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<http://dx.doi.org/10.1109/LWC.2015.2402126>

PUBLISHER

© IEEE

VERSION

AM (Accepted Manuscript)

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Jumba, Vikas, Saeedeh Parsaeefard, Mahsa Derakhshani, and Tho Le-Ngoc. 2019. "Resource Provisioning in Wireless Virtualized Networks via Massive-mimo". figshare. <https://hdl.handle.net/2134/21229>.

Resource Provisioning in Wireless Virtualized Networks via Massive-MIMO

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Abstract—This letter proposes a dynamic resource provisioning scheme for an OFDMA wireless virtualized network (WVN), where one base-station equipped with a large number of antennas serves users belonging to a number of service providers via different slices. In particular, joint power, sub-carrier, and antenna allocation problems are presented for both perfect and imperfect channel knowledge cases, aiming to maximize a sum-utility while maintaining a minimum rate per slice. Subsequently, relaxation and variable transformation are applied to develop the efficient algorithm to solve the formulated non-convex, combinational optimization problem. Simulation results reveal the benefits of applying a large number of antennas in this setup and evaluate the network performance for different system conditions.

Index Terms—Large number of antennas, resource provisioning, wireless network virtualization.

I. INTRODUCTION

Wireless network virtualization is a promising approach to provide service customization for next-generation wireless networks. In wireless virtualized networks (WVNs), limited wireless resources (i.e., power and spectrum) are shared among different groups of users referred to as slices. Each slice may have a different set of quality-of-service (QoS) requirements, which calls for effective resource provisioning algorithms in WVNs to maximize the sum utility of all slices, while holding the minimum required rate of each slice [1].

However, due to the random nature of wireless channels and, power and spectrum limitations, there is always a non-zero probability that the minimum required rate cannot be satisfied. Thus, this will cause infeasibility problem for resource provisioning and lead to a poor network performance. In this paper, to expand the feasibility region, we take advantage of the large spatial degree of freedom introduced by massive multi-input-multi-output (MIMO) technology. In massive MIMO, each base station (BS) is equipped with a large number of antennas serving single-antenna multiple users.

Developing the massive-MIMO scales up the MIMO multiplexing gain provided that the exact channel state information (CSI) of all users are available at BS [2]. However, extracting the precise values of CSI requires ideal orthogonal pilot signals between different BSs which is practically infeasible [2]. In this paper, taking this issue into account, we consider two cases: 1) perfect CSI where it is ideally assumed to have all the precise values of CSI; 2) imperfect CSI where the effect of non-orthogonal pilots is considered in the achievable rate.

Subsequently, we formulate a resource provisioning problem for the up-link transmission in a WVN. The objective is

to maximize the sum utility of slices subject to the minimum required rate of each slice and transmit power of each user within each slice. We introduce a new utility function representing the difference between the total achieved user rate and its corresponding costs for allocated power and antennas. Considering two different pricing mechanisms for the allocated power and antennas enables effective control of inter-slice interference and available antennas in WVN. To the best of our knowledge, there exists no related work in the context of WVN with massive MIMO.

As the formulated problem is both non-convex and combinatorial, it suffers from high computational complexity. To develop an efficient algorithm, we apply variable transformations and constraint relaxations. Simulation results reveal that the values of power and antenna pricing variables have a significant impact on the total achieved user throughput.

The rest of this paper is organized as follows. Section II introduces the system model and problem formulations. Section III provides a solution for the formulated resource provisioning problem followed by Section V where the simulation results are presented. Section VI provides concluding remarks.

