Optimizing Resource Planning for Next-Generation Satellite Communication Systems

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***Abstract*—A satellite communication system will be vital in providing services for increasingly heterogeneous 5G and beyond applications. However, before the satellite can be launched or operated in space, the service operator and manufacturers must design it to meet this diverse demand. In this paper, we propose an efficient resource planning method for the next generation of satellite communication systems. This method enables service operators and manufacturers to determine the necessary specifications of the satellite, such as the number of spot beams, DC power, antenna size, mass, and cost, to meet the requirements of 5G and beyond applications. We develop an algorithm that combines a search algorithm, greedy algorithm, and convex optimization to estimate these parameters. We evaluate the proposed algorithm's performance against benchmark schemes through extensive numerical results, demonstrating superior resource planning capabilities.**

***Index Terms*—5G/beyond applications, Convex optimization, Greedy algorithm, Resource planning, Search algorithm.**

I. Introduction

As satellites are capable of covering large geographical areas with minimal ground infrastructure, they offer an attractive option for meeting the increasing heterogeneous demands/services, such as media broadcasting, backhauling, broadband, Internet of Things (IoT), and new emerging 5G/beyond applications [1], [2]. To meet the diverse demands, the satellite must function in spatial-temporal mode by effectively managing its resources, including power and bandwidth. Several studies have been conducted on satellite resource management, focusing on meeting user demand requirements [3], [4]. However, these techniques are constrained by satellite payload architecture, Direct Current (DC) power, antenna size, and coverage area. In this case, improper estimation of DC power, antenna size, and improper design of the coverage area may lead to user dissatisfaction and high operational costs. Moreover, satellite mass and cost are restricted by the capacity of the launching process and manufacturers, which may impact the satellite's ability to meet user demands. Hence, it is crucial to efficiently plan the satellite's resources/abilities before launching to meet the needs of the operators, manufacturers, and end users.

Payload resource planning has been addressed partially in the SatCom literature. [5] has discussed capacity-optimization requirements for broadband communication satellites with multi-beam coverage, considering satellite antenna propagation effects, frequency reuse, and fixed payload power within a given technical and commercial parameter set. However, it assumes a fixed power to calculate the system capacity and it has not considered other factors such as user locations, demand, and individual user capacity. These significantly impact the design of satellite communication systems, including antenna size selection and beam number determination. Authors in [6] studied a link budget maximization framework for the satellite using the Gravitational Search Algorithm by optimizing carrier frequency, power, and antenna gain. On a similar approach, [7] aimed to optimize the payload configuration to maximize system throughput regarding payload and platform constraints such as power, bandwidth, and mass. However, these works have not provided comprehensive information regarding optimization problem formulation. They have also not considered other constraints, such as the mass, operation costs, location, altitude, and antenna size information of the launched satellite. In addition, they have not optimized the required beam number and corresponding transmit power to cover a given geographical area based on the statistical information of user location and demands. Although the optimization of the number of spot beams and beam placement has been investigated in [8]–[12], its interaction/impact with/on the satellite DC power, mass, cost, and antenna size has not been explored yet.

This paper proposes an algorithm to optimize the parameters and resources needed for next-generation satellite communication systems, addressing the long-term requirements of users and operators. We formulate an optimization problem for resource planning, determining the necessary number of spot beams (including beam pattern and placement design), DC power, antenna size, cost, and satellite mass while considering coverage area, user location, and demand. Our algorithm combines a search algorithm, greedy algorithm, and convex optimization to solve this problem. We evaluate the performance of the proposed algorithm against benchmark schemes through extensive numerical results, demonstrating superior resource planning capabilities compared to the benchmarks.

II. Scenario Planning and Problem Formulation

A. Scenario Planning

In this work, we focus on determining the right design parameters for a satellite that will be launched to the altitude H (m) at lat and lon degrees to provide multi-beam broadband internet service to multiple cities in a pre-determined zone (e.g., Europe). In this zone, each city is considered a virtual user (VU) with an estimated long-term aggregate demand. Let D_m (Mbps) be the average traffic demand for VU m. Here, the considered period can be one day and D_m can be estimated based on the statistical information. We presume the satellite has a circular aperture reflector antenna with multiple feeders, creating N spot beams for serving all VUs, which can be optimized based on the VU locations and demands. Regarding VU-beam association, one introduces new variable $\{x_m^n\}$ as,

