

An Energy-Efficient Clustering Algorithm for Satellite IoT Forest Monitoring Systems

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Abstract—Satellite Internet of Things (IoT) provides a promising solution for forest monitoring in remote and infrastructure-limited areas. However, direct transmission from every sensor node to a geostationary Earth orbit (GEO) satellite may cause excessive energy consumption due to long propagation distance, vegetation-induced attenuation, and severe path loss. To address this issue, this paper proposes an energy-aware outage-guided multi-hop clustering algorithm for satellite IoT forest monitoring systems. In the proposed scheme, sensor nodes with sufficient residual energy and reliable satellite links are selected as data collection stations (DCSs), while the remaining nodes forward their sensed data to the corresponding DCSs through reliable sensor-node-to-sensor-node (SN-to-SN) links. The communication models incorporate free-space path loss, vegetation attenuation, atmospheric attenuation, and small-scale fading effects. Based on these models, the proposed algorithm constructs multi-hop clusters to reduce the number of energy-intensive satellite transmissions. Simulation results show that the proposed scheme improves normalized energy efficiency and extends network lifetime compared with the random-selection benchmark.

Index Terms—Satellite IoT, forest monitoring, clustering, multi-hop communication, energy efficiency.

I. INTRODUCTION

Forest monitoring is essential for environmental protection, disaster prevention, and sustainable forest management. Wireless sensor networks (WSNs) have been widely adopted for forest monitoring applications because they can support distributed sensing and event detection over large-scale forest areas [1], [2]. By deploying battery-powered sensor nodes, environmental information such as temperature, humidity, smoke concentration, vibration, and other abnormal signals can be collected for early warning and decision making. However, forest environments are usually characterized by dense vegetation, irregular terrain, and limited infrastructure, which make reliable data transmission and long-term network operation challenging.

Space-air-ground integrated networks (SAGINs) provide a promising architecture for enabling ubiquitous connectivity in remote and infrastructure-limited areas [3]. In particular, satellite Internet of Things (IoT) is suitable for forest monitoring scenarios where terrestrial communication infrastructure is unavailable or costly to deploy. Through satellite links, sensing data collected from forest sensor nodes can be delivered to remote servers for further analysis and emergency response. Existing studies have investigated UAV-assisted and satellite-assisted IoT systems for wildfire detection and forest monitoring [4]–[6]. Nevertheless, many satellite IoT-based monitoring

schemes rely on direct transmission from each sensor node to a geostationary Earth orbit (GEO) satellite.

Although direct sensor-node-to-satellite transmission provides a simple network architecture, it may lead to excessive energy consumption in practical forest deployments. This is mainly because GEO satellite links suffer from long propagation distances, severe free-space path loss, vegetation-induced attenuation, and atmospheric attenuation. To maintain reliable satellite communication, sensor nodes may need to transmit with relatively high power [7]. Since sensor nodes in forest environments are usually powered by limited-capacity batteries and are difficult to recharge or replace, direct satellite transmission from all sensor nodes can significantly shorten the network lifetime.

Clustering and data aggregation provide an effective solution to reduce the number of energy-intensive satellite transmissions. Instead of allowing every sensor node to directly access the GEO satellite, a subset of sensor nodes can be selected as data collection stations (DCSs). The remaining nodes transmit their sensed data to the corresponding DCSs through short-range sensor-node-to-sensor-node (SN-to-SN) links. The DCSs then aggregate the collected data and forward the processed information to the GEO satellite. However, DCS selection and cluster formation in forest-based satellite IoT systems are nontrivial. A suitable DCS should have sufficient residual energy and reliable satellite connectivity. Moreover, due to vegetation blockage and distance-dependent attenuation, some sensor nodes may not directly reach a DCS, making multi-hop forwarding necessary for improving network connectivity.