II. NETWORK MODEL AND PROBLEM FORMULATION

We consider the up-link transmission in an orthogonal frequency division multiple access (OFDMA) WVN where a BS with M antennas serves a set of slices $\mathcal{G} = \{1, \dots, G\}$. Each slice $g \in \mathcal{G}$ has a set of single-antenna users denoted by $\mathcal{N}_g = \{1, \dots, N_g\}$ and requires a minimum rate R_g^{rsv} . It should be noted that $N = \sum_{g \in \mathcal{G}} N_g$ and $N \ll M$. Consider $\mathbf{M} = [\mathbf{M}_1, \dots, \mathbf{M}_G]$ as the allocated antenna vector for all slices where $\mathbf{M}_g = [\mathbf{M}_{n_g}]_{n_g=1}^{N_g}$, $\mathbf{M}_{n_g} = [M_{n_g,1}, \dots, M_{n_g,K}]$, and $M_{n_g,k}$ is the number of antennas allocated to user n_g on sub-carrier k . Let $\mathbf{w} = [\mathbf{w}_1, \dots, \mathbf{w}_G]$ be the sub-carrier assignment vector for all slices where $\mathbf{w}_g = [\mathbf{w}_{n_g}]_{n_g=1}^{N_g}$, $\mathbf{w}_{n_g} = [w_{n_g,1}, \dots, w_{n_g,K}]$, and $w_{n_g,k} = 1$ indicates that sub-carrier k is allocated to user n_g and otherwise $w_{n_g,k} = 0$.

In this setup, let $\mathbf{h}_{n_g,k} \in \mathbb{C}^{1 \times M_{n_g,k}}$ be the channel vector of user n_g on sub-carrier k , where $h_{n_g,k,m_{n_g,k}}$ is the channel coefficient of user n_g on sub-carrier k and antenna $m_{n_g,k}$. More specifically, $h_{n_g,k,m_{n_g,k}} = g_{n_g,k,m_{n_g,k}} \sqrt{d_{n_g}}$ where $g_{n_g,k,m_{n_g,k}}$ represents the small-scale fading coefficient with variance of 1, and d_{n_g} denotes the large-scale fading coefficient of user n_g on sub-carrier k . Note that d_{n_g} includes both path loss and shadowing [2]. Practically, the channel

coefficients are estimated by the BS based on the uplink pilots with duration τ at the specific part of the coherence interval of T [3]. In the perfect CSI case, the up-link received sample at BS after using the linear detector from user $n_g \in \mathcal{N}_g$ on sub-carrier k is [3]

$$y_{n_g,k}^{\text{Perf}} = \sqrt{P_{n_g,k}} \mathbf{h}_{n_g,k} \mathbf{f}_{n_g,k}^{\text{Perf}} x_{n_g,k} + I_{n_g,k} + \mathbf{z}_{n_g,k} \mathbf{f}_{n_g,k}^{\text{Perf}}, \quad (1)$$

where $x_{n_g,k}$ and $\mathbf{f}_{n_g,k}^{\text{Perf}} \in \mathbb{C}^{M_{n_g,k} \times 1}$ represent the transmit symbol and the precoding vector of user n_g on sub-carrier k , respectively. Moreover, $P_{n_g,k}$ is the transmit power of user n_g on sub-carrier k and $\mathbf{z}_{n_g,k}$ is a vector of additive white Gaussian noise (AWGN) at the BS with zero mean and power spectral density σ , which is assumed to be independent and identically distributed (i.i.d.) for all users over all sub-carriers. For notational simplicity, we normalize σ to 1 and thus $P_{n_g,k}$ is the transmit SNR and dimensionless. $I_{n_g,k} = \sum_{g \in \mathcal{G}} \sum_{n' \neq n_g} \sqrt{P_{n',k}} \mathbf{h}_{n',k} \mathbf{f}_{n',k}^{\text{Perf}} x_{n',k}$ is the interference from other users to user n_g . In the imperfect CSI case, due to pilot contamination error in the channel estimation and the linear detector, the received signal from user n_g on sub-carrier k is [3]

$$y_{n_g,k}^{\text{Imperf}} = \sqrt{P_{n_g,k}} \tilde{\mathbf{h}}_{n_g,k} \mathbf{f}_{n_g,k}^{\text{Imperf}} x_{n_g,k} + \delta_{n_g,k}(\mathbf{P}) \quad (2)$$

