Network Slice Admission Control and Resource Allocation in LEO Satellite Networks: A Robust Optimization Approach

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***Abstract*—Network slicing has become an essential technology for the future network. Obviously, it will play an important role in satellite networks as well. To address that quality of service (QoS) may be severely affected by embedding satellite virtual networks (SVNs), we propose a method for SVN admission control that can effectively guarantee the QoS of network slices by admitting SVNs embedded in the physical satellite networks. Specifically, firstly, we propose a two-stage SVN embedding mechanism that decouples short-term resource allocation from long-term admission control and resource leasing. Then, we consider the case of uncertain system capacity due to the highly dynamic nature of the satellite networks topology, and model the admission control problem as a robust optimization problem. The robust problem is transformed into a convex counterpart by using the Bernstein approximation. Finally, we solve the resource allocation problem by converting it into a convex problem. The simulation results show the effectiveness of the proposed method.**

***Index Terms*—Low-earth-orbit satellite, network slicing, admission control, resource allocation, robust optimization**

I. Introduction

The 6G requires the support of Non-Terrestrial Networks (NTNs) to facilitate ubiquitous and high-capacity global connectivity [1]. Low Earth Orbit (LEO) satellites in NTN provide an affordable solution for global coverage networks [2]. Therefore, the convergence of LEO satellite networks and terrestrial networks is an inevitable trend for B5G and even 6G to meet the growing demand [3].

Network Slicing (NS) is a technology by creating virtual networks to provide customized services for various needs as defined by 3rd Generation Partnership Project (3GPP) [4]. NS uses network virtualization to flexibly allocate infrastructure resources to meet the diverse Quality of Service (QoS) requirements of user terminals [5]. NS has been widely recognized as a promising technology and has been well studied in terrestrial networks [6]. NS is expected to bring greater flexibility to satellite network operators, reduce construction and operating costs, and expand the range of applications for satellite communications [7]. Recently, NS in satellite networks has attracted extensive interest from researchers [8], [9]. A detailed framework for slicing satellite integration within 5G is presented [10].

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However, virtualization can significantly affect user QoS in Virtual Networks (VNs), because VNs share the same physical network, and in particular, the highly dynamic nature of the LEO satellite networks topology leads to system capacity instability that can have a serious impact on user QoS in SVN. Admission control for requesting embedded VNs is one of the important ways to ensure QoS for users in VNs. A fast embedding algorithm for SVN is proposed [11]. An embedding algorithm for multivariate SVN considering various constraints of satellite networks is proposed [12].

Therefore, to address the problem that users sharing the same physical satellite networks may have a serious impact on SVN user QoS, we propose a method to effectively guarantee the user QoS and the resource utilization of SVNs by selecting appropriate SVNs embedded in the physical network. The contributions of this paper are as follows. Firstly, we propose a two-stage SVN embedding mechanism that decouples short-term resource allocation from long-term admission control and resource leasing. The long-term admission control and resource leasing are then described as robust optimization problems, which are then solved by transforming them into convex optimization problems using the Bernstein approximation. Finally, the resource allocation is modelled as a maximally fair bandwidth allocation problem and solved after being transformed into a convex optimization problem.

The rest of this paper is organized as follows. Section II introduces the system model and describes the problem of SVN embedding. Section III presents a two-stage mechanism for embedding SVN and decomposes the SVN embedding problem according to this mechanism. Section IV discusses simulation results. Finally, we conclude in Section V.

II. System Model and Problem Statement

A. Business Model

We refer to the architecture in [13] to separate the roles of satellite networks virtualization into three logical roles, including Satellite Infrastructure Provider (SInP), Satellite Virtual Network Operator (SVNO) and Satellite Service Provider (SSP). SInP owns the satellite networks infrastructure resources and physical radio resources. SVNO leases physical resources from SInP for operations. SSP provides services directly to users. Specifically, firstly, SVNO converts the service request into an

SVN demand request when the SSP initiates a service request. Then, SVNO decides whether to respond to the request from the SSP based on the request and the currently available leased network resources. SVNO leases resources from SInPs and then embeds the corresponding SVN into the physical network if the SVNO receive the request. Finally, the SSP provides services to the user through the SVN provided by SVNO.

