CHANNEL SIMULATION WITH LARGE-SCALE TIME EVOLUTION IN IRREGULAR CELLULAR NETWORKS

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ABSTRACT

We consider a cellular network where base stations with widely different power capabilities (power subclasses) are deployed in a highly inhomogeneous or irregular pattern—referred to in this work as an *irregular cellular network*. A simulation framework with slow scale time variation appropriate for irregular networks is proposed. A relevant resource allocation framework as well as shadowing and path loss models are discussed. Finally, the time evolution methodology is detailed. It is believed that the proposed simulation framework will be important in the evaluation of slowly adaptive algorithms such as those studied as part of 3GPP LTE Self Organizing Networks (SON).

Index Terms— autonomous cellular networks, irregular cellular networks, wireless channel simulation, self organizing networks (SON), wireless network dynamics

1. INTRODUCTION

Fundamentally important changes in dynamic user behavior have been driving the emergence of more flexible and adaptive cellular networks. This paper considers a network consisting of base stations (BSs) with widely different power capabilities, or power subclasses, that are deployed in a highly irregular or inhomogeneous fashion. Such a network shall be referred to here as the *irregular cellular network* [1-3]. A similar concept, called network heterogeneity or heterogeneous networks, has recently become popular [4]. However, the main trend in that case has been to consider the large BSs and the small BSs basically as separate networks, or tiers. In contrast, the irregular network is expected to have a unified air interface. In addition, the available BS power subclasses will not need to be limited by the classical categories such as femto, pico and macro-BSs. Simulation of irregular networks is discussed in the following.

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1.1. The drop-based simulation concept and its modification for irregular networks

The *simulation drop* concept is commonly used in state-of-the-art channel simulations of the cellular network. It is included in the WINNER II project [5] and in the evaluation guidelines for the 3GPP LTE network [6]. A drop—as commonly defined—is a random deployment of mobile terminals. In a drop simulation, large-scale parameters such as path loss and shadow fading are fixed, and there is only virtual movement of terminals, which results in the multipath fading due to the Doppler effect. The time scale of multipath variation is important as it represents the granularity of classical user scheduling. In LTE, the time unit for user scheduling is known as the subframe [7]. The gradual time evolution of multipath fading is modelled in the simulation according to the theory extensively discussed in the literature [7]. In order to obtain statistically representative results, a large number of subframes are simulated in each drop. Also for the same reason, a large number of drops are used in the overall simulation. Notably, however, the time evolution of the terminal positions and the large scale channel parameters at the drop level is typically not modeled; in fact, each drop is normally generated independently from other drops. It is argued in the following that time evolution of drops will need to be modeled for emerging and future networks.

Recently, various adaptive algorithms (functions) working at much slower time scales than the fading, or the subframe in LTE, have gained much attention in the literature. The algorithms include dynamic cell assignment [8], dynamic clustering [1] and BS power control [9] as well as the adaptive organization of interference coordination schemes [10]. Such functions have also been studied in context of 3GPP LTE Self Organizing Networks (SON) [11]. In implementing slowly adaptive functions, that essentially work at the time scale of the drop, it becomes important to minimize algorithm and signaling complexity. This is especially true if centralized decision making or coordination is required for the specific implementation. We note that implementation complexity can be reduced by considering that the evolution of the cellular channel and environment is gradual in time, meaning that each execution of the function can utilize the information from the previous execution. In order to accurately evaluate the performance of such reduced-complexity adaptive algorithms, it is necessary to model the time evolution of the cellular channel and environment.

In this paper, we propose a general framework to model the time evolution at the slow time scale in the context of irregular networks. For the purpose of modelling, we consider a modification of the original drop-based simulation. Specifically, the simulation drop is re-defined as an independent deployment of both BSs and terminals, and time evolution is generated by introducing a series of small dynamic changes on each drop. Each modified version of the drop is referred to as a *subdrop*. Both terminal and BS dynamics are considered. The rest of this paper gives details on the simulation framework. Section 2 discusses the system model and the framework for resource allocation. Section 3 introduces the channel models. Section 4 discusses the methodology for network time evolution. Section 5 summarizes the overall simulation framework, and section 6 gives a conclusion.

