Low-Complexity Robust Beamforming with Blockage Prediction for Millimeter-Wave Communications

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***Abstract*—We propose a low-complexity robust beamforming algorithm for millimeter-wave (mmWave) Coordinated Multi-Point (CoMP) architectures subject to random path blockages due to moving objects such as human bodies and the low-scattered nature of mmWave channels. In order to tackle this difficulty without dealing with computationally-demanding possible combinations of channel statistics, which are considered to be a bottleneck of the existing state-of-the-art method for this issue, we introduce a weighted-sum formulation of the latter problem as well as the associated effective weight design, which is shown to be efficient from a complexity point-of-view in comparison with the other state-of-the-art alternatives. Aiming to clarify the above, complexity-order analyses in terms of floating-point operations per second (flops) are also provided for both the proposed and state-of-the-art robust beamforming designs for mmWave path blockages. Simulation results illustrate the superior performance of the proposed method to the state-of-the-art in terms of the performance-complexity trade-off, also demonstrate the legitimacy of the complexity analyses derived in this paper.**

I. Introduction

Due to the ever-growing demands for high-volume data rate transmission, massive connectivity, and lower latency, millimeter-wave (mmWave) systems, which aim at higher frequency bands between 24 GHz and 300 GHz, have been considered to be a key enabler for future wireless-based applications such as augmented reality (AR), connected viecles, and Internet of Things (IoT) networks [1]–[3]. In light of the above, mmWave communications have been intensively developed in the last decade while addressing its inherent bottlenecks such as severe signal power attenuation compared to the conventional microwave systems due to not only the over-the-air radio power loss proportional to the carrier frequency but also absorption by atmospheric gases such as oxygen [4]. In order to circumvent this issue, hybrid beamforming mechanisms leveraging benefit of allowing systems to be equipped with a larger number of antenna elements thanks to the shorter carrier wavelengths of mmWave systems have been proposed in the literature [5]–[8]. These literatures demonstrate the fact that such severe path attenuation effects can be compensated with spatial degrees of freedom and antenna gains. The authors in [7] have proposed a hybrid precoder architecture for point-to-point communication scenarios with dynamic switching and quantized phase shifters with the focus on practical implementations and hardware cost reduction, whereas [8] considered a multiuser wideband mmWave system with limited feedback information from users so as to reduce the overhead, both of which illustrate the feasibility of giga bits per second (Gbps) communications even under such severe path attenuation.

Although major challenges to enable mmWave systems seem to have been addressed in the literature, a fundamental bottleneck of mmWave communications is still left to be tackled, namely, susceptibility to random path blockage due to moving obstacles such as human bodies and cars [9]–[12]. A machine learning-based proactive received power prediction method ($i.e.$, blockage prediction) with the aid of spatio-temporal image sensing has been proposed in [13], [14], whereas a stochastic learning driven robust beamforming design to capture crucial blockage patterns has been proposed in [15]. In addition to the aforementioned progress, the authors in [16] have proposed a robust beamforming design based on the well-known worst-case optimization approach for Coordinated Multi-Point (CoMP) architectures, which jointly maximizes the sum of worst cases corresponding to each user's achievable throughput. Although the approach proposed in [16] has shown robustness against unpredictable path blockages, one may notice that a bottleneck of [16] is an exponentially growing complexity burden, which stems from the core idea of the worst-case optimization approach, posing unscalability with the number of users, antennas, and base-stations (BSs) in the system.

In order to tackle this complexity issue, this paper proposes a weighted-sum formulation as a low-complexity alternative to the latter approach, which enables complexity reduction while maintaining similar throughput performance with [16]. To that end, we leverage recently proposed convexification techniques [17]–[19] ($i.e.$, quadratic transform (QT) and Lagrangian

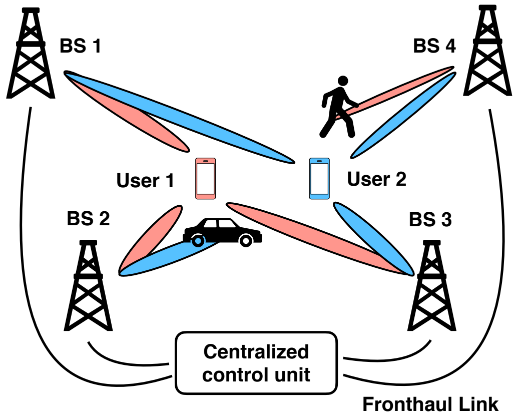

Fig. 1. Illustration of a downlink mmWave communication system subject to random blockages, where B BSs equipped with N_t transmit antennas simultaneously and collaboratively serve K single-antenna downlink users.

dual transform (LDT)), yielding a series of low-complexity quadratic minimization sub-problems, which is derived in this article. Also, analytical expressions for required complexity order to solve the latter formulation have been provided, being compared with that of the state-of-the-art to clarify the low-complexity argument of the proposed method. Finally, an effective weight design for the proposed method is also shown in this article, which together with the proposed formulation illustrates the effectiveness of the proposed art.

