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A node placement strategy using Moth flame Optimization algorithm to improve network coverage of WSNs

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ABSTRACT

The significant challenges of wireless sensor networks include the connectivity and coverage, which is impacted by the node placement. Accordingly, the cost-effective deployment could be achieved with the optimal sensor node placement in the monitored area. The maximum coverage should be provided by the sensor nodes' positions with maximized network lifetimes. Researchers aim to achieve an optimal deployment that increases the coverage rate and network lifetime with minimization in energy consumption. Moth-Flame optimization algorithm is a bio-inspired optimization method that is used to solve k-coverage node deployment on target based WSN. However the conventional MFO algorithm suffers from premature convergence and stagnation problems. In this work, a new approach of MFO with mutation capability - MUMFO has been introduced to balance the exploration and exploitation capability of the traditional MFO and to increase coverage rate and connectivity. The moths are divided into three categories namely 'good', 'average' and 'bad' moths, based on the evaluated fitness values and mutation is performed among these categorized moths. The proposed strategy of MUMFO node deployment strategy has been compared with the existing node deployment strategies PSOIL & EDEM node placement methods. The MUMFO algorithm's effectiveness has been demonstrated in the simulation results that achieved better data delivery rate, minimal energy consumption rate, and maximum coverage.

Keywords: Energy consumption, connectivity rate, optimum coverage, Moth-Flame Optimization algorithm, optimal sensor nodes, WSN.

I. INTRODUCTION

WSNs include different interconnected devices with limited processing power and lower energy source [1]. The sensed environment is enabled and monitored it based on different sensors at anytime from anywhere. The communication of these devices is occurred and collaborate them to achieve the mission.

The broad range of applications have been included in the WSNs due to the easier deployment, lower cost, and flexibility of the sensor devices, such as disaster detection and control, home automation, defence and military surveillance, industrial processes, safety and medicine, environmental monitoring, smart and logistics transport, etc. [2]. The limited energy sources are included in the sensor network nodes. In most of the sensor networks' proposed protocols, the major considerations for designing are maximum network lifetime, and optimum sensor nodes' energy resources utilization [3].

In the sensor target coverage, the main issue is the sensors' placement, which estimates the essential properties, like network lifetime, cost, accuracy, and coverage connectivity [4]. Within the area, it's necessary to coverage each target by k nodes at least in this application type. It's not suitable to make the random deployment of nodes as it doesn't ensure the complete connectivity and network coverage. In case of expensive sensor node or their position is affect the operation significantly, the pre-planned sensor deployment is used [5]. The number of deployed nodes can be minimized with the deterministic placement that leads to the minimized network cost. Additionally, the transmitted messages' count to the base station can be reduced by minimizing the deployed sensor number. Thus, the energy consumption can be reduced globally and extended the network lifetime. In all of the deployment strategies, it's critical to ensure the optimal connectivity and coverage over the network [6].

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It's important to estimate the sensor nodes' optimal locations to deploy them effectively as their positions can be impacted the sensing coverage, operational lifetime, and energy consumption [7]. Therefore, the effective and careful deployment of sensor node is required while a trade-off is existed between the network coverage and nodes' energy consumption. The energy consumption will be reduced with the closer sensor nodes but the coverage area of a network will be smaller. The numerous research works have been attracted to this scenario on deploying the WSN sensor node.

In many of the sensor deployment formulations, the main challenge is the optimal node placement [8]. To determine the sub-optimal solutions, different heuristics have been considered to handle such type of complexity. These optimization strategies is static in nature specifically that means the candidate positions' quality has been analysed based on the structural quality metrics, such as network connectivity, distance, or the analysis on the fixed topology [9]. The strategies are classified into the static approaches. As the initial positions' optimality may become void in the network operation, some of the methods have been advocated the dynamic adjustment of locations of nodes by relying on the network state and other relevant external factors. For example, the traffic patterns can be changed according to the monitored nodes or not balanced the load among nodes that causing the severe bottlenecks of a network [10].

As the new nodes are joined in the network or the existing nodes are running out of energy, the application-level interest and the available network sources may be changed.

To achieve the optimum connectivity and coverage rates, a new approach has been introduced by using the Mutated Moth Flame Optimization algorithm (MUMFO). A new mutation strategy has been proposed in this work for balancing the MFO algorithm's exploitation and exploration capability. Based on the fitness values, the MUMFO node placement strategy has been categorized into three types, such as 'bad', 'average', and 'good' moths after evaluating the fitness of moths. From each bad and good category, two random moths are chosen for mutation and the difference between bad and good moths has been added in the third moth, which is selected from the average moth.

