Joint Optimization of Power Consumption and Load Balancing in Wireless Dynamic Network Architecture

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***Abstract*—The concept of the wireless dynamic network architecture (DNA) stands for a system design, which allows terminals to convert into temporary access points (APs) when necessary. In this paper, we propose a framework to solve the problem of load balancing in DNA. Particularly, the user association in DNAs is optimized to minimize the number of active APs and the network cost in terms of tradeoff between power and load, while ensuring users' quality of service (QoS). In general, such a problem is a non-convex mixed integer nonlinear program in the sense that its continuous relaxation is a non-convex problem. To solve this optimization, we use the standard continuous relaxation method and approximate the relaxed problem by a series of second order cone programs with the aid of successive convex approximation (SCA) framework. Numerical results show that the proposed algorithm converges within a few iterations and jointly minimizes the network cost and the number of APs in the network.**

***Index Terms*—User association, SOCP, AP and power consumption minimization, load balancing, downlink beamforming, convex optimization.**

I. Introduction

The popularity of wireless communication networks has been significantly increased during the last decade. Thus, the utilization of wireless resources has become one of key factors in terms of satisfying the quality of service (QoS) and maintaining the required system performance. With recent developments, the wireless devices like smart phones and tablets have the ability to operate as end terminals as well as access points (APs). This allows us to broaden the network coverage, but on the other hand increases its dynamics. Such architectures are referred as dynamic wireless network architectures (DNAs), since the number of available APs and their positions can rapidly vary with time [1], [2]. However, maximizing the number of active APs in the network may not always guarantee improved system performance [3]. Specifically, it increases the power consumption of the network and AP reimbursement thus, the selection of APs which maximizes the design criterion of interest is crucial. Furthermore, with the dynamic behaviour of the network, optimizing the number of active APs is important to maintain the system reliability.

The above argument was indeed the main point of many previous studies. The works in [4]–[6] studied the energy consumption minimization problems to select the smallest set of APs while ensuring users' QoS. In [4], Yang *et al.* proposed an iterative algorithm to optimize both energy and user association in green cellular networks while Xu *et al.* [6] introduced a simple algorithm to determine the number of active base stations using a Lagrange multiplier method. The authors in [7] presented a learning algorithm to optimize the load balancing and active number of base stations in small cell networks. In [8], the number of active base stations and downlink transmission power are jointly optimized using coordinated multipoint transmission. To solve this problem, SOCP based iterative optimization algorithm with branch and cut method was presented. Moreover, Li *et al.* in [9], introduced a method to achieve higher throughput in IEEE 802.11 networks while optimizing the active number of APs using a game theoretical approach. Particularly, Hong *et al.* [10] highlighted some problems regarding the use of non-cooperative game theoretical approaches to solve resource allocation problems in wireless networks. Moreover, cluster based load balancing approach for a computer network was proposed in [11], since fully centralized (or fully decentralized) networks may not perform well in terms of scalability (or with lack of information in each server).

In this paper, we address the problem of joint load balancing and minimizing the number of active APs in DNAs by using a convex optimization based method. The complexity of the network increases with the number of APs and users in the network, thus network clustering is introduced to promote the scalability of the network under consideration. Here, a multi antenna transmission, multiple input single output (MISO) system is considered to increase the network spectral efficiency where the transmitted message is weighted by a beamformer. To optimize the set of active APs and user association, two binary variables are introduced. The challenge is that, even for these binary variable is fixed, the resulting continuous optimization problem is still NP-hard [1]. In general, the complexity of an optimization problem increases when binary or integer variables are introduced, compared to the continuous counterpart. To solve the considered mixed integer nonlinear program, we first relax the binary variables to be continuous. However the relaxed problem is still non-convex and thus, we use successive convex approximation (SCA) method to handle it. By introduced transformations, we arrive at a second order cone program (SOCP) in each step of the proposed iterative procedure. The proposed algorithm converges in a few iterations and the relaxed variables are very close to zero at convergence.