B. System Model

We assume that there are S=$|\mathcal{S}=\{1,...,s,...,\mathrm{S}\}|$ SInPs that can cover the same area, and the area is covered by a unique satellite for each SInP, so the satellite deployed by the SInP s can be denoted by the same symbol s. Assuming that the network is fully shared, the SVNO can lease physical resources from any SInP. Denoting the lease ratio of satellite s by $p_s \in [0,1]$. In general, the SInP may need to keep some resources for itself [14], i.e., the resources are not fully leasable. Let $p_s^{\max}$ denote the upper limit of the leasable ratio, so

$$p_s \in [0, p_s^{\max}], \forall s \tag{1}$$

Denoting the price of fully leased satellite s by c_s, the leasing cost paid by SVNO to SInP s can be obtained as

$$c_s^{\text{svno}} = p_s c_s, \forall s \tag{2}$$

We assume that there are K= $|\mathcal{K}=\{1,...,k,...,\mathrm{K}\}|$ service requests arriving from SSPs, and each SSP requests only one SVN to serve its users, then the SVN can be denoted by the same notation k. The requested SVNs are dynamically embedded in the physical network, and the SVNO accepts the embedded requests from these SVNs if the physical network resources can meet their demands. Let a_k be the admission indicator of SVN k, if admitted, $a_k=1$, if blocked, $a_k=0$, so the binary constraint can be obtained as

$$a_k \in \{0,1\}, \forall k \tag{3}$$

Let ϕ_r and ϕ_p denote the admission reward and blocking penalty for SVN k, respectively, so the revenue earned by SVNO is

$$R_{\text{svno}} = \sum_{k\in\mathcal{K}} (a_k \phi_k^r - (1-a_k)\phi_k^p) - \sum_{s\in\mathcal{S}} p_s c_s \tag{4}$$

Assuming that user arrivals in SVN k obey a Poisson process with intensity λ_k, denoting by r_k the minimum rate requirement for the SVN k to provide the service, the average traffic of SVN k requests is denoted as $\rho_k = r_k \lambda_k$ according to the similar study in [15]. The resource allocation strategy is denoted as $\mathbf{y} = \{\mathbf{y}_1, ..., \mathbf{y}_k, ..., \mathbf{y}_K\}$, where $\mathbf{y}_k = \{\mathbf{y}_{k,1}, ..., \mathbf{y}_{k,i}, ..., \mathbf{y}_{K,|\mathcal{U}_k|}\}$ denotes the resource allocation strategy for the users in SVN k, where $\mathcal{U}_k$ denotes the set of users in SVN k. The capacity $C_k(\mathbf{d}_k, \mathbf{p}, \mathbf{y}_k)$ allocated to the SVN k is decided by the user distribution $\mathbf{d}_k$, the leasing strategy $\mathbf{p}$ and the resource allocation strategy $\mathbf{y}_k$. The system can be in a stable state only if the allocated traffic is not less than the requested throughput, so the system stability constraint is

$$\sum_{k\in\mathcal{K}} a_k \rho_k \le \sum_{k\in\mathcal{K}} C_k(\mathbf{d}_k, \mathbf{p}, \mathbf{y}_k) \tag{5}$$

Let $\mathbf{y}_{k,i} = (l_{k,i}^s, \beta_{k,i}^s)$ denotes the resource allocation strategy for the ith user $u_{k,i}$ in the SVN k, where $l_{k,i}^s$ is the the associate indicator for user $u_{k,i}$ and satellite s. The user in the admitted SVN is associated with only one satellite, and the satellite does not serve the user in the rejected SVN, the constraint can be obtained as

$$l_{k,i}^s \in \{0,1\}, \forall s,k,i \tag{6}$$

$$\sum_{s\in\mathcal{S}} l_{k,i}^s = a_k, \forall k,i \tag{7}$$

where $\beta_{k,i}^s$ denotes the proportion of resources allocated to the user $u_{k,i}$ by the satellite s. The resources allocated to the user $u_{k,i}$ by the satellite s no more than the resources leased by the SVNO, we can obtain the constraint as

$$\sum_{k\in\mathcal{K}} \sum_{u_{k,i}\in\mathcal{U}_k} a_k l_{k,i}^s \beta_{k,i}^s \le p_s, \forall s \tag{8}$$