Notation: Throughout the article, matrices and vectors are expressed respectively by bold capital and small letters, such as in $\boldsymbol{X}$ and $\boldsymbol{x}$. The transpose and hermitian (transpose conjugate) operators are respectively denoted by $(\cdot)^\mathrm{T}$ and $(\cdot)^\mathrm{H}$, while the l_p-norm operators is respectively denoted by $\|\cdot\|_p$.

II. System Model

Consider the downlink of a narrowband single carrier CoMP system with mmWave spectra, in which multiple synchronized BSs connected through wired fronthaul links with a centralized high-performance server cooperatively serves single-antenna downlink users subjected to random blockages as depicted in Fig.1. For later convenience, let us define two different sets corresponding to BSs and users, *i.e.*, $b \in \mathcal{B} \triangleq \{1, 2, ..., B\}$ and $\mathcal{K} \triangleq \{1, 2, ..., K\}$, assuming BS and user indexes are respectively given by $b \in \mathcal{B}$ and $k \in \mathcal{K}$. Furthermore, it is assumed throughout the article that each BS is equipped with N_t transmit antennas and subject to the maximum transmit power constraint $P_{\max,b}$.

As for the mmWave channel modeling, the number of arriving paths from the b-th BS to the k-th user can be modeled as a Poisson random variable with intensity λ [20], namely,

$$M_{b,k} \sim \max(1, \mathrm{Poisson}(\lambda)), \tag{1}$$

with which channel estimates obtained at the training phase by virtue of reciprocity of standard time division duplex (TDD) mechanisms can be modeled as

$$\hat{\boldsymbol{h}}_{b,k} = \sqrt{\frac{1}{M_{b,k}}} \left\{ g^1_{b,k} \boldsymbol{a}_T(\phi^1_{b,k}) + \sum_{m=2}^{M_{b,k}} g^m_{b,k} \boldsymbol{a}_T(\phi^m_{b,k}) \right\}, \tag{2}$$

where $\phi^m_{b,k}$ is the angle of departure (AoD) of the m-th path from the b-th BS to the k-th user, $\boldsymbol{a}_T(\cdot)$ denotes an array response vector at the transmitter, and the associated path gain $g^m_{b,k}$ can be modeled as

$$g^m_{b,k} \sim \mathcal{CN}(0, 10^{-\mathrm{PL}^m_{b,k}/10}), \tag{3}$$

where $\mathrm{PL}^m_{b,k} = \alpha + 10\beta \log 10(d_{b,k}) + \xi$ [dB] is path loss between b-th BS and k-th user, $d_{b,k}$ expresses the distance (in meter) between b-th BS and k-th user, and α, β, and ξ are determined according to [21].

In presence of random blockage, however, the channel might suffer from inconsistency between the actual instantaneous channel and (2), leading to performance degradation. In order to model random blockage effects, we have adopted the probabilistic blockage model considered in [15], [16], in which a blockage of the line of sight (LoS) path between b-th BS and k-th user is assumed to occur with probability $q^{\mathrm{block}}_{b,k} \in [0, 1]$. Following the state-of-the-art [16], it is worth noting that blockages are assumed to happen only at LoS paths between users and BSs. It is further assumed that such blockage probabilities can be obtained before transmission thanks to blockage prediction methods such as [13], [14]. From the above, the actual channel between the b-th BS and the k-th user can be modeled as

$$\boldsymbol{h}_{b,k} = \sqrt{\frac{1}{M_{b,k}}} \left\{ \omega_{b,k} g^1_{b,k} \boldsymbol{a}_T(\phi^1_{b,k}) + \sum_{m=2}^{M_{b,k}} g^m_{b,k} \boldsymbol{a}_T(\phi^m_{b,k}) \right\}, \tag{4}$$

where $\omega_{b,k} \in \{0, 1\}$ denotes a random variable according to $q^{\mathrm{block}}_{b,k}$ being 1 when the LoS is unblocked and 0 otherwise.