Our contributions

- The mutated moth flame optimization strategy is considered for balancing the exploitation and exploration of the MFO algorithm.
- In the proposed MUMFO node placement strategy, the moths are categorised as good, average and bad moths according to the fitness evaluation.
- The optimal position for the nodes are calculated after mutating the fitness values of every moths using mutation process.
- The optimal node positioning strategy using MUMFO increases the network connectivity by placing nodes in the appropriate placements and improves the data delivery rate.

Coverage Model for WSN

In a 2D region, the m number of sensor nodes have been placed in the WSN model and they can represent as N = {N1, N2,….Nm}. However, the ith node position is defined as Ni = (xi, yi), where i = (1,2,….m). From the grid point G(x,y), the Euclidean distance can be determined for ith node by using the below formula (1):

$$d = \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad \text{Eq (1)}$$

Where, x and y represent the grid point coordinates G and xi and yi represent the sensor node Ni's coordinates.

A binary detection model is followed in our work and coverage of the sensor node N_i at grid point G is defined as follows equation (2):

$$CV_{xy}(N_i) = \{1,\ d \leq r\ 0,\ otherwise \quad \text{Eq (2)}$$

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Where, r and d indicate the node's sensing radius and the Euclidean distance between the grid point and ith sensor node.

The coverage optimization is having the core objective of providing the sufficient coverage rate based on the lower number of sensor nodes. Based on the coverage rate, the performance of a network has been determined using below equation (3):

$CVR = \frac{GP_{sum}}{P*Q}$ Eq (3)

The area 2D is partitioned into the grid points P*Q. The sensor nodes coverage involves the summation of grid points that represent as GP_{sum}.

Problem statement

The problem in achieving network coverage is the sensor nodes need to be placed at minimum number of selected potential positions to full fill the target coverage. Let's consider the target areas as $T_{area} = \{t_1, t_2, t_3 \ldots t_n\}$. A set of given possible points are represented as $P_{pos} = \{p_1, p_2, p_3, \ldots p_n\}$. The CR_n reprensts the communication range of the nodes. The sensing range can be denoted as SR_n. The distance between the nodes and target area can be represented as $dis(t_i, s_j)$. The coverage of the node can be represented as follows equation (4),

$COV = \{s_j \mid dis(t_i, s) \leq SR_n\}$ Eq (4)

II. Literature survey

The considerable attention has been given to problem of a node placement for linear network topologies. Tran et al., [11] has proposed a method of joint network coding and adaptive power control via the regulation of transmission power for improving the bandwidth usage and reducing the overall energy consumption. The effective results have been achieved using the approach than the previous existing methods. Guo et al., [12] has investigated the issue of node placement for monitoring of oil pipelines under the equal-distance and equal-power node placement methodologies. Two heuristics have been proposed for proper distribution of sensor nodes with their power levels that focusing on achieving the prolonged network lifetime. Additionally, it aims to increase the sensor nodes' density that are nearer to the BS and configure them for data transmission at low power levels. A mathematical model has suggested for validating the heuristics of the network and enhanced network lifetime of 29% than the equal distance placement method. 6 of 31 power levels have been used by focusing on the transmission power only. For real deployment of sensor nodes, the approach is not implemented while the exchanged messages are required to be acknowledged at the receiver.

Li et al., [13] has proposed a new method based on the optimal number of nodes and the compressive sensing. By restricting the higher number of nodes utilization, it can reduce the number of drill holes in the pipelines while detecting the leakages of pipelines. In real case, it's not practical to implement such type of algorithm because of the restrictions in the sensor network, such as limited sensing range and not getting the leak signal for longer distance based on the sensor nodes usage.

Saunhita Sapre et al., [14] has proposed the methodology of two phase relay node placement, including the SNs clustering in the first place and second phase uses the metaheuristc algorithms, such as Biogeography based optimization algorithm (BBO), Bat algorithm (BA), differential equation (DE), and Moth Flame Optimization (MFO). The simulation results demonstrate that the MFO algorithm is outperformed in resolving the fault tolerant relay node placement issue.

Saunhita Sapre and S.Mini et al., [15] have proposed a multi-objective decomposition based moth flame optimization (MOMFO/D) algorithm to resolve the issue of relay node placement. Based on three different quality indicatiors, like maximum spread, spacing metric, and inverted generational distance, the Pareto-optimal fronts have been obtained by assessing the simulation results. The proposed algorithm shows the superior results than

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the existing optimizers, such as multi-objective evolutionary algorithm and multi-objective non-dominated sorted moth flame optimizer.

Nitin Mittal et al., [16] has considered to implement the clustering, which is an efficient data aggregation technique to reduce the energy consumption among sensor nodes. For WSNs operations, the proper CH selection and load balancing are the crucial aspects in the efficient routing protocol. The threshold-sensitive energy-efficient clustering protocol (TECP) based on the moth fame optimization (MFO) has been proposed to achieve the load balancing and energy minimization. The proposed methodology has been outperformed the existing methods based on the analysis of simulation results in terms of stability period, lifetime, and energy consumption.

