L'HOMME CONNECTÉ

Resource Allocation Challenges in Future Wireless Networks

Mohamad Assaad

Department of Telecommunications, Supelec, {Mohamad.Assaad}@supelec.fr

Mots-clefs: *Resource allocation, Wireless networks, distributed optimization. Nash equilibrium seeking*

Abstract
Future wireless networks are expected to be dense, self-organizing, energy efficient and cost effective. The network will be thus complex and will consist of a number of autonomously heterogeneous subsystems that should dynamically adapt their actions to ensure that the receivers decode packets correctly. Several nodes in the network should perform their actions in a fully decentralized way without exchanging information between each other (or with limited information exchange). This adds additional challenges to the problems of resource allocation in wireless networks. Our aim here is to provide a brief overview of the main resource allocation challenges in future wireless networks. An example of a resource allocation framework that does not require information exchange between the transmitters is provided.

Introduction
The proliferation of wireless multimedia applications necessitates the development of more advanced wireless systems that can support the expected high amount of mobile data traffic in the next years. It has been adopted by the 3GPP that the future 5G cellular networks must support the 1000-fold increase in traffic demand. This requires not only developing new physical layer techniques, e.g. Massive MIMO [1] and Millimeter wave (mmWave) [2], but also adopting a new architecture of the network. In fact, the increase of the capacity of macro cells cannot meet the requirement of future traffic demands. The network must have a more distributed architecture. Therefore, a user centric architecture would be adopted and the current concepts of uplink and downlink would be then reconsidered. The concept of Cloud RAN (Radio Access Network) is also emerging [3] where the processing of multiple base stations (that can be connected to a server platform through high rate backhaul) can be performed using real time virtualization techniques. Furthermore, smarter devices will be used and device-to-device (D2D) communications may be used in order the enable the exchange of traffic directly between users. Local caching of popular video traffic at devices and RAN edge can be used as well [4]. This will increase the capacity and spectral efficiency of the network. In this new architecture, two nodes can communicate with each other through various possible heterogeneous nodes (base station, small cell, D2D, multi-hop, etc.). Clearly, this will create additional challenges in allocating the resources in the network.

1. Resource Allocation in Future Wireless Networks
The resource allocation frameworks will be impacted by the new architecture of the network. Fully distributed algorithms that consider the advanced physical layer and traffic patterns must be developed. In addition, due the increase in number of users and resources, these algorithms must have very low computational complexity. One can therefore summarize the main challenges in developing resource allocation strategies as follows,

- The complexity of the problem: the computational complexity is the main issue to check especially with the increase of number of users and resources (e.g. massive MIMO). For NP-hard problems, low complexity sub-optimal solutions must be developed.
- The physical layer: the resources to allocate and the form of the resource optimization framework (e.g. convex/non-convex, combinatorial, etc.) depend mainly on the physical layer.
- The traffic pattern and QoS/QoE: this will add stochastic constraints to the optimization framework depending on the service used (real time, streaming, etc.).
- The non-existence of a central entity that can handle the allocation (e.g. D2D) and the amount of information exchange (signaling) between transmitters. This changes radically the formulation of the problem and the mathematical tools used to solve it (stochastic game theory, distributed optimization, distributed learning, etc.).
- The connectivity of the nodes especially in D2D communication.
- The availability at the transmitter of the system state information (e.g. CSI).

It is worth mentioning that some of the aforementioned points are already considered in the design of current resource allocation strategies. However, their impact will be more prominent in future wireless networks.

Several mathematical tools can be used to formulate and solve the resource allocation problems: game theory (and mean field game), distributed optimization, stochastic control, stochastic network optimization, learning, stochastic geometry, etc. These tools can be of great help to solve the problems in future wireless networks. In fact, there has been in the past substantial work on resource allocation using the aforementioned tools. For example, different approaches, mainly based on gradient descent/ascent method and distributed learning [5-7], have been developed to solve distributed optimization problems. Game theory has been an area of active research over the past decade (e.g. one can refer to [8] and the references therein). Recently, Nash equilibrium-seeking techniques have attracted a lot of attention due to their ability of dealing with distributed settings with limited information exchange in the network [9-12].
On the other hand, the aforementioned optimization and game frameworks tend to ignore the stochastic nature in the traffic patterns. However, the network must cope with a wide range of stochastic dynamics since the multimedia traffic is time varying and bursty in nature. In order to ensure QoS of the users, strong stability of the queues of the users is a necessary condition to fulfill in this case. Stochastic network optimization and stochastic control techniques can be then used in this context (e.g. one can refer to [13] and the references therein). Furthermore, randomized allocation policies can be used to develop such strategies as well. For example, decentralized scheduling algorithms were developed in series of works [14-18] with varying complexities and performances. A class of CSMA-based scheduling algorithms [19-22] is shown to have interesting throughput guarantees. However, most of the aforementioned works can only be used either for simple physical layer (conflict graph, etc.) or if one has an accurate abstraction of the physical layer. The extension of such policies to deal with the advanced physical layer of future networks is a challenging task.

