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Energy Optimized Cluster Head Selection Based on Multi-Objective Sand Cat Swarm Optimization in Under Water Wireless Sensor Networks

Seema Swamy Gowda[1]* **Ambika Ramalingappa[2]**

[1]*Department of Electronics and Communication Engineering, Sir M Visvesvaraya Institute of Technology, Visvesvaraya Technological University, Belagavi-590018, India*
[2] *Department of Electronics and Communication Engineering, BMS Institute of Technology and Management, Visvesvaraya Technological University, Belagavi-590018, India*
* Corresponding author's Email: seema_ec@sirmvit.edu

Abstract: Underwater wireless sensor networks (UWSNs) are the kind of wireless sensor networks which is deployed in an underwater environment with the help of physical sensors. UWSN has applications in different fields like the management of disasters, and navigating the underwater environment and marine species. The nodes present in the UWSN do not have an inbuilt battery, so the available energy sources must be used effectively. To retain energy efficiency in UWSN, effective clustering and routing protocols must be utilized in the UWSN environment. But, the cluster-based routing approaches are effective only for conventional wireless sensor networks. Moreover, the problem related to void hole occurs from sensor node and enhances energy dissipation which helps to minimize the life span of UWSN. So, the research proposed multi-objective sand cat swarm optimization (M-SCSO) for the selection of optimistic cluster heads (CH) and provides a better routing path for the transmission of data without a void hole problem. The parameters such as distance between neighbouring nodes, distance between base station and cluster head, residual energy, and node degree are considered while selecting optimistic CHs using MSCSO. Secondly, energy-efficient routing is processed using MSCSO to deliver data packets in the shortest path. The results obtained through experimental validation represent effectiveness of proposed method. The proposed approach obtained a better packet delivery rate (PDR) of 99.32% whereas the existing emperor penguin optimized Q learning achieved PDR of 90%.

Keywords: Clustering, Energy efficiency, Routing, Packet delivery rate, Sand cat swarm optimization, Underwater wireless sensor networks.

1. Introduction

A major part of the earth's surface is enclosed with water in the form of seas, rivers, and streams. Numerous unknown and hidden resources in the ocean must be uncovered, whereas undersea habitats are far too complicated for humans to figure out. As a result, using wireless technology to explore the undersea world is a possible solution [1]. Underwater wireless sensor networks (UWSN) are developing technology which will be utilized to observe and find changes in the aquatic environment [2,3]. UWSN is comprised of a collection of sensors and self-driving underwater vehicles to sense and collect the data. The underwater sensors transmit data directly or indirectly to the sensors which are placed above the water surface. The data from the sink is then transferred to the offshore center, where it is analyzed and studied. UWSN sensors are positioned underwater to evaluate density, temperature, and pressure [4, 5]. UWSN is widely employed in a variety of fields, including tracking the targets, monitoring oil spills and submarine detection, and catastrophe inhibition [6]. The UWSN confronts several challenges, including high network dynamics, costly implementation, limited accessible bandwidth, and limited battery energy.

Underwater sensors' battery energy is limited, and these batteries cannot be easily replenished in the ocean [7]. The UWSN consumes a lot of energy because of its unpredictable time delay, and high bit error rate [8-10]. The UWSN failure nodes are caused by the node's restricted battery source [11]. During the time of data transmission, the void hole occurs due to the rise of dead nodes and affects the reliable transmission from source to destination node. An effective routing results in the trustworthy broadcasting of data packets but it is a significant issue in UWSN due to varying factors [12, 13]. The data-collecting system is based on a cluster that is being developed to improve the network's energy efficiency [14]. The basic goal is to divide the network into small parts known as clusters. The CH represents a whole cluster by experimental information from sensors and broadcasting to the sink using the CH as the next hop [15]. The suggested optimization-based clustering technique reduces total routing distance and sensor overhead. The proposed approach performs effective clustering and routing to find an optimal path to transmit data from source to destination node.

