with mean value of 0 and variance of 1, f_i is the fitness value of a sparrow.f_{gb} and f_w are recent global best as well as worst fitness measures, ε is a minimum constant and it avoids zero-division-error. If $f_i > f_{gb}$, then sparrow is at border of a group. Now P_{GBest} is the safe position of the sparrow in the centre of population. If $f_j = f_{gb}$, then sparrow is in the middle of the group are aware of the risk and migrates closer to the edge.

$$P_{i,j}^{(t+1)} = \begin{cases} P_{GBest}^{t} + \beta \cdot \left|P_{i,j}^{t} - P_{GBest}^{t}\right| & \text{iff}_i > f_{gb} \\ P_{i,j}^{t} + K \cdot \left(\frac{\left|P_{i,j}^{t} - P_{Worst}^{t}\right|}{(f_j - f_w) + \varepsilon}\right) & \text{iff}_i = f_{gb} \end{cases} \tag{5}$$

2.2. Differential evolution

Differential Evolution (DE) (Storn and Price, 1997) is a simple, stochastic, and direct efficient search method proposed by Rainer Storn and Kenneth Price in the year 1997. The memory capacity enables it to dynamically track the current search with robustness. Due to its fast convergence characteristic and small computational time it aids in solving optimization problems for global optimization over continuous spaces. The evolving process is proficient over 'g' generations to reach an optimal solution. The fitness value on the objective function helps to decide and categorize each organism, resulting in a complete solution to the given problem. Like every other evolutionary algorithm, the early stage is an initialization phase followed by three major operations namely mutation, crossover, and selection.

2.3. Initialization

In the population size 'N', genome (or) chromosome 'P' is arbitrarily created by uniformly distributed random vector 'R'∈[0,1] within lower 'LB' and upper bounds 'UB', Every individual signifies a solution in 'D' dimension with few parameters called as decision or control variables. The population size remains constant over the optimization process and $P_{i,g}$ can be initialized as in the equation (6) (Storn and Price, 1997), Here $P = \{x_{i,} \cdots x_N\}; i = 1, 2, ..N;$

$$P_{i,g}^{D} = LB + R\ (UP - LB) \tag{6}$$

2.4. Mutation

DE creates a parameter called donor vector (DV) by adding the weighted difference between two randomly selected vectors(X). This is called a mutation. r_1, r_2, r_3 ∈[1,] are three random numbers. Mutation rate or variation factor F∈ [0,2] is a real and constant number that controls the amplification degree of differential variable $(X_{r_2} - X_{r_3})$. DV is generated principally for the new generation g + 1 by equation (7) (Storn and Price, 1997) for each D-dimensional target vector (TaV),

$$DV_{g+1} = X_{r_1} + F * (X_{r_2} - X_{r_3}) \tag{7}$$

2.5. Crossover

Crossover operation increases diversity of the population. The donor vectors parameters exchange information with the target vector to produce trial vector (TV) as in equation (8). (Storn and Price, 1997) Where $j = 1, 2..D$; uniformly distributed random number $r \in [0, 1], \delta \in [0, D]$ is a random integer that guarantees that TV gets at least one parameter from DV. Crossover Probability Rate CPR∈ [0, 1] is a user-defined constant that controls the fraction of parameter values copied from the DV.

$$TV_{ij,g+1} = \left\{ \begin{array}{ll} DV_j & \text{if } (r \leqslant CPR\ ) OR(\ j = \delta) \\ TaV_j & \text{if } (r > CPR)\ AND\ (j \neq \delta) \end{array} \right\} \tag{8}$$

2.6. Selection

If TV produces a lower fitness value compared to TaV through a greedy selection, then TV substitutes the TaV in selection. The vector with optimal fitness will become a member of the next generation. Once the last TV has been tested, the optimal chosen of all becomes the next generation in the evolutionary cycle. The selection process and the fitness function are calculated of all the offspring by equation (9) (Storn and Price, 1997), where f_i is the fitness function objective of TaV and TV is an offspring corresponding to the TaV. Each population vector must serve once as the TaV so that NP competitions take place in one generation.

$$f_{TV_i} < f_i, \begin{array}{ll} TaV_i = & TV_i \\ f_i = & f_{TV_i} \end{array} \tag{9}$$

3. The proposed model-An Energy Efficient Cluster Head Selection using Improved Sparrow search algorithm using Differential evolution (EECHS-ISSADE)

Initially, the hybrid Sparrow search algorithm using Differential evolution is required for enhancing the diversity of SSA searching potential. A hybrid optimization algorithm combines more than one algorithm so that the suitable features of the original algorithm can be fully exploited. Further SSA is noted to be a time-consuming lengthy process and it also does not have a robust global search capability, but DE algorithm has dormant ability in exploration for simplifying the global search process and is suitable for the exploitation of search space due to its slower convergence. The active behavior of SSA looks for the optimal solution in 'd' dimensional space with a higher convergence rate, stability, along with high search efficiency of DE in each area. DE has been used to determine the optimal solution for clustering problems. It has been mostly used to solve any clustering problem directly or integrating with other approaches. The dynamic features of SSA and DE algorithms sustain the grade of exploitation and exploration in the CH selection. So, DE and SSA algorithms complement each other's results certainly ensuring better performance and hence a novel Improved Sparrow search algorithm using Differential Evolution (ISSADE) model overcome above-said limitations in SSA helps in solving CH selection in WSN and termed as Energy Efficient Cluster Head Selection using Improved Sparrow search algorithm using Differential evolution (EECHS-ISSADE). The flowchart of the ISSADE is given in Fig. 2. We assume population equal to the number of nodes. Hence, the addition or removal of any nodes would change the vector dimension and it would require re-clustering. The main aim of the fitness function is to find the best solution for an individual in less time and sustain useful information. The energy level is equal to the fitness value of each sparrow in SSA. In the WSN scenario, the nodes that coordinate with the global best positions are taken and the nodes that are nearest to these coordinates. In SSA, the producers have maximum fitness in searching for food. The scroungers observe and obey the producer by offering optimal food sources to enhance predation value. For the scroungers, the forging strategy is determined by their energy level which may be high or low. Primarily vector initialization of sparrow population followed by mutation, crossover, and selection operation is given in the following section. Our proposed model uses SSA for vector representation. The sparrow's positions are generated randomly within the limit and are shown in the matrix form as in equation (10). The initial vector consists of the randomly generated distribution number Rand [0,1]. Each row is a fitness function solution for the optimization problem,