Motivated by these observations, this paper proposes an energy-aware outage-guided multi-hop clustering algorithm for satellite IoT forest monitoring systems. The proposed scheme selects DCSs by jointly considering residual energy and satellite-link outage probability, and constructs clusters through reliable single-hop or multi-hop SN-to-SN links.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 1, we consider a forest-based satellite IoT monitoring system consisting of I battery-powered sensor nodes and one geostationary Earth orbit (GEO) satellite. The set of sensor nodes is denoted by $\mathcal{I} = \{1, 2, \dots, I\}$. The sensor nodes are randomly deployed in a rectangular

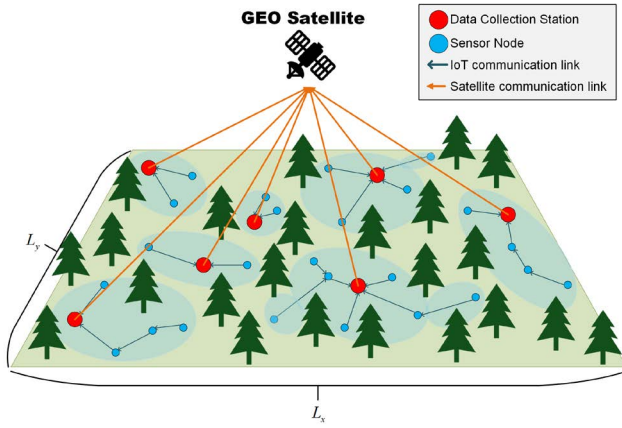


Fig. 1. Forest-based Satellite IoT monitoring systems.

forest monitoring area with dimensions $L_x \times L_y$. The three-dimensional location of sensor node i is denoted by

$$\mathbf{u}_i = [x_i, y_i, z_i]^T, \quad i \in \mathcal{I}, \quad (1)$$

where $0 \leq x_i \leq L_x$, $0 \leq y_i \leq L_y$, and $0 \leq z_i \leq H_{\max}$. The location of the GEO satellite is denoted by $\mathbf{u}_s = [x_s, y_s, z_s]^T$. The distances between sensor nodes i and j , and between sensor node i and the GEO satellite are respectively given by

$$d_{i,j} = \|\mathbf{u}_i - \mathbf{u}_j\|, \quad d_{i,s} = \|\mathbf{u}_i - \mathbf{u}_s\|. \quad (2)$$

To reduce the energy consumption caused by direct satellite transmission from all sensor nodes, a subset of sensor nodes is selected as data collection stations (DCSs). The remaining nodes forward their sensed data to the corresponding DCSs through single-hop or multi-hop sensor-node-to-sensor-node (SN-to-SN) links. Each DCS aggregates the received data and transmits the processed information to the GEO satellite.

A. Communication Model

For the SN-to-SN link, both free-space path loss and vegetation-induced excess attenuation are considered. Let f_I and λ_I denote the carrier frequency and wavelength of the SN-to-SN link, respectively. The free-space path loss in dB is given by

$$L_{i,j}^{\text{FS,I}} = 20 \log_{10} \left(\frac{4\pi d_{i,j}}{\lambda_I} \right). \quad (3)$$

According to the ITU-R vegetation attenuation model, the vegetation-induced excess attenuation in dB is modeled as

$$A_{i,j}^{\text{veg,I}} = A_m^{\text{I}} \left[1 - \exp \left(-\frac{d_{i,j} \gamma_I}{A_m^{\text{I}}} \right) \right], \quad (4)$$

where γ_I is the specific attenuation in dB/m, and A_m^{I} is the maximum vegetation attenuation. Therefore, the large-scale channel power gain of the SN-to-SN link is expressed as

$$\ell_{i,j}^{\text{I}} = G_t^{\text{I}} G_r^{\text{I}} 10^{-\frac{L_{i,j}^{\text{FS,I}} + A_{i,j}^{\text{veg,I}}}{10}}, \quad (5)$$

where G_t^{I} and G_r^{I} denote the transmit and receive antenna gains of the terrestrial IoT interface, respectively. The complex channel coefficient is modeled as