Notations: Boldface lower and upper case letters are used to denote vectors and matrices, respectively. $\Re(\mathbf{x})$ and $\Im(\mathbf{x})$ represent the real and imaginary parts of a complex vector $\mathbf{x}$, respectively. $\mathbb{R}^{m\times n}$ and $\mathbb{C}^{m\times n}$ represent the space of real and complex matrices of dimension given in superscript, respectively. $\mathbf{X}^T$ represents transpose of $\mathbf{X}$ and $\mathbf{1}_{m\times n}$ denotes the $m \times n$ matrix of all 1s. The absolute value of a scalar y is defined by $|y|$, and $\|\mathbf{y}\|_2$ represents the Euclidean norm of a vector $\mathbf{y}$. For two vectors $\mathbf{x}$ and $\mathbf{y}$ of the same size, their inner product is denoted by $\langle \mathbf{x}, \mathbf{y}\rangle$, i.e., $\langle \mathbf{x}, \mathbf{y}\rangle = \mathbf{x}^T\mathbf{y}$.

II. Network Model and Problem Formulation

We study the downlink transmission, where APs communicate with the users in a single hop manner as illustrated in Fig. 1. We clustered the network with frequency reuse factor

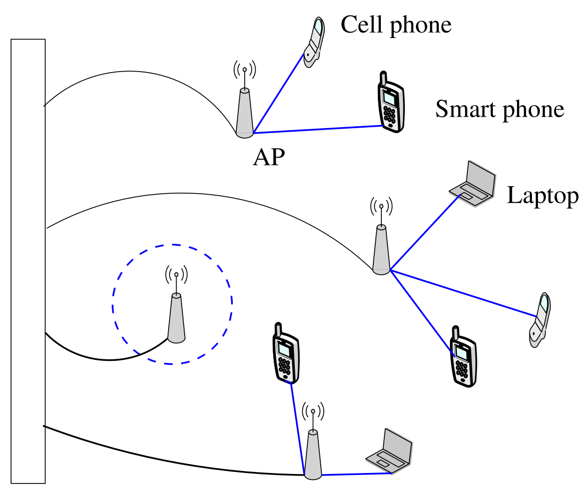

Fig. 1: An example of the considered system model. One cluster is considered with $\mathcal{I} = 4$ and $\mathcal{J} = 7$. The AP covered in blue dashed line implies the not selected AP for communication at the moment ($\mathcal{K} = 3$).

3 and thus, inter-cluster interference has ignored. Further, assume that central server handles each cluster. Therefore, the proposed algorithms are supposed to run on each cluster. Then, we consider a cluster with J single antenna users and I APs, each equipped with T transmit antennas. Let $\mathcal{I} = \{1, 2, \ldots, I\}$ and $\mathcal{K} \subseteq \mathcal{I}$ be the sets of available and active APs, respectively. $\mathcal{J} = \{1, 2, \ldots, J\}$ denotes the set of users in the network. We introduce two binary selection variables a_i and s_{ij} to represent the status of the AP i and the connection status between user j and AP i, respectively, i.e.,

$$a_i = \begin{cases} 1 & \text{if access point } i \text{ is active} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

and

$$s_{ij} = \begin{cases} 1 & \text{if user } j \text{ selects AP } i \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

The APs are equipped with multiple antennas such that they can transmit using linear beamforming. To minimize inter-user interference and maximize its own data rate, a user has to select the most appropriate AP among all possible connections. We assume that all users in the network are able to get the service and users' data is not shared among APs. Since, each user is served by only one AP, the following constraint must hold.

$$\textstyle\sum_{\forall i\in\mathcal{I}} s_{ij} = 1, \quad \forall j \in \mathcal{J}. \tag{3}$$

