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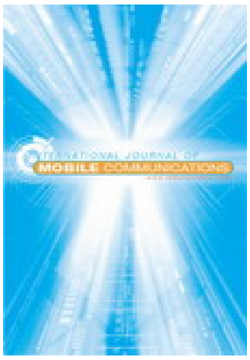

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Energy-efficient coverage in wireless sensor networks based on stacked contractive auto encoder with Manta Ray foraging optimisation algorithm

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Energy-efficient coverage in wireless sensor networks based on stacked contractive auto encoder with Manta Ray foraging optimisation algorithm

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Abstract: In this manuscript, energy-efficient coverage in WSN based on stacked contractive auto encoder with Manta Ray foraging optimisation algorithm is proposed. Initially, IF-RFKM clustering approach is proposed for dividing the ROI as several clusters and defines the cluster head. Then SCAE determines the sensing radius for best coverage and move sensor nodes accordingly. Finally, MRFO algorithm is proposed for increasing the network lifespan by decreasing energy consumption in the sensor nodes. The proposed EECO-SCAE-MRFO-WSN method is implemented in MATLAB, its effectiveness is validated under performance metrics, such as coverage rate, covering percentage, delay, throughput, computation time, network lifetime, residual energy and energy consumption. The proposed EECO-SCAE-MRFO-WSN method has attained 36.8%, 34.75%, 21.86% higher coverage rate, 34.6%, 30.9%, 26.87% lower delay, 7.96%, 12.65%, 9.65% higher network lifetime, and 19.87%, 16.8%, 10.9% lower energy consumption than the existing methods, like energy-efficient coverage enhancement for 3-D WSN depending on vampire bat optimiser (EECO-VBO-WSN).

Keywords: Manta Ray foraging optimisation; region of interest; stacked contractive auto encoder; SCAE; wireless sensor network.

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1 Introduction

WSN is a set of lower power small sensor nodes designed to monitor and record environmental conditions in various positions (Hallafi et al., 2022). WSN comprise huge count of distributed sub-nodes to gather data from other nodes. The two major issues of WSNs are attaining maximal coverage and optimising network lifespan (Jiao et al. 2020; Balaji et al., 2020). The deployed sensor nodes track maximal area of ROI when the coverage area is maximised (Sahoo et al., 2020). WSN contains tiny and low-cost sensor devices among sensing and wireless communication (Shajin et al., 2022a; Rajesh et al., 2022a). Also, it has rapid deployment, self-organisation and fault tolerance among broad applications, for example environmental monitor, clinical care, pension service, intelligent transportation and manufacturing scheme (Sachan et al., 2021). Various performance metrics including area coverage, network connectivity, overall network lifetime is impacted by sensor deployment (Alghamdi, 2020; Shajin et al., 2022b; Mohanty et al., 2020). Subsequently, the network performance can be affected by sensor field coverage because the coverage rate regulates the tracking capacity of sensing area, therefore, this is deemed as quality of service measurement in wireless sensor network (Behura and Kabat, 2020; Rajesh et al., 2022b). Area coverage influences how the sensitive zone is monitored (Si et al., 2020; Elhoseny et al., 2020). The major purpose of area coverage is to maximise the sensitive area's identification rate (Zagrouba and Kardi, 2021). Reconfiguring the sensors can be a useful strategy to gain maximum coverage. Sensitisers are applied in the sensing area randomly, because this is lesser cost, but it causes coverage holes at the field of sensing. The judicious reconfiguration of mobile sensors after initial deployment can raise the network coverage by eradicates coverage problems (Manju Bhambu and Kumar, 2020). Network lifespan is the time that network sensors alive to cover enys area. WSNs face a number of limitations, including restricted and non-rechargeable battery power, insufficient memory, and constrained processing capability. It is crucial to maximise the network's lifespan, because sensor nodes are often battery-powered (Rawat and Chauhan, 2021). If battery runs out, then it becomes ineffective on account of multiple sensor nodes are usually dispersed in remote locations, like dense forests, battlefields, underwater (Kumar et al., 2021). This is difficult to change the batteries of sensor nodes. Hence, this is necessary to improve the network lifespan through enhancing coverage region of sensor nodes in WSN (Prabu et al., 2020).

In recent days, many researchers are approved numerous bio-inspired metaheuristic intelligence algorithms for enhancing the efficiency of coverage area energy consumption in WSN, which do not provide sufficient coverage region, network lifetime, routing algorithms, and sensor nodes distribution (Lu et al., 2019; Pustokhina et al., 2021). The existing algorithm (Zhao et al., 2019; Chowdhury and De, 2021; Zhao et al., 2020a; Chawra and Gupta, 2022; Malisetti and Pamula, 2022; Zivkovic et al., 2020; Soundari and Jyothi, 2020) could not able to deal the diverse coverage issue in WSN. To overcome these problems, some solutions should be presented to fix this problem. Existing works have energy-efficient lower coverage optimisation performance, high energy consumption, and high latency (Preetham et al., 2022; Wang et al., 2020) that are overcome by this work.

The major contribution of this research work is abridge below

- Energy-efficient coverage in WSN depending on stacked contractive auto encoder with MRFO algorithm (EECO-SCAE-MRFO-WSN) is proposed.
- Initially, IF-RFKM (Preetham et al., 2022) clustering approach is utilised to separate the ROI into several clusters, also find cluster centre in the network.
- Then stacked contractive auto encoder (SCAE) (Wang et al., 2020) determines sensing radius for ideal coverage and change the sensor nodes position.
- Finally, MRFO algorithm (Zhao et al., 2020b) is used for enhancing the network lifespan by minimising the energy usage of sensor nodes.
- The proposed EECO-SCAE-MRFO-WSN is done in MATLAB, and its efficacy is assessed with the help of some performance metrics.
- Then the performance of the proposed EECO-SCAE-MRFO-WSN method is analysed to the existing EECO-VBO-WSN (Zhao et al., 2019), EECO-GSO-KMA-WSN (Chowdhury and De, 2021) and EECO-DPA-IVBO-WSN (Zhao et al., 2020a) models.

Remaining manuscript is structured as below. The related works are deliberated in Section 2, the proposed method is illustrated in Section 3, the results and discussion are exemplified in Section 4, and finally, conclusion is presented in Section 5.