We assume that the licensed spectrum used by different SInPs is orthogonal, so there is no interference between different satellites, and the average transmit power of satellite s can be obtained as q_s using the fixed power mechanism, therefore, the spectral efficiency between satellite s and user $u_{k,i}$ can be obtained using Shannon's formula as

$$\eta_{k,i}^s = \log_2(1 + \frac{g_{k,i}^s q_s}{\sigma^2}), \forall s,k,i \tag{9}$$

where $g_{k,i}^s = 10^{(G(\theta)+G_r+L_f)/10}$ denotes the downlink channel gain between the satellite s and the user $u_{k,i}$, G_r denotes the user receive antenna gain, L_f denotes the free space propagation loss, σ^2 denotes the power spectral density of additive Gaussian white noise, and $G(\theta)$ denotes the satellite to user transmit antenna gain at the z-axis angle. Assuming that the antenna's z-axis always points to the subsatellite point, and referring to the radiation characteristics of the satellite single-beam antenna given in the International Telecommunication Union Recommendation ITU-S.672 [18], the reference model for the estimation of $G(\theta)$ is modeled as

$$G(\theta) = \begin{cases} G_s - 3(\theta/\theta_\alpha)^2 \text{dBi}, & 0 \le \theta \le 2.58\theta_\alpha \\ G_s - 20\text{dBi}, & 2.58\theta_\alpha \le \theta \le 6.32\theta_\alpha \\ G_s - 25\lg(\theta/\theta_\alpha)\text{dBi}, & 6.32\theta_\alpha \le \theta \le \theta_\beta \\ 0\text{dBi}, & \theta_\beta \le \theta \end{cases} \tag{10}$$

where G_s is the maximum gain of the satellite transmitting antenna, θ_α is the half-beam angle of the satellite, and θ_β is the value of the third equation in (10) when $G(\theta)=0$.

Let B_s denotes the downlink bandwidth from satellite s to the user terminal, the traffic $r_{k,i}$ allocated to user $u_{k,i}$ is determined by the resource allocation strategy $\mathbf{y}_{k,i}$, and the traffic obtained from user $u_{k,i}$ allocation can be obtained as

$$r_{k,i} = \sum_{s\in\mathcal{S}} l_{k,i}^s \beta_{k,i}^s B_s \eta_{k,i}^s, \forall k,i \tag{11}$$

and the user rate constraint can be obtained as

$$\sum_{s\in\mathcal{S}} l_{k,i}^s \beta_{k,i}^s B_s \eta_{k,i}^s \ge r_k, \forall k,i \tag{12}$$

C. Problem Statement

Our optimization objective of admission control is the maximum revenue of SVNO, we consider user fairness, so the optimization objective of resource allocation is to maximize the fair bandwidth allocation. The system utility U of resource allocation can be obtained as

$$U = \sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}}\sum_{u_{k,i}\in\mathcal{U}_k} l_{k,i}^s \ln(\beta_{k,i}^s B_s \eta_{k,i}^s) \tag{13}$$

Based on the above analysis, the optimization problem of this paper can be obtained as follows.

$$\begin{aligned} \mathbf{P1}: &\max_{\mathbf{a},\mathbf{p},\mathbf{y}} R_{\text{svno}} + U \\ &\text{s.t. } (1)(3)(5)(6)(7)(8)(12) \end{aligned} \tag{14}$$

III. Solution to the Problem

A. A Two-stage SVN Embedding Mechanism

The three optimization variables in problem $\mathbf{P1}$ are hard to solve simultaneously, because SSP needs to request SVN some time in advance. Which means that there are variables that should be optimized before the user arrives, i.e., the admission control and resource leasing are completed before the user arrives, while the resource allocation decision must be available after the admission decision and after the user arrives. To solve these mismatched optimization problems, we propose a two-stage embedding mechanism for SVNs as shown in Fig. 1, which decomposes the optimization problem $\mathbf{P1}$ into two stages to proceed. In the first stage, the admission control and resource leasing strategies are jointly optimized, and the SVNO applies admission control to the requesting SVN and leases resources from the SInP based on the SVN traffic demand and the estimated satellite capacity. In the second stage, under the condition of obtaining the admission control strategy and leasing strategy, the SVNO allocates resources to the arriving users in the prospective SVN, including satellite association and physical resource allocation.