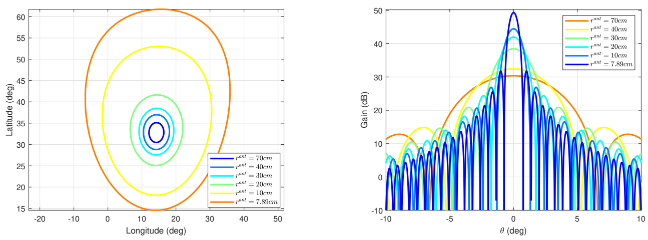
$$x_m^n = \begin{cases} 1, & \text{if VU } m \text{ is served by beam } n, \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

Let $\mathcal{M}_n$ be the set of VUs served by beam n whose cardinality can defined as $|\mathcal{M}_n| = M_n = \sum_{\forall m} x_m^n$. We assume that the VUs belonging to the same beam are served with an equal time-sharing TDMA approach. Hence, the probability that the signal of user m is transmitted at any time if it is served in beam n, can be given as $1/M_n$.

1) Satellite Beam Pattern Requirements: Let r^{ant} be the aperture-antenna radius based on which the beam pattern gain can be defined as [13]

$$\mathcal{G}(\theta) = G_{\mathsf{max}} \begin{cases} 4\left|\dfrac{J_1\left(\frac{2\pi}{\lambda} r^{\mathsf{ant}} \sin(\theta)\right)}{\frac{2\pi}{\lambda} r^{\mathsf{ant}} \sin(\theta)}\right|^2, & \text{if } 0 < \theta \leq \frac{\pi}{2}, \\ 1, & \text{if } \ \theta = 0, \end{cases} \tag{2}$$

where $J_1(\cdot)$ is the first-kind-first-order Bessel function, $G_{\mathsf{max}} = (\frac{2\pi r^{\mathsf{ant}}}{\lambda})^2$ is the maximum antenna gain, θ is the angle between the investigating direction and beam center viewed from satellite, λ is the carrier wavelength. Examples of beam patterns with latitude vs. longitude and gain vs. θ axes for different values of r^{ant} are depicted in Fig. 1. Hereafter, r^{ant} will be optimized to obtain an efficient efficient beam pattern covering the target area and satisfying VU demands.



(a) Beam pattern on earth surface (b) Beam pattern in 2D

Fig. 1: Beam pattern for different r^{ant} values

2) Satellite Mass and Cost Requirements: To estimate the satellite cost and mass according to N, authors in [5] developed a model based on historical data provided by satellite operators and manufacturers. Following this work, generating N beams may need $K \geq N$ antenna elements. This, in turn, impacts the number of high-power amplifiers (HPAs) and other hardware components needed for signal processing and propagation. Consequently, the satellite's cost and mass vary depending on the value of N[1]. Exploiting this model given in [5], the satellite cost (M€) and mass (kg) can be estimated as

$$\mathtt{Cost}(N) = 180 + 1.8N, \tag{3}$$

$$\mathtt{Mass}(N) = 4000 + 912N^{0.2}. \tag{4}$$

[1]Note that this paper does not cover the design of antenna elements or the number of hardware components required for the satellite.

3) Satellite DC Power and Shannon Capacity Requirements: The main contributions to the DC power of the satellite are the total transmit/radiated power and the dissipation power of HPAs. The DC power can be described as

$$P^{\mathsf{DC}} = \sum_{\forall(n,m)} x_m^n p_m^n / M_n + N\alpha P_{\mathsf{dis}}^{\mathsf{HPA}} + \zeta, \tag{5}$$

where p_m^n is the transmit power corresponding to user m's signal via beam n, $P_{\mathsf{dis}}^{\mathsf{HPA}}$ is the HPA dissipation power, ζ is the dissipation power corresponding to other satellite components, and α is the HPA number per beam transmission. Regarding the probability of user m's transmission is $1/M_n$, the average capacity achieved by VU m can be estimated as

$$C_m = \sum_{\forall n} x_m^n (B/M_n) \log_2(1 + \gamma_m^n), \tag{6}$$

where B is the total transmission bandwidth and γ_m^n represents the corresponding SINR of user m via beam n,

$$\gamma_m^n = \frac{x_m^n g_m^n p_m^n}{\sum_{\forall j \neq n} g_m^j \sum_{u \in \mathcal{M}_j} x_u^j p_u^j / M_j + BN_0}, \tag{7}$$

and N_0 is the noise spectral density, $g_m^n = G_{\mathsf{R}} G_m^n / (4\pi \frac{d_m}{\lambda})^2$ is channel gain of VU m for beam n, G_{R} and $G_m^n = \mathcal{G}(\theta_m^n)$ are the receiver and transmitter antenna gain, θ_m^n is the angle between beam n direction and VU m, and d_m is the distance between VU m and the satellite. Here, the interference is estimated based on the user transmission probabilities.