2. Example of a resource allocation framework [11]

We provide here an example of a resource allocation framework that can be applied in the context of future networks. The scenario consists in a network of n interacting nodes or agents where each one has a reward function to maximize. The decision of each node has an impact on the rewards of the other nodes. Without loss of generality, the network is modeled as a set of transmitter-receiver pairs that interact with each other. Each transmitter-receiver pair has its own reward function that depends on the action of all the nodes in the network. The reward depends also on the state of the nodes (e.g. channel state) that is assumed to be a stochastic ergodic process. Unlike most of existing work (e.g. gradient based techniques, etc.), we assume that the reward function of each node has a complicated structure or unknown expression, e.g. user goodput or throughput. Recall that no closed form expression for rate/goodput is available especially for advanced coding scheme. Furthermore, we assume that each transmitter can only exchange an estimation of its own reward (i.e. numerical real value) with its own receiver. No other information exchange is allowed in the network.

The objective is to optimize a long-term reward function for all the nodes as follows,

$$\underset{a_j \in \mathrm{A}_j}{Sup}\ \mathrm{E}_S\left(r_j(S,a_j,a_{-j})\right)\ \forall\, j=1,\ldots,N$$

Where A_j is the action space of node j, **S** is the state space of the whole system, and the node reward $r_j(S,a_j,\mathbf{a}_{-j})$ is a smooth function. The state space **S** is a stochastic ergodic process that evolves such that $E_{\mathbf{S}}(r_j(S,a_j,\mathbf{a}_{-j}))$ is always finite.

In order to provide a solution to the aforementioned problem, we use the framework of Nash equilibrium seeking with continuous action spaces. Recently, there has been an increasing interest in non-model based Nash/extremum seeking techniques [9-10]. Distributed learning algorithms based on sinus perturbation, vanishing sinus perturbation and stochastic non-sinusoidal perturbations are developed (e.g. [9-10]). Although the above works are very promising, they do not cover the case of stochastic state dependent reward, which is very common in wireless networks where the channel is time varying. In [11-12], we have extended the framework of [9] to a more realistic wireless network scenario where the time is discrete and the payoff functions are stochastic state dependent.

We first propose a discrete leaning algorithm that can be applied separately by each transmitter/node. At each time k, each node applies the following algorithm [11]:

$$a_j(k)=\alpha_j(k)+b_j\sin\left(\omega_j t_k+\varphi_j\right)$$
$$\alpha_j(k)=\alpha_j(k-1)+\varepsilon_k b_j z_j\sin\left(\omega_j t_k+\varphi_j\right)r_j(k)$$

Where $a_j(k)$ is the action of the user at time k and $r_j(k)$ is the estimated numerical value of the reward of node j at time k. The other parameters in the aforementioned two equations are predefined constants.

In [11], we prove that our algorithm converges locally to a state independent Nash equilibrium for vanishing step size. Furthermore, we provide an error bound for the convergence for fixed step size. In addition, in [12], we have applied the above framework to the problem of power control in wireless networks. We have shown numerically that the aforementioned algorithm converges to Nash equilibrium. One can refer to [12] for more details.

References

[1] T. Marzetta, “Non-Cooperative Cellular Wireless with Unlimited Numbers of Base Station Antennas,” IEEE Transactions on Wireless Communications, vol. 9, no. 11, Nov. 2010, pp. 3590-3600.

[2] Z. Pi and F. Khan, “An Introduction to Millimeter-wave Mobile Broadband Systems,” IEEE Comm. Mag., vol. 49, no. 6, 2011, pp. 101-107.