Now, introducing a vector $\boldsymbol{f}_{b,k} \in \mathbb{C}^{N_\mathrm{t} \times 1}$ to denote a transmit beamforming vector at the b-th BS towards the k-th downlink user, the received signal at the k-th user taking into account the inter-user interference can be written as

$$y_k = \sum_{b \in \mathcal{B}_k} \boldsymbol{h}^\mathrm{H}_{b,k} \boldsymbol{f}_{b,k} x_k + \sum_{u \in \mathcal{K} \setminus k} \sum_{b \in \mathcal{B}_u} \boldsymbol{h}^\mathrm{H}_{b,k} \boldsymbol{f}_{b,u} x_u + n_k \tag{5}$$

$$= \boldsymbol{h}^\mathrm{H}_k \boldsymbol{f}_k x_k + \sum_{u \in \mathcal{K} \setminus k} \boldsymbol{h}^\mathrm{H}_k \boldsymbol{f}_u x_u + n_k, \tag{6}$$

where x_k is a normalized data symbol (*i.e.* $\mathbb{E}\{|x_k|^2\} = 1$), $n_k \sim \mathcal{CN}(0, \sigma^2_k)$ is the circularly symmetric complex additive while Gaussian noise (AWGN) at the k-th user, and we implicitly define

$$\boldsymbol{h}_k \triangleq \left[\boldsymbol{h}^\mathrm{T}_{1,k}, ..., \boldsymbol{h}^\mathrm{T}_{B,k} \right]^\mathrm{T} \tag{7}$$

$$\boldsymbol{f}_k \triangleq \left[\boldsymbol{f}^\mathrm{T}_{1,k}, ..., \boldsymbol{f}^\mathrm{T}_{B,k} \right]^\mathrm{T}. \tag{8}$$

In light of the received signal expression given in (5), the associated signal to interference plus noise ratio (SINR) for the k-th user to recover its intended signal can be expressed as

$$\Gamma_k = \frac{|\boldsymbol{h}_k^{\mathrm{H}} \boldsymbol{f}_k|^2}{\sigma_k^2 + \sum_{u\in\mathcal{K}\setminus k} |\boldsymbol{h}_k^{\mathrm{H}} \boldsymbol{f}_u|^2}, \tag{9}$$

where Γ_k is a random variable that varies with channel dynamics due to blockages, indicating that its instantaneous realization is unavailable at the BSs and the resultant performance needs to be compensated by means of beamforming technology.

III. Robust Beamforming Design

In this section, we introduce our proposed low-complexity robust beamforming design for mmWave CoMP systems subject to random blockages, while reviewing the state-of-the-art method [16] to emphasize its complexity bottleneck. Given all the above, let us start with review of [16].

A. Worst-Case Optimization

As briefly described above, the robust beamforming design proposed in [16] relies on the well-known robust optimization mechanism, which aims at ensuring all the utility functions to be greater than or equal to the minimum quantity among them. Introducing the design parameter L, the state-of-the-art methods have resorted to a worst-case optimization in consideration of $C(B,L)$ blockage patterns, where $C(B,L)$ is given by

$$C(B,L) = \sum_{t=0}^{B-L} \binom{B}{t}. \tag{10}$$

From the above design method, the beamforming vector is obtained based on the following optimizatoin problem

$$\begin{aligned} &\underset{\boldsymbol{F},\ \alpha_k}{\text{maximize}} && \sum_{k\in\mathcal{K}} \log\left(1+\alpha_k\right) && \text{(11a)}\\ &\text{subject to} && \Gamma_k^c \geq \alpha_k,\ \forall k,\ \forall c && \text{(11b)}\\ &&& \sum_{k\in\mathcal{K}} \|\boldsymbol{f}_{b,k}\|_2^2 \leq P_{\max,b}\ \forall b, && \text{(11c)}\end{aligned}$$

where, $\boldsymbol{F} = [\boldsymbol{f}_{1,1},\ \boldsymbol{f}_{1,2},...,\boldsymbol{f}_{B,K}] \in \mathbb{C}^{BN_{\mathrm{t}}\times K}$ denotes an optimization variable concatenating all the transmit beamforming vectors, α_k is an slack variable to cap from below the SINRs corresponding to the k-th user, $c \in \{1,2,...,C(B,L)\}$ is the index of the blockage pattern. We define the channel for the k-th user corresponding to each blockage pattern c as $\boldsymbol{h}_k^c$. For example, assuming that $B=3$ and there is a blocker between the second BS and the k-th user, then the corresponding channel is expressed as $\boldsymbol{h}_k^c \triangleq [\boldsymbol{h}_{1,k}^{\mathrm{T}}, \boldsymbol{0}, \boldsymbol{h}_{3,k}^{\mathrm{T}}]^{\mathrm{T}}$. In light of the above expression, Γ_k^c is expressed as