$$h_{i,j}^{\text{I}} = \sqrt{\ell_{i,j}^{\text{I}}} g_{i,j}^{\text{I}}, \quad (6)$$

where $g_{i,j}^{\text{I}} \sim \mathcal{CN}(0, 1)$ denotes Rayleigh fading. Let P_I denote the fixed transmit power for SN-to-SN communication and $\sigma_I^2 = N_0 B_I$ denote the receiver noise power. The instantaneous SNR and achievable rate of the SN-to-SN link are respectively given by

$$\Gamma_{i,j}^{\text{I}} = \frac{P_I \ell_{i,j}^{\text{I}} |g_{i,j}^{\text{I}}|^2}{\sigma_I^2}, \quad (7)$$

and

$$R_{i,j}^{\text{I}} = B_I \log_2(1 + \Gamma_{i,j}^{\text{I}}). \quad (8)$$

For clustering and multi-hop route construction, the average SNR is used to determine whether a reliable SN-to-SN link can be established as

$$\bar{\Gamma}_{i,j}^{\text{I}} = \frac{P_I \ell_{i,j}^{\text{I}}}{\sigma_I^2}. \quad (9)$$

Accordingly, the adjacency indicator is defined as

$$a_{i,j} = \begin{cases} 1, & i \neq j, \bar{\Gamma}_{i,j}^{\text{I}} \geq \Gamma_I^{\text{th}}, \\ 0, & \text{otherwise,} \end{cases} \quad (10)$$

where Γ_I^{th} is the SN-to-SN SNR threshold. The adjacency matrix is denoted by $\mathbf{A} = [a_{i,j}] \in \{0, 1\}^{I \times I}$. For the SN-to-GEO satellite link, the free-space path loss, vegetation attenuation, and atmospheric attenuation are considered. Let f_S and λ_S denote the carrier frequency and wavelength of the satellite link, respectively. The free-space path loss in dB is

$$L_{i,s}^{\text{FS,S}} = 20 \log_{10} \left(\frac{4\pi d_{i,s}}{\lambda_S} \right). \quad (11)$$

Let θ_i denote the elevation angle from sensor node i to the GEO satellite, and let H_c denote the effective canopy height. The effective propagation distance inside the vegetation layer is approximated as

$$d_{i,s}^{\text{veg}} = \min \left\{ d_{i,s}, \frac{[H_c - z_s]^+}{\sin \theta_i} \right\}, \quad (12)$$

where $[x]^+ = \max\{x, 0\}$. The vegetation-induced attenuation of the satellite link is modeled as

$$A_{i,s}^{\text{veg,S}} = A_m^{\text{S}} \left[1 - \exp \left(-\frac{d_{i,s}^{\text{veg}} \gamma_S}{A_m^{\text{S}}} \right) \right]. \quad (13)$$

Let $A_{i,s}^{\text{atm}}$ denote the atmospheric attenuation in dB, which follows the ITU-R atmospheric attenuation model. The large-scale channel power gain of the SN-to-GEO satellite link is then written as

$$\ell_{i,s}^{\text{S}} = G_t^{\text{S}} G_r^{\text{S}} 10^{-\frac{L_{i,s}^{\text{FS,S}} + A_{i,s}^{\text{veg,S}} + A_{i,s}^{\text{atm}}}{10}}, \quad (14)$$

where G_t^S and G_r^S are the transmit and receive antenna gains of the satellite link, respectively. The satellite channel coefficient is modeled as

$$h_{i,s}^S = \sqrt{\ell_{i,s}^S g_{i,s}^S}, \quad (15)$$

where $g_{i,s}^S$ follows Rician fading. Let P_S denote the fixed satellite transmission power and $\sigma_S^2 = N_0 B_S$ denote the receiver noise power. The satellite-link SNR is given by

$$\Gamma_{i,s}^S = \frac{P_S \ell_{i,s}^S |g_{i,s}^S|^2}{\sigma_S^2}. \quad (16)$$