$$f(x) = \begin{bmatrix} f([SP_{1,1} & SP_{1,2} & \cdots & SP_{1,d} \\ f([SP_{2,1} & SP_{2,2} & \cdots & SP_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ f([SP_{n,1} & SP_{n,2} & \cdots & SP_{\mathrm{n(k)},d} \end{bmatrix} \begin{bmatrix} f_{obj_1} \\ f_{obj_2} \\ \vdots \\ f_{obj_n} \end{bmatrix} \tag{10}$$

From the population, the best vector TaV is selected by the mutation operator with help of the Mutation Rate (MR). The new offspring $SP_{(g+1)}$is shown in equation (11). The probability of generating two distinct vectors are random and additionally, it is mutated according to three random numbers r_1, r_2, r_3. The difference of the vectors $\in$ [0,1] in mutation operation and maybe the cognizant reason of resultant to be negative. So, the algorithm should generate components of the difference in vector in such a way that it can satisfy the range. Each sparrow goes through the evolution of all operations in the population until the best solution is achieved.

$$SP_{g+1} = SP_{r_1} + MR * \left(SP_{r_2} - SP_{r_3}\right) \tag{11}$$

The Euclidean distance between a sparrow and best sparrow $SPbest_{i,j}$ chosen is calculated as in the equation (12)

$$dist = \sqrt{\sum_{i=1}^{N} \left(SP_{i,j} - SPbest_{i,j}\right)^2} \tag{12}$$

As in equation (13), a recombination operation between DV andTaV is performed to form a new generation of offspring called a trial vector. Here binomial cross-over is used with a predefined Crossover Probability Rate (CPR). If $r \le CPR$, donor vector ($BestDV$) is chosen otherwise, target vector $BestTaV$ is chosen. As of DE algorithm, SF and CPR are set to fixed values for almost all solutions.

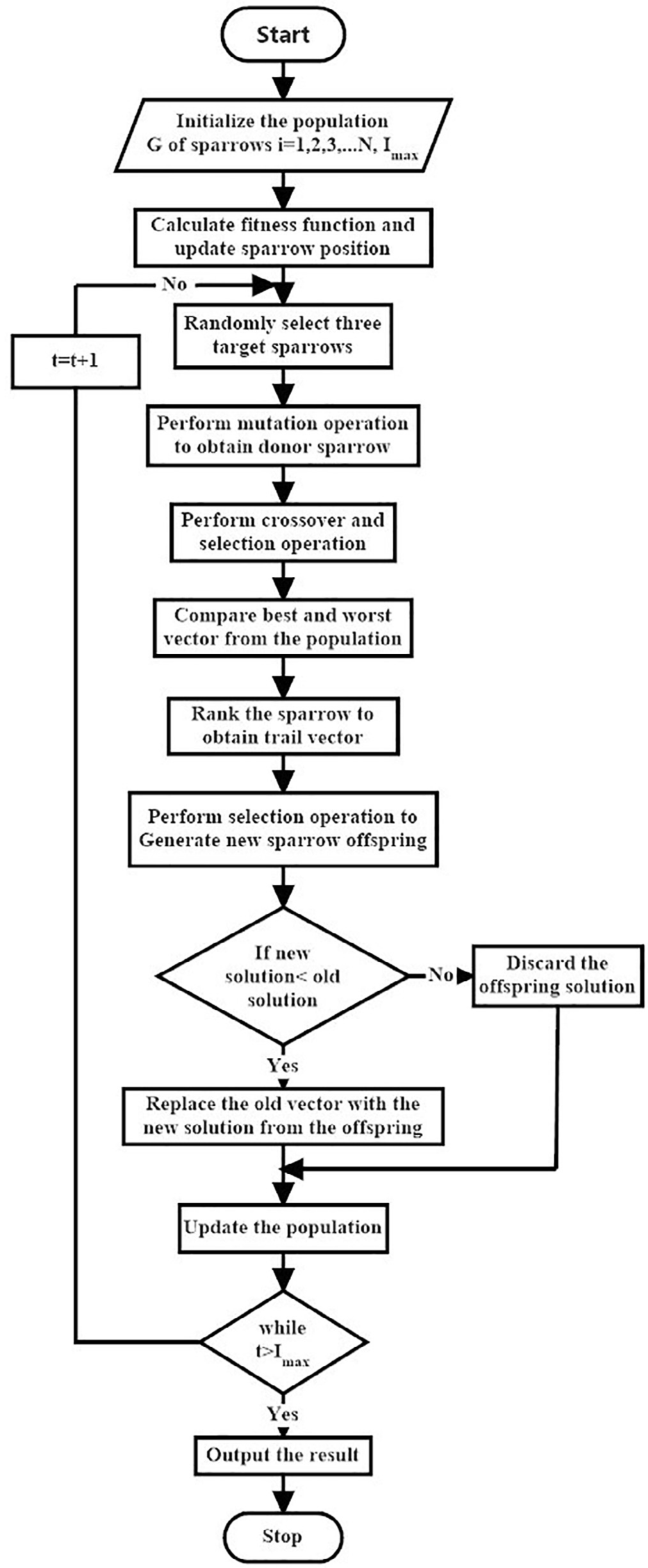

Fig. 2. Flowchart of ISSADE Algorithm.

