

Robust Lyapunov Optimization for Multihop Communication in LEO Satellite Networks

Zhemin Huang

*Department of Electrical and Computer Engineering
New York University
Brooklyn, NY, USA
zh2782@nyu.edu*

Zhu Han

*Department of Electrical and Computer Engineering
University of Houston
Houston, TX, USA
zhan2@uh.edu*

Zhong-Ping Jiang

*Department of Electrical and Computer Engineering
New York University
Brooklyn, NY, USA
zjiang@nyu.edu*

Yong Liu

*Department of Electrical and Computer Engineering
New York University
Brooklyn, NY, USA
yongliu@nyu.edu*

Abstract—With the development of space-air-ground integrated networks, Low Earth Orbit (LEO) satellite networks are envisioned to play a crucial role in providing data transmission services in the 6G era. However, the increasing number of connected devices leads to a surge in data volume and bursty traffic patterns. Ensuring the communication stability of LEO networks has thus become essential. While Lyapunov optimization has been applied to network optimization for decades and can guarantee stability when traffic rates remain within the capacity region, its applicability in LEO satellite networks is limited due to the bursty and dynamic nature of LEO network traffic. To address this issue, we propose a robust Lyapunov optimization method to ensure stability in LEO satellite networks. We theoretically show that for a stabilizable network system, traffic rates do not have to always stay within the capacity region at every time slot. Instead, the network can accommodate temporary capacity region violations, while ensuring the long-term network stability. Extensive simulations under various traffic conditions validate the effectiveness of the robust Lyapunov optimization method, demonstrating that LEO satellite networks can maintain stability under finite violations of the capacity region.

Index Terms—Robust Lyapunov Optimization, network Routing Control, queueing theory.

I. INTRODUCTION

The rapid expansion of the Internet of Things (IoT) and the proliferation of wireless devices have significantly increased data traffic, challenging the capabilities of the sixth-generation (6G) networks to deliver ubiquitous, reliable global data services and extensive connectivity [1]. Traditional terrestrial networks face obstacles such as uneven infrastructure development and limited backhaul capacity, thus limiting their ability to handle the escalating data traffic [2]. LEO satellite networks, which consist of hundreds to thousands of low-Earth orbit (LEO) satellites, offer a promising solution by providing high-capacity backhaul, seamless global coverage, and flexible network access services [3]. These networks not only enhance mobile communication services in remote areas beyond the

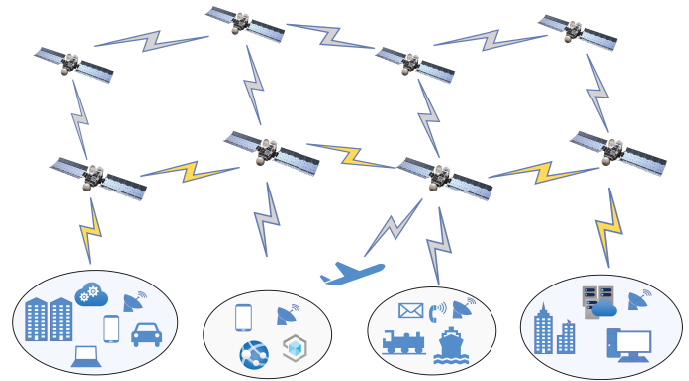


Fig. 1. Illustration of LEO satellite networks in a space-air-ground integrated network.

reach of terrestrial networks, but also offer faster and more reliable services than current wireless technologies [4], [5]. As a critical complement to terrestrial networks, LEO satellite networks are poised to play a vital role in the development of the next-generation networks.

Moreover, Starlink predicts that LEO satellite networks will provide reliable global connectivity over the next 20 years [6]. LEO satellite networks will be integrated with terrestrial systems to offer broadband Internet services to both consumers and enterprises [7]. The architecture of the space-air-ground integrated network, illustrated in Fig. 1, highlights the critical role of LEO satellite networks in extending mobile broadband and machine-type communication services to areas beyond terrestrial wireless networks, such as oceans, skies, and remote regions. This integration ensures seamless global data flow.

With the ongoing construction of LEO satellite networks, these systems will become vital for rapid information diffusion, addressing the surge in online social networks, advanced mobile networks, and the proliferation of IoT devices [8]. This growth causes an information explosion and increased

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data burstiness within LEO satellite networks. Consequently, efficiently transmitting, delivering, and processing the massive amount of generated data becomes crucial. As a result, traffic routing control in LEO satellite networks emerges as a critical issue [9]. Existing research has explored routing strategies from various perspectives, including hop-count [10], load-balancing [11], and latency [12]. Despite these efforts, ensuring system stability in LEO satellite networks remains a significant open challenge, especially considering the burstiness characteristic of traffic flows.