2. SYSTEM MODEL AND SCHEDULING

We consider an irregular cellular network consisting of a set of BSs $\mathcal{N}$ and a set of terminals $\mathcal{K}$. BSs $n \in \mathcal{N}$ and terminals $k \in \mathcal{K}$ are placed over an area according to a uniform random distribution. Downlink communication is considered. At a given time, terminal k is assigned to a single BS, $n(k)$. Each BS belongs to a power subclass $s \in \mathcal{S}$, which is characterized by a distinct power capability $P_{s,max}$. The power subclass of BS n is denoted as s_n. The actual power level of a BS, P_n, is bounded as $0 \le P_n \le P_{s_n,max}$. The BS assignment, $n(k)$, of each terminal and the power level, P_n, of each BS is updated periodically with the changes in the network.

An orthogonal frequency division multiple access (OFDMA) scheme is considered with the set of available subcarriers denoted by $\mathcal{C}$. The channel power gain, $g_{k,n,c}$, between BS n and terminal k on subcarrier $c \in \mathcal{C}$ is computed as the product of the distance-dependent path loss component, $PL_{k,n}$, slowly-varying shadowing component, $SF_{k,n}$, and the fast-varying multipath component, $m_{k,n,c}$:

$$g_{k,n,c} = PL_{k,n} SF_{k,n} m_{k,n,c}.$$

Scheduling of the OFDMA subcarriers is performed every subframe. According to the current framework, the power budget P_n of each BS is divided evenly across the C subcarriers. As an additional level of flexibility, the BS powers are allowed to switch on and off for each subcarrier at every subframe. The scheduling and resource allocation is based on the proportional fair criterion [12], for which the optimization problem to be solved by each BS is

$$\max \textstyle\sum_{k\in\mathcal{K}_\mathrm{n}} \log(\overline{R_{kn}}). \tag{1}$$

where $\mathcal{K}_\mathrm{n}$ is the set of terminals assigned to BS n, and $\overline{R_{kn}}$ is the long-term average rate for terminal k served by BS n. For a single frequency system at a given subframe t, the optimization of (1) is equivalent to scheduling terminal $k_n^*(t)$, knowing instantaneous rate $r_{kn}(t)$ and average rate $\overline{R_{kn}(t)}$:

$$k_n^*(t) = \arg\, \max_{k\in\mathcal{K}_n} \frac{r_{kn}(t)}{\overline{R_{kn}(t)}}.$$

For each scheduled terminal, $\overline{R_{kn}(t)}$ is updated according to

$$\overline{R_{kn}(t)} = \left(1-\frac{1}{T}\right)\overline{R_{kn}(t-1)} + \left(\frac{1}{T}\right) r_{kn}(t),$$

where T is the averaging window size selected for smooth averaging.

2.1. Resource allocation and adaptation framework

In order to compute instantaneous rates for proportional fair scheduling, each BS ideally needs to have the knowledge of the interference originating from all the other BSs. However, the network-wide exchange of the interference information at every subframe would lead to prohibitive signalling complexity, especially for multicarrier systems. A solution has therefore been proposed [1] where the BS set $\mathcal{N}$ is partitioned into subsets referred to as *clusters*. Interference information is exchanged among BSs inside each cluster, that is, scheduling coordination occurs inside a cluster. Each cluster, however, operates independently from all other clusters. Note that the set of clusters is updated with the changing network dynamics at the slow time scale of variation. As discussed earlier in the section, the BS assignments $n(k)$ and BS power levels P_n also need to be dynamically updated at the slow time scale of variation. It is important to note that the slow time scale corresponds to the subdrop (the name given to each modified version of a simulation drop in the proposed simulation framework). A dynamic framework for resource allocation is considered with two time levels of adaptation, largely based on the work in [1]. At the slow (subdrop) time scale, users are assigned to terminals, BS power levels are adjusted and clusters are formed. At the fast (subframe) time scale, multicarrier proportional fair resource allocation (scheduling and on-off power switching) is performed with coordination inside each cluster.

