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Multi-objective Sand Cat Swarm Optimization Algorithm for Cluster Head and Routing Path Selection in WSN

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Abstract: A wireless sensor network (WSN) is a collection of nodes fitted with small sensors and transceiver elements that are utilized for sensing, tracking, and data collection in a variety of situations. Sensor energy is considered a significant resource due to the difficulty in providing battery a backup to sensors when they are deployed in an uncontrolled or wild area. Integrating clustering & routing strategies are the optimal techniques for saving sensor node energy. Cluster heads (CHs) are selected carefully for load balancing throughout the clustering process. Therefore, multi-objective sand cat swarm optimization (MSCSO) algorithm is proposed to maximize the efficiency of energy in WSN. The optimum cluster heads from the network are selected and the path through the cluster head is identified by utilizing MSCSO. The proposed MSCSO decreases the usage of energy of nodes when maximizing the transmission of data in the WSN. The performances of MSCSO are evaluated based on alive nodes, energy consumption, throughput, and life expectancy for 100 nodes and attained better performance than other methods like low energy adaptive clustering hierarchy (LEACH), distributed energy efficient clustering (DEEC) and threshold-distributed energy efficient clustering (T-DEEC). The MSCSO is compared with existing methods such as fractional artificial lion (FAL) algorithm, taylor-spotted hyena optimization (Taylor-SHO) algorithm, energy centric multi objective salp swarm algorithm (ECMOSSA) and whale based tunicate swarm algorithm – aquila optimizer (WTSA-AO) and shows that the MSCSO algorithm improves the performance by reducing energy consumption of 0.0208J, 0.0350J and 0.04045J for 200, 400 and 600 rounds respectively.

Keywords: Cluster head, Energy efficiency, Multi-objective sand cat swarm optimization algorithm, Throughput, Wireless sensor network.

1. Introduction

Wireless sensor networks (WSN) comprise hundreds or thousands of sensor nodes dispersed throughout the environment and utilized to gather process, and sense data. These inexpensive sensor nodes have greater information sensing, processing, and transmission capacities [1]. The development of the internet of things (IoT) has made it possible for heterogeneous devices to work together to accomplish common goals [2]. An essential part of IoT spheres where interoperability between different heterogeneous elements which is required in wireless sensor networks (WSNs) [3]. In wireless sensor networks (WSNs), node heterogeneity can be indicated regarding the connectivity of links, computation, energy, and further heterogeneities like a scenario of mobility and so on. A network of countless tiny nodes is known as a node of sensors that makes up the wireless sensor network (WSN) [4]. With the technology of microelectromechanical systems recently advanced, the sensors in WSN are becoming better and more difficult, making it promising to execute them for advanced applications [5]. There are different kinds of WSNs, including multi-media WSN, underground WSN, mobile WSN, and underwater WSN. One of a sensor node's most important functions is disseminating data from the network and sending it to the sink. There are numerous uses, including military, agricultural, medical, and environmental monitoring [6].

Energy efficiency is a main problem in wireless sensor networks, as sensor nodes are activated by utilizing a battery. The sensor nodes primarily have limited battery life, a small memory size range, and limited computational power [7]. These sensor nodes are fundamentally designed to function in hostile environments, so the battery inside of them cannot be replaced [8]. One of the key strategies for maintaining node power is to optimize routing in the form of energy efficiency. The clustering assists in organizing the sensor nodes known as clusters. With various cluster functions of the cluster, the cluster has one cluster head (CH) [9]. Information is gathered by CH from the cluster's participants and sent to the sink. It appears that the use of sensors is altering how people interact with their surroundings, particularly when a collection of sensors network known as wireless sensor networks (WSNs) is formed [10]. The researchers have done various methods using various techniques but only a few studies are partially well with fewer limitations such as existing methods consumes more energy, comprised the maximum number of rounds at various phases of dead nodes (DNs). This was due to less amount of energy flow created by optimized CH selection as well as intra-cluster communication and the residual energy of network was degraded when Base Station was located outside the network. So, to enhance the efficiency of energy the multi-objective sand cat swarm optimization algorithm is proposed. The proposed algorithm is utilized for cluster head selection and identifying the efficient routing path. The contributions are described as follows:

- The efficiency of energy cluster head and routing path selection are proposed to improve the network lifetime of WSN. The MSCSO algorithm is proposed for selecting the correct cluster heads which helps to minimize the node's energy consumption.
- Then, the path towards the cluster head moves identified effectively by utilizing the proposed MSCSO algorithm which helps to decrease the utilization of energy.
- The detection cluster head with the minimum neighbor nodes and the shortest base station distance is utilized to decrease the energy spent by the nodes and maximize the delivery of the packet.