To investigate system stability, Lyapunov optimization is a powerful mathematical tool for developing stable scheduling strategies in network optimization. In large-scale multi-hop networks, such as LEO satellite networks, Lyapunov optimization is particularly effective for routing control. This is because it only requires solving linear programming problems and relies on queue backlog observations rather than detailed system dynamics [13], [14], [15], [16]. For instance, the Distance-based Back-Pressure Routing (DBPR) algorithm addresses load balancing in LEO satellite networks by optimizing queue backlogs and propagation delays using a distance delay-based routing metric [17].

While Lyapunov optimization is an effective tool for designing routing controllers with stability guarantees, it typically assumes that traffic flow remains within the capacity region [15]. However, given the bursty nature of traffic flow in LEO satellite networks, this assumption is often unrealistic. This significantly underestimates the resilience and capacity region of these networks. In this paper, we propose robust Lyapunov optimization to provide a robust guarantee for the stability of LEO satellite networks. Our main contributions are summarized below:

- To portray the characteristics of LEO satellite networks, we propose a multi-hop queueing network model based on the Walker Constellation, ascending and descending satellites, and the inter-satellite link (ISL) model. This model incorporates LEO satellite topology information into the queueing network model, leading to more accurate modeling and contributing to better control policies.
- To the best of our knowledge, we are the first to propose the robust Lyapunov optimization framework. Unlike traditional Lyapunov optimization, which ensures system stability by requiring network traffic to remain within or interior to the capacity region, robust Lyapunov optimization demonstrates that a stabilizable network system can tolerate finite violations of the capacity region while maintaining network stability. This method provides a robust guarantee of stability for LEO satellite networks, even when subjected to dynamic traffic burstiness.

The rest of this paper is organized as follows: Section II introduces the system model of LEO satellite networks. Section III presents the proposed scheme using robust Lyapunov optimization. Section IV provides simulation results and performance evaluation. Finally, Section V offers concluding remarks and future work.

II. SYSTEM MODEL

A. Multi-Hop Queueing Network Model

1) *ISL Channel Model*: As illustrated in Fig. 1, we study the connection of ground users through a LEO satellite network. Each user is covered and serviced by an access satellite. We assume that during data transmission, each ground user maintains a continuous connection with a single access satellite [18]. Although in practical scenarios, ground users may switch their access satellite due to the movement of the Earth and satellites, the variation in network topology remains regular when satellites are evenly distributed [19].

In the LEO satellite network, each satellite is considered a node, with the set of neighboring nodes of node i denoted by \mathcal{N}_i . The network operates in slotted time $t \in \{0, 1, 2, \dots\}$, and the time horizon is T . During each time slot, routing and transmission scheduling decisions are made to ensure that all data reach their intended destinations. The network handles K classes of data, with data of class k destined for sink d_k . The set of data classes is denoted by \mathcal{K} . The link capacity between nodes i and j is represented as C_{ij} .

At the beginning of time slot t , each node i has $Q_{ik}(t)$ buffered packets of class k and receives $a_{ik}(t)$ external packets of class k . For simplicity, we assume that $Q_{ik}(0) = 0$ for each node i and class k . Simultaneously, routing decisions are made, with $f_{ijk}(t)$ denoting the number of packets of class k transmitted to a neighbor j , as decided by the network controller under a given policy. The set of all $f_{ijk}(t)$ at time t is denoted by $\mathcal{F}(t)$. Mathematically, the queue backlogs evolve according to the following rule:

$$Q_{ik}(t+1) = \left[Q_{ik}(t) + a_{ik}(t) - \sum_{j \in \mathcal{N}_i} f_{ijk}(t) \right]^+ + \sum_{j \in \mathcal{N}_i} \tilde{f}_{jik}(t) \quad (1)$$

where $\tilde{f}_{jik}(t)$ represents the actual number of packets transmitted.

Considering physical limitations, without loss of generality, we further assume that:

$$0 \leq a_{ik}(t) \leq D, \quad 0 \leq f_{ijk}(t) \leq D, \quad \forall i, j, k, t \quad (2)$$

for some constant $D \geq 0$.