$$SP_{ij,g+1} = \begin{Bmatrix} BestDV_j & if\ (r \leqslant CPR\ ) \\ BestTaV_j & if\ (r > CPR) \end{Bmatrix} \tag{13}$$

The selection operation resolves the selection of offspring from either TaV or newly generated TV will survive to the next generation. Both vectors are evaluated by the derived fitness function. The

TV replaces theTaV if the TV has a better fitness value; otherwise, the target vector is retained in the population. If the producers find the best food, then it leaves the place to compete for food. The new position of producers is given as in equation (14), Here $j = 1, 2, \cdots, d; \alpha \in [0, 1], SP^t_{i,j}$ is the rate of j^{th} dimension of i^{th} sparrow at t^{th} iteration. An alarm value $AV \in [0, 1]$ and safety threshold $ST \in [0.5, 1.0]$, Q is a random value that applies simple distribution and L denotes a matrix of $1 \times d$ for all elements < 1. Each solution has its distinctive features that can evolve in each step, but few may be the end. Every individual shares location and involves in the search process. When $AV < ST$, refers that no predators exist, and producer gets into wider search mode. When $AV \geqslant ST$, then few sparrows have found the predator, and it is vital to defense them by flying to safer regions, Only rare scroungers follow producers prominently.

Based on the objective function BestSP, a new offspring evolves. If the objective function result of the new hybrid approach is better than the objective function output for the worst sparrow, then then they can obtain the food of a producer and new solution is chosen, the existing worst solution is discarded.

$$SP^{(t+1)}_{i,j} = \begin{cases} SP^t_{i,j} \cdot \exp\left(\frac{-i}{\alpha \cdot I_{\max}}\right) & \text{if } AV < ST \\ SPTV^t_{i,j} + Q \cdot L & \text{if } AV \geqslant ST \end{cases} \quad (14)$$

The position for a scrounger is given in equation (15) within maximum iterations $I_{\max}$ using step size control parameter β with mean value of 0 and a variance of 1.

$$SP^{(t+1)}_{i,j} = SP^t_{GBest} + \beta \cdot \left|SP^t_{i,j} - SP^t_{GBest}\right|^{(t+1)} \quad (15)$$

Algorithm 1 for the proposed model EECHS-ISSADE

Initialize nodes randomly in 2D space**,**
Randomly initialize of population G
Evaluate the objective function for all the (node) sparrow
While (not maximum iteration) do
Apply each node 'i' to a cluster 'k'
for i = 1 to N node ***do***
Randomly select three nodes from population
Calculate distance between nodes by Euclidean distance
Update mutant sparrow population
Generate new population
Perform recombination process
if (rand<CPR) then
Perform selection operation
else
Replace the sparrow population G with optimal fitness
Re-evaluate the objective function for all the sparrow
Update the SPbest position of the population and they are chosen as CH
end for
t = t + 1
end while
return Best solution

The position of all nodes is calculated and updated for every round up to maximum number of iterations I_{max}. By equation (15), the solution of the problem is an index of the 'k' numbers of CH. For every iteration, the CH collect information of all the CM in the cluster by sending data and finally transfer to the BS. The neighbour nodes that occupy near to the node has higher energy compared to the CH. Each individual sparrow lifetime subject to its fitness value which is calculated using the above said fitness function that includes parameters like residual energy, number of CH, intra-cluster communication distance and distance amid CH to BS. Here the distance parameter depends on RE and CH. If the CH is low in number, then the distance between the CH and BS has high intra cluster distance. Likewise, if the CH count is high in number then the intra cluster distance will be low but the distance amid CH to BS becomes high. The pseudocode of EECHS-ISSADE is given in algorithm 1. If the number of iterations reaches maximum iteration I_{max}, then the algorithm stops else, continues to search for best result.

4. Simulation study

The performance of EECHS-ISSADE algorithm has been simulated using MATLAB R2018a on an Intel(R) Core (TM) i5 processor, 2.80 GHz CPU and 16 GB RAM on the Microsoft Windows 10 platform. The experiments are done by presuming a WSN set-up with nodes and BS positioned in 200*200 m^2 area. The parameter setting of the presented model is given in Table 3. Our proposed model uses the hierarchical clustering protocol model. The homogenous network is considered for the proposed model. All the nodes have same memory, processing speed with transmission and reception abilities. In this paper, free space network model is considered to transfer 'n' bits of data using a transmitter in sending circuit and receiver in receiving circuit with distance 'd'. DE entails: initialization, population, Variation factor (F)∈[0,2], Crossover Probability Rate (CPR)∈[0.5,1] and Maximum Iteration (I_{max}). The scaling factor decides the amount of perturbation in the mutation process. If the limit is co-related, then the high value of the Crossover probability rate works better. ISSADE depends on F = 0.5, Mutation rate = 0.006 and CPR = 0.5 are set. All parameters have been optimally chosen to refer to similar research works and on executing numerous trials processes. In Tabu PSO (Vijayalakshmi and Anandan,2019), C1 = C2 = 1. The local best position is determined by PSO and the global best position is calculated by setting the Tabu list with PSO result and Tabu memory is set to zero. And by using the swap move methods in the routes, tabu memory is initialized. The new position is chosen from the existing fitness value in the list and the solution with minimum hop routing is chosen as best.