$$\Gamma_k^c = \frac{|\boldsymbol{h}_k^{c\mathrm{H}} \boldsymbol{f}_k|^2}{\sigma_k^2 + \sum_{u\in\mathcal{K}\setminus k} |\boldsymbol{h}_k^{c\mathrm{H}} \boldsymbol{f}_u|^2}. \tag{12}$$

The constraints (11c) represents the maximum transmit power constraint of each BS. Also, constraints (11b) represents the lower bounds of the SINR for each user.

One may notice from the above that as the number of users, BSs, and transmit antennas increases, the complexity required to solve (11) exponentially grows due to the combinatorial nature of the number of additional constraints given in (11b). In other words, $C(B,L)$ clearly shows the combinatorial nature of the state-of-the-art robust beamforming design, indicating its shortcomings in practice.

B. Proposed Method

The total amount of floating-point operations per second (flops) required to solve the optimization problem given in (11) is partially characterized with the number of constraints to be considered, which will be described in detail in Section IV. In a real environment, it is assumed that there are many users in the coverage area formed by multiple BSs, which leads to an increase in the computational complexity. To this end, we hereafter propose a weighted-sum formulation with the focus on the complexity reduction.

We consider an optimization problem of

$$\begin{aligned} &\underset{\boldsymbol{F}}{\text{maximize}} && \sum_{k\in\mathcal{K}} \sum_{c=1}^{C(B,1)} w_k^c \log_2(1+\Gamma_k^c) && \text{(13a)}\\ &\text{subject to} && \sum_{k\in\mathcal{K}} \|\boldsymbol{f}_{b,k}\|_2^2 \leq P_{\max,b}\ \ \forall b, && \text{(13b)}\end{aligned}$$

where w_k^c denotes a weight to determine the priority of each blockage pattern. Due to the non-convexity, (13) is a non-deterministic polynomial (NP)-hard problem, which requires an effective convexification technique to efficiently solve the above weighted-sum problem.

To this end, we introduce two convexification methods, namely LDT and QT, proposed in [17], [18], and the optimization problem (13) can now be reformulated as

$$\begin{aligned} &\underset{\boldsymbol{F}}{\text{maximize}} && \mathcal{F}(\boldsymbol{F}) && \text{(14a)}\\ &\text{subject to} && \sum_{k\in\mathcal{K}} \|\boldsymbol{f}_{b,k}\|_2^2 \leq P_{\max,b}\ \ \forall b, && \text{(14b)}\end{aligned}$$

where

$$\begin{aligned}\mathcal{F}(\boldsymbol{F}) = &\sum_{k\in\mathcal{K}} \sum_{c=1}^{C(B,1)} w_k^c \log_2(1+\beta_k^c) - \sum_{k\in\mathcal{K}} \sum_{c=1}^{C(B,1)} w_k^c \beta_k^c \\ &+ \sum_{k\in\mathcal{K}} \sum_{c=1}^{C(B,1)} 2\mathrm{Re}\left\{ t_k^{c\mathrm{H}} \sqrt{w_k^c(1+t_k^c)} \boldsymbol{h}_k^{c\mathrm{H}} \boldsymbol{f}_k \right\} \\ &- \sum_{k\in\mathcal{K}} \sum_{c=1}^{C(B,1)} |t_k^c|^2 \left(\sigma_k^2 + \sum_{u\in\mathcal{K}} |\boldsymbol{h}_k^{c\mathrm{H}} \boldsymbol{f}_u|^2 \right),\end{aligned} \tag{15}$$

where LDT- and QT-induced variables are given by

$$\beta_k^c = \frac{\left|\boldsymbol{h}_k^{c\mathrm{H}} \boldsymbol{f}_k^{(i)}\right|^2}{\sigma_k^2 + \sum_{u\in\mathcal{K}\setminus k} \left|\boldsymbol{h}_k^{c\mathrm{H}} \boldsymbol{f}_u^{(i)}\right|^2} \tag{16}$$

$$t_k^c = \frac{\sqrt{w_k^c(1+t_k^c)}\boldsymbol{h}_k^{c\mathrm{H}} \boldsymbol{f}_k^{(i)}}{\sigma_k^2 + \sum_{u\in\mathcal{K}} \left|\boldsymbol{h}_k^{c\mathrm{H}} \boldsymbol{f}_u^{(i)}\right|^2}, \tag{17}$$

whose derivation is given by Appendix A.