where $\tilde{\mathbf{h}}_{n_g,k}$ is the estimated channel vector including the contamination error, $\mathbf{P} = [\mathbf{P}_1, \dots, \mathbf{P}_G]$ is the allocated power vector of all slices in which $\mathbf{P}_g = [\mathbf{P}_{n_g}]_{n_g=1}^{N_g}$ and $\mathbf{P}_{n_g} = [P_{n_g,1}, \dots, P_{n_g,K}]$, $\mathbf{f}_{n_g,k}^{\text{Imperf}} \in \mathbb{C}^{M_{n_g,k} \times 1}$ is the precoding vector in the imperfect CSI case, and $\delta_{n_g,k}(\mathbf{P})$ is the function of contamination error, interference and noise (See Appendix). Using maximum ratio combining (MRC) detector with $M \rightarrow \infty$, the rate of user n_g on sub-carrier k is derived in Appendix as

$$R_{n_g,k} = \begin{cases} \log_2(1 + P_{n_g,k} d_{n_g,k} M_{n_g,k}), & \text{for perfect CSI,} \\ \frac{T-\tau}{T} \log_2(1 + \tau P_{n_g,k}^2 d_{n_g,k}^2 M_{n_g,k}), & \text{for imperfect CSI,} \end{cases} \quad (3)$$

and the total achieved rate of user n_g is $R_{n_g}(\mathbf{P}, \mathbf{w}, \mathbf{M}) = \sum_{k \in \mathcal{K}} w_{n_g,k} R_{n_g,k}$. Now, we define utility function of slice g as

$$U_g(\mathbf{P}, \mathbf{w}, \mathbf{M}) = \sum_{n_g \in \mathcal{N}_g} R_{n_g}(\mathbf{P}, \mathbf{w}, \mathbf{M}) - c_g^M \sum_{n_g \in \mathcal{N}_g} \sum_{k \in \mathcal{K}} w_{n_g,k} M_{n_g,k} - c_g^P \sum_{n_g \in \mathcal{N}_g} \sum_{k \in \mathcal{K}} w_{n_g,k} P_{n_g,k}, \quad (4)$$

where c_g^M and c_g^P are pricing factors for the number of allocated antennas and the transmit power of slice g , respectively. Hence, the resource provisioning problem can be written as

$$\max_{\mathbf{P}, \mathbf{w}, \mathbf{M}} \sum_{g \in \mathcal{G}} U_g(\mathbf{P}, \mathbf{w}, \mathbf{M}), \quad (5)$$

subject to the following constraints C1 – C4.

C1: Exclusive sub-carrier allocation in OFDMA implies:

$$w_{n_g,k} \in \{0, 1\} \text{ and } \sum_{g \in \mathcal{G}} \sum_{n_g \in \mathcal{N}_g} w_{n_g,k} \leq 1, \quad \forall k \in \mathcal{K}.$$

C2: Transmit power limitation for each user n_g implies:

$$\sum_{k \in \mathcal{K}} w_{n_g,k} P_{n_g,k} \leq P_{n_g}^{\max}, \quad \forall n_g \in \mathcal{N}_g, \quad \forall g \in \mathcal{G},$$

where $P_{n_g}^{\max}$ is the maximum transmit power of user n_g .

C3: Minimum required rate, R_g^{rsv} , of slice $g \in \mathcal{G}$ implies:

$$\sum_{n_g \in \mathcal{N}_g} R_{n_g} \geq R_g^{\text{rsv}}, \quad \forall g \in \mathcal{G}.$$

C4: Control on the number of antennas allocated to each slice to preserve the fairness between slices and to improve the energy efficiency for the WVN can be expressed as [2],

$$\sum_{n_g \in \mathcal{N}_g} \sum_{k \in \mathcal{K}} w_{n_g,k} M_{n_g,k} \in \{M_g^{\min}, M_g^{\min+1}, \dots, M_g^{\max}\},$$

for each slice $g \in \mathcal{G}$ where $M_g^{\min}$ and $M_g^{\max}$ are the minimum number of reserved antennas and the maximum allowable number of allocated antennas for slice g , respectively.

Since (5) has combinatorial properties, it involves high computational complexity. Next, we propose an efficient algorithm to solve this problem by applying variable transformations and constraint relaxation.

