Computer Communications 36 (2013) 1373–1386

Contents lists available at SciVerse ScienceDirect

Computer Communications

journal homepage: www.elsevier.com/locate/comcom

Satisfying demands in a multicellular network: A universal power allocation algorithm ☆

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ARTICLE INFO

Article history:
Received 30 September 2011
Received in revised form 26 February 2012
Accepted 8 April 2012
Available online 27 April 2012

Keywords:
Cellular networks
MIMO
Power allocation
Stochastic approximation
Ordinary differential equations

ABSTRACT

Power allocation to satisfy user demands, in the presence of large number of interferers (in a multicellular network), is a challenging task. Further, the power to be allocated depends upon the system architecture, for example upon components like coding, modulation, transmit precoder, rate allocation algorithms, available knowledge of the interfering channels, etc. This calls for an algorithm via which each base station in the network can simultaneously allocate power to their respective users so as to meet their demands (whenever they are within the achievable limits), using whatever information is available of the other users. The goal of our research is to propose one such algorithm which in fact is universal: the proposed algorithm works from a fully co-operative setting to almost no co-operation and or for any configuration of modulation, rate allocation, etc. schemes. The algorithm asymptotically satisfies the user demands, running simultaneously and independently within a given total power budget at each base station. Further, it requires minimal information to achieve this: every base station needs to know its own users demands, its total power constraint and the transmission rates allocated to its users in every time slot. We formulate the power allocation problem in a system specific game theoretic setting, define system specific capacity region and analyze the proposed algorithm using ordinary differential equation (ODE) framework. Simulations further confirm the effectiveness of the proposed algorithm. We also demonstrate the tracking abilities of the algorithm.

In heterogeneous networks, it is hard to expect the various agents to update their algorithms in a synchronous manner. Using two time scale stochastic approximation analysis we study the proposed algorithm operating in a simple example scenario, wherein the heterogeneous agents update (their power profiles) at different speeds.

Further, backed by numerical examples (for various generic example scenarios), we show that the algorithm converges to the same power profile, as long as the demands remain same, irrespective of the disparities in the operating speeds at different agents.

1. Introduction

Multi-input multi-output (MIMO) combined with network densification promise improved network coverage and capacity for mobile broadband access. But, due to an increased number of transmit antennas and or the proximity of base stations (BS), users at cell edges experience a higher degree of interference from neighboring base stations.

Network MIMO or other forms of BS co-operation enable sharing complete or statistical knowledge of channel states (CS) amongst neighbors via back-haul links to alleviate interference and offer better rates to users. When back-haul is not available, each BS may estimate the local channel state information and use the same for better performance. In some cases, a low rate feedback from the receiver indicating the QoS of the current transmissions is utilized, while in the worst case the transceivers are designed with no CS information. Thus we have a variety of systems with varying degrees of the information about the interfering channels. However the goal in each is the same: satisfy the demands of all the users. We may require higher power profiles to satisfy the same demands when working with lesser information. Further diverse situations can arise because of the system configuration like modulation, precoding, channel coding, resource allocation etc.

☆ This article is a journal version of the paper [13] presented in WiOpt 2011, Princeton, USA.

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http://dx.doi.org/10.1016/j.comcom.2012.04.009

For a given vector of power constraints at various base stations, Shannon capacity gives the maximum achievable rate, i.e., the capacity region. This is an upper bound. We define "system specific capacity region" (achievable rate region of a given system) which depend on coding (space–time, channel), modulation, channel state information availability, synchronization, feedback errors and many other things. Given a system architecture with a chosen set of parameters which define its rate allocation, modulation, etc., the achievable rates are usually inferior to the theoretical rates and the system specific capacity region is defined based on these rates. The system-specific capacity region for the same power constraint varies: for example it shrinks if the number of supported discrete rates reduce. Thus, the power allocated to any user to achieve the same demand rate varies with the set of system parameters.

The main contribution of this paper is a universal algorithm which can work with many of the systems mentioned above. It satisfies asymptotically the demands of all the users irrespective of the system in which it is operating, albeit with different power profiles. *Each base station requires minimal information: its user's demands, its total power constraint and the current transmission rates to its users.* The amount of data information transmitted successfully in a slot (per slot) basically represents the current transmission rates. These current transmission rates are decided by the serving base stations either using complete CSIT (algorithm can also be used as a centralized scheme in this case) or has to be estimated completely blindly or using some partial information. These are also influenced by the underlying channel.

In cellular networks, the scenarios can change with time. For example a base station can become active suddenly, the demands may change etc. We demonstrate via simulations that the proposed algorithms can also track the changes.