B. Problem formulation

In this section, we optimize the satellite's resource parameters required to satisfy the VUs' long-term demand while providing an acceptable quality of service (QoS). Since resource planning is affected by the satellite beam pattern coverage, we consider an optimization problem to minimize the N subject to the QoS, r^{ant}, power, mass, and cost constraint of the satellite, which is written as follows.

$$\min_{\{N, r^{\mathsf{ant}}, p_m^n, x_m^n\}} \quad N \tag{8a}$$

$$\mathtt{s.t.}\ (\mathcal{T}1): \sum_{\forall m} \min\left(\frac{x_m^n C_m}{D_m}, 1\right) / M_n \geq \mathrm{QoS}^{\mathsf{b}}, \forall n, \tag{8b}$$

$$(\mathcal{T}2): \sum_{\forall m} \min\left(\frac{C_m}{D_m}, 1\right) / M \geq \mathrm{QoS}^{\mathsf{sys}}, \tag{8c}$$

$$(\mathcal{T}3): r_{\mathsf{min}}^{\mathsf{ant}} \leq r^{\mathsf{ant}} \leq r_{\mathsf{max}}^{\mathsf{ant}}, \tag{8d}$$

$$(\mathcal{T}4): P^{\mathsf{DC}} \leq P_{\mathsf{max}}^{\mathsf{DC}}, \tag{8e}$$

$$(\mathcal{T}5): 0 \leq p_m^n \leq P_{\mathsf{max}}^{\mathsf{HPA}}, \forall (n,m), \tag{8f}$$

$$(\mathcal{T}6): \frac{\mathtt{Cost}(N)}{\mathtt{Cost}_{\mathsf{max}}} \leq 1,\ (\mathcal{T}7): \frac{\mathtt{Mass}(N)}{\mathtt{Mass}_{\mathsf{max}}} \leq 1, \tag{8g}$$

where $(\mathcal{T}1)$ and $(\mathcal{T}2)$ stand for the demand satisfaction for every beam and system, which must satisfy at least the minimum QoS of the per beam $\mathrm{QoS}^{\mathsf{b}} \in (0,1]$ and the system $\mathrm{QoS}^{\mathsf{sys}} \in (0,1]$, respectively. The $(\mathcal{T}3)$ is the antenna radius constraint, and the $(\mathcal{T}4)$ and the $(\mathcal{T}5)$ are the satellite DC power and the amplifier power constraint, respectively. Furthermore, the $(\mathcal{T}6)$ is the normalized cost of the satellite constraint, while the $(\mathcal{T}7)$ is the normalized mass of the satellite constraint.

***Remark** 1: Problem* (8) *is non-convex due to the nonlinearity of the SINR, the dependent summation function of* $(\mathcal{T}2)$ *and* $(\mathcal{T}4)$ *on* N *as well as the concavity* $(\mathcal{T}1)$ *and* $(\mathcal{T}2)$*. Hence, solving* (8) *using convex optimization techniques may not be possible. To tackle the problem, we will integrate searching, greedy, and iterative convex optimization approaches. Specifically, a two-stage solution approach will be developed to address problem* (8) *in the following section.*

III. Proposed Two-Stage Solution Approach

A. First Stage: Optimize N with Estimated Power

In this stage, we aim to minimize N that satisfies the system QoS requirement for a given power transmission $p_m^n, \forall(n,m)$, which is formulated as

$$\min_{\{N, r^{\mathsf{ant}}, x_m^n\}} \quad N \quad \mathtt{s.t.} \quad (\mathcal{T}1)-(\mathcal{T}3), (\mathcal{T}6), (\mathcal{T}7). \tag{9}$$

This problem is non-convex due to $(\mathcal{T}1)-(\mathcal{T}3)$. To tackle it, a searching approach is employed to determine the r^{ant}. Subsequently, a greedy algorithm is applied to cluster VUs, and each cluster can be served by one spot beam.

