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Energy-efficient Dynamic Mobile Sink Path Planning for Data Acquisition for Wireless Sensor Networks

Srinivasulu Boyineni[1], Dr.K. Kavitha[2], Dr.Meruva Sreenivasulu[3]
[1]Research Scholar, Department of CSE, Annamalai University, Chidambaram, India.
srinivasulu.inf@gmail.com
[2]Associate Professor, Department of CSE, Annamalai University, Chidambaram, India.
kavithacseau@gmail.com
[3]Professor and Head, Department of CSE, K.S.R.M College of Engineering, Kadapa, Andhra Pradesh, India,
mesrinu@rediffmail.com

ABSTRACT

Wireless sensor networks (WSNs) are widely used in various applications such as defense, forest fire, healthcare, structural health monitoring, etc., because of its flexibility, low cost and tiny. In WSNs, the sensor nodes are scattered over the target area to acquire the data from the environment and transmit it to the base station via single or multi-hop communication. Due to the sensor nodes' constrained battery, the sensor nodes near the base station are more involved in data transmissions. These relay nodes drain more energy and die soon, leading to a hotspot/energy-hole problem. Several algorithms have been proposed in the literature to address the hotspot problem using the mobile sink. However, most of the existing approaches are highly computational and also provide a static solution only. In this context, we proposed an energy-efficient dynamic mobile sink path construction with low computational complexity for data acquisition in WSNs. We use the minimum spanning tree-based clustering for selecting the data collection points and a computational geometry-based method to identify the visiting order of the data collection points by the mobile sink. Our proposed work is better than the existing approaches in terms of average energy consumption, network lifetime, fairness index, buffer utilization, etc.

Key words: Wireless Sensor Networks, Mobile sink, Energy-efficient, Minimum Spanning Tree, Clustering.

1. INTRODUCTION

Wireless sensor networks (WSNs) are more prevalent in recent years due to its vast applications such as Domotics, forest fire, defense, healthcare, security surveillance etc. The WSNs are also playing a vital role in the Internet of Things (IoT) [1]. In WSNs, a set of sensor nodes (SNs) are scattered to acquire the data and transmit it to the base station (BS) for further analytics. These data transmissions use either single-hop or multi-hop communication mechanisms. Single-hop communications are used when the SNs are in the range of BS. So, in most cases, the data transmission uses multi-hop communications. The battery-equipped SNs consume more energy due to heavy transmissions rather than for processing the data. Significantly, the SNs which are near to the BS consumes more power due to the relay. These heavy consumptions cause hotspots or energy-hole problems in the WSNs. The hotspot or energy-hole problem isolates a part of the WSNs from the BS [2, 3].

A mobile sink (MS) is introduced to gather the data from the sensor nodes by traveling in the network which avoids the data relay between the SNs [4,5]. However, visiting each SN in the network is difficult which delays data collection as well as data loss due to limited buffers. Instead of visiting each SN in the network, the MS visits a set of data collection points called rendezvous points (RPs). All the remaining SNs can send their data to the nearest RPs. The optimal selection of the RPs improves the data collection process by prolonging the network lifetime. However, choosing the best RPs in the WSNs is a challenging task. Because, choosing the large number of RPs, increases the traveling time of the MS and because of its limited number of RPs increases the data relay between the SNs and RPs. Deciding the best RPs in the network is not only a challenging task, but also a trajectory among them. There are several works in the literature to address this challenge, but most of them are static as of my knowledge [6,7]. The secured message delivery-based vehicular communication is presented in [8].

In this context, this paper proposes an Energy-efficient Dynamic Mobile Sink Path planning (EDMSP) algorithm for WSNs which improves the efficiency of the data gathering approach by prolonging the network lifetime. The EDMSP initially select the best set of dynamic RPs using minimum spanning tree (MST)-based clustering. There are several MST-based clustering methods in the literature [9,10], but we perform a novel clustering method in this work according the

varying the nodes energies and buffers. During the cluster formation we give priority to residual energies and available buffers. So, the RPs dynamically changes in each tour of the MS. Once the RPs are identified, a low computational path among them is constructed using a simple geometric method. Most of the existing path construction algorithms are computationally heavy, but we propose a low computational approach for solving the purpose.
However, the path may not be the optimal but feasible. In WSNs, the MS path may not be short all the time, some time longer path also improves the performance.