2 Related works

Among the frequent research work of energy-efficient coverage in WSN, some of the latest investigations were reviewed in this part.

Zhao et al. (2019) have suggested energy-efficient coverage development for 3 dimensional WSN depending on vampire bat optimiser. The presented method was to upgrade the coverage effect the dynamic partition of cellular grids. Virtual bats and virtual preys were introduced by improving the vampire bat optimiser and it was responsible for solving the problems of lessening and balancing sensors energy cost. The stacking strategy dependent on cellular grids was presented to identify the deployment positioning of sensor. Lessening total energy consume and balancing residual energy of node solves the problems are coverage enhancement problem and the multi-objective optimisation.

Chowdhury and De (2021) have presented energy-efficient coverage optimisation in WSN on the basis of Voronoi-Glowworm swarm optimisation-K-means method. By using the minimum number of active nodes, the coverage areas were enhanced for the K-means algorithm, Glowworm swarm optimisation and Voronoi cell structure. Furthermore, the deployed networks lifetime was improved when the energy was decreased by using the multiple hop transmission together with sleep-wake for the deployed sensor nodes. The result shows that the coverage area upto 99.99% with better active sensor nodes count.

Zhao et al. (2020b) have introduced energy-efficient coverage development for WSN utilising dynamic partition approach for cellular grids as well as enhanced vampire bat optimiser. They revealed the necessary minimal count of sensor networks and the deployment location for sensors. The task assignment problem was get from conversion of coverage rate and energy consumption optimisation problem. When the sensors count was variable, the dynamic partition approach raised the coverage effect for cellular grids. Finally, if the amount of cellular grids was not equivalent to the sensors, at that time the asymmetric assignment problem was solved.

Chawra and Gupta (2022) have presented energy efficient wake-up schedule for raising the lifespan of network, coverage and connectivity based upon Memetic algorithm in 3 dimensional WSN. To prove the performance of the presented scheme in different network scenarios an extensive simulation experiments has to done and its performances were compared with two latest existing schemes. The presented method gives better coverage ratio, ideal count of active sensor nodes, and lifespan of network.

Malisetti and Pamula (2022) have suggested energy efficient cluster basis routing for WSN utilising moth levy adopted artificial electric field together with customised grey wolf optimisation algorithms. To maximise the network lifetime, an innovative method for cluster base routing was applied, it creates the routing progress effectively. In which the selection process of optimum CH for more effectiveness it was activated through energy consideration, distance amid cluster head and base Station, node degree, distance amid the sensor nodes, and time of death node.

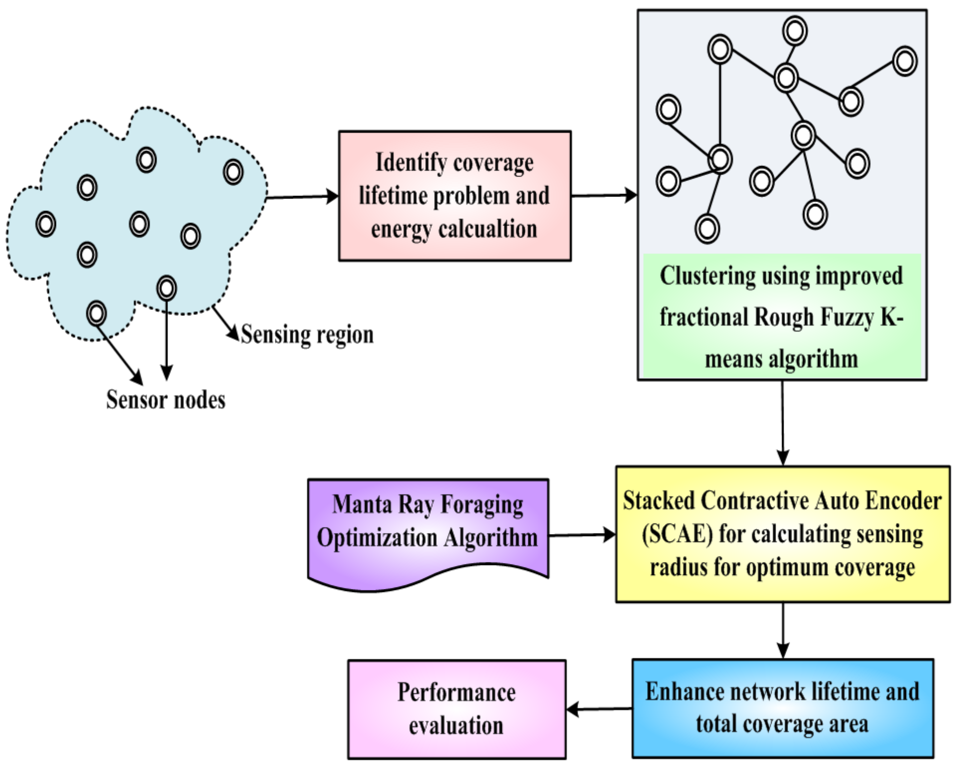
Zivkovic et al. (2020) have presented enhanced grey wolf algorithm for energy efficient WSN. To raise the network lifetime optimisation, the improved version of grey wolf algorithm was applied. By comparing the presentation of presented exploration enhanced grey wolf algorithm with the traditional LEACH algorithm, particle swarm optimisation and basic grey wolf approach that were all process of performances were experimented with similar experimental conditions.

Soundari and Jyoti (2020) VL have presented an effective machine-learning strategy for intelligent data collection in WSN. Monkey tree search base location-aware smart collector (MTS_LASC) was presented. MTS_LASC was very dynamic and attractive case that consists of distributed smart collectors as well as centralised meta-heuristic Monkey Tree Search engine utilised to solve the complex issues. The distributed smart collector was embedded to MTS. It was able to use a fuzzy inference method to analyse, classify, integrate, and distribute data gathered from sensors to the sink. The simulation outcomes show high delivery rate by lessening unnecessary packet transmission and maintaining reliability through data aggregation, but the network lifetime was low.

3 Proposed methodology

In this manuscript, energy-efficient coverage in WSN depending on stacked contractive auto encoder with MRFO algorithm (EECO-SCAE-MRFO-WSN) is proposed. Initially, IF-RFKM clustering model is applied to separate the ROI as numerous clusters, and then find the cluster centre in the network. Then SCAE determines the sensing radius for better coverage and change the sensor nodes position. Finally, MRFO algorithm (Zhao et al., 2020b) is used for enhancing the network lifespan by minimising the energy usage of the sensor nodes. The block diagram of proposed EECO-SCAE-MRFO-WSN model is shown in Figure 1. The detailed description of the proposed methodology is given below.