The rest of the part of research is described as follows: the related works on the cluster head and routing path selection techniques are given in section 2. The proposed MSCSO algorithm is given in section 3. The outcomes and comparative analysis are given in section 4. The overall conclusion of the research is given in section 5.

2. Literature survey

Prakash [11] introduced a fractional artificial lion (FAL) Algorithm for safe and secure routing in wireless sensor networks. FAL was a combination of fractional calculation, lion optimization algorithm (LOA) and artificial bee colony (ABC). FAL was mainly created for secure routing by identifying the best optimal path for communication. The path which has maximum throughput and energy, minimum distance, and alive node was chosen as the best path depending on the maximum value of fitness. The method has a good balance between exploration and exploitation. The FAL based clustering and routing was affected due to size of network.

Kalburgi and Manimozhi [12] presented a taylor-spotted hyena optimization (Taylor-SHO) for energy-effective selection of cluster heads based on the securable routing of data and failure tolerance in wireless sensor networks. The presented method was utilized for the efficient cluster head selection processes by utilizing certain fitness measures and the modified k-Vertex disjoint path routing (Mod-kVDPR) technique which was utilized for data routing. The method was acquired with greater convergence speed with minima elimination. The residual energy of network was degraded when Base Station was located outside the network.

Fang [13] implemented a trust management based and low energy adaptive clustering hierarchy protocol (LEACH-TM) for the energy-efficient hierarchical routing protocol in WSN. The implemented method has the amount of dynamic decision cluster head nodes, the energy of residual and neighbor nodes density was assumed to constrain the cluster size for improving the efficiency of energy. The method was suitable for resolving the issues like application of distributed authorization and avoiding data packet loss. The method cannot analyse the last die node.

Yin [14] developed an energy-aware trust technique that depends on $AODV$ protocol and multi-path routing method (EATMR) for improving the security in wireless sensor networks. The developed model includes two major steps, first open-source development model algorithm (ODMA) was utilized for nodes clustering and second clustering-based routing was utilized. The process of routing followed the $AODV$ protocol and multiple path technique with consideration of energy-aware trust. The method provided better security with lower complexity. The cluster head selection taken only the distance and energy in EATMR method.

Devi and Sethukarasi [15] suggested a hybrid improved whale artificial ecosystem optimization

(IWAEO) for efficient energy routing in wireless sensor networks. The implemented method was a combination of improved whale and artificial ecosystem optimization algorithms. The method of an energy-efficient routing protocol can utilize to choose the best cluster heading and the nodes which were utilized for data forwarding. The advantages of choosing a cluster heading that improved the network life span, energy consumption is minimized when transmitting the data from nodes of the sensor to related BS, improved reliability and latency was minimized. At various node counts, the implemented protocol has been automatically disconnected.

Gundeboyina Srinivasalu and Hanumanthappa Umadevi [16] presented an energy centric multi objective salp swarm algorithm (ECMOSSA) for relevant cluster head (CH) selection and route generation. The selection of cluster head was done by utilizing five various fitness function values like residual energy, intra cluster distance, distance from cluster head to base station, node degree and centrality. Routing path generation is done by utilizing three various fitness function values like residual energy of cluster head, distance between cluster head and base station and node degree. The relevant route generation utilizing ECMOSSA decreased the node’s energy depletion. The presented method consumed more energy.

Jatinder Pal Singh and Anuj Kumar Gupta [17] implemented a whale based tunicate swarm algorithm – aquila optimizer (WTSA-AO) method for cluster head (CH) selection and routing path generation. The cluster head selection was done by whale based tunicate swarm algorithm (WTSA) utilizing five fitness functions like node degree, cluster head coverage, distance from BS, distance between CHs and residual energy. Cluster heads routing was done with aquila optimizer and optimum routes between cluster heads and base station were chosen utilizing AO and fitness function. The energy needed for intra-cluster communication within a cluster was minimized and AO optimum routes decreased the energy needed during inter-cluster communication. The implemented method comprised the maximum number of rounds at various phases of dead nodes (DNs). This was due to less amount of energy flow created by optimized CH selection as well as intra-cluster communication.