[3] China Mobile, “C-RAN: The Road Towards Green RAN,” CRAN International Workshop, Beijing, China, Apr. 2010.

[4] N. Golrezaei et al., “Femtocaching and Device-to-Device collaboration: a New Architecture for Wireless Video Distribution,” IEEE comm. Mag., vol. 51, no. 1, Apr. 2013, pp. 142-149.

[5] Bianchi, P.; Jakubowicz, J.; ”On the Convergence of a Multi-Agent Projected Stochastic Gradient Algorithm,” Automatic Control, IEEE Transactions on, 2013.

[6] S. Ram, V. Veeravalli, A. Nedic,”Distributed and Recursive Parameter Estimation in Parameterized Linear State-Space Models,” Automatic Control, IEEE Transactions on, vol.55, no.2, pp.488-492, Feb. 2010 doi: 10.1109/TAC.2009.2037460

[7] Yiping Xing; Chandramouli, R.; Stochastic Learning Solution for Distributed Discrete Power Control Game in Wireless Data Networks, IEEE/ACM Transactions on Networking, Volume: 16, Issue: 4, 2008 , Page(s): 932 - 944

[8] S. Lasaulce & H. Tembine, Game Theory and Learning in Wireless Networks: Fundamentals and Applications, 336 pages, Elsevier, July 2011, ISBN: 9780123846983.

[9] P. Frihauf, M. Krstic, and T. Basar, “Nash equilibrium seeking in noncooperative games,” IEEE Transactions on Automatic Control, 57(5), May 2012

[10] Paul Frihauf, Miroslav Krstic, and Tamer Bassar, Nash Equilibrium Seeking for Dynamic Systems with Non-Quadratic Payoffs, Preprints of the 18th IFAC World Congress Milano (Italy) August 28 - September 2, 2011.

[11] A.F. Hanif, H. Tembine, M. Assaad and D. Zeghlache, "On the Convergence of a Nash Seeking Algorithm with Stochastic State Dependent Payoffs", under review.

[12] A.F. Hanif, H. Tembine, M. Assaad and D. Zeghlache, "Distributed Stochastic Learning for Continuous Power Control in Wireless Networks", IEEE SPAWC 2012.

[13] M. Neely, Stochastic Network Optimization with Application to Communication and Queueing Systems, Morgan and Claypool, 2010.

[14] L. Tassiulas. Linear complexity algorithms for maximum throughput in radio networks and input queued switches. In IEEE International Conference on Computer Communications, (INFOCOM 98), 2008.

[15] A. Eryilmaz, A. Ozdaglar, D. Shah, and E. Modiano. Distributed cross- layer algorithms for the optimal control of multihop wireless networks. IEEE/ACM Trans. Netw., 18(2):631–651, April 2010.

[16] A. Eryilmaz, R. Srikant, and J. Perkins, Stable Scheduling Policies for Fading Wireless Channels, IEEE/ACM Trans. Netw., vol. 13, no. 2, pp. 411-424, Apr. 2005.

[17] L. Bui, S. Sanghavi, and R. Srikant, Distributed Link Scheduling With Constant Overhead, IEEE/ACM Trans. Netw., vol. 17, no. 5, pp. 1467-1480, Oct. 2009. 54

[18] C. Joo, X. Lin, and N. Shroff, Understanding the Capacity Region of the Greedy Maximal Scheduling Algorithm in Multi-Hop Wireless Networks, in IEEE INFOCOM, Apr. 2008.

[19] L. Jiang and J. Walrand, A Distributed CSMA Algorithm for Throughput and Utility Maximization in Wireless Networks, IEEE/ACM Trans. Netw., vol. 18, no. 3, pp. 960-972, Jun. 2010. 54, 60

[20] S. Rajagopalan, D. Shah, and J. Shin, "Network adiabatic theorem: an efficient randomized protocol for contention resolution," In Proc. ACM International Conference on Measurement and Modeling of Computer Systems (SIGMETRICS 09), 2009.

[21] J. Ghaderi and R. Srikant, "On the design of efficient csma algorithms for wireless networks," In IEEE Conference on Decision and Control (CDC 10), 2010.

[22] S. Lakshminarayana, B. Li, M. Assaad, A. Eryilmaz and M. Debbah, A Fast-CSMA Based Distributed Scheduling Algorithm under SINR Model, IEEE International Symposium on Information Theory, Cambrigde, MA, USA, 2012.