1) Searching Algorithm: To optimize N, we first need to determine the appropriate antenna radius value r^{ant} in $[r^{\mathsf{ant}}_{\mathsf{min}}, r^{\mathsf{ant}}_{\mathsf{max}}]$. Selecting a small value for r^{ant} results in a wide beam width, reducing the value of N. However, the transmitted power is dispersed over the wide beam, leading to lower antenna gain and SINR. In this scenario, the system may fail to satisfy constraints $(\mathcal{T}1)$ and $(\mathcal{T}2)$. On the other hand, choosing a large r^{ant} narrows the beam width, resulting in higher antenna gain. Nevertheless, this approach covers a smaller area and requires a larger N, which increases the cost, satellite mass, and DC power consumption.

Given the wide range of possible r^{ant} in $[r^{\mathsf{ant}}_{\mathsf{min}}, r^{\mathsf{ant}}_{\mathsf{max}}]$, evaluating every possible value is time-consuming. To address this, we employ the Binary Searching method, as detailed in **Algorithm** 1. The algorithm begins by calculating r^{ant} as the midpoint of the potential range. Using a Greedy approach, it determines the required N for the chosen r^{ant}. If all constraints are satisfied, the algorithm replaces the higher endpoint of the interval with r^{ant}. If the constraints are not met, it replaces the lower endpoint with r^{ant}. These steps are repeated until the difference between the interval endpoints is smaller than the threshold δ_{thr1}, where $0 < \delta_{thr1} << 1$ is a termination criterion ensuring a minimal value.

2) Greedy N-Determining Algorithm: This section presents a greedy algorithm to determine N for a given r^{ant} based on the beam pattern formulated in (2), which is summarized in **Algorithm** 2. This greedy approach sequentially places beams until the target area is covered. Herein, the center of each beam is simply defined based on the Maximal Aggregate Power Metric. It selects the VU m as the center of the beam when the aggregate power of VUs within that beam is the highest. Then, the algorithm performs VU-to-beam association to distribute VUs to each beam.

Algorithm 1 Stage 1: Optimize N with estimated power

Initialize: Set $r^{\mathsf{ant}}_{\mathsf{min}}, r^{\mathsf{ant}}_{\mathsf{max}}$
while $\left(r^{\mathsf{ant}}_{\mathsf{min}} - r^{\mathsf{ant}}_{\mathsf{max}} > \delta_{thr1}\right)$ **do**
    $r^{\mathsf{ant}} = \frac{r^{\mathsf{ant}}_{\mathsf{min}} + r^{\mathsf{ant}}_{\mathsf{max}}}{2}$
    Algorithm 2: Greedy Algorithm
    if $(\mathcal{T}5)$ & $(\mathcal{T}7)$ & **then**
        if $(\mathcal{T}1)$ & $(\mathcal{T}2)$ & $(\mathcal{T}3)$ **then**
            $r^{\mathsf{ant}}_{\mathsf{min}} \leftarrow r^{\mathsf{ant}}$
        else
            $r^{\mathsf{ant}}_{\mathsf{max}} \leftarrow r^{\mathsf{ant}}$
        end if
    else
        $r^{\mathsf{ant}}_{\mathsf{max}} \leftarrow r^{\mathsf{ant}}$
    end if
end while
Output: N and r^{ant}

Finding Beam Centers: Let $\mathbf{A} \in \mathbb{R}^{M \times M}$ be the adjacency matrix whose (m, m')-th element, denoted by $[\mathbf{A}]_{m,m'}$, is defined as follows

$$[\mathbf{A}]_{m,m'} = \begin{cases} 1, & \text{if } \theta_{m,m'} \le \theta_m^{3dB}, \\ 0, & \text{otherwise}, \end{cases} \tag{10}$$

where $\theta_{m,m'}$ represents the angle from the satellite between VUs m and m' and θ_m^{3dB} is the beam width. When VU m is considered as the beam center, VU m' can be only added to VU m's beam if $\theta_{m,m'} \le \theta_m^{3dB}$. Since M possible beam centers are available, selecting $N \le M$ beam centers is required while satisfying (9). For this, let us consider the estimated transmitted power of the m'th VU without interference as follows:

$$P_{m,m'} = \left(2^{D_m/B} - 1\right) BN_0 / g_m^{m'}, \tag{11}$$

where $g_m^{m'}$ denotes the channel gain of VU m' if its beam center is VU m. After the adjacency matrix of VUs is defined, a VU is selected as the beam center if the total corresponding required power estimated as in (11) of all VUs is the highest, which is determined as follows:

$$m = \arg\max_{m \notin \mathcal{M}} \Big\{ \sum_{\forall_{m'}, m' \notin \mathcal{M}} [\mathbf{A}]_{m,m'} P_{m,m'} \Big\}, \tag{12}$$

where the set $\mathcal{M}$ is initially empty. It is updated when a beam center is determined using (12) as $\mathcal{M} \leftarrow m$, $[\mathbf{A}]_{m,m'} == 1, \forall_{m'}$. The algorithm continues to find all the best beam centers from (12) until $|\mathcal{M}| == M$.

