LS-NRO: LEO-Satellite Network Resources Optimization for Future 6G Communication Systems

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Abstract

The objective of future sixth-generation (6G) networks is to provide global access to communication systems. Terrestrial networks are expanding in metropolitan areas, but there is no well-established distant user data traffic transmission infrastructure at the moment (i.e., users who are unable to access terrestrial networks). Our proposal investigates the best resource allocation mechanism in a communication system and suggests a heterogeneous network architecture of future 6G communication systems for the global connectivity of remote users. As a consequence, for remote users' access to the communication network, a network architecture based on LEO satellites is given. Higher data speeds with the future broadband spectrum, lower power consumption, and the low mass of LEO-satellite offer remote users communication benefits. Our numerical findings can be used to anticipate the potential of LEO satellite-based communication prospects in future wireless networks.

I. Introduction

The aim of 6G is to create a connected world, which requires global connection. As a result, human activity in this period will shift substantially from space to the air, land, and sea. To enable global wireless coverage for 6G networks, marine users must be integrated to construct a multidimensional space-air-ground-sea network [1], [2]. Furthermore, 6G networks will be distinct from present network configurations due to zero-touch and intent-based technologies that will increase network efficiency, maintenance, and operating expenses [3], [4]. This network will be comprised of several different and vertical applications that will be convoluted and multi-dimensional, including imaging, radar, location, navigation, sensing, control, caching, computation, and communication [5]. Furthermore, its architecture will take into account the integration of networks with exceptionally low latency in wireless communication with extremely high throughput demands.

Non-terrestrial networks (NTS) which are comprised of space and airborne platforms, will be a critical component of the forthcoming sixth-generation (6G) wireless cellular networks, enabling ubiquitous and ultra-high capacity wireless communication. As a supplement to terrestrial infrastructure, space, and airborne stations have enormous potential for promoting flexible global connectivity in densely populated areas, cost-effective network coverage in public safety situations, last-mile service delivery, and backhaul in remote, rural, and difficult-to-access zones [1].

Based on the preceding discussion, we suggest that a low earth orbit (LEO) satellite equipped with multi-access edge computing (MEC) be used in conjunction with terrestrial satellite terminals (TSTs) for ground users. Because optical fibers and ground base stations are in short supply for distant communications, which must operate in a highly complex and diversified environment, reliable transmission and traffic steering performance for service-oriented remote communication networks is constrained. As a result, our suggested solution will allow remote users to connect to the current network infrastructure.

II. System Model

We consider the LEO-satellite-based communication network for remote users which are unable to access the existing terrestrial network infrastructure services as shown in Fig. 1. We consider the LEO-satellite[1] is equipped with network-providing resources. Here, satellites need to provide backhaul services to the set of $\mathcal{N}$ of N terrestrial satellite terminals (TSTs) which are under their coverage region. The composite channel model which captures the large and small scale fading between satellite and its associated TST n can be defined as:

$$g_n = \alpha_n 10^{\frac{-\beta_n}{10}} g_s g_n, \quad \forall n \in \mathcal{N}, \tag{1}$$

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[1]Hereinafter, the LEO-satellite is considered as a satellite unless otherwise stated.