The optimization variables of the first stage include admission control strategy and resource leasing strategy, so the optimization objectives of the first stage is

$$\max_{\mathbf{a},\mathbf{p}} R_{\text{svno}} \tag{15}$$

To obtain the first stage subproblem, we need to remove the second stage independent constraints of problem $\mathbf{P1}$ and decouple the optimization variables that are coupled with the second stage. Firstly, since (6), (7), (8) and (12) are constraints independent of the first-stage decision, they are removed directly. Then, since the user distribution and resource allocation in (5) are unknown at the time of the first stage decision, they need to be decoupled, but direct decoupling is very difficult due to the different time scales, so we adopt an indirect decoupling method. Since the capacity available from satellites is related to the network state and user distribution, and the motion of satellites has regularity, the capacity available from the current system can be estimated based on the current network state

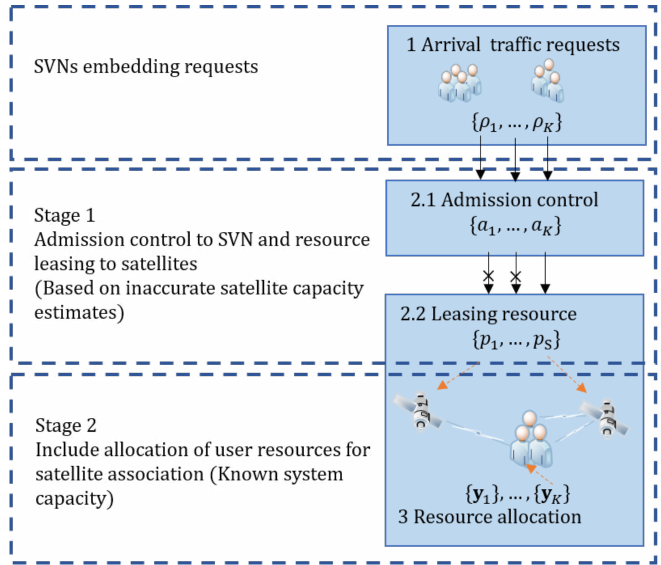

Fig. 1. The two-stage mechanism for SVN embedding.

and random users, and then the expected value of the capacity available from the system in the current state is obtained by combining the historical data as

$$E[C_s^t] = \alpha_s C_s^t + \beta_s E[R_s^{t-}] \tag{16}$$

where $E[R_s^{t-}]$ denotes the system capacity expectation at the last evaluation when satellite s in the current state, C_s^t denotes the estimate of the maximum capacity currently available from the satellite based on the current state of the satellite and randomly generated users. α_s is the ratio constant used to reconcile the current network state with the historical network state, and $\alpha_s + \beta_s = 1$, so that (5) can be rewritten as

$$\sum_{k\in\mathcal{K}} a_k \rho_k - \sum_{s\in\mathcal{S}} p_s E[C_s^t] \leq 0 \tag{17}$$

Based on the above analysis, the optimization problem $\mathbf{P2}$ for the first stage can be obtained as follows

$$\begin{aligned} \mathbf{P2}: &\max_{\mathbf{a},\mathbf{p}} R_{\text{svno}} \\ &\text{s.t. } (1)(3)(17) \end{aligned} \tag{18}$$

The optimization variable in the second stage is the resource allocation strategy, so the optimization objective of the second stage can be obtained as

$$\max U \tag{19}$$

From the above analysis, (6), (7), (8) and (12) are directly retained in the second stage, and (1) and (3) are are directly deleted. (5) is also removed directly, as the second stage is completed after the first stage. The second stage is to allocate resources to the users who are allowed into the SVN set $\mathcal{K}_a = \{k|a_k = 1, k \in \mathcal{K}\}$, so $a_k = 1$ in (7) and (8), so (7) and (8) are rewritten as

$$\sum_{s\in\mathcal{S}} l_{k,i}^s = 1, \forall k, i \tag{20}$$

$$\sum_{k\in\mathcal{K}_a}\sum_{u_{k,i}\in\mathcal{U}_k} l_{k,i}^s\beta_{k,i}^s \le p_s, \forall s \tag{21}$$

