JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2717 - 2723
https://publishoa.com
ISSN: 1309-3452

CANOS: Connectivity-Aware Neighbor Orchestration Scheme for Handling Coverage Holes in Wireless Sensor Networks

R.Rajesh
Research Scholar, Department of Information Technology, Annamalai University,
Chidambaram, Tamil Nadu- 608002, India
mtechrajeshr@gmail.com

Dr.V. Tamizhazhagan
Assistant Professor, Department of Information Technology, Annamalai University,
Chidambaram, Tamil Nadu- 608002, India
rvtamizh@gmail.com

ABSTRACT

Wireless Sensor Network (WSN) operations are confined to the available node energy due to which limited application support is available. Energy constraints result in coverage holes in the network, degrading the node-to-node transmissions. Therefore energy conservation and transmission rates are to be evenly balanced without compromising the network efficiency and service parameters. In this article, a Connectivity-Aware Neighbor Orchestration Scheme (CANOS) is introduced for optimizing the fore-mentioned balancing cause. The proposed scheme identifies transmission applicable network slices for neighbor orchestration. In this orchestration process, operational neighbor availability and destination connecting probability are analyzed. Based on the analysis, the network slice with transmission-ability is framed and communication is pursued. A decisive training method recommends the slice forming and de-forming instances for surpassing the region-wise coverage holes. In this training process, neighbor availability and connecting probabilities with energy constraints are considered. Therefore, the outcome is an endurable route to the destination, with a high coverage factor, high network lifetime, and energy utilization.

Keywords—Coverage Hole, Decisive Training, Learning Recommendation, Network Slice, WSN

Introduction

Wireless Sensor Network (WSN) is employed in real-time scenarios such as health-care, tracking, surveillance, and environment monitoring. The main problem in WSN is coverage because this will reduce the performance of the network [1]. The main thing in coverage is the ratio, location, function, and degree of the coverage area. A node that is defaced due to energy exhaustion results in a coverage hole in WSN applications [2]. Patchable holes are holes that are patched during deployment of a new sensor node whereas un-patchable holes cannot be patched during deployment. Hybrid hole healing algorithms are used to identify the patching holes and it leads to cover the holes [3]. Coverage hole repair using the cascaded neighbor intervention method is used to repair the coverage holes. This method will automatically detect the holes and repairs them mitigating coverage gap. The main function of the algorithm is to reduce the percentage of coverage holes in WSN [4].

Wireless Sensor Network (WSN) is used in applications like surveillance, monitoring environment, disaster management, etc. Connectivity is the only thing that accompanies coverage. Connectivity will be broken, when deployment, signal problem, loss in signal problems occurred. Connectivity depends on the path or location of the nodes [5]. A protocol named, Geographical Adaptive Fidelity (GAF) with connectivity awareness is used to avoid the local decrease in WSN. While using this GAF the overall energy consumption is decreased. GAF is an energy-saving model which helps to schedule the functions of the nodes and maintain the connectivity of the network [4, 6]. By using GAF, the energy level is maintained in a sequenced manner so that there will be no decrease in the performance of the nodes. Maintaining the performance of connectivity will lead to an increase in the efficiency, sources and will decrease the energy of transmission. To achieve this, monitor the resources of the process, the communications between the users and the service [2, 7].

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2717 - 2723
https://publishoa.com
ISSN: 1309-3452

Related Works

Khelil et al. [8] has proposed a distributed algorithm that is used in healing holes named hybrid hole healing algorithm (3HA). It addresses the coverage hole problem by replacing distance based nodes in different positions. The initial patching position list is Voronoi vertices which are present within the holes. Integer linear programming will reduce the list as much as possible. This process is repeated until the Voronoi vertices are covered.

The coverage hole problem is generic in WSNs and to overcome this issue, the detection and mitigation algorithm was introduced by Feng et al. [9]. Based on a less complex subnet, the network topology is analyzed. To make cluster nodes, activate the inactive nodes in void regions and then the gap is covered in the network. When compared with BFNP and HPA, the accuracy of detecting holes is higher by the proposed method.

Das et al. and Debbarma et al. [10] have proposed an improved coverage hole patching technique (CHPT) based on tree algorithm. For the detection of hole patching, the Delaunay triangle and void circle properties are used. Estimating the location of the hole is done by the inner empty circle property. During experiments, CHPT shows increased results when compared with the earlier technique.