B. LEO Satellite Networks System

1) *Walker Constellation*: In this paper, we focus on Walker-Delta constellations (e.g. StarLink), where satellites are uniformly distributed within their orbits. Typically, a Walker-Delta constellation-based LEO satellite network can be represented by the tuple $\langle N_P, M_P, \alpha \rangle$, where N_P is the number of orbit planes, M_P is the number of satellites per plane, and α is the orbital inclination with respect to the equator. The commonly used system characteristic formulas for Walker-Delta:

- $\Delta\Omega = \frac{2\pi}{N_P}$ is the difference in the right ascension of the ascending node (RAAN) between adjacent planes.

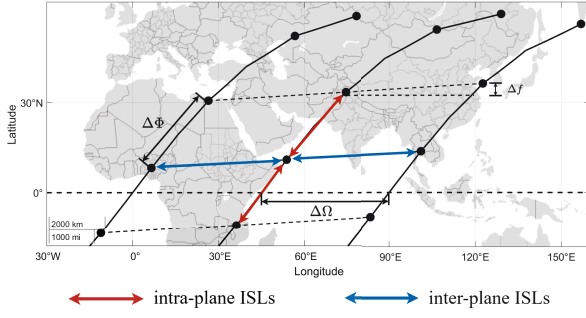


Fig. 2. Illustration of LEO satellite networks and inter-satellite links.

- $\Delta\Phi = \frac{2\pi}{M_P}$ represents the phase difference between consecutive satellites in each plane.
- $\Delta f = \frac{2\pi F}{N_P M_P}$ denotes the phase offset between satellites in neighboring planes, where F is phasing factor and $F \in [1 - N_P, N_P - 1]$.

As shown in Fig. 2, in the Inter-Satellite Link (ISL) connection mode, each satellite establishes four permanent ISLs with its neighboring satellites: two intra-plane links and two inter-plane links. Considering the link instability caused by the high relative motion between neighboring ascending and descending satellites, no inter-plane links are established between them.

Based on [20], the link capacity (in bps) of the ISL between satellites i and j , denoted by C_{ij} is given as follows:

$$\begin{cases} C_{ij} = \frac{P_t G_i G_j L_{ij}}{k_B U_s (E_b/N_0)_{req} A}, \\ L_{ij} = \left(\frac{c}{4\pi \cdot SR \cdot f} \right)^2, \end{cases} \quad (3)$$

where P_t is the transmission power of the transmitting satellite. G_i and G_j are the transmitting antenna gain of LEO satellite i and the receiving antenna gain of LEO satellite j respectively. Additionally, k_B represents the Boltzmann constant (in JK^{-1}) and U_s denotes the total system noise temperature (in K). $(E_b/N_0)_{req}$ is the required ratio of received energy-per-bit to noise density, and A is the link margin. L_{ij} is the free space loss of the ISL, c is the speed of light (in km/s), SR is the slant range (in km), and f is the communications center frequency (in Hz) of ISLs.

III. ROBUST LYAPUNOV OPTIMIZATION-BASED NETWORKS ROUTING CONTROL

Lyapunov optimization is a widely used tool for designing feasible routing strategies with stability guarantees. Its core principle is based on the Lyapunov's second method, which states that if a system is subjected to small disturbances while in its stable state, it will always stay near the stable equilibrium as long as the drift of the Lyapunov function is less than or equal to zero. When applying Lyapunov optimization to the design of network routing strategies, we first define a quadratic Lyapunov function of the queue backlog sizes. This

TABLE I
VARIABLE NOTATIONS AND DEFINITION

Notation	Definition
N	The number of queues in the queueing network
\mathcal{N}_i	The set of neighboring nodes of node i
\mathcal{K}	The set of data types
C_{ij}	The link capacity between nodes i and j
d_k	The destination of the data of class k
T	The time horizon
$L(t)$	Lyapunov function value at time t
$\Delta L(t)$	Lyapunov drift at time t
B	An upper bound for Lyapunov drift
$Q_{ik}(t)$	The queue backlog of class k at node i at time t
$a_{ik}(t)$	The number of external packets of class k arriving at node i at time t
$f_{ijk}^\pi(t), \tilde{f}_{ijk}^\pi(t)$	The planned and actual number of packets of class k transmitted from nodes i to j at time t
N_P	Number of orbit planes
M_P	Number of satellites per plane
α	Orbit inclination with respect to the equator

function serves as a scalar measure of the instability level of the network system, as shown below:

$$L(t) = \frac{1}{2} \sum_{i,k} Q_{ik}^2(t), \quad (4)$$

where $L(t)$ is a positive definite Lyapunov function that equals zero if and only if all queue backlogs $Q_{ik}(t)$ are zero. To control the growth of the Lyapunov function in (4), we minimize the one-slot Lyapunov drift $\Delta L(t) \triangleq L(t+1) - L(t)$ during each time slot:

$$\begin{aligned} \Delta L(t) &= L(t+1) - L(t) \\ &\leq B + \sum_{i,k} Q_{ik}(t) \Delta Q_{ik}(t), \end{aligned} \quad (5)$$

where B is a constant that depends on the maximum service rate and maximum arrival rate, derived using the assumptions in (2), and $\Delta Q_{ik}(t)$ is the queue difference, defined as:

$$\begin{cases} B = N^3 K D^2 + N K D^2 + N^2 K D^2, \\ \Delta Q_{ik}(t) = a_{ik}(t) - \sum_{j \in \mathcal{N}_i} f_{ijk}(t) + \sum_{j \in \mathcal{N}_i} f_{jik}(t), \end{cases} \quad (6)$$

Considering stochastic network dynamics, taking the conditional expectation of (5) yields:

$$\mathbb{E}[\Delta L(t)|Q(t)] \leq B + \sum_{i,k} Q_{ik}(t) \mathbb{E}[\Delta Q_{ik}(t)|Q(t)]. \quad (7)$$

To minimize the Lyapunov drift $\Delta L(t)$, it is equivalent to minimizing

$$\sum_{i,k} Q_{ik}(t) \mathbb{E} \left[\sum_{j \in \mathcal{N}_i} f_{jik}(t) - \sum_{j \in \mathcal{N}_i} f_{ijk}(t) | Q(t) \right] \quad (8)$$

By the principle of opportunistically minimizing an expectation, the above expectation can be minimized by minimizing

the function inside it, i.e.,

$$f^\pi(t) = \arg \min_f \sum_{i,k} Q_{ik}(t) \cdot \left[\sum_{j \in \mathcal{N}_i} f_{jik} - \sum_{j \in \mathcal{N}_i} f_{ijk} \right], \quad (9)$$

$$s.t. \quad f_{ijk} \geq 0, \quad \sum_k f_{ijk} \leq C_{ij}.$$

If the traffic flow always remains within the capacity region, the expectation $\mathbb{E}[\Delta Q_{ik}(t)|\mathbf{Q}(t)]$ in (7) will be negative. Let it be a value greater than zero, denoted as $\epsilon > 0$, i.e.,

$$\mathbb{E} \left[a_{ik}(t) - \sum_{j \in \mathcal{N}_i} f_{ijk}(t) + \sum_{j \in \mathcal{N}_i} f_{jik}(t) | \mathbf{Q}(t) \right] \leq -\epsilon. \quad (10)$$

This implies that as long as the queue backlog in the network system is sufficiently large, i.e., $\sum_{i,k} Q_{ik}(t) \geq \frac{B}{\epsilon}$, the Lyapunov drift $\Delta L(t)$ will always be less than or equal to zero. Consequently, it will drive the network system back to a stable state. Specifically, the queue backlog in the network system will be constrained within $\frac{B}{\epsilon}$ over the long term, as shown below:

$$\lim_{t \rightarrow \infty} \mathbb{E} \left[\sum_{i,k} Q_{ik}(t) \right] \leq \frac{B}{\epsilon}. \quad (11)$$

Based on the above analysis, we can see that in designing a routing controller based on Lyapunov optimization, to obtain routing strategies with stability guarantees, it is necessary to assume that the traffic of the network system always remains within the capacity region, i.e., $\mathbb{E} \left[a_{ik}(t) - \sum_{j \in \mathcal{N}_i} f_{ijk}(t) + \sum_{j \in \mathcal{N}_i} f_{jik}(t) | \mathbf{Q}(t) \right] \leq -\epsilon$. It is of interest to note that ϵ represents the distance between the traffic flow and the boundary of the capacity region. However, considering the bursty nature of traffic flow, this assumption is unrealistic and overly conservative. This raises the question: *Do we need to continually expand the LEO satellite network system to handle occasional traffic burstiness?* The answer is *no*. Clearly, the above assumption significantly underestimates the network system's capacity and resilience.