3. Proposed methodology

The research proposed a Multi-objective sand cat swarm optimization algorithm which is utilized the cluster head and routing path selection. The efficiency of energy cluster head and routing path selection are proposed to maximize the network lifetime of the wireless sensor networks and the MSCSO algorithm makes good optimization and provides better accuracy. The overall process involved in the cluster head and routing path selection is represented pictorially in Fig. 1 as follows:

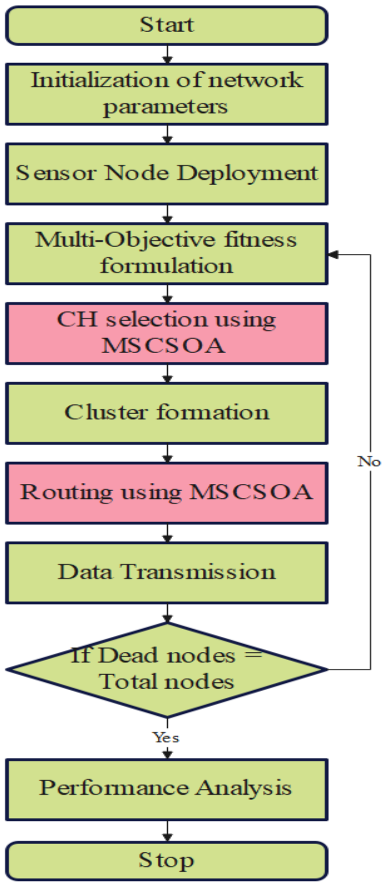

Figure. 1 Workflow of proposed methodology

3.1 Sensor initialization

The sensors are randomly placed in the network, then cluster heads are selected by utilizing MSCSOA. The WSN generates clusters after selecting the cluster heads. Then again, the MSCSOA is used to determine the path from the transmitter CH to the MS. The following portions are broadly explained the CH and route selection process.

3.2 Cluster head selection using MSCSOA

The sand cat swarm optimization (SCSO) algorithm is a metaheuristic algorithm that has a balance action in phases of exploitation and exploration which is utilized for cluster head selection. The limitations of SCSO are low convergence and not correctly identifying the global

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optima, particularly for difficult problems. The SCSO algorithm depends on the global optimum position and it affects the performance of the algorithm. The proposed multi-objective sand cat swarm optimization (MSCSO) algorithm harnesses the advantages of an SCSO algorithm. This algorithm incorporates several key components, including rapid non-dominated sorting, an elite strategy, a crowding operator, and a comparison operator based on crowding degree. With these enhancements, the MSCSO algorithm demonstrates the ability to effectively detect low-frequency noise associated with sand cats [16].

3.2.1. Initialization

In SCSO, the values of variables are determined as sand cats and it is an array of $1 \times d$ dimensions that represents the solution for the problem in the optimization of $d - dimensional$. At the end of the iteration, the best solution is chosen based on the sand cat with the best value and in the next iteration other cats are tried to move towards this cat. In each iteration, the best solution represents the cat that is nearest to the prey.

3.2.2. Search for prey

The advantages of SCSO from the detection of the low-frequency capacity of sand cat which is below $2\ KHz$. The mathematical representation with iteration, the value of r_G reduce from $2\ to\ 0$ to attain the prey. For identifying the prey, take that range of sensitivity starts from $2\ KHz\ to\ 0$ as described in the Eq. (1). The value of s_M is taken as

$$r_G = s_M - \frac{s_M \times iter_c}{iter_{max}} \tag{1}$$

Where, $iter_c$ represents the present iteration, $iter_{max}$ represents the highest iteration.

The main parameter which maintains the transmission between the phases of exploitation and exploration is R which is acquired by Eq. (2). Because of this adaptive strategy, the two phases of the transmission will much more balanced.

$$R = 2 \times r_G \times rand(0,1) - r_G \tag{2}$$

Search space is initialized randomly among two determined limits. The limit of sensitivity of every sand cat is varied, to ignore the trap of local optimum is described below as Eq. (3),

$$r = r_G \times rand(0,1) \tag{3}$$

$$\overrightarrow{Pos}(t+1) = r \cdot \left(\overrightarrow{Pos_{bc}}(t) - rand(0,1) \cdot \overrightarrow{Pos_c}(t)\right) \tag{4}$$

Every cat updates their position by the best position $\overrightarrow{Pos_{bc}}$, their present position $\overrightarrow{Pos_c}$ and their range of sensitivity (r) and which is described above as Eq. (4).

3.2.3. Attack prey

To mathematically develop the model for attack prey of SCSO the distance among present and best positions (Pos_c and Pos_b) respectively, is calculated and described below as Eqs. (5) and (6). In addition, the range of sensitivity of sand cats is taken as a circle and SCSO utilizes the roulette selection approach for selecting an angle of every sand cat.

$$Pos_{rnd} = |rand(0,1) \cdot Pos_b(t) - Pos_c(t)| \tag{5}$$

$$\overrightarrow{Pos}\,(t+1) = \overrightarrow{Pos_b}(t) - r \cdot \overrightarrow{Pos_{rnd}} \cdot cos\theta \tag{6}$$

By using the above two Eqs. (5) and (6), the distance between the present and best position is calculated and the attacked prey of SCSO is also calculated.

