

Co-Optimization of Satellite Wake-Up and Routing for Lifetime and Delay Balance in LEO Constellations

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Abstract—Traditional routing algorithms in low Earth orbit (LEO) satellite networks optimize performance metrics such as delay but are often energy-unaware, leading to constellation energy imbalance and connection lifetime reduction. To address this, we propose a Simulated Annealing-based Hierarchical Satellite Optimizer (SA-HSO), i.e., a hierarchical framework that co-optimizes total service delay and satellite battery lifetime. Specifically, our proposed SA-HSO first formulates an equivalent objective function to minimize the weighted sum of delay and lifetime consumption. Then, it employs an upper-level simulated annealing algorithm to dynamically select the number and set of active satellites, coupled with a lower-level routing optimizer. Simulations show that SA-HSO reduces the normalized objective value by 41.5% and 66.7% compared to the greedy and random activation schemes, respectively. Meanwhile, it improves the energy balance by 33.4% and 48.3%, respectively. Our method effectively balances the energy use and delay reduction, while achieving sustained constellation operation with 99% service reliability.

Index Terms—LEO satellite networks, Energy-aware routing, Hierarchical optimization, Lifetime-delay tradeoff.

I. INTRODUCTION

Low Earth orbit (LEO) satellite networks are increasingly vital for providing ubiquitous communications across the globe. In particular, high bandwidth and security can be offered with the use of laser inter-satellite links (ISL) and associated routing schemes [1], [2], [3]. Albeit laser ISL is energy-efficient, the associated acquisition, tracking, and pointing systems require continuous power. This could result in considerable battery energy depletion, particularly during eclipse periods [4]. Since the lifetime of a satellite is often constrained by the health and cycle life of its battery, careful energy management is essential to extend the battery life and ensure sustainable satellite operation [5].

Energy-aware routing has been explored to mitigate battery degradation and extend network lifetime. For instance, [6]

proposed green laser ISL planning to periodically switch ISL working states to prolong the battery lifetime. An energy-saving routing algorithm based on a time-varying graph was proposed in [7] for reliable end-to-end file transmission in LEO satellite networks. Similarly, a Q-learning approach was adopted in [8] to optimize power allocation and balance inter-satellite workloads, thus leading to reduced battery strain and extended network lifetime. In addition, [9] leveraged digital twins and multipath adaptive routing to co-optimize energy and communication performance. [10] demonstrated a trade-off between delay- and power-based optimization in satellite constellation routing.

Despite these advances, most existing methods assume a fixed number of active satellites and do not jointly optimize satellite activation with routing on multi-service demand. To address this gap, we present a Simulated Annealing-based Hierarchical Satellite Optimizer (SA-HSO), a novel framework that co-optimizes the satellite wake-up and routing strategy to balance energy consumption and service latency. This optimizer is first formulated as a mixed integer nonlinear programming (MINLP) problem and then solved via a two-level optimization architecture. The upper level employs a simulated annealing (SA) algorithm to dynamically select the number and set of active satellites, while the lower level concurrently optimizes the routing paths and bandwidth allocation for all traffic demands. The main contributions of this paper are summarized as follows.

- We present a novel routing framework for large-scale LEO constellations that incorporates dynamic satellite wake-up and realistic traffic pattern modeling, enabling joint optimization of battery lifetime and communication delay on multi-service demand.
- We formulate the co-optimization problem and design a hierarchical solver, with an upper-level SA algorithm for dynamic selection of active satellites and a lower-level iterative congestion pricing-based optimizer for efficient routing.

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- Extensive simulations demonstrate that our approach achieves an effective lifetime-delay balance, with at least 41.5% joint reduction in energy consumption and delay cost compared to the greedy and random activation schemes, while maintaining 99% routing success rate under diverse service requirements.