In this paper, we propose robust Lyapunov optimization to provide a more rigorous stability analysis for Lyapunov optimization-based network routing control methods. The core idea of robust Lyapunov optimization is that, for a stabilizable network, the traffic flow does not need to remain within the network capacity region at every time slot. It can violate the capacity region, but as long as these violations are finite, robust Lyapunov optimization can ensure the stability of the network system.

Lemma 1. *Let $L(t)$ be a discrete-time function defined on $[0, T)$ ($0 < T \leq +\infty$), satisfying the following inequality:*

$$L(t+1) \leq cL(t) + d_1(t)L(t) + d_2(t), \quad t = 0, 1, \dots \quad (12)$$

where $-1 < c < 1$, d_1 and d_2 are non-negative time functions satisfying:

$$\sum_{t=0}^T (d_1(t))^\sigma \leq S_1 \quad \text{and} \quad \sum_{t=0}^T (d_1(t))^\xi \leq S_2, \quad (13)$$

where $\sigma > 1$, $\xi > 1$. Under this assumption, $L(t)$ is bounded from the above on $[0, T)$ and, precisely:

$$L(t) \leq K_1 L(0) + K_2 \quad \forall t \in [0, T) \quad (14)$$

with K_1 and K_2 depending only on σ , ξ , S_1 and S_2 .

Moreover, if T is infinite, then

$$\limsup_{t \rightarrow \infty} L(t) \leq 0. \quad (15)$$

Proof. The proof of Lemma 1 is based on the discrete-time Gronwall lemma and Hölder's inequality [21]. A detailed proof will be provided in a subsequent journal version. \square

Lemma 1 indicates that the Lyapunov function does not need to be strictly monotonically decreasing to ensure system stability. While it may fluctuate during its descent, as long as the overall trend is downward, the system will remain stable. In the context of network routing control, the controller greedily minimizes the Lyapunov drift $\Delta L(t)$ by solving an optimization problem. However, due to the bursty nature of traffic flow, it is challenging to guarantee that the Lyapunov function will be monotonically decreasing, i.e., $\Delta L(t) \leq 0, \forall t$. But the stability of the network system is still guaranteed as long as the overall trend of the Lyapunov function remains downward, as shown in Theorem 1.

Theorem 1. *The network system (1)-(2) under the control policy (9) is robustly stable.*

IV. NUMERICAL EXPERIMENTS

To validate the effectiveness of robust Lyapunov optimization, we evaluated its performance on a Celestri-based LEO satellite network system. The Celestri Walker-Delta constellation is represented by the tuple $\langle N_P = 7, M_P = 9, \alpha = 48^\circ \rangle$ and has an orbital altitude of 1,400 km.

The ISL link capacity between adjacent satellites is calculated using (3). Based on the work of [20], the transmitting and receiving antenna gains for all satellites are set to 35 dB, with a transmission power P_t of 70 W. The communications center frequency is 15 GHz, with a total system noise temperature U_s of 25 dB K. The required ratio of received energy-per-bit to noise density $(E_b/N_0)_{req}$ is 10 dB, and a link margin A of 3 dB. The arrival nodes and sink nodes in the LEO satellite network are randomly generated, including 15 arrival nodes and 15 sink nodes. The link capacities between the sink nodes and the destination $(C_{S \rightarrow D})$ are set to 0.3 Gbps. The time slot is set to 1 second, and the simulation time horizon T is set to 12,000 seconds. At the beginning of each time slot, external packets arrive at the arrival nodes according to a uniform distribution as follows:

- Celestri: Celestri: $\mathbf{a}(t) \sim \text{Unif}\{0, \dots, 0.5\}$, $t \in [0, T]$.

Additionally, considering the bursty nature of traffic flow, the arrival nodes of the LEO satellite network system will experience dynamic traffic burstiness. This burstiness affects each arrival node at stochastic time periods but with a consistent duration of 10 seconds, i.e., $d_B = 10s$. The starting times

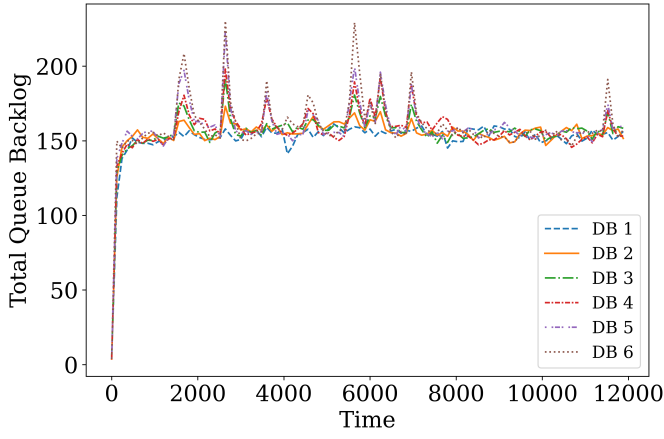


Fig. 3. Queue backlog evolution under dynamic burstiness.