B. Energy and Reliability Constraints

The system operates in a slotted manner. Let n denote the slot index and E_i^n denote the residual energy of sensor node i at the end of slot n . Each sensor node is equipped with a battery of maximum energy $E_{\max}$. A regular sensor node consumes energy for basic operation and SN-to-SN transmission, and its residual energy is updated as

$$E_i^n = E_i^{n-1} - E_b - P_I T_I, \quad i \notin \mathcal{D}^n, \quad (17)$$

where E_b is the basic sensing and circuit energy, T_I is the SN-to-SN transmission duration, and $\mathcal{D}^n$ denotes the set of selected DCSs in slot n . If node i is selected as a DCS, its residual energy is updated as

$$E_i^n = E_i^{n-1} - E_b - P_S T_S - E_{i,\text{rx}}^n - E_{i,\text{agg}}^n, \quad i \in \mathcal{D}^n, \quad (18)$$

where T_S is the satellite transmission duration, $E_{i,\text{rx}}^n$ is the receiving energy, and $E_{i,\text{agg}}^n$ is the data aggregation energy. A sensor node is active in slot n only if it has sufficient energy for basic operation and terrestrial transmission. The active node set is defined as

$$\mathcal{I}_a^n = \{i \in \mathcal{I} \mid E_i^{n-1} \geq E_b + P_I T_I\}. \quad (19)$$

To avoid selecting low-energy nodes as DCSs, the DCS candidate set is defined as

$$\mathcal{I}_c^n = \{i \in \mathcal{I}_a^n \mid E_i^{n-1} \geq \alpha E_{\max}\}, \quad (20)$$

where $0 < \alpha < 1$ is the residual-energy threshold ratio. Since each DCS must forward aggregated data to the GEO satellite, satellite-link reliability is used as a DCS selection metric. Let η_S denote the minimum spectral efficiency requirement of the satellite link. The satellite-link outage probability of node i is

$$P_{i,s}^{\text{out}} = \Pr(\log_2(1 + \Gamma_{i,s}^S) < \eta_S). \quad (21)$$

The corresponding SNR threshold is

$$\Gamma_S^{\text{th}} = 2^{\eta_S} - 1. \quad (22)$$

Thus,

$$P_{i,s}^{\text{out}} = F_{|g_{i,s}^S|^2} \left(\frac{\Gamma_S^{\text{th}} \sigma_S^2}{P_S \ell_{i,s}^S} \right), \quad (23)$$

where $F_{|g_{i,s}^S|^2}(\cdot)$ is the CDF of the normalized Rician channel power gain.

C. Problem Formulation

The objective is to reduce the number of selected DCSs while maintaining energy feasibility, satellite-link reliability, SN-to-SN connectivity, and cluster-size constraints. Let $\mathcal{C}_k^n$ denote the cluster associated with DCS $k \in \mathcal{D}^n$, and let N_t denote the maximum cluster size. The clustering problem in slot n can be formulated as

$$\min_{\mathcal{D}^n, \{\mathcal{C}_k^n\}} |\mathcal{D}^n| \quad (24a)$$

$$\text{s.t. } \mathcal{D}^n \subseteq \mathcal{I}_c^n, \quad (24b)$$

$$|\mathcal{C}_k^n| \leq N_t, \quad k \in \mathcal{D}^n, \quad (24c)$$

$$\mathcal{C}_k^n \cap \mathcal{C}_{k'}^n = \emptyset, \quad k \neq k', \quad (24d)$$

$$\exists \mathcal{P}_{i \rightarrow k}^n, \quad i \in \mathcal{C}_k^n, \quad k \in \mathcal{D}^n, \quad (24e)$$

$$a_{u,v} = 1, \quad \forall (u,v) \in \mathcal{P}_{i \rightarrow k}^n. \quad (24f)$$

Here, $\mathcal{P}_{i \rightarrow k}^n$ denotes a feasible single-hop or multi-hop SN-to-SN path from sensor node i to DCS k . The formulated problem is combinatorial due to the joint DCS selection, cluster association, and multi-hop path construction. Therefore, a low-complexity energy-aware outage-guided clustering algorithm is developed in the next section.