The summary of the contributions of this paper are:

- The best set of RPs is identified using MST-based clustering approach by considering the residual energy and the available buffer of each SNs.
- A low computational path is constructed using computational geometry method, for traversing the MS in the network to acquire the data from RPs.
- The derived Computational complexity of the proposed EDMSP algorithm when compared with existing approaches is better.
- The performance of the proposed work is compared with the recently published MS-based data collection algorithms such as WRP [5], EAPC [11] and eACO-MSPD [12] using various performance metrics in different scenarios.

The remaining sections of this article are arranged as follows. In Section 2, we perform the literature study of the recently published mobile sink-based data gathering approaches. In Section 3, we formulate the problem and present the proposed EDMSP algorithm. In Section 4, we provide the experimental results of the proposed and existing models. Finally, we concluded the paper, in Section 6.

2. RELATED WORKS

we provide the literature study of recently published mobile sink-based data collection mechanisms.

Mobile sink-based path planning by being aware of energy is constructed in [11] using a convex polygon approach for WSNs. This work initially selects the data collection points called RPs and later constructs the path using a convex polygon mechanism. In this, the path is longer compared to the other approach, but it results in the less computational complexity. In [13], the authors determine efficient data collection points called RPs and the path between them using ant colony optimization (ACO) mechanism for WSNs. In this, the ACO technique is used for both RPs selection and path planning. The same authors extended this work in [12] by modifying the ACO probability function to minimize the complexity and number of iterations. In this, the virtual RPs mechanism added to minimize the transmissions between SNs and RPs, so that the energy consumption will be reduced.

A cluster-based mechanism is introduced for data collection using MS in WSNs by visiting a limited number of RPs in [14]. In this, the authors identify the efficient RPs based on the energy drain of the sensor nodes and the path is based on the travelling sales person problem. This approach is computationally heavy. A data aggregation mechanism has been proposed in [15] for WSNs using mobile sink. In this a hierarchical data aggregation mechanism has been introduced. This protocol performs efficient data collection but it leads to heavy energy consumptions. In [16], the authors introduced flow-based data collection for WSNs by minimizing the traveling path of the mobile sink. A heuristic approach is used to achieve the efficient data gathering using mobile sinks.

In [17], the authors present an energy-efficient mobile sink based data routing and clustering approach for WSNs. Initially, the authors perform the clustering of the sensors based on the energy consumption during the data transmissions and later introduce the routing strategy using mobile sink. This approach uses a greedy approach to perform the mobile sink path whereas dynamic scheduling is required in the real time environment. The authors in [18] proposed an efficient mobile sink trajectory using particle swarm optimization approach for WSNs. The primary objective of this approach is to minimize the traveling distance of the mobile sink in the WSNs. However, minimum traveling distance is not a best solution for the data gathering process and efficient data collection with minimal data loss is an important task for the WSNs. An efficient data collection process is introduced using mobile sink for 3D WSNs in [19]. In this, the authors used a hierarchical clustering algorithm for clustering and a simple computational geometry method for MS path planning. This approach takes heavy computational complexity to address the issue.

From the above discussion, we notice that most of the existing approaches focus on optimal data collection point's selection and a minimum path among them. But, it requires constructing a dynamic path by increasing the data collection strategy.

3. PROPOSED WORK

We describe the system model along with the problem formulation followed by the proposed algorithm.

3.1 System Model and Problem Formulation

We consider a WSN as a undirected graph *G(S,D)*, where

$S=\{s_1, s_2, \ldots, s_n\}$ indicates the set of SNs and D is the distance matrix of the S. The communication range of a sensor node is indicated using r. The two SNs s_i and s_j can communicate their data when $d_{ij} \leq r$, where $d_{ij} \in D$ indicates the distance between the nodes i and j. The BS of the network is placed randomly and it is indicated using s_0. The RPs in the network is indicated using $M\forall(M \in S)$. Initially, the buffer size of each SNs is unique and it is represented using B. At particular time t, the number of packets available in the buffer or amount of buffer occupied by the SN i is represented using BO_i. The tour length at k^{th} tour is denoted using T_k and average tour length is denoted using T_a. The number of tour indicated using δ.