Dynamic BS assignment, dynamic clustering as well as proportional fair scheduling and fast power-switching are performed according to algorithms discussed in [1]. However, to our knowledge, no algorithm has been proposed in the literature for dynamic adjustment of BS powers, $\{P_n\}$, in irregular networks. Using the assumption that the power budget of each BS is divided evenly across all C subcarriers (with possible fast power switching), we infer that the choice of the set $\{P_n\}$ has a direct effect on average rates $\overline{R_{kn}}$ for each user k. Thus, it is proposed that $\{P_n\}$ be chosen according to proportional fairness:

$$\{P_n^*\} = \max_{\{P_n\}} \sum_k \log(\overline{R_{kn}}).$$

A detailed power adjustment algorithm is beyond the scope of the paper, and is left for future work.

3. CHANNEL MODELS

Channel models appropriate for the irregular network are discussed in this section. Firstly, the modelling of multipath fading with evolution in time and frequency has been discussed extensively in the literature. According to the ITU recommendations, the ray cluster method is used in multipath modelling for LTE. For more details, the reader may refer to existing work [6, 7]. The current paper deals with the slow-time-scale variation, thus the focus of the discussion will be shadowing and distance-dependent path loss models for the irregular cellular network.

In particular, with respect to shadowing, it becomes important in irregular cellular networks to have an accurate model for shadowing correlation over space. One particular application is in generating shadowing for two channel links involving two closely-located BSs and their respective assigned users. Due to the close location of the BSs, the topographical properties around the BSs are expected to be similar, potentially leading to closely-correlated shadowing values. In [13], the type of link described was referred to as a non-common-endpoint link, and a shadowing model with appropriate correlation was proposed. The model in that work is adopted in this paper.

A second issue is the study of the dependence of shadowing and path loss model parameter values on the topographic properties around BSs with different power subclasses. Due to the different physical environments implied, it is expected that the parameter values change based on the BS power subclasses associated with both the transmitter and the receiver (as well as, potentially, with any point along the path of the BS-terminal link in question) [7, 14]. We note that a general theory for the environment and BS power subclass dependence is not well understood [14] and is beyond the scope of this paper. In the current work, the model parameter values for the link between a given BS n and terminal k will be assumed to depend on the power subclass of BS n, s_n, and the power subclass of the BS associated with terminal k, $s_{n(k)}$. In the rest of this paper, $s_{n(k)}$ will be denoted in shorthand notation as $s_{(k)}$. For a model parameter χ, the dependence is, therefore, expressed as $\chi = \chi(s_n, s_{(k)})$.

3.1. Distance-dependent path loss model

Let $A = A(s_n, s_{(k)})$ be the fitting parameter that includes the path loss exponent, $B = B(s_n, s_{(k)})$ the intercept parameter, $C = C(s_n, s_{(k)})$ the parameter for path loss frequency dependence, and $X = X(s_n, s_{(k)})$ the environment-specific parameter. Furthermore, d_{kn} is the distance between terminal k and BS n in metres and f_c is the system frequency in GHz. The distance-dependent path loss between terminal k and BS n is a function of the BS power subclasses and is given in the form [5]

$$PL_{k,n}(s_n, s_{(k)})\ [\text{dB}] = A(s_n, s_{(k)}) \log_{10}(d_{kn}) + B(s_n, s_{(k)})$$
$$+ C(s_n, s_{(k)}) \log_{10}\left(\frac{f_c}{5.0}\right) + X(s_n, s_{(k)}).$$

3.2. Shadowing model

Spatially correlated shadowing is generated by first forming a Gaussian shadowing potential field over the network area. The potential field is a random process whereby each realization is a function from the plane to the real numbers.

Consider a deployment scenario with shadowing standard deviation $\sigma_0 = \sigma_0(s_n, s_{(k)})$ (in dB) and correlation distance, $d_c = d_c(s_n, s_{(k)})$, in metres. The shadow fading for a single BS-terminal link, as a function of BS power subclasses, is generated in the following steps:

- Step 1: Generate the BS potential level X_n and the terminal potential level $X_{(k)}$ such that X_n and $X_{(k)}$ are jointly Gaussian random variables with standard deviation $\sigma_{k,n}$ and correlation $\rho_{k,n}$ given by

$$\sigma_{k,n} = \sigma_0(s_n, s_{(k)})/\sqrt{2}$$

$$\rho_{k,n} = \rho(d_{kn}) = \frac{\sigma_0^2(s_n, s_{(k)})}{2} \exp\left(-\frac{d_{kn}}{d_c(s_n, s_{(k)})}\right)$$