The channel between user j and AP i is denoted by a complex row vector $\mathbf{h}_{ij} \in \mathbb{C}^{1\times T}$ and the message for user j is linearly weighted by a column vector $\mathbf{w}_{ij} \in \mathbb{C}^{T\times 1}$ before being transmitted from AP i. The transmitted power of the APs is modelled by two states: 'ON' state and 'OFF' state [7]. When AP is in the ON state it is assumed to consume processing power p_{bb} to operate its radio frequency components and base band unit. When an AP is in the OFF state, even with no data transmission it consumes fraction of p_{bb} power to sense the system and receive the control signals. Thus, for a given parameter $\eta \in [0, 1)$, the total transmitted power of the each AP i is modelled as

$$P_i^{tot} = \textstyle\sum_{j\in\mathcal{J}} \|\mathbf{w}_{ij}\|_2^2 + a_i p_{bb} + (1 - a_i)\eta p_{bb}. \tag{4}$$

For simplicity we define two vectors, $\mathbf{h}_j = [h_{j,1}, h_{j,2}, \ldots h_{j,I}] \in \mathbb{C}^{1\times IT}$ as the aggregated channel vector of the jth user and $\mathbf{w}_j = [\mathbf{w}_{j,1}^T, \mathbf{w}_{j,2}^T, \ldots \mathbf{w}_{j,I}^T]^T \in \mathbb{C}^{IT\times 1}$ as the aggregated beamformer vector of user j. Then, the signal to noise and interference ratio (SINR) of user j is given by

$$\gamma_j = \frac{|\mathbf{h}_j\mathbf{w}_j|^2}{\sigma_j^2 + \sum_{\forall l\in\mathcal{J}, l\neq j} |\mathbf{h}_j\mathbf{w}_l|^2}, \quad \forall j \in \mathcal{J}, \tag{5}$$

where σ_j^2 is the variance of the additive white Gaussian background noise. Thus, the data rate of user j is written as

$$R_j = \log(1 + \gamma_j), \quad \forall j \in \mathcal{J}. \tag{6}$$

Further, consider λ_j and x_j as the packet arrival rate and mean packet size for each user, respectively [12]. In general, we can consider that service rate for user j is equal to R_j. Then the load of user j is given by

$$L_j = \frac{\lambda_j x_j}{R_j}, \quad \forall j \in \mathcal{J}. \tag{7}$$

Thus, the total cost of the network becomes

$$NC = \alpha_1 \textstyle\sum_{\forall i\in\mathcal{I}} P_i^{tot} + \alpha_2 \sum_{\forall j\in\mathcal{J}} L_j, \tag{8}$$

where α_1 and $\alpha_2 (> \alpha_1)$ are two different weighting variables which are defined to trade-off load balancing and power minimization. The main objective is to minimize the total cost of the network, which is mathematically modeled as

$$(\tilde{\mathcal{P}}) \triangleq \begin{cases} \min\limits_{\mathbf{s},\mathbf{w},\mathbf{a},\mathbf{v}} \alpha_1 \sum_{\forall i\in\mathcal{I}} P_i^{tot} + \alpha_2 \sum_{\forall j\in\mathcal{J}} L_j & \text{(9a)}\\ \text{s.to} \quad \gamma_j^{min} \leq \gamma_j \ \forall, \quad j\in\mathcal{J} & \text{(9b)}\\ \sum_{\forall j\in\mathcal{J}} a_i \|s_{ij}\mathbf{w}_{ij}\|_2^2 \leq p_i^{max}, \quad \forall i\in\mathcal{I} & \text{(9c)}\\ a_i = \{0,1\}, \quad \forall i\in\mathcal{I} & \text{(9d)}\\ s_{ij} = \{0,1\}, \quad \forall i\in\mathcal{I},\forall j\in\mathcal{J} & \text{(9e)}\\ 1_{1\times I}\mathbf{s}_j = 1, \quad \forall j\in\mathcal{J}. & \text{(9f)} \end{cases}$$

In (9), p_i^{max} and γ_j^{min} represent the maximum transmitted power of AP i and the minimum SINR of user j, respectively.