III. PROPOSED ALGORITHM

To obtain a low-complexity solution to (5), we relax the conditions C1, C3, and C4, by considering $w_{n_g,k}$ as a continuous variable in the interval $[0, 1]$ and the numbers of allocated antennas to be non-negative real-valued. In the new definition, $w_{n_g,k}$ indicates the fraction of time that sub-carrier k is assigned to user n_g for a specific transmission frame. Furthermore, we define two new variables: $x_{n_g,k} = w_{n_g,k} P_{n_g,k}$ and $y_{n_g,k} = w_{n_g,k} M_{n_g,k}$. For $M_{n_g,k} \gg 1$, R_{n_g} can be approximated and represented as $\tilde{R}_{n_g} \approx \sum_{k \in \mathcal{K}} w_{n_g,k} \log_2(\frac{x_{n_g,k} y_{n_g,k} d_{n_g,k}}{w_{n_g,k}^2})$ for perfect CSI case or $\frac{T-\tau}{T} \sum_{k \in \mathcal{K}} w_{n_g,k} \log_2(\frac{\tau x_{n_g,k}^2 y_{n_g,k} d_{n_g,k}^2}{w_{n_g,k}^3})$ for imperfect CSI case, which are convex functions with respect to $x_{n_g,k}$, $y_{n_g,k}$, and $w_{n_g,k}$ [4], [5]. Consequently, conditions C1-C4 are changed to the following $\tilde{\text{C1}} - \tilde{\text{C4}}$, respectively,

$$\tilde{\text{C1}} : w_{n_g,k} \in [0, 1] \text{ and } \sum_{g \in \mathcal{G}} \sum_{n_g \in \mathcal{N}_g} w_{n_g,k} \leq 1, \quad \forall k \in \mathcal{K},$$

$$\tilde{\text{C2}} : \sum_{k \in \mathcal{K}} x_{n_g,k} \leq P_{n_g}^{\max}, \quad \forall n_g \in \mathcal{N}_g, \quad \forall g \in \mathcal{G},$$

$$\tilde{\text{C3}} : \sum_{n_g \in \mathcal{N}_g} \tilde{R}_{n_g} \geq R_g^{\text{rsv}}, \quad \forall g \in \mathcal{G},$$

$$\tilde{\text{C4}} : M_g^{\min} \leq \sum_{n_g \in \mathcal{N}_g} \sum_{k \in \mathcal{K}} y_{n_g,k} \leq M_g^{\max}, \quad \forall g \in \mathcal{G},$$

and (5) is transformed to

$$\max_{\mathbf{x}, \mathbf{w}, \mathbf{y}} \sum_{g \in \mathcal{G}} \tilde{U}_g(\mathbf{x}, \mathbf{w}, \mathbf{y}), \quad (6)$$

subject to : $\tilde{\text{C1}} - \tilde{\text{C4}}$,

where $\mathbf{x}$ and $\mathbf{y}$ are vectors of all $x_{n_g,k}$ and $y_{n_g,k}$, and

$$\tilde{U}_g(\mathbf{x}, \mathbf{w}, \mathbf{y}) = \sum_{n_g \in \mathcal{N}_g} \tilde{R}_{n_g}(\mathbf{x}, \mathbf{w}, \mathbf{y}) - c_g^M \sum_{n_g \in \mathcal{N}_g} \sum_{k \in \mathcal{K}} y_{n_g,k} - c_g^P \sum_{n_g \in \mathcal{N}_g} \sum_{k \in \mathcal{K}} x_{n_g,k}.$$

Since (6) involves continuous variables and convex functions, we can solve it with the following Lagrange function.