VU-to-beam association: The VU m is associated with a beam if the angle between the VU m and the beam is smaller than the angle between other beams, as given by

$$n = \arg\min_{n \in \mathcal{M}^{\mathsf{center}}} \{\theta_m^n, \forall_n\} \tag{13}$$

***Remark** 2: Since the VU-to-beam association is determined using* (13)*, we can directly obtain* x_m^n *using* (1).

B. Second Stage: Optimize Power with Estimated N

This section aims to optimize the required power satisfying the VUs demand in each beam regarding constraints $(\mathcal{T}4)$ and

Algorithm 2 GREEDY ALGORITHM

$n \leftarrow 1$, $\mathcal{M} \leftarrow \{\}$, $\mathcal{M}^{\text{center}} \leftarrow \{\}$,$\mathcal{M}_n \leftarrow \{\}$
M is number of users
while $(|\mathcal{M}| < M)$ **do**
  Apply (12)
  $\mathcal{M}^{\text{center}} \leftarrow m$
  $\mathcal{M} \leftarrow m$, $[\mathbf{A}]_{m,m'} == 1, \forall_{m'}$
  $n \leftarrow n + 1$
end while
Output: $N \leftarrow |\mathcal{M}^{\text{center}}|$
for $m = 1$ to M **do**
  Apply (13)
  $\mathcal{M}_n \leftarrow m$
  Apply (1)
end for
Output: $\mathcal{M}_n,$, x_m^n, $\forall_{n,m}$

Algorithm 3 STAGE 2: OPTIMIZE POWER WITH ESTIMATED N

Initialize: feasible point $(q_m^n)^{(v)}$; $v \leftarrow 0$
while $|\frac{g_m^n (q_m^n)^{(v)} q_m^n}{I_m^{(v)}} - \frac{g_m^n ((q_m^n)^{(v)})^2 I_m}{(I_m^{(v)})^2}| > \delta_{thr2}$ **do**
  $v \leftarrow v + 1$
  Solve (16) to obtain q_m^n
  Update $(q_m^n)^{(v)} \leftarrow q_m^n$
end while
: Output: $p_m^n = (q_m^n)^2, \forall_{m,n}$

$(\mathcal{T}5)$. To do so, we target an optimization problem minimizing the total transmit power and unmet system capacity as follows,

$$\min_{p_m^n, \forall_{n,m}} \sum_{\forall(n,m)} p_m^n / M_n P_{\text{max}}^{\text{DC}} + \sum_{n=1} \max\left(1 - \frac{C_m}{D_m}, 0\right) \texttt{s.t.} (\mathcal{T}4), (\mathcal{T}5). \tag{14}$$

This is non-convex due to the nonlinearity of SINR, and we solve it iteratively using the success convex approximation method. First, we replace the max function using an upper bound slack variable s_m, with constraints $(\mathcal{T}8) : s_m \geq 0$ and $(\mathcal{T}9) : 1 - \frac{C_m}{D_m} \leq s_m$. Additionally, we replace γ_m^n by lower bound slack variable Γ_m^n which is given by

$$(\mathcal{T}10) : \Gamma_m^n \leq \frac{2 g_m^n (q_m^n)^{(v)} q_m^n}{I_m^{(v)}} - \frac{g_m^n ((q_m^n)^{(v)})^2 I_m}{(I_m^{(v)})^2}, \tag{15}$$

where $q_m^n = \sqrt{p_m^n}$ and $(q_m^n)^{(v)}$ is the previous value of q_m^n; $I_m = \sum_{\forall j \neq n} g_m^j \sum_{u \in \mathcal{M}_j} x_u^j (q_u^j)^2 / M_j + BN_0$ is the interference and $(I_m)^{(v)}$ is the previous values of I_m. Details on derivation (15) can be found in [14]. Then, (14) becomes

$$\min_{q_m^n, \forall_{n,m}} \sum_{\forall(n,m)} \frac{(q_m^n)^2}{M_n} P_{\text{max}}^{\text{DC}} + s_m^n \texttt{s.t.} (\mathcal{T}4), (\mathcal{T}5), (\mathcal{T}8) - (\mathcal{T}10). \tag{16}$$