The contributions of the manuscript are given as follows:

1. The research proposed MSCSO to discover CH from normal sensor nodes and help to improve the energy efficiency in UWSN. Because of capability of SCSO to maintain the balance among exploration and exploitation stages, optimal CH solutions are obtained.
2. The proposed method detects the void hole which helps to minimize the dissipation of energy by choosing energy-efficient CH during data packet transmission.
3. Moreover, the proposed MSCSO is used in the process of detecting an optimal path from the CH to the base station. Thus, proposed MSCSO is used in process of enhancing life expectancy with improved data delivery.

The remaining of this research paper is given as: Section 2 depicts related works and proposed method is presented in section 3. Section 4 and section 5 show experimental results and the overall conclusion of this research respectively.

2. Related works

In this section, the recent research based on clustering and routing in UWSN is described.

Priyalakshmi and Murugaveni [16] have introduced energy-efficient opportunistic routing with the emperor penguin optimized Q learning technique for UWSN. The suggested approach was designed for minimizing issues related to void hole and energy dissipation. The Q-Learning approach acts as a void detection factor and EPO helps in the effective transmission of data from the node at the sensor to the sink. Moreover, a various path from void hole region is analysed with help of an optimized Q-value. However, suggested method does not suit for higher transmission range.

Roshani V. Bhaskarwar [17] have introduced cluster-based routing protocol named as energy efficient UWSN clustering protocol (EEUCP). The sensor nodes of underwater in various layers were separated to clusters by K means. The fuzzy logic (FL) method was introduced for optimal cluster head (CH) selection for every cluster network. The fuzzy rules were determined by utilizing 3 input variables such as residual energy (RE), distance to surface sink (DSS) and packet delivery ratio (PDR) of each sensor in cluster. The EEUCP method increases data delivery while improving energy efficiency. At the same time, the suggested approach lacks data aggregation in the underwater environment.

Gowda and Ramalingappa [18] have introduced multi-objective energy-based improved jellyfish swarm optimization (MOEIJSO) to perform CH selection and routing UWSN. The multi-hop routing was created by employing ant colony optimization (ACO) to distribute data packets. As a result, the MOEIJSO-ACO approach increases data delivery while improving energy efficiency. However, the battery efficiency of the sensors is diminished while the range of transmission is increased.

Tiwari and Singh [19] have introduced an energy-optimized cluster head selection using the enhanced remora optimization algorithm (ECERO) in UWSN. Moreover, load among closely related nodes was diminished with the help of a sleep scheduling approach located near the cluster nodes. The suggested approach shows an effective performance when it is evaluated with real-time network analysis. Moreover, the suggested approach could overwhelm the issues based on huge data. However, the suggested approach faced delays and reduced network lifespan.

Sun [20] have introduced multi-objective routing (MOR) for under water acoustic wireless sensor networks (UAWSN). The relay selection algorithm (RSA) is used for delay-sensitive and insensitive scenarios for various quality of services. RSA selects relays by considering energy and delay with enhanced network lifespan and packet delivery ratio (PDR). The suggested approach minimizes the weights according to the delay-related parametric and helps to enhance the network lifetime. However, the suggested approach was not designed to perform routing for multi-objective fitness functions.

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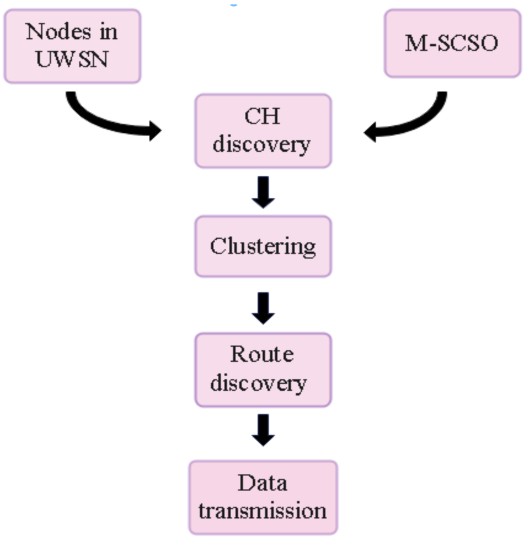

Figure. 1 The process of energy efficient clustering and routing using MSCSO

Subramani [21] have introduced a metaheuristic clustering with a routing (MCR) in UWSN to improve energy efficiency. In this research, cultural emperor penguin optimizer-based clustering (CEPOC) was used in the process of cluster generation. Moreover, grasshopper optimization was used to perform routing based on the list of nodes, distance, and energy. However, suggested method does not consider balancing factor that is responsible for maintaining balance among the clusters and enhancing the performance.