- Step 2: Compute the shadowing, $SF_{k,n}$, as a function of X_n and $X_{(k)}$ according to

$$SF_{k,n}(s_n, s_{(k)})\ [\text{dB}] = f(X_n, X_{(k)}) = \text{sgn}(X_n + X_{(k)})\, |X_n - X_{(k)}|$$

4. TIME EVOLUTION METHODOLOGY

As defined in section 1, a simulation drop is an independent deployment of BSs and terminals, and the subdrop is the name given to each dynamically modified version of a drop. In anticipation of greater dynamism in future irregular networks, BS dynamics are also considered. The list of network dynamics therefore includes gradual terminal arrivals, departures and movement; BS deployments, outages and movement as well as changes in the large-scale channel parameters. Time evolution methodology is discussed in detail in this section.

Let $\mathcal{P}$ be the set of drops used in the simulation, $\mathcal{B}_p$ the set of subdrops associated with drop $p \in \mathcal{P}$ and $\mathcal{F}_b$ the set of subframes associated with subdrop $b \in \mathcal{B}_p$. The number of subdrops used in each drop is equal, that is, $B_p = B;\ p \in \mathcal{P}$. Similarly, an equal number of subframes is utilized in each subdrop, or $F_b = F;\ b \in \mathcal{B}$. For consistency of notation, the initial deployment of a drop before any time evolution is referred to as subdrop 0. The remaining subdrops associated