II. SYSTEM MODEL

Energy-aware routing system for LEO satellite networks is shown in Fig. 1. The network consists of $\mathcal{V} = \{1, 2, \dots, V\}$ satellites and $\mathcal{G} = \{1, 2, \dots, G\}$ ground stations, collectively denoted as node set $\mathcal{N} = \mathcal{V} \cup \mathcal{G}$. Throughout this paper, the indices m and n are used to denote any generic node in $\mathcal{N}$. The complete set of links is given by $E = E_{\text{ISL}} \cup E_{\text{GSL}}$, where E_{ISL} denotes laser ISL and E_{GSL} represents ground-to-satellite links (GSL). In our model, when a satellite enters sleep mode, its inter-satellite links are considered unavailable. For any satellite node $i \in \mathcal{V}$, we denote its set of neighboring nodes as $\mathcal{N}(i) = \{j \mid (i, j) \in E\}$. To handle network dynamicity, the time is divided into fixed snapshots (ΔT) during which the topology is considered static. In each snapshot, satellites are classified into the two disjoint subsets of satellites in the Earth's eclipse $\mathcal{V}_E$ and those in sunlight $\mathcal{V}_S$, such that $\mathcal{V} = \mathcal{V}_E \cup \mathcal{V}_S$.

End-to-end transmission begins with traffic mapping to visible satellites, followed by a joint optimization that determines satellite modes, routing paths, and bandwidth allocation to concurrently minimize energy consumption and delay cost, concluding with data forwarding as scheduled.

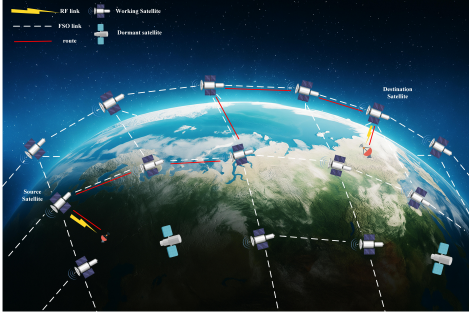


Fig. 1. The proposed energy-aware satellite network architecture with dynamic wake-up management.

A. Solar Eclipse Model

The energy status of a satellite is primarily determined by solar power availability, which makes reliable eclipse detection essential to activate energy-saving measures. Therefore, we employ a cylindrical eclipse model based on vector geometry in [11], as shown in Fig. 2. This model provides a computationally efficient binary classification on eclipse detection, which is sufficient for our routing objective.

Satellite i is considered to be in eclipse if and only if both of the following conditions are satisfied. Firstly, the satellite is on the night side of the Earth, which is mathematically expressed as

$$\vec{r}_i \cdot \vec{r}_{\text{sun}} < 0, \quad (1)$$

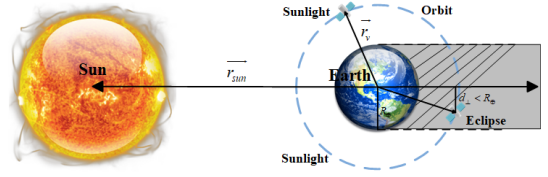


Fig. 2. Cylindrical eclipse model based on vector geometry.

where $\vec{r}_i$ is the position vector of satellite i in the Earth-Centered Inertial frame, and $\vec{r}_{\text{sun}}$ is the position vector of the Sun. Secondly, the satellite is within the Earth's shadow cylinder, with the condition given by

$$d_{\perp} = \|\vec{r}_i\|^2 - \frac{(\vec{r}_i \cdot \vec{r}_{\text{sun}})^2}{\|\vec{r}_{\text{sun}}\|^2} < R_{\oplus}^2, \quad (2)$$

where $R_{\oplus}$ is the mean equatorial radius of the Earth.

B. Satellite Aging Model

The lifetime of a satellite depends on both battery lifetime and fuel for its control. This model focuses on battery degradation, a primary near-term constraint. The battery degradation is influenced by solar panel charging efficiency, and is captured through power consumption and aging estimation. Specifically, the power consumption of an active satellite i , denoted as P_i^{active} , is modeled as

$$P_i^{\text{active}} = P_i^{\text{base}} + P_i^{\text{ISL}} + P_i^{\text{GSL}} + P_i^{\text{proc}}, \quad (3)$$

where P_i^{base} denotes the basic platform power consumption for satellite operations, P_i^{ISL} and P_i^{GSL} denote the power consumption of ISL and GSL, respectively, both comprising fixed and linear traffic-dependent components, and P_i^{proc} denotes the power consumption of data processing [12]. It is worth noting that P_i^{proc} follows a nonlinear relationship with traffic load, given as [12, eq.(3)]

$$P_i^{\text{proc}} = \mu \left(\sum_{k \in K} \sum_{j \in \mathcal{N}(i)} f_{ij}^k \right)^{\alpha}, \quad (4)$$