Figure 1 Block diagram of the proposed EECO-SCAE-MRFO-WSN model (see online version for colours)



3.1 Problem definition of coverage-lifetime

Increasing network coverage is necessary for improving network lifetime which is mainly based on minimisation of energy dissipation of sensor nodes. In this, the sensor nodes must reorganise the starting positions that are used to enhance the coverage and minimise degraded energy because of sensor mobility, sensing capability, and redundancy in the coverage area. In this, the problem of the model is defined as redistributing sensor nodes from their original positions for retaining a balance among the dissipated energy and coverage area. Here, IF-RFKM clustering model is used for clustering, which can obtain the cluster centres used as the centres of sensor nodes. The motion of the sensors to their optimal position is governed by a SCAE. The proposed EECO-SCAE-MRFO-WSN model is formally represented as an extension problem that aims to maximise the network lifetime through total area improvement and total energy consumption reduction.

In WSN, the energy-efficient coverage optimisation using proposed EECO-SCAE-MRFO-WSN model is formally represented as the maximisation issue that can maximise the network lifetime through maximising the enys region and diminishing overall energy utilisation. The problem of WSN is calculated using equation (1)

$$\begin{aligned} &\max \sum ix_i \\ &\xrightarrow{\text{subject to}} \sum_p B_{ip} x_i \le l_i \left(\forall s_i\right) \\ &x_i \ge 0\left(\forall C_p\right) \end{aligned} \tag{1}$$

here sensor cover index is denoted as i, sensor cover is denoted as x_i, sensor node is represented as s_i with index i, the lifespan of given sensor nodes are denoted as l_i, set of sensor cover is C_p along index p, constraint matrix constant is represented as B_{ip} that is calculated as $B_{ip} = \begin{cases} 1 & \text{if } s_i \in C_p \\ 0 & \text{otherwise} \end{cases}$.

3.2 Clustering using IF-RFKM

In this work, IF-RFKM clustering approach is used to divide the ROI as various clusters and find the cluster centre in the network. Here, the sensor nodes are divided into various cluster sets. The attributes taken into account to choose the clusters in the sensor nodes are represented by input parameters fed to fuzzification. The resulting fuzzy parameters tune in IF-RFKM automatically. With some uncertainty, the membership function parameters are characterised under input data's variation range. The RFKM clustering incorporates the concept of a random k-dependent fuzzy set. Here, Euclidean distances are varied by fuzzy membership degrees (FMD) initialised to dissimilar scales. K-means clustering acts via separate data as a set of clusters determined by centroids. The related boundary objects have been interpreted in clusters 1 and 2. From which, cluster 1 boundary object is placed in its related cluster location, whereas cluster 2 boundary object is placed betwixt cluster 1 and 2 at the region. These created from datasets randomly. Thus, 2 clusters are used to cluster the nodes from the network. The steps of the RFKM clustering strategy are explained below: FMD are determined by equation (2)

$$\mu_{mk} = \frac{1}{\sum_{j=1}^{l} \left({h_{mk}}/{h_{jk}} \right)^{\frac{2}{n-1}}} \tag{2}$$

Let parameter n denotes amount of fuzzifier, $n \in (1, \infty)$ makes various fuzzy grades, μ implicates object's membership degree A_k to cluster D_m. Wherein $\mu \in [0, 1]$ along $\sum_{m=1}^{l} \mu_{mk} = 1$. The h_{mk} parameter refers distance matrix. FMD compute the dissimilarity range of inputs representing the attributes and the uncertainty levels representing the degree of attribute values variation.

If object in the cluster is positioned in a minimal approximation, assume that the object is non-competitive and self-governing of other clusters. The fuzzy membership is assigned with degree 1 in the minimum approximation. So, the newly fuzzy member is created that is exhibited in equation (3)

$$\mu_{mk} = \begin{cases} \dfrac{1}{\sum_{j=1}^{l} \left(h_{mk} / h_{jk} \right)^{\frac{2}{n-1}}} & \text{if } A_k \in \hat{D}_m \\ 1 & \text{if } A_k \in \bar{D}_m \end{cases} \tag{3}$$

here h_{mk} signifies minimal distance amongst A_k and enys cluster centres. If present any other distances h_{jk} amidst A_k then distance deviation h_{jk}–h_{mk} smaller than current threshold, D_m denotes count of clusters. RFKM clustering has smooth fuzzy boundaries and low approximations.

A local fuzzy measure is used to find the boundary object including fewer associated clusters. A global fuzzy measure determines every object belonging to every cluster. At local fuzzy measurement, if the boundary object A_2 is placed betwixt clusters 1 and 2, the fuzzy membership belonging to clusters 1, 2 is improved locally. Therefore, local fuzzy measurement is responsible for local fuzzy development. The cluster centre iteration is revealed in equation (4)

$$u_m = \begin{cases} T_g \times \dfrac{\sum_{A_k \in D_m} \mu^n{}_{mk} A_k}{\sum_{A_k \in D_m} \mu^n{}_{mk}} + T_f \times \dfrac{\sum_{A_k \in \hat{D}_m} \mu^n{}_{mk} A_k}{\sum_{A_k \in \hat{D}_m} \mu^n{}_{mk}} & \text{if } D_m \neq \phi \wedge \hat{D}_m \neq \phi \\ \dfrac{\sum_{A_k \in D_m} \mu^n{}_{mk} A_k}{\sum_{A_k \in D_m} \mu^n{}_{mk}} & \text{if } D_m \neq \phi \wedge \hat{D}_m = \phi \\ \dfrac{\sum_{A_k \in D_m} \mu^n{}_{mk} A_k}{\sum_{A_k \in D_m} \mu^n{}_{mk}} & \text{if } D_m = \phi \wedge \hat{D}_m \neq \phi \end{cases} \tag{4}$$

here T_g and T_f denotes the weight coefficients of lesser and boundary region $T_g + T_f$. and $T_g > T_f$. Later certain progressive enhancements, classic rough K-means cluster mode is activated; A_k needs object on h_{mk} distance from centre u_m of cluster D_m. Thus, objects positioned in the same lower boundary region are recognised with different FMD. The output parameters acquired through the fuzzy system are optimised by upgraded partial RFKM clustering technique. Many adaptation laws result from stability analysis that enables the sliding surface to be 'zeroed' that is exhibited in equation (5)

$$R = D_a^{1-p} F + \alpha D_x^{-p} F \tag{5}$$

where R signifies count of overlapping clusters, α signifies positive steady, parameter F implies computation fault; $0 < p < 1$; D_a, D_x denotes clusters' lesser and upper bound. The computation error is determined in equation (6)

$$F = b(\vartheta / v) - b_c \tag{6}$$

Consider v parameter as input vector, b as output vector from fuzzy system, b_c as chosen output, ϑ as consequent parameters vector.