Problem (16) is a convex optimization and can be solved by convex optimization tools. **Algorithm** 3 describes steps to optimize the satellite's transmit power to satisfy the VU demand. First, it initialize $(q_m^n)^{(v)}$ and obtains its current (q_m^n) value by solving (16). Then, the algorithm updates $(q_m^n)^{(v)}$ by (q_m^n) and solves again (16). The algorithm repeats the above until it converges to a stationary point with the termination criteria shown inside (16) **while**$\{.\}$**do**.

TABLE I: SYSTEM PARAMETERS

Parameter	Value
Bandwidth per beam (B)	225 MHz
Uniform power allocation per beam	10 W
QoS^{b}	90%
QoS^{sys}	95%
Noise power density (N_0)	-204 dBW/Hz
Maximum Available DC power for SP $(P_{\text{DC}}^{max} - \zeta)$	3700W
Maximum HPA power $(P_{\max}^{HPA})$	100W
HPA efficiency (η)	0.7
Dissipation HPA power $P_{\text{dis}}^{\text{HPA}}$	$(1 - \eta) P_{\max}^{HPA}$
HPA number per beam (α)	1
The mean traffic demand (β)	10 Mbs
$\texttt{Mass}_{\text{Cost}}$, $\texttt{Mass}_{\text{max}}$	$360M$€, 6290.8kg
Threshold $\delta_{thr1}, \delta_{thr2}$	10^{-4}

IV. SIMULATION RESULTS

For the simulation setting, we consider a geostationary (GEO) satellite[2] located at 13^oE with an altitude of 35786 km to serve 500 VUs distributed geographically within the $(30^o, 75^o)$ and $(-25^o, 60^o)$ latitude and longitude, respectively. The detailed parameters used for this simulation result are shown in Table I. In these simulations, the results are obtained according to 200 different demand realizations, each of which is generated by employing the Poisson distribution [14]. Specifically, VU m's demand is generated as

$$D_m = -\beta \log(1 - \chi_m), \tag{17}$$

where β is the mean VU traffic demand and χ_m is a value generated from a uniform random number in $(0, 1)$. For comparison purposes, three benchmark schemes[3] are selected for implementation in these simulations, described as follows:

1) Weighted Grid-Based Beam Placement (WGBP) Method: This method is a regular grid approach, where each beam center is determined as follows:

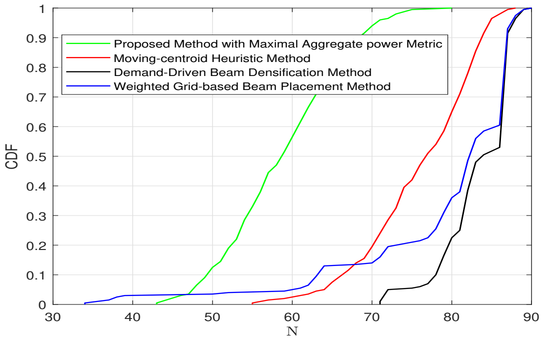
- Step 1: Locate the first beam center at VU that has minim latitude and longitude $(\phi_{\text{lat}}^i, \phi_{\text{lon}}^j)$.
- Step 2: Determine the next beam center at latitude ϕ_{lat}^i and longitude as $\phi_{\text{lon}}^{j+1} = \phi_{\text{lon}}^j + \phi^{3dB}\sqrt{3}$ and include the VUs located within the ϕ^{3dB} beam width of this beam to the set $\mathcal{L}_{i,j}$.
- Step 3: Update $\phi_{\text{lat}}^i \leftarrow \phi_{\text{lon}}^i + \phi^{3dB}\sqrt{3}$, go to Step 2.
- Step 4: Update each beam center by weighted mean [8] of VUs latitude and longitude within that beam as $\phi_{\text{lat}}^i = \frac{\sum_{l \in \mathcal{L}_{i,j}} D_l \phi_{\text{lat}}^l}{\sum_{l \in \mathcal{L}_{i,j}} D_l}$ and $\phi_{\text{lon}}^j = \frac{\sum_{l \in \mathcal{L}_{i,j}} D_l \phi_{\text{lon}}^l}{\sum_{l \in \mathcal{L}_{i,j}} D_l}$, respectively.