where μ is a scaling coefficient, α is a nonlinear exponent, and f_{ij}^k denotes the flow rate of service k from satellite i to a neighboring satellite j . Note that $(\sum_{k \in K} \sum_{j \in \mathcal{N}(i)} f_{ij}^k)$ denotes the total traffic flow rate routed through satellite i . In addition, the specific power consumption is formally constrained with the satellite's location and its operational mode $m_i \in \{0, 1\}$, i.e., sleep or wake-up. In this way, the total power consumption for any satellite i is thus expressed as

$$P_i = \begin{cases} (1 - m_i)P_i^{\text{sleep}} + m_i P_i^{\text{active}}, & \forall i \in \mathcal{V}_E \\ P_i^{\text{active}}, & \forall i \in \mathcal{V}_S \end{cases} \quad (5)$$

where P_i^{sleep} denotes the fixed baseline power consumption in sleep mode. Based on (5), the battery state denoted as B_i through the snapshot interval ΔT is thus defined as

$$B_i(t + \Delta T) = \begin{cases} B_i(t) - P_i \Delta T, & \forall i \in \mathcal{V}_E \\ \min(B_{\text{max}}, B_i(t) + (P_{\text{sun}} - P_i) \Delta T), & \forall i \in \mathcal{V}_S. \end{cases} \quad (6)$$

where B_{max} is the maximum battery capacity and P_{sun} denotes the solar power generated by the satellite's panels when in sunlight. For an eclipsing satellite, the battery purely discharges, while for a sunlit satellite, its final state is determined by the net energy balance.

Aging is characterized by depth of discharge (DOD). The DOD state of satellite i at any time t is denoted by $D_i(t)$, calculated as [13]

$$D_i(t) = \frac{\int_0^t P_i(\tau) d\tau}{B_{max}} = \frac{B_{max} - B_i(t)}{B_{max}}, \quad (7)$$

where the power consumption is assumed to be a constant P_i within one snapshot, causing the instantaneous DOD, i.e., $D_i(\tau)$ increases linearly from $D_i(t)$ during the snapshot interval. Furthermore, the battery cycle life consumption ΔL_i over the snapshot is modeled as a continuous process, whose calculation requires the use of the $D_i(\tau)$ [14]. That is, ΔL_i is calculated as

$$\Delta L_i = \int_t^{t+\Delta T} f(D_i(\tau)) \frac{P_i}{B_{max}} d\tau, \quad (8)$$

where the instantaneous aging rate is given by the nonlinear function $f(D_i(\tau))$, defined as

$$f(D_i(\tau)) = 10^{A(D_i(\tau)-1)} (1 + A \ln 10 D_i(\tau)), \quad (9)$$

where A is a battery-specific constant obtained from empirical cycle life tests. The total lifetime consumption for an eclipsing satellite is then calculated by substituting (9) into (8).

C. Traffic Model

To accurately capture real-world conditions, it is imperative for the traffic model to incorporate the spatial and temporal heterogeneity of global user demand. Our traffic model includes three important features of temporal dynamics, geographical nonuniformity, and service heterogeneity. We generate each traffic demand, which is formulated as a specific service k , using the following process.

1) Temporal dynamics in tidal traffic effects

To model how user activity changes over time, following local daily patterns, a time adjustment factor $\lambda(g, t)$ is added for each region g :

$$\lambda(g, t) = 1 + A_t \cos\left(\frac{2\pi(t - t_{peak})}{T_{day}}\right), \quad (10)$$

where t_{peak} is the local time at which traffic peaks in the region, $T_{day} = 24$ is the total duration of a day in hours, and A_t is the tidal amplitude coefficient, representing the magnitude of variation between peak and off-peak traffic.

2) Geographical distribution and inter-region affinity

The Earth's surface is divided into a number of geographic regions. Each region is given a user density value μ_g , based on real-world Internet user data. This creates a global disparity in traffic volume. Therefore, the traffic flow from region g to region h is modeled as

$$T^{gh}(t) = u_g \frac{u_h \lambda(h, t) d(g, h)^{-\gamma}}{\sum_{k \in R, k \neq g} u_k \lambda(k, t) d(g, k)^{-\gamma}}, \quad (11)$$

where R represents all levels of user density, γ is the coefficient of decay of the geographical distance and $d(g, k)$ is the physical distance between the centers of regions g and h .