4.1. Network model

In this paper, the WSN data structure considered for a two-dimensional sensing region has a substantial number of homogeneous nodes with equivalent processing and communication capability that are deployed randomly. The nodes become stationary and need not be monitored after positioning. The nodes are not aware of the location, so it does not entail any position discovery system like GPS. The communication links amid the nodes within the transmission range are stable, wireless, and symmetric. Cluster formation is one of the hierarchical routing protocols processes that provide an energy-efficient scalable network. Each cluster elect's CH based on transmission distance and remaining energy. The Cluster Members (CM) could be allocated under any Cluster Head (CH) only when it is within the transmission radius. Likewise, CH and BS persist unchanged through the iteration. A single iteration is a period from the moment a CH is elected to the selection of the next CH. Each iteration has some rounds and each round has setup, intra-cluster communication and inter-cluster communication phases. In an individual setup phase, the nodes either send messages to select a new CH or send network setup and maintenance messages if there is no need to reselect a new CH. CHs is repeated once several rounds. In the cluster during the intra cluster communication phase, CH compresses the messages received from

Table 3
Simulation parameters.

Parameters	Value
Sensor field area	200x200 m^2
Number of nodes(n)	100
Percentage of cluster head	5–10%
Radio propagation model	Free space
Min and Max Position of BS	[0,200]
Antenna model	Omni directional antenna
Initial energy (E_0)	0.5 J
Electronics energy (E_{elec})	70 nJ/bit
Energy for free space (E_{fs})	10 pJ/bit/m^2
Energy for multipath (E_{mp})	0.0013 pJ/bit/m^4
Packet size	4096 bits
Energy data aggregation (E_{DA})	5 nJ/bit/signal
MAC	802.11
Number of rounds (I_{max})	2000
Scaling Factor(ε)	0.5
Crossover Probability Rate	0.5

CM into a single message. In the inter cluster communication phase only CH retain the radio on to transmit the compressed data to the BS. Each CH always stay awake and contact the radio using CSMA/CA. The CM may sleep in the inter cluster communications to save energy. CSMA/CA supports both intra cluster and inter cluster communication. Within the sensing region, the BS can change its position and can have suitable information about the network. Each node uses a CSMA MAC protocol and broadcast Node ID (unique identity) and rank using a ranking function. This rank with positive integer value helps to choose next CH. It also shares the RE to the BS to check if they have reached the threshold energy value to be elected as CH.

$$\mathrm{Rank}(\mathrm{ni},\mathrm{CHi}) \tag{16}$$

The main criteria of selecting CH is to minimize the objective function as in equation (17), Where scaling factor $SF \in [0,1]$,

$$F(X) = SF \times F_1 + (1 - SF) \times F_2 \tag{17}$$

F_1 as in equation (18) considers the Euclidean distance of nodes to respective CH, later to the BS and nodes that belong to another cluster. Every node considers distance, energy and delay when calculating the cost of the network.F_2as in equation (19) is the ratio of initial energy of all alive nodes to the total energy of the CH in current round.

$$F_1 = \frac{\sum_{i=1}^{N}\mathrm{Dist}(\mathrm{node}_i,\mathrm{CH})}{\mathrm{nodes}_{c+1}} \tag{18}$$

$$F_2 = \frac{\sum_{i=1}^{N}\mathrm{E}_{\mathrm{init}_{\mathrm{node}}}}{\sum_{i=1}^{N}E_{\mathrm{CH}}} \tag{19}$$

The fitness function F(X) of a node is based on the optimal CH selection as in equation (20) where $(\mathrm{Max}_{Dist}(BS,CH)$ is the maximum average distance from CH to BS. The maximum average distance amid CM and CH is $(\mathrm{Max}_{Dist}(CM_{ij},CH_j)$. The total number of nodes is always greater than the CH.

$$F(X) = \frac{Max(\mathrm{node}_{RE})}{\mathrm{Min}((\mathrm{Max}_{Dist}(BS,CH)) + (\mathrm{Max}_{Dist}(CM_{ij},CH_j)))} \tag{20}$$

Though the nodes have a fixed energy level, the energy consumption is not even since it is reliant on the distance from the BS or CH. This reduces the complexity and improves the scalability as the number of nodes increases.

