Collaborative Spectrum Sharing for Hybrid Satellite-Terrestrial Networks with Large-Scale CSI

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Abstract—Satellites and terrestrial cellular networks can be integrated together for extended broadband coverage in e.g., maritime communication scenarios. The co-channel interference (CCI) is a challenging issue for spectrum sharing between satellites and terrestrial networks. Different from previous studies that adopt full channel state information (CSI) or CSI with Gaussian estimation errors for CCI mitigation, we consider a more practical case with only slowly-varying large-scale CSI to facilitate overhead reduction. A joint power and channel allocation scheme is proposed for the terrestrial system, under the constraint of leakage interference to satellite mobile terminals (MTs). The proposed scheme provides near-optimal performance according to both theoretical analysis and simulation results.

Index Terms—Hybrid satellite-terrestrial network, co-channel interference, power allocation, channel allocation, large-scale channel state information.

I. INTRODUCTION

The terrestrial fifth generation (5G) and beyond network is able to provide a high communication rate, but its coverage performance crucially depends on available base station (BS) sites. In rural or maritime areas, without densely deployed BSs, the broadband coverage region of terrestrial networks is usually quite limited [1]. Thereby, satellite communications can be integrated for extended broadband coverage, leading to a hybrid satellite-terrestrial network (HSTN) [2].

In a HSTN, the spectrum may be shared between satellite and terrestrial systems, to alleviate the spectrum scarcity problem. This will inevitably bring harmful co-channel interference (CCI), damaging the satellite-terrestrial coordination gain. In [2], spectral co-existence of Fixed Satellite Service (FSS) with the Fixed-Service (FS) terrestrial links was investigated in Ka band, which has shown that the CCI is a crucial issue for exploiting the potential of satellite-terrestrial spectrum sharing. To mitigate CCI, A. H. Khan et al. proposed a low-complexity semi-adaptive beamformer [3]. In [4], S. Sharma et al. proposed transmit beamforming techniques to maximize the Signal to Interference plus Noise Ratio (SINR) of the terrestrial link, while mitigating the interference towards the satellite terminals. In addition, the hybrid analog-digital beamforming was optimized for a HSTN in [5]. These studies provide useful insights for mitigating CCI. However, all of them have assumed full channel state information (CSI), which is generally feasible for fixed services, but is very difficult to practically implement for mobile services.

In mobile scenarios, the channel generally experiences both slowly-varying large-scale fading and fast-varying small-scale Rayleigh fading [6]. The acquisition of full CSI will occupy tremendous system overhead in practice. Moreover, although the satellite gateway is connected to the terrestrial central processor to facilitate inter-system coordination, as shown in Fig. 1 the two systems are still asynchronous relative to one another, and information exchanging between satellite and terrestrial systems is usually limited. Taking Fig. 1 as an example, if the terrestrial BSs send pilot signals to satellite mobile terminal (MT) #4 or #5, the returned information has to experience a long transmission delay back to the central processor. This delay time may be hundreds times of the terrestrial transmission duration. In a nutshell, it is quite challenging to acquire full CSI in a practical HSTN.

In this paper, we focus on the HSTN with mobile services. Different from previous efforts by considering CSI with Gaussian estimation errors [7], we consider a more practical case that only the slowly-varying large-scale CSI is known, for which the performance gain is still elusive. The large-scale CSI is location dependent, which thus can be acquired in an offline manner [8], [9]. Using only the large-scale channel parameters, we formulate a joint power and channel allocation problem to mitigate CCI. A novel resource allocation scheme is proposed. Simulation results validate the promising feasibility of using only the large-scale CSI in a practical HSTN.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As illustrated in Fig. 1, we consider a HSTN consisting of $N$ terrestrial BSs, $K$ terrestrial MTs equipped with $M$ antenna elements each, and $K$ satellite MTs. For the terrestrial part, all the BSs are connected to the central processor. The satellite gateway is also connected to the terrestrial central processor by optical fibers, to enable the coordination between satellite and terrestrial systems.
Denote the expectation operator, which is introduced to eliminate the influence of unknown small-scale channel parameters, given in channel $j$.\[E\] denotes the expectation operator, which is introduced to eliminate the influence of unknown small-scale channel parameters, given in channel $j$.\[J\] denotes the interference suppression parameter of satellite $j$.\[ \nu_j \sigma_j \] denotes the interference suppression parameter of satellite $j$.\[ P_T^{\text{LIMITED}} \] denotes the transmit power constraint for terrestrial MT $i$, and $h_{ij}$ represents the channel coefficient from terrestrial BSs to the satellite MT in channel $j$.\[ H_{ij} = S_{ij} \begin{bmatrix} l_{ij1}^t & \vdots & l_{ijN}^t \end{bmatrix} \] (2a)\[ h_j = \nu_j s_j \begin{bmatrix} l_{j1}^s & \vdots & l_{jN}^s \end{bmatrix} \] (2b)