3.2.4. Exploration and exploitation

The flexible values of parameters $r_G\ and\ R$ have assured the stage of exploitation and exploration that enable the SCSO to logically move between two stages. Eq. (7) represents the updated position of every sand cat in the process of exploitation and exploration. When the $|R| \leq 1$, sand cats are leading attack its prey or else sand cats task identify a new probable solution in the region of global.

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{Pos_b}(t) - Pos_{rnd} \cdot cos\theta \cdot r & |R| \leq 1 \\ r \cdot \left(\overrightarrow{Pos_{bc}}(t) - rand(0,1) \cdot \overrightarrow{Pos_c}(t)\right) & |R| > 1 \end{cases} \tag{7}$$

By using the above Eq. (7) identifies the position update of every sand cat during the process of exploitation and exploration.

3.3 Multiobjective fitness formulation:

Neighbor node distance (f_{CH1}), the distance between BS to CH (f_{CH2}), residual energy (f_{CH3}) and node degree (f_{CH4}) are fitness measures used for selecting an optimal cluster head. The multi-objective MSCSOA's fitness is measured by utilizing Eq. (8),

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$$f = a_1 \times f_{CH1} + a_2 \times f_{CH2} + a_3 \times f_{CH3} + a_4 \times f_{CH4} \quad (8)$$

Where, $a_1\ to\ a_4$ represents the weight parameters that are assigned to each fitness measure. The following are the MSCSOA fitness measures:

3.3.1. Distance between the neighbor nodes

The distance between neighbor nodes is defined in this section. The energy decadence of the node is majorly based on the transmission path distance [17]. The node's consumption of energy is less when a chosen node has little distance of transmission through the Base Station (BS). The distance between the neighbor nodes (f_{CH1}) is described below as Eq. (9),

$$f_{CH1} = \sum_{j=1}^{m} \left(\sum_{i=1}^{I_j} dis(s_i, CH_j)/I_j \right) \quad (9)$$

Where, $dis(s_i, CH_j)$ shows the distance between two neighbor nodes i and CH_j,

I_j represents the number of neighbor nodes which belong to Cluster Head.

3.3.2. Distance between base station to cluster head

The distance between base station (BS) and to cluster head (CH) is defined in this section. The energy consumption of the node is majorly based on the distance towards the transmission path. For example, if base station is located far away from the cluster head, there requires much energy for the transmission of data. Then, there is sudden fall of cluster head can happen because of the high consumption of energy. So, the node has a small distance from the Base Station taken during the transmission of data [18]. The distance between BS to CH (f_{CH2}) is described in Eq. (10),

$$f_{CH2} = \sum_{i=1}^{m} dis(CH_j, BS) \quad (10)$$

Where $dis(CH_j, BS)$ represents the distance between BS to CH_j.

3.3.3. Residual energy

The residual energy of the cluster head is defined in this section. Cluster head performs variant tasks in a network such as gathering information from sensor nodes and transmission of data to the base station. Cluster head needs more energy to achieve these tasks, and because of that the node which has more energy residual is considered to be cluster head [19]. The residual energy (f_{CH3}) is described in Eq. (11),

$$f_{CH3} = \sum_{i=1}^{m} \frac{1}{E_{CH_i}} \quad (11)$$

Where, E_{CH_i} represents the i^{th} cluster residual energy.

3.3.4. Node degree

The number of sensor nodes are associated with the relative cluster head is defined in this section. The cluster head with a small number of sensors is chosen, because cluster heads with more members of a cluster loss their energy in a smaller duration [20]. The node degree (f_{CH4}) is described in Eq. (12),

$$f_{CH4} = \sum_{i=1}^{m} I_i \quad (12)$$

Where, I_i represents the number of sensor nodes associated with CH_i.

The fitness measures utilized are used to select the relative cluster heads from regular nodes. Energy is utilized to define if the cluster head contains sufficient energy because low energy cluster head leads to information loss. The distance between a neighbor node and base station to the cluster head is utilized to maximize the energy efficiency of wireless sensor networks that reflects in the long-life span of the network. Node degree is utilized to increase the connection between the cluster head & cluster manager.

3.4 Cluster formulation

Cluster managers are allocated to cluster headings from the MSCSOA in cluster formation. The cluster is produced following the distance and also the residual energy, where the potential function is considered at the time of cluster formulation as described in Eq. (13)

$$Potential\ function\ (N_i) = \frac{E_{CH}}{DT(N_i, CH)} \quad (13)$$

From the results of Eq. (13), the sensors are associated with the Cluster Head which has higher residual energy and also the shortest distance of travel.