4.2. Energy model

The radio wave propagation model is considered in the proposed model and it is based on energy depletion which is directly proportional to distance 'd' amid sender and receiver as in Fig. 3. If 'd' is minimum than the threshold value then it uses free space(fs) method with energy consumption $E_{fs}*d^2$ else it uses multipath (mp) method with energy consumption $E_{mp}*d^4$. Total energy cost uses $E_S(n,d)$and$E_R(n)$as in equation (21), Energy spent in an idle state E_{idle}, and on current$E_{current}$

$$E_{NetTotal} = E_S(n,d) + E_R(n) + E_{idle} + E_{current} \tag{21}$$

Besides, the energy required for sending *n*-bit message across 'd' with crossoverdistance$d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}}$ as in equation (22)

$$E_S(n,d) = \begin{cases} n*E_{elec} + n*E_{fs}*d^2, \mathrm{if} d < d_0 \\ n*E_{elec} + n*E_{mp}*d^4, \mathrm{if} d \geq d_0 \end{cases} \tag{22}$$

where E_{elec} is the energy needed by electronic circuits,E_{fs} is the energy required by an amplifier in free space,E_{mp} is the energy required by multi-path.E_{elec} is based on various aspects like digital coding, modulation, filtering, and signal distribution. If the sender sends the n-bit message, then the total energy required is given as in the equation (23).

$$E_{STotal}(n,d) = E_{Selec}(n) + E_{Samp}(n,d) \tag{23}$$

here $E_{Selec}(n)$ is the energy needed to send 'n' bit message by the sender. It can also be perceived that the energy consumption of the sender depends on message length and not on the distance. $E_{Samp}(n,d)$ is the energy required to amplify the signal to reach the receiver circuit and it includes both the message length and communication distance. Since the receiver consumes more energy to successfully receive the n-bit message, it is expressed in equation (24),

$$E_R(n) = n*E_{elec} \tag{24}$$

where, $E_{Relec}(n)$ is the energy required to receive n-bits at the receiver. The residual energy is shown by equation (25),

$$E_{RE} = E_{Current} - E_S(n,d) + E_R(n) \tag{25}$$

The energy is used only on data transmission between CM or CH. The LT of CH is the ratio of RE to the Euclidean distance between the CH and BS as in equation (26).

$$LT(node,CH) = \frac{E_{RE}}{E_{Net_{Total}}} \tag{26}$$

Network lifetime depends on overall energy consumption. If the node energy decreases below the threshold value i.e., if $E_{RE} \leq 0.$, then it is assumed to be dead.

5. Results analysis and discussion

QoS parameters like energy consumption and throughput are deemed for enhancement of network lifetime and also for ensuring the reliability in the network. For each iteration, overall energy consumption estimates the efficiency of the algorithm. If energy consumption increases, the RE also increases. Likewise, throughput evaluates the number of packets transmitted successfully to the BS on every round. The network lifetime increases with an increase in energy efficiency that is well-defined as the number of rounds till the last node is alive. In EECHS-ISSADE, nodes are randomly distributed in the given search space as in Fig. 4. At first, BS broadcasts a message to the nodes which has precise energy capacity. Then, each node computes its exact distance to the BS using Euclidean distance. This errand helps in selecting the exact energy level for

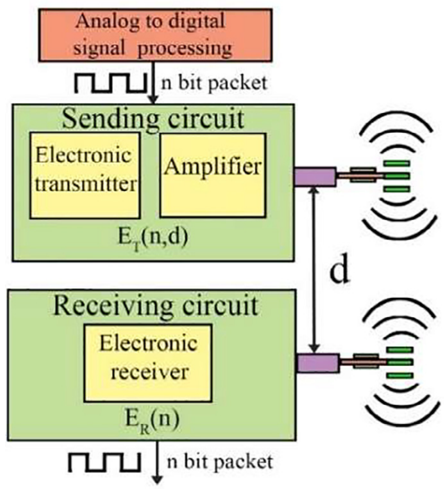

Fig. 3. Energy model.

creating communication to the BS, such that it estimates different positions of the nodes as in Fig. 5. The clustering simulated by ISSADE is depicted in Fig. 6 with 100 nodes. Here individual clusters are denoted using diverse shapes like circle, triangle, inverted triangle, rhombus, and square. Each cluster has a CH elected using the parameters like residual energy and distance. In EECHS-ABC (Ahmad et al., 2019), CH is selected based on residual energy, distance from the sink station, and intra-cluster distance. The fitness function is improved using ABC optimization. The objective of this optimization is to reduce energy consumption in WSN. For optimizing the routing and CH selection, the hybrid PSO and TS process (Vijayalakshmi and Anandan,2019), selects CHs effectively improving the routing as well as enhancing the network lifetime. Tabu PSO technique alleviated the mean end to end delay with average packet loss rate and improved the ratio of alive nodes with the varying number of nodes. This paper considers the energy-delay trade-off using the distance between CH and CM.

5.1. Analysis of alive nodes

Fig. 7 reveals the number of alive nodes determined with experimentation simulation assessed with a different number of rounds ranging from 0 to 2000. The alive nodes are highly constant from the end since the convergence of the Fig. 8. Dead nodes in the networkhybrid scheme is faster in estimating an optimal solution. Further, it prevents low-energy nodes from being nominated as CH, thereby maximizing the network lifetime expectancy. In LEACH (Heinzelman et al., 2002), the number of alive nodes starts minimizing when the number of rounds is 50 and is found to be zero as the round reaches 770. In contrast, EECHS-ABC (Ahmad et al., 2019) tried to enhance the count of alive nodes but started minimizing when the number of rounds is 50 and became zero as it reaches 1210. Likewise, the TABU-PSO method started reducing when the number of rounds is 250 and completely died in 1320 rounds. However EECHS- ISSADE enhance the alive node count in the network by 16%, 19%, and 23% compared to the LEACH, TABU-PSO, EECHS-ABC, respectively.