Mobile Wireless Sensor Network (MWSN) aims at sensing or locating a particular place in an environment. Etancelin et al. [11] have proposed a decentralized algorithm for reducing the impact of coverage holes and maximizing network lifespan. With the help of the local interaction between the sensors, the coverage and lifetime are achieved. This proposed method is mostly for balancing between the lifetime and coverage.

To assure service quality, coverage holes have to patch. Le Nguyen et al. [12] have proposed a method to patch the holes. A time and energy-efficient protocol for locating and patching coverage holes (TELPAC) is introduced. The main goal is to detect the approximate location of the hole by using hexagon tessellation. When compared with the existing protocols TELPAC is a less time-consuming process.

Repairing the coverage holes is a challenging process in Heterogeneous Wireless Sensor Network (HWSN). To overcome the coverage problem, Guo et al. [13] have designed a multi-factor collaborative hole repair optimization algorithm (FCH-ROA) in the HWSN. This algorithm relies on the additive node features for optimization. Considering a 2-D network region, the Voronoi polygon is divided into static nodes. A direction-dependent connectivity between the idle nodes is established. Based on the distance of the node coverage holes will be repaired.

Khalifa et al. [14] introduced a distributed algorithm named cascaded neighbor intervention. This method will automatically detect the holes and repairs them to restore the coverage of the network. The algorithm diminishes the ratio of network coverage holes. The experimental result shows the efficiency of the algorithm.

Clustering in coverage holes will help to increase the performance of mobility, efficiency, and scalability of the network. Gharaei et al. [15] have proposed a new method with the help of clustering, named as energy-efficient and coverage guaranteed unequal sized clustering (ECUC) scheme. This method achieves high energy efficiency and lifetime of the process by solving the coverage issues.

Proposed Scheme

The proposed scheme addresses the coverage hole problem in constraint-based WSN. The constraints in energy conservation and data transmission are identified and network slices are used for surpassing holes. In this scheme, the slice-forming metrics such as availability (ρ) and connectivity $(\complement)$ used for retaining seamless transmissions. In this scheme, decisive training is used for identifying neighbors satisfying the discussed constraints, and hence a network slice is retained.

Problem Definition: The considered metrics are used for framing a network slice that sustains transmission and prevents energy failures. Therefore,

$$\left.\begin{array}{c} \rho = \begin{cases} 1, if\ d(n,n^*) \leq R(n)||R(n^*) \\ 0, otherwise \end{cases} \\ and \\ \rho_S = \prod_{i=1}^{n^*}(\rho_i * \complement_i) \\ where \\ \complement = \frac{E_r}{E_o} + \frac{E_c}{E_o.T} \end{array}\right\} \quad (1)$$

In the equation, the ρ is defined based on distance d between node n and its neighbor n^* provided the range (R) of either is equal to the distance. The place probability (ρ_S) is defined based on remaining energy (E_r), consumed (E_c), initial energy (E_0) and transmission (T). A network slice (S) is composed of n and n^* until a destination is reached. The probability for orchestrating a neighbor within a S is defined as $\rho_N = \frac{E_r}{T}.\rho - \frac{E_c}{(n+n^*)} \forall E_r \geq E_c$. This probability is verified before and after the inclusion or exclusion of n^*. Therefore, based on the above definitions, the n or n^* needs to balance the transmission and $E_r \geq E_c$ constraints. In the following section, the slice formation based on n or n^* orchestration is discussed.

Slice Formation: The independent nodes are orchestrated based on d and R conditions to reach the destination. However this combination of (n, n^*) forms the initial S for relaying packets. The S formation using n and n^* is defined using equation (2)

$$\left.\begin{array}{c} \mathcal{F}_S = \int (n-1) dT + \int \frac{(n^*+1)}{d}\, d\mathrm{C} \\ such\ that \\ (n-1) \in dT = 0 \leq \rho < 1\ (minimum) \\ and \\ (n^*+1) \in dC = \rho_S = 1\ (maximum) \\ provided\ \rho_S . \mathcal{F}_S = \mathrm{C} . \mathcal{F}_{in}\ \forall\ i \in n^* \\ and\ hence \\ \frac{E_r}{T}\, dT - E_c d_{\mathrm{C}} = \arg\max\{1, n^*\} \end{array}\right\} \quad (2)$$

Equation (2) defines the formation factor $\mathcal{F}_S$based on T and E_c. Therefore, the least possible condition of $(n-1)$ and maximum possibility (n^*+1) is evenly balanced. The failure in either of the condition results in an energy hole, preventing S formation. This is hence formulated for new T and decreasing E_o wherein equation (1) values are to be retained. Now, the above function is validated using decisive training for identifying the $\mathcal{F}_s$ feasibility. The feasibility impossible criteria are identified as based on the imbalance conditions. The conditions are identified based on the failing conditions of minimum and maximum defined in equation (2). The decisive learning and training process is presented in Fig. 1.