Following (11), the probability of selecting h is obtained by normalizing the affinity from g to h with the sum of the affinities from g to all possible destinations, which is given by

$$P_{h|g}(t) = \frac{T^{gh}(t)}{\sum_{k \neq g} T^{gk}(t)}. \quad (12)$$

3) Service heterogeneity and classes of service

Real-world network traffic contains different types of applications with very different needs. This model uses two main service types: real-time traffic and best-effort traffic. Real-time traffic for applications needs to arrive very quickly, like video calls, online games, and voice messages, whose main requirement is a strict maximum delay limit. While best-effort traffic handles delay-tolerant applications like file downloads and emails with a more relaxed delay limit.

For each service k , the service class is randomly assigned with a configurable probability P_{RT} . The maximum tolerable delay is then determined accordingly:

$$T_k^{\max} = \begin{cases} T_{\text{strict}} & \text{with probability } P_{RT} \\ T_{\text{relaxed}} & \text{with probability } 1 - P_{RT} \end{cases}, \quad (13)$$

where $T_{\text{strict}} \ll \Delta T$ and $T_{\text{relaxed}} \ll \Delta T$, ensuring that all services can be completed within one snapshot duration. Each service k is finally represented as

$$k = (s_k, d_k, a_k, T_k^{\max}), \quad (14)$$

where s_k and d_k are the satellites of origin and destination mapped from regions g and h , a_k is the size of the data and $T_k^{\max}$ is the maximum tolerable delay.

D. Problem Formulation

The joint optimization of satellite wake-up and routing strategy is formulated as a MINLP problem. With the objective to minimize both the total lifetime consumption and service delay, the problem is formulated as

$$\min \left\{ \sum_{i \in \mathcal{V}_E} \Delta L_i, \sum_{k \in K} T_k \right\} \quad (15)$$

s.t.

$$\sum_{m \in \mathcal{N}(n)} y_{nm}^k - \sum_{m \in \mathcal{N}(n)} y_{mn}^k = \begin{cases} 1 & n = s_k \\ -1 & n = d_k \\ 0 & \text{otherwise} \end{cases}, \quad (16)$$

$$\forall k \in K, \forall n \in \mathcal{N}, \quad (16)$$

$$\sum_{m \in \mathcal{N}(n)} y_{mn}^k \leq 1, \quad \forall n \in \mathcal{N} \setminus \{g_s^k\}, \forall k \in K, \quad (17)$$

$$\sum_{m \in \mathcal{N}(n)} y_{mi}^k + \sum_{m \in \mathcal{N}(n)} y_{im}^k \leq 2m_i, \forall k \in K, \forall i \in \mathcal{V}_E, \quad (18)$$

$$\sum_{k \in K} f_{mn}^k \leq c_{mn}, \quad (19)$$

$$f_{mn}^k \leq M y_{mn}^k, \quad \forall (m, n) \in E, \forall k \in K, \quad (20)$$

$$f_k^{\min} \leq f_{mn}^k + M(1 - y_{mn}^k), \forall k \in K, \forall (m, n) \in E, \quad (21)$$

$$T_k \leq T_k^{\max}, \quad \forall k \in K, \quad (22)$$

$$B_i(t + \Delta T) \geq B_{\min}, \quad \forall i \in V. \quad (23)$$

$$\begin{aligned} \text{Variables: } & m_i \in \{0, 1\}, \quad \forall i \in \mathcal{V}_E, \\ & f_{mn}^k \geq 0, \quad \forall (m, n) \in E, \forall k \in K, \\ & y_{mn}^k \in \{0, 1\}, \quad \forall (m, n) \in E, \forall k \in K. \end{aligned}$$

Constraints (16)–(22) formulate the routing and resource allocation framework. Flow conservation is enforced by (16) for each service k at node n , while (17) guarantees single-path routing without splitting. Constraint (18) links satellite operational modes m_i to routing paths y_{mn}^k , preventing traversal through sleep-mode satellites in eclipse zones. Link capacity c_{mn} is bounded by (19), and big- M constraints (20)–(21) logically connect routing variables y_{mn}^k with flow variables f_{mn}^k . Specifically, (20) ensures zero bandwidth allocation on unused links, and (21) enforces minimum rate $f_k^{\min}$ on selected links. Constraint (22) bounds the end-to-end delay T_k , which is calculated as

$$T_k = \sum_{(m,n) \in E} \frac{d_{mn}}{c} y_{mn}^k + \frac{a_k}{\min_{\{(m,n) \in E | y_{mn}^k = 1\}} f_{mn}^k}, \quad (24)$$

where d_{mn} is the length of link (m, n) and c is the speed of light. The minimum is taken over all links actually used by service k . Constraint (23) ensures the battery energy never falls below a safe minimum level $B_{\min}$.