Cuong Trinh et al., [17] has been presented a distributed fuzzy clustering scheme with the use of two fuzzy logic controllers (FLCs) for organizing the network into some clusters. For selection of fuzzy sink, another FLC is used based on the cluster heads (CHs) and considered the multiple mobile sink nodes. The Moth-Flame optimization algorithm is used to tune the proposed FLCs and minimized the rules. The simulation results prove that the distance-based RED congestion control method and the proposed clustering method are effective in terms of reduced number of retransmissions, improved lifespan of the network, and mitigation of packet loss.

A.Albaseer et al., [18] has been presented the adaptive clustering algorithm to deploy multiple sensors by selecting the cluster head adaptively. The incoming traffic from the members is aggregated and is delivered to the next cluster head until it is reached to the BS. The significant energy saving results have been achieved than the contemporary approaches.

Slaheddine Chelbi et al., [19] has been introduced a new approach with the integration of particle swarm optimization and iterated local search (PSO-ILS) for improving the connectivity rate and optimum coverage among sensor nodes. The optimal position determination (OPD) algorithm has been used to detect the positions optimally. The efficient performance results in ensuring the full connectivity and full coverage of target point with the implementation of proposed technique in comparison to the other existing techniques like DE, PSO, and GA.

III. Proposed method

Moth flame optimization

Sayedali Mirjalili et al., (2015) [20] has developed the MFO algorithm, which is a population based algorithm that was inspired by the transverse movement of moths seen in the nature. Similar to the butterflies, moths are attracted to the light sources and are a species of insects to move towards it. The special nocturnal movement mechanism, known as transverse orientation that has been included in the moths. If in case the light source is distant far away, the transverse orientation has been enabled the moths to fly in a linear path fashion. The spiral path is followed by the moths to move towards the nearer light source.

MFO algorithm considers two essential components, such as flames and moths, which are candidate solutions. In the updation method, the difference is there between two lies. In the search space, the moths are considered as the search agents and the moths attained the best positions during their lifetime, known as flames. However, the flames consider as the moths' footprints during the search space exploration. A better solution could be found out by every moth around a flame during its lifetime and its current location updates if found. Hence, its best position is never lost [21] [22].

For evaluation, M moths' initial population is considered in MFO. In the nd-dimensional hyperspace, the global solution is required to be found. Here, d is the dimension and n are the number of optimal parameters that required to be determined. At Xid, a moth i will be located, where $1 \leq d \leq nd$ and $1 \leq i \leq M$. Based on a fitness function $p(x_1, x_2, \dots\dots x_{nd})$, each moth is evaluated, where $p : R^{nd} \rightarrow R$.

Based on a full connectivity parameter as the fitness function, the moth population is evaluated. Primarily, the number of moths and flames are considered as equivalent. With the consideration of number of iteration, the number of flames are determined as follows equation (5):

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$n_{flames} = round\left(N - l * \frac{N-1}{Iter_{max}}\right)$ Eq (5)

Where, $iter_{max}$ refers to the total number of iterations, N is the maximum number of flames, and l indicates the current iteration number.

The positions of moth is updated using the logarithmic spiral equation in regarding the flame positions, as follows equation (6):

$MO_{id} = dis_{id} \,.\, e^{bt} \,.cos\, cos\, (2\pi t) \; + Fl_{jd}$ Eq (6)

Where, Fl_{jd} and MO_{id} represent the jth flame and ith moth in d dimension. $t \in [-1, 1]$ is a random number and b defines as the spiral shape, while dis_{id} is the Euclidean distance between jth flame and ith moth in d dimension. MFO complexity is $O(m^2)$, where m indicates the number of moths.

The below-mentioned figure 1 shows the detailed flowchart of MFO algorithm:

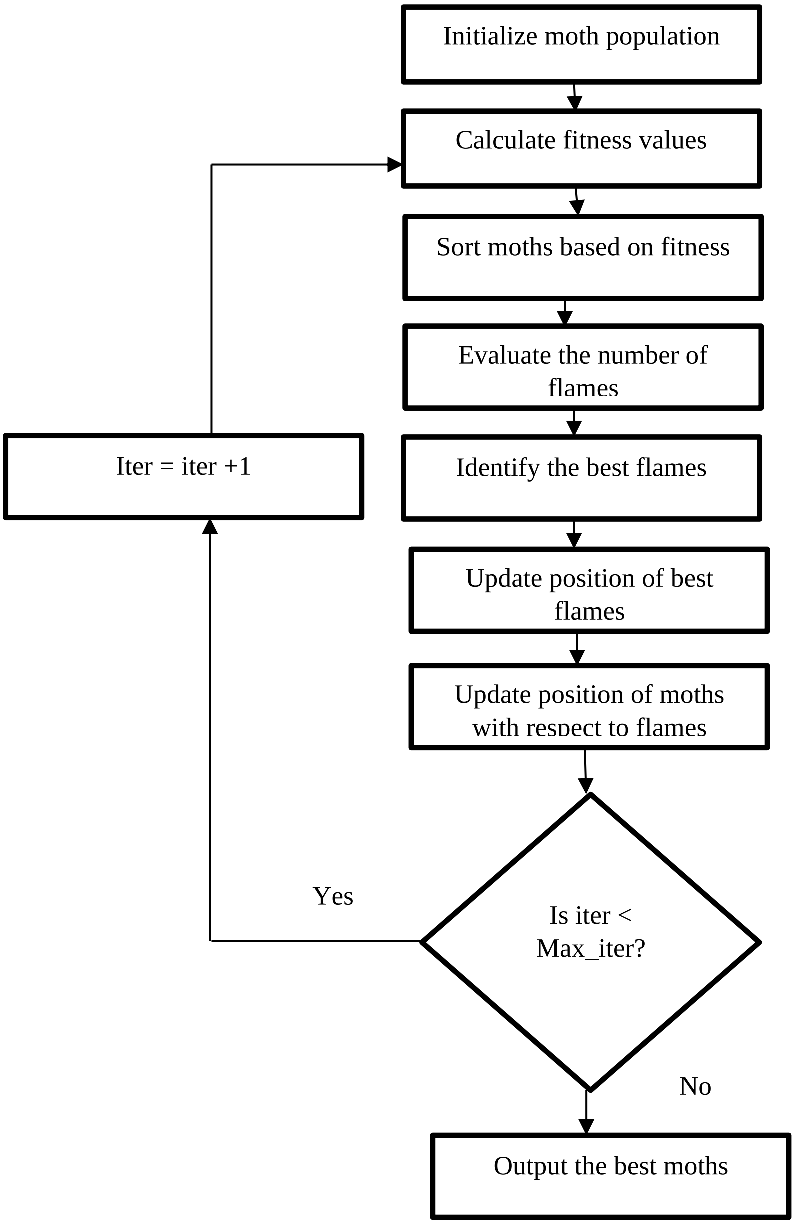

Fig. 1: MFO algorithm flowchart

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Optimal node positioning using MUMFO strategy

Different complex real-world engineering design issues have been resolved using the classical MFO algorithm. But, the algorithm has been faced the issues like stagnation and premature convergence. The MFO algorithm effectiveness has been computed by considering the fitness values. Compared to the previous population, the better improvement of fitness values is showed with the current generation moths for each generation. The fitness value doesn't improved significantly, but it can deduce that all moths convergence is done to the specific location. It's necessary to increase the population of moths and solutions diversity consequently. Figure 2 shows the working process of proposed method.