Algorithm 1 Proposed Robust Beamforming Scheme

Input: Initial estimate : $\boldsymbol{F}^{(0)}$
Output: Optimized beamforming vector : $\boldsymbol{F}$

Set $i = 1$
repeat
  Calculate $w_k^c, \forall k, \forall c$ from(18) with $\boldsymbol{F}^{(i-1)}$.
  Solve (14) with $\boldsymbol{F}^{(i-1)}$ and denote the local optimal values as $\boldsymbol{F}^{(i)}$.
  increment $i = i + 1$.
until convergence

Thanks to the LDT and QT, the weighted-sum formulation can be efficiently solved by convex optimization solvers, $i.e.$, second-order methods such as interior point methods [22]. Therefore, a challenge left to be conquered is a design of weights introduced in (13), which strongly affects the throughput performance.

In this paper, we adopt the following design of w_k^c proportional to $q_{b,k}^{\text{block}}$ to capture critical blockage patterns, namely,

$$w_k^c = \frac{p_k^c(q_{b,k}^{\text{block}})}{1 + \log_{10}\left(1 + \gamma_k^c(q_{b,k}^{\text{block}})\right)}, \tag{18}$$

where $p_k^c(q_{b,k}^{\text{block}})$ denotes a probability corresponding to occurrence of a blockage pattern c, γ_k^c is SINR given the current solution $\boldsymbol{f}_k^{(i)}$.

The proposed low-complexity alternative for the robust beamforming design problem subject to random blockages, which has been formulated as a series of quadratically-constrained quadratic programs while avoiding an increase in the number of additional constraints, is summarized as a pseudo-code in Algorithm 1.

IV. Complexity Analysis

As mentioned above, in this section, we provide analytical expressions of complexity order in terms of flops required to solve the proposed convexified problem given in (14), while comparing the latter with that of the state-of-the-art based on the well-known worst-case optimization technique [16], clarifying the argument that the proposed method is a low-complexity alternative to [16].

According to [23], assuming that a given convex optimization problem is solved via second-order interior point methods, the total number of Newton steps (iterations) N required to converge to an ε-solution can be upper-bounded by

$$N \leq \left\lceil \frac{\log\left(m/\left(t^{(0)}\varepsilon\right)\right)}{\log \mu} \right\rceil \left(\frac{m(\mu - 1 - \log \mu)}{\tau} + c \right), \tag{19}$$

where τ, c are constant, μ is a design parameter related to the convergences speed (rate), m is the number of inequality constraints in the optimization problem.

Suppose that μ and the required duality gap reduction factor are fixed, then, the upper bound on the number of Newton steps grows proportional to $m \log m$, $i.e.$, $\mathcal{O}\left(m \log m\right)$.

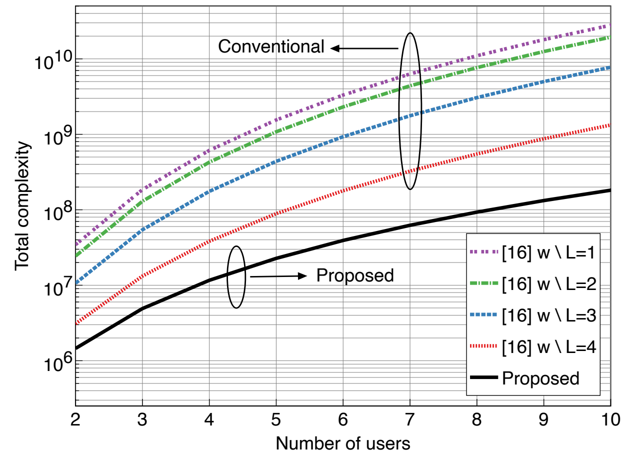

Fig. 2. Total complexity comparisons with the proposed and conventional methods as a function of the number of downlink users to be served for a fixed number of BSs.