III. SIMULATED ANNEALING-BASED HIERARCHICAL SATELLITE OPTIMIZER

To address the difficulty of solving (15), we consider the co-optimization of minimizing lifetime consumption and total delay. Specifically, we first reformulate the objective function in (15) into a weighted sum of normalized lifetime consumption and total delay. That is, we have

$$F(m_i, f_{mn}^k, y_{mn}^k) = \omega_L \frac{\sum_{i \in \mathcal{V}_E} \Delta L_i}{\sum_{i \in \mathcal{V}_E} L_i^{\text{total}}} + (1 - \omega_L) \frac{\sum_{k \in K} T_k}{\sum_{k \in K} T_k^{\max}}, \quad (25)$$

where ω_L is a weighting coefficient that quantifies the relative importance assigned to minimizing lifetime consumption versus delay. Therefore, the optimization problem is reformulated as

$$\begin{aligned} \min & F(m_i, f_{mn}^k, y_{mn}^k) \\ \text{s.t.} & (16) - (23). \end{aligned}$$

A. Problem Decomposition

To solve the above optimization problem, we propose a SA-HSO algorithm here. The core challenge lies in the tight coupling between the discrete satellite mode selection variables. Therefore, our hierarchical optimizer decouples these decisions into two levels, where the upper-level SA algorithm is deliberately designed to explore solutions with a varying number of active satellites, guided by a success-aware cost function to dynamically balance energy savings against network routing at the lower level.

1) Problem SA-HSO-Upper to optimize m_i

The upper-level problem is to select the optimal set of active satellites in the eclipse zone, represented by the binary variables m_i . That is, guided by the routing solution from the lower level, Problem SA-HSO-Upper to optimize m_i can be formulated as

$$\begin{aligned} \min & F \\ \text{s.t.} & m_{s_k} = 1, \quad \forall k \in K: s_k \in \mathcal{V}_E, \end{aligned} \quad (26)$$

$$m_{d_k} = 1, \quad \forall k \in K: d_k \in \mathcal{V}_E, \quad (27)$$

$$m_i = 1, \quad \forall i \in \mathcal{V}_S. \quad (28)$$

$$\text{Variables: } m_i \in \{0, 1\}, \quad \forall i \in \mathcal{V}_E.$$

Constraints (26) and (27) enforce the activation of service endpoints (s_k, d_k) by requiring any such satellite within $\mathcal{V}_E$ to be in active mode.

2) Problem SA-HSO-Lower to optimize f_{mn}^k and y_{mn}^k

Given a fixed set of active satellites from the upper-level, the lower-level problem finds the optimal routing and bandwidth allocation. This Problem SA-HSO-Lower is thus formulated as

$$\begin{aligned} \min & F \\ \text{s.t.} & (16) - (23). \end{aligned}$$

$$\begin{aligned} \text{Variables: } & f_{mn}^k \geq 0, \quad \forall (m, n) \in E, \forall k \in K, \\ & y_{mn}^k \in \{0, 1\}, \quad \forall (m, n) \in E, \forall k \in K. \end{aligned}$$

B. Upper-Level: SA-driven Wake-up Optimizer

The objective function (25) is a complex, nonlinear function with respect to m_i , which thus makes it intractable for classical integer programming to solve Problem SA-HSO-Upper. Therefore, we employ a SA metaheuristic to search for a high-quality solution. And our approach improves upon a standard SA algorithm with several key innovations to make the upper-level optimizer more efficient.

1) High-quality initialization

This is constructed by first activating all satellites in sunlight V_{sunlit} and all service endpoint satellites $V_{\text{endpoints}}$ to form a protected base network. Then, we add a set of “elite” eclipse-zone satellites, V_{elite} , with the selection score S_i calculated as

$$S_i = 0.5 \frac{E_i}{E_{\max}} + 0.5 C_i^{\text{betweenness}}. \quad (29)$$

Here, S_i is the score for candidate satellite i , $\frac{E_i}{E_{\max}}$ is its normalized battery energy, and $C_i^{\text{betweenness}}$ is its network centrality score. The equal weights of 0.5 represent a balanced heuristic, assigning equal importance to energy preservation and network connectivity. This design choice avoids bias towards either objective in the initial solution. The initial set of active satellites is therefore $V_{\text{initial}} = V_{\text{sunlit}} \cup V_{\text{endpoints}} \cup V_{\text{elite}}$.