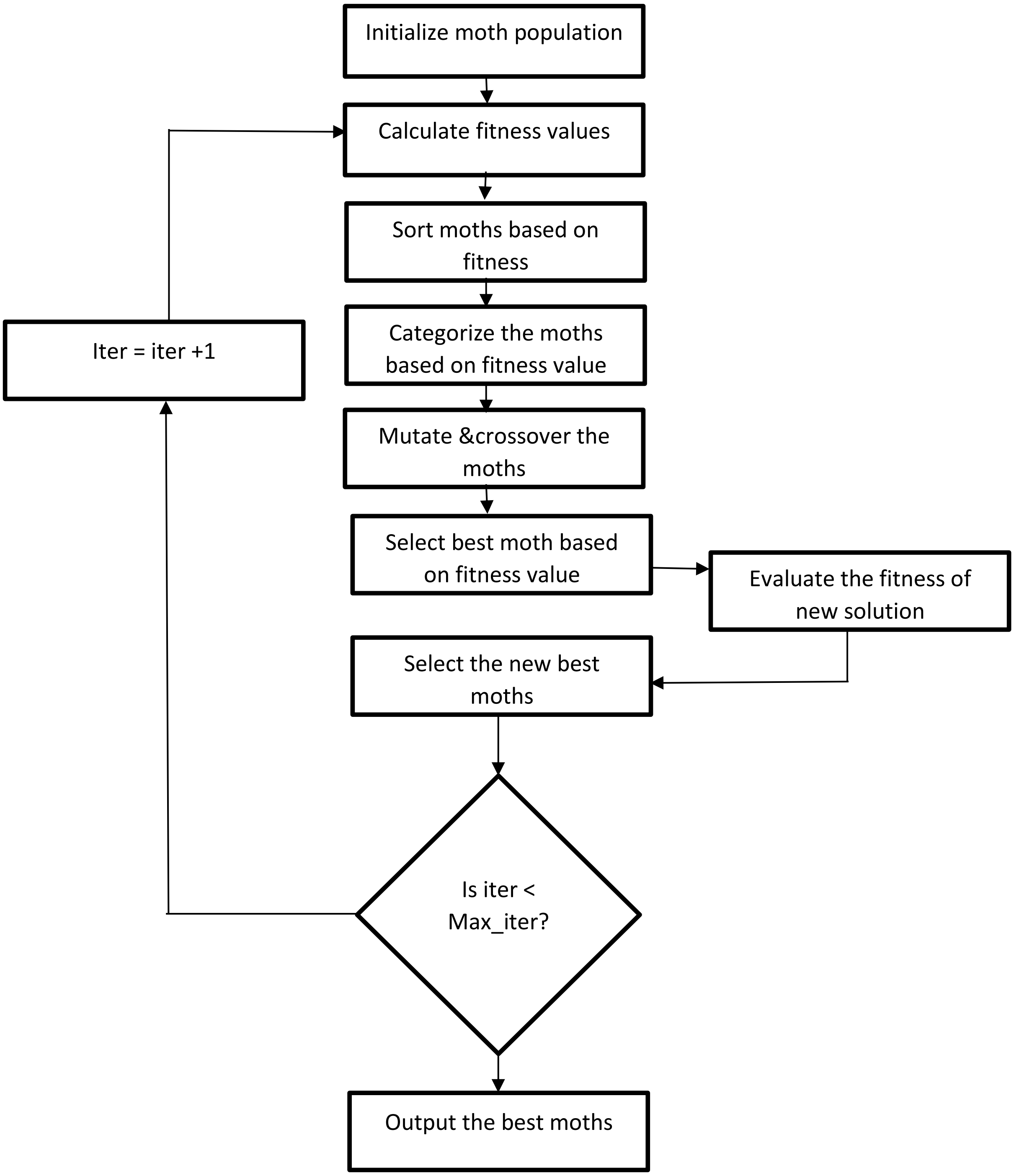

Fig. 2: flowchart of proposed MUMFO node placement strategy

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The new mutation strategy has been proposed in the MUMFO scheme for balancing the exploitation and exploration capability of the MFO algorithm. Based on the fitness values, moths are categorized into three types, such as 'bad', 'average', and 'good' moths after evaluating the fitness values in the strategy of MUMFO node placement. From the bad and good categories, two random moths are chosen for mutation and the difference between bad and good moths is added to the chosen third moth that is chosen from the average moth. Some percentage of moths are considered as good moths, while the same percentage of bottom moths are taken bad moths. The remaining are the average moths in available moths.

Two different random moths have been selected from bad and good categories of each one for mutation. To the chosen third moth from the set of average moths, the difference is added and the equation (7) is as follows for the proposed mutation scheme:

$$XG_{new} = XG_{avg} + \alpha * \left(XG_{good} + XG_{bad}\right) - Eq\ (7)$$

Where, XG_{bad}, XG_{good}, and XG_{avg} refer the bad, good, and average categories of moths, respectively.

$\alpha \in [0, 2]$ indicates the scaling factor for controlling the evolution rate of the moth population. In a crossover operation, the resultant moth is included for generating the set of new solutions. Based on the fitness values, the best individuals are chosen in each generation and they represent as follows equation (8):

$$XG_{cr} = \{XG_{avg}, \quad if\ rand\ (0,1) \geq \delta\ XG_{new}, \quad otherwise \qquad - Eq\ (8)$$

Where, $\delta \in [0,1]$ refers to the crossover rate. The source moth fitness is compared with the mutated moth's fitness and selected the moth of better fitness value for next generation.

Pseudo code for the proposed algorithm

##

Initialize the moth population M_i

For each $i = 1: n$ do

Calculate the fitness function f_i

End for

While ($iteration \leq \ max\_iteration$) do

Sort the moths based on fitness f_i

Identify $XG_{avg}, XG_{good}\ and\ XG_{bad}$ moth population

Mutate the identified moths as per $Eq\ (1)$

Perform crossover as per $Eq\ (2)$

Evaluate the fitness of the new solution

Update the moth positions

Select the best moths as solution

End while

End

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IV. Result and discussion

This section will illustrate the experimental setup followed for performance evaluation and discuss the results of the simulation outcomes. In the experimental simulation part, we simulated the proposed algorithm using NS-2 simulator tool & verified the performance of the algorithm by adjusting the parameters and compared it with other algorithms. The network area is fixed as 1000x600. The network size is varied from 100 to 500 nodes. The sensor nodes are assigned with 100j initial energy. The SINK position is fixed at (500,300) in all the simulation experiments. CBR is configured as traffic type in the network. In order to validate the efficiency of node deployment based on proposed MUMFO strategy, the simulation trials are conducted by varying the above listed parameters. The performance of proposed MUMFO based node deployment strategy is compared with cluster based node deployment approach (EDEM) [18] that used adaptive clustering strategy for grouping the nodes and PSOILS [19] approach that uses PSO incorporated with integrated local search strategy to determine the optimal node position. The simulation parameters for MUMFO are shown below in Table 1.

