Throughput Analysis on Cognitive Radio Networks for AMI Meters in Smart Grid

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Abstract— **In this paper a framework is presented based on 4G Cognitive Radio (CR) network capable of communicating with high numbers of geographically dispersed smart meters for command and control feature concurrently with private cellular network. Our approach uses pervasive smart grid systems (i.e. cloud data centers) as the central communication and optimization infrastructure supporting metropolitan area based smart meter infrastructure. In this paper, we investigate the performance of various scheduling algorithms in context with CR units to provide a satisfactory tradeoff between maximizing the system capacity, achieving fairness among cognitive users. We lay as a framework evaluation 3GPP LTE system model simulations. Our system level simulation results show that the 4G CR network model meets the smart grid protocols requirements for a multi-user CR network of Smart meters.**

Keywords-4G Cognitive radio networks, cloud data center, scheduling algorithms, and smart meters

I. INTRODUCTION

We consider the future smart grid as leveraging Information and Communications Technology (ICT) facilitated by the smart meter (also named as Advance Infrastructure Metering (AMI)) information networks. The smart meter enables the flow of real-time information within the power utility, between the power utility and its customers. It is essential for AMI to be networked since it enables system wide sensing, utility and customer linkages, and future self healing capability.

Communication network infrastructures represent a very large capital expense. Research on CR has evolved from SDR (see [1-2]) with an objective of efficient utilization of radio spectrum. In this paper, we analyze CR in the context of smart energy systems. Although there have been significant advances and improvements in CR hardware, algorithms, and protocols, less attention has been given to developing ubiquitous and pervasive metropolitan scale CR networks, particularly with respect to smart grid information networking[3]. A metropolitan infrastructure based CR networks is shown in Fig. 1. In this context, there are major challenges to overcome such as Secondary Users (SU) should sense the spectrum and timely model the behavior of the Primary Users (PU). The other issue is how the SUs manage the available spectrum resources and share the resources among the SUs to satisfy the smart grid protocol requirements and meeting the interference constraints suggested by the FCC Spectrum Policy Task.

In such a system, our objective for SUs (i.e. AMI) is to efficiently transmit their delay sensitive traffic over the network and meet the QoS requirements of the smart grid protocol. In this paper, we investigate different scheduling polices that maximize the downlink sum throughput in the given area and achieving fairness among the SUs. We present an opportunistic scheduling policy that exploits both maximizing the downlink sum throughput and fairness under time-varying channel conditions for multi-user CR network in a metropolitan based environment.

Several authors have defined aspects of AMI networking in smart grids. Mesh, Ethernet and cellular AMI network topology for smart grid has been proposed. In [4] the authors propose mesh networks of Zigbee based transmission architecture. In [5], the authors discuss communication infrastructure based on Ethernet (LAN and WAN). The approach will support automated meter readings and customer home appliance connections. However, wireline systems are not always available. Customer subscription to service must occur and wired system can be challenging to rapidly redeploy, particularly in swiftly enveloping emergencies.

The authors in [6] describe a framework for RF mesh networking interfaced with high speed WiMAX access networks. In [7], overview of architecture, hardware platform, is reported to enable CR for smart grid communications. Our work discusses the CR network infrastructure architecture from 4G perspective. We also present multi-user performance analysis of various scheduling algorithms in context with AMI units considering the delay occurred due to offloading the processes to cloud in our architecture.

II. 4g Cognitive radio framework

A. *4G cognitive radio system architecture*

We presume a LTE network as a CR LTE network (4G CR), if the LTE work is adopted the CR techniques. We consider a cloud data center infrastructure based CR network coexisting with PU network shown in Fig.1. The coverage of both the CR base station and PU network base station are similar. As depicted in the Fig. 1 at the center of the each cell, there is base-station which is shared as e Node-B for PUs and as antenna for SUs. The PU base-station only serves to PUs as it lacks the CR protocols capabilities to support SUs. However, it may consider supporting certain features in order to communicate with SUs.