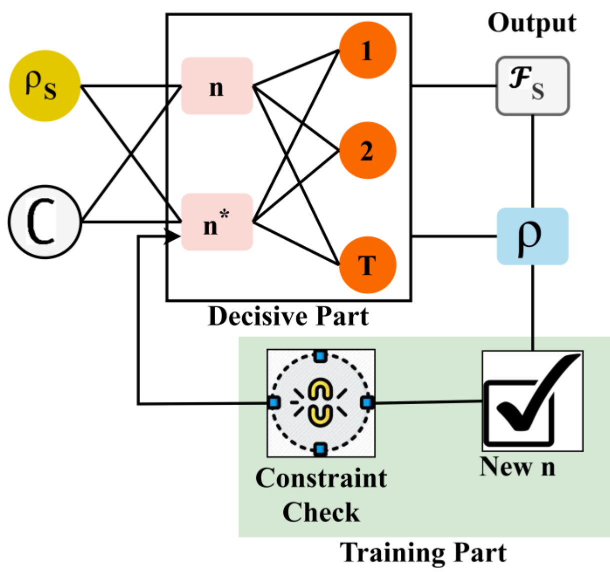

Fig.1 Decisive Learning and Training Illustration

In the learning and training process, ρ_S and C are the inputs that validate the presence of n or n^* or both throughout T. If the availability is high, then $\mathcal{F}_S$ is the output. Contrarily, if a constraint is stuck, then *the* $0 \leq \rho < 1$ condition is analyzed. Therefore the decisive part ensures availability and maximum $\mathcal{F}_S$and hence the mediate instances (α) throughout T is defined as in equation (3)

$$\left.\begin{array}{c} \alpha_1 = \frac{1}{n}\frac{\rho_1}{\rho_{S1}} - \frac{n^*}{n}\frac{E_{c_1}}{E_0} \\ \alpha_2 = \frac{n_1^*}{n}\frac{\rho_2}{\rho_{S2}} - \frac{n_2^*}{n}\frac{E_{c_2}}{E_0} \\ \vdots \\ \alpha_T = \frac{n_{T-1}^*}{n}\frac{\rho_T}{\rho_{ST}} - \frac{n_T^*}{n}\frac{E_{CT}}{E_0} \end{array}\right\} \begin{array}{c} Constraint = 0 \\ Constraint = 0 \leq \rho < 1 \\ \vdots \\ Constraint = 0 \leq \rho < 1\ and\ \arg\min\{1, n^*\} \end{array}\Bigg\} \quad (3)$$

The constraint is identified in the decisive part for which training is induced. The training instances identify the constraint violating instance of T. Based on the identified constraint, the training forarg $\max\{1, n^*\}$ maximization and ρ_S. $\mathcal{F}_S$

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2717 - 2723
https://publishoa.com
ISSN: 1309-3452

Maximization is pursued. The training is instigated from the second T observed in α. Therefore, the training instances (β) from the above are given as in equation (4).

$$\left.\begin{aligned}\beta_2 &= \left(\frac{E_{C_1}}{E_{r_2}} - \frac{\rho_1}{\mathcal{F}_{S_1}}\right) + \frac{n_1^*}{\rho_{S_1}.n}\\ \beta_3 &= \left(\frac{E_{C_2}}{E_{r_3}} - \frac{\rho_2}{\mathcal{F}_{S_2}}\right) + \frac{n_2^*}{\rho_{S_2}.n}\\ &\vdots\\ \beta_T &= \left(\frac{E_{C_{T-1}}}{E_{r_T}} - \frac{\rho_{T-1}}{\mathcal{F}_{T-1}}\right) + \frac{n_{T-1}^*}{\rho_{S_{T-1}}.n}\end{aligned}\right\} \quad (4)$$

The training instances are required to reform S based on constraint-less neighbor orchestration. In the sequential T, the above instance occurrence is required for identifying n^*. Therefore S reformation is based on $(n^* + 1)$ leaving out (n). Thus the slice formation is performed based on $(n^* + 1)$. In this case, the formation is redefined based on $(n^* + 1)$ as defined in equation (5).