Table1: Simulation parameter table

Parameter	**Value**
Network area	1000m x 600m
Number of sensor nodes	100, 200, 300, 400, 500
Routing protocol	AODV
Initial energy	100 j
Simulation time	100 s
SINK position	(500,300) (fixed)
Traffic type	CBR
Packet size	512
Transmission agent	UDP

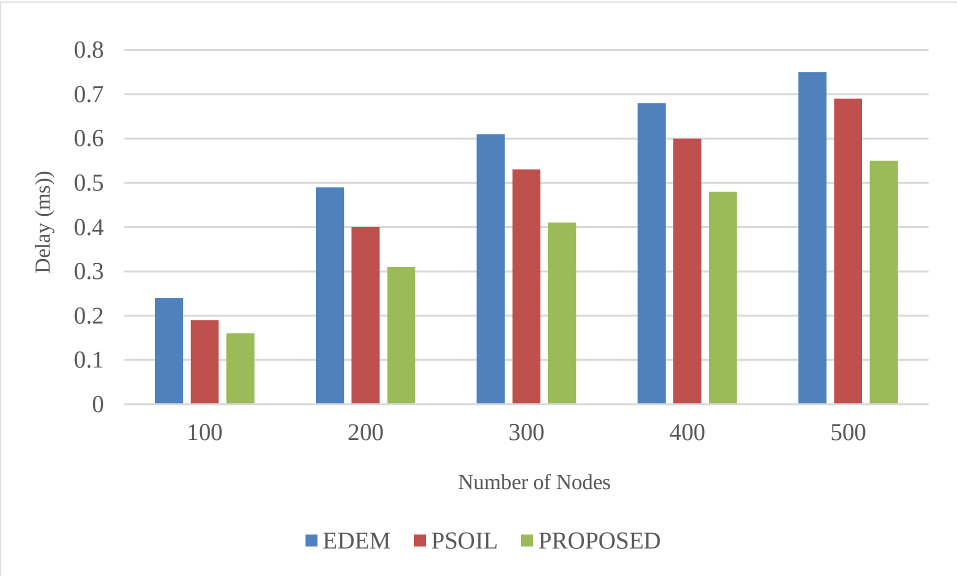

Fig. 3: End to End Delay

NODE	**PROPOSED**	**PSOIL**	**EDEM**
100	0.16	0.19	0.24
200	0.31	0.40	0.49
300	0.41	0.53	0.61

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400	0.48	0.60	0.68
500	0.55	0.69	0.75

The definition of end-to-end delay is described as the time taken for data packets transmission over the network from source to destination node. The end-to-end delay evaluation results of the proposed technique are showed in the above table. The spiral node placement strategy combined with mutation process used in the proposed MUMFO method determines the optimal positions for the sensor nodes which improves the coverage between the nodes. With the improved connectivity, the sensor nodes are able to connect with the neighbor nodes with minimum time delay which results in overall reduction in end to end delay. The minimum average delay experienced in the network was 0.20ms whereas the previous methods yields high delay up to 0.78ms compared to the proposed method. Figure 3 represent the graphical presentation of Overall Delay.