III. PROPOSED CLUSTERING ALGORITHM

The problem formulated in Section II is combinatorial because it involves DCS selection, cluster association, and multi-hop path construction over the SN-to-SN connectivity graph. Exhaustive search becomes computationally infeasible for large-scale forest monitoring systems. Therefore, this section proposes a low-complexity energy-aware outage-guided multi-hop clustering algorithm. The proposed algorithm consists of two main steps in each slot. First, a DCS is selected from the candidate set $\mathcal{I}_c^n$ according to the satellite-link outage probability. Specifically, among the unassigned DCS candidates, the node with the lowest outage probability is selected as the DCS. This criterion favors sensor nodes with more reliable GEO satellite connectivity. Second, starting from the selected DCS, the cluster is expanded layer by layer based on the adjacency matrix $\mathbf{A}$. This multi-hop expansion enables sensor nodes that cannot directly reach the DCS to be connected through reliable SN-to-SN forwarding links. Let $\mathcal{U}^n$ denote the set of unassigned active sensor nodes in slot n , where $\mathcal{U}^n = \mathcal{I}_a^n$ initially. For a selected DCS k , the cluster associated with k is denoted by $\mathcal{C}_k^n$. The frontier set at the m -th layer is denoted by $\mathcal{F}_k^{(m)}$, where $\mathcal{F}_k^{(0)} = \{k\}$. Given the frontier set $\mathcal{F}_k^{(m-1)}$, the candidate node set at the m -th layer is defined as

$$\mathcal{V}_k^{(m)} = \left\{ j \in \mathcal{U}^n \setminus \mathcal{C}_k^n \mid \exists i \in \mathcal{F}_k^{(m-1)}, a_{i,j} = 1 \right\}. \quad (25)$$

If the number of candidate nodes exceeds the remaining cluster capacity, the candidates are ranked according to their strongest SN-to-SN link quality to the current frontier. The connection metric of node j is defined as

$$\chi_j = \max_{i \in \mathcal{F}_k^{(m-1)}, a_{i,j}=1} \bar{\Gamma}_{i,j}^I. \quad (26)$$

Algorithm 1 Proposed Clustering Algorithm

Require: $\mathcal{I}_a^n, \mathcal{I}_c^n, \mathbf{A}, \{P_{i,s}^{\text{out}}\}, N_t$

Ensure: $\mathcal{D}^n$ and $\{\mathcal{C}_k^n\}_{k \in \mathcal{D}^n}$

- 1: Initialize $\mathcal{D}^n \leftarrow \emptyset$ and $\mathcal{U}^n \leftarrow \mathcal{I}_a^n$.
 - 2: **while** $\mathcal{U}^n \neq \emptyset$ and $\mathcal{I}_c^n \cap \mathcal{U}^n \neq \emptyset$ **do**
 - 3: Select $k^* = \arg \min_{i \in \mathcal{I}_c^n \cap \mathcal{U}^n} P_{i,s}^{\text{out}}$.
 - 4: Set $\mathcal{D}^n \leftarrow \{k^*\}$, $\mathcal{C}_{k^*}^n \leftarrow \{k^*\}$, and $\mathcal{F}_k^m \leftarrow \{k^*\}$.
 - 5: **while** $\mathcal{F}_k^m \neq \emptyset$ and $|\mathcal{C}_{k^*}^n| < N_t$ **do**
 - 6: Find unassigned neighbors of $\mathcal{F}_k^m$ according to $\mathbf{A}$.
 - 7: Rank the neighbors by their maximum average SNR to $\mathcal{F}_k^m$.
 - 8: Add the top-ranked nodes to $\mathcal{C}_{k^*}^n$ until $|\mathcal{C}_{k^*}^n| = N_t$.
 - 9: Update $\mathcal{F}_k^m$ as the newly added nodes.
 - 10: **end while**
 - 11: Update $\mathcal{U}^n \leftarrow \mathcal{U}^n \setminus \mathcal{C}_{k^*}^n$.
 - 12: **end while**
 - 13: Each sensor node forwards data to its DCS through the constructed SN-to-SN path.
 - 14: Each DCS aggregates the received data and transmits it to the GEO satellite.
 - 15: Update residual energy according to the energy model in Section II.
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The nodes with larger χ_j are given higher priority. For each selected node j , its parent relay node is determined by