Let $m_{\text{conv.}}$ and $m_{\text{prop.}}$ be the number of constraints of the conventional and proposed methods respectively, which can be expressed as

$$m_{\text{conv.}} = \sum_{t=0}^{B-L} \binom{B}{t} K + B \tag{20a}$$

$$m_{\text{prop.}} = B. \tag{20b}$$

As the outer iterations of interior point methods can be determined by the above, let us turn our attention to the complexity required at each inner iteration of interior point methods. To this end, let us define n to be the number of total dimensions of optimization variables. According to [24], the lower bound of the amount of flops required at each inner iteration can be expressed as $\mathcal{O}(n^3)$. Therefore, introducing $n_{\text{conv.}}$ and $n_{\text{prop.}}$, respectively, as the volume of total optimization variable space of the conventional and proposed method, which can be written as

$$n_{\text{conv.}} = BN_{\text{t}}K + K \tag{21a}$$

$$n_{\text{prop.}} = BN_{\text{t}}K. \tag{21b}$$

In light of the above, the total computational complexity required to find ε-solution of the optimization problem is, respectively, proportional to

$$O_{\text{conv.}} = \mathcal{O}\left(n_{\text{conv.}}^3 \times m_{\text{conv.}} \cdot \log(m_{\text{conv.}})\right) \tag{22a}$$

$$O_{\text{prop.}} = \mathcal{O}\left(n_{\text{prop.}}^3 \times m_{\text{prop.}} \cdot \log(m_{\text{prop.}})\right), \tag{22b}$$

where one can notice that the combinatorial nature of the state-of-the-art method severely affects the total required flops.

In order to numerically confirm the above complexity analyses, Fig.2 offers flops comparisons of the proposed method against the state-of-the-art method with different design parameters L as a function of the number of users K, where we assume that each BS is equipped with $N_{\text{t}} = 8$ and the number of BSs is $B = 4$. Fig.2 shows that the proposed

TABLE I
SIMULATION PARAMETERS

Number of users	K	3
Number of BSs	B	4
Number of antennas	N_{t}	8
Noise variance	σ_k^2	-96 [dBm]
Maximum transmit power	$P_{\max,b}$	30 [dBm]
Carrier frequency	f_{c}	28 [GHz]
Bandwidth	W	20 [MHz]
Target throughput	R_{targ}	160 [Mbps]

method is capable of reducing computational complexity by up to $1/100$ to find an optimal solution to the optimization problem in comparison with the state-of-the-art method. More interestingly, one may also notice that the proposed method slowly grows with the increase of the number of users K unlike the state-of-the-art method, which implies robustness and feasibility of the proposed method even when K becomes large.

V. Simulation Results

In this section, we evaluate the effective throughput performance of the proposed method in comparison with the state-of-the-art via software simulation. We assume that $B = 4$ BSs, equipped with $N_{\mathrm{t}} = 8$ transmit antennas and located at each corner of the square with the inter-site spacing of 100 [m], simultaneously serve $K = 3$ single-antenna downlink users subject to the maximum power constraint $P_{\max,b} = 30$ [dBm]. It is assumed that the noise variance at the k-th user σ_k^2 is equal to -96 [dBm] and CoMP transmission is carried out with the carrier frequency of 28 [GHz] and its bandwidth of 20 [MHz]. Introducing a new variable R_{targ} to express the target throughput required by the system, the effective throughput $T_{\mathrm{eff},k}$ can be defined as

$$T_{\mathrm{eff},k} \triangleq \mathbb{E}[a_k R_k], \tag{23}$$

where

$$R_k = W \log_2(1 + \Gamma_k) \tag{24a}$$

$$a_k = \begin{cases} 1 & (R_k \geq R_{\mathrm{targ}}) \\ 0 & (R_k < R_{\mathrm{targ}}), \end{cases} \tag{24b}$$

with W denoting the sub-carrier bandwidth. Summarizing the above, we have listed system parameters considered in this section in Table I for the sake of readability.

Our effective throughput comparisons start with Fig.3, which illustrates the effective throughput performance of the methods for different blockage probability. It is worth noting that we assume all blockage probability are equal to q^{block} ($i.e.$, $q_{b,k}^{\mathrm{block}} = q^{\mathrm{block}}$), for the sake of simplicity. One may observe from the figure that the conventional non-robust sum-rate maximization approach (corresponding to [16] with $L = 4$) significantly degrades as the blockage probability increases, whereas the approaches of [16] with $L \in \{1, 2, 3\}$ are relatively resilient when the blockage probability is in the moderate and severe regions. More interestingly, the proposed method achieves the almost same performance as state-of-the-art method, while significantly reducing the complexity as described in Section IV.