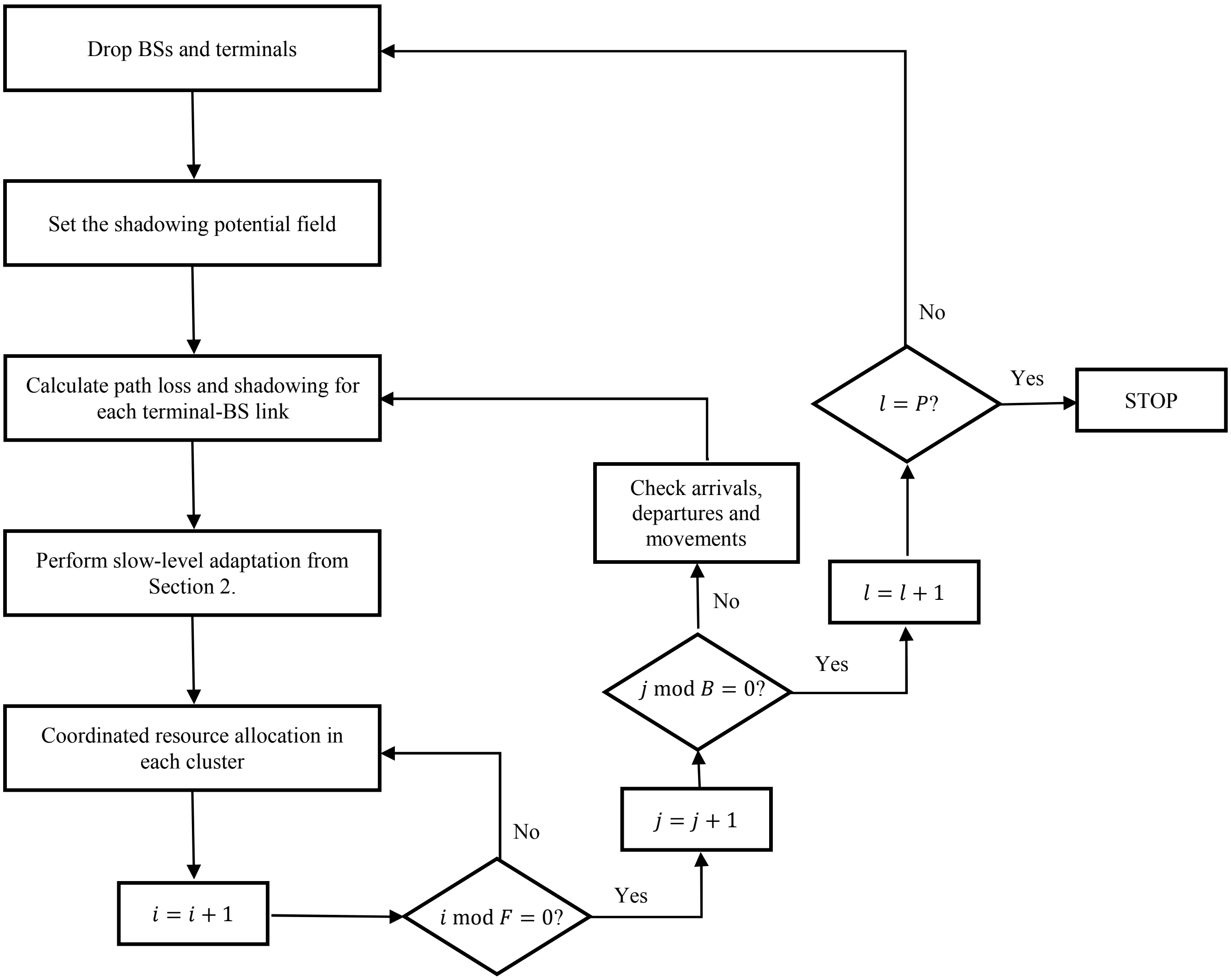

Fig. 1. The overall channel simulation framework. Here, F is the number of subframes in each subdrop, B is the number of subdrops in each drop and P is the number of drops. i, j and l are counters which are initialized to 0.

with the drop are numbered from 1 to $B - 1$. It is important to note that for all subdrops associated with a drop, the shadowing potential field realization as discussed in Section 3.2 is fixed. In other words, the dynamism in subdrops results solely from gradual changes relating to BSs and terminals on a given and fixed topography.

Let $\mathcal{N}_{(b)}$ and $\mathcal{K}_{(b)}$ be the set of BSs and terminals active at subdrop b, respectively. Specifically, $\mathcal{N}_{(0)}$ and $\mathcal{K}_{(0)}$ denote the set of BSs and terminals active at subdrop 0. At each subsequent subdrop $1 \leq b \leq B$, $[\Delta \mathrm{K}_a]_{(b)}$ terminals arrive at uniform randomly distributed locations according to the standard Poisson distribution

$$f(i; \lambda_t) = Pr\left([\Delta \mathrm{K}_a]_{(b)} = i\right) = \frac{{\lambda_t}^i e^{-\lambda_t}}{i!},$$

where $f(\ )$ denotes the probability mass function, and $\lambda_t > 0$ is the Poisson parameter. Each terminal departs the system after a holding time, τ_k, expressed in number of subdrops. τ_k is generated according to the following steps:

- Step 1: A virtual holding time, x, is generated according to the exponential probability mass function with parameter $\mu_t > 0$:

$$f(x) = \begin{cases} \mu_t e^{-\mu_t x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

- Step 2: The actual holding time, τ_k, is then given by

$$\tau_k = \lfloor x \rfloor$$

Terminal holding times, τ_k, determine $[\Delta K_d]_{(b)}$, the number of terminals departing at subdrop b. The total number of terminals remaining at subdrop b is updated according to

$$K_{(b)} = K_{(b-1)} + [\Delta K_a]_{(b)} - [\Delta K_d]_{(b)}$$

The simulation framework optionally allows for BSs to be deployed (arrive) and have outages (depart the system). I_{bs} is an indicator parameter which is set to 0 if BSs are not allowed to arrive and depart (that is, the set $\mathcal{N}_{(0)}$ is fixed over the drop), and to 1 if arrivals and departures are allowed. BS arrivals and departures are determined according to the methodology for terminal arrivals and departures with Poisson parameter λ_{bs} and exponential parameter μ_{bs}. The total number of BSs remaining at subdrop b is updated according to

$$N_{(b)} = N_{(b-1)} + [\Delta N_a]_{(b)} - [\Delta N_d]_{(b)}$$

It is assumed that every subdrop, terminals move by a randomly generated displacement in a random direction. The direction of movement over the xy-plane is represented by angle $\theta_{k,b}$, which is drawn from a uniform distribution in $[0, 2\pi]$. The displacement, denoted as $\Delta d_{k,b}$, is drawn from a uniform distribution in $\left[\Delta d_{t,min}, \Delta d_{t,max}\right]$.