Overall, the outcomes of the existing approaches exhibit problems related to energy efficiency, poor network lifespan, and end-to-end delay. Moreover, in most of the research, the multi-objective fitness values are not taken into consideration. So, this research introduced an effective optimization algorithm named M-SCSO to perform an effective routing over the networks of UWSN.

3. Energy-efficient clustering and routing using M-SCSO

This research introduced an energy efficient transmission of data which is performed using MSCSO based clustering and routing in underwater WSN. The energy consumption of the sensors is diminished with the help of clustering and detection of the shortest path to deliver the data by overcoming the void hole problem. The process involved in effective clustering and routing using M-SCSO is depicted in Fig. 1 as follows:

3.1 Initialization of sensors

At initial phase, the nodes in UWSN are positioned in a randomized manner which is followed by a selection of cluster heads using MSCSO. When cluster head is chosen from network, the formation of clusters takes place in UWSN. Moreover, the routing path from CH to the BS is identified with the help of MSCSO.

3.2 Optimal selection of CH using MSCSO

The proposed MSCSO is used in process of optimal selection of CH from the sensor nodes of UWSN. The SCSO algorithm is inspired by two features comprised of the search and attack phase. The SCSO algorithm controls the transition between the stages of exploration and exploitation in a balanced manner with minimal parametric operation. This process of CH maintenance helps to overcome the problems related to void holes. Moreover, SCSO is developed as an MSCSO to select the optimistic cluster heads from the sensor nodes.

3.2.1. Population initialization

Initially, a candidate matrix is generated to a population of sand cat to start M-SCSO algorithm. The matrix is created based on the size of the problem $(N_{pop} \times N_d)$, where $(pop = 1, \dots\dots, n)$. The best parameter values for the problem are chosen based on fitness cost of sand cat which is attained by the M-SCSO.

3.2.2. Iterative process

The iterative process includes exploration and exploitation, where, the exploration includes the searching mechanism of M-SCSO algorithm. The exploitation includes attacking the prey. In an iterative process, each sand cat will generate value for relevant function. Once the first iteration is accomplished, sand cat having lowest cost during the

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iteration is selected as superior solution, and remaining sand cats attempt to make progress near the best cat in the following iteration. Since optimal explanation in every individual iteration may indicate a cat at a nearby range to prey.

3.2.2.1. Exploration

The M-SCSO algorithm is defined from the search ability of sand cats, where the mechanism depends on less-frequency noise emission. The ability of sand cats to sense low frequencies is 2kHz. For each problem, solution of every sand cat is characterized is shown in Eq. (1)

$$X_i = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{id}) \quad (1)$$

The sensitivity of each cat is determined by their hearing ability in low frequencies, which is an advantage of the M-SCSO algorithm.it is believed that the cat can sense between the range of 2kHz to 0. The search space is generated at random within the defined bounds. During the searching stage, every current search agent's position is updated depending on random position. As a result, search agents can investigate new areas of the search space. To avoid local optimal trap, the sand cat has a different sensitivity range that is linearly reduced between 0 to 2 by using Eq. (2)

$$\overline{r_G} = s_M - \left(\frac{2 \times S_M \times iter_c}{iter_{Max} + iter_{max}}\right) \quad (2)$$