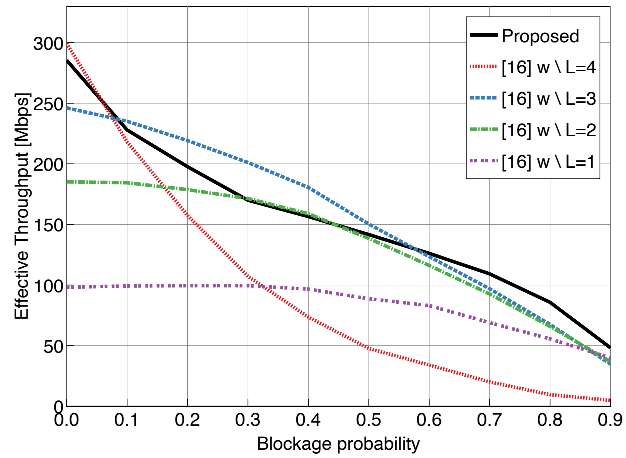

Fig. 3. Comparison of the achievable effective throughput performance of the proposed and conventional methods as a function of blockage probability. Please notice that for the sake of simplicity, we assume $q_{b,k}^{\mathrm{block}} = q^{\mathrm{block}}$ for all b and k.

In Fig.3, the *average* performance of the distinct two methods in terms of the effective throughput was compared, implying that their stochastic behaviors were veiled by the mean operator. In light of the above, we now turn our attention to cumulative distribution function (CDF) comparisons of the achievable throughput performance of the methods. With that in mind, Fig.4 illustrates CDFs of the throughput performance of the proposed and conventional methods for different blockage probabilities ($i.e.$, $q^{\mathrm{block}} = 20\%,\ 40\%,\ 60\%$). As shown in the figure, it is found that the proposed method possesses different CDF curves compared with the state-of-the-art method, unlike Fig.3. In these last comparisons, it can be seen that the proposed method plays a rule between [16] with $L = 4$ and [16] with $L \neq 4$.

VI. Conclusion

We proposed the low-complexity robust beamforming algorithm for mmWave CoMP architectures subject to random path blockages based on a weighted-sum formulation exploiting the side information given by blockage prediction methods. In order to tackle the non-convexity of the sum of log utility functions, we resort to LDT and QT techniques to yield a simple convex quadratically-constrained quadratic formulation, which is shown to be superior to the state-of-the-art in terms of computational complexity. Simulation results illustrated the superior performance of the proposed method against the state-of-the-art in terms of the performance-complexity trade-off while confirming the complexity analyses derived in this paper.

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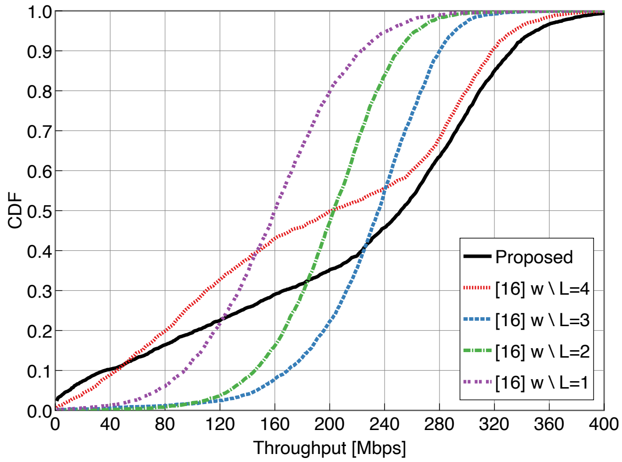
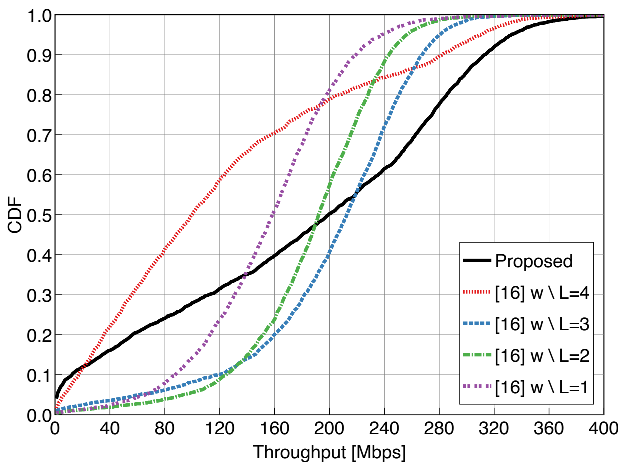
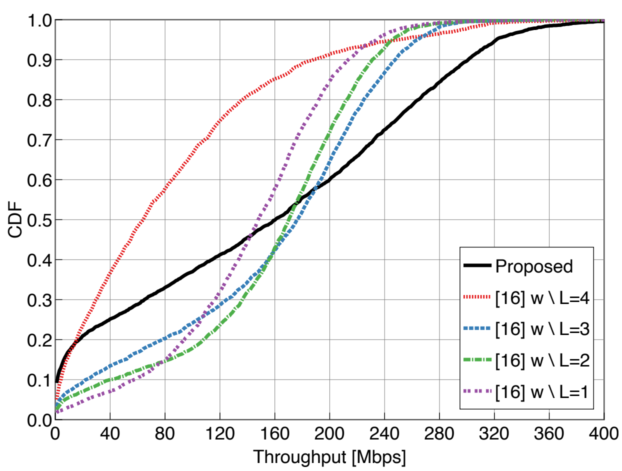