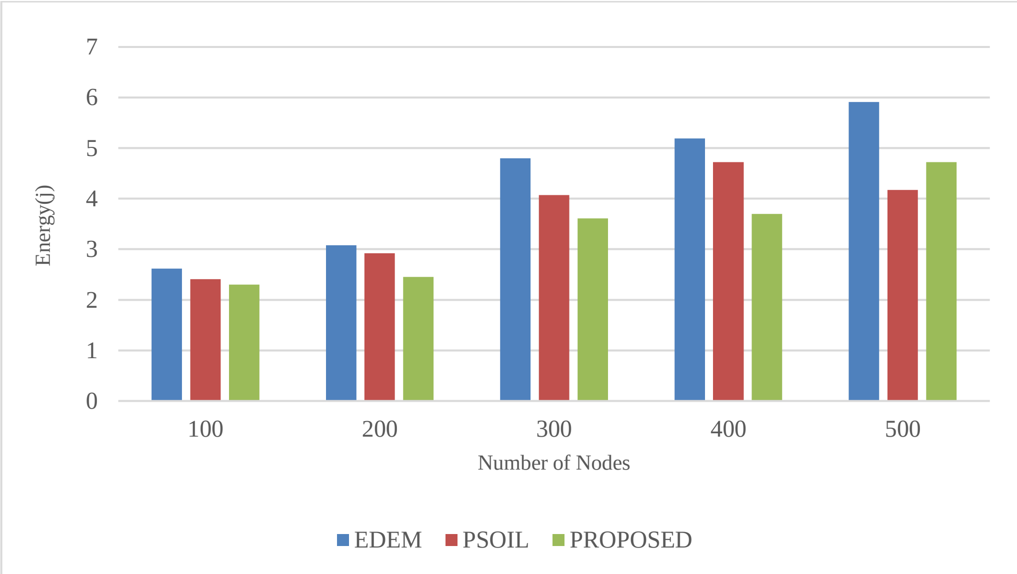

Fig. 4: Energy consumption

NODE	**PROPOSED**	**PSOIL**	**EDEM**
100	2.30	2.41	2.62
200	2.45	2.92	3.08
300	3.61	4.07	4.80
400	3.70	4.72	5.19
500	4.72	4.17	5.91

The network activities have been performed based on the sensor nodes with initial energy, which is depleted for each network activity. For improving the network lifetime, the energy should be optimized. The improved MUMFO has been used to perform the efficient node placement and the trade-off is reduced between exploitation and exploration of MFO. Among the sensor nodes, the unnecessary energy consumption is reduced that results in the lower energy consumption. The proposed technique was resulted as the average energy consumption rate of 2.5 j. figure 4 shows the graphical representation of Energy performance.

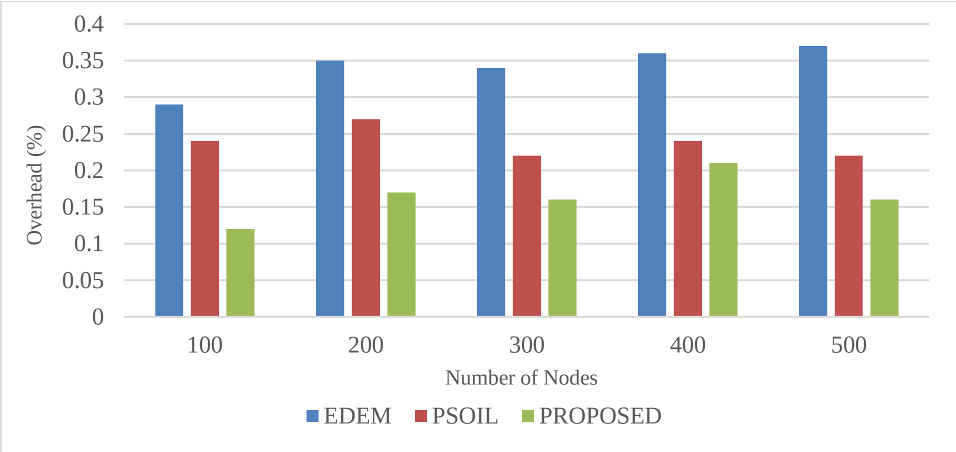

Fig. 5: Routing overhead

NODE	PROPOSED	PSOIL	EDEM
100	0.12	0.24	0.29
200	0.17	0.27	0.35
300	0.16	0.22	0.34
400	0.21	0.24	0.36
500	0.16	0.22	0.37

Broadcasting control packets is a part of route discovery and route maintenance. Number of control packets are broadcasted across the network during runtime. The overhead is related to the amount of control packets broadcasted. Less control packets minimize the overhead of the network. The improved coverage among the sensor nodes due to efficient node placement strategy used in mutated MFO algorithm improves the network coverage that covers the entire network area so efficiently without losing the connectivity among the sensor nodes. So the control packet broadcasting was kept minimized due to increased link stability. The average overhead of the proposed method recorded was 0.18 which is very low compared to the previously used methods. Figure 5 represent the routing overhead of overall network.