Where, $\overline{r_G}$ is the general sensitive range of sand cats, $iter_c$ is the current iteration, and s_M is the value based on the hearing features of the sand cat. The transition control among exploration and exploitation phases is maintained by vector R as shown in Eqs. (3) and (4)

$$\vec{R} = 2 \times \overrightarrow{r_G} \times rand(0,1) - \overrightarrow{r_G} \quad (3)$$

$$\vec{r} = \overrightarrow{r_G} \times rand(0,1) \quad (4)$$

Where, $\vec{r}$ is the sensitive range of sand cat, the count of iteration is 100, where, $\overline{r_G}$ value is >1. Due to this, the final parameter will maintain the balance of transition among exploration and exploitation stages. The location of each sand cat is rationalized to identify best prey position. Using Eq. (5) sand cat finds the best position of prey.

$$\overrightarrow{Pos}(t+1) = \vec{r}.\left(\overrightarrow{Pos_{bc}}(t) - rand(0,1).\overrightarrow{Pos_c}(t)\right) \quad (5)$$

Where the best candidate position is represented by $\overrightarrow{Pos_{bc}}$ and present position of sand cat is given by $\overrightarrow{Pos_c}$.

3.2.2.2. Exploitation

A sand cat's next position will be anywhere among its current position and hunting position when random values of R, are in range [-1, 1]. When R ≤1, the M-SCSO algorithm pushes hunting agents to exploit; if not hunting agents are pushed to explore and identify prey. Each cat avoids local best trap by using a different radius during the exploration. The distance between best position and present position is represented in Eq. (6)

$$\overrightarrow{Pos_{rand}} = \left|rand(0,1).\overrightarrow{Pos_b}(t) - \overrightarrow{Pos_c}(t)\right|,$$

$$\overrightarrow{Pos}(t+1) = \overrightarrow{Pos_b}(t) - \vec{r}.\overrightarrow{Pos_{rand}}.\cos(\theta). \quad (6)$$

Where the best position and current position are represented as $\overrightarrow{Pos_b}$ and $\overrightarrow{Pos_c}$, the randomized position of the individuals is denoted as $\overrightarrow{Pos_{rand}}$.

This characteristic is also one of the effective criteria for exploitation. The position enhancement of every sand cat in both exploration and exploitation is calculated using Eq. (7)

When $|R| \leq 1$, sand cats are directed to attack the prey or else assigned to the task of scheduling new tasks. Where, the sensitivity of the sand cat is determined in the circle, and direction of movement is given by random angle (θ) which will be chosen between 0 and 360.

3.3 Derivation of multi-objective functions for MSCSO

The multi-objective functions such as distance between neighbouring nodes (α_1), distance between base station and the cluster head (α_2), residual energy (α_3) and node degree (α_4) are considered while selecting optimistic cluster heads using MSCSO. The mathematical formulation of fore mentioned multi-objective functions utilized in the process of MSCSO is represented in Eq. (8) as follows:

$$F_c = \alpha_1 \times f_1 + \alpha_2 \times f_2 + \alpha_3 \times f_3 + \alpha_4 \times f_4 \quad (8)$$

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

Where the weighted values which are allotted to every individual fitness function are represented as $\alpha_1 - \alpha_4$. The definition of the aforementioned fitness functions is described as follows:

- One of the fitness functions utilized to choose optimal fitness function is distance among neighbouring nodes. It is defined as distance among neighbouring node which is necessary for transmitting data packets from a node to another, while distance among neighbouring nodes is low, then nodes energy consumption in UWSN is reduced. The mathematical formula for evaluating distance among neighbouring nodes is given in Eq. (9):

$$f_1 = \frac{d(i,j)}{R} \tag{9}$$

Distance among neighbouring nodes is described as $d(i,j)$ and R represents distance of neighbourhood radius.

- The transmission distance among CH and base station is described as path where UWSN data packets travel from source to destination and that is evaluated by utilizing Eq. (10). The higher transmission distance causes high energy consumption, but proposed MSCSO efficiently reduces distance and gives superior output in CHs selection.

$$f_2 = \sum_{i=1}^{m} dis(H_{i,}D_v) \tag{10}$$

Where node at destination is described as D_v and distance between i^{th} vehicle in habitat H and DV is described as $dis(H_{i,}D_v)$.