where $S_{ij}$ and $s_j$ denote the fast-varying small-scale Rayleigh fading, which is usually difficult to fully obtain in practice, and $l_{ijn}^t$, $n = 1, 2, \ldots, N$, and $l_{ijn}^s$, $n = 1, 2, \ldots, N$, denote the large-scale fading from terrestrial BS $n$ to terrestrial MT $i$, and to the corresponding satellite MT, respectively, in channel $j$. Note that both $l_{ijn}^t$ and $l_{ijn}^s$ vary slowly and can be obtained from historical data or via very small amount of system overhead.

In (2b), $\nu_j$ denotes the interference suppression parameter of the array antenna, which is commonly adopted at the satellite MT.

The problem in (1) has a complicated objective function. Moreover, it includes continuous optimization for power allocation, in addition to the combinatorial optimization for channel allocation. It is a hybrid integer/continuous optimization problem, which is normally hard. One way to obtain the optimal solution is exhaustive search. However, the complexity is $O(K!)$.

III. Optimized Resource Allocation Scheme

In what follows, we will solve the problem in (1) via the divide-and-conquer approach. According to (2b), we first rewrite the problem as

\[
\max_{i=1}^{K} \log_2 \det \left( I_M + \frac{\sum_{j=1}^{K} z_{ij} H_{ij} \mathbf{P}_{ij} H_{ij}^H}{\sum_{j=1}^{K} z_{ij} \mathbf{J}_{ij}^t + \sigma^2} \right) \tag{3a}
\]

s.t.

\[
\sum_{j=1}^{K} z_{ij} \text{tr}(\mathbf{P}_{ij}) \leq P_i, \quad i = 1, 2, \ldots, K \tag{3b}
\]

\[
\mathbb{E} \sum_{i=1}^{K} z_{ij} h_j^t \mathbf{P}_{ij} h_j^H \leq \mathbf{J}_{ij}^t, \quad j = 1, 2, \ldots, K \tag{3c}
\]

\[
\sum_{i=1}^{K} z_{ij} = 1, \sum_{j=1}^{K} z_{ij} = 1, z_{ij} \in \{0, 1\} \tag{3d}
\]

Then, to further decouple the integer and continuous optimization parts, we consider the following power allocation subproblem for terrestrial MT $i$ if it is scheduled in channel $j$:

\[
\max \log_2 \det \left( I_M + \frac{H_{ij} \mathbf{P}_{ij} H_{ij}^H}{\mathbf{J}_{ij}^t + \sigma^2} \right) \tag{4a}
\]

s.t.

\[
\sum_{n=1}^{N} p_{ijn} \leq P_i \tag{4b}
\]

\[
\sum_{n=1}^{N} p_{ijn} (l_{ijn}^s)^2 \leq \mathbf{J}_{ij}^t \tag{4c}
\]
In (3b), the average achievable rate of terrestrial MT $i$ is maximized as described in (3a), subject to the transmit power constraint in (3b) and the leakage interference constraint to satellite MTs in (3c). The key difficulty of solving the problem lies in the expectation operator $E$ in (3b), which actually requires complicated integral operation. In the following, we first simplify the problem and then transform it into a standard max-min problem, which can be efficiently solved.