5.2. Analysis of dead nodes

The death of the first and last nodes for the LEACH (Heinzelman et al., 2002) happened approximately in 50 and 750 rounds, respectively, while the death of the first and last nodes for the TABU-PSO (Vijayalakshmi and Anandan,2019) was visualized around 250 and 1300 rounds. The death of the first and last nodes of the EECHS-ABC (Ahmad et al., 2019) was visualized in the 50 and 1200 rounds. However, EECHS- ISSADE exhibited predominant results since the death of the first and last nodes is visualized only in the 300 and 1600 rounds respectively. The nodes with low energy are prohibited after death, and by selecting high energy nodes to play the role of cluster head for the objective of creating load balance in the network, such that low energy nodes do not die soon. The percentage of dead nodes in the network is also highly prevented by the proposed model EECHS- ISSADE scheme to a maximum level of 18%, 22%, and 25%, remarkable to the benchmarked LEACH, TABU-PSO, and EECHS-ABC. And as in Fig. 8, it is apparent that the proposed EECHS-ISSADE using SSA and DE show

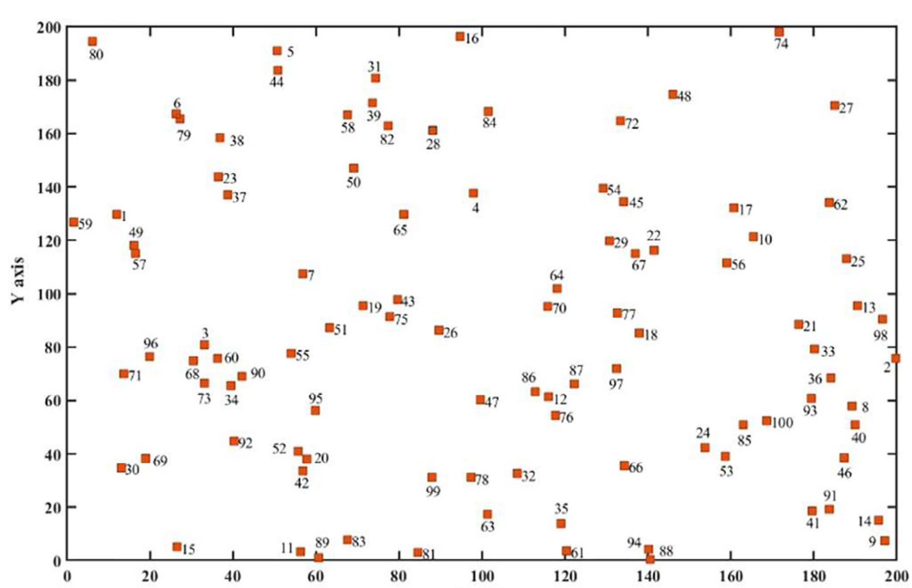

Fig. 4. Random generation of nodes in 200*200 m^2.

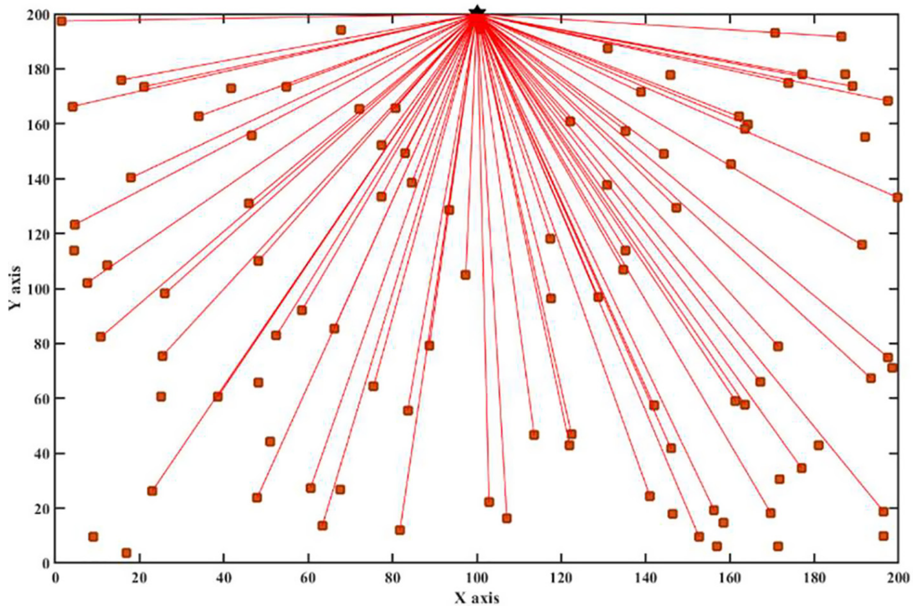

Fig. 5. Broadcast data of BS (100*200) to all nodes.