2) Safe pruning and random addition

The algorithm explores new solutions by either adding a random eclipse satellite or removing one. The pruning move is designed to be safe and it is not allowed to remove any satellite from the protected base network, including endpoints or sunlit satellites.

3) Success-aware search guidance

To guide the search, the SA-HSO minimizes a penalized cost function, which adds a large penalty to the true objective (25) for each service that fails to find a route. Furthermore, the algorithm always prefers a solution with a higher routing success rate and only considers their objective function values when success rates are equal.

C. Lower-Level: Iterative Routing Optimizer

Given the active satellite set from the upper level, the lower-level optimizer determines feasible routes and bandwidth allocation. To manage computational complexity, we employ a heuristic method that begins by pre-calculating a fixed bandwidth requirement for each service based on its delay constraint and finding a set of K -shortest candidate paths. The algorithm then proceeds iteratively. In each iteration, denoted by index i , every service independently selects the path from its candidate set that has the lowest total cost. The key to this process is the dynamic link cost function, which acts as a pricing mechanism and is updated in each iteration, with the cost calculated as

$$c_{mn}^{(i)} = \omega_D \text{DeCost}_{mn}^{(i)} + (1 - \omega_D) \text{LiCost}_{mn}, \quad (30)$$

where $\text{DeCost}_{mn}^{(i)}$ represents the delay-based cost, which includes propagation delay plus a nonlinear penalty that increases with link congestion in iteration i . LiCost_{mn} represents the lifetime cost, which is static within the snapshot and adds a penalty to links connected to low-energy satellites. Link costs are updated after each iteration to reflect the new traffic distribution, and a damping factor is used to ensure stable convergence. This iterative process allows the services to collectively reach a balanced routing solution.

D. Overall Workflow and Implementation

This optimizer integrates the upper-level SA-based mode selector and the lower-level iterative routing optimizer, into a single, cohesive workflow. For any given time snapshot, the complete SA-HSO algorithm proceeds as follows:

- 1) **Initialization:** A strong initial solution is constructed. This involves activating all satellites in the sunlit zone and all service endpoint satellites to form a protected base network. This set is then augmented by adding a small number of “elite” eclipse-zone satellites, selected based on their energy and network centrality scores.
- 2) **Iterative search:** The main SA optimization loop begins. In each iteration, a neighboring solution is generated by either adding a random eclipse satellite or removing a nonprotected one.
- 3) **Solution evaluation and update:** The lower-level iterative routing optimizer is invoked to evaluate the quality of this new solution. Based on a penalized cost function and the Metropolis criterion, the new solution is either accepted or rejected. The algorithm continuously tracks the best-so-far solution, prioritizing higher routing success rates.
- 4) **Termination:** The process terminates when the SA temperature cools below a predefined threshold, returning the

best active satellite set and corresponding routing plan found during the search.

IV. SIMULATION RESULTS AND ANALYSIS

A. Simulation Setup

Simulations are conducted on a large-scale LEO constellation analogous to systems like OneWeb, comprising 1152 satellites arranged in 24 orbits of 48 satellites each at a 1050 km altitude, with 20/10 Gbps ISL/GSL bandwidths [12], respectively. The dynamic orbital data for the constellation are generated using the Systems Tool Kit (STK). Each satellite is modeled with a 160 watt-hour (Wh) battery capacity.

The snapshot interval ΔT is set to 5 minutes, based on the static topology described in Section II. We evaluate the algorithm performance over 20 consecutive snapshots. In (25), the weighting coefficient W_L is set to be 0.5 to assign equal importance to minimizing both the lifetime and delay. To manage computational complexity, the simulation adopts the heuristic from Section III-C, fixing service bandwidth to the pre-calculated $f_k^{\min}$. The key parameters for our proposed SA-HSO algorithm, including 100 iterations per snapshot for the upper-level SA, 5 K -shortest paths and 10 iterations for the lower-level routing, are determined through preliminary experiments to ensure convergence while maintaining computational feasibility.