Based on the above analysis, the optimization problem $\mathbf{P3}$ of the second stage can be obtained as

$$\begin{aligned}\mathbf{P3}: \max_{\mathbf{y}} &\sum_{s\in\mathcal{S}}\sum_{k\in\mathcal{K}_a}\sum_{u_{k,i}\in\mathcal{U}_k} l_{k,i}^s \ln(\beta_{k,i}^s B_s \eta_{k,i}^s) \\ \text{s.t. } &(6)(12)(20)(21)\end{aligned} \tag{22}$$

B. Robust Admission Control Strategy

Unfortunately, the available capacity of satellites is time-varying because the topology of satellite networks is highly dynamic due to the fast movement of LEO satellites and the distribution of users is unknown, which leads to the constraint (17) not being directly applicable to solve practical problems. A possible solution to this problem is to directly change the stochastic parameters with uncertainty to upper or lower bounds that satisfy the demand, so that the resulting solution is always feasible in practice. However, such an approach leads to a great waste of resources, since the random parameters are upper or lower bounds that generally occur with low probability. Therefore, in order to improve resource utilization and to guarantee QoS to users with high probability, the "hard" constraint (17) can be converted to a tolerable "soft" constraint, i.e., the original constraint is allowed to be unsatisfied with an acceptable low probability. Assuming that the probability that the "hard" constraint being satisfied at least $1-\tau$, the constraint (16) can be converted into the following chance constraint.

$$Pr\left\{\sum_{k\in\mathcal{K}} a_k\rho_k - \sum_{s\in\mathcal{S}} p_s E[C_s^t] \le 0\right\} \ge 1-\tau \tag{23}$$

Although the chance constrained optimization problem is hard to solve directly, it can be solved efficiently using the Bernstein approximation [16]. Consider a chance constraint of the following form

$$Pr\left\{f_0(\mathbf{p}) + \sum_{s\in\mathcal{S}} \eta_s f_s(p) \le 0\right\} \ge 1-\tau \tag{24}$$

where $\mathbf{p}$ is a certain parameter with and η_s is a random variable with marginal distribution ξ_s. For a given distribution η_s, if the constraint satisfy the following three assumptions: 1) $f_n(\mathbf{p})$ is affine with respect to $\mathbf{p}$, where $s = 1, 2, ..., \mathrm{S}$. 2) The random variables η_n are mutually independent, where $s = 1, 2, ..., \mathrm{S}$. 3) η_s has bounded support $[-1, 1]$, where $s = 1, 2, ..., \mathrm{S}$. The chance constraint can be converted into the following relatively conservative convex approximation form

$$\begin{aligned}&f_0(\mathbf{p}) + \sum_{s\in\mathcal{S}} \max\{\mu_s^- f_s(p), \mu_s^+ f_s(p)\} \\ &+ \sqrt{2\ln(\frac{1}{\tau})}\left(\sum_{s\in\mathcal{S}}(\sigma_s f_s(p))^2\right)^{1/2} \le 0\end{aligned} \tag{25}$$

In constraint (23), firstly, $a_k \in \{0,1\}$ is relaxed to $\tilde{a}_k \in [0,1]$. Then, the uncertain parameter C_s^t is processed using the Bernstein approximation, so that the original constraint is satisfied with at least the probability of $1-\tau$. Since the satellite motion is regular, we assume that the bounded support $[C_s^{t,l}, C_s^{t,h}]$ for the capacity available from the satellite s can be obtained from the historical data, and the parameter ξ_s is obtained after introducing the auxiliary variables $\Gamma_s^l = (C_s^{t,h} - C_s^{t,l})/2 \neq 0$ and $\Gamma_s^h = (C_s^{t,h} + C_s^{t,l})/2$ to normalize C_s^t as

$$\xi_s = \frac{C_s^t - \Gamma_s^h}{\Gamma_s^l} \in [-1, 1] \tag{26}$$

Clearly, the three assumptions for which the Bernstein approximation holds are satisfied after treating the chance constraint (23). Let $f_s(p) = \Gamma_s^l\alpha_s p_s$ and $f_0(\mathbf{p}) = \sum_{k\in\mathcal{K}} \tilde{a}_k r_k - \sum_{s\in\mathcal{S}} \Gamma_s^h \beta_s p_s E[R_s^{t-}]$, then (24) is equivalent to (23). Substitute $f_s(p)$ and $f_0(\mathbf{p})$ into (25), we obtain