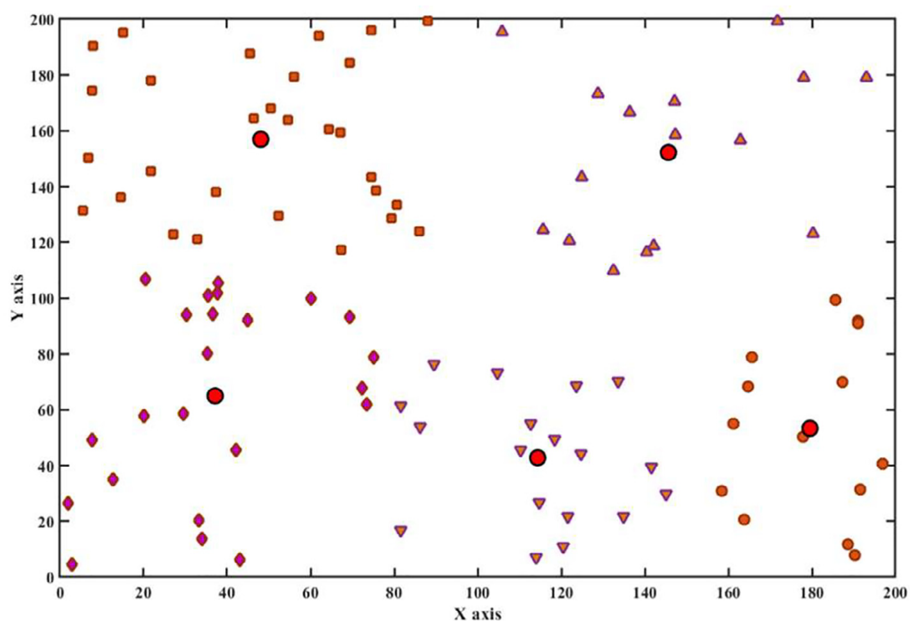

Fig. 6. Cluster formation using EECHS-ISSADE.

unsurpassed outcomes for energy optimization in WSN which is evident in the graph the residual energy dropping to zero after almost 1001 rounds.

5.3. Analysis of residual energy

Fig. 9 shows the residual energy of EECHS-ISSADE where LEACH algorithm involves in random selection of cluster heads among the nodes and the residual energy drops to zero at 290th round. But EECHS-ABC (Ahmad et al., 2019) gives better performance than LEACH (Heinzelman et al., 2002) to a certain range of 503rd round approximately but still does not last for long. Similarly, TABU-PSO (Vijayalakshmi and Anandan,2019) endures for 730 rounds due to the incorporation of PSO; the high-efficiency searching algorithm which changes from one solution to another in search for the best solution. But still, this becomes a challenging problem when considering the balance between exploration and exploitation since it takes a longer time to achieve the optimal solution. Fig. 10 shows the residual energy of EECHS-ISSADE in higher outcomes for the objective of energy optimization in the WSN environment. Hence, hybrid ISSADE uses high searching efficiency that makes exploration and exploitation attained at a faster rate to gain an improved result.

5.4. Analysis of throughput

The throughput is the ratio of packets received by the receiver from the transmitter to the time taken by the receiver to deliver

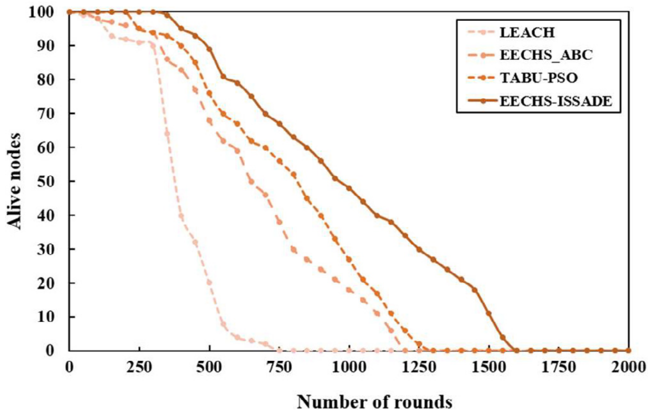

Fig. 7. Alive nodes in the network.

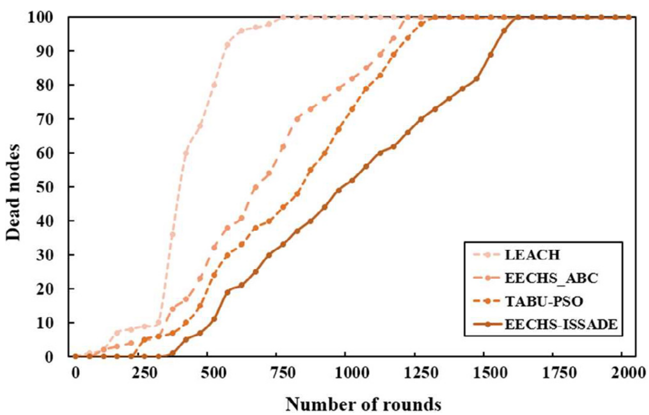

Fig. 8. Dead nodes in the network.

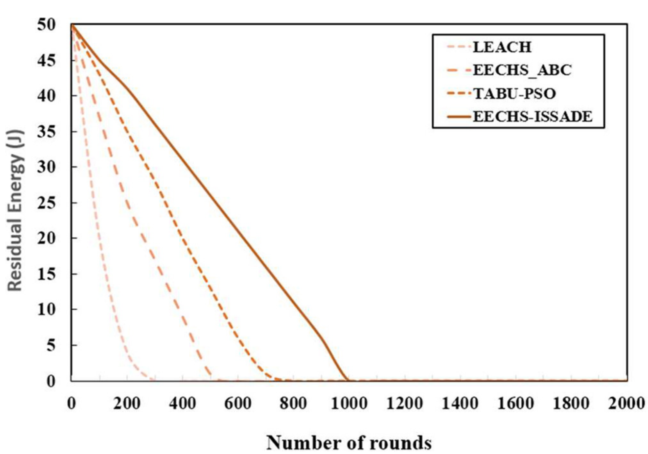

Fig. 9. Residual energy analysis with varying iteration.

the last packet. Here the packet size is measured in bits.. As in Fig. 11, the throughput of the network is highest in EECHS-ISSADE due to the combination of best search features from SSA with the dynamic potential capability of DE. The reason for that is the throughput is directly proportional to the number of alive nodes. The maximum throughput 0.451 Mbps is visualized with the various schemes. However, the throughput reduces as the number of rounds increases. For example, the throughput of the EECHS-ABC is minimized at 600 rounds compared to the other. The throughput of TABU-PSO (Vijayalakshmi and Anandan, 2019) is improved by 950 rounds compared with EECHS-ABC (Ahmad et al.,2019). However, EECHS-ISSADE was the potential in maintaining the throughput to a considerable level for more than 1250 rounds. Even though the throughput of the LEACH (Heinzelman et al., 2002) is maintained in till 525 rounds, it starts to minimize from 750 rounds.