III. Proposed Convex Optimization Algorithm

We first deal with the binary variables in (9). To this end, we note that the constrains (9c)-(9e) can be equivalently rewritten as

$$a_i = \{0,1\}, \quad \forall i\in\mathcal{I} \tag{10a}$$
$$s_{ij} \leq a_i, \quad \forall i\in\mathcal{I},\forall j\in\mathcal{J} \tag{10b}$$
$$\mathbf{w}_{ij} = s_{ij}\mathbf{w}_{ij}, \quad \forall i\in\mathcal{I},\forall j\in\mathcal{J} \tag{10c}$$
$$\sum_{\forall j\in\mathcal{J}} \|\mathbf{w}_{ij}\|_2^2 = a_i \sum_{\forall j\in\mathcal{J}} \|\mathbf{w}_{ij}\|_2^2, \quad \forall i\in\mathcal{I} \tag{10d}$$
$$s_{ij} = \{0,1\}, \quad \forall i\in\mathcal{I},\forall j\in\mathcal{J} \tag{10e}$$
$$a_i \sum_{\forall j\in\mathcal{J}} \|\mathbf{w}_{ij}\|_2^2 = a_i \sum_{\forall j\in\mathcal{J}} s_{ij}\|\mathbf{w}_{ij}\|_2^2, \quad \forall i\in\mathcal{I}. \tag{10f}$$

When $a_i = 0$, i.e, when the AP is inactive, the equalities $s_{ij} = 0$ and $\mathbf{w}_{ij} = 0$ (i.e., (10a) - (10d)) hold true. Similarly, when there is no transmission between user j and AP i, i.e., $s_{ij} = 0$, $\mathbf{w}_{ij}$ will equal to zero (i.e., (10e) and (10f)). In order to convexify the above constraints, we simply consider the continuous relaxation of (10a), i.e, $0 \leq a_i \leq 1$. As a result, (10e) can be ignored and (10b) can be modified as $0 \leq s_{ij} \leq a_i$. By introducing new optimization variable v_{ij}, the maximum transmitted power from AP i to user j, we can represent (10c), (10d) and (10f) as a combination of

$$\|\mathbf{w}_{ij}\|_2^2 \leq s_{ij}v_{ij}, \quad \forall j\in\mathcal{J},\forall i\in\mathcal{I} \tag{11}$$

and

$$\sum_{\forall j\in\mathcal{J}} v_{ij} \leq a_i p_i^{max}, \quad \forall i\in\mathcal{I}. \tag{12}$$

Then, the joint optimization problem to minimize the active number of APs and the cost can cast as follows:

$$(\tilde{\mathcal{P}}) \triangleq \begin{cases} \min\limits_{\mathbf{s},\mathbf{w},\mathbf{a},\mathbf{v}} \alpha_1 \sum_{\forall i\in\mathcal{I}} P_i^{tot} + \alpha_2 \sum_{\forall j\in\mathcal{J}} L_j & \text{(13a)}\\ \text{s.to} \quad \gamma_j^{min} \leq \gamma_j \ \forall j\in\mathcal{J} & \text{(13b)}\\ \|\mathbf{w}_{ij}\|_2^2 \leq s_{ij}v_{ij}, \quad \forall j\in\mathcal{J},\forall i\in\mathcal{I} & \text{(13c)}\\ 1_{1\times J}\mathbf{v}_j \leq a_i p_i^{max}, \quad \forall i\in\mathcal{I} & \text{(13d)}\\ 1_{1\times I}\mathbf{s}_j = 1, \quad \forall j\in\mathcal{J} & \text{(13e)}\\ 0 \leq a_i \leq 1, \quad \forall i\in\mathcal{I} & \text{(13f)}\\ 0 \leq \mathbf{s}_j \leq a_i, \quad \forall i\in\mathcal{I} & \text{(13g)} \end{cases}$$

where, $\mathbf{s}_j = [s_{1j}, s_{2j}, \ldots, s_{Ij}]^T \in \{0,1\}^I$ is the vector consisting of I binary selection variables associated with user j, and $\mathbf{v}_j = [v_{1j}, v_{2j}, \ldots, v_{Ij}]^T$ is the vector of transmitted power from all APs related to the user j.