$$\begin{aligned}&\sum_{k\in\mathcal{K}} \tilde{a}_k r_k - \sum_{s\in\mathcal{S}}\left(\gamma_s\alpha_s p_s + \beta_s p_s E[R_s^{t-}]\right) \\ &- \sqrt{2\ln(\frac{1}{\tau})}\left(\sum_{s\in\mathcal{S}}(\sigma_s\Gamma_s^l\alpha_s p_s)^2\right)^{1/2} \le 0\end{aligned} \tag{27}$$

where $\gamma_s = \Gamma_s^h - \mu_s^+\Gamma_s^l$, the solution obtained by replacing (27) with (23) leads (5) to be satisfied with at least the probability of $1-\tau$, i.e., leads the problem $\mathbf{P2}$ to be satisfied with at least the probability of $1-\tau$. In this study, based on the properties of ξ_s, we set $\mu_s^+ = 0.5$ and $\sigma_s = \sqrt{1/12}$.

Based on the above analysis, the optimization problem $\mathbf{P2}$ is transformed into the following problem.

$$\begin{aligned}\tilde{\mathbf{P}}\mathbf{2}: &\max_{\tilde{\mathbf{a}},\mathbf{p}} R_{\text{svno}} \\ &\text{s.t. } (1)(27), \tilde{a}_k \in [0,1], \forall k\end{aligned} \tag{28}$$

Obviously, problem $\tilde{\mathbf{P}}\mathbf{2}$ is a convex problem, which can be solved directly using the interior point method to obtain the relaxed $\{\tilde{a}_k\}^*$ and the corresponding $\{\tilde{p}_s\}$. Since $\{\tilde{a}_k\}^*$ is the relaxed optimal admission control strategy, then $\{\tilde{p}_s\}$ is the upper bound of the optimal leasing strategy. In order to reduce the gap with the upper bound, we complete the $\{\tilde{a}_k\}^*$ rounding and then substitute it into $\tilde{\mathbf{P}}\mathbf{2}$ for solving again to get $\{p_s\}^*$. Now, we get the first stage of strategy.

C. Resource Allocation

Because the admission control in the first stage uses a robust optimization approach, it leads to a possible shortage of leased resources, which leads to the fact that the QoS of all arriving users cannot all be guaranteed, i.e., constraints (12) and (20) lead to a possible unsolvability of problem $\mathbf{P3}$. To guarantee the QoS of the served users and the solvability of the problem $\mathbf{P3}$, session-level admission control is added in the resource allocation stage, so that constraints (12) and (20) are replaced with constraints (29) and (30), respectively, as follows.

$$\sum_{s\in\mathcal{S}} l_{k,i}^s\beta_{k,i}^s B_s\eta_{k,i}^s \ge l_{k,i}^s r_k, \forall k\in\mathcal{K}_a, i \tag{29}$$

$$\sum_{s\in\mathcal{S}} l_{k,i}^s \le 1, \forall k\in\mathcal{K}_a, i \tag{30}$$

Now, the problem is always solvable, but it is hard to solve the problem directly for the following reasons: 1) The problem is non-convex due to the binary variable $l_{k,i}^s$. 2) The multiplicative coupling of variables $l_{k,i}^s$ and $\beta_{k,i}^s$ in the constraint leads to a non-convex problem. 3) The multiplication of the variable $l_{k,i}^s$ and the concave function about $\beta_{k,i}^s$ in the objective function leads to a non-convex problem.

Obviously, the problem is a MINLP problem, which is usually non-convex and NP-hard, and it is hard to find its global optimal solution, so it must be simplified and transformed into a convex problem for solution. Firstly, the binary constraint $l_{k,i}^s \in \{0,1\}$ is relaxed to $l_{k,i}^s \in [0,1]$ on a continuous interval, and the relaxed $\tilde{l}_{k,i}^s$ can be interpreted as a time-sharing factor, which represents the time ratio of user $u_{k,i}$ associated with satellite s. Then, because the objective function and the variables $l_{k,i}^s$ and $\beta_{k,i}^s$ in (29) are multiply coupled leading to the problem is still non-convex. For this problem, we define auxiliary variables $\varsigma_{k,i}^s = l_{k,i}^s \beta_{k,i}^s$, when user $u_{k,i}$ is associated with satellite s, $l_{k,i}^s = 1$, there is $\varsigma_{k,i}^s = \beta_{k,i}^s$, when user $u_{k,i}$ is not associated with satellite s, $l_{k,i}^s = 0$, to maximize the utility, satellite does not allocate resources to user $u_{k,i}$, so $\beta_{k,i}^s = 0$, there is $\varsigma_{k,i}^s = \beta_{k,i}^s$. We can obtain the problem $\tilde{\mathbf{P}}\mathbf{3}$ as

