Energy Aware Metaheuristics based Path Planning Technique with Mobile Sinks for Wireless Sensor Networks

K. Umamaheswari [1] ,Research Scholar, Dept of ECE , Koneru Lakshmaiah Education Foundation(Deemed to be university), Guntur,A.P,India.

Assistant Professor, EIE Department, V.R.Siddhartha Engineering College, Vijayawada,A.P,India.

E mail :: kunduru.uma@gmail.com

Dr. A. Kiran Kumar[2], Associate Professor, Dept of ECM,,Koneru Lakshmaiah Education Foundation(Deemed to be university), Guntur,A.P,India.

E mail : : kiran.anumandla@kluniversity.in

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Abstract

In recent years, wireless sensor networks (WSN) becomes a vital part of the emerging Internet of Things (IoT) due to their applicability in several real time applications. But a crucial challenge that exists in the WSN is due to maximum energy dissipation of the nodes and minimum network lifetime. Some of the possible solutions to accomplish reduced energy utilization and increased lifetime of WSN are clustering, routing, data aggregation, etc. With this motivation, this article introduces an energy aware metaheuristics based path planning with mobile sinks (EAM-PPMS) technique for WSN. The goal of the EAM-PPMS technique is to choose cluster heads (CHs) and optimal paths for MS. The EAM-PPMS technique initially performs chicken swarm optimization (CSO) based clustering process to pick out a set of CHs and organize the network into a set of clusters. Besides, the water strider algorithm (WSA) based path planning technique for MS is derived to reach the destination in an optimal way. The path planning technique is mainly based on the derivation of objective function with the minimization of cost, distance, and delay. The extensive simulation analysis of the EAM-PPMS technique is carried out and the results are inspected in terms of different measures like NODN Analysis, Loss packet and NRE Analysis for both Homogeneous and Heterogeneous Environments. The simulation results portrayed the betterment of the EAM-PPMS technique compared to the recent approaches.

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1. Introduction

The wireless sensor network (WSN), comprised of a massive amount of static or mobile sensor nodes in a multi-hop and self-organizing method, is extensively utilized in medical health, environmental monitoring, military, building monitoring, smart homes, etc [1]. In the water area detection of classical WSN, terminal node transmits data to sink node through multi-hop [2]. But multi-hop communication aims at creating an energy hole. In another word, the node near the sink node, undertake numerous data transmission tasks, and therefore exhausting the energy or consuming a lot of energy, would loss the connectivity of the whole wireless network. Simultaneously, the multi-hop communication produces further transmission overhead because of the collision caused by data transmission and frequent communication among the nodes [3]. To resolve the abovementioned problem, a WSN using mobile nodes has been developed. The sink node is continued through mobile terminal to gather information that prevents uneven energy consumption and energy hole, extends the lifetime of the entire network, as well as enhances the reliability of data transmission and the flexibility of data collection [4]. Various energy-effective methodologies have been carried out for extending the node life cycle and maintaining the battery power [5]. Duty-cycle scheduling approach is one of these approaches which allows the sensor to carry out sleep mode occasionally without disturbing the WSN process. An alternative method is using an energy-effective routing technique which balances the power utilization in all the sensors [6]. When the data aggregation model is utilized for integrating different or similar sensor information as to single packet, and thus a decrease from data communication can be attained, and also lifetime of the node is prolonged [7]. Another energy-efficient approach is for deploying mobile sensor nodes which travel through the sensing fields and change their location according to the energy levels of another node.

The mobile sink changes their position from the sensing region for collecting the information in the sensors and increase lifetime of the network [8]. It is noteworthy that the abovementioned energy effective methods might coexist in similar sensor fields. The sensors deplete sufficient energy to carry out data transmission and sensing towards the sink nodes [9]. The sensors nearer to the sink nodes consume their remaining energy quicker when compared to the distant nodes because of heavy data traffics when transmitting the other sensor information. Sensor deaths near the sink nodes would lower sensing coverage and cause topology disruption [10]. This scenario is named a hot-spot problem and results in hindering the aggregation of sensory information and isolating the sink nodes over the networks. The mobile sink node is applied to mitigate the hot-spot problem while visiting all the sensors in the sensory area at the time of gathering information. But the sink node traveling might be taking considerable time, particularly in larger sensor domains, and therefore some packets might be dropped by sensors because of finite buffer size [11]. Consequently, efficient delay-aware mechanism is demanded extending the network lifetime and reducing the packet losses.

Kirsan et al. [12] present multihop simulated annealing (MhSA-LEACH) using a LEACH protocol based intraclustermultihop transmission. The election of intermediate node in multihop technique is performed by utilizing SA model on Traveling Salesman Problem (TSP). Hence, the multihop nodes were chosen according to the shorter distances and could only be skipped one time by using the probability concept, resultant in an optimum node path. Pang et al. [13], proposed a path-based path equalization algorithm (PEABR) to alter the paths of MN, additionally equalize and decrease the distance of the MN for satisfying the constrained condition, and improve the path planning system. Lastly, experiment was conducted by utilizing Matlab simulator, and the experiment that was carried out in laboratory environments showed the effectiveness and of feasibility the model.

In Houssein et al. [14], the Harris hawks' optimization (HHO) technique is applied for solving these problems and then Prim's shortest path method is utilized for reconstructing the networks by making minimal communication path from the sink to the remaining sensors. Das and Jena [15] introduce an advanced methodology to calculate an optimum collision free trajectory path for every robot from complex and known environments. The issues under discussion have been resolved by applying an improved PSO (IPSO) using evolutionary operator (EOP). During the current situation, PSO is enhanced by the concepts of governance in human society and 2 evolutionary operators like multi-crossover inherited under the GA, besides bee colony operatorsfor improving the strengthening ability of IPSO model.