Based on the random matrix theory (refer to Theorem 2.53 in [10] for the principal theory, and refer to [11] for a more concise expression), we have

$$
E \log_2 \det \left( I_M + \frac{H_{ij}P_{ij}H_{ij}^H}{\sigma_i^2 + \sigma^2} \right)
$$

$$
\approx \sum_{n=1}^{N} \log_2(1 + \frac{p_{ijn}(l_{ijn}^t)^2}{(\sigma_i^2 + \sigma^2)\chi_{ij}})
$$

$$
+ M \log_2(1 + \sum_{n=1}^{N} \frac{p_{ijn}(l_{ijn}^t)^2}{(\sigma_i^2 + \sigma^2)\chi_{ij} + p_{ijn}(l_{ijn}^s)^2})
$$

$$
- M \log_2 e \left[ \sum_{n=1}^{N} \frac{p_{ijn}(l_{ijn}^t)^2}{(\sigma_i^2 + \sigma^2)\chi_{ij} + p_{ijn}(l_{ijn}^s)^2} \right]
$$

$$
\triangleq \Upsilon_{ij}.
$$

(5)

where $\chi_{ij}$ is an introduced parameter and satisfies

$$
\chi_{ij} = 1 + \sum_{n=1}^{N} \frac{p_{ijn}(l_{ijn}^t)^2}{(\sigma_i^2 + \sigma^2)\chi_{ij} + p_{ijn}(l_{ijn}^s)^2}.
$$

(7)

However, $\Upsilon_{ij}$ cannot be directly used as the objective function, as it is a function of $\chi_{ij}$, which follows a hard-to-optimize fixed-point equation as shown in (7). We further set

$$
x_{ij} = \ln(\chi_{ij}).
$$

(8)

$$
y_{ij}(x_{ij}) = \sum_{n=1}^{N} \log_2(1 + \frac{p_{ijn}(l_{ijn}^t)^2}{(\sigma_i^2 + \sigma^2)e^{x_{ij}}})
$$

$$
+ M \log_2 e \left[ x_{ij} + e^{-x_{ij}} \right].
$$

(9)

Then, from (5–7), we can observe that

$$
\Upsilon_{ij} = y_{ij}(\ln(\chi_{ij})) - M \log_2 e.
$$

(10)

The first-order and second-order derivatives of $y_{ij}(x_{ij})$ can be derived respectively as

$$
\frac{dy_{ij}}{dx_{ij}} = M \log_2 e (1 - e^{-x_{ij}})
$$

$$
- M \log_2 e \sum_{n=1}^{N} \frac{p_{ijn}(l_{ijn}^t)^2}{(\sigma_i^2 + \sigma^2)e^{x_{ij}} + p_{ijn}(l_{ijn}^s)^2}
$$

(11)

$$
\frac{dy_{ij}}{dx_{ij}} = M \log_2 e e^{-x_{ij}}
$$

$$
+ M \log_2 e \sum_{n=1}^{N} \frac{p_{ijn}(l_{ijn}^t)^2(\sigma_i^2 + \sigma^2)e^{x_{ij}}}{(\sigma_i^2 + \sigma^2)e^{x_{ij}} + p_{ijn}(l_{ijn}^s)^2}.
$$

(12)

According to (7), it is easy to see that

$$
\frac{dy_{ij}}{dx_{ij}} \bigg|_{x_{ij}=\ln(\chi_{ij})} = 0
$$

(13)

and

$$
\frac{d^2y_{ij}}{dx_{ij}^2} > 0.
$$

(14)

Therefore, $y_{ij}$ is convex with respect to $x_{ij}$. When $x_{ij} = \ln(\chi_{ij})$, $y_{ij}$ achieves its minimum value. Consequently, combining (10) we have

$$
\Upsilon_{ij} = \min_{x_{ij}>0} y_{ij} - M \log_2 e.
$$

(15)

Then, substituting $y_{ij}$ as the objective function, we can simplify the problem as

$$
R_{ij} = \max_{p_{ijn}} \min_{x_{ij}} \ y_{ij}
$$

(16a)

$$
\text{s.t.} \quad \sum_{n=1}^{N} p_{ijn} \leq P_i
$$

(16b)

$$
\sum_{n=1}^{N} p_{ijn}(l_{ijn}^s)^2 \leq \sigma_i^2
$$

(16c)

$$
x_{ij} > 0
$$

(16d)

which is a standard max-min optimization problem [12]. The objective function $y_{ij}$ is concave with respect to $p_{ijn}$ and convex with respect to $x_{ij}$. It can be solved via the existing tools for the max-min optimization problem.