- The residual energy is described as energy that exist in after data transmission performed. The node with greater residual energy is taken for UWSN communication and intermediate nodes in transmission path transfer and receive data packets among nodes. Residual energy is evaluated utilizing by Eq. (11):

$$f_3 = \frac{E_{max} - E_i}{E_{max} - E_{min}} \tag{11}$$

Where the residual energy of the individual node is described as E_i.

- The final fitness parameter is taken as node degree and that is represented as total count of edges linked to node. Node degree is computed by Eq. (12):

$$f_4 = \sum_j a_{ij} \tag{12}$$

Where a_{ij} describes node total degree and it is computed through adding in-degree and out-degree of node.

The aforementioned fitness functions are used in process of selecting the optimal cluster heads from sensor nodes. The rest of the energy present in the sensor nodes is used to evaluate the probability of the failure node while broadcasting the failure nodes. Furthermore, the factors based on distance and the cluster heads are used to evaluate the balancing factor and enhance the energy efficacy in UWSN.

3.4 Formation of clusters

Next to the stage of choosing CHs using MSCSO, cluster members are allotted to corresponding cluster heads. The potential functions such as distance and residual energy are considered for the creation of clusters. The potential function for cluster generation takes place using Eq. (13) as follows:

$$Potential\ function = \frac{E_{CH}}{dis(N_i, CH)} \tag{13}$$

3.5 Routing path creation utilizing MSCSO

After cluster head selection, route is identified for transferring data without loss and with less delay. In the manuscript, MSCSO has key part in producing routing path and supports to attain state of energy efficiency. The fitness functions like distance of energy and amount of hops are taken for developing routing path. The nodes which are included to minimal hops are appropriate to process routing with a balance between nodes. The stages followed for developing routing path by utilizing the proposed MSCSO are given below:

1. At initial stage, population of a sand cat is initialized through feasible path from CH to destination and sand cat dimension is equal to whole number of intermediate nodes that is existing in routing path.
2. After exploration and exploitation stages, fitness of every path is updated. The fitness function is evaluated by using Eq. (14) while developing routing path.

$$F_r = \beta_1 \times f_1 + \beta_2 \times f_2 + \beta_3 \times f_3 \tag{14}$$

Where weighted parameters of fitness functions

Table 1. Simulation parameters

Parameter	Value
No.of. Sensors	100,300
BS location	100,100,100
Size of network	$500 \times 500 \times 500m^3$
The energy of initial sensor	0.55J
Packet size	4000 bits

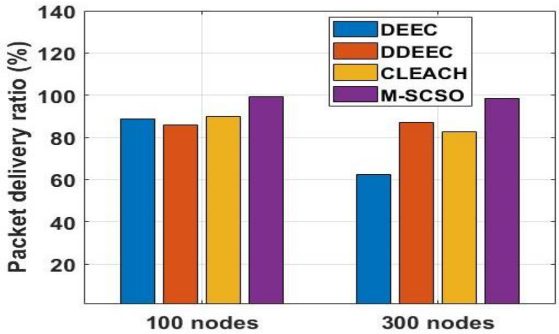

Figure. 2 Evaluation of PDR for 100 nodes and 300 nodes

like distance between CH and base station (f_1), residual energy (f_2), and node degree (f_3) respectively. Thus, fitness function described afore are utilized to detect optimum route with low energy consumption.

4. Results and analysis

The results acquired while evaluating proposed MSCSO are deliberated in this section. The simulation of the proposed MSCSO takes place in MATLAB R2020b and the system used for implementation is specified with i5 processor, 6 GB RAM, and Windows 11 operating system. The simulation parameters that are considered while simulation of proposed MSCSO is described in Table 1:

4.1 Performance analysis

The performance of proposed MSCO is estimated through packet delivery ratio (PDR), throughput, and packet loss ratio (PLR). The proposed method is compared with existing distributed energy efficient clustering (DEEC) [22], developed distributed energy efficient clustering (DDEEC) [23], and cluster -low energy adaptive clustering hierarchy (C-LEACH) [24]. The comparison was done based on two different node counts such as 100 and 300. Secondly, the performance of proposed method is estimated based on count of alive nodes and dead nodes.