Wang et al. [16] developed an enhanced ACO method to avoid difficulties in static environment which address the problem of a low path quality and single evaluation factor of the classical ACO mechanism in path planning. The advances are ii) the corner system is proposed as a post-processing technique of path optimization for additional smoothing the path, ii) the pheromone upgrade equation is improved, iii) the probability selection equation of the ACO is improved, and iv) a fuzzy planner is created based on the complete assessment model of fuzzy mathematics and the analytic hierarchy procedure to completely determine and estimate the impacts of environmental factor[22-25].

This article introduces an energy aware metaheuristics based path planning with mobile sinks (EAM-PPMS) technique for WSN. The EAM-PPMS technique initially performs chicken swarm optimization (CSO) based clustering process to pick out a set of CHs and organize the network into a set of clusters. Followed by, the water strider algorithm (WSA) based path planning technique for MS is derived to reach the destination in an optimal way. Furthermore, the path planning technique is mainly based on the derivation of objective function with the minimization of cost, distance, and delay. Comprehensive experimental validation of the EAM-PPMS technique is performed and the results are inspected interms of varying aspects.

2. The Proposed Model

In this study, an effective EAM-PPMS technique has been developed to choose CHs and optimal paths for MS.Fig. 1 illustrates the work flow of EAM-PPMS manner. The presented EAM-PPMS technique involves two major processes namely CSO based clustering and WSA based path planning. The WSA based path planning technique for MS is derived to reach the destination in an optimal way. The operational principle of each module is discussed in the following:

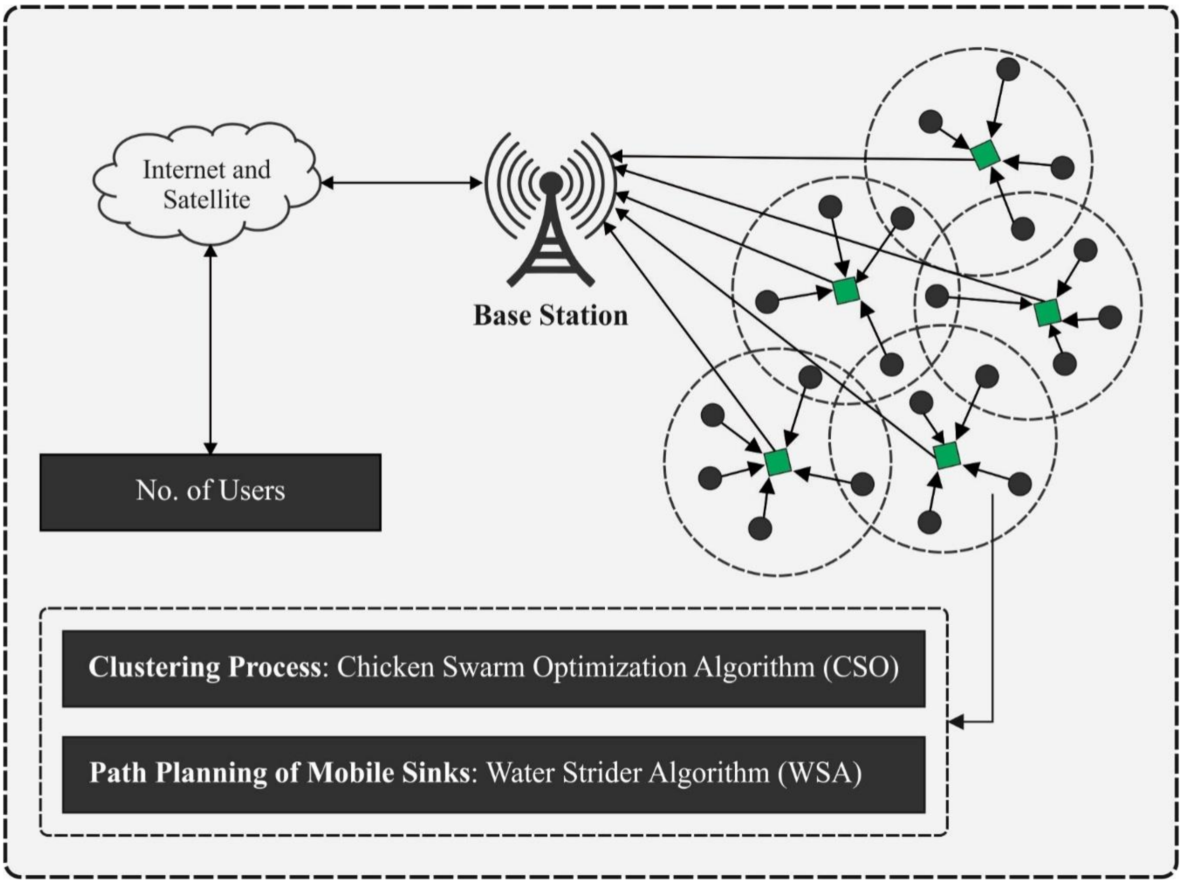

Fig. 1. Workflow of EAM-PPMS technique

In presented model, the power of the electromagnetic wave weakens as the distance between the transmitter and the receiver rises. The power used by a wireless sensor to receive and send l bit data could be denoted as E_{Rx} and E_{Tx}, correspondingly.