2) Demand-Driven Beam Densification (DBD) Method: Proposed in [9], this method determines N by using weighted k-means algorithm and Calinski–Harabasz (CH) index from a given range of $N_{\text{min}} \leq N \leq N_{\text{max}}$. In this simulation, N_{min} is 1, and N_{max} is the number of beams used in the WGBP Method.

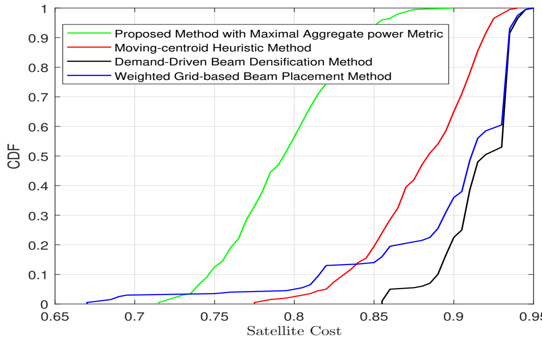
3) Moving-Centroid Heuristic (MCH) Method: This approach initially randomly selects a VU and uses its latitude and longitude as temporary positions for the beam center. Then, it

[2]The proposed method can also be applied to Non-Geostationary Orbit (NGSO) satellites.

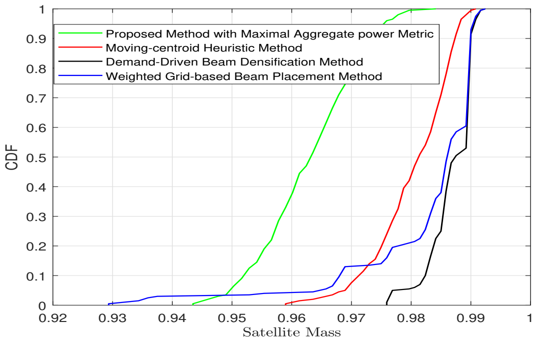
[3]Note that the benchmark schemes are executed for different values of r^{ant} using **Algorithm** 1 to optimize N and to satisfy the constraints of (6).



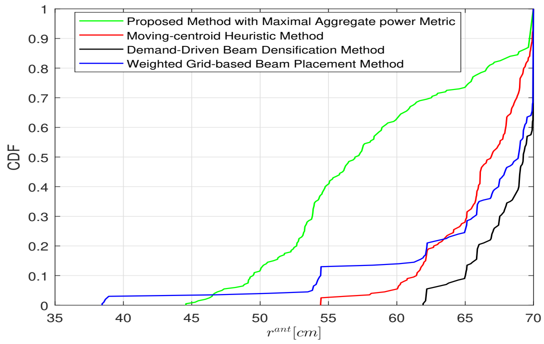
(a) Optimized N



(b) Cost of the Satellite



(c) Mass of the Satellite



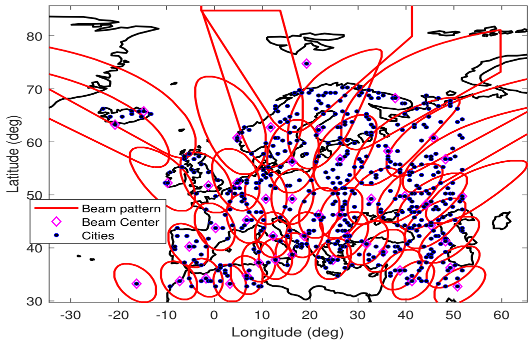
(d) optimized r^{ant}

Fig. 2: Resource requirements for different demand realization.

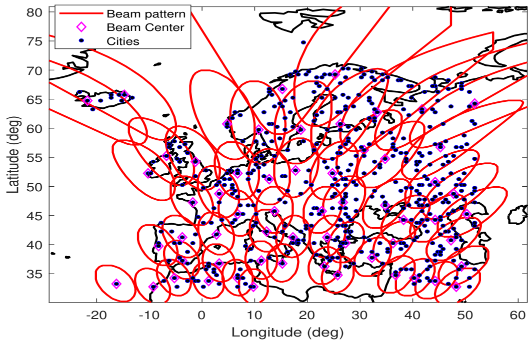
chooses the closest VU to the beam center and forms a cluster with the initially selected VU. The latitude and longitude of the clustered VUs are averaged to update the beam center. This process continues as long as the clustered VUs remain within half of the beam's width from the updated center. If a VU falls outside this range, it is removed from the cluster, and the remaining VUs define the cluster. The algorithm repeats this procedure to create additional clusters, which effectively represent spot beams [10].