Caputo derivative of h as p is described in below equation (7):

$$C_a^{1-p} h(a) = \frac{1}{\Im(1-p)} \int_0^a (a-\tau)^{-p} \frac{c}{ca} h(\tau) c\tau \tag{7}$$

here $\Im(1\text{–}p)$ denotes Gamma operation, $h(a)$ implicates normalised distance among the data component, $h(\tau)$ signifies objects at boundary region. Here, t ϑ consequential parameters is tuned to lessen the computation time and get better decision is shown in equation (8)

$$\vartheta = \left[t_1, \ldots.., t_N, \overline{t}_1, \ldots., \overline{t}_N\right]^W \tag{8}$$

Let parameter N specifies number of rules. Input variables range is divided as N sections. The grade of membership is assumed in all sections. The enys number of rules is identical to the enys number of membership degree. IF-RFKM gives advantages of partial-order fuzzy set as well as RFKM clustering networks. It aids in efficient clustering of sensor nodes when the process of decision-making.

3.3 *Stacked contractive auto encoder for calculating sensing radius for optimum coverage*

In this, SCAE determines the sensing radius for ideal coverage, then vary the location of sensor nodes to the optimum positions. Normally, SCAE contains multiple hidden layers to encode and a set of symmetric layers to decode, where the every layer output is fed as to the next layer. The superscript numbers indicate the individuality of hidden layer, the subscript numbers indicate dimension of layer.

At the stage of SCAE encoding, the N^{th} hidden layer learns N^{th} order features from $(N\text{–}1)^{\text{th}}$ layer output. Here, 1sthidden layer learns the features of first-order through the raw input, 2nd hidden layer learns the features of second-order depends on the features of first-order. In this, higher layers learn high-order features. At SCAE decoding stage, $(N\text{–}1)^{\text{th}}$ layer has been reconstructing from $N1^{\text{th}}$ order features via the N^{th} layer output, until reconstructed the input. The processes of encoding and decoding for SCAE network is given in equation (9) and equation (10),

$$x^N = f\left(w^N x^{N-1} + b^N\right); N = 1, 2, \ldots\ldots\ldots k \tag{9}$$

$$z^{N-1} = g\left(w'^N z^N + b'^N\right) \tag{10}$$

where x denotes input data, x^N represent N^{th} order features that is attained by N^{th} hidden layer, x^k represent the k^{th} order features with low dimensional that is attained by N^{th} hidden that is conveyed to the classifier. In this, k denotes the total number of hidden layers in SCAE. Also, the non-linear activation function are denotes as f and g, weight matrices are mentioned as w, w' and b, b' is the bias values. Additionally, the objective function for identifying the sensing radius for optimum coverage and move sensor nodes are calculated using equation (11)

$$\begin{aligned} Obj_{SCAE}^{N} &= \frac{1}{k}\sum_{i=1}^{k}\left(x^{(i,N-1)} - z^{(i,N-1)}\right)^2 \\ &+ \lambda^N \sum_{i=1}^{k}\left(\frac{1}{d_N}\sum_{j=1}^{d_N}\left[x_j^{(i,N)}\left(1-x_j^{(i,N)}\right)\right]^2 \times \frac{1}{d_N d_{N-1}}\sum_{t=1}^{d_{N-1}}\left\|w_{t_j}^{k}\right\|^2\right) \end{aligned} \tag{11}$$

Consider the feature dimensions of $(N–1)^{\text{th}}$ layer along N^{th} layer is denoted as $d_{N–1}$ and d_N, sensing radius with respect to time is denoted as j, t and penalty coefficient of N^{th} SCAE network is denoted as λ^N that is set when the penalty value is lower than reconstruction error, but the size of reconstruction error is same, and higher classification performance can be achieved. MRA algorithm is proposed to improve the presentation of SCAE used to move sensor nodes to optimum positions by optimising SCAE parameters, which is explained as following.