For performance comparison, we implement three baseline algorithms including a greedy approach that prioritizes high-energy satellites for activation, a random activation strategy, and a full activation baseline representing traditional energy-unaware routing.

B. Performance Evaluation and Analysis

Here, we first evaluate the objective sum of normalized lifetime consumption and total delay in our scheme. As shown in Fig. 3, our proposed SA-HSO algorithm achieves the best performance with an objective value of 0.031, which is 41.5% lower than that of the Greedy approach. This improvement stems from SA-HSO’s hierarchical optimization that dynamically balances energy consumption and delay, avoiding the energy hotspots created by static activation strategies. In comparison, Random and Full Activation strategies yield higher objective values of 0.093 and 0.195, respectively, since they fail to adaptively manage the energy-delay tradeoff, while Full Activation consistently overusing critical satellites and accelerating battery degradation.

Energy balance, measured by the standard deviation of satellite battery levels, is critical for sustainable network operation. Fig. 4 shows that SA-HSO maintains the best energy balance with an average standard deviation of 5.74 Wh. This represents a substantial improvement of 33.4% over the Greedy approach and 48.3% over the Random scheme, while drastically outperforming Full Activation. This advantage stems from SA-HSO’s intelligent deactivation of nonessential eclipse-phase satellites, which promotes more balanced traffic distribution and prevents premature energy depletion in critical nodes.

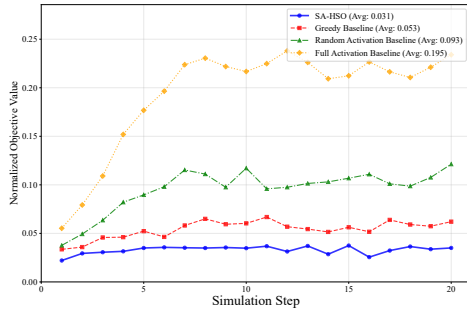


Fig. 3. Normalized objective value versus Simulation step.

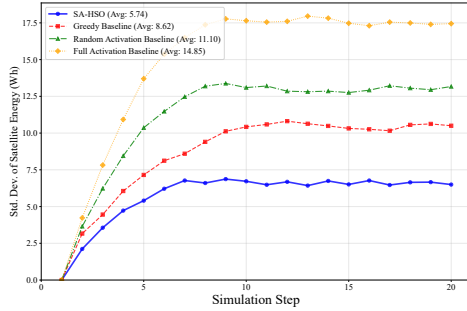


Fig. 4. Satellite energy standard deviation versus Simulation step.

Service reliability under varying network loads is considered here, which is measured by the average routing success rate. As shown in Fig. 5, SA-HSO maintains a consistently high routing success rate of 99% across different traffic volumes, demonstrating the robustness of our hierarchical optimization in preserving connectivity while managing the energy-delay tradeoff. The Full Activation baseline achieves 100% success but at the cost of unsustainable energy usage, as it maintains all satellites active regardless of actual traffic demand. In contrast, the Random activation strategy suffers from frequent connectivity issues with only 55% success, highlighting that uncoordinated satellite sleep patterns disrupt end-to-end paths and compromise service reliability.

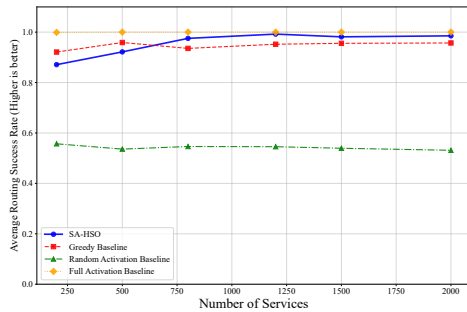


Fig. 5. Routing success rate versus Number of services.

V. CONCLUSION

This paper is concerned with the critical challenge of balancing network performance against energy sustainability

in LEO satellite networks. We have proposed the SA-HSO as a hierarchical framework that co-optimizes satellite operational modes and routing paths to balance energy consumption and communication delay. It has been shown that the proposed SA-HSO consistently outperforms baseline approaches, achieving at least 41.5% reduction in joint delay and energy consumption while maintaining service reliability above 99%. This balanced performance highlights the effectiveness of our co-optimization framework in managing the energy-delay tradeoff without compromising the network connectivity. Future work will explore adaptive policy optimization and real-time resource re-configuration through deep reinforcement learning for dynamic network conditions.