$$\mathcal{F}_S = (\alpha_T.\rho) + \left(\beta_T.\,\frac{d\complement}{d}\right) - \left(\frac{n^*+1}{n}\right) \quad (5)$$

Now the new possibility induces training and decisive instances that are either arbitrary or consequent. Now, by equating equations (2) and (5),

$$\left.\begin{aligned}(n-1)dT + \left(\frac{n^*+1}{d}\right) d\complement &= (\alpha_T.\rho) + \left(\beta_T.\frac{d\complement}{d}\right) - \left(\frac{n^*+1}{n}\right)\\ (n-1)d + \left(\frac{n^*+1}{n}\right) &= \alpha_T.\rho - \left(\frac{n^*+1}{n}\right)\ [if\ \beta_T = 0]\\ \rho &= \frac{1}{\alpha_T}\left[\frac{2(n^*+1)}{n} + (n-1)d\right]\end{aligned}\right\} \quad (6)$$

In equation (6), the maximum possibility for achieving maximum ρ. It requires non-replicating nodes (suppressing the condition in equation (2) for reaching the destination. Therefore, for the condition $0 \le \rho < 1$, the ρ in equation (6) is the n^* available probability. Thus reformation and destination reachability it's achieved; the $\mathcal{F}_S$ unmatching results in new n^* and hence the previous n is detained.

Transmission Efficiency: The proposed scheme maximizes transmission by reducing the coverage holes. The hole induced regions are surpassed using n^* leaving out n and thereby ensuring connectivity. In the neighbor identification process, S formation is analyzed fore-hand from which $\mathcal{F}_S$ is satisfied using n^*. An illustration of the coverage hole mitigation is given in Fig. 2.

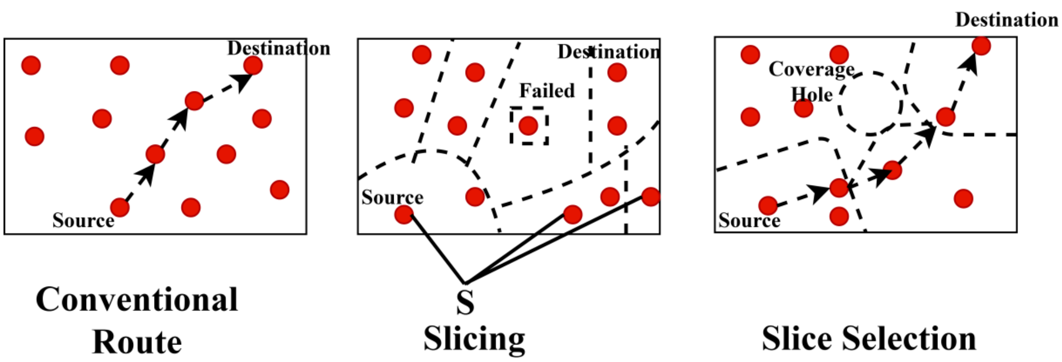

Fig. 2 Coverage Hole Mitigation Process

The conventional route is valid until $E_r \ge E_c$ after which the n fails, resulting in a coverage hole. The coverage hole is mitigated by reforming S for which the metrics in equation (1) have to surpass the constraints in equation (2). However, the slice selection relies on α_T and β_T for preventing unnecessary transmission failures. Therefore, the selection of a new S using n^* is estimated as

$$\left.\begin{aligned}\mathcal{F}(S, n^*) &= \frac{(n^*-1)}{n}.\mathcal{F}_S\left(d \times \frac{E_c}{E_r}\right)\\ \forall\, \rho_S.\frac{n^*}{n} &= \sum_{i=1}^{n^*} \complement_i.\rho_{S_i}\\ &and\ any\ n^* \in S\ satisfies\\ (n^*+1) \in d\complement &= \rho_S = 1\ (maximum)\end{aligned}\right\} \quad (7)$$

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2717 - 2723
https://publishoa.com
ISSN: 1309-3452

This estimation prevents energy ceased nodes to be available in the S. The condition given in equation (2) is to be satisfied in either α_T or β_T for selecting n^*. Therefore the changes experienced for the nodes are used for identifying a new S. Based on the S, the transmission efficient nodes are identified. Hence, the scenario with new augmentation (of nodes) needs to satisfy the above criteria. In the different transmission instances based on the failed nodes, new S is reformed with energy sufficient nodes. A replacement/ change in a node is induced by the decisive part α_T, contrarily, the detraining is ensured based on β_T and the previous instances. Hence, the transmission levels are retained, preventing losses.