The optimization problem in (13) is an NP hard problem. To find a high-quality solution, we resort to the SCA method to approximate (13) by a sequence of convex problems. We remark that the SCA method has been shown to be effective in various problems, which motivates the iterative algorithm proposed below. First toward this end, NC can be rewritten as

$$NC = \alpha_1 \sum_{\forall i\in\mathcal{I}} \Big(\sum_{j\in\mathcal{J}} \|\mathbf{w}_{ij}\|_2^2 + a_i p_{bb} + (1-a_i)\eta p_{bb} \Big) + \alpha_2 \sum_{\forall j\in\mathcal{J}} \lambda_j x_j z_j \tag{14}$$

where,

$$z_j \geq \frac{1}{\log\Big(1 + \frac{|\mathbf{h}_j\mathbf{w}_j|^2}{\sigma_j^2 + \sum_{\forall l\in\mathcal{J}, l\neq j} |\mathbf{h}_j\mathbf{w}_l|^2}\Big)}, \quad \forall j\in\mathcal{J} \tag{15}$$

are newly introduced variables. Note that the objective function is now convex and the constraint (15) need to be simplified. Without loosing optimality it can be represented as

$$z_j t_j \geq 1, \tag{16a}$$
$$t_j \leq \log(\theta_j), \tag{16b}$$
$$(\theta_j - 1)u_j \leq |\mathbf{h}_j\mathbf{w}_j|^2, \tag{16c}$$
$$u_j \geq (\sigma_j^2 + \sum_{\forall l\in\mathcal{J}, l\neq j} |\mathbf{h}_j\mathbf{w}_l|^2). \tag{16d}$$

Note that, (16b) and (16d) are convex. To handle the non-convex constraints, we use the equality $4\langle\mathbf{x},\mathbf{y}\rangle = ||\mathbf{x}+\mathbf{y}||_2^2 - ||\mathbf{x}-\mathbf{y}||_2^2$ to simplify various relations. By applying this equality and the first order Taylor expansion, we can approximate (16a) as

$$4 + (z_j - t_j)^2 \leq +2\langle z_j^{(n)} + t_j^{(n)}, z_j - z_j^{(n)} + t_j - t_j^{(n)}\rangle + (z_j^{(n)} + t_j^{(n)})^2. \tag{17}$$

Further, we note that (13b) can be considered as combination of (16d) and

$$\gamma_j^{min} u_j \leq |\mathbf{h}_j\mathbf{w}_j|^2. \tag{18}$$

Since (18) and (16c) have the same format, we can convexify those as

$$\frac{1}{4}(\theta_j - 1 + u_j)^2 \leq 2\Re\big(\mathbf{w}_{ij}^{(n)T}\mathbf{h}_{ij}^T\mathbf{h}_{ij}(\mathbf{w}_{ij} - \mathbf{w}_{ij}^{(n)})\big) + 2\Im\big(\mathbf{w}_{ij}^{(n)T}\mathbf{h}_{ij}^T\mathbf{h}_{ij}(\mathbf{w}_{ij} - \mathbf{w}_{ij}^{(n)})\big) + \frac{1}{4}(\theta_j{}^{(n)} - 1 - u_j^{(n)})^2 + |\mathbf{h}_{ij}\mathbf{w}_{ij}^{(n)}|^2 + \frac{1}{2}\langle\theta_j{}^{(n)} - 1 - u_j^{(n)}, \theta_j - \theta_j{}^{(n)} - u_j + u_j^{(n)}\rangle, \tag{19a}$$

and

$$\gamma_j^{min} u_j \leq |\mathbf{h}_{ij}\mathbf{w}_{ij}^{(n)}|^2 + 2\Re\big(\mathbf{w}_{ij}^{(n)T}\mathbf{h}_{ij}^T\mathbf{h}_{ij}(\mathbf{w}_{ij} - \mathbf{w}_{ij}^{(n)})\big) + 2\Im\big(\mathbf{w}_{ij}^{(n)T}\mathbf{h}_{ij}^T\mathbf{h}_{ij}(\mathbf{w}_{ij} - \mathbf{w}_{ij}^{(n)})\big), \tag{19b}$$

respectively.