4.1.1. Packet delivery ratio (PDR)

PDR is proportion of data packets that is

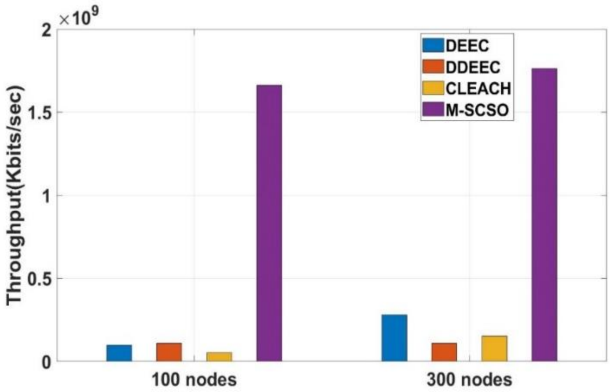

Figure. 3 Evaluation of throughput for 100 nodes and 300 nodes

effectively received at destiny and whole data packets developed in source node. The pictorial presentation of PDR estimation is given in Fig. 2 and that is computed by utilizing Eq. (15):

$$PDR = \frac{\text{Number of data packets received at destination}}{\text{Total number of data packets created at the source node}} \times 100\% \quad (15)$$

The outcomes from Fig. 2 represent that proposed M-SCSO achieved better PDR when evaluated with existing methods. For example, when the proposed approach is evaluated for 300 nodes, M-SCSO achieved a PDR of 99% which is comparatively greater than existing methods. The superior outcome of suggested method is because of its efficiency in maintaining balance between exploration and exploitation stages which helps to detect an optimal route for transferring data packets.

4.1.2. Throughput

The throughput is distinct as total count of data packets which successfully received from source to destination node. The value of throughput is computed by bits per second. The pictorial presentation of throughput estimation for various node counts is described in Fig. 3.

The results from Fig. 3 shows the graphical representation of the results when it is evaluated for two different node count for 100 and 300. The proposed method attained superior throughput for both the node counts and proved its effectiveness. For example, proposed method attains throughput of 17 Kbps which is relatively higher than the existing DEEC, DDEEC and C-LEACH. An optimal result is because of eliminating the multiple distortions and generation of an optimal routing path utilizing MSCSO that aids in better throughput than existing methods.