$$E_{Tx}(l,d)=\begin{cases} l\cdot E_{elec}+l\cdot \varepsilon_{fs}\cdot d^2, d<d_0 \\ l\cdot E_{elec}+l\cdot \varepsilon_{amp}\cdot d^4, d\geq d_0 \end{cases} \tag{1}$$

$$E_{Rx}(l,d)=l\cdot E_{elec} \tag{2}$$

Where as E_{elec} denotes the circuit energy loss coefficient to send and receive unit bit data. When the broadcast distance is lesser when compared to the threshold d_0, power amplifier loss uses a free-space method. Or else, the attenuation algorithm is utilized. ε_{fs} and $\mathcal{E}_{am}1$, indicates the energy needed for every bit of data transmitted by the amplifier in the two methods, correspondingly. The lower the d_0 is, the higher the possibility of utilizing the multi-path attenuation algorithm l is, leads to a shorter network lifetime and better the energy consumed. Widely employed constant value is given below:

$$d_0=60\mathrm{m}, \mathrm{Elec}=50\mathrm{nJ/bit}, \varepsilon_{fs}=10\mathrm{pJ/(bit\cdot m^2)}, \varepsilon_{amp}=0.0013\mathrm{pJ/(bit\cdot m^4)}.$$

Since the node in the cluster only needed to forward the information gathered to the CH node, the power utilization of the member node in all the clusters are shown in the following:

$$E_{mem}(j)=l\cdot E_{elec}+l\cdot \varepsilon_{fs}\cdot d^2(j) \tag{3}$$

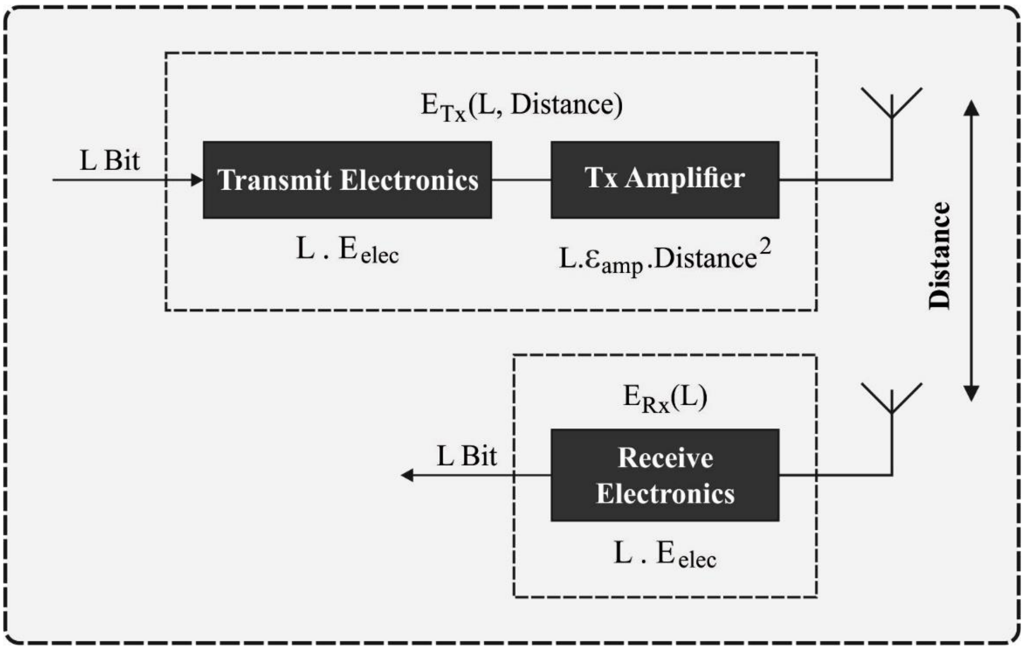

Fig. 2. First order radio energy model

Fig. 2 illustrates the first order radio of energy model. While d(j) represents the distance between CH node and the member node j. Since the CH nodes need to combine the information of each node in the cluster, later send the incorporated information. The power utilization of all the CH nodes are given in the following:

$$E_{CH}(i) = E_R(i) + E_F(i) + E_{Tx}(i) \quad (4)$$

$$E_R(i) = l \cdot E_{elec} \cdot Num_{CH}(i) \quad (5)$$

$$E_F(i) = l \cdot E_{fuse} \cdot Num_{CH}(i) \quad (6)$$

Where, $E_R(i)$ denotes the energy used by the CH node i to gather the information of each node in the cluster. $E_F(i)$indicates the energy used by the CH node i for data integration of the gathered node data in the cluster. $Num_{CH}(i)$denotes the amount of nodes in the cluster which belongs to CH node i. $E_{Tx}(i)$ signifies the power utilization of the CH node i to send 1 bit of information to another CH or sink node, evaluated using Eq. (1). The constant $E_{fuse} = 5nJ/bit$.

2.1. Stage 1: CSO based Cluster Construction Process

CSO is a SI optimization model developed by Meng et al. [17]. This model splits a chicken flock into chick, rooster, and hen groups as per the individual fitness value of the chicken flock. Next, the chicks, roosters, and hens search in the solution space in a certain manner. All the particles in the model signify a possible solution to the problem. Lastly, the fitness value of the three groups is widely compared to detect the global optimum particle and the global optimum value. Rooster corresponds to the individual with the optimal fitness value in the flock. They could detect food in a broader space. The position upgrade respective to the rooster is given below.

$$X_{i,j}^{t+1} = X_{i,j}^{t} * (1 + R\,an\,dn(0, \sigma^2)) \quad (7)$$

$$\sigma^2 = \begin{cases} 1, \mathrm{iff}_l \le f_k, \\ \exp\left(\frac{f_k - f_1}{|f_i| + \varepsilon}\right), \mathrm{otherwise} \end{cases} k \in [1, N], k \ne i. \tag{8}$$

Randn $(0, \sigma^2)$represent a Gaussian distribution with a mean of 0 and a standard deviation of $\sigma^2 \varepsilon$ indicate the minimum constant in the computation. To prevent failures from dividing by zero, k is the label of a rooster arbitrarily chosen in the rooster population. findicate the fitness respective to x. The location of the hen is upgraded as follows