In heterogeneous networks, various agents (for example macro cells and micro cells) can operate at different speeds. However they still can interfere with each other. We consider a simple example scenario and demonstrate using the two time scale stochastic approximation analysis that the proposed algorithm converges to the same power profile irrespective of the disparities in the update rates. We then illustrate the same for general scenarios using numerical simulations. The following are the contributions of this paper:

(1) A system specific game theoretic problem formulation using the system specific capacity region.
(2) A *Stochastic Approximation* based universal power allocation algorithm in an interference limited multi-cell network.
(3) Various properties (e.g. convergence) of the proposed algorithm is analyzed using an ODE framework.
(4) Simulation results demonstrate the effectiveness of the proposed algorithm for a variety of systems.
(5) We also establish the tracking capabilities of the algorithm.
(6) We illustrate the robustness of the proposed algorithm against the disparities in update rates at various agents.

1.1. Related work

For an excellent survey on power control in wireless networks, the reader is referred to [2] and the references there-in (e.g. [3,5–8]). In recent years, several authors have addressed distributed power control strategies with various levels of co-operation for a given system configuration (e.g. [3,5–7,10] etc). Typically, the design objective is to *maximize* the total sum rate of all the users subject to BS power constraints or to *minimize* the total transmit power satisfying some SINR constraints of the users.

Most of the existing algorithms aim at either optimizing the total power spent keeping the QoS above a required level (e.g. [5–7] etc.) and or optimize the QoS while keeping the power utilized within a given budget (e.g. [10]). But our algorithm does not optimize, it only meets the demands (in the form of average transmission rates) on average asymptotically.[1] This relaxation helps us in proposing an algorithm that requires minimal information (hence has minimal complexity) at the transmitters: rates at which the information is correctly transmitted to the user in every slot. Data is pumped out from the transmitter and hence these rates are readily known to the transmitter. Hence this algorithm does not require any extra information and this can be exploited in many more ways. For example, one can probably use this algorithm in networks with heterogeneous cells, i.e., when each cell has a system configuration that can be different from the other cells.

A related concept, called satisfying equilibrium, is defined and studied in a recent paper ([9]). Here they define the satisfying equilibrium as any profile at which the QoS of all the users is either better or the same as the specified level. Basically, the set of satisfying equilibrium represents the domain of optimization for the problems that optimize the total power utilized while maintaining the QoS. In our paper, we propose an algorithm that satisfies the demands for all the users at exactly the specified level via a stochastic approximation based zero finding method. As already discussed, this zero finding method greatly simplifies the algorithm. To the best of our knowledge this is the first paper that proposes to take advantage of the relaxation obtained by avoiding the optimization.

1.2. Organization

We introduce the system model in Section 2. In Section 3, we describe the system specific problem formulation. The algorithm and its analysis is presented in Section 4. Section 5 provides simulations. Section 6 discusses heterogeneous agents. Appendix contains example systems and proofs.

1.3. Notations

Boldface lower-case symbols represent vectors, capital boldface symbols denote matrices ($\mathbf{I}_N$ is the $N \times N$ identity matrix). Hermitian transpose is denoted $(\cdot)^H$ while $\mathbf{tr}[\mathbf{X}]$ represents the trace of matrix $\mathbf{X}$. All logarithms are base-2 logarithms. Small letters represent the scalars. Let a_k represent the kth component of the vector $\mathbf{a}$. If the vector is already indexed like for example in $\mathbf{p}_j$, then $p_{k,j}$ represents its kth component. Let $(\mathbf{p}.\mathbf{s})$ represent the component-wise product, i.e., $(\mathbf{p}.\mathbf{s})_k = p_k s_k$ for all k while $\sqrt{\mathbf{p}}$ represents component wise square root. $\mathbf{E}[\cdot]$ denotes expectation and $\mathbf{E}_\mathbf{s}$ is expectation w.r.t to $\mathbf{s}$ when conditioned (if any) on the other random variables.

2. System model

We consider a multi-cell MIMO system. Each base station has M transmit antennas and is communicating with K single-antenna users (see Fig. 1). Every user experiences both intra-cell (transmissions from parent BS) and inter-cell (transmissions from neighboring BS) interference. Each user in a cell demands a certain rate and all these rates have to be jointly satisfied by the BS (present in the cell) while operating within a total power constraint.

Let $\mathbf{H}_{j,l}$ represent the $K \times M$ channel matrix, when the users in cell j receive signals from the BS of cell l and let its elements be given by zero-mean unit-variance i.i.d. complex Gaussian entries. Let $\mathbf{n}_j$ represent the additive white Gaussian noise at the receivers of

[1] We show the demand meeting power profile to be a NE of a 'leaky' game. We call this game 'leaky', because the utility of the game is upper bounded by the demands (see Definition 5, Section 3.1). In summary our aim is to provide a channel, to each one of the users, whose (system specific) capacity is more than or equal to the user's demand.