We consider free space energy model for the proposed EDMSP. The amplification energy (α_a), the circuit take α_t energy to transmit a bit and α_r to receive a bit. The SN i consumes energy to transfer β-bits to the node j is computed using Equation (1) as shown below

$$E_{ij}{}^{t} = \beta\alpha_t + \beta\alpha_a d_{ij}{}^{2} \tag{1}$$

To receive β-bits form node j to i, the node i consume energy as shown in Equation (2).

$$E_i{}^{r} = \beta\alpha_r \tag{2}$$

The total energy consumed by the node i to receive or transfer the data to other nodes is computed as shown in Equation (3).

$$E_i = E_{ij}{}^{t} + E_i{}^{r} \tag{3}$$

The network lifetime (N) is measured using the time in minutes until the first node despite its energy completely in the network during the data collection process.

$$N = \frac{E_0}{\max E_i} \forall 1 \leq i \leq n \tag{4}$$

We can achieve the objective in Equation (4), by determining the best RPs and dynamic path among them.

3.2. Energy-efficient Dynamic Mobile Sink Path Planning

We present the proposed Energy-efficient Dynamic Mobile sink Path Planning (EDMSP) algorithm. This algorithm mainly performs the two operation including RP selection and trajectory planning.

3.2.1. RP Selection

We consider graph G as an input and partition it into k times. To partition the network, we use minimum spanning tree (MST)-based clustering approach. Initially, we construct MST (Γ) using Prims' algorithm. Once the MST is determined, we start the clustering operation on the Γ, which is derived from the G. While we perform the clustering using MST, we continuously remove the inconsistent edges from Γ until k-1 times, when we require k clusters. The inconsistent node can be determined mainly using two features such as the longer edge between any nodes and the smaller density between the nodes. We can identify the inconsistent edges between the node i and j by determining the Equation (6) as shown below:

$$\chi_{ij} = \frac{d_{ij}}{\xi_i + \xi_j} + \frac{(B_i + B_j)^{\varphi}}{(\hat{E}_i + \hat{E}_j)^{\gamma}} \tag{6}$$

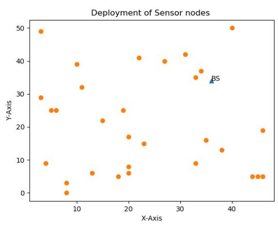
where d_{ij} is the Euclidean distance between the nodes i and j. B_i is the available buffer at node i and B_j is the available memory/buffer at node j. B_i is computed as $(B_i = B - BO_i)$ at a time t. $\hat{E}_i$ and $\hat{E}_j$ are the residual energies of the SNs i and j. It is calculated as $(\hat{E}_i = E_0 - E_i)$. φ and γ are the heuristic information for available buffer(B_i and B_j) and residual energies ($\hat{E}_i$ and $\hat{E}_j$),respectively. The heuristic values φ and γ are ranging between 0 to 1 (i.e. $0 < \varphi \mid \gamma \leq 1$). ξ_i is the local density and ξ_j is the global density determined using Equation (7).

$$\xi_i = \sum_j \exp\left(-\frac{d_{ij}{}^{2}}{2\times\sigma^2}\right)\forall j \in S \tag{7}$$

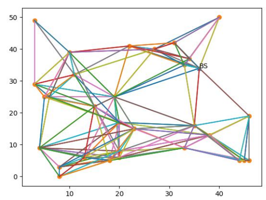
where σ is the variance. The construction of MST is static but cluster formation varies which depends on the residual energy and the available buffer of the SNs in each tour of the MS.

Once we determine the χ_{ij} between all the SNs in the Γ, we delete the edge between the nodes i and j from Γ, where χ_{ij} value is maximum. We repeat this process k-1 to achieve k clusters. From each cluster, we identify the centroid and make the centroid as a data collection point for the MS called as an RP. The clusters are termed as $\{C_1, C_2, \ldots, C_k\}$.

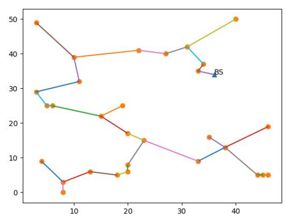
Figure 1(a) shows the initial deployment of the sensor nodes in the network. Here, we deployed a sink and 30 SNs randomly in the area of 50 *sq. meters*. Figure 1(b) shows that the Graph G of the deployed SNs according to the communication range provided i.e. 20 *meters*. Figure 1(c), shows the MST using the prims' algorithm. Once the MST is formed, we remove the inconsistent nodes from the tree shown in Figure 1(d). The cluster head from each cluster is shown in Figure 1(e) and it is treated as the data collection point i.e. RP.