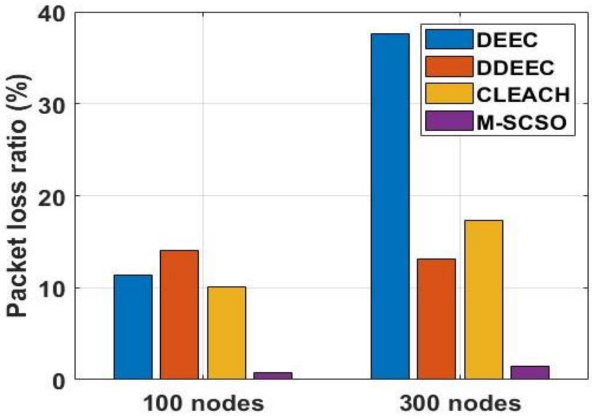

Figure. 4 Evaluation of PLR for 100 nodes and 300 nodes

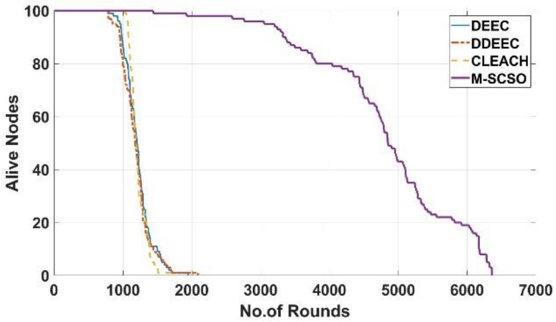

Figure. 5 Evaluation of alive nodes

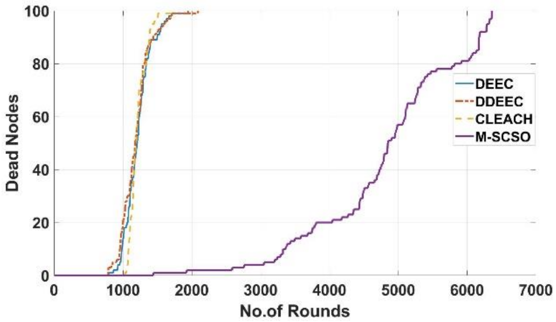

Figure. 6 Evaluation of dead nodes

4.1.3. PLR

Packet loss ratio (PLR) is defined as the total number of packets that get dropped while transmitting data from source to destination node. Fig. 4 gives pictorial representation for packet loss ratio for 100 and 300 nodes.

The outcomes from Fig. 4 depict that proposed M-SCSO has a minimum packet loss ratio when compared with existing ones. The packet loss ratio of the proposed approach for 300 nodes is 3% which is comparatively less than the existing approaches. The better result is due to the the capability of the proposed approach to transmit data packets without loss.

4.1.4. Alive nodes and dead nodes

The alive nodes are the count of nodes that are comprised of enough energy to perform reliable communication over UWSN and the dead nodes are the count of nodes that depletes the entire energy. Figs. 5 and 6 depicted below presents the comparison of the proposed approach with existing ones based on alive and dead nodes respectively. The balancing factor in the proposed approach helps to maintain a balance among the clusters with the shortest route for transmission.

4.2 Comparative analysis

In this section, outcomes of proposed method are estimated with existing approaches like EPO-Q [16], MOEIJSO-ACO [18] and CEPOC [21]. The performance of the proposed MSCSO and the existing EPO-Q is evaluated based on PDR, PLR and throughput for different node counts ranging from 100 to 500. Table 2 depicted below presents the results acquired when implementing proposed method with existing EPO-Q.

The outcomes from Table 2 show that proposed approach attained superior outcomes in all metrics when compared to existing EPO-Q. For example, the PDR of existing EPO-Q for 500 nodes is 90% whereas proposed method attained PDR of 99.32%. The better result is due to the MSCSO finding an optimal path to deliver data packets from source to destination node. The results from Table 3 represent that proposed method attained superior results in performance metric of alive node, dead node and remaining energy (J) when compared with existing ECERO method.

Secondly, the proposed MSCSO is evaluated with the existing MOEIJSO-ACO based on energy consumption and the count of alive nodes and dead nodes. Table 4 depicted below presents the results acquired when estimating proposed method with MOEIJSO-ACO for different number of rounds from 200 to 1200.

The result from Table 4 shows that the proposed M-SCSO achieved better results through minimizing energy consumption, increased count of alive nodes and minimum count of dead nodes. For example, the total energy consumption of M-SCSO for 1200 rounds is 9.99% whereas the existing MOEIJSO-ACO has consumed 11.54% and CEPOC has consumed 100% of total energy. This better result is due to the efficiency of the proposed M-SCSO in detecting the shortest path to transmit the data. Fig. 7 depicted below presents pictorial representation for comparison of total energy consumption for various

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Table 2. Comparison of EPO-Q and M-SCSO for different node counts from 100 to 500

Performances	Methods	Number of nodes				
		100	200	300	400	500
Throughput (Mbps)	EPO-Q [16]	98	97.5	96.5	95	94.5
	M-SCSO	97×10^3	98×10^4	99.7×10^4	109×10^4	116×10^4
PDR (%)	EPO-Q [16]	60	69	80	88	90
	M-SCSO	97.9	98.5	98.99	99.21	99.32
PLR (%)	EPO-Q [16]	40	31	22	11	10
	M-SCSO	2.1	1.5	1.01	0.79	0.68

Table 3. Comparison of ECERO and M-SCSO for different node counts from 100 to 500

Performances	Methods	Number of nodes			
		500	1000	1500	2000
Alive node	ECERO [19]	100	100	100	93
	M-SCSO	100	100	100	99
Dead node	ECERO [19]	0	0	0	7
	M-SCSO	0	0	0	1
Remaining Energy (J)	ECERO [19]	23	17	12	7
	M-SCSO	24.58	24.01	23.45	22.9

