

IAC-25,B2,6,5,x100706

Optimizing UE Context Dissemination in Sparse LEO Constellations for Cellular IoT Services in 5G/6G Networks

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Abstract

Sparse Low Earth Orbit (LEO) constellations supporting NB-IoT services through store-and-forward operations face a critical optimization challenge: determining which satellite subset should maintain User Equipment (UE) contexts to ensure service continuity while minimizing resource consumption. This paper presents and evaluates three algorithmic approaches for optimal satellite subset selection: exhaustive search, greedy heuristics, and tabu search metaheuristics.

Using detailed orbital simulations of a 16-satellite Walker Star constellation, we analyze algorithm performance across diverse geographic locations. Results demonstrate that tabu search achieves optimal subset selection with substantially improved computational efficiency compared to exhaustive approaches. Our analysis reveals pronounced geographic dependencies, with equatorial regions requiring seven satellites (44% of constellation) for 24-hour service coverage while polar regions need substantially fewer.

The work provides practical algorithmic foundations for resource optimization in sparse satellite constellations, with implications extending beyond NB-IoT to any discontinuous network with predictable contact periods.

Keywords: 6G, LEO NTN, Store & Forward, NB-IoT, UE Context Dissemination, Optimization

1. Introduction

The evolution toward 6th Generation (6G) wireless networks envisions seamless global connectivity through the integration of terrestrial and Non-Terrestrial Networks (NTNs). Among the enabling technologies, NarrowBand-IoT (NB-IoT) has emerged as a cornerstone protocol for massive Machine Type Communications (mMTC), offering power-efficient communication for massive deployments of resource-constrained devices [1].

Following foundational NTN extensions in 3rd Generation Partnership Project (3GPP) Release 17 [2], Release 19 introduces Store and Forward (S&F) capabilities for NB-IoT in NTNs, enabling intermittent service through regenerative payload architectures [3]. This advancement addresses a critical gap for sparse low Earth orbit (LEO) constellations that provide global coverage with minimal satellites, where discontinuous feeder link connectivity necessitates onboard processing and temporary message storage capabilities.

A fundamental challenge in sparse LEO deployments is determining the optimal subset of satellites that should maintain specific User Equipment (UE) contexts to ensure

service continuity while minimizing resource consumption. Unlike dense constellations where context can be distributed across numerous satellites, sparse configurations require careful optimization to balance service quality against bandwidth limitations, storage constraints, and synchronization overhead.

This paper addresses the satellite subset selection problem through multiple algorithmic approaches, building upon our previously proposed 3GPP-compliant architecture for S&F operation [4, 5]. We formulate the problem as a constrained optimization challenge and evaluate three distinct solution methodologies: exhaustive search for optimal baselines, greedy heuristics for computational efficiency, and tabu search metaheuristics for near-optimal performance.

Our contributions include formal problem formulation for satellite subset selection in sparse LEO constellations, implementation and comparative analysis of multiple optimization algorithms, comprehensive performance evaluation across diverse geographical scenarios, and practical insights for operational deployment in resource-constrained satellite environments.

The remainder of this paper is organized as follows. Section 2 presents the background on S&F operations in NTN and formulates the satellite subset selection problem mathematically. Section 3 describes our simulation environment, reference constellation model, and evaluation methodology. Section 4 details the three algorithmic approaches including exhaustive search, greedy heuristics, and tabu search metaheuristics with complexity analysis. Section 5 presents comprehensive performance evaluation results across diverse geographical scenarios and discusses the implications for system design. Section 6 concludes the paper with key findings and future research directions.

2. Background and Problem Formulation

2.1. Store and Forward Operations in NTNs

The S&F paradigm enables satellite operations during periods of disconnected feeder link availability. When satellites operate with regenerative payloads [6], they can terminate Non-access Stratum (NAS) signaling on-board, temporarily storing both control and user plane messages for subsequent transmission when connectivity is restored [4].

This approach fundamentally differs from traditional transparent payload architectures where satellites function purely as bent-pipe relays. The regenerative architecture enables critical protocol procedures to complete within single visibility windows, significantly improving service quality for Internet of Things (IoT) devices with limited power budgets [7].

2.2. UE Context Management in Multi-Satellite Scenarios

UE context encompasses essential state information required for service continuity, including security parameters, identity information, and session management data [8]. In multi-satellite environments, this context must be available at any satellite that may serve the UE, creating a fundamental distribution challenge.

The complete dissemination of UE context to all satellites would require n transmission operations for a constellation of n satellites, imposing substantial overhead on bandwidth-constrained feeder links. This motivates partial dissemination strategies where context is selectively distributed based on coverage patterns and service requirements [5].

2.3. Problem Formulation

The satellite subset selection problem can be formally defined as follows. Given a constellation $S = \{s_1, s_2, \dots, s_n\}$ of satellites and a UE at location u , determine the minimum subset $X \subseteq S$ such that the revisit

time requirement T_{max} is satisfied.