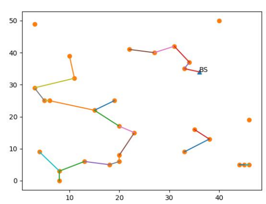
(a) Initial deployment of 30 SNs and a base station



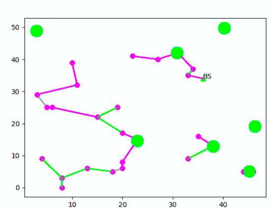
(b) Graph of the network connection with the communication range of 20



(c) Construction of Minimum spanning tree using Prims' algorithm



(d) Clustering using removal of inconsistent edges in MST



(e) RPs selection

Figure 1 Illustration of MST-based Clustering

3.2.2. MS Path Planning

An efficient Path of the MS will improve the data gathering process by minimizing the data collection delay in the WSNs. So, it is a very important stage to enhance the performance of the network. In the literature, the TSP mechanisms are adopted through various techniques, but they require more computation to construct the path for MS such as TSP, ACO, PSO, etc. In this work, we propose a simple and low computational path construction for MS using computational geometric method. The main objective of path determination is visiting order of the points available in *M*.

The step-by-step procedure of the path construction algorithm is as follows:

1. Identify the left most (*L*) and right most (*R*) RP from *M* based on its X-axis values.
2. Draw a line between *L* and *R*
3. Separate all the locations of M as they come either above or below the line. Assume, the points above the line are stored in *A* and below the line are stored in *Z*.
4. Sort all the points of *A* in non-increasing (decreasing) order based on X-axis value.
5. Sort all the points of *Z* in non-decreasing (increasing) order based on X-axis value.
6. Merge all the points of *Z* followed by *A*, store in M_p
7. Perform the circular operation on M_p until the BS becomes the first element.

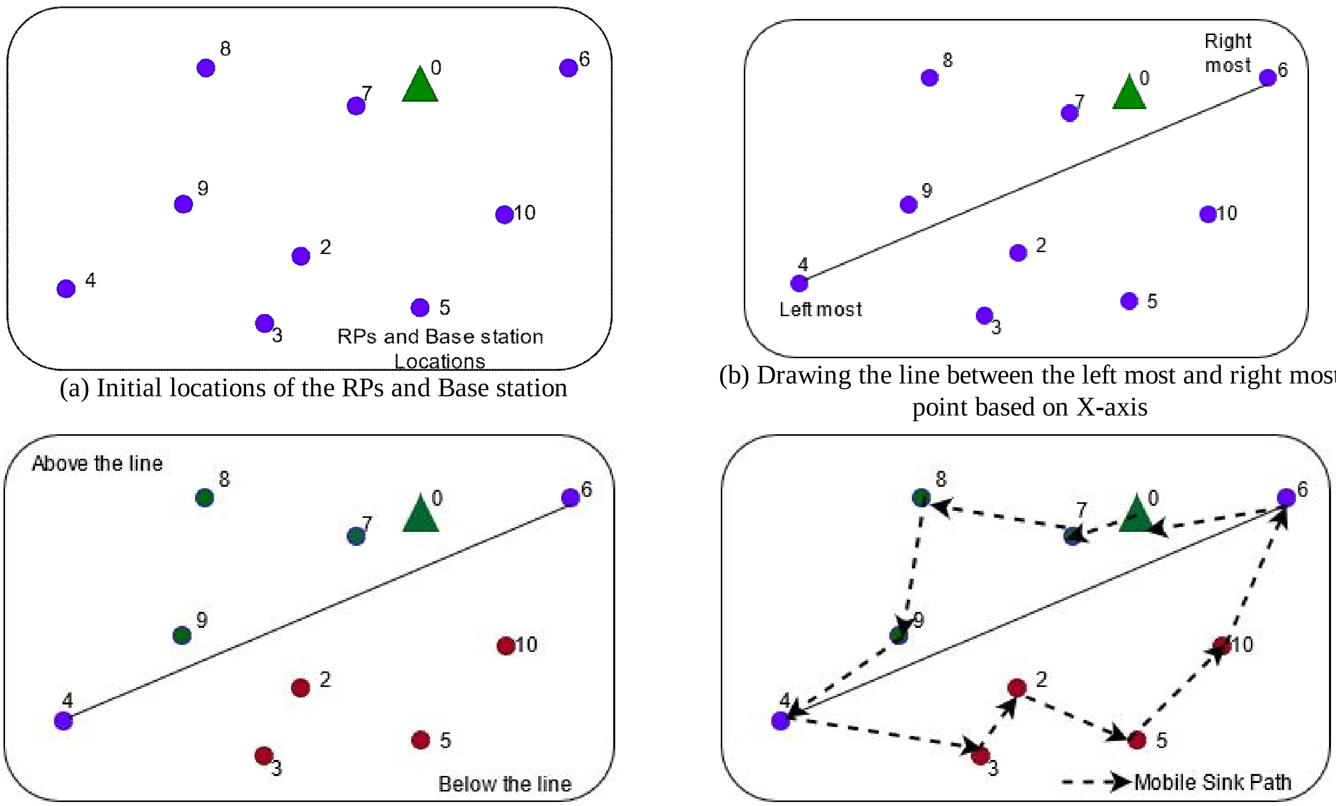
For better understanding of the proposed path planning, we illustrate through example in Figure 2. In this illustration, we considered 10 RP nodes and a base station.