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S1 * \mathrm{Rand} * \left(x_{r1,j}^{t} - x_{lJ}^{t}\right) + S2 * \mathrm{Rand} * \left(x_{r2,j}^{t} - x_{lJ}^{t}\right) \tag{9}$$

$$S1 = \exp\left((f_i - f_{r1})/(\mathrm{abs}(f_j) + \varepsilon)\right) \tag{10}$$

$$S2 = \exp\left(f_{r2} - f_i\right) \tag{11}$$

Whereas Rand denotes an arbitrary value within [0,1]. r1signifies the label of a rooster arbitrarily chosen from the population as the spouse of ith hen [18]. r2shows the label of a chick arbitrarily chosen, and $r1 \ne r2. f_i > f_{r1}$ and $f_i > f_{r2}$, so $S2 > 1 > S1$. When $S1 = 0$, it implies that the ith hen could only steal food from another chick. When $S2 = 0$, the ith hen would be in its territory foraging. The location of the chick is upgraded by

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL * \left(x_{m,j}^{t} - x_{i,j}^{t}\right) \tag{12}$$

$x_{m,j}^{t+1}$denotes the location of the mother of ith chick. FLdenotes an arbitrary variable, that implies that the chick would follow its mother for searching food. Considering individual differences, the FL of every chick would be in the interval of (0,2).

The CSO technique aims to choose a set of nodes for working as CH as that minimized the energy utilized to data broadcast. For instance, the optimized objective is for determining an optimum set of nodes for working as head which prolongs the network lifespan and minimizes the energy utilized. The main purpose of this technique is for maximizing the lifespan of network (δ_n^n) which end once the primary node dies and it can be computed as:

$$\delta_n^1 = \min_{s \in S} \delta_s \tag{13}$$

where, δ_s refers the lifespan of node s and S signifies the group of nodes from the networks. Assume that n sensor nodes were shared equally, and it can k cluster. So, it must n/k nodes per cluster (1 CH and $(n/k) - 1$ CMs). Entire energy utilized by CH (e_{CH}) to a single round was provided as:

$$e_{CH} = \left(\frac{n}{k} - 1\right). E_{Rx}(b) + \frac{n}{k}. b. E_{DA} + E_{Tx}(b, d_{toBS}). \tag{14}$$

The CM node sends their information to its CH, since the outcome, the whole energy utilized by CM node on iteration as follows [19]:

$$e_{CM} = E_{Tx}(b, d_{toCH}). \tag{15}$$

where, d_{toBS} and d_{toCH} stands for the average distance amongst the head node as well as BS, and the average distance amongst member node as well as CH correspondingly. The whole energy utilization from a cluster under the iteration as:

$$E_{consumed}^{cluster} = e_{CH} + e_{CM} \tag{16}$$

The purpose is for maximizing δ_n^1 with minimized entire energy utilized from the network per round thereby CH rotation attained to balance energy utilized. Since the outcome, the FF was provided as:

$$F = \frac{\sum_{i=1}^{k} E_{consumed}^{cluster}(i)}{a + \sum_{i=1}^{k} E_{consumed}^{cluster}(i)} + \left(\frac{\beta}{a+\beta}\right) \tag{17}$$

where the amount of CHs signified as k, β implies the entire amount of time the chosen nodes effort as CH and a represent the constant superior to 0.

2.2. Stage 2: WSA based Optimal Path Planning Process

Once the clusters are produced, the next level is to determine the optimal paths. The WSA is a population-based SI optimization model which is motivated by the water strider life cycle. WSA stimulates territorial behavior, water striders' feeding, succession, mating style, and intelligent ripple communication models. This strategy was executed for utilizing mathematical expressions which represent WSA by [20]. As a result of the surface tension of the water and hydrophobic legs of WS, this family of animals has attained a natural capability to live on surface of the water. For male striders, protecting from their mating partner is the major reason why the strider establishes a territory for them and female WSs, protecting them from their food resources. One male is known as 'keystone' strider and usually, all the territories are lived by a certain amount of female striders. Through oscillating their legs on surface of the water, the strider produces ripples using distinct amplitudes, frequencies, and durations, where they can transmit various kinds of data with each other. Based on the features that every signal has, various kinds of data, namely courtship, positioning the pray, and repelling the invader. The incoming signal is attained by a sensory receptor organ on their leg. Also, this organ could differentiate signals that are being released by prey insects trapped on the top of the water. The pre-copulatory calling signals are conveyed through a male insect that would make a response by positive or negative messages from the female insects. As per that feedback, the striders will be updating their location as follows

$$\begin{aligned} WS_i^{t+1} &= WS_i^t + R.\,rand;\ \text{Positive response} \\ WS_i^{t+1} &= WS_i^t + R.\,(1 + rand);\ \text{negative response} \end{aligned} \tag{18}$$

In which WS_i^t represent the location of ith WS in the t^{th} cycle, as well as rand denotes an arbitrary value within [0,1]

$$R = WS_F^{t-1} - WS_i^{t-1} \tag{19}$$

The exploratory, exploitative, local optimal avoidance, convergence, and additional features are considered by employing it on a massive amount of multi-modal unimodal composite, biased, and shifted functions [21].