$$\begin{aligned} \mathcal{L}(\mathbf{x}, \mathbf{w}, \mathbf{y}, \lambda_{n_g}, \phi_g, \theta_g, \psi_g) = & \\ & - \sum_{g \in \mathcal{G}} \tilde{U}_g + \sum_{n_g \in \mathcal{N}_g} \lambda_{n_g} \left(\sum_{k \in \mathcal{K}} x_{n_g, k} - P_{\max} \right) \\ & + \sum_{g \in \mathcal{G}} \phi_g (R_g^{\text{rsv}} - \sum_{n_g \in \mathcal{N}_g} \tilde{R}_{n_g}) \\ & + \sum_{g \in \mathcal{G}} \theta_g (M_g^{\min} - \sum_{n_g \in \mathcal{N}_g} \sum_{k \in \mathcal{K}} y_{n_g, k}) \\ & + \sum_{g \in \mathcal{G}} \psi_g \left(\sum_{n_g \in \mathcal{N}_g} \sum_{k \in \mathcal{K}} y_{n_g, k} - M_g^{\max} \right), \end{aligned} \quad (7)$$

where $\lambda_{n_g}, \phi_g, \theta_g$ and ψ_g are the Lagrange multipliers for $\widetilde{\text{C2}}, \widetilde{\text{C3}}$ and $\widetilde{\text{C4}}$. Now, we propose an iterative approach to solve the dual problem of (7), in the following algorithm.

Algorithm:

Initialization:

Set $\mathbf{w}^*(l=0) = 1$, $\mathbf{P}_{n_g}^*(l=0) = P_{n_g}^{\max}/K$, and $\mathbf{M}^*(l=0) = M_g^{\max}$ for all $n_g \in \mathcal{N}_g$ and $g \in \mathcal{G}$. Initialize $l_{\max} \gg 1$, $0 < \varepsilon \ll 1$, $\lambda(l=0)$, $\psi(l=0)$ and $\theta(l=0)$.

Repeat:

- Update dual variables, $\lambda_{n_g}, \phi_g, \theta_g$ and ψ_g , by gradient descent method for all $g \in \mathcal{G}$ where $[x]^+ = \max\{x, 0\}$:

$$\lambda_{n_g}(l+1) = \left[\lambda_{n_g}(l) + \delta_{\lambda_{n_g}} \frac{\partial \mathcal{L}}{\partial \lambda_{n_g}} \right]^+, \forall n_g \in \mathcal{N}_g,$$

$$\phi_g(l+1) = \left[\phi_g(l) + \delta_{\phi_g} \frac{\partial \mathcal{L}}{\partial \phi_g} \right]^+, \forall g \in \mathcal{G},$$

$$\theta_g(l+1) = \left[\theta_g(l) + \delta_{\theta_g} \frac{\partial \mathcal{L}}{\partial \theta_g} \right]^+, \forall g \in \mathcal{G},$$

$$\psi_g(l+1) = \left[\psi_g(l) + \delta_{\psi_g} \frac{\partial \mathcal{L}}{\partial \psi_g} \right]^+, \forall g \in \mathcal{G}.$$
- Using the above updated parameters for $(l+1)$, compute $P_{n_g, k}^*(l+1)$ and $M_{n_g, k}^*(l+1)$ for all $n_g \in \mathcal{N}_g$, and $k \in \mathcal{K}$.

For $l+1$	Perfect CSI case	Imperfect CSI case
$P_{n_g, k}^*$	$\left[\frac{1+\phi_g}{\ln(2)(\lambda_{n_g} + c_g^P)} \right]_0^{P_{n_g}^{\max}}$	$\frac{(T-\tau)}{T} \left[\frac{2(1+\phi_g)}{\ln(2)(\lambda_{n_g} + c_g^P)} \right]_0^{P_{n_g}^{\max}}$
$M_{n_g, k}^*$	$\left[\frac{1+\phi_g}{\ln(2)(\psi_g - \theta_g + c_g^M)} \right]_0^{M_g^{\max}}$	$\frac{(T-\tau)}{T} \left[\frac{1+\phi_g}{\ln(2)(\psi_g - \theta_g + c_g^M)} \right]_0^{M_g^{\max}}$

where $[x]_a^b = \min\{b, \max\{x, a\}\}$.