Initial deployment locations of the RPs are shown in Figure 2(a). From the figure 2(a), we identify the leftmost and rightmost points based on the X-axis values and node 4 and 6 are leftmost and rightmost nodes, respectively. Now, we construct a line between them as shown in Figure 2(b). Now, we have to identify the remaining nodes which are either below the line or above the line. It is decided by constructing a matrix using the three points such as leftmost, rightmost and the point which we have to identify whether it is above or below the line. For example, To decide whether point 3 resides either above or below the line, we use a matrix as shown below

$$Y_3 = \begin{bmatrix} x_4 & x_6 & x_3 \\ y_4 & y_6 & y_3 \\ 0 & 0 & 0 \end{bmatrix}$$

We find the det value using the above matrix, which determines whether the point 3 lies below, above or on the line depends on the $|Y_3|$.

If $|Y_3| = 0$ then the node 3 is on the line, In case $|Y_3| > 0$, then the point 3 resides above the line and if $|Y_3| < 0$, then the point 3 resides below the line. Similarly, we check all the nodes and decide whether the node lies above, below or on the line. In this example, the nodes 2, 3, 5, 10 are below the line and, 0, 7, 8, 9 are above the line as shown in Figure 2 (c). The sorting order of the points below the line based on the x-axis is 3, 2, 5, 10 and the descending order of the points above the line is 0, 7, 8 and 9. Merging these points becomes the final visiting order as 4, 3, 2, 5, 10, 6, 0, 7, 8 and 9. But, the mobile sink starts visiting from the Base station, so we need to perform the circular rotate operation until the base station becomes the first visiting node. After performing the circular rotate, the order becomes 0, 7, 8, 9, 4, 3, 2, 5, 10 and 6.



(a) Initial locations of the RPs and Base station

(b) Drawing the line between the left most and right most point based on X-axis

(c) Separating the points above and below the line using different colors

(d) Order of visit and path planning

Figure 2 Illustration of Mobile sink Path Planning

3.3. Computational Complexity

The computational complexity of the proposed EDMSP is derived as follows. The EDMSP primarily performs the RPs selection and path planning for the MS. While determining the RPs, this approach uses MST-based clustering using Prims' algorithm followed by the edge removal. The time complexity of Prims' algorithm is $O(|\mathrm{E}|\log n)$ where, $|E|$ indicates the number of edges and n indicates number of nodes. The worst case time complexity to decide the inconsistent nodes in the MST is $O(\mathrm{E}^2)$. The number of edges in the n node MST is n-1. We can rewrite the notation as $\mathrm{O}(n^2)$. The time complexity taken to plan the path or visiting order through the RPs depends on varying the steps. To perform the leftmost and rightmost points in the RP set takes $\mathrm{O}(|M|)$, where $|M|$ indicates the number of RPs i.e ($|M|<n$). The time complexity to decide whether a point lies below or above the line is $\mathrm{O}(|M|)$. To sort the elements either in ascending or descending order will take $\mathrm{O}(|M|\log|M|)$. The overall complexity taken to plan the visiting order is $\mathrm{O}(|M|\log|M|)$. The total complexity of the proposed EDMSP is $O(|\mathrm{E}|\log n) + \mathrm{O}(n^2) + \mathrm{O}(|M|\log|M|)$ and it is asymptotically equals to $\mathrm{O}(n^2)$. So, the final computational complexity of the proposed EDMSP is $\mathrm{O}(n^2)$.