The hyperbolic constraint (13c) is a convex constraint and it can be rearranged as an SOCP constraint as

$$\|2\mathbf{w}_{ij}\ ; s_{ij} - v_{ij}\|_2 \leq s_{ij} + v_{ij}. \tag{20}$$

In summary, the optimization problem at the $(n+1)$th iteration of the proposed algorithm is given by

$$(\mathcal{P}_{n+1}) \triangleq \begin{cases} \underset{\mathbf{s},\mathbf{w},\mathbf{a},\mathbf{z},\mathbf{v},\mathbf{u},\theta,\mathbf{t}}{\text{minimize}} & \alpha_1 \sum_{\forall i \in \mathcal{I}} P_i^{tot} + \alpha_2 \sum_{\forall j \in \mathcal{J}} \lambda_j x_j z_j \quad \text{(21a)} \\ \text{subject to} & \text{(13d)-(13g) (16b), (16d), (17),} \\ & \text{(19), (20).} \quad \text{(21b)} \end{cases}$$

To conclude this section, we outline the proposed method to solve the final optimization problem in **Algorithm 1**.

Algorithm 1: Joint cost and active APs minimization algorithm.

Initialization:

1: Set $n = 0$ and generate $\mathbf{s}^{(0)} \in \{0, 1\}$ such that the constraints in (3) are satisfied. For a known $\mathbf{s}^{(0)}$, solve the following convex feasibility problem to obtain the feasible set of beamformers.

$$\text{find } \mathbf{w} \quad \text{(22a)}$$

$$\text{subject to } \gamma_j^{\min} \leq \gamma_j, \ \forall j \in \mathcal{J} \quad \text{(22b)}$$

$$\textstyle\sum_{j \in \mathcal{J}} s_{ij}^{(0)} \|\mathbf{w}_{ij}\|_2^2 \leq p_i^{\max}, \forall i \in \mathcal{I} \quad \text{(22c)}$$

is a convex problem.

2: If (22) is feasible, using $\mathbf{w}$, $\mathbf{s}^{(0)}$, calculate $\boldsymbol{\theta}^{(0)}, \mathbf{t}^{(0)}$, $\mathbf{u}^{(0)}$ and $\mathbf{z}^{(0)}$ by setting the inequalities in the constraints in which they appear to be equality. If (22) is infeasible, feasible point may achieve by repeating step 1 with regenerated $\mathbf{s}^{(0)}$.

Main loop:

3: **repeat**

4: Solve $(\mathcal{P}_{n+1})$ to find an optimal solution which denotes as $(\mathbf{w}^*, \boldsymbol{\theta}^*, \mathbf{t}^*, \mathbf{z}^*, \mathbf{u}^*, \mathbf{s}^*)$.

5: Update $(\mathbf{w}^{(n+1)}, \boldsymbol{\theta}^{(n+1)}, \mathbf{t}^{(n+1)}, \mathbf{z}^{(n+1)}, \mathbf{u}^{(n+1)}, \mathbf{s}^{(n+1)}) = (\mathbf{w}^*, \boldsymbol{\theta}^*, \mathbf{t}^*, \mathbf{z}^*, \mathbf{u}^*, \mathbf{s}^*)$

6: $n \rightarrow n + 1$

7: **until convergence**

IV. Numerical Results

In this section, performance of the algorithm is evaluated by extensive numerical experiments. Here, One cluster is considered with $I = 3$ for different J and T. The values of the simulation parameters are shown in Table I, unless otherwise stated. Channels are modelled as $\mathcal{CN}(\mathbf{0}, \mathbf{I})$ distribution. The algorithm is implemented in MATLAB environment using the solver SDPT3 through the parser CVX. The stopping criteria for algorithm is when the difference between two successive iterations is less than $\epsilon = 10^{-6}$.