Results and Discussion

In this subsection, the proposed scheme's performance is analyzed using network simulator experiments. A sensor network region of $750m \times 500m$ is used for placing 100 sensor nodes. The E_0 is set as 20J for each node for which the transmission range is set as 25m. In this experiment, energy utilization, coverage factor, and network lifetime metrics are analyzed for comparison. The comparative analysis is performed with the existing 3HA [8] and FCH-ROA [13] methods discussed in the related works section.

Energy Utilization

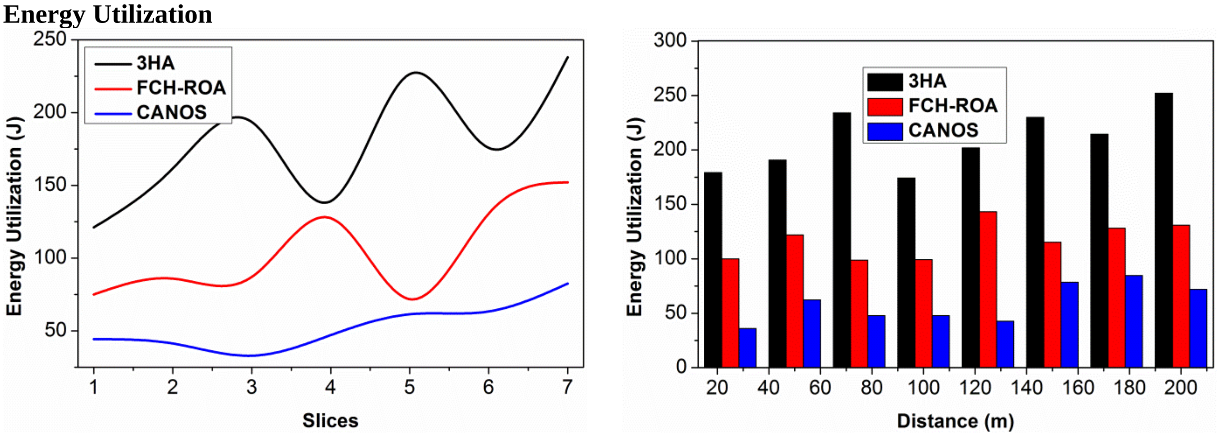

Fig. 3 Energy Utilization Analysis

Fig. 3 presents the comparative analysis for energy utilization based on S and d. The proposed scheme differentiates nodes based on $(n^* + 1) \in d\complement = \rho_S = 1$ in the training and decisive phases. Based on the training instances, the constraints failing instances are identified and hence S reformation is induced. This process is non-replicable preventing early energy exhaust. Therefore, a node utilization from 1 to T transmission is prevented retained energy conservation. The reserved/ unused energy is exploited for the condition satisfying T, achieving fair energy efficiency.