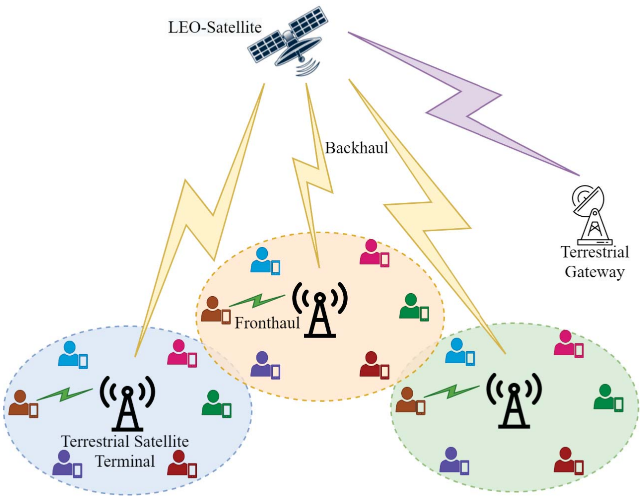

Fig. 1: Illustration of LEO-Satellite Communication System

where α_n denotes the Rician fading channel coefficient which account for small scale fading of TST n channel, g_s and g_n denote the antenna gain of satellite and TSTs respectively, and $\beta_n = \tilde{\gamma} + 10\gamma \log_{10}(\frac{d_n}{d_0}) + \phi$ captures the large-scale fading on mmWave between satellite and TST n. Here, $\tilde{\gamma}$ represents the intercept parameter (path loss at reference distance d_0), γ is the slope of the fit (path loss exponent), d_n reflects this distance between satellite and TST n, and ϕ is the model deviation in fitting represented by a zero-mean Gaussian random variable with standard deviation ω [6]. The TST n backhaul throughput can be define as:

$$R_n^{\text{backhaul}} = \tau_n B_n \log_2\Big(1 + \frac{g_n \mu_n P_n}{N_0 \tau_n B_n}\Big), \tag{2}$$

where N_0 is the noise power spectral density, $\tau_n B_n$ is the allocated bandwidth, and $\mu_n P_n$ is the transmit power of satellite for each TST n.

III. Problem Formulation

Our objective is to maximize the total backhaul throughput of satellite by optimizing bandwidth $\tau_n B_n$ allocation and the transmit power $\mu_n P_n$ among the associated TSTs. Mathematically, we can define our problem as follows:

$$\begin{aligned}
\textbf{P1:}\ \underset{\boldsymbol{\tau},\boldsymbol{\mu}}{maximize}\quad & \sum_{n=1}^{N} R_n^{\text{backhaul}} && \text{(3a)}\\
\text{subject to}\quad & \sum_{n=1}^{N} R_n^{\text{backhaul}} \le R^{\text{limit}}, && \text{(3b)}\\
& \sum_{n=1}^{N} \tau_n B_n = B^{\text{total}}, && \text{(3c)}\\
& \sum_{n=1}^{N} \mu_n P_n = P^{\text{total}}, && \text{(3d)}\\
& \tau_n B_n \ge 0,\ \forall n \in \mathcal{N}, && \text{(3e)}\\
& \mu_n P_n \ge 0,\ \forall n \in \mathcal{N}, && \text{(3f)}
\end{aligned}$$

where R^{limit} represents that the maximum backhaul value should be less than their capacity, B^{total} indicate the total available bandwidth of satellite, and P^{total} indicate the available power capacity of the satellite.

IV. Proposed Solution

We can modify our problem into convex optimization by multiplying the objective function with the negative sign, and then the problem will become the minimization problem with the convex objective function. However, to solve this problem with a standard optimization tool, i.e., CVXPY [7], we need to follow the disciplined convex programming (DCP) set of rules [8]. In our problem, two decision variables bandwidth allocation $\tau_n B_n$ and transmit power $\mu_n P_n$ are in division form in the objective function, which violates the rule of DCP programming. To rephrase the optimization problem in DCP format, we use CVXPY's kl_div function, which computes the Kullback-Leibler divergence. Due to space limitation, we omit the derivation part, and the simplified form of the objective function can be given as follows:

$$-R_n^{\text{backhaul}} = \text{kl\_div}\Big\{\tau_n B_n, \Big(\tau_n B_n + \frac{g_n \mu_n P_n}{N_0}\Big)\Big\} - \frac{g_n \mu_n P_n}{N_0}. \tag{4}$$

Now, the modified problem can be given as:

$$\begin{aligned}
\textbf{P2:}\ \underset{\boldsymbol{\tau},\boldsymbol{\mu}}{minimize}\quad & \sum_{n=1}^{N} -R_n^{\text{backhaul}} && \text{(5a)}\\
\text{subject to}\quad & \sum_{n=1}^{N} R_n^{\text{backhaul}} \le R^{\text{limit}}, && \text{(5b)}\\
& \sum_{n=1}^{N} \tau_n B_n = B^{\text{total}}, && \text{(5c)}\\
& \sum_{n=1}^{N} \mu_n P_n = P^{\text{total}}, && \text{(5d)}\\
& \tau_n B_n \ge 0,\ \forall n \in \mathcal{N}, && \text{(5e)}\\
& \mu_n P_n \ge 0,\ \forall n \in \mathcal{N}, && \text{(5f)}
\end{aligned}$$

This problem can now be addressed using CVXPY since the objective function is now in DCP form. Therefore, after solving this problem, we can find the optimal value of bandwidth allocation and transmit power.