TABLE I: Simulation Parameter values

System Parameters	Value
I, T, J	3, 3-4, 1-5
γ^{min}, P^{max}	-7 dBW, 42 dBm
α_1, α_2	1,12
x, λ	2, $1s^{-1}$
η, p_{bb}	0.5, 30 dBm

Fig. 2 illustrates the convergence property of the proposed algorithm. Curves are obtained for $J = 2$ and $J = 3$ with different channel realizations (CH1 and CH2). The proposed algorithm converges within few iterations and convergence rate of the algorithm relatively insensitive with the number of users. At convergence, a_i implies the probability of that AP to be active. It is numerically seen that when a_i is nearly a binary, algorithm achieves best local optimal. Therefore, if a_i is less than 0.5, but not nearly equal to zero, algorithm need to be re-optimized by allocating current users in the ith APs to next highest probable AP in order to achieve lowest network cost.

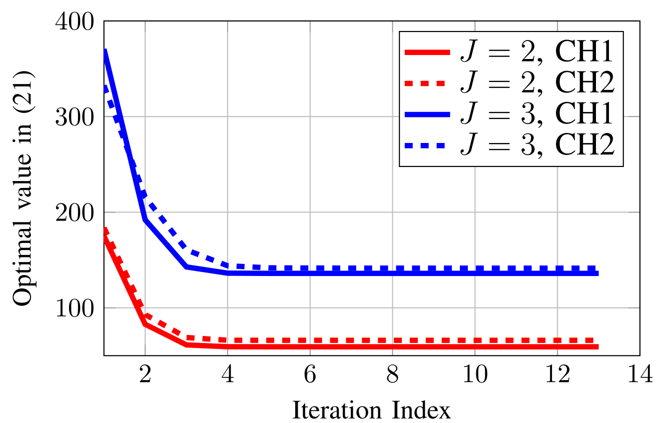

Fig. 2: Convergence property of the algorithm for $J = 2$ and $J = 3$.

Power consumption to transmit 1 b/s/Hz Or $\frac{1}{\text{Energy efficiency}}$ $EE_{tot}^{-1} = \sum_{\forall i \in \mathcal{I}} P_i / \sum_{\forall j \in \mathcal{J}} R_j$ of the network and percentage of active APs are presented in Fig. 3 and Fig. 4, respectively. The results are averaged over 500 channel realizations. Since we jointly optimize the active number of APs with network cost, the following discussions apply to both Figs 3 and 4. When the number of transmission antennas at each AP increases, degree of freedom increases accordingly.

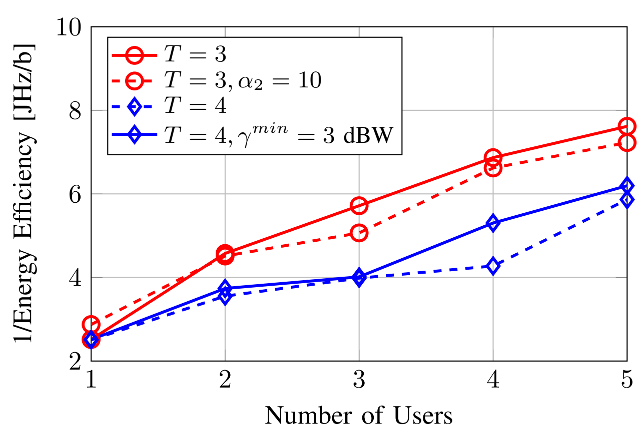

Fig. 3: EE_{tot}^{-1} of the system with different T, α_2 and γ^{min} with respect to J. Since arrival rate and packet length are considered as same for all the users, this is proportional to the power/load value.