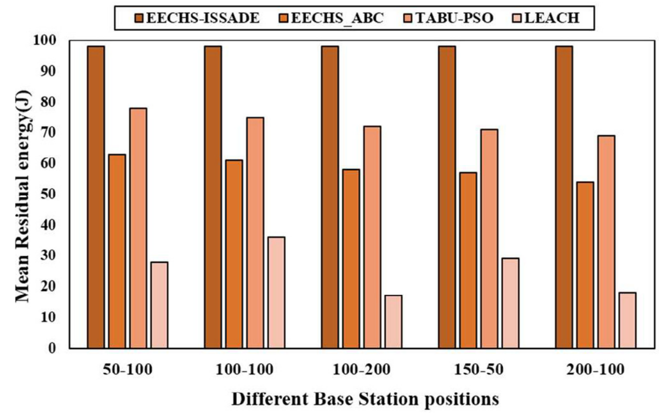

Fig. 10. Mean residual energy using different BS.

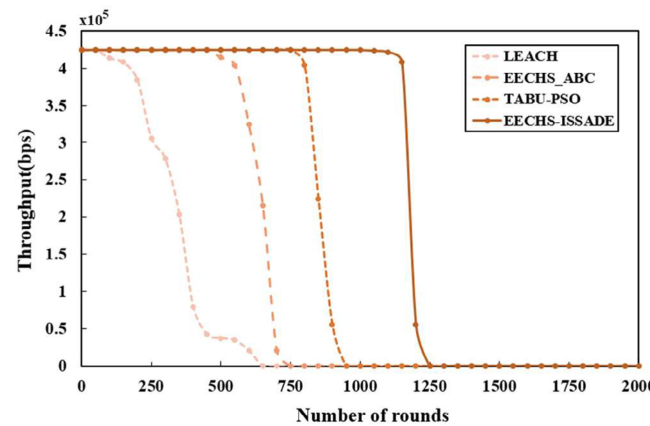

Fig. 11. Throughput analysis with varying iteration.

Fig. 12 validates the mean throughput results of EECHS-ISSADE performance to prove that the proposed is predominant over the compared approaches independent of the position of the Base station. This potential performance is mainly due to the improved exploitation degree imposed over the selection of optimized CH on the network.

5.5. Complexity analysis

The computational time analysis of the proposed model EECHS-ISSADE is compared with LEACH, TABU-PSO (Vijayalakshmi and Anandan,2019), and EECHS-ABC algorithms. While EECHS-ISSADE enhances network performance by balancing exploitation and exploration in finding CH. The network energy is made highly stable since the nodes with the worst fitness are not selected as CH. Hence the computational cost of EECHS-ISSADE is low and it depends upon the objective function including the time.

6. Conclusion

Based on the features of the Sparrow search algorithm, ISSADE algorithm is proposed in this paper to enhance the ability of

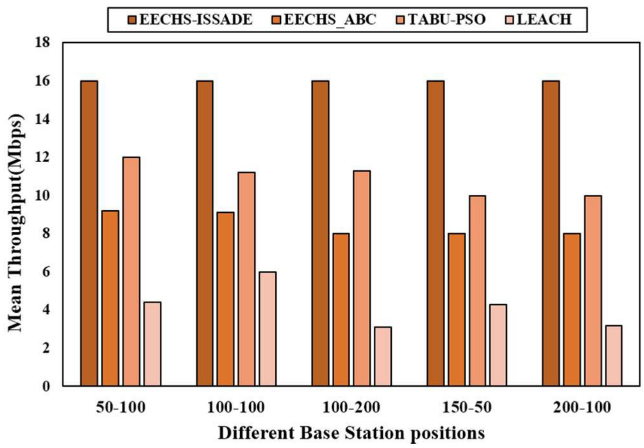

Fig. 12. Mean throughput using different BS.

exploitation and avoid the trap of falling into local optima. ISSADE does not introduce extra operators except operators in SSA and DE, which makes it simple and efficient. Initially, EECHS-ISSADE efficiently selects CH using the estimated RE. If any node has high RE than the existing CH within the cluster, then it is replaced. Here CH is distributed non uniformly, the stability of CH is high. Experimental results show that ISSADE outperforms competitive ability to quest global optima than the other methods compared. Though DE method is prevalent because of its exploration and exploitation abilities, for addressing large-scale data it takes more time to complete mutation, crossover, and selection methods. Subsequently, the fixed mutation rate and crossover probability rate may lead to premature convergence affecting the network performance. Hence for a large problem, the parameter altering method can be considered for assigning optimal arithmetic value for this resulting robustness in the network. Further, the sparrow search algorithm can also be combined with variations of the Differential evolution algorithm to unravel the problem of cluster head selection. The future scope of the proposed model can be applied to achieve enhanced performance in coverage and connectivity issues. For the BS position, future work can also be focused to extend the performance in WSN by considering base station mobility. The network performance can be improved further by including all substantial parameters for Cluster Head Selection with any meta-heuristic method to formulate the novel hybrid methods.

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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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