In the WSA based path planning technique, optimizing mobile sink path is most NP hard problem which needed the estimation of closed shortest path with minimal cost as well as delay. The optimization path is passed with existing group of sojourn points in which all sojourn points are going to see once. The multi-objective evolutionary algorithms (MOEAs) are considered as better solutions to multiple-criteria decision-making (MCDM) issues as MOEAs estimation encompass several metrics. The established technique intended that minimize concurrently the delay, distance, and cost of mobile sink path. Assume that ξ refers the sojourn point and S is group of ξ $(i, j = 1, 2, \dots, m)$, $C_{i,j}$ refers the cost of moving in ξ_i to ξ_j, $d_{i,j}$ denotes the distance in ξ_i to ξ_j , and $\tau_{i,j}$ defines the traveling delay in ξ_i to ξ_j. The decision variable 0 has provided in Eq. (20). But the main purposes to minimize the delay, cost, and distance are offered in Eq. (21)-(23) correspondingly.

$$\Gamma_{i,j} = \begin{cases} 1 & \text{if } \xi_j \text{ is visited from } \xi_i \\ 0 & \text{otherwise} \end{cases} \tag{20}$$

$$\mathbb{C}: \mathrm{Min} \sum_{i}^{m} \sum_{j}^{m} C_{i,j}\, \Gamma_{i,j} \tag{21}$$

$$\mathbb{D}: \mathrm{Min} \sum_{i}^{m} \sum_{j}^{m} d_{i,j}\, \Gamma_{i,j} \tag{22}$$

$$\mathbb{T}: \mathrm{Min} \sum_{i}^{m} \sum_{j}^{m} \tau_{i,j}\, \Gamma_{i,j} \tag{23}$$

But the optimized constraints are: $\sum_{i}^{m} \Gamma_{i,j} = 1$ to every i as well as j, the estimated route is not be selected several times $(\Gamma_{i,j} + \Gamma_{j,i} \leq 1)$ and $\Gamma_{i,j} \geq 1$.

3. Experimental Validation

3.1 Experimental Setup

The simulation of the projected models is carried out with the help of Network Simulator 3 (NS3).

Parameter	**Values**
Node count	50, 100, 200
Target area	500*500m
Simulation prior	50-200s
Pause time	5-25s
Maximum speed rate	5-25mps
Transmission radius	25-250m

This section examines the energy efficiency and lifetime analysis of the EAM-PPMS technique under homogeneous and heterogeneous networks. Table 1 and Fig. 3 offer the number of alive nodes (NOAN) analysis of the EAM-PPMS technique on the homogenous network. The results show that the EAM-PPMS technique has offered improved outcomes with the higher NOAN under all rounds. For instance, with 1000 rounds, the EAM-PPMS technique has provided increased NOAN of 200 nodes whereas the LEACH, SEA-SMS, and SEA-MMS techniques have obtained reduced NOAN of 190, 160, and 168 nodes respectively. Likewise, with 2000 rounds, the EAM-PPMS technique has attained raised NOAN of 144 nodes whereas the LEACH, SEA-SMS, and SEA-MMS techniques have obtained reduced NOAN of 1, 87, and 115 nodes respectively.

Table 1 NOAN Analysis of EAM-PPMS technique under Homogeneous Network

No. of Simulation Rounds	LEACH	SEA-SMS	SEA-MMS	EAM-PPMS
0	200	200	200	200
500	200	194	195	200
1000	190	160	168	200
1500	120	131	146	186
2000	1	87	115	144
2500	0	68	91	119
3000	0	1	79	87
3500	0	0	41	60
4000	0	0	0	25

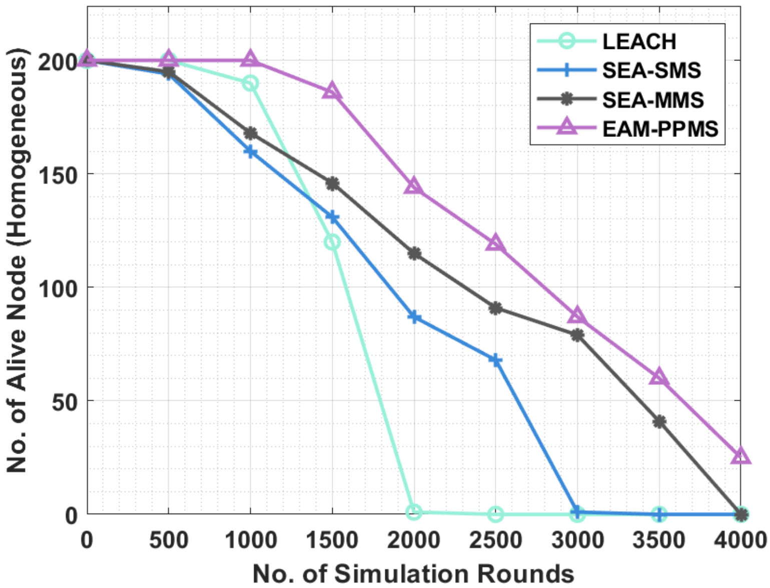

Fig. 3. Comparative NOAN Analysis of EAM-PPMS technique on Homogeneous Network

Table 2 and Fig. 4 inspect the number of alive nodes (NOAN) analysis of the EAM-PPMS technique on the heterogeneous network. The results revealed that the EAM-PPMS technique has obtained better outcomes with the higher NOAN under all rounds.