$$p(j) = \arg \max_{i \in \mathcal{F}_k^{(m-1)}, a_{i,j}=1} \bar{\Gamma}_{i,j}^I. \quad (27)$$

Therefore, each associated sensor node has a feasible single-hop or multi-hop path to its DCS, and all forwarding links satisfy the SN-to-SN reliability requirement.

The proposed algorithm reduces energy consumption by decreasing the number of DCSs required for GEO satellite transmission. The outage-guided DCS selection improves satellite-link reliability, while the multi-hop expansion allows more sensor nodes to be served through short-range SN-to-SN forwarding links. Therefore, the proposed design improves energy efficiency and extends network lifetime with low implementation complexity.

IV. SIMULATION RESULTS

In this section, simulation results are presented to evaluate the performance of the proposed energy-aware outage-guided multi-hop clustering algorithm. The proposed scheme is compared with a random-selection benchmark, where DCSs are randomly selected from the available sensor nodes and multi-hop forwarding is not employed. For fairness, both schemes are evaluated under the same node deployment, channel model, and energy model.

The performance is evaluated using normalized energy efficiency and network residual energy ratio. The energy efficiency of a scheme is defined as

$$\text{EE}_{\text{sch}} = \frac{\sum R_{\text{sch}}}{\sum E_{\text{sch}}}, \quad (28)$$

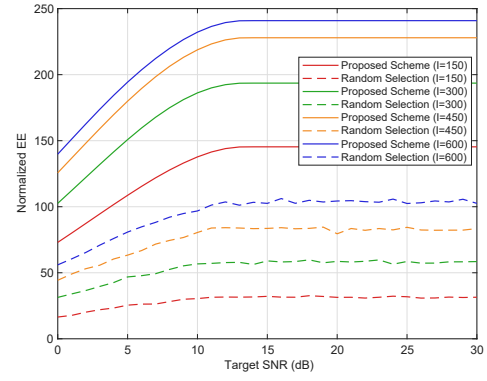


Fig. 2. Energy efficiency for fixed area (150m×150m).

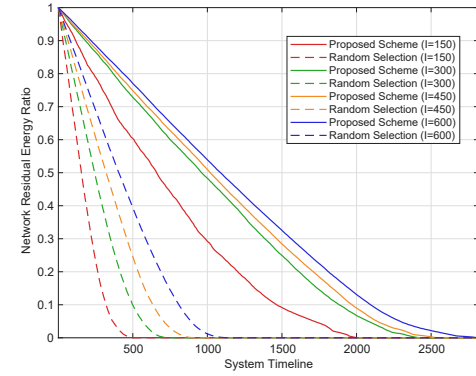


Fig. 3. Network lifetime for fixed area (150m×150m).

where $\sum R_{\text{sch}}$ and $\sum E_{\text{sch}}$ denote the accumulated communication rate and total energy consumption of the considered scheme, respectively. The normalized energy efficiency is defined with respect to the all-direct-satellite transmission reference as

$$\text{NEE} = \frac{\text{EE}_{\text{sch}}}{\text{EE}_{\text{AllSat}}} \times 100\%, \quad (29)$$

where $\text{EE}_{\text{AllSat}}$ denotes the energy efficiency when all sensor nodes directly transmit to the GEO satellite. The network residual energy ratio is defined as

$$E_{\text{ratio}}(n) = \frac{\sum_{i \in \mathcal{I}} E_i^n}{IE_{\text{max}}}, \quad (30)$$

which characterizes the remaining energy level of the entire network at slot n .