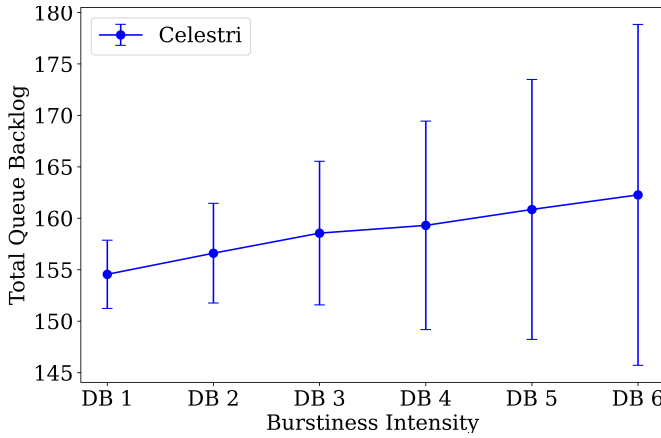


Fig. 4. Statistical results of queue backlog evolution under dynamic burstiness.

of burstiness periods are uniformly selected throughout the entire simulation time horizon, i.e., $t_B \in \text{Unif}\{0, \dots, 12,000\}$. The burstiness intensity is categorized into six levels.

To validate the effectiveness of robust Lyapunov optimization, we examine its performance under varying intensities of dynamic traffic burstiness. For simplicity, there is only one class of traffic, and all packets can exit the system via any of the sink nodes leading to the destination d . In this scenario, due to the absence of admission control, the controller admits all external arrivals at the arrival nodes. It then determines which neighboring satellites will relay the buffered packets to ensure they reach destination d by solving (9) [15], using a classical Lyapunov optimization-based routing algorithm.

In the absence of dynamic traffic burstiness, the expected external arrivals per time slot are $0.5 \times 0.5 \times 15 = 3.75$ (Gbps), while the total service rate is $0.3 \times 15 = 4.5$ (Gbps). Clearly, the traffic is within the capacity region, allowing the network controller to keep the entire network stable. Note that the link capacities between neighboring nodes are sufficiently large and will not become bottlenecks for the network. However, considering the impact of dynamic traffic burstiness, at burstiness intensity level 6, the expected external arrivals in

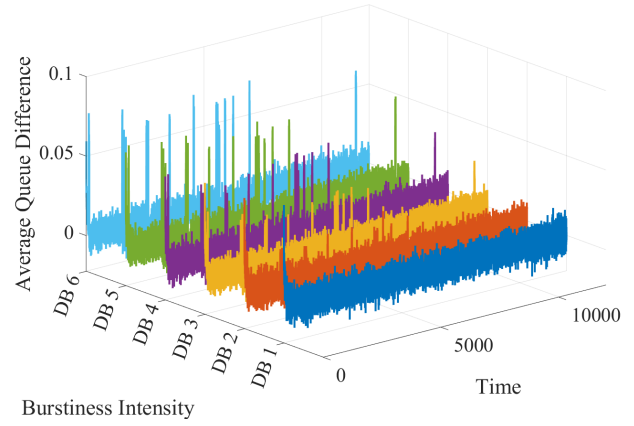


Fig. 5. Queue backlog evolution under dynamic burstiness.

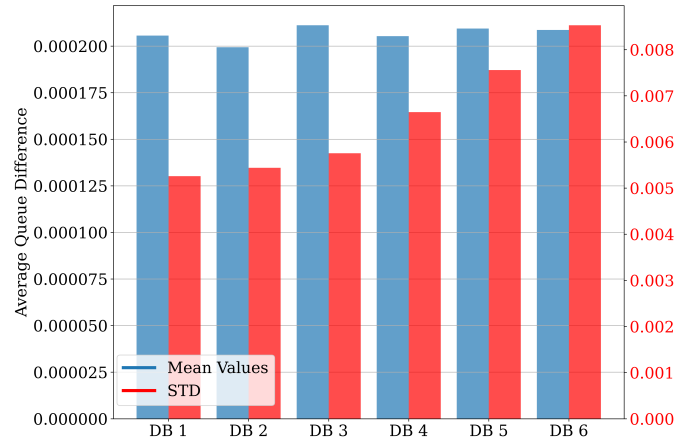


Fig. 6. Statistical results of the average queue difference evolution under dynamic burstiness.