- Perform sub-carrier allocation for all $n_g \in \mathcal{N}_g$ and for all $k \in \mathcal{K}$, where by applying KKT conditions [6], [7],

$$\frac{\partial \mathcal{L}}{\partial w_{n_g, k}} = (1 + \phi_g) \times \quad (8)$$

$$\begin{cases} \log_2(P_{n_g, k} d_{n_g} M_{n_g, k}) - \frac{2}{\ln(2)}, & \text{perfect CSI} \\ \frac{(T-\tau)}{T} \left(\log_2(\tau P_{n_g, k}^2 d_{n_g}^2 M_{n_g, k}) - \frac{3}{\ln(2)} \right), & \text{imperfect CSI,} \end{cases}$$

and consequently, the optimal sub-carrier allocation $w_{n_g, k}^*(l+1)$ can be derived as in [4], i.e., $w_{n_g, k}^*(l+1) = 1$, if $\frac{\partial \mathcal{L}}{\partial w_{n_g, k}} > 0$, $w_{n_g, k}^*(l+1) = 0$, otherwise.

- Set $l = l + 1$

Until $\|\mathbf{P}(l+1) - \mathbf{P}(l)\| \leq \varepsilon$ or $l \geq l_{\max}$.

Finally, the optimum integer $M_{n_g, k}^*$ is selected as $\lfloor M_{n_g, k}(l) \rfloor$ where $\lfloor x \rfloor$ denotes the largest integer less than or equal to the value of x .

IV. SIMULATION RESULTS

To evaluate the performance of WVN with the proposed algorithm, we consider one BS serving two slices (i.e., $G = 2$) with $N_1 = N_2 = 4$. Furthermore, we assume $K = 64$ and $P_{n_g}^{\max} = 0$ dB. After precoding, channel is modelled as $\|h_{n_g, k, m_{n_g, k}}\|^2 = d_{n_g} = D_{n_g}^{-\beta}$ where $\beta = 3$ is the path loss exponent and $D_{n_g} \in [0.2, 0.6]$ is the distance of user n_g to BS. Furthermore, we set $\varepsilon = 10^{-4}$ for Algorithm 1 and $R_1^{\text{rsv}} = R_2^{\text{rsv}} = 2$ bps/Hz unless otherwise stated. T is selected based on the parameters in [3] and simulations are based on the ratio of τ/T . All the results are presented in terms of average rate over 100 channel realizations based on random locations of the users. When R_g^{rsv} does not hold for a channel realization, the total rate is set to zero. Also, to demonstrate the effect of c_g^M and c_g^P , we consider three sets with different values of c_g^M and c_g^P . For Set 1, we have $c_g^M = c_g^P = 0$ which means that the utility of each user is equal to its rate. For Set 2, we have $c_g^M = 0.07$ and $c_g^P = 1$. Set 3 imposes higher restrictions to use antennas and power by employing $c_g^M = 0.09$ and $c_g^P = 2$.

Fig. 1 shows that the total rate is a non-decreasing function of $M_g^{\max}$ in both perfect and imperfect CSI cases where $\frac{\tau}{T} = 0.3$. This can be explained by the fact that the feasibility regions are expanded as $M_g^{\max}$ increases. However the utility function is formulated as a decreasing function of c_g^P and c_g^M , so that by increasing the costs from Set 1 to Set 3, the total rate of WVN is decreased. As a result, the increase in the achieved rate is reduced for large values of $M_g^{\max}$, especially for high c_g^P and/or c_g^M , e.g., for $M_g^{\max} > 75$, the total rate for Sets 2 and 3 is almost unchanged. Furthermore, due to the channel estimation errors, the performance with imperfect CSI is worse than that with perfect CSI for all sets, as expected.

To demonstrate the effects of R_g^{rsv} , Fig. 2 plots the total rate versus R_g^{rsv} for Set 1, where $\frac{\tau}{T} = 0.3$, $M_1^{\max} = M_2^{\max} = 100$, and $R_1^{\text{rsv}} = R_2^{\text{rsv}} = R_g^{\text{rsv}}$. It can be observed that in both perfect and imperfect CSI cases, the total rate decreases with increasing R_g^{rsv} . This is because increasing R_g^{rsv} shrinks the feasibility region for convex optimization problem (5) and thus reduces the optimal value of objective function [5].