4. EXPERIMENTAL RESULTS

We compare various performance metrics of the WSNs such as average energy consumption (AEC), Fairness index of EC (FIEC), Network lifetime (NL), Buffer Utilization (BU) and Average Tour Length (ATL). We perform the simulation using 50-500 SNs and 500 *sq. meters* area. All the SNs and BS in both the scenarios are deployed randomly. We use the Python Simulator (Python 3.7.x) to perform the simulations. The data transmission rate of the channel in the network 80 *Kb/sec*. The packet size is assumed to be 30 *bytes*. The MS speed is limited to 1 *meter/sec*. The communication range (r) of any SN is 15-50 *meters*. The EC for amplification is set to 0.029 $mJ/bit/m^2$, receiver circuit and transmitter circuit is set to 0.042 *mJ/bit*. 100 *Joules* is the SNs initial energy.

4.1. Average Energy Consumption

The average energy despite while performing the data collection from the environment and transmission to RPs or MS of any SN in a tour of MS is treated as average energy consumption.

It is measured using Equation. (8) as shown below

$$E_a = \sum_{i=1}^{n}\sum_{k=1}^{\delta}\frac{E_i}{n\times\delta} \quad (8)$$

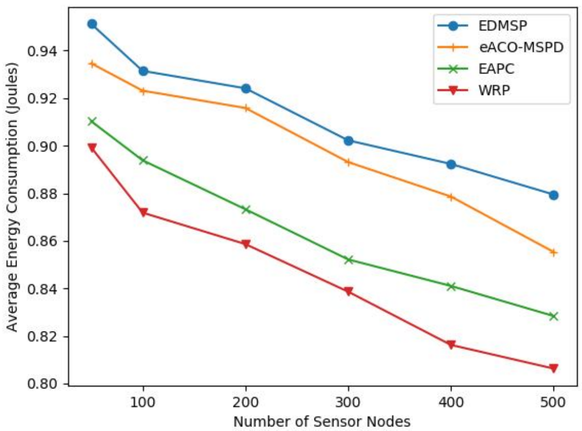


Figure 3 Average Energy Consumption of the Sensor nodes

The E_a is computed with a different number of SNs in both the scenarios. From Figure 3, shows the comparison of E_a for the large network. Here, the improvement of the E_a of the proposed work is 9-16% better than eACO-MSPD, 13-25% better than WRP and 17-39% better than WRP algorithms. The improved performance of the proposed work is observed because of identifying the best RPs and dynamic path among them.

4.2. Fairness Index of Energy Consumption

The Fairness index (FI) of the EC determine energy consumptions' equal share of a bottleneck. The E_a determines the average of the EC, but it does not determine any particular part of the network that is consuming more energy than other parts. There are several ways to calculate FI and we adopted the method from [19] it is shown as follows

$$FI = 1-\left(\frac{2\times E_s}{\max E_i - \min E_i}\right)\forall(1\le i\le n) \quad (9)$$

where E_s indicates the energy consumption's standard deviation and it is calculated using Equation (10)

$$E_s = \sqrt{\frac{\sum_{i=1}^{n}(E_i - E_a)^2}{n}} \quad (10)$$

We examine the FIEC in WSN environment in Figure 4. The FI is shown in Figure 4 we notice that the proposed EDMSP results around 0.95112 to 0.96474 values as a fairness index. These values are better compared to the other existing approaches such as eACO-MSPD, EAPC and WRP. The improved FIEC of the proposed EDMSP is notice because of the efficient scheduling of the MS in the network.