3.4 *Manta Ray foraging optimisation algorithm for optimising SCAE parameters*

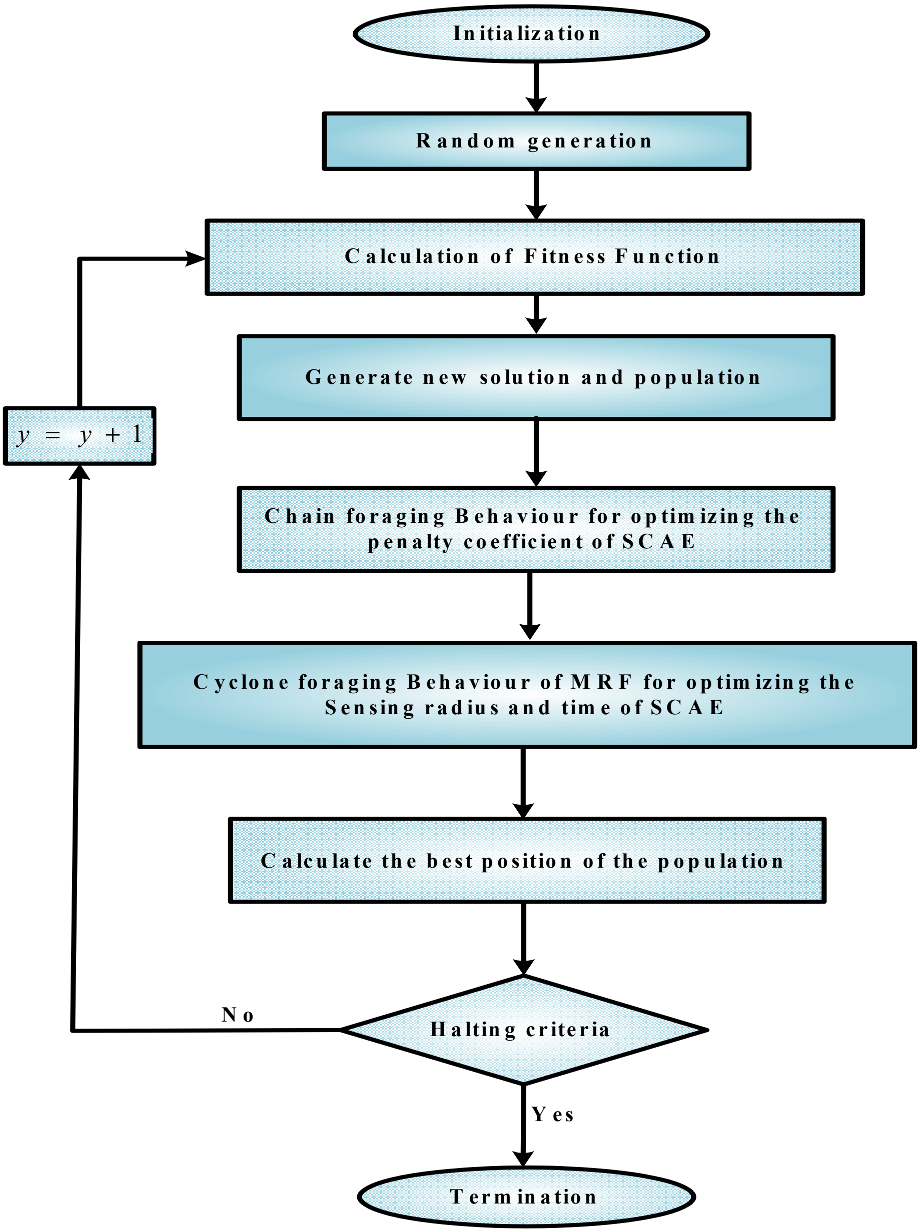
In this work, MRF algorithm is proposed for optimising SCAE parameters, which is used to change the sensor node positions to optimal place. Also, this improvement is enhance the network lifetime and total coverage area of the network. Here, the MRF optimisation method mimics the Manta Rays foraging activities. The three foraging processes employed in this algorithm are chain, cyclone, and somersault perform the MRFO performance. The test outcomes show that the proposed technique performs noticeably greater than those popular metaheuristic. In chain foraging strategy, many Manta Rays begin foraging; they establish a sequence one after the other. Smaller male Manta Rays swim on top of female ones and piggyback on their backs in time with the females' pectoral fin beats. So, Manta Rays coming behind them will pick up any slits that their predecessors missed. Cyclone foraging is the second method of foraging. Lots of Manta Rays assemble when the amount of plankton is really high. As their heads and tails spiral together to create the spiraling vertex in cyclone's eye, the filtered water maximise the surface. As a consequence, the plankton is drawn into its large jaws. Somersault foraging is the final foraging tactic. Manta Rays engage in a series of backward somersaults in order to attract plankton when they discover a food source. Manta Rays maximise their intake of food by performing somersaults, which are random, frequent, local, and cyclical movements. Figure 2 portrays the flow chart representation of MRF algorithm. The stepwise process of MRF algorithm is illustrated beneath

Step 1 Initialisation: The initial position of MRF every possible solution y_i has generated randomly in nearness to the initial position is represented in equation (12) as follows

$$\left\|y_i - y_0\right\| \le n \tag{12}$$

where $i = 1,2,3\ldots, n$, specifies count of sensor nodes.

Figure 2 Flow chart representation of Manta Ray foraging optimisation (MRF) algorithm (see online version for colours)



Step 2 Random generation: After initialisation process, the input parameters are created in random. Therefore, the values of the Manta Ray foraging optimisation method are chosen depending on the situation of explicit hyper-parameter.

Step 3 Fitness function: Create the random solution using the initialised values. The objective function shows the optimisation parameter value of SCAE as penalty coefficient λ^N of the N^{th} network and sensing radius with respect to time is denoted as j, t, this is expressed in equation (13)

$$Fitness\ function = Optimize\left(\lambda^N, j, t\right) \tag{13}$$

Generate initial solution using a group of random initial feasible solutions according to the equation (12). Afterwards, the each iteration creates a resolution of population on the basis of given equation (14).

$$y_{i+1} = y_i + \gamma * D_{Ri} \tag{14}$$

Let D_{Ri} represents i^{th} random directions to reach the solution.

Step 5 Chain foraging behaviour for optimising the parameter: Manta Rays construct a foraging chain by lining up from head to tail. Individuals accept the first movements towards the food and one in front of them. The best solution is updated for each person in every iteration. This is specified in equation (15)

$$\alpha = 2r\lambda^N \sqrt{\left|\log(r)\right|} \tag{15}$$

where α indicates the weighted coefficient, r denotes the random vector at [0, 1] range. In this equation (10), optimise the parameter λ^N.

Step 6 Cyclone foraging behaviour of MRF for optimising the parameter j and t: Manta Ray swarms move in a line to form a spiral pattern as they forage using the cyclone foraging technique, where each one swims toward the one in front of it. An individual emulates one in front of him, also move towards the food spirally. The mathematic modelling for spiral-shape movement of Manta Rays in two dimensional space is represented in equation (16)

$$\beta = 2te^{r1\frac{S(j)-s+1}{S}} \cdot \sin(2\pi r_1) \tag{16}$$

From equation (16), β indicates weight coefficient, $s(j)$ denotes maximum number of iterations for the sensing radius of nodes, and r denotes random vector at [0, 1] range.

Step 7 Calculate the best position of the population: The MRF algorithm is continuously search for the ideal point by utilising the best solution as early resolution for the subsequent iteration.

Step 8 Termination: The optimum parameter of SCAE as penalty coefficient λ^N of the N^{th} network and sensing radius with respect to time is denoted as j, t are considered and optimised using MRF optimisation, which repeats step 3 until fulfill $y = y + 1$ halting criteria. Thus, the MRF optimisation has achieved high performance by attaining optimal positions of sensor nodes, which improves the efficacy of proposed technique.