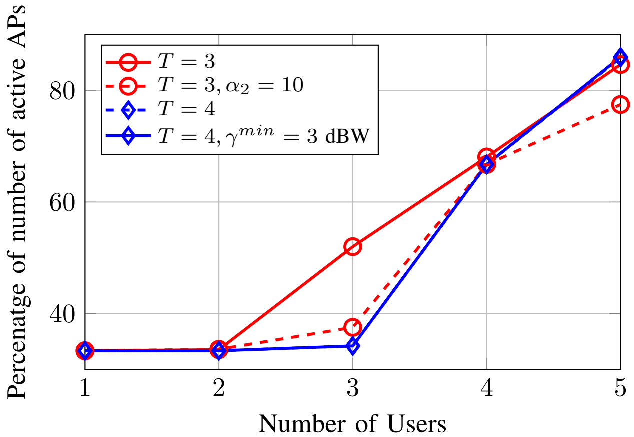

Fig. 4: Percentage usage of the APs with respect to the number of users J in the system.

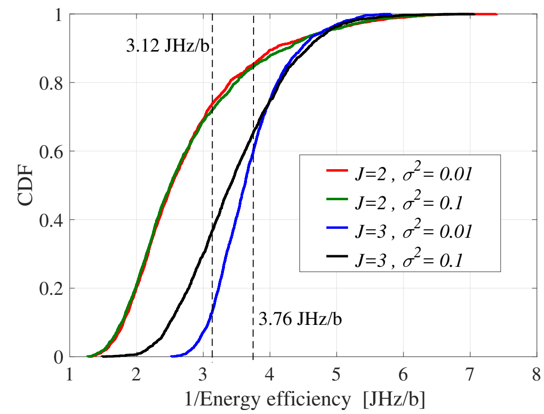

Fig. 5: CDF of the EE_{tot}^{-1} with Gaussian channel estimation errors having zero mean and different variances. System has been analyzed for 10000 channel realization with $J = 2$ and $J = 3$.

Therefore, when compare the results for $T = 3$ and $T = 4$, it is clear that the number of active APs and EE_{tot}^{-1} decreases with T. Further, we observe that the EE_{tot}^{-1} and number of active APs increase with number of users in the network. The reason is that, when J increases, it is enforced to transmit more power to maintain required users' SINR, since level of interference increases with J. Similarly, when the minimum SINR requirement increases (blue colour curves), the EE_{tot}^{-1} increases, since it requires more power to achieve higher rates under higher interference. Moreover, we can notice that number of active APs and EE_{tot}^{-1} vary with pricing value α_2. Thus, by selecting optimal values for α_1 and α_2, we can reduce network cost and active APs further. However, we are planning to consider this in our future work.

Sensitivity of the proposed algorithm is studied toward channel estimation errors in Fig. 5. First, a set of channel realizations for two systems with $T = 3, J = 2$ and $T = J = 3$ is generated, which is referred to as the perfect channel state information (CSI). **A**lgorithm 1 io this perfect channel estimate, which results in a EE_{tot}^{-1} of 3.31 JHz/b and 3.76 JHz/b for $J = 2$ and $J = 3$, respectively (shown by the dashed lines in Fig. 5). To compute an empirical CDF, we model the actual channel vectors as the sum of the perfect CSI and channel estimation errors which are assumed to follow Gaussian distribution with zero mean and variance σ^2. When σ^2 increases, the CDF is more spread, which means the EE_{tot}^{-1} deviate further from the expected value.

V. Conclusion

In this paper, an iterative algorithm has been proposed to optimize the number of APs and the resulting network cost of the downlink of DNAs. The considered problem is a nonconvex mixed integer program which is difficult to solve. To find a high-performance solution, we have used a standard continuous relaxation method in which binary variables are simply relaxed to be continuous and successive approximation method is then used to derive an iterative algorithm. Our extensive numerical results have proved that the proposed algorithm converges rapidly and achieves lower cost with a small number of APs. Moreover, it has proved that this algorithm is less sensitive toward the channel estimation errors.

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