Coverage Factor

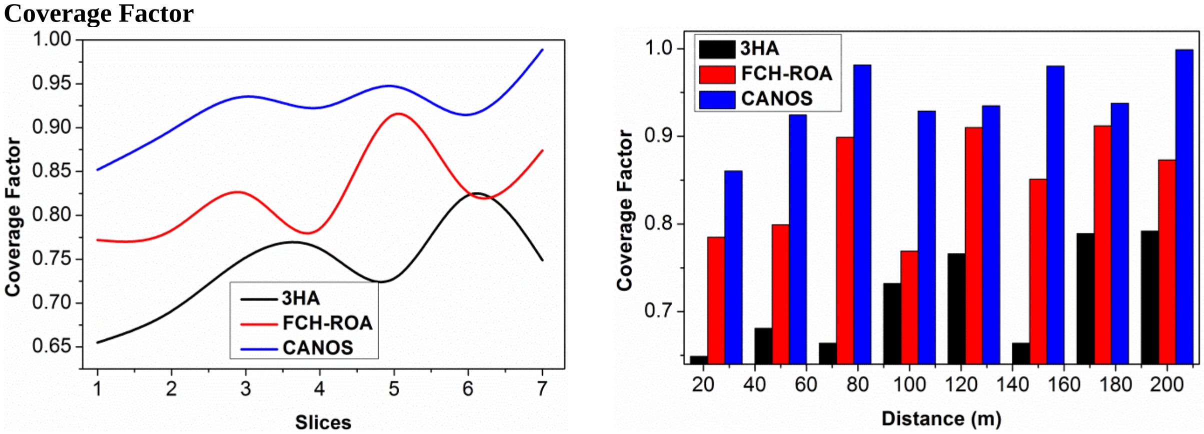

Fig. 4 Coverage Factor Analysis

The proposed scheme addresses the coverage hole problem by retaining nodes on their energy levels. The $\complement$ and $\mathcal{F}_S$ features are used for destination connectivity and coverage maximization. Therefore, the S available by mitigating $0 \leq \rho < 1$ condition such that $\rho = \frac{1}{\alpha_T}$ [.] is the least possible condition 0. This ensures node availability either using n or n^* such

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2717 - 2723
https://publishoa.com
ISSN: 1309-3452

that $\mathcal{F}(S, n^*)$ maximizes $\rho_S = 1$. Therefore the reformation also ensures surpassing instances for node coverage. This is common for varying S and d as presented in Fig.4.

Network Lifetime

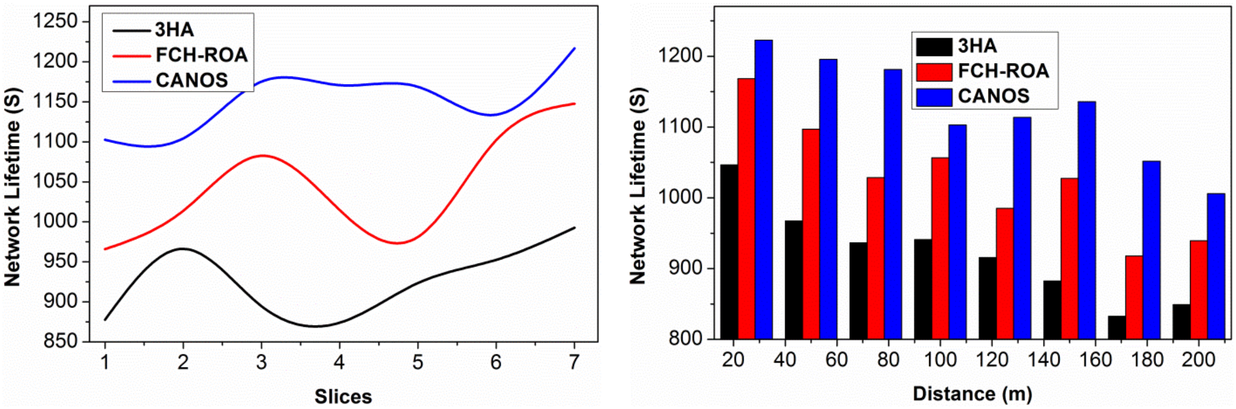

Fig. 5 Network Lifetime Analysis

The first node exhaustion in a network is estimated as the network lifetime. The proposed scheme retains the node's lifetime by preventing weak nodes from participating in T. A node satisfying $E_r \geq E_C$ is first selected for T whereas as energy drains the constraint has to be altered. In the decisive phase, the $\rho_S . \mathcal{F}_S = \complement, f_i \forall i \in n^*$ maximizes constraint less T. Contrarily, the training part influences n^* selection leaving out n (energy deficient) for aiding $\mathcal{F}_S$ and $\mathcal{F}(S, n^*)$. Therefore, influencing a n throughout T is prevented, leaving out its last energy levels. This retains the network lifetime at a fair level [Refer to Fig 5]. In Tables 1 and 2, the comparative analysis is summarized for different S and T

Table 1 Comparative Analysis for Different S

Metrics	**3HA**	**FCH-ROA**	**CANOS**
Energy Utilization (J)	238.01	152.13	82.492
Coverage Factor	0.749	0.874	0.9889
Network Lifetime (s)	992.55	1147.63	1216.987

Inference: The proposed scheme achieves 19.24% less energy utilization, 8.87% high coverage, and 12.07% high network lifetime.

Table 2 Comparative Analysis for Different d

Metrics	**3HA**	**FCH-ROA**	**CANOS**
Energy Utilization (J)	252.19	130.91	71.921
Coverage Factor	0.792	0.873	0.9989
Network Lifetime (s)	849.24	939.31	1005.877

Inference: The proposed scheme achieves 15.61% less energy utilization, 8.32% high coverage, and 11.09% high network lifetime.