4 Results with discussion

The simulation result of proposed energy-efficient coverage in wireless sensor network depending on SCAE with Manta Ray foraging optimisation algorithm (EECO-SCAE-MRFO-WSN) is analysed in this section. The simulation is done in MATLAB using PC along Windows 10 operating system, 2GB RAM, Intel i3 core processor. The performance metrics is analysed. The simulation parameter of EECO-SCAE-MRFO-WSN method is tabulated in Table 1.

Table 1 Simulation parameters of the proposed EECO-SCAE-MRFO-WSN method

Parameters	*Value*
No. of iterations	1,000
ROI dimension	$(50 \times 50)m^2$
No. of deployed sensor nodes	1,000
Initial energy of sensor nodes	2-6J
Packet size	500 bits
Threshold battery power	0.02 J

4.1 Performance metrics

The calculation of the proposed EECO-SCAE-MRFO-WSN technique performance metrics, like coverage rate, covering percentage, delay, throughput, computation time, network lifetime, residual energy and energy consumption are analysed.

4.1.1 Throughput

It defines the rate of data transferring from source to various amount of nodes that is specified in equation (17)

$$Throughput = \frac{No.of\ packets\ sent * packet\ size}{Time} \tag{17}$$

4.1.2 Delay

This is the time consumes for sending packet from sender to the receiver that is computed by equation (18)

$$delay = P_{ST} - P_{RT} \tag{18}$$

where P_{ST} implicates the time of packet sending, P_{RT} implicates the time of packet receiving.

4.1.3 Network lifetime

It determines how many rounds the network activates its functioning that means how much rounds nodes die at the field during tasks processing. The network lifespan calculation is exhibited in equation (19)

$$Network\ lifetime = \min_j \left[\frac{\sum_{k=1} DN_{jk} * K_j}{M_k} \right] \tag{19}$$

Let DN_{jk} implies coverage matrix, K_j implies sensor node life, M_k implies nodes count.

4.1.4 Energy consumption

The energy consumed amount via the sensor nodes is given in equation (20)

$$EC = \left[\sum_{m=1} CH_F(m) + \sum_{n=1} DN_F(n) \right] \tag{20}$$

here the energy consume through CH indicates $CH_F(m)$, the energy consume through cluster member denotes $DN_F(n)$.

4.2 Comparative analysis of performance metrics

In this section, the performance metrics like coverage rate, covering percentage, delay, throughput, computation time, network lifetime, residual energy, energy consumption of the proposed EECO-SCAE-MRFO-WSN approach is compared with existing EECO-VBO-WSN (Zhao et al., 2019), EECO-GSO-KMA-WSN (Chowdhury and De, 2021) and EECO-DPA-IVBO-WSN (Zhao et al., 2020a) methods respectively.

Figure 3 Comparison of coverage rate (see online version for colours)

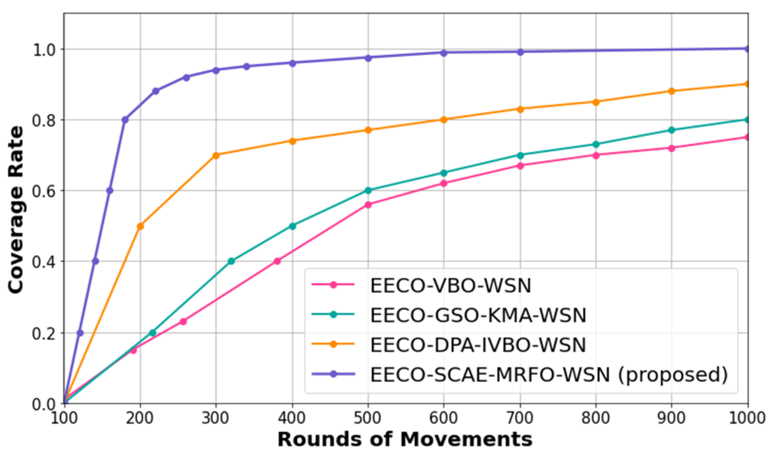


Figure 3 represents coverage rate comparison. Here, the proposed EECO-SCAE-MRFO-WSN method has attained 36.8%, 34.75%, 21.86% higher coverage rate for 200 rounds of movements, 34.76%, 30.09%, and 26.7% higher coverage rate for 400 rounds of movements, 33.97%, 30.7%, and 25.86% higher coverage rate for 600 rounds of movements, 32.8%, 29.87%, and 24.86% higher coverage rate for 800 rounds of movements, 28.97%, 25.76%, and 16.98% higher coverage rate for 1,000 rounds of movements than the existing methods like EECO-VBO-WSN, EECO-GSO-KMA-WSN, and EECO-DPA-IVBO-WSN respectively.

Figure 4 implicates covering percentage comparison. Here, the proposed EECO-SCAE-MRFO-WSN method has attained 0.02%, 0.1%, and 0.05% higher covering percentage for 200 rounds of movements, 18.9%, 15.76%, and 15.76% higher covering percentage for 400 rounds of movements, 34.87%, 32.65%, and 28.7% higher covering percentage for 600 rounds of movements, 38.7%, 37.9%, and 30.98% higher covering percentage for 800 rounds of movements, 37.8%, 31.7%, and 26.78% covering percentage rate for 1,000 rounds of movements than the existing methods like EECO-VBO-WSN, EECO-GSO-KMA-WSN, and EECO-DPA-IVBO-WSN respectively.

Figure 4 Comparison of covering percentage (see online version for colours)

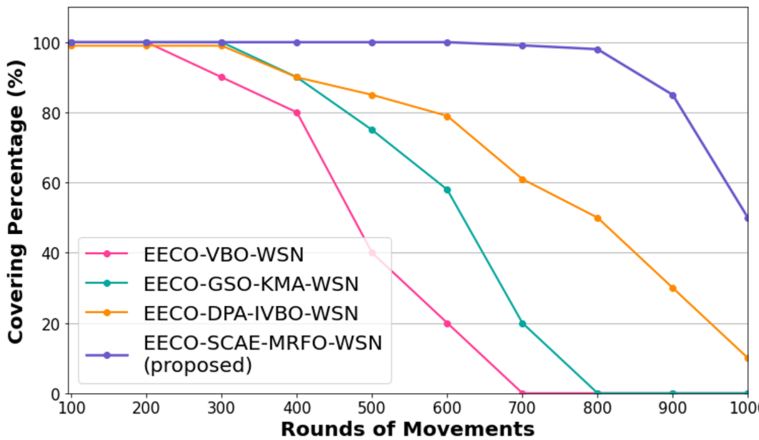


Figure 5 Comparison of delay (see online version for colours)