The optimization objective is to minimize the subset size while satisfying application-specific service requirements:

$$\begin{aligned} &\text{minimize} && |X| \\ &\text{subject to} && t_{\text{revisit}}(X) \leq T_{\text{max}} \\ &&& X \subseteq S \end{aligned} \quad (1)$$

where T_{max} represents the maximum acceptable revisit time for the target application.

This formulation maps directly to the classical set covering problem, which is known to be NP-hard. Consequently, exact solutions exhibit exponential computational complexity, motivating the development of efficient heuristic approaches for practical deployment scenarios.

3. Simulation Environment and Assumptions

3.1. Reference Constellation and Simulation Setup

Our evaluation employs a Walker Star LEO constellation [9] detailed in our previous work [5], comprising 16 satellites distributed across four orbital planes at 550 km altitude in polar orbits. This configuration represents a realistic sparse constellation scenario that provides global coverage while operating under the resource constraints typical of commercial LEO deployments.

The orbital simulation utilizes General Mission Analysis Tool (GMAT) software [10] with subsequent data processing performed in MATLAB and Python environments. The constellation maintains near-polar orbits with a 95.6-minute orbital period, enabling comprehensive global coverage through natural orbital precession. Ground segment infrastructure consists of five strategically distributed stations at Kiruna, Hartebeesthoek, Perth, Fairbanks, and Poker Flat, providing realistic feeder link connectivity patterns for sparse constellation operations.

3.2. Evaluation Methodology and Geographic Coverage

Algorithm performance assessment encompasses 612 UE locations distributed across a 10° global grid spanning latitudes from -80° to 80° . This distribution captures the significant orbital mechanics variations that directly impact satellite revisit characteristics, from the challenging equatorial regions with extended gaps to the polar areas with frequent overpasses due to orbital convergence effects.

The evaluation framework incorporates multiple target revisit times ranging from 8 to 96 hours, representing diverse IoT application requirements. Mission-critical applications demanding frequent connectivity correspond to shorter revisit intervals, while delay-tolerant monitoring

and sensing applications accommodate longer service gaps. Each UE location assumes stationary IoT devices with 2 KB context requirements encompassing security parameters, NAS state information, and session management data.

Performance assessment examines both solution quality through subset size optimization and revisit time achievement, alongside computational efficiency measured through execution time and memory consumption. This dual focus enables comprehensive evaluation of the fundamental trade-offs between algorithmic optimality and practical deployment feasibility in resource-constrained satellite environments.

4. Satellite Subset Selection Algorithms

4.1. Exhaustive Search Algorithm

The exhaustive search evaluates all possible subsets to identify the optimal solution. For each subset $X \subseteq S$, the algorithm computes the revisit time based on satellite visibility patterns and retains the minimum-cardinality subset satisfying the constraint $t_{\text{revisit}}(X) \leq T_{\text{max}}$.

While guaranteeing optimality, the computational complexity of $O(2^n)$ limits practical application to small constellation sizes. For our 16-satellite constellation, this translates to evaluating 65,536 possible combinations, requiring substantial computational resources even for modest constellation sizes.

4.2. Greedy Heuristic

The greedy algorithm iteratively selects satellites that provide maximum coverage improvement at each step. This approach, inspired by classical set covering heuristics [11], achieves $O(n^2 \cdot m)$ complexity where m represents the number of evaluated time points.

The algorithm initializes with an empty subset and iteratively adds the satellite providing the greatest reduction in revisit time:

$$s_{\text{next}} = \arg \min_{s \in S \setminus X} t_{\text{revisit}}(X \cup \{s\}) \quad (2)$$

This process continues until the target revisit time is achieved or no further improvement is possible. While not guaranteeing optimality, the greedy approach typically produces near-optimal solutions with dramatically reduced computational requirements.

4.3. Tabu Search Metaheuristic

Tabu search employs memory structures to escape local optima and explore the solution space more effectively [12]. Our implementation maintains a tabu list of recently visited solutions, preventing cycling and encouraging exploration

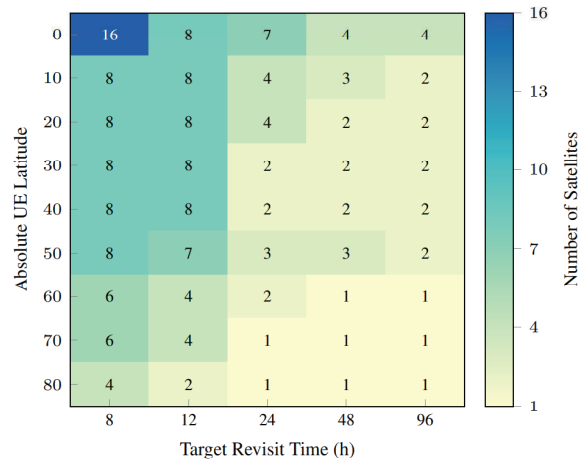


Fig. 1: Minimum number of satellites required to achieve target revisit times (8, 12, 24, 48, 96 h) across latitudes 0°–80°. For the 24 h target, equatorial regions require seven satellites, with the requirement decreasing towards the poles.

of diverse satellite combinations.