Substituting $R_{ij}$, $i, j = 1, 2, ..., K$, for the continuous optimization part, we can recast the problem in (3) as

$$
\max \sum_{i=1}^{K} \sum_{j=1}^{K} z_{ij}R_{ij}
$$

(17a)

$$\text{s.t.} \quad \sum_{j=1}^{K} z_{ij} = 1, \sum_{i=1}^{K} z_{ij} = 1, z_{ij} \in \{0, 1\}
$$

(17b)

which fortunately becomes a standard maximum weighted-matching problem for a weighted bipartite graph [13]. It can be efficiently solved by the Kuhn-Munkres algorithm with complexity $O(K^3)$ [13].

In a nutshell, we solve the complicated initial problem in (3) hierarchically. The continuous power allocation subproblem in (3) (finally transformed as (16) is first solved by adopting the random matrix theory and the max-min optimization tool. Then, the remaining integer channel allocation problem in (17) is solved by the Kuhn-Munkres algorithm. A detailed description of the algorithm is shown as Algorithm 1.

In the solving process, the only non-equivalent transformation lies in eliminating the expectation operator based on the random matrix theory. According to (11), $\Upsilon_{ij}$ is a quite accurate approximation for the average achievable sum rate. Thus, the proposed scheme may output a near-optimal solution to the problem. In summary, we have to solve $K^2$ max-min subproblems and one maximum weighted-matching problem. The overall complexity is $O(K^3)$ with large $K$.

IV. SIMULATION RESULTS

We consider $N = 4$ terrestrial BSs, $K = 3$ terrestrial MTs (equipped with $M = 4$ antenna elements each), and $K = 3$ satellite MTs, which are randomly deployed with uniform
distributions. Three channels are assumed, in each of which one terrestrial MT and one satellite MT are simultaneously served. For the channel parameters, we assume that the path-loss exponent is 4, the standard deviation of shadowing is 8, and the interference suppression parameter of the array antenna at satellite MTs is -20 dB. The noise power is -107 dBm, and $\gamma_k^c = -117$ dBm, $k = 1, 2, 3$.

Fig. 2 depicts the average achievable rate of terrestrial MT #1 in channel #1. The waterfilling [14] and equal power allocation schemes are taken for comparison, for which the total transmit power will be reduced when the leakage interference exceeds the threshold. We can observe that the proposed power allocation scheme provides a dramatic gain over other schemes, especially when the transmit power constraint becomes larger. We also show the achievable sum rate by different channel allocation schemes in Fig. 3. It can be seen that the proposed channel allocation scheme provides the same performance as that by exhaustive search, which however requires a computational complexity of $O(K!)$. Moreover, the superiority of the proposed scheme over the random one indicates that channel allocation based on large-scale CSI only can still offer a significant gain for HSTNs.

V. CONCLUSIONS

In this paper, we have addressed the problem of collaborative spectrum sharing for HSTNs. In order to reduce the system overhead for CSI acquisition, we have proposed a novel resource allocation scheme, which uses the slowly-varying large-scale CSI only. By leveraging the max-min optimization tool and the Kuhn-Munkres algorithm, the proposed scheme has a complexity of $O(K^3)$. More importantly, it can offer nearly the same achievable sum rate as that by exhaustive search with complexity $O(K!)$.