Table 4. Comparison of MOEIJSO-ACO, CEPOC and M-SCSO for various number of rounds from 200 to 1200

Performances	Methods	Number of rounds				
		200	400	600	800	1200
Total energy consumption (%)	MOEIJSO-ACO [18]	2.12	4.2	7.15	9.53	11.54
	CEPOC [21]	3	12	22	42	100
	M-SCSO	1.89	2.93	4.78	7.24	9.99
Alive node	MOEIJSO-ACO [18]	400	399	399	399	394
	CEPOC [21]	400	400	400	400	0
	M-SCSO	400	400	400	400	398
Dead node	MOEIJSO-ACO [18]	0	1	1	1	6
	CEPOC [21]	0	0	0	0	400
	M-SCSO	0	0	0	0	2

Table 5. Comparison of MOEIJSO-ACO, CEPOC and M-SCSO in terms of Life expectancy

Performances	Methods	Number of rounds
FND	MOEIJSO-ACO [18]	182
	CEPOC [21]	852
	M-SCSO	1002
HND	MOEIJSO-ACO [18]	4185
	CEPOC [21]	1121
	M-SCSO	9577
LND	MOEIJSO-ACO [18]	9089
	CEPOC [21]	1187
	M-SCSO	11156

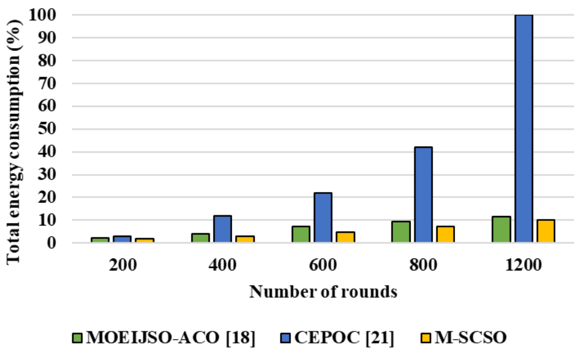

Figure. 7 Comparison of total energy consumption

counts of rounds from 200 to 1200. In Table 5, the life expectancy such as first node die (FND), half node die (HND) and last node die (LND) of proposed method is compared with existing MOEIJSO-ACO and CEPOC methods.

5. Conclusion

In this research, an effective optimization-based clustering and routing approach is introduced to enhance the network life span and energy efficiency of UWSN. The MSCSO is introduced to select an

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optimistic cluster head and to identify shortest path for transmitting data packets. The parameters like distance between neighbouring nodes, distance between base station and cluster head, residual energy, and node degree are considered while selecting optimistic CHs using MSCSO. Secondly, the energy-efficient routing is performed with help of MSCSO to deliver data packets in the shortest path. The results obtained through experimental validation represent effectiveness of proposed method. The total energy consumption of MSCSO for 1200 rounds is 9.99% whereas the existing MOEIJSO-ACO has consumed 11.54% of total energy. In the future, hybridization-based optimization algorithms will be used to enhance the overall performance of clustering and routing over UWSN.

Notation

Notations	Descriptions
$\vec{r_G}$	Range of sand cats
$iter_c$	Current iteration
s_M	Value based on the hearing features of the sand cat
$\vec{r}$	Sensitive range of sand cat
$\overrightarrow{Pos_{bc}}$	Best candidate position
$\overrightarrow{Pos_c}$	Current position of the sand cat
$\overrightarrow{Pos_b}$	Best position
$\overrightarrow{Pos_{rand}}.$	Randomized position
(θ)	Random angle
$\alpha_1 - \alpha_4$	Weighted values
$d(i,j)$	Distance among the neighboring nodes
R	Neighborhood radius
D_v	node at the destination
H	Habitat
$dis(H_{i,}D_v)$	Distance between the i^{th} vehicle in H and DV
E_i	Residual energy of the individual node
a_{ij}	Total degree of the node
f_1	Distance between CH and base station
f_2	Residual energy
f_3	Node degree

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, visualization, have been done by 1st author. The supervision and project administration, have been done by 2nd author.

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