3.5 Routing path selection

In the energy model, the consumption of energy of the network node is proportional to the distance of transmission. If cluster head transfers data to the mean shift in a single-hop communication, they

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would spend a significant amount of energy, specifically if they are located far away from the mean shift and will expire early because of energy losses. To control the usage of node energy and enhance energy consumption, an MSCSO algorithm is utilized to build inter-cluster routing. Select the possible transfer function for a cluster head is described as shown in Eq. (14),

$$P_{ij}^{k}(t) = \begin{cases} \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l\epsilon N_k}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}} & if\ j \in N_k \\ 0 & otherwise \end{cases} \quad (14)$$

Where, η_{ij} represents the value of heuristic,

τ_{ij} represents the intensity of pheromone,

$\alpha\ and\ \beta$ are the parameters that are utilized for managing the related importance of value of heuristic and intensity of pheromone,

N_k shows the set of nodes which k^{th} The cat has not seen it yet.

The intensity of the pheromone and the value of the heuristic are added based on cluster head data stored in the routing table. The value of the heuristic is updated based on the distance between cluster heads and the formula is described in Eq. (15),

$$\eta_{ij} = \varphi_1 \frac{e^{E_{j-remain}}}{d_{ij}} + \varphi_2 \frac{1}{N_j(2-cos\theta)} \quad (15)$$

Where, $E_{j-remain}$ represents the remaining energy of cluster head next hop,

d_{ij} represents the distance between cluster head (i) and cluster head (j),

N_j represents the number of members in the j^{th} cluster,

θ represents the angle between the line from cluster head i to the mean shift.

$\varphi_1\ and\ \varphi_2$ represents the coefficients of weight.

In the above Eq. (15) represents the value of the heuristic which contains a distance, energy and also angle term. The factor of distance defines the path length from the cluster head to the next hop. The decreasing transmission of data distance and usage of network energy. The factor energy assures that the next-hop cluster head selected has enough energy to function as a relay node, thus balancing the cluster head's load. The factor of angle would assist in preventing the gyration leap difficulty. By including the three criteria in the heuristic factor, their efficiency is improved and also the next hop selection is much more focused, lowering cluster head consumption of energy and increasing usage of energy. The updating of pheromones is important for selecting a path. A novel pheromone updating technique is implemented to enable the path with more balanced energy. The pheromone updating method is described in Eq. (16),

$$\tau_{ij}(t+1) = (1-v)\tau_{ij}(t) + v\Delta\tau_{ij}(t) \quad (16)$$

Where v represents the coefficient of pheromone volatility,

$v\Delta\tau_{ij}(t)$ represents the increments of pheromones.

3.6 Fitness formulation

The value of weight is taken for every value of fitness that is utilized to convert the values of fitness function into one objective named route cost.

$$C_k = \varphi_1 E_r + \varphi_2 d_{CH,BS} + \varphi_3 N_D \quad (17)$$

The route cost (C_k) is added in the value of pheromone quantity and the route cost is described in Eq. (17). The Distance between the cluster head to the base station (f_{R1}) and Residual energy (f_{R2}) are the fitness measures utilized for routing path selection.

3.6.1. Distance between cluster head to the base station

The distance between base station (BS) and to cluster head (CH) is defined in this section. The consumption of energy of the node is majorly based on the distance towards the transmission path. For example, if base station is located far away from the cluster head, there requires much energy for the transmission of data. Then, there is sudden fall of cluster head can happen because of the high consumption of energy. So, the node with a small distance from base station is taken in the process of transmission of data. The distance between BS to CH (f_{R1}) is described below as Eq. (18),

$$f_{R1} = \sum_{i=1}^{m} dis(CH_j, BS) \quad (18)$$

Where $dis(CH_j, BS)$ represents the distance between BS to CH_j.

3.6.2. Residual energy

The residual energy of the routing path is defined in this section. The routing path needs more energy to achieve these tasks, because of that the node with more energy residual is taken to the routing path. The residual energy (f_{R2}) is described below as Eq. (19),

Table 1. Parameters for simulation

Parameter	Value
Size of Network	900m × 900m
No. of nodes	100
Location of MS	random
Initial energy	$0.55J$
Transmitter energy	$50mJ/bit$
Energy of free space model	$10pJ/bit/m^2$
Energy of power amplifier	$0.0013pJ/bit/m^4$
Size of packet	$4000bits$

$$f_{R2} = \sum_{i=1}^{m} \frac{1}{E_{CH_i}} \quad (19)$$

Where, E_{CH_i} represents the i^{th} cluster residual energy.

The fitness measures such as residual energy are utilized to ignore the sensor node which has insufficient energy. Because, in the process of communication the less energy sensor node develops a failure node. The distance between the cluster head to base station is utilized to acquire the short path which decreases the consumption of energy.