To study further the effect of τ on the performance of WVN, we focus on Set 1 with $M_g^{\max} = \{200, 150\}$ and plot the rate versus $\frac{\tau}{T}$ in Fig. 3. Obviously, when $0.1 \leq \frac{\tau}{T} \leq 0.3$, the rate increases with increasing $\frac{\tau}{T}$ benefiting from the more accurate CSI estimation. However, for $0.3 \leq \frac{\tau}{T} \leq 0.9$, the spectral efficiency of WVN is decreased with increasing $\frac{\tau}{T}$ due to the fact that most of the transmission time wastes for pilot signals. Therefore, considering the optimum values of $\frac{\tau}{T}$ to reach the best performance of WVN is essential. Fig. 3 also highlights that increasing $M_g^{\max}$ can increase the total rate for any τ due to the feasibility region expansion.

To further study the effects of pricing on the total rate of WVN, in Fig. 4, the total rate is plotted versus c_g^M and c_g^P . Obviously, the total rate is decreased with increasing c_g^M

Fig. 1: Total rate vs. $M_g^{\max}$

Fig. 2: Total rate vs. R_g^{rsv}

Fig. 3: Total rate vs. τ/T

Fig. 4: Total Rate vs. c_g^P and c_g^M

and c_g^P . However, the effect of increasing c_g^M is much more profound compared to that of c_g^P . This is because in massive MIMO, we have $M_g^{\max} \gg P_{n_g}^{\max}$, e.g., compare $M_g^{\max} > 100$ and $P_{n_g}^{\max} = 0$ dB. Figures 3 and 4 highlight that allocating dynamic and optimal pricing values for WVN and optimum value of τ/T are essential to reach the best performance which are left for the future work.

V. CONCLUSION

Utility-based resource provisioning for massive-MIMO-based WVN was investigated in this letter for perfect and imperfect CSI scenarios. We propose an efficient iterative algorithm to solve the developed resource allocation problems. Via simulation results, the effects of power and antenna pricing mechanisms on the performance of WVN were investigated.

VI. APPENDIX: DERIVATION OF USER RATE $R_{n_g,k}$ IN (3)

For mutually independent $1 \times n$ vectors $\mathbf{p} = [p_1, \dots, p_n]$ and $\mathbf{q} = [q_1, \dots, q_n]$ whose elements are i.i.d. zero-mean, unity-variance random variables (RVs), it can be shown by the law of large numbers that $\lim_{n \rightarrow \infty} \frac{1}{n} \mathbf{p} \mathbf{p}^H \xrightarrow{a.s.} 1$ and $\lim_{n \rightarrow \infty} \frac{1}{n} \mathbf{p} \mathbf{q}^H \xrightarrow{a.s.} 0$ where $\xrightarrow{a.s.}$ denotes the almost sure convergence.

For *perfect* CSI using MRC, $\mathbf{f}_{n_g,k} = \mathbf{h}_{n_g,k}^H$ [3], and the SINR of user n_g on sub-carrier k is $\gamma_{n_g,k}^{\text{Perf}} = P_{n_g,k} \|\mathbf{h}_{n_g,k}\|^4 / (\|I_{n_g,k}\|^2 + \|\mathbf{h}_{n_g,k}\|^2)$. According to the law of large numbers for large $M_{n_g,k}$, $\|\mathbf{h}_{n_g,k}\|^2 \rightarrow M_{n_g,k} d_{n_g}$ and $\|I_{n_g,k}\|^2 \rightarrow 0$. Thus, $R_{n_g,k}^{\text{Perf}} = \log_2(1 + P_{n_g,k} d_{n_g} M_{n_g,k})$ as shown in (3).