Table 2 NOAN Analysis of EAM-PPMS technique under Heterogeneous Network

No. of Simulation Rounds	SEP	TEEN	SEA-SMS	SEA-MMS	EAM-PPMS
0	200	200	200	200	200
500	200	199	198	200	200
1000	200	172	182	186	200
1500	183	90	165	170	199
2000	125	11	147	161	180
2500	67	1	114	146	161
3000	11	0	100	123	148
3500	1	0	86	111	134
4000	0	0	77	101	124
4500	0	0	49	86	103
5000	0	0	19	79	91
5500	0	0	1	59	80
6000	0	0	0	40	62
6500	0	0	0	22	35
7000	0	0	0	0	20

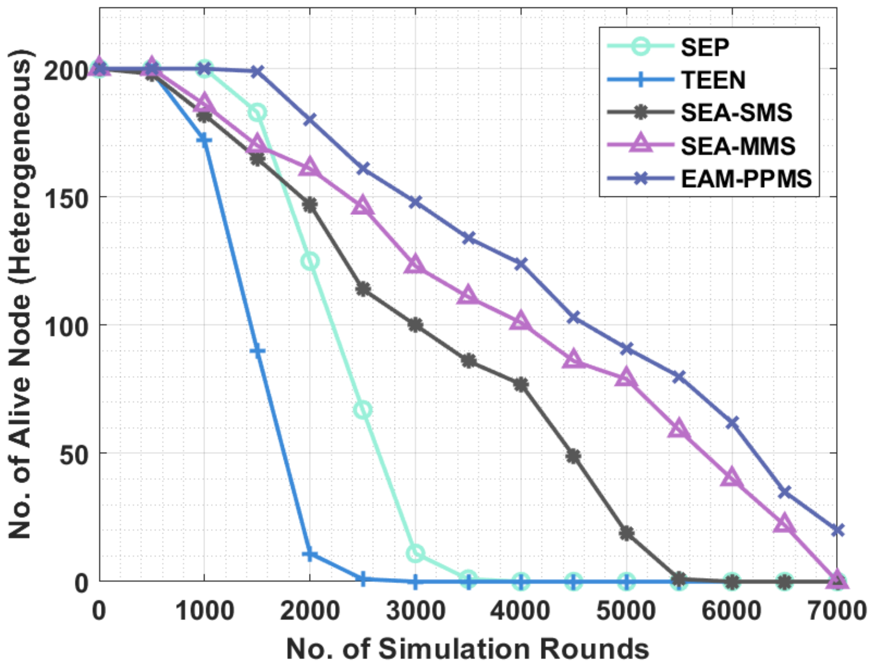

Fig. 4. Comparative NOAN Analysis of EAM-PPMS technique on Heterogeneous Network

For instance, with 1500 rounds, the EAM-PPMS technique has developed maximum NOAN of 199 nodes whereas the SEP, TEEN, SEA-SMS, and SEA-MMS techniques have obtained reduced NOAN of 183, 90, 165, and 170 nodes respectively. Likewise, with 2000 rounds, the

EAM-PPMS technique has attained raised NOAN of 180 nodes whereas the SEP, TEEN, SEA-SMS, and SEA-MMS techniques have obtained reduced NOAN of 125, 11, 147, and 146 nodes respectively.

The number of dead node analyses (NODN) of the EAM-PPMS technique under homogeneous network is offered in Table 3 and Fig. 5. The results reported the betterment of the EAM-PPMS technique with lower NODN. For instance, under 1500 rounds, the EAM-PPMS technique has resulted in reduced NODN of 14 nodes whereas the LEACH, SEA-SMS, and SEA-MMS techniques have reached to increasing NODN of 80, 69, and 54 nodes respectively. Moreover, under 3500 rounds, the EAM-PPMS technique has resulted in reduced NODN of 140 nodes whereas the LEACH, SEA-SMS, and SEA-MMS techniques have reached to higher NODN of 200, 200, and 159 nodes respectively.

Table 3 NODN Analysis of EAM-PPMS technique under Homogeneous Network

No. of Simulation Rounds	LEACH	SEA-SMS	SEA-MMS	EAM-PPMS
0	0	0	0	0
500	0	6	5	0
1000	10	40	32	0
1500	80	69	54	14
2000	199	113	85	56
2500	200	132	109	81
3000	200	199	121	113
3500	200	200	159	140
4000	200	200	200	175

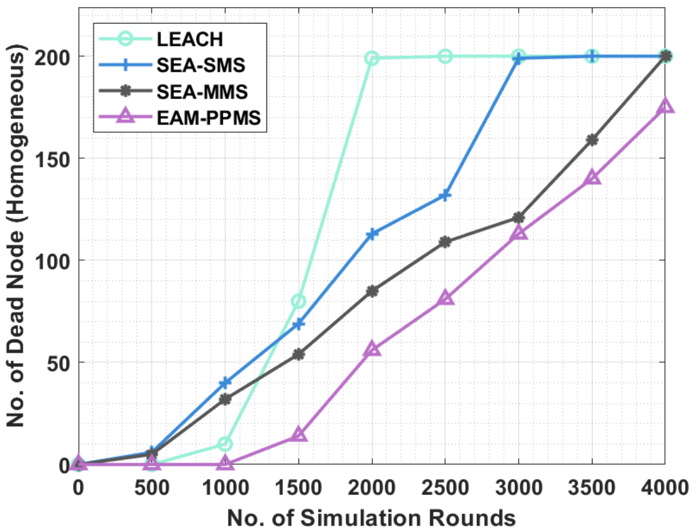

Fig. 5. Comparative NODN Analysis of EAM-PPMS technique on Homogeneous Network

The NODN of the EAM-PPMS technique under heterogeneous network is offered in Table 4 and Fig. 6. The figure displayed the superior outcome of the EAM-PPMS technique with least values of NODN.