Fig. 2a shows the CDF of N for different demand realizations across all methods. The proposed method requires fewer beams than the benchmarks. For example, at 96% of the demand realizations, the optimized N using the proposed method is 71, while for the MCH method, the WGBP method, and the DBD method, it is 84, 88, and 88, respectively. The proposed method returns fewer beams because it identifies the most effective beam centers and optimizes the antenna size to cover the target area while meeting constraints (6). Fig. 2b depicts the CDF of the satellite cost for all schemes. We observe that the proposed method minimizes the satellite cost compared to the benchmark methods. For instance, at 96% of demand realizations, it optimizes the normalized cost of the satellite to be 0.855. In contrast, using the MCH method, the cost of the satellite increases by 8%, and for the DBD and WGBP methods, it increases by 9.9% compared to the proposed method. Fig. 2c shows the CDF of the satellite mass for different demand realizations across all methods. Similar to the satellite cost, the proposed method minimizes the satellite mass requirement compared to the benchmark schemes. For example, at 96% of demand realizations, the proposed method reduces the satellite mass by 1.21% compared to the MCH method and by 1.5% compared to the DBD and WGBP methods. Fig. 2d depicts the CDF of the antenna radius for the proposed method and the benchmark schemes across different demand realizations. The proposed method requires a smaller antenna size than the benchmark schemes. An example of a beam pattern for the proposed method with two different demand realizations is shown in Fig. 3, where a larger antenna size corresponds to more beams than a smaller antenna size.

Fig. 4 illustrates the available DC power required for signal processing by the satellite under different demand scenarios across all schemes. The proposed method more accurately estimates the DC power needed to meet VU demand compared to benchmark schemes. This improvement is due to the proposed method's use of fewer beams, which in turn requires fewer HPAs. Consequently, the system's power dissipation for signal processing is reduced compared to benchmark schemes that necessitate more HPAs due to a higher number of beam requirements. Fig. 4a shows the DC power with uniform power allocation, without applying the power optimization method described in III-B. In contrast, Fig. 4b depicts the DC power after applying the power optimization method from III-B. The power optimization method provides a more accurate estimation of DC power than uniform power allocation.

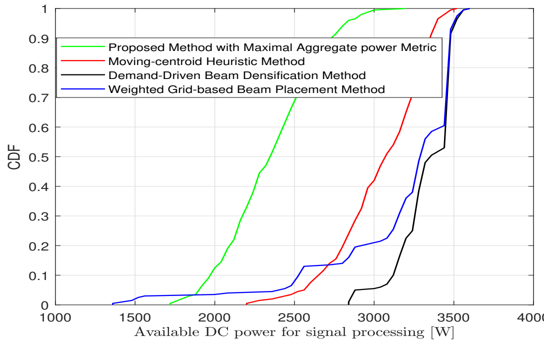


(a) $N = 46$, $r^{ant} = 47cm$

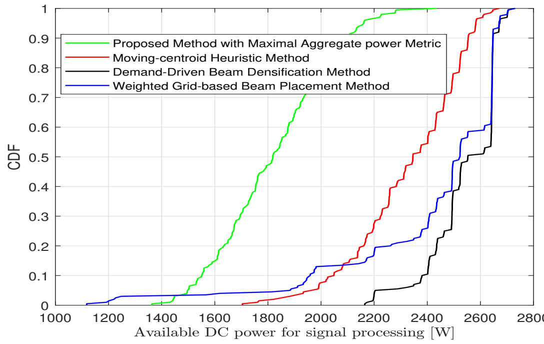


(b) $N = 60$, $r^{ant} = 53.3cm$

Fig. 3: Beam pattern examples of the proposed method.



(a) Uniform power allocation



(b) Optimized power allocation

Fig. 4: Available DC power for signal processing.

V. Conclusion

This paper presents a resource planning optimization framework for next-generation SatCom systems. It enables service operators and manufacturers to determine the essential specifications of the satellite, such as the number of beams, DC power, antenna size, mass, and cost, needed to meet end-user requirements. The proposed method demonstrates superior resource planning compared to benchmark schemes.

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