For *imperfect* CSI in (2),

$$\delta_{n_g,k}(\mathbf{P}) = \sum_{g \in \mathcal{G}} \sum_{n'_g \neq n_g} \sqrt{P_{n'_g,k}} \tilde{\mathbf{h}}_{n'_g,k} \mathbf{f}_{n_g,k}^{\text{Imperf}} x_{m_g,k}$$

$$- \sqrt{P_{n_g,k}} \sum_{g \in \mathcal{G}} \sum_{n'_g \in \mathcal{N}_g} \mathbf{e}_{n'_g,k} \mathbf{f}_{n_g,k}^{\text{Imperf}} x_{m_g,k} + \mathbf{z}_{n_g,k} \mathbf{f}_{n_g,k}^{\text{Imperf}}$$

where $\mathbf{e}_{n_g,k} = \mathbf{h}_{n_g,k} - \tilde{\mathbf{h}}_{n_g,k}$ whose elements are RVs with zero mean and variance $\frac{P_{n_g,k}^{\text{Pilot}} d_{n_g}}{P_{n_g,k}^{\text{Pilot}} d_{n_g} + 1}$ and $P_{n_g,k}^{\text{Pilot}} = \tau P_{n_g,k}$ [3]. With MMSE-based channel estimation, the elements of $\tilde{\mathbf{h}}_{n_g,k}$ are i.i.d. RVs with zero mean and variance $\frac{P_{n_g,k}^{\text{Pilot}} d_{n_g}^2}{P_{n_g,k}^{\text{Pilot}} d_{n_g} + 1}$ [3].

With MRC precoder, $\mathbf{f}_{n_g,k}^{\text{Imperf}} = \tilde{\mathbf{h}}_{n_g,k}^H$. Since $\mathbf{e}_{n'_g,k}$ and $\mathbf{h}_{n'_g,k}$ are independent of $\tilde{\mathbf{h}}_{n_g,k}$ and $\mathbf{f}_{n_g,k}^{\text{Imperf}}$, the first term of $\delta_{n_g,k}(\mathbf{P})$ is zero and second term is equal to $\sqrt{P_{n_g,k}} \mathbf{e}_{n_g,k} \mathbf{f}_{n_g,k}^{\text{Imperf}} x_{n_g,k}$. Thus, the SINR for the imperfect CSI case is $\gamma_{n_g,k}^{\text{Imperf}} = P_{n_g,k} \|\tilde{\mathbf{h}}_{n_g,k}\|^4 / (P_{n_g,k} \|\mathbf{e}_{n_g,k}\|^2 + \|\tilde{\mathbf{h}}_{n_g,k}\|^2)$

$$= \frac{M_{n_g,k}^2 P_{n_g,k} (P_{n_g,k}^{\text{Pilot}} d_{n_g}^2)^2}{M_{n_g,k} P_{n_g,k} (\frac{P_{n_g,k}^{\text{Pilot}} d_{n_g}^2}{P_{n_g,k}^{\text{Pilot}} d_{n_g} + 1})^2 + M_{n_g,k} (\frac{P_{n_g,k}^{\text{Pilot}} d_{n_g}^2}{P_{n_g,k}^{\text{Pilot}} d_{n_g} + 1})^2}$$

By some mathematical manipulations, $\gamma_{n_g,k}^{\text{Imperf}} = \frac{M_{n_g,k} P_{n_g,k}^{\text{Pilot}} P_{n_g,k} d_{n_g}^2}{P_{n_g,k} d_{n_g} + P_{n_g,k}^{\text{Pilot}} d_{n_g} + 1}$. Now, by substituting $P_{n_g,k}^{\text{Pilot}} = \tau P_{n_g,k}$ and considering $P_{n_g,k} = \rho_{n_g,k} / \sqrt{M_{n_g,k}}$ [3], we have $\gamma_{n_g,k}^{\text{Imperf}} = \frac{\tau \rho_{n_g,k}^2 d_{n_g}^2}{1 + (1 + \tau) \rho_{n_g,k} d_{n_g} / \sqrt{M_{n_g,k}}}$. When $M_{n_g,k} \rightarrow \infty$, we have $\gamma_{n_g,k}^{\text{Imperf}} = \tau \rho_{n_g,k}^2 d_{n_g}^2 = \tau P_{n_g,k}^2 d_{n_g}^2 M_{n_g,k}$. Thus, as shown in (3), $R_{n_g,k} = \frac{T - \tau}{T} \log_2(1 + \tau P_{n_g,k}^2 d_{n_g}^2 M_{n_g,k})$ where $(T - \tau)/T$ is the fraction of transmission frame for sending the actual data [3].

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