$$
\begin{aligned}
\tilde{\mathbf{P}}\mathbf{3}: & \max_{\{\tilde{l}_{k,i}^s\},\{\varsigma_{k,i}^s\}} \sum_{s\in\mathcal{S}} \sum_{k\in\mathcal{K}_a} \sum_{u_{k,i}\in\mathcal{U}_k} l_{k,i}^s \ln\left(\frac{\varsigma_{k,i}^s}{\tilde{l}_{k,i}^s} B_s \eta_{k,i}^s\right) \\
\text{s.t. } & \text{C1}: \sum_{s\in\mathcal{S}} \tilde{l}_{k,i}^s \le 1, \forall k, i \\
& \text{C2}: \sum_{k\in\mathcal{K}_a} \sum_{u_{k,i}\in\mathcal{U}_k} \tilde{l}_{k,i}^s \varsigma_{k,i}^s \le p_s, \forall s \\
& \text{C3}: \sum_{s\in\mathcal{S}} \varsigma_{k,i}^s B_s \eta_{k,i}^s \ge \tilde{l}_{k,i}^s r_k, \forall k, i \\
& \text{C4}: \tilde{l}_{k,i}^s \in [0,1], \forall s, k, i
\end{aligned}
\tag{31}
$$

The C2 and C3 in $\tilde{\mathbf{P}}\mathbf{3}$ obtained by variable substitution are linearly constrained. Fortunately, according to the nature of the perspective function, it is known that the objective function of problem $\tilde{\mathbf{P}}\mathbf{3}$ is simultaneously transformed into the perspective function of the concave ln(·) function by variable substitution, and since the perspective operation is convexity-preserving, the objective function of $\tilde{\mathbf{P}}\mathbf{3}$ is a linear summation of a series of concave functions. In summary, the problem obtained by variable substitution is a typical convex problem that can be solved directly using the interior point method to obtain the resource allocation strategy.

IV. Simulation Results and Discussions

Our simulation is based on MATLAB. For simplicity, the proposed admission control method is denoted as Robust Optimization Admission Control (ROAC). In this paper, ROAC is compared with two admission control strategies that do not possess robustness. The first is Worst Case Admission Control (WCAC), which means that the strategy always uses $C_s^{t,l}$ as an estimate of the available capacity. The second is Fixed Admission Control (FAC), which means that the strategy always uses $\Gamma_s^{t,h}$ as the predicted value of the available capacity. The main simulation parameters are shown in Table I.

TABLE I
Main Parameters

Parameters	Value
Orbital Altitude	{600,700,800} km
Number of LEO Satellites	5
Carrier Frequency	16 GHz
Bandwidth of Satellites	10.5 MHz
Maximum Satellite Transmitting Antenna Gain	41.6 dBi
User Receive Antenna Gain	20 dBi
Power Density of Noise	-174 dBm/Hz
Minimum SNR Required for Coverage	-10 dB
Maximum Uncertainty in Capacity Estimates	±10%
User Data Rate	{0.5, 0.6, 0.7, 0.8} Mbps
Leasing Price	1 unit/MHz
Admission Reward	1 unit/SVN
Blocking Penality	2 unit/SVN

Fig. 2 shows the effect of SVN arrival rate on SVN blocking probability. Firstly, it shows that higher SVN arrival rate means more resources are required, which leads to higher SVN blocking probability with limited resources. Among the three strategies, the WCAC has the highest SVN blocking probability, because it considers that the system capacity always has the largest (worst) uncertainty. The FAC has the lowest SVN blocking probability, because it does not consider the uncertainty of the system capacity and allows more SVNs to be embedded in the physical network. Clearly, our proposed ROAC reflects a balance between the WCAC and FAC, as it is based on practical situations that properly take into account the highly dynamic nature of the LEO satellite networks topology leading to system capacity uncertainty, which would result in a balanced admission control strategy.