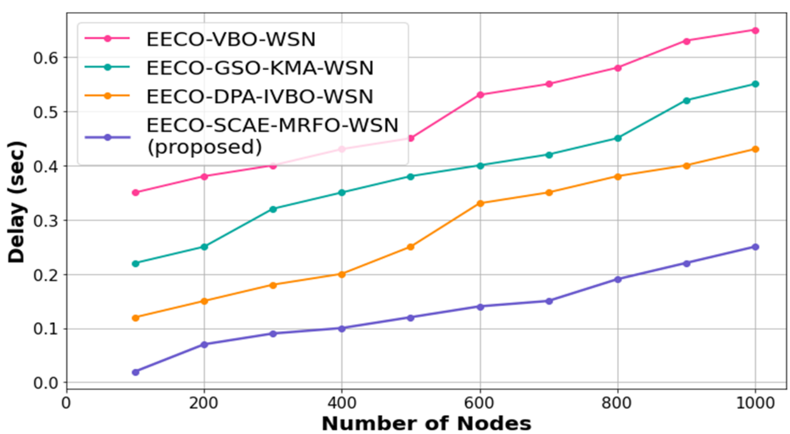


Figure 5 represents delay values comparison. Here, the proposed EECO-SCAE-MRFO-WSN method has attained 34.6%, 30.9%, and 26.87% lower delay for 200 number of nodes, 35.76%, 29.08%, and 25.86% lower delay for 400 number of nodes, 34.08%, 31.98%, and 27.85% lower delay for 600 number of nodes, 37.98%, 32.7%, and 27.65% lower delay for 800 number of nodes, 38.6%, 32.75%, and 28.96% lower delay for 1,000 number of nodes than the existing methods like EECO-VBO-WSN, EECO-GSO-KMA-WSN, and EECO-DPA-IVBO-WSN respectively.

Figure 6 Comparison of network lifetime (see online version for colours)

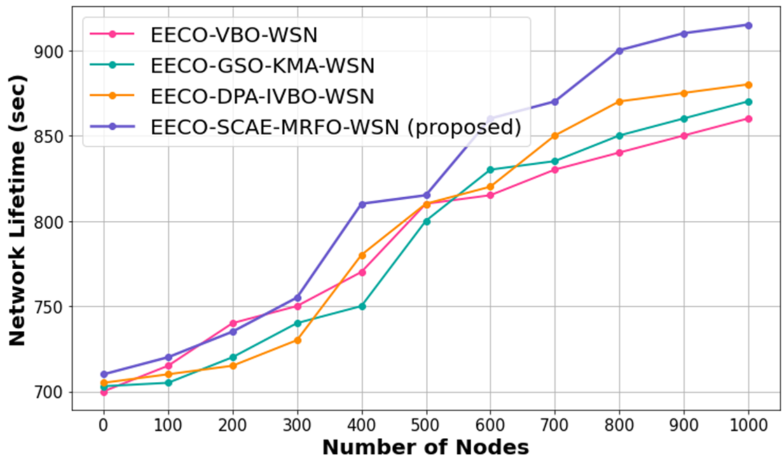


Figure 6 shows network lifetime comparison. Here, the proposed EECO-SCAE-MRFO-WSN method has attained 7.96%, 12.65%, and 9.65% higher network lifespan for 100 count of nodes, 12.76%, 13.87%, and 8.45% higher network lifespan for 400 count of nodes, 16.97%, 14.75%, and 13.78% higher network lifespan for 600 count of nodes, 18.97%, 15.06%, and 10.98% higher network lifetime for 800 count of nodes, 18.97%, 16.7%, and 11.65% higher network lifetime for 1,000 count of nodes than the existing methods, like EECO-VBO-WSN, EECO-GSO-KMA-WSN, and EECO-DPA-IVBO-WSN respectively.

Figure 7 Comparison of computation time (see online version for colours)

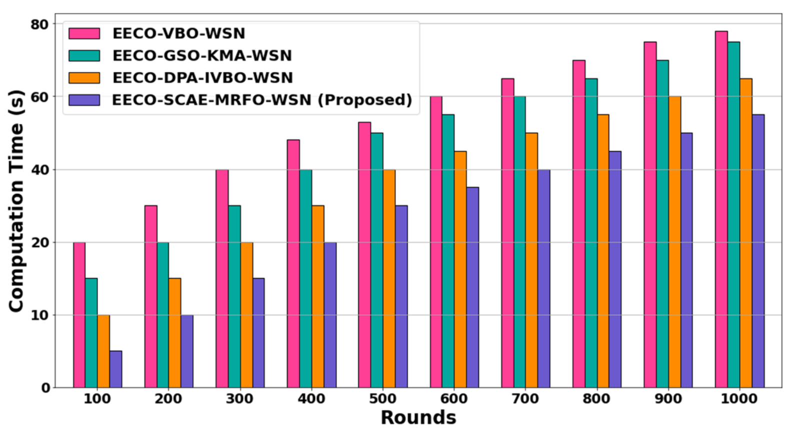


Figure 7 portrays computation time comparison. Here, the proposed EECO-SCAE-MRFO-WSN method has attained 24.76%, 20.98%, and 16.8% lower computation time for 200 rounds of movements, 28.97%, 23.76%, and 17.98% lower computation time for 400 rounds of movements, 27.98%, 24.76%, and 18.76% lower computation time for 600 rounds of movements, 28.09%, 23.97%, and 19.08% lower computation time for 800 rounds of movements, 28.67%, 22.87%, and 16.98% lower computation time for 1,000 rounds of movements than the existing methods like EECO-VBO-WSN, EECO-GSO-KMA-WSN, and EECO-DPA-IVBO-WSN respectively.