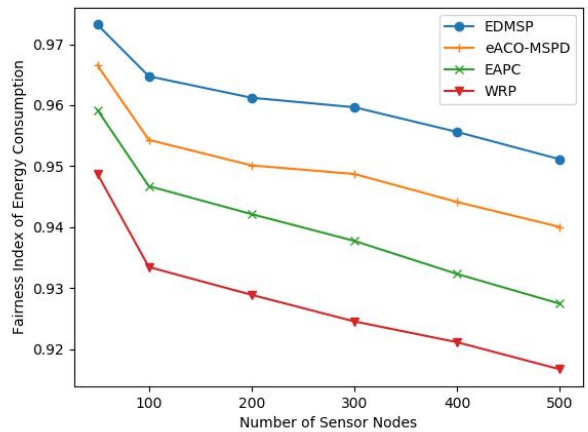


Figure 4 Fairness Index of Energy Consumption

4.3. Network Lifetime

The network lifetime (*N*) is the important metric to judge the performance of the proposed algorithms [20]. It is measured using time (in *minutes*). The time until the first node despite its energy completely is considered as *N*. It is denoted mathematically using Equation (4) (repeated here for reference).

$$N = \frac{E_0}{\max E_i}\forall 1\le i\le n$$

We estimate the *N* of proposed EDMSP with the existing eACO-MSPD, EAPC and WRP approaches. From Figure 5, we notice that the proposed EDMSP is 117 *minutes* to189 *minutes* longer than eACO-MSPD algorithm. Similarly, EDMSP is 179 *minutes* to 266 *minutes* longer than EAPC and 272 *minutes* to 368 *minutes* longer than WRP algorithms.

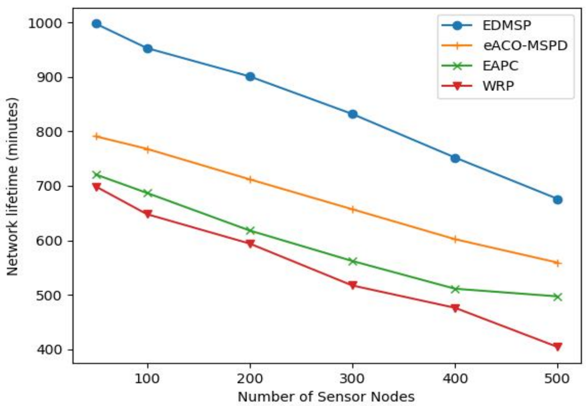


Figure 5 Network Lifetime

4.4. Buffer Utilization

The amount of memory of a SN utilized during the data transmission in the network is considered as Buffer utilization (BU). It is an important metric to decide the efficiency of the data collection process. Because, prolonging the memory size will take a long time to transfer the data to the MS, so the MS needs to spend more time at a particular node or RP. The BU of a network is considered using Equation (12) as shown below

$$BU = \frac{\sum_{i=1}^{n} BO_i}{B \times n} \tag{12}$$

where BO_i indicates the buffer occupancy or number of packets allocated by node i at the time t. In general BO_i is always less than B (i.e. $BO_i < B$).

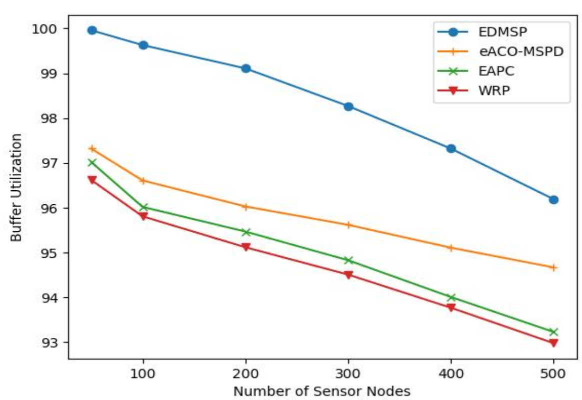


Figure 6 Buffer Utilization

The BU of the proposed and existing methods are compared using two scenarios in Figure 6. The BU of the network is calculated as a percentage. From Figure 6, we observe the BU of the proposed work is always higher than the existing approaches. The improved BU of the proposed work is noticed as 3-4%, 4-6% and 4-8%, compared to the eACO-MSPD, EAPC and WRP, respectively. The efficient BU is noticed because of the best RP selection mechanism incorporated in the proposed work.