V. Simulation Results and Discussion

We choose a 1000 m $\times$ 1000 m square area divided into 100 m $\times$ 100 m grid regions for our simulations, in which we randomly uniformly deploy 10 TSTs, as illustrated in Fig. 2. All statistical data are averaged over numerous independent testing rounds in which the satellite and TST locations are randomized. The entire transmit power budget for satellite is P = 36 dBm, and the bandwidth spectrum is B = 20 MHz. We consider an uncorrelated Rician fading channel with parameter α_n = 1.59. The key simulation parameters are summarized in Table I.

TABLE I: Simulation Parameters

Parameters	Values
Total Transmit Power	P = 33 dBm
Noise Power Spectral Density	$N_0 = -174$ dB/Hz
Total System Bandwidth	B = 20 MHz
TST Antenna Gain	g_n = 25 dBi
Satellite Antenna Gain	g_s = 30 dBi
Standard deviation	ω = 0.1
reference distance pathloss	$\tilde{\gamma}$ = 46.4
pathloss exponent	γ = 2
Rician fading parameter	α_n = 1.59

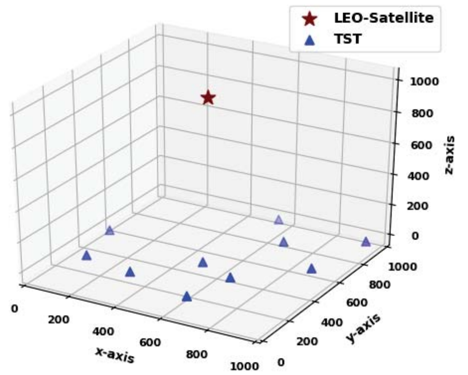

Fig. 2: Network Topology

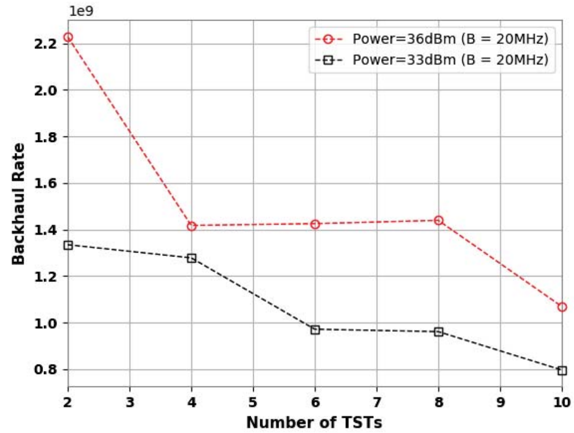

Fig. 3: Backhaul Rate vs number of TSTs

Fig. 3 represents the total satellite backhaul rate versus the total number of associated TSTs. Here, we considered two network configurations, i.e., the total transmit power budget has two values P = 33 dBm and P = 36 dBm. It can be observed from the given plot that in both configurations the total backhaul rate decreases with the increment of associated TSTs. The reason behind this behavior is that as the number of associated TSTs increases in the system, the total capacity of the satellite network resources, i.e., transmit power, and bandwidth spectrum decreases. Moreover, interference and noise are also added to the communication system, which also degrades the performance.

VI. Conclusion

We investigated the future 6G communication system resource optimization in this work. We investigated LEO-satellite with TST in particular for network resources given to ground users who are unable to obtain services from existing terrestrial network infrastructures. By optimizing satellite transmit power and bandwidth spectrum allocation, we proposed a network backhaul rate maximization problem. Our proposed solution yields the best results for optimizing network resources.

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