some time slots increase to $0.5 \times 0.5 \times 15 + 5.5 \times 0.5 = 6.5$ (Gbps), exceeding the network system's total service rate. This raises the question: *Can the LEO satellite network system remain stable under dynamic traffic burstiness?* This scenario falls outside the explanatory scope of the traditional Lyapunov optimization. However, according to Robust Lyapunov Optimization, the answer is *yes*. We will explain this based on simulation results in the sequel.

In our simulation experiments, we first examine the impact of varying degrees of dynamic traffic bursts on network queue backlogs, i.e., $\sum_{i,k} Q_{ik}(t)$. The results are illustrated in Fig. 3. Our findings demonstrate that the proposed robust Lyapunov optimization method maintains network system stability across different intensities of dynamic traffic bursts. Notably, the queue backlogs of various LEO constellation systems exhibit fluctuations throughout the entire experimental time range T . These fluctuations are attributed to the randomized selection of time slots for traffic bursts. Despite these variations, the overall stability of the system remains largely unaffected. We also observe that as the intensity of dynamic traffic bursts increases, the network system's queue backlogs correspondingly rise.

Fig. 4 presents the statistical results of queue backlogs, clearly showing an upward trend in the steady-state mean of network system queue backlogs as the intensity of dynamic traffic bursts increases. More significantly, the impact on the standard deviation of queue backlogs is even more pronounced: higher burst intensities lead to greater variability in queue backlogs.

We then investigate the impact of varying traffic burst intensities on the average queue difference, i.e., $\sum_{i,k} \mathbb{E}[\Delta Q_{ik}(t)|Q(t)]/N$, in LEO satellite network systems, as illustrated in Fig. 5. The data reveals persistent fluctuations in the average queue difference throughout the entire experimental timeframe T , due to the influence of dynamic traffic bursts. This observation deviates from the stability assumptions of the traditional Lyapunov optimization theory. Notably, this deviation is not confined to specific moments but persists throughout the experiment. Despite these challenging conditions, our proposed robust Lyapunov optimization method successfully maintains network system stability, aligning with theoretical predictions. This outcome suggests that for a stabilizable network system, it is not necessary for the system to strictly remain within the capacity region at every time slot. As long as excursions beyond the capacity region are limited, the system can still maintain the overall stability. We also note that as the intensity of dynamic bursts increases, the fluctuations in the average queue difference become more pronounced. Fig. 6 presents statistical results of the average queue difference under various intensities of dynamic traffic bursts. The data clearly shows that the mean of the average queue difference is slightly above zero. Furthermore, we observe that the standard deviation increases with the intensity of dynamic bursts, consistent with the simulation results shown in Fig. 5.

V. CONCLUSION

In this paper, we focus on the stability issues of LEO satellite constellation network systems. Traditional Lyapunov optimization, based on the Lyapunov's second stability criterion, assumes that network traffic must remain within the capacity region at all times to ensure system stability. However, this assumption is overly conservative and underestimates the resilience and the actual capacity of LEO satellite networks. To address this limitation, we have proposed a robust Lyapunov optimization method. Unlike the traditional approaches, this new method provides rigorous stability guarantees for network systems that would be considered unstable under the conventional frameworks. Our research demonstrates that network traffic flows do not have to strictly remain within the capacity region at all times. Instead, network systems can tolerate limited capacity violations while maintaining the overall stability. Through extensive simulation experiments on a Celestri-based LEO satellite network system, we validate the effectiveness of the proposed robust Lyapunov optimization method under varying intensities of dynamic traffic burstiness, demonstrating that LEO satellite networks can maintain stability under finite violations of the capacity region.