REFERENCES

[1] O. Onireti, J. Qadir, M. Imran, et al., “Will 5G see its blind side? evolving 5G for universal internet access,” in Proc. ACM Works. Global Access to the Internet for All, Florianopolis, Brazil, Aug. 2016, pp. 1–6.
[2] E. Lagunas, S. Sharma, S. Maleki, et al., “Resource allocation for cognitive satellite communications with incumbent terrestrial networks,” IEEE Trans. Cogn. Commun. Netw., vol. 1, no. 3, pp. 305–317, Sep. 2015.
[3] A. H. Khan, M. A. Imran, and B. G. Evans, “Semi-adaptive beamforming for OFDM based hybrid terrestrial-satellite mobile system,” IEEE Trans. Wireless Commun., vol. 11, no. 10, pp. 3424–3433, Oct. 2012.
[4] S. Sharma, S. Chatzinotas, and B. Ottersten, “Transmit beamforming for spectral coexistence of satellite and terrestrial networks,” in Proc. CROWNCOM, Washington DC, USA, Jul. 2013, pp. 275–281.
[5] M. Vazquez, L. Blanco, X. Artiga, and A. Neira, “Hybrid analog-digital transmit beamforming for spectrum sharing satellite-terrestrial systems,” Proc. IEEE SPAWC, Edinburgh, UK, Jul. 2016, pp. 1–5.
[6] A. M. K., “Channel estimation and detection in hybrid satellite-terrestrial communication systems,” IEEE Trans. Veh. Tech., vol. 65, no. 7, pp. 5764–5771, Jul. 2016.
[7] S. Vassaki, M. Poulakis, A. Panagopoulos, and P. Constantinou, “Power allocation in cognitive satellite terrestrial networks with QoS constraints,” IEEE Commun. Lett., vol. 17, no. 7, pp. 1344–1347, Jul. 2013.
[8] Y. Liu, C.-X. Wang, J. Huang, J. Sun, and W. Zhang, “Novel 3-D nonstationary mmWave massive MIMO channel models for 5G high-speed train wireless communications,” IEEE Trans. Veh. Tech., vol. 68, no. 3, pp. 2077–2086, Mar. 2019.
[9] W. Feng, Y. Chen, N. Ge, and J. Lu, “Optimal energy-efficient power allocation for distributed antenna systems with imperfect CSI,” IEEE Trans. Veh. Tech., vol. 65, no. 9, pp. 7759–7763, Sep. 2016.
[10] A. Tulino and S. Verdù, “Random matrix theory and wireless communications,” Found. Trends Commun. Inf. Theory, vol. 1, no. 1, 2004.
[11] W. Feng, Y. Wang, N. Ge, J. Lu, and J. Zhang, “Virtual MIMO in multi-cell distributed antenna systems: coordinated transmissions with large-scale CSIT,” IEEE J. Sel. Areas Commun., vol. 31, no. 10, pp. 2067–2081, Oct. 2013.
[12] W. Murray and M. L. Overton, “A projected Langrangian algorithm for nonlinear minimax optimization,” SIAM J. Sci. Stat. Comp., vol. 1, no. 3, pp. 345–370, Sep. 1980.
[13] H. Saip and C. Lucchesi, “Matching algorithms for bipartite graph,” Relatorio T ecnico, vol. 700, no. 3, 1993.
[14] H. Zhang, L. Dai, L. Xiao, and Y. Yao, “Spectral efficiency of distributed antenna systems with random antenna layout,” Electron. Lett., vol. 39, no. 6, pp. 495–496, Mar. 2003.

Algorithm 1 Solving (3) in a hierarchical way.

1: for $i = 1$ to $K$ do
2: for $j = 1$ to $K$ do
3: Recast the power allocation subproblem in (4) into a max-min problem in (16). Then solve it by standard tools and derive $R_{ij}$.
4: end for
5: end for
6: Formulate a weighted bipartite graph using $R_{ij}$ as the corresponding weight;
7: Solve the maximum weighted-matching problem in (17) by the Kuhn-Munkres algorithm and derive $z_{ij}$.
8: Output: $z_{ij}$, $i = 1, 2, \ldots, K$, $j = 1, 2, \ldots, K$. 

Fig. 2. Achievable rate of different power allocation schemes.

Fig. 3. Achievable sum rate of different channel allocation schemes.