(a) Blockage probability $q^{\text{block}} = 20\%$



(b) Blockage probability $q^{\text{block}} = 40\%$



(c) Blockage probability $q^{\text{block}} = 60\%$

Fig. 4. CDF of the throughput of the proposed and conventional methods.

Appendix A
Proof of Theorem 1

We consider the following non-convex function,

$$\sum_{k\in\mathcal{K}}\sum_{c=1}^{C(B,1)} w_k^c \log_2(1+\Gamma_k^c) \tag{25}$$

$$= \sum_{k\in\mathcal{K}}\sum_{c=1}^{C(B,1)} w_k^c \log_2\left(1+\frac{|\boldsymbol{h}_k^{\mathrm{H}}\boldsymbol{f}_k|^2}{\sigma_k^2+\sum_{u\in\mathcal{K}\backslash k}|\boldsymbol{h}_k^{\mathrm{H}}\boldsymbol{f}_u|^2}\right). \tag{26}$$

Applying LDT, we can approximate the non-convex function (26) as a function of

$$\sum_{k\in\mathcal{K}}\sum_{c=1}^{C(B,1)} w_k^c \log_2(1+\beta_k^c) + \sum_{k\in\mathcal{K}}\sum_{c=1}^{C(B,1)} w_k^c\beta_k^c + \sum_{k\in\mathcal{K}}\sum_{c=1}^{C(B,1)} \frac{w_k^c(1+\beta_k^c)|\boldsymbol{h}_k^{\mathrm{H}}\boldsymbol{f}_k|^2}{\sigma_k^2+\sum_{u\in\mathcal{K}}|\boldsymbol{h}_k^{\mathrm{H}}\boldsymbol{f}_u|^2}, \tag{27}$$

where,

$$\beta_k^c = \frac{|\boldsymbol{h}_k^{c\mathrm{H}}\boldsymbol{f}_k^{(i)}|^2}{\sigma_k^2+\sum_{u\in\mathcal{K}\backslash k}|\boldsymbol{h}_k^{c\mathrm{H}}\boldsymbol{f}_u^{(i)}|^2}. \tag{28}$$

However, since the third term is a non-convex function, it is necessary to approximate the convex function from the viewpoint of computational efficiency. Therefore, applying QT to third term, we obtain the convex function of

$$\sum_{k\in\mathcal{K}}\sum_{c=1}^{C(B,1)} w_k^c \log_2(1+\beta_k^c) + \sum_{k\in\mathcal{K}}\sum_{c=1}^{C(B,1)} w_k^c\beta_k^c + \sum_{k\in\mathcal{K}}\sum_{c=1}^{C(B,1)} 2\mathrm{Re}\left\{t_k^{c\mathrm{H}}\sqrt{w_k^c(1+\beta_k^c)}\boldsymbol{h}_k^{\mathrm{H}}\boldsymbol{f}_k\right\} + \sum_{k\in\mathcal{K}}\sum_{c=1}^{C(B,1)} |t_k^c|^2(\sigma_k^2+\sum_{u\in\mathcal{K}}|\boldsymbol{h}_k^{\mathrm{H}}\boldsymbol{f}_u|^2), \tag{29}$$

where,

$$t_k^c = \frac{\sqrt{w_k^c(1+t_k^c)}\boldsymbol{h}_k^{c\mathrm{H}}\boldsymbol{f}_k^{(i)}}{\sigma_k^2+\sum_{u\in\mathcal{K}}|\boldsymbol{h}_k^{c\mathrm{H}}\boldsymbol{f}_u^{(i)}|^2}. \tag{30}$$

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