3.7 Cluster maintenance

The maintenance of clusters is considered the major significant stage to balance the load among clusters. The clusters near to base station observe their energy quickly because of the traffic of the inter-cluster. The maintenance of the cluster stage is needed to delete the failure node. This will improve in the lifetime when transmits information from the source node to the base station. Whether the cluster head residual energy crosses beyond the level of threshold, the MSCSOA is initialized again to the network cluster. The cluster heads are chosen from the clustering algorithm and MSCSOA is utilized to acquire the path of routing towards the cluster heads to base station.

In the proposed method, an efficient selection of cluster head is processed by the MSCSO algorithm. The cluster heads are chosen by considering four various parameters such as distance between neighbor nodes, distance between base station to cluster head, residual energy, and node degree. The above-mentioned parameters are utilized to choose the optimum cluster head from the collection of nodes. The node’s residual energy is monitored repeatedly by utilizing the base station to ignore the failure of the node in the process of transmission of data. The optimum path transmission from the source node to the base station through the cluster head is acquired by utilizing the MSCSO algorithm. It identifies the short path to decrease the utilization of the energy of nodes. The MSCSOA-based optimal cluster head selection and route production lead to describe effective energy in WSN. Hence, the efficient energy in WSN is utilized to maximize the lifetime of the network and the total amount of packets transmitted to the base station during the data transmission.

4. Performance evaluation

4.1 Simulation environment

The proposed MSCSO algorithm is simulated by utilizing the MATLAB R2020a tool. The computer is powered by an i5 CPU with 6 GB of RAM. This MSCSO simulation model consists of 100 sensor nodes distributed in a $900m \times 900m$ area. The location of MS is always random and the sensors are initialized with $0.55J$ of energy. Table 1 lists the parameters for the simulation examined for this study.

4.2 Performance analysis

The MSCSO algorithm’s performance is evaluated using alive and dead nodes, energy consumption, residual energy, life expectancy, packet loss ratio, a packet sent to bs, and Throughput. The MSCSO is compared to traditional methodologies such as low energy adaptive clustering hierarchy (LEACH) which is a measurable level of sensor network lifespan by matching node consumption of energy. Distributed energy efficient clustering (DEEC) is the cluster-based solution for multiple level and two-level energy heterogeneous WSN. The threshold distributed energy efficient clustering (T-DEEC) chooses the CHs from greater energy nodes, thus enhancing energy efficiency and also network lifespan.

4.2.1. Alive nodes

Alive nodes have enough energy to distribute data. Fig. 2 depict the performance of alive nodes in MSCSO algorithm with LEACH, DEEC, and T-DEEC. According to the findings such as in 600 rounds, the alive nodes for MSCSO, LEACH, DEEC, and T-DEEC are 100, 0, and 0 respectively. As a result, MSCSO includes a higher number of alive nodes than LEACH, DEEC, and T-DEEC. The efficient of energy cluster head and route finding is utilized to reduce the amount of energy consumed by the sensors, resulted in more alive nodes.

4.2.2. Total energy consumption

In WSNs, energy is the most important aspect of improving network performance. Sensing, processing, and receiving data consumes the required