We define the system stability probability as the ratio of the number of successes associated with reaching all users to the number of user arrivals, i.e., the probability that the problem $\mathbf{P2}$ can be solved. Fig. 3 shows the effect of different strategies on the system stability probability. Among the three strategies, the WCAC obtains the highest probability of leading to system stability, which is about 91%. The FAC leads to the lowest probability of system stability, which is about 50%. Our proposed ROAC obtains the solution leading to system stability with a probability of about 84%, and ROAC can improve the stability of the system by about 34% compared with the FAC.

To demonstrate the benefits of balancing our ROAC, we conducted simulations from the user perspective and the system perspective, respectively. Firstly, we measure the user QoS performance in terms of user satisfaction (the ratio of the total number of users receiving the service to the total number of users arriving among all users embedded in the SVN). As shown in Fig. 4, user satisfaction is highest under WCAC with about 99.5%, which satisfies the user service requests in the SVN well, resulting in almost all users being served. User satisfaction is lowest under FAC, about 91.6%, because more SVNs are running in the network, resulting in more users not being

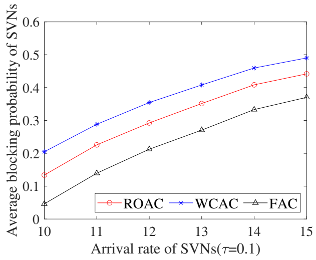

Fig. 2. The effect of SVN arrival rate on blocking probability.

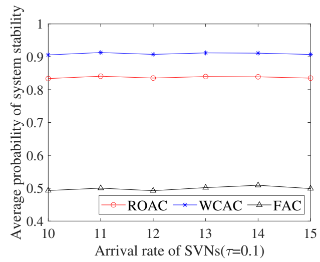

Fig. 3. Probability of system stability under different admission control strategies.

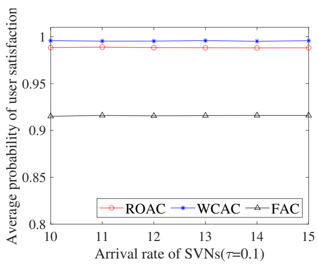

Fig. 4. Probability of user satisfaction under different admission control strategies.

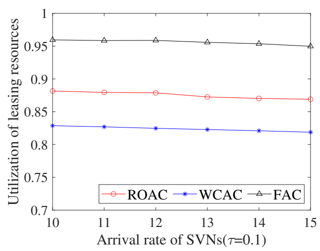

Fig. 5. The utilization of leasing resources under different admission control strategies.

served. Our proposed ROAC takes into account the uncertainty of the appropriate system capacity, and the satisfaction rate is about 98.8%, which is only 0.7% lower than WCAC, but 7.2% higher than FAC. Then, we use the utilization of system leased resources (the ratio of the minimum resources required to reach the user to the leased resources) as a measure of system performance. As shown in Fig. 5, the resource utilization under WCAC, FAC, and ROAC strategies are about 81%, 95% and 85%, respectively. Obviously, the resource utilization of ROAC achieves a good balance between WCAC and FAC.

In summary, our proposed ROAC guarantees user QoS in SVN better than FAC and saves resources better than WCAC. ROAC strikes a balance between user QoS and resource utilization, which is more feasible when solving practical problems. ROAC avoids the low resource rate caused by WCAC and the severe impact on user QoS caused by FAC.

V. Conclusion and Future Work

In this paper, we studied the admission control and resource allocation problems of SVN, in order to solve the problem that the QoS of users in SVN is severely affected by the uncertainty of satellite capacity. Firstly, we decoupled admission control and physical resource leasing from physical resource allocation. Considering the uncertainty of system capacity, the SVN admission control and physical resource leasing problem was then modelled as a parametric uncertainty model with chance constraints, and based on this, robust admission control and resource leasing strategies are proposed. Finally, the resource allocation was modelled as a maximum fair bandwidth allocation problem and is transformed into a convex optimization problem to solve. Simulation results have shown that the proposed ROAC can better improve the resource utilization and guarantee the QoS of users compared with WCAC and FAC. Future work is in progress to consider the impact of more uncertain parameters on the system.

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