The algorithm generates neighborhood solutions through satellite swaps and additions/removals, evaluating each candidate against the objective function. The tabu tenure parameter, set to \sqrt{n} iterations based on empirical tuning, balances exploration and exploitation. Aspiration criteria allow exceptional solutions to override tabu status when they improve upon the best-known solution.

Convergence typically occurs within 100–200 iterations for our constellation size, providing an effective balance between solution quality and computational efficiency. The metaheuristic nature enables adaptation to varying constellation configurations and optimization objectives without algorithm restructuring.

5. Results and Discussion

5.1. Geographic Dependency Analysis

Our analysis reveals pronounced geographic variations in satellite requirements for achieving target revisit times. Figure 1 shows the minimum number of satellites required to meet representative targets (8, 12, 24, 48, and 96 h) across latitude. As an illustrative case, for a 24 h target, equatorial regions require seven satellites (44% of the constellation), while higher latitudes need substantially fewer due to orbital convergence.

Equatorial regions consistently require seven satellites (44% of the constellation) due to limited orbital overlap, while polar regions benefit from orbital convergence, requiring substantially fewer satellites. This geographic dependency directly impacts system design decisions for

Table 1: Algorithm Performance Comparison for Equatorial UE Location

| Algorithm | Satellites Required | Execution Time | Solution Quality |
|-------------|---------------------|----------------|------------------|
| Exhaustive | 7 | 412.3 s | Optimal |
| Greedy | 8 | 0.8 s | Near-optimal |
| Tabu Search | 7 | 3.2 s | Optimal |

global IoT services.

5.2. Algorithm Performance Comparison

Table 1 presents comparative performance metrics across the three algorithms for representative UE locations at the equator.

The tabu search achieves optimal results with substantially improved computational efficiency compared to exhaustive search, making it suitable for operational deployment. The greedy algorithm provides the fastest execution with minimal quality degradation, offering a practical option for real-time applications.

5.3. Implications for System Design

These findings have significant implications for sparse constellation operators. The ability to reduce context dissemination overhead while maintaining service quality enables more efficient utilization of bandwidth-constrained feeder links. Furthermore, the geographic variations suggest opportunities for location-aware optimization strategies that adapt dissemination patterns based on UE distribution.

The computational efficiency of the tabu search algorithm enables dynamic re-optimization as constellation configurations evolve or UE distributions change. This adaptability proves essential for operational systems where satellite failures, maintenance windows, or changing traffic patterns require responsive resource allocation strategies.

6. Conclusions

This paper addresses the critical challenge of optimal satellite subset selection for UE context dissemination in sparse LEO constellations supporting NB-IoT services. Through comprehensive algorithmic development and evaluation, we demonstrate that intelligent subset selection can maintain service requirements while substantially reducing resource consumption compared to constellation-wide dissemination approaches.

Our key findings include: (1) geographic location significantly influences optimal subset requirements, with equatorial regions requiring substantially more satellites than polar regions for equivalent service levels; (2) tabu

search metaheuristics achieve optimal results with dramatically improved execution times compared to exhaustive approaches; (3) selective context dissemination enables substantial reduction in system overhead while maintaining application-specific service quality; and (4) algorithm scalability characteristics make heuristic approaches essential for realistic constellation deployments.

The implications extend beyond immediate resource optimization. As 3GPP standards continue evolving toward comprehensive S&F support in NTN [3], our research provides practical algorithmic foundations for addressing resource optimization challenges in globally distributed yet sparse satellite constellations.

Future research directions include extending the optimization framework to incorporate dynamic UE mobility patterns, developing multi-objective formulations that simultaneously optimize multiple performance criteria, and investigating adaptive algorithms that respond to changing constellation characteristics and traffic patterns. Additionally, integration with machine learning approaches may enable predictive optimization based on historical usage patterns and orbital dynamics.

As satellite constellations expand to support massive IoT deployments, the algorithmic approaches presented here offer a framework for balancing global coverage aspirations with practical resource constraints, enabling sustainable and scalable satellite-based IoT services for underserved regions worldwide.

Acknowledgements

This work was supported and funded by the European Union's Horizon Europe under Grant Agreement no. 101096526 (ETHER). Furthermore, this research was funded in part by the Spanish MCIN/AEI/10.13039/501100011033 through project PID2019-106808RA-I00, PID2023-146378NB-I00 and by Secretaria d'Universitats i Recerca del departament d'Empresa i Coneixement de la Generalitat de Catalunya with the grant number 2021 SGR 00330.

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