Table 4 NODN Analysis of EAM-PPMS technique under Heterogeneous Network

No. of Simulation Rounds	**SEP**	**TEEN**	**SEA-SMS**	**SEA-MMS**	**EAM-PPMS**
0	0	0	0	0	0
500	0	0	2	0	0
1000	0	28	18	14	0
1500	17	110	35	30	1
2000	75	189	53	39	20
2500	133	199	86	54	39
3000	189	200	100	77	52
3500	199	200	114	89	66
4000	200	200	123	99	76
4500	200	200	151	114	97
5000	200	200	181	121	109
5500	200	200	199	141	120
6000	200	200	200	160	138
6500	200	200	200	178	165
7000	200	200	200	200	180

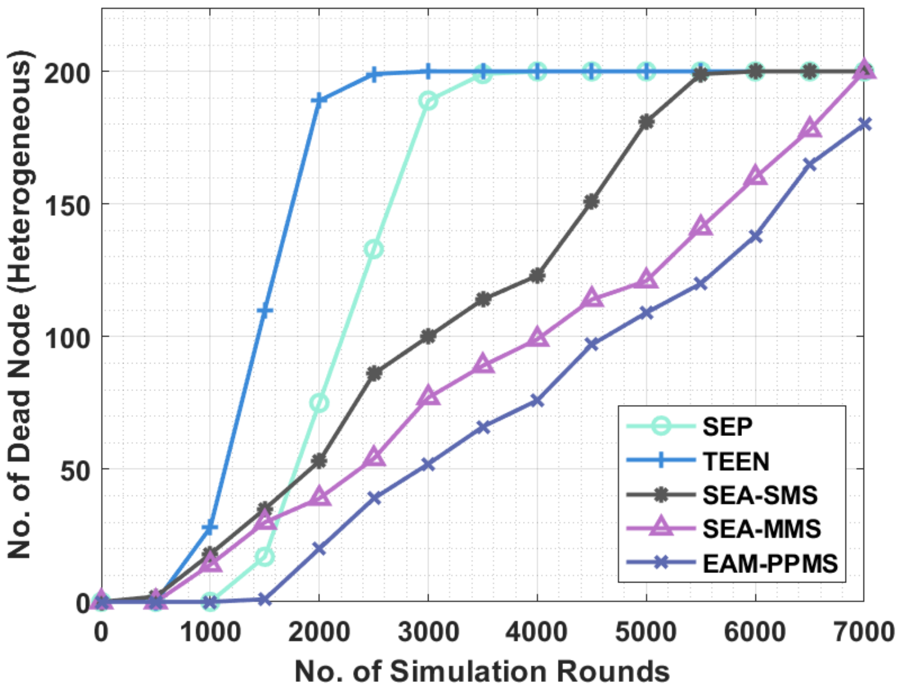

Fig. 6. Comparative NODN Analysis of EAM-PPMS technique on Homogeneous Network

For instance, under 1500 rounds, the EAM-PPMS technique has accomplished minimum NODN of 1 node whereas the SEP, TEEN, SEA-SMS, and SEA-MMS techniques have demonstrated maximum NODN of 17, 110, 35, and 30 nodes respectively. Moreover, under 3500 rounds, the EAM-PPMS technique has exhibited least NODN of 66 nodes whereas the SEP, TEEN, SEA-SMS, and SEA-MMS techniques have resulted in increased NODN of 199, 200, 114, and 89 nodes respectively.

An extensive lost packets analysis of the EAM-PPMS technique with MMS-WSN technique is depicted in Table 5 and Fig. 7. The experimental values portrayed that the EAM-PPMS technique has resulted in least number of lost packets compared to MMS-WSN on the transmission of 2000 packets. With 40 distances, the EAM-PPMS technique has lost 0 packets whereas the MMS-WSN technique has lost 123 packets.

Table 5 Lost Packets Analysis of EAM-PPMS technique

Distance	**Sent Packets**	**MMS-WSN**	**EAM-PPMS**
10	2000	0	0
20	2000	0	0
30	2000	1	0
40	2000	123	0
50	2000	502	112
60	2000	653	452
70	2000	781	632
80	2000	1264	813
90	2000	1475	1136
100	2000	1600	1256

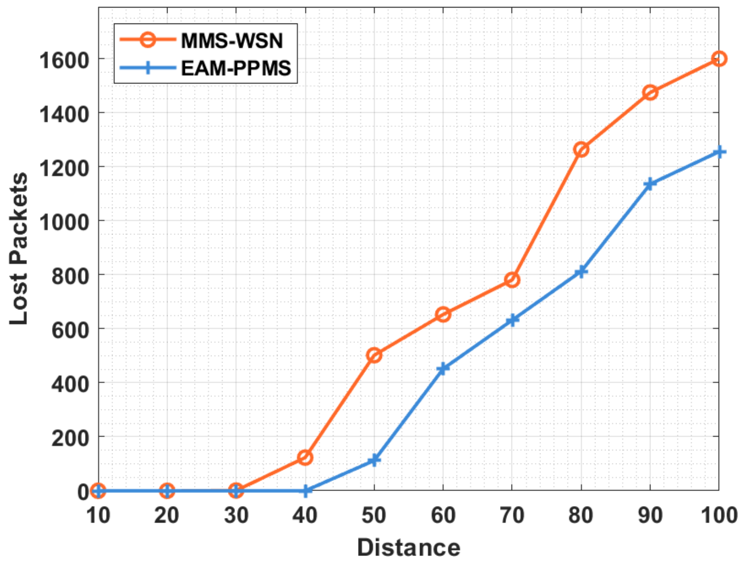

Fig. 7. Comparative Packet Loss Analysis of EAM-PPMS technique

Eventually, with 50 distances, the EAM-PPMS technique has lost 112 packets whereas the MMS-WSN technique has lost 502 packets. Meanwhile, with 80 distances, the EAM-PPMS technique has lost 813 packets whereas the MMS-WSN technique has lost 1264 packets.

Finally, with 100 distances, the EAM-PPMS technique has lost 1256 packets whereas the MMS-WSN technique has lost 1600 packets.

The Network Remaining Energy (NRE) analysis of the EAM-PPMS technique with recent methods is made in Table 6 and Fig. 8. The simulation results demonstrated that the EAM-PPMS technique has resulted in increased NRE.