Fig. 2 shows the normalized energy efficiency under the fixed-area scenario. The proposed scheme achieves higher normalized energy efficiency than the random-selection benchmark for all considered values of I . This is because the proposed algorithm selects DCSs with reliable satellite links and sufficient residual energy, while multi-hop SN-to-SN forwarding allows more sensor nodes to be served by each selected DCS. As a result, the number of energy-intensive GEO satellite transmissions is reduced. Moreover, as I increases, the node density becomes higher, which increases the probability of establishing reliable SN-to-SN links and improves the clustering performance.

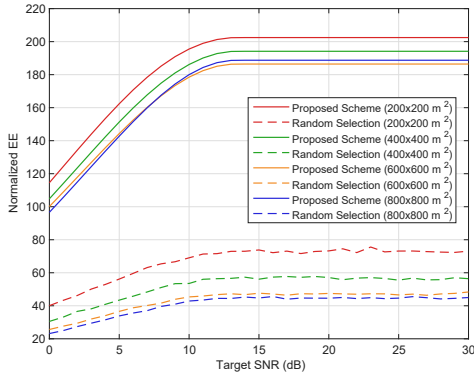


Fig. 4. Energy efficiency with a fixed the number of sensor nodes ($I=500$).

Fig. 3 shows the network residual energy ratio under the fixed-area scenario. The proposed scheme exhibits a slower energy depletion rate than the random-selection benchmark. This demonstrates that the proposed DCS selection and multi-hop clustering mechanism can effectively extend the network lifetime. In particular, denser deployments provide more feasible forwarding paths, allowing the proposed algorithm to form larger clusters and distribute the data forwarding burden more efficiently.

Fig. 4 presents the normalized energy efficiency when the number of sensor nodes is fixed at $I = 500$ and the monitoring area is enlarged. The proposed scheme still outperforms the random-selection benchmark for all area sizes. However, the normalized energy efficiency decreases as the monitoring area increases. This is because a larger monitoring area reduces the node density and increases the average SN-to-SN communication distance. Consequently, fewer links can satisfy the SNR threshold Γ_I^{th} , and more DCSs are required to cover the network, resulting in higher satellite transmission energy consumption.

Fig. 5 shows the network residual energy ratio under the fixed-node scenario. As the monitoring area increases, the network lifetime decreases for both schemes due to the reduced SN-to-SN connectivity. Nevertheless, the proposed scheme maintains better residual energy performance than the random-selection benchmark. These results verify that the proposed outage-guided DCS selection and multi-hop clustering design can improve energy efficiency and prolong network lifetime, especially when sufficient SN-to-SN connectivity is available.

V. CONCLUSION

This paper proposed an energy-aware outage-guided multi-hop clustering algorithm for satellite IoT forest monitoring systems. In the proposed scheme, sensor nodes with sufficient residual energy and reliable satellite links are selected as DCSs, while the remaining nodes forward their sensed data to the corresponding DCSs through reliable SN-to-SN links. By exploiting multi-hop clustering, the proposed algorithm reduces the number of energy-intensive GEO satellite transmissions and improves the overall energy utilization. Simulation results show that the proposed scheme achieves higher

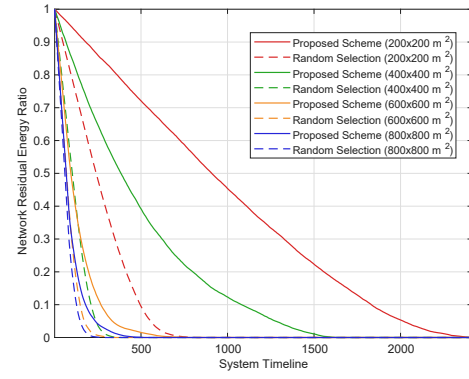


Fig. 5. Network lifetime with a fixed the number of sensor nodes ($I=500$).

normalized energy efficiency and slower energy depletion than the random-selection benchmark under different node densities and monitoring-area sizes. These results demonstrate the effectiveness of the proposed design for energy-constrained satellite IoT forest monitoring applications.