4.5. Average Tour Length

The tour length in each trajectory may be varied, because of the dynamic RP and path selection adopted by the proposed work. So, we compare the ATL of the proposed work in two scenarios. In the scenario#1, we vary the transmission ranges of the SNs from 30 to 50 *meters*. In the scenario#2, we consider the varying WSNs area from 100 *sq. meters* to 500 *sq. meters* with fixed number of SNs. Decreasing the ATL values increases the delay of reaching the MS to a RP, so that buffer can be utilized efficiently and data gathering process performed efficiently. The ATL is defined as the average distance travelled by the MS until the first SN despite its energy completely. It is denoted mathematically using Equation. (13) shown below.

$$T_a = \frac{1}{\lceil \delta \rceil} \sum_{k=1}^{\lceil \delta \rceil} T_k \tag{13}$$

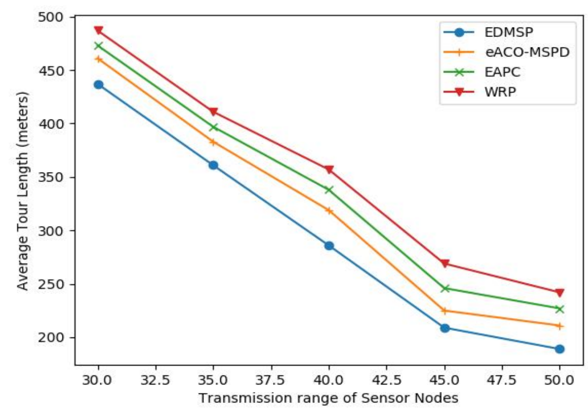


Figure 7 Average Tour Length Vs. Transmission Range of Sensor nodes

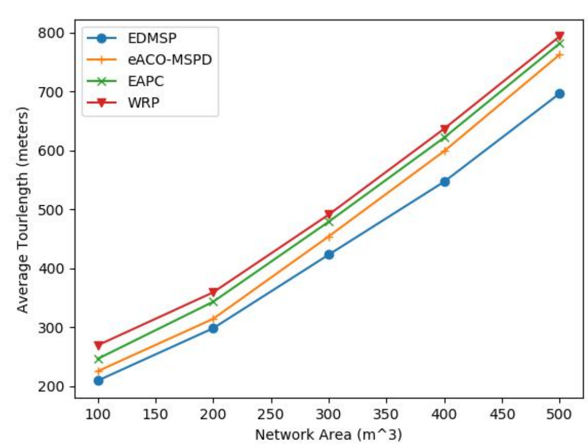


Figure 8 Average Tour Length Vs. Network Area Size

Figure 7 shows the ATL by varying the transmission ranges of the SNs. Here, we find the proposed EDMSP algorithm results least ATL compared to the other existing approaches. The tour length of the proposed EDMSP is reduced approximately 9-17 *meters* than eACO-MSPD, 11-23 *meters* than EAPC and 14-27 *meters* than WRP. Similarly, in addition to increasing the area size of the WSN, the proposed work led to lower ATL compared to the eACO-MSPD, EAPC and WRP approaches as shown in Figure 8. The tour length of the proposed work is reduced while considering the varying area size of the network approximately 5-9 meters, 7-16 meters and 9-21 meters, compared to the eACO-MSPD, EAPC and WRP algorithms, respectively. However, they look slightly different but these improvements affect the N and E_a.

5. CONCLUSION

In Mobile sink-based data gathering approaches, RPs selection and MS path planning play a vital role in enhancing the WSNs. In this context, this paper proposed an Energy-efficient Dynamic Mobile Sink Path planning (EDMSP) algorithm. This algorithm mainly performs the dynamic RPs selection and the low computational path between them. The RP selection mechanism adopts MST-based clustering by considering the residual energies and available buffer capacities. Once the RPs are determined, a simple computational geometry method is used to find the visiting order of the RPs by the MS. The resultant algorithm performs the data gathering operation with low asymptotic time complexity, i.e., $O(n^2)$. The proposed EDMSP algorithm is evaluated in two different scenarios by varying the network size and area. We compare the results using various performance metrics and the proposed work outperforms among them. In this approach, we consider the nodes which generate the data continuously. In the future work, we take the event-driven sensor nodes in the network where the data generated only when the event occurs.

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