Spectrum Spatial Reuse by Small Cells: The Necessary Condition for Wireless Capacity Scaling

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Mobile data traffic is growing at an unprecedented rate well beyond the capacity of today's 3G network. Many researches [1,2] forecast that by 2014, an average mobile users will consume 7GB of traffic per month which is 5.4 times more than today's average user consumes per month, and the total mobile data traffic throughout the world will reach about 3.6 exabytes per month, 39 times increase from 2009. There are several approaches in consideration to meet this explosive traffic growth, one of which is upgrading today's 3G network to a next-generation cellular network with enhanced PHY technology. However, the enhancement of PHY technologies approaches its theoretical limit and may not scale well with the explosive growth rate of mobile data traffic. According to Cooper's law shown in Fig. 1, the number of voice calls carried over radio spectrum has been increased by a million times since 1950, and Cooper also predicted that this would continue for the foreseeable future [3]. Of that million times improvement, roughly 25 times was from using more spectrum, 5 times was from using frequency division, and another 5 times was from the enhancement of PHY technologies. But the lion's share of the improvement – a factor of about 2700 – Cooper suggested was the result of spatial reuse of spectrum in smaller and smaller cells. Cooper's law tells us that despite being close to the Shannon limit, there is no end for practical increases in wireless capacity if we are prepared to invest in an appropriately dense infrastructure.

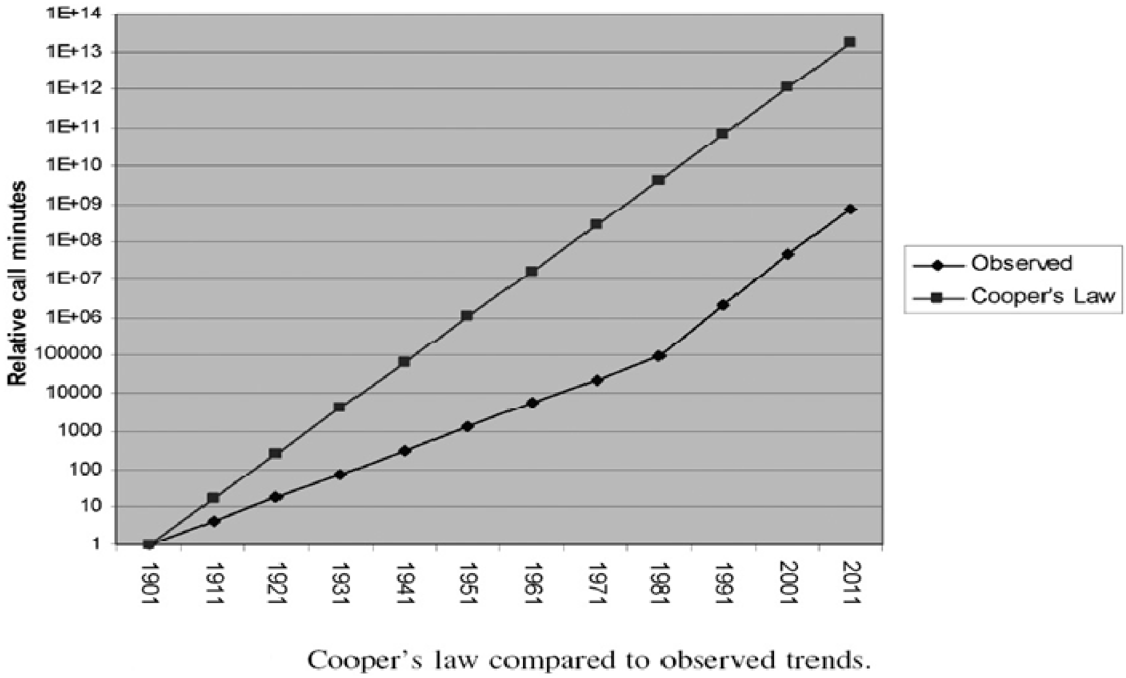

Fig. 1 Cooper's Law

The small cell gain, however, comes at a high cost. As the infrastructure becomes denser with the addition of smaller cells, inter-cell interference (ICI) inevitably becomes higher and more complex to manage. Thus, a key technical challenge in scaling wireless capacity by increasing the density of cells is how to effectively manage ICI in such a complex cellular deployment. Another important technical requirement for small-cell networks is self-*x* capability of cells where *x* includes configuration, optimization, diagnosis, healing etc. since small-cell base stations would be less reliable and in many cases their deployment/removal and on/off would be done by individual subscribers in an ad hoc manner, not by operators in a pre-planned manner. The self-*x* capability is an enabler for fully-distributed autonomous network management that can realize the small cell gain without suffering much from exponentially growing complexity of network management.

ICI management problem can be tackled at PHY layer and also at upper layers such as MAC, routing, transport layers. Techniques such as Successive Interference Cancelation, Interference Alignment are the examples of PHY-layer ICI management techniques. Mathematically, ICI management problem at upper layers and self-*x* problem can be tackled in the light of stochastic network utility maximization (NUM) problem with queue stability constraint [4-6], which is generally given by

$$\max_{R\in\Lambda}\sum_{s}U_s(R_s) \qquad (1)$$

where $R=[R_s]$ is the vector of long-term average rates of all users in the network, Λ is the long-term rate region of the network that can be shown to be always convex if the randomness in wireless channels has a finite set of states and the sequence of states forms an irreducible Markov chain with stationary distribution, and U_s is a concave utility function of user *s*. Assume that exogenous arrivals to the network follow a stochastic process with finite mean and each wireless link is equipped with a transmission queue.