Conclusion

A connectivity-aware neighbor orchestration scheme is introduced for maximizing network coverage by addressing the coverage hole problem. This scheme relies on network slices for improving connectivity without additional energy drain. The neighbors are selected based on energy and connectivity constraints and thereby, reducing the coverage hole's impact. The training and decisive processes are independent in recommending a new neighbor and slice reformation. This improves

JOURNAL OF ALGEBRAIC STATISTICS
Volume 13, No. 2, 2022, p. 2717 - 2723
https://publishoa.com
ISSN: 1309-3452

the transmission efficiency and network lifetime, without dwelling the failed nodes. From the experimental analysis it is seen that the proposed scheme achieves 19.24% less energy utilization, 8.87% high coverage, and 12.07% high network lifetime for different slices.

References

[1] Wang, J., Ju, C., Kim, H. J., Sherratt, R. S., & Lee, S. (2019). A mobile assisted coverage hole patching scheme based on particle swarm optimization for WSNs. *Cluster Computing*, *22*(1), 1787-1795.
[2] Hajjej, F., Hamdi, M., Ejbali, R., & Zaied, M. (2020). A distributed coverage hole recovery approach based on reinforcement learning for Wireless Sensor Networks. *Ad Hoc Networks*, *101*, 102082.
[3] Zhang, Y., Zhang, X., Fu, W., Wang, Z., & Liu, H. (2014). HDRE: Coverage hole detection with residual energy in wireless sensor networks. *journal of communications and networks*, *16*(5), 493-501.
[4] Senouci, M. R., & Mellouk, A. (2019). A robust uncertainty-aware cluster-based deployment approach for WSNs: Coverage, connectivity, and lifespan. *Journal of Network and Computer Applications*, *146*, 102414.
[5] Natarajan, P., & Parthiban, L. (2020). k-coverage m-connected node placement using shuffled frog leaping: Nelder–Mead algorithm in WSN. *Journal of Ambient Intelligence and Humanized Computing*, 1-16.
[6] Chen, D. R., Chen, L. C., Chen, M. Y., & Hsu, M. Y. (2019). A coverage-aware and energy-efficient protocol for the distributed wireless sensor networks. *Computer Communications*, *137*, 15-31.
[7] Qin, D., Ma, J., Zhang, Y., Feng, P., Ji, P., & Berhane, T. M. (2018). Study on connected target coverage algorithm for wireless sensor network. *IEEE Access*, *6*, 69415-69425.
[8] Khelil, A., Beghdad, R., & Khelloufi, A. (2020). 3HA: hybrid hole healing algorithm in a wireless sensor networks. *Wireless Personal Communications*, 1-19.
[9] Feng, X., Zhang, X., Zhang, J., & Muhdhar, A. A. (2019). A coverage hole detection and repair algorithm in wireless sensor networks. *Cluster Computing*, *22*(5), 12473-12480.
[10] Das, S., & Debbarma, M. K. (2020). CHPT: an improved coverage-hole patching technique based on tree-center in wireless sensor networks. *Journal of Ambient Intelligence and Humanized Computing*, 1-12.
[11] Etancelin, J. M., Fabbri, A., Guinand, F., & Rosalie, M. (2019). DACYCLEM: A decentralized algorithm for maximizing coverage and lifetime in a mobile wireless sensor network. *Ad hoc networks*, *87*, 174-187.
[12] Le Nguyen, P., Nguyen, K., Vu, H., & Ji, Y. (2019). Telpac: A time and energy efficient protocol for locating and patching coverage holes in wsns. *Journal of Network and Computer Applications*, *147*, 102439.
[13] Gou, P., Mao, G., Zhang, F., & Jia, X. (2020). Reconstruction of coverage hole model and cooperative repair optimization algorithm in heterogeneous wireless sensor networks. *Computer Communications*, *153*, 614-625.
[14] Khalifa, B., Al Aghbari, Z., Khedr, A. M., & Abawajy, J. H. (2017). Coverage hole repair in WSNs using cascaded neighbor intervention. *IEEE Sensors Journal*, *17*(21), 7209-7216.
[15] Gharaei, N., Al-Otaibi, Y. D., Butt, S. A., Sahar, G., & Rahim, S. (2019). Energy-efficient and coverage-guaranteed unequal-sized clustering for wireless sensor networks. *IEEE Access*, *7*, 157883-157891.