REFERENCES

- [1] Y. Zhang, W. Jiang, P. Wan, A. Liu, H. Han, J. Mu, S. Liu, W. Gu, S. Huang, and Z. Feng, "Building an efficient satellite network routing scheme: Challenges and opportunities," *IEEE Communications Standards Magazine*, vol. 9, no. 2, pp. 30–38, 2025.
- [2] X. Li, W. Xu, H. Wang, and S. Huang, "Space laser communication assisted protection scheme against SRLG failures in terrestrial optical networks," *J. Lightwave Technol.*, vol. 41, no. 8, pp. 2261–2275, 2023.
- [3] X. Li, Y. Liu, T. Liu, D. Li, X. Yan, C. Zhao, F. Ruan, and S. Huang, "Pre-calculated space-ground integrated structure (P-SGIS) against link cut set (LCS) failures in space-ground integrated optical networks," *Opt. Express*, vol. 32, no. 27, pp. 47 757–47 782, 2024.
- [4] D. Bhattacharjee, P. G. Madoery, A. U. Chaudhry, H. Yanikomeroglu, G. K. Kurt, P. Hu, K. Ahmed, and S. Martel, "On-demand routing in LEO Mega-constellations with dynamic laser inter-satellite links," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 60, no. 5, pp. 7089–7105, 2024.
- [5] J. Yang, C. Du, W. Liu, T. Wang, L. Yan, Y. Gao, X. Cheng, P. Zuo, Y. Ma, G. Yin, and J. Xie, "State-of-health estimation for satellite batteries based on the actual operating parameters – health indicator extraction from the discharge curves and state estimation," *J. Energy Storage*, vol. 31, p. 101490, 2020.
- [6] Y. Liu, X. Li, D. Li, C. Zhao, and S. Huang, "Green laser inter-satellite link planning in satellite optical networks: trading off the battery lifetime and network throughput using numerical quantization," *J. Opt. Commun. Networking*, vol. 16, no. 9, pp. 868–880, 2024.
- [7] N. Zhang, Z. Na, and B. Lin, "Time-varying graph based inter-orbit link selection energy-saving routing for LEO satellite networks," in *2023 IEEE Globecom Workshops (GC Wkshps)*, 2023, pp. 432–436.
- [8] H. Tsuchida, Y. Kawamoto, N. Kato, K. Kaneko, S. Tani, S. Uchida, and H. Aruga, "Efficient power control for satellite-borne batteries using Q-learning in low-earth-orbit satellite constellations," *IEEE Wireless Commun. Lett.*, vol. 9, no. 6, pp. 809–812, 2020.
- [9] G. Xu, L. Wang, S. Chen, L. Zhu, M. Guizani, and L. Shi, "Mpaee: A multipath adaptive energy-efficient routing scheme for low earth orbit-based industrial internet of things," *IEEE Internet Things J.*, vol. 12, no. 17, pp. 34 793–34 805, 2025.
- [10] P. Bergmann, T. Hoffeld, O. B. Fernandez, and G. Dietl, "Satellite constellation routing: Trade-off between delay- and power-based optimization," in *2025 Joint European Conference on Networks and Communications 6G Summit (EuCNC/6G Summit)*, 2025, pp. 781–786.
- [11] V. K. Srivastava, P. Mishra, and B. Ramakrishna, "Satellite ephemeris prediction for the earth orbiting satellites," *Aerospace Systems*, vol. 4, no. 4, pp. 323–334, 2021.
- [12] Y. Jing, Z. Yang, Y. Zhao, H. Wang, W. Wang, S. Rahman, and J. Zhang, "Energy-efficient routing based on a genetic algorithm for satellite laser communication," *Optics Express*, vol. 31, no. 5, pp. 8682–8695, 2023.
- [13] Z. Yang, Y. Zhao, Y. Jing, H. Wang, W. Wang, and J. Zhang, "An energy-efficient routing scheme for prolonging lifetimes of optical satellite networks," in *2022 Asia Communications and Photonics Conference (ACP)*, 2022, pp. 1191–1195.
- [14] Y. Yang, M. Xu, D. Wang, and Y. Wang, "Towards energy-efficient routing in satellite networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 3869–3886, 2016.