The framework also (optionally) allows for each BS to move according to the same random movement model, with a fixed probability of movement denoted by π_{bs}. BS movement model parameters are $\Delta d_{bs,min}$ and $\Delta d_{bs,max}$. Finally, setting $\pi_{bs} = 0$ indicates that BS movement is disallowed.

5. OVERALL SIMULATION FRAMEWORK

The overall simulation framework is illustrated in Fig. 1. A large number of drops are used in the simulation. For each drop, the BSs and terminals are deployed, and the shadowing potential field is fixed. B subdrops are generated through gradual network dynamics, which include terminal and BS arrivals, departures and movements. The shadowing and path loss for each wireless link is re-calculated at every subdrop. Resource allocation is performed according to the two time-level framework discussed in section 2. The complexity of the simulation framework is seen to be proportional to PBF, compared to traditional simulation (without slow evolution) that has complexity proportional to PF.

6. CONCLUSION

With the emergence of irregular cellular networks and popularity of slow-time-scale adaptive algorithms (such as those in 3GPP LTE SON), there is a need for simulation methodologies with time evolution. In this paper, a channel simulation framework with time evolution, based on a modified simulation drop concept, was proposed. Terminal, BS and channel dynamics were considered. The subdrop was introduced as the step-wise evolved version of the simulation drop. Channel models were discussed with an emphasis on distance-dependent path loss and shadowing. The time evolution methodology was introduced. The evolution methodology is parameterized so that it can be used for a variety of different situations. It is believed that the channel simulation framework will be important in the evaluation of future slow-time-scale adaptive algorithms for emerging cellular networks.

REFERENCES

[1] B. Golkar and E. S. Sousa, "Resource allocation in autonomous cellular networks," *IEEE Trans. Wireless Commun*., vol. 12, no. 11, pp. 5572-5583, Nov. 2013.

[2] L. Kayili and E. Sousa, “Cell outage compensation for irregular cellular networks,” to appear in *WCNC 2014*.

[3] E. S. Sousa, “Autonomous infrastructure wireless networks,” U.S. Patent, publication number: Wo/2005/120101. December 2005.

[4] S. Parkvall, A. Furuskar, and E. Dahlman, “Evolution of LTE toward IMT-advanced,” *IEEE Commun. Mag.,* vol. 49, no. 2, pp. 84–91, Feb. 2011.

[5] IST-WINNER II Deliverable 1.1.2 v.1.2, “WINNER II Channel Models,” IST-WINNER2, Tech. Rep., 2008.

[6] ITU-R M.2135, Requirements related to technical performance for IMT-Advanced radio interface(s), Std., 2008.

[7] F. Khan, *LTE for 4G Mobile Broadband: Air Interface Technologies and Performance*. Cambridge University Press, 2009.

[8] K. Son, S. Chong, and G. de Veciana, “Dynamic association for load balancing and interference avoidance in multi-cell networks,” *IEEE Trans. Wireless Commun.*, vol. 8, no. 7, pp. 3566–357, Jul. 2009.

[9] S. E. Nai, T. Q. S. Quek, and M. Debbah, “Shadowing time-scale admission and power control for small cell networks,” in *IEEE Int. Symp. Wireless Pers. Multimedia Commun.,* Taipei, Taiwan, Sep. 2012.

[10] B. Rengarajan, A.L. Stolyar, and H. Viswanathan, “Self-organizing dynamic fractional frequency reuse on the uplink of OFDMA systems,” in *Proc. 44th Annual Conf. Information Sciences and Systems (CISS)*, 2010, pp. 1-6.

[11] O. G. Aliu et al., “A Survey of Self Organisation in Future Cellular Networks,” *IEEE Commun. Surveys Tuts*, 2012. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6157579

[12] F. P. Kelly, “Charging and rate control for elastic traffic,” *European Transactions on Telecommunications*, vol. 8, pp. 33-37, 1997.

[13] B. Golkar and E. S. Sousa, "A network shadow fading model for autonomous infrastructure cellular networks", in *20th European Signal Processing Conference (EUSIPCO)*, August 2012.

[14] S. S. Szyszkowicz, H. Yanikomeroglu and J. S. Thompson, “On the feasibility of wireless shadowing correlation models,” *IEEE Trans. Veh. Technol.,* vol. 59, no. 9, pp. 4222-4236, Nov. 2010.