Figure 8 Comparison of residual energy balance (see online version for colours)

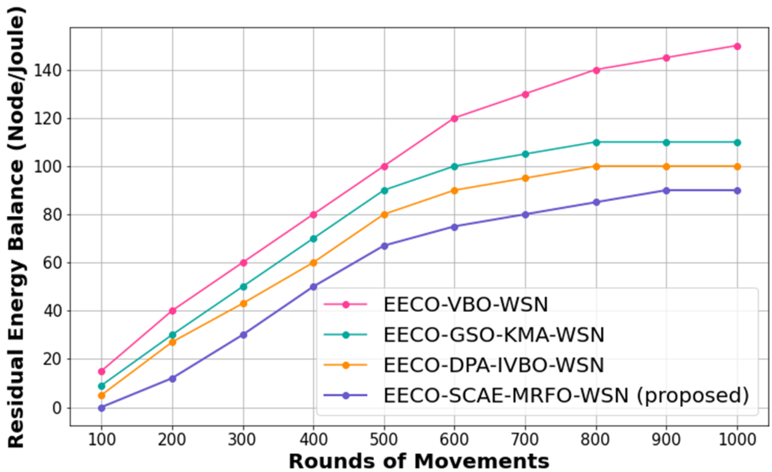


Figure 8 displays comparison of residual energy balance. Here, the proposed EECO-SCAE-MRFO-WSN method has attained 25.87%, 20.09%, and 18.76% lower residual energy for 200 rounds of movements, 24.87%, 20.97%, and 16.98% lower residual energy for 400 rounds of movements, 31.98%, 27.98%, and 22.76% lower residual energy for 600 rounds of movements, 33.76%, 26.87%, and 21.98% lower residual energy for 800 rounds of movements, 35.7%, 27.97%, and 22.87% lower residual energy for 1,000 rounds of movements than the existing methods like EECO-VBO-WSN, EECO-GSO-KMA-WSN, and EECO-DPA-IVBO-WSN respectively.

Figure 9 Comparison of throughput (see online version for colours)

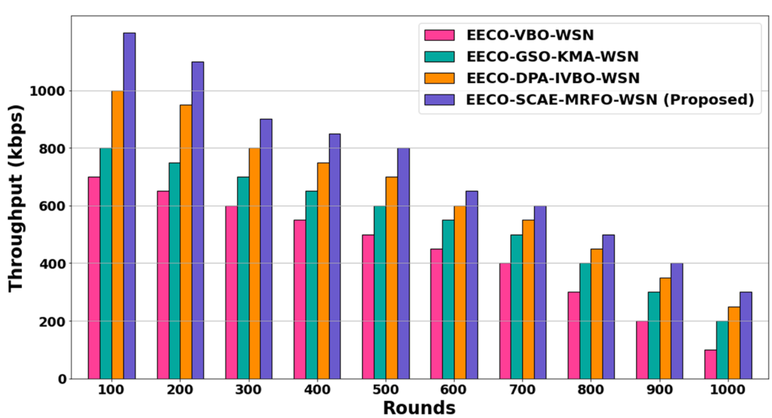


Figure 9 portrays comparison of throughput values. Here, the proposed EECO-SCAE-MRFO-WSN method has attained 27.87%, 23.65%, and 19.87% higher throughput for

200 rounds of movements, 26.86%, 22.65%, and 19.87% higher throughput for 400 rounds of movements, 25.56%, 22.76%, and 20.07% higher throughput for 600 rounds of movements, 24.87%, 19.87%, and 14.65% higher throughput for 800 rounds of movements, 26.75%, 16.90%, and 12.94% higher throughput for 1,000 rounds of movements than the existing methods like EECO-VBO-WSN, EECO-GSO-KMA-WSN, and EECO-DPA-IVBO-WSN respectively.

Figure 10 Comparison of energy consumption (see online version for colours)

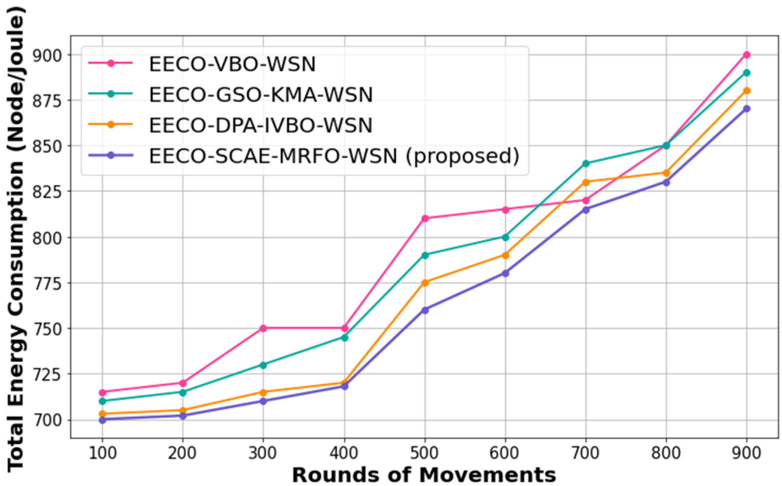


Figure 10 represents comparison of energy consumption. Here, the proposed EECO-SCAE-MRFO-WSN attains19.87%, 16.8%, and 10.9% lesser energy consumption for 200 rounds of movements, 25.76%, 24.09%, and 7.98% lower energy consumption for 400 rounds of movements, 23.76%, 18.96%, and 15.87% lower energy consumption for 600 rounds of movements, 15.87%, 13.65%, and 10.9% lower energy consumption for 800 rounds of movements, 16.87%, 13.76%, and 9.8% lower energy consumption for 1000 rounds of movements than the existing methods like EECO-VBO-WSN, EECO-GSO-KMA-WSN, and EECO-DPA-IVBO-WSN respectively.

5 Conclusions

In this manuscript, energy-efficient coverage in WSN depending on SCAE with Manta Ray foraging optimisation algorithm (EECO-SCAE-MRFO-WSN) is successfully implemented. Thus, the proposed EECO-SCAE-MRFO-WSN algorithm improves the network lifetime by decreasing the energy consumption. The proposed method is implemented in MATLAB, its efficiency is assessed with the help of some performance metrics, like coverage rate, covering percentage, delay, throughput, computation time, network lifetime, residual energy and energy consumption. The proposed EECO-SCAE-MRFO-WSN method has attained 18.9%, 15.76%, and 15.76% higher covering percentage, 24.76%, 20.98%, and 16.8% lower computation time, 24.87%, 20.97%, and 16.98% lower residual energy, 27.87%, 23.65%, and 19.87% better throughput than the existing EECO-VBO-WSN, EECO-GSO-KMA-WSN, and EECO-DPA-IVBO-WSN methods respectively.

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