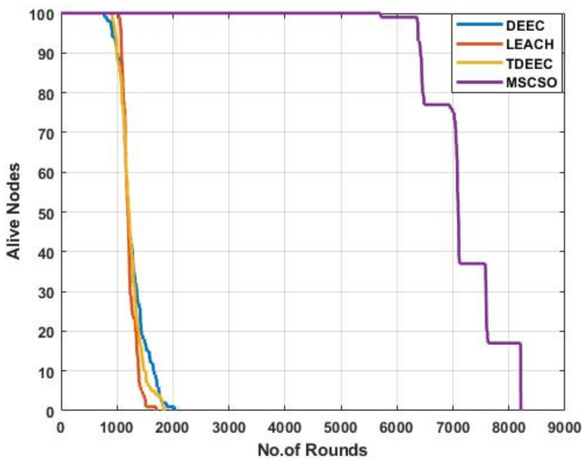

Figure. 2 Alive node vs No. of rounds

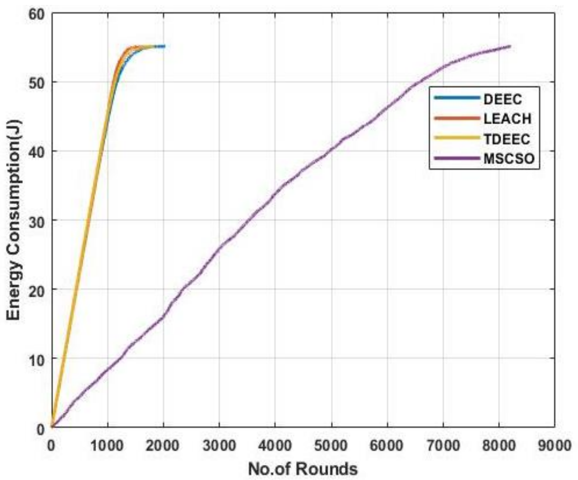

Figure. 3 Energy consumption vs No. of rounds

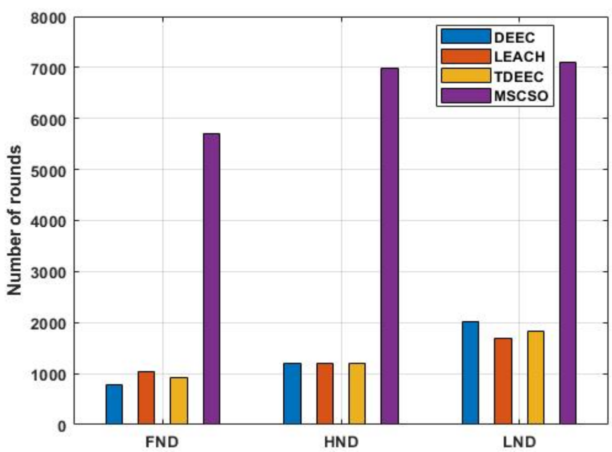

Figure. 4 Comparison of life expectancy

energy for the respective process. Fig. 3 depicts the comparison between the proposed MSCSO with LEACH, DEEC, and T-DEEC in terms of energy consumption (EC). According to the graph, the proposed MSCSO algorithm consumed less energy than the existing LEACH, DEEC, and T-DEEC approaches.

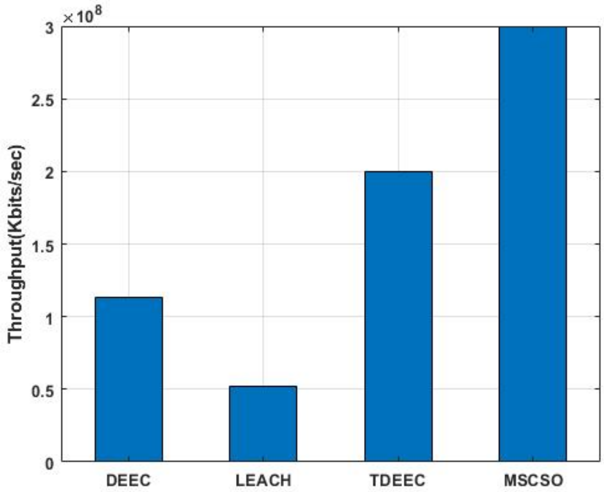

Figure. 5 Comparison of throughput

4.2.3. Life expectancy

The period that nodes are active when transferring data packets is defined as the Life expectancy. The life expectancy is calculated utilizing three separate parameters: first node die (FND), half node die (HND), and last node die (LND). Fig. 4 depicts the life expectancy performance of MSCSO with LEACH, DEEC, and T-DEEC. According to the graph, the MSCSO has a longer life span than the LEACH, DEEC, and T-DEEC. The use of MSCSO to develop energy-efficient CH selection and routing increases life span.

4.2.4. Throughput

Throughput is described as several bits transforming into the base station over a wireless sensor network. Throughput is measured by bits per second. Fig. 5 depicts the throughput performance of MSCSO with LEACH, DEEC, and T-DEEC. According to the graph, the MSCSO has the highest throughput than the LEACH, DEEC, and T-DEEC techniques.

4.3 Comparative analysis

This section gives a comparative analysis of the MSCSO algorithm. The existing methods such as FAL [11], Taylor-SHO [12], ECMOSSA [16] and WTSA-AO [17] are utilized to assess the effectiveness of the MSCSO for 200, 400 and 600 rounds in terms of energy consumption, throughput, alive nodes and delay. In Table 2, the residual energy (J), throughput (%) and alive nodes of MSCSO is compared with FAL [11], even when number of rounds in network is increased to 600, MSCSO is still able to keep the network alive with higher number of alive nodes. In Table 3, the energy consumption (J)

Table 2. Comparison analysis of MSCSO with FAL

Parameters	Methods	No. of rounds		
		200	**400**	**600**
Residual Energy (J)	FAL [11]	0.39	0.28	0.2
	MSCSO	0.5335	0.51250	0.4966
Throughput (%)	FAL [11]	96	95.2	95
	MSCSO	98.89	98.91	99.04
Alive nodes	FAL [11]	96	82	64
	MSCSO	100	100	100

Table 3. Comparison analysis of MSCSO with Taylor-SHO

Parameters	Methods	No. of rounds		
		200	**400**	**600**
Energy Consumption (J)	Taylor-SHO [12]	0.2	0.34	0.41
	MSCSO	0.0208	0.0350	0.04045
Throughput (kbps)	Taylor-SHO [12]	3000	5800	8750
	MSCSO	3.34×10^5	4.98×10^5	9.01×10^5