It is known that the above NUM problem can be asymptotically solved by solving the following MAC-layer problem in (3) in conjunction with the transport-layer algorithm in (2) (here we assume that route is fixed for all flows for simplicity)[4-6]. At time t, each source s independently determines its instantaneous data rate $r_s(t)$ by

$$r_s(t)=U_s'^{-1}\left(\sum_{l\in L(s)}q_l(t)\right) \qquad (2)$$

where $L(s)$ is the set of links on the route of flow s and $\sum_{l\in L(s)}q_l(t)$ is the end-to-end queue length of flow s at time *t*. Note that this form of source congestion control can be easily implemented at transport layer in a fully distributed manner by the help of end-to-end signaling to carry queue length information to the source. In fact, the necessity of end-to-end signaling can be removed without losing optimality if each flow has separate queue at every link.

The key technical challenge lies in the MAC-layer problem, expressed by the following network-wide weighted sum rate maximization problem

$$\max_{P}\sum_{l}q_l(t)r_l(t,P) \qquad (3)$$

where $q_l(t)$ is the queue length of link *l* at time *t*, $P=[P_l]$ is the vector of power allocations of all links in the network and $r_l(t,P)$ is achievable rate of link *l* at the power allocation *P* given network-wide channel state at time *t*. This problem is indeed a core problem that arises in any wireless networking problem, for instance, ICI management problem in a cellular network, modeled by a stochastic NUM problem, is nothing but finding *P* repeatedly at each time *t* from (3). Note, however, that the problem not only requires centralized computation using global information but is also computationally very expensive. As an illustrative example, consider an important special case of the problem that each P_l can take either 0 or its maximum value and, furthermore, the choice of P is restricted not to activate any two interfering links simultaneously for conflict-free transmission. Then, the original problem is reduced to so called max-weight scheduling problem [7,8] that is a central research theme of multi-hop wireless networking research community. The max-weight scheduling problem is a NP-hard problem since it involves a weighted maximum independent set problem of NP-hard complexity. As another example, consider ICI management problem in a multi-carrier, multi-cell network [9,10]. The corresponding MAC-layer problem turns out to be a centralized joint optimization problem of user scheduling and power allocation, which is computationally very expensive since the user scheduling involves multiple NP-hard problems and the power allocation involves nonconvex optimization.

There have been several works to find low-complexity, distributed algorithms for the max-weight scheduling problem and the dynamic ICI management problem. In [8], a randomized algorithm, called as pick-and-compare algorithm, has been proposed. The algorithm asymptotically solves the max-weight scheduling problem with linear complexity but the reduction of complexity comes at the cost of slow convergence and increased delay. In [11,12], distributed maximal/greedy scheduling algorithms have been studied but they yield approximate schedules losing throughput optimality. Recently, in [13-15] it is shown that CSMA algorithms can asymptotically solve the max-weight scheduling problem if the product of back-off time and packet transmission time is adjusted as an exponential function of the weight $q_l(t)$ and the first prototype implementation on a real 802.11 hardware has been reported in [16]. Nevertheless, finding and prototyping low-complexity, distributed max-weight scheduling algorithms is still an open problem that has many issues to be resolved, one of which is delay issue. The max-weight scheduling intrinsically suffers from large delay incurred by queue buildup and thus how to reduce delay while minimizing loss in throughput optimality is one of the top priority research issues. On the other hand, research on low-complexity, distributed algorithms for the ICI management problem has received relatively less attention from networking community and there are only a few notable works [9,10] available in the literature. In [9], a concept of reference user has been introduced to decentralize the network-wide optimization and to lessen the involved computational complexity but the algorithm cannot guarantee throughput optimality. Proof of concept through prototype implementation, for instance, prototyping and evaluation on a real 802.11 hardware, is also an important research direction in this area. The key question to be answered there is how much capacity gain one can actually achieve by adding low-complexity, fully distributed ICI management functionality in a massively and arbitrarily deployed WiFi access points environment.

In summary, the MAC-layer problem in (3) is a core problem that inevitably arises and needs to be solved in any wireless network whose objective is to maximize network-wide sum utility. ICI management in small-cell networks is an important special case of the general problem. Development and experimental validation of low-cost, fully distributed algorithms for the problem is a very challenging research issue and the key step to realize self-*x* small-cell networks that are believed to be the most effective way to scale wireless capacity continuously without known limit.
The theory suggests that source congestion control to be in the form of (2) but in reality TCP does source congestion control. Another interesting questions are how TCP interacts with the MAC-layer problem and what modification is necessary for TCP.

Network greening is a rapidly emerging research area. From a radio resource control point of view, network greening is in a loose sense a dual problem of the stochastic NUM. Maximizing network capacity for a given power budget is reciprocal to minimizing power consumption for a given capacity requirement. Thus, study on small-cell networks from a network greening point of view would be another important research direction.

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