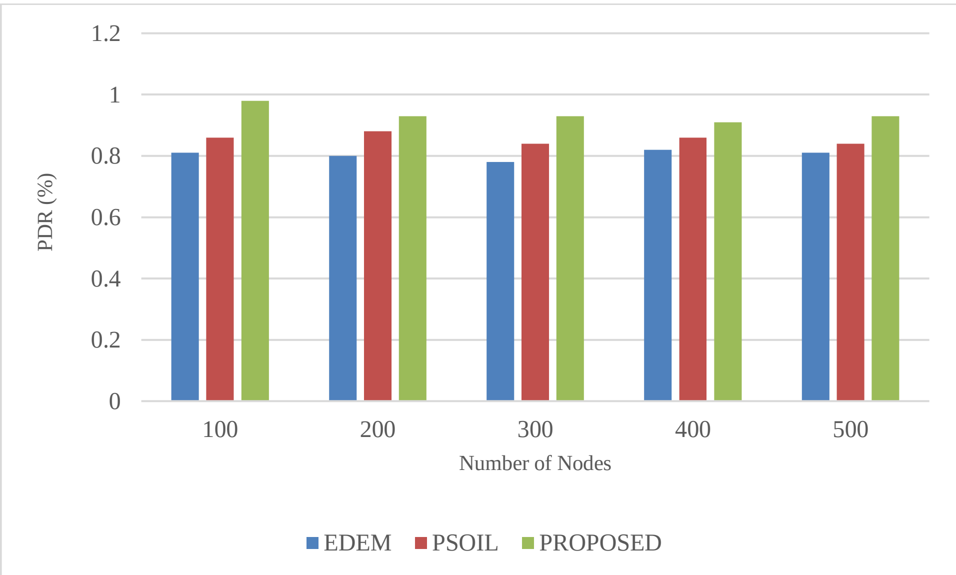

Fig. 6: Packet delivery ratio

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NODE	PROPOSED	PSOIL	EDEM
100	0.98	0.86	0.81
200	0.93	0.88	0.80
300	0.93	0.84	0.78
400	0.91	0.86	0.82
500	0.93	0.84	0.81

PDR can be demonstrated as the ratio between received data packets at the receiver end and the sent data packets by the sender. The placement of sensor nodes at the optimal position determined by the mutated MFO node placement strategy and the coverage improvement between the nodes due to the optimal placement that assists the nodes to forward the data to the target node successfully. The maximum PDR of 0.94% is achieved by the proposed technique while the existing methods were delivered the average PDR rate of 0.87, which is lower PDR rate comparatively. Figure 6 shows the delivery ratio of overall network performance.

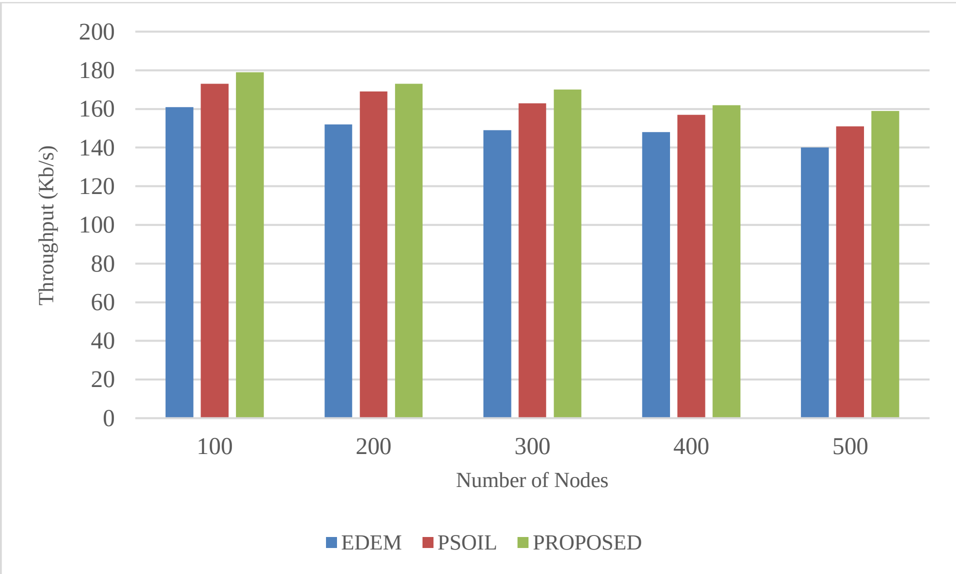

Fig. 7: Throughput

NODE	PROPOSED	PSOIL	EDEM
100	179	173	161
200	173	169	152
300	170	163	149
400	162	157	148
500	159	151	140

Throughput is described as the measurement of processing the total number of data units in a given time period. The optimal placement of the sensor nodes at the position determined by the proposed mutated MFO strategy and the improved coverage among the sensor nodes helps to improve the data aggregation. The higher throughput rate is resulted by the proposed technique than the existing methods from the above table. In the experiment, the proposed method maintained the average throughput rate as up to 168kbps whereas the existing methods maintained low throughput rate than the proposed one. Figure 7 represent the overall throughput of network.

Conclusion

In this work, we have proposed a met heuristic optimal node placement algorithm named MUMFO that combines the advantages of the traditional MFO to place the nodes in an optimal locations. The conventional MFO algorithm suffers from premature convergence and stagnation problems. In order to balance the exploration and exploitation capability of the traditional MFO, mutation is integrated along with the MFO optimization strategy. The fitness of the moths are evaluated as per MFO and the moths are divided into three categories namely 'good', 'average' and 'bad' moths based on evaluated fitness values. In order to overcome the exploration and exploitation nature of MFO, mutation is performed among the categorized moths and an optimal solution is achieved from the final mutated moths. The proposed MUMFO node deployment strategy has been compared with the existing node deployment strategies PSOIL & EDEM node placement methods. The simulation results reveal that the proposed MUMFO strategy achieved better data delivery rate, minimal energy consumption rate, and maximum coverage.

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