REFERENCES

- [1] U. Siddique, H. Tabassum, E. Hossain, and D. I. Kim, "Wireless backhauling of 5g small cells: challenges and solution approaches," *IEEE Wireless Communications*, vol. 22, no. 5, pp. 22–31, Oct. 2015.
- [2] X. Ge, H. Cheng, M. Guizani, and T. Han, "5g wireless backhaul networks: challenges and research advances," *IEEE Network*, vol. 28, no. 6, pp. 6–11, Nov. 2014.
- [3] N. U. Hassan, C. Huang, C. Yuen, A. Ahmad, and Y. Zhang, "Dense small satellite networks for modern terrestrial communication systems: Benefits, infrastructure, and technologies," *IEEE Wireless Communications*, vol. 27, no. 5, pp. 96–103, Sep. 2020.
- [4] J. Liu, Y. Shi, Z. M. Fadlullah, and N. Kato, "Space-air-ground integrated network: A survey," *IEEE Communications Surveys and Tutorials*, vol. 20, no. 4, pp. 2714–2741, May 2018.
- [5] Y. Su, Y. Liu, Y. Zhou, J. Yuan, H. Cao, and J. Shi, "Broadband leo satellite communications: Architectures and key technologies," *IEEE Wireless Communications*, vol. 26, no. 2, pp. 55–61, April 2019.
- [6] I. Del Portillo, B. G. Cameron, and E. F. Crawley, "A technical comparison of three low earth orbit satellite constellation systems to provide global broadband," *Acta Astronautica*, vol. 159, pp. 123–135, Mar. 2019.
- [7] J. Guo, D. Rincon, S. Sallent, L. Yang, X. Chen, and X. Chen, "Gateway placement optimization in leo satellite networks based on traffic estimation," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 4, pp. 3860–3876, Mar. 2021.
- [8] B. Al Homssi, A. Al-Hourani, K. Wang, P. Conder, S. Kandeepan, J. Choi, B. Allen, and B. Moores, "Next generation mega satellite networks for access equality: Opportunities, challenges, and performance," *IEEE Communications Magazine*, vol. 60, no. 4, pp. 18–24, Apr. 2022.
- [9] Y. Yang, M. Xu, D. Wang, and Y. Wang, "Towards energy-efficient routing in satellite networks," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 12, pp. 3869–3886, Sep. 2016.
- [10] J. Tao, Z. Na, B. Lin, and N. Zhang, "A joint minimum hop and earliest arrival routing algorithm for leo satellite networks," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 12, pp. 16 382–16 394, June 2023.
- [11] Z. Zhang, C. Jiang, S. Guo, Y. Qian, and Y. Ren, "Temporal centrality-balanced traffic management for space satellite networks," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 5, pp. 4427–4439, May 2018.
- [12] Z. Li, H. Zhang, C. Liu, X. Li, H. Ji, and V. C. M. Leung, "Online service deployment on mega-leo satellite constellations for end-to-end delay optimization," *IEEE Transactions on Network Science and Engineering*, vol. 11, no. 1, pp. 1214–1226, Jan.-Feb. 2024.
- [13] L. Tassiulas and A. Ephremides, "Stability properties of constrained queueing systems and scheduling policies for maximum throughput in multihop radio networks," in *29th IEEE Conference on Decision and Control*, Honolulu, HI, Dec. 1990, pp. 2130–2132, vol.4.
- [14] B. Awerbuch and T. Leighton, "A simple local-control approximation algorithm for multicommodity flow," in *Proceedings of IEEE 34th Annual Foundations of Computer Science*, Palo Alto, CA., Nov. 1993, pp. 459–468.
- [15] M. Neely, *Stochastic network optimization with application to communication and queueing systems*. Springer Nature, 2022.
- [16] M. Neely, E. Modiano, and C. Rohrs, "Dynamic power allocation and routing for time varying wireless networks," in *Twenty-second Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM)*, San Francisco, CA., Jul. 2003, pp. 745–755, vol.1.
- [17] X. Deng, L. Chang, S. Zeng, L. Cai, and J. Pan, "Distance-based back-pressure routing for load-balancing leo satellite networks," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 1, pp. 1240–1253, Jan. 2022.
- [18] Q. Chen, G. Giambene, L. Yang, C. Fan, and X. Chen, "Analysis of inter-satellite link paths for leo mega-constellation networks," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 3, pp. 2743–2755, Mar. 2021.
- [19] J. Wang, L. Li, and M. Zhou, "Topological dynamics characterization for leo satellite networks," *Computer Networks*, vol. 51, no. 1, pp. 43–53, Jan. 2007.
- [20] A. Golkar and I. Lluch i Cruz, "The federated satellite systems paradigm: Concept and business case evaluation," *Acta Astronautica*, vol. 111, pp. 230–248, Jun.–Jul. 2015.
- [21] R. P. Agarwal, *Difference equations and inequalities: theory, methods, and applications*. CRC Press, 2000.