Table 4. Comparison analysis of MSCSO with ECMOSSA

Parameters	Methods	No. of rounds		
		200	**600**	**800**
Total Energy of nodes (J)	ECMOSSA [16]	44.70	32.44	25
	MSCSO	49.76	48.21	47.53
Alive nodes	ECMOSSA [16]	100	100	100
	MSCSO	100	100	100

Table 5. Comparison analysis of MSCSO with WTSA-AO

Parameters	Methods	No. of rounds		
		200	**500**	**800**
Alive nodes	WTSA-AO [17]	50	50	37
	MSCSO	50	50	50
Throughput (kbps)	WTSA-AO [17]	0.6×10^4	1.7×10^4	3.7×10^4
	MSCSO	2.3×10^5	3.7×10^5	4.9×10^5
Delay(sec)	WTSA-AO [17]	0.07	0.125	0.135
	MSCSO	0.002	0.09	0.12

and throughput (kbps) of MSCSO is compared with Taylor-SHO [12], the attainment of high throughput in MSCSO is due to fitness function utilized in cluster head and routing which helps in selection of best CH and optimal routes. These fitness function helps to maintain parameters of residual energy. By maintaining the residual energy, number of alive nodes can be kept alive for longer time. As a result, the number of data packets transferred to the BS increased. In Table 4, the total energy of nodes (J) and alive nodes of MSCSO is compared with ECMOSSA [16], total energy of nodes for MSCSO is improved by taking distance for an optimal CH selection and by generating a shortest path using MSCSO. In Table 5, the alive nodes, throughput (kbps) and delay (sec) of MSCSO is compared with WTSA-AO [17] the MSCSO avoids node and link failure by considering node residual energy during routing path generation which helps better packet delivery rate, that results in better throughput. The proposed MSCSO method attained minimum delay of 0.002, 0.09 and 0.12 seconds for 200, 500 and 800 rounds respectively because of data transmitted quickly and with minimal delay.

From the above-mentioned Table 2, Table 3, Table 4 and Table 5 shows that the proposed MSCSO performs well than the FAL [11], Taylor-SHO [12], ECMOSSA [16] and WTSA-AO [17].

5. Conclusion

In this research, the MSCSO algorithm is proposed to maximize the efficiency of energy in WSNs. The proposed MSCSO is utilized to select optimum Cluster Heads, followed by the MSCSO also utilized to determine the path from the transmitter cluster head to the destination. The detection cluster head with the minimum neighbor nodes and the shortest base station distance is utilized to reduce the energy spent by the nodes. Following that, the clusters are balanced using the cluster head balancing factor in the MSCSO, which assists in reducing the energy spent by the nodes. The MSCSO algorithm is utilized to establish reliable data transmission in WSN and selects the shortest path with the fewest node degrees. Based on the data, it is determined that the MSCSO algorithm performs well than the FAL, Taylor-SHO, ECMOSSA, WTSA-AO, LEACH, DEEC, and T-DEEC. The alive nodes of the MSCSO algorithm for 600 rounds are 100, which is higher than LEACH, DEEC, and T-DEEC. In the future, the security model based on clustering and routing protocol will be implemented for improving security.

Notations

Notation	Description
$iter_c$	Present iteration
$iter_{max}$	Highest iteration
Pos_c	Present position of cat
Pos_b	Best position of cat
r	Range of sensitivity
f_{CH1}	Neighbor node distance
f_{CH2}	Distance between BS to CH
f_{CH3}	Residual energy
f_{CH4}	Node degree
a_1 to a_4	Weight parameters
$dis(s_i, CH_j)$	Distance between two neighbor nodes i and CH_j
I_j	Number of neighbor nodes
$dis(CH_j, BS)$	Distance between BS to CH_j
E_{CH_i}	i^{th} cluster residual energy
I_i	Number of sensor nodes
N_i	Potential function
η_{ij}	Heuristic value
τ_{ij}	Intensity of pheromone
α and β	Parameters utilized for managing the related importance of heuristic value and intensity of pheromone
N_k	set of nodes
$E_{j-remain}$	Remaining energy of cluster head next hop
d_{ij}	Distance between cluster head (i) and cluster head (j)
N_j	Number of members in the j^{th} cluster
θ	Angle between the line from cluster head i to the mean shift
φ_1 and φ_2	Coefficients of weight
v	Coefficient of pheromone volatility
$v\Delta\tau_{ij}(t)$	Increments of pheromones
C_k	Route cost
f_{R1}	Distance between the cluster head to the base station
f_{R2}	Residual energy

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

For this research work all authors' have equally contributed in Conceptualization, methodology, validation, resources, writing—original draft preparation, writing—review and editing.

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