Table 6 NRE Analysis of EAM-PPMS technique

No. of Simulation Rounds	SEP	TEEN	SEA-SMS	SEA-MMS	EAM-PPMS
0	110.00	110.00	110.00	110.00	110.00
1000	25.41	36.60	44.05	56.93	69.47
2000	6.43	13.21	19.99	29.82	43.04
3000	0.33	5.07	9.14	15.92	25.41
4000	0.00	1.68	4.06	7.78	15.92
5000	0.00	0.00	1.00	4.06	9.48
6000	0.00	0.00	0.00	2.02	6.09
7000	0.00	0.00	0.00	1.34	5.41

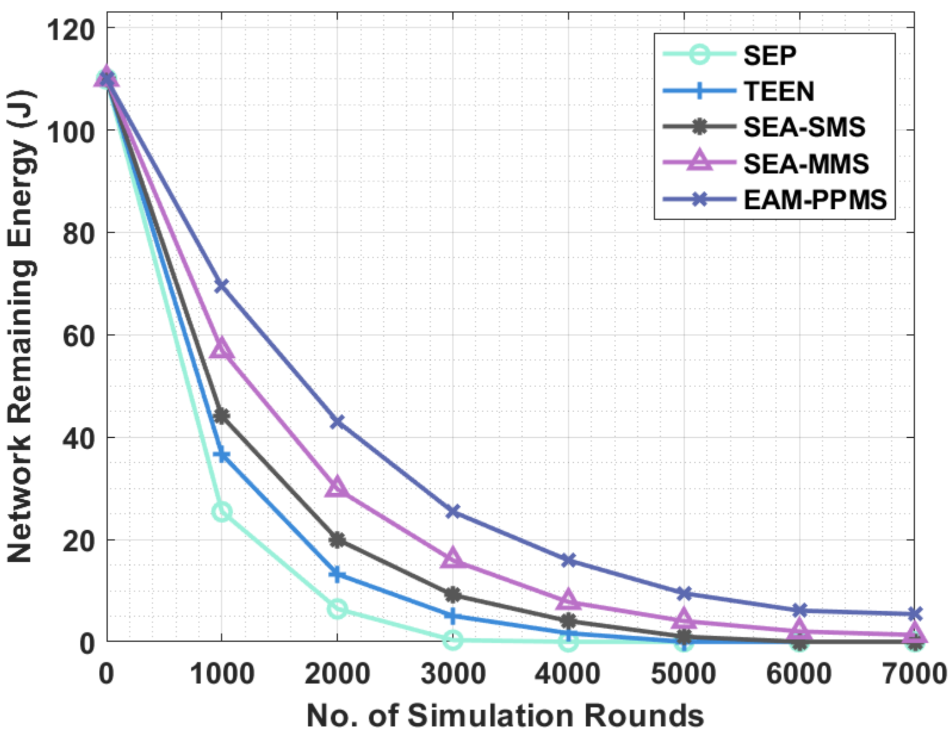

Fig. 3. Comparative NRE Analysis of EAM-PPMS technique on Homogeneous Network

For instance, with 1000 rounds, the EAM-PPMS technique has resulted in a maximum NRE of 69.47J whereas the SEP, TEEN, SEA-SMS, and SEA-MMS techniques have needed maximum NRE of 25.41J, 36.60J, 44.05J, and 56.93J respectively. From the results and discussion, it is obvious that the EAM-PPMS technique has outperformed the other techniques under different aspects.

4. Conclusion

In this study, an effective EAM-PPMS technique has been developed to choose CHs and optimal paths for MS. The presented EAM-PPMS technique involves two major processes namely CSO based clustering and WSA based path planning. The WSA based path planning technique for MS is derived to reach the destination in an optimal way. Furthermore, the path planning technique is mainly based on the derivation of objective function with the minimization of cost, distance, and delay. The number of alive nodes (NOAN) analysis of the EAM-PPMS technique on the homogenous network. The results show that the EAM-PPMS technique has offered improved outcomes with the higher NOAN under all rounds. For instance, with 1000 rounds, the EAM-PPMS technique has provided increased NOAN of 200 nodes whereas with 4000 rounds, the EAM-PPMS technique has provided reduced NOAN of 25 nodes. The number of alive nodes (NOAN) analysis of the EAM-PPMS technique on the heterogeneous network. The results show that the EAM-PPMS technique has offered improved outcomes with the higher NOAN under all rounds. For instance, with 2000 rounds, the EAM-PPMS technique has provided increased NOAN of 180 nodes whereas with 7000 rounds, the EAM-PPMS technique has provided reduced NOAN of 20 nodes. The number of dead node analyses (NODN) of the EAM-PPMS technique under homogeneous network. The results show that the EAM-PPMS technique has offered improved outcomes with the higher NODN under all rounds. For instance, with 2000 rounds, the EAM-PPMS technique has provided increased NODN of 56 nodes whereas with 4000 rounds, the EAM-PPMS technique has provided increased NODN of 175 nodes. The number of dead node analyses (NODN) of the EAM-PPMS technique under heterogeneous network. The results show that the EAM-PPMS technique has offered improved outcomes with the higher NODN under all rounds. For instance, with 2000 rounds, the EAM-PPMS technique has provided reduced NODN of 20 nodes whereas with 7000 rounds, the EAM-PPMS technique has provided increased NODN of 180 nodes. The simulation results portrayed the betterment of the EAM-PPMS technique compared to the recent approaches. Therefore, the EAM-PPMS technique can be applied as an effective path planning approach for WSN with mobile sink. In future, the path planning performance of the WSA can be improved by the incorporation of oppositional based learning (OBL) concept for population initialization.

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