REFERENCES

- [1] C. Streck and S. M. Scholz, "The role of forests in global climate change: whence we come and where we go," *Int. Affairs*, vol. 82, no. 5, pp. 861–879, Oct. 2006.
- [2] B. Haq, M. A. Jamshed, K. Ali, B. Kasi, S. Arshad, M. K. Kasi, I. Ali, A. Shabbir, Q. H. Abbasi, and M. U. Rehman, "Tech-Driven Forest Conservation: Combating Deforestation With Internet of Things, Artificial Intelligence, and Remote Sensing," *IEEE Internet Things J.*, vol. 11, no. 14, pp. 24551–24568, Jul. 2024.
- [3] Y. Xiao, Z. Ye, M. Wu, H. Li, M. Xiao, M. S. Alouini, A. Al-Hourani, and S. Ciono, "Space-Air-Ground Integrated Wireless Networks for 6G: Basics, Key Technologies, and Future Trends," *IEEE J. Sel. Areas Commun.*, vol. 42, no. 12, pp. 3327–3354, Dec. 2024.
- [4] O. M. Bushnaq, A. Chaaban, and T. Y. Al-Naffouri, "The Role of UAV-IoT Networks in Future Wildfire Detection," *IEEE Internet Things J.*, vol. 8, no. 23, pp. 16984–16999, Dec. 2021.
- [5] H.-H. Liu, R. Y. Chang, Y.-Y. Chen, and I.-K. Fu, "Sensor-Based Satellite IoT for Early Wildfire Detection," in *Proc. IEEE Globecom Workshops*, 2021.
- [6] H.-H. Liu, R. Y.-Y. Chen, I.-K. Fu, and H. V. Poor, "Sensor Deployment and Link Analysis in Satellite IoT Systems for Wildfire Detection," in *Proc. IEEE GLOBECOM*, 2022.
- [7] X. Chen, Z. Xu, and L. Shang, "Satellite Internet of Things: Challenges, Solutions, and Development Trends," *Front. Inf. Technol. Electron. Eng.*, vol. 24, no. 7, pp. 935–944, Jul. 2023.
- [8] B. M. Lee, and H. Yang, "Optimized power control strategy in Massive MIMO for distributed IoT networks," *Future Gener. Comput. Syst.*, vol. 141, pp. 433–447, Apr. 2023.
- [9] ITU-R, "Calculation of free-space attenuation," Recommendation ITU-R P.535-3, 2016.
- [10] ITU-R, "Attenuation in vegetation," Recommendation ITU-R P.833-10, 2021.
- [11] Z. Zhang, X. Hu, X. Qian, and C. Liu, "Satellite Selection and Communication Window Prediction for Metasurface-Enabled Satellite Communication Systems," *IEEE Trans. Commun.*, vol. 74, pp. 4493–4506, 2026.
- [12] ITU-R, "Attenuation by atmospheric gases," Recommendation ITU-R P.676-11, 2016.
- [13] D.-H. Jung, J.-G. Ryu, W.-J. Byun, and J. Choi, "Performance Analysis of Satellite Communication System Under the Shadowed-Rician Fading: A Stochastic Geometry Approach," *IEEE Trans. Commun.*, vol. 70, no. 4, pp. 2707–2721, Apr. 2022.
- [14] B. Aoum, R. Boutaba, Y. Iraqi and G. Kenward, "Gateway Placement Optimization in Wireless Mesh Networks With QoS Constraints," *IEEE J. Sel. Areas Commun.*, vol. 24, no. 11, pp. 2127–2136, Nov. 2006.