Placement of a Cognitive Radio Antenna on the BTS tower may occur in tandem with deployment of the cellular provider antenna. The CR senses the spectral environment over a wide frequency band, particularly the spectrum in the cell region. It identifies the unused bands in the spectrum. These bands could be owned by cellular companies or license television band owners, but are not limited to these bands or to licensed bands. Sensed information using the CR is relayed to cloud data center. In principle, eNode-B which terminates the air interface protocol and first point of contact for PU is located at the primary user base-station. However, in proposed architecture all the cognitive radio service, waveform service, protocols service, security service, scheduling and control services are displaced into cloud data center. The CR services indentify unused frequency bands, the relevant cognitive services residing in the cloud data center generates a clear to send (CTS) signal.

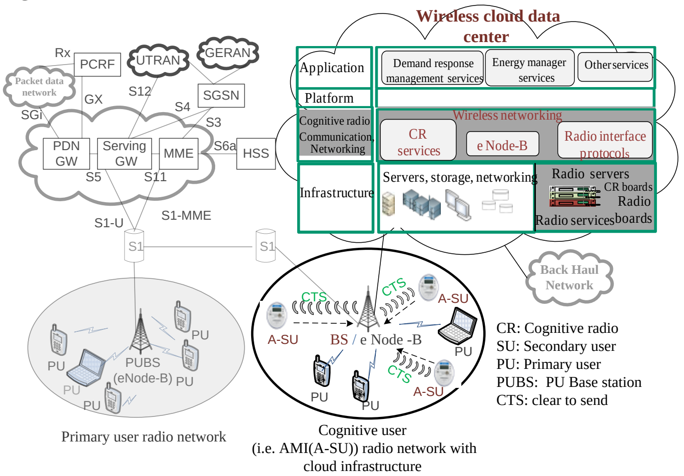

Fig. 1. 4G CR network system architecture: Scenario of multiple AMI meters serviced by cognitive radio network infrastructure enabled by cloud center coexisting with private cellular network

The CTS is sent back to the AMI meters through the feedback channel via base station. Eventually, the CR antenna relays CTS signals to every AMI in the cell region for uplink transmission.

1) Pervasive smart grid systems

The energy services of the future can be privately contracted services or public services. The cloud center enables convenient, on-demand network access to a shared pool of configurable, computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort. There are different cloud computing platform classifications. Standard architectures includes Abi (or Abiquo), Nimbus Open Nebula, Azure (Microsoft), Google (App Engine), Blue (IBM) and Mosso (Rackspace). Fig.1. depicts the model for a cloud data center architecture optimized for based smart grids. Our Wireless Cloud Data (WCD) model is organized into four principle layers: application layer, platform layer, CR communication and networking layer and infrastructure layer. The first two layers are akin to existing cloud architectures. However, the lower two layers are augmented to enable the CR networking and wireless services. CR communication and networking layer provides services such as cognitive radio services, waveform services, Radio Link Control (RLC), and Medium Access Control (MAC) services. CR services, which provide spectrum management and spectrum sensing, are discussed in detail in section III. The infrastructure layer facilitates the effective integration of computing resources, storage, networks to deploy applications and operating systems. We augment our cloud infrastructure microprocessor racks with FPGA boards targeted to processing high computation rate processes typically associate with CR services, communication waveform signal processing and coding.

III. CR SYSTEM MODEL

In the paper system model 4G cellular network is considered with N_{su} secondary users sharing the spectrum simultaneously with N_{pu} primary users. It is presumed in the context that the secondary users (i.e. AMI meters) are fixed in sense of geographical location and yields to fixed first and second statistical moments of SINR.

A. Spectrum Sensing

The spectrum sensing is one of the main layer tasks for CR system to obtain the spectrum usage information and the presence of PUs. Spectrum detection is based on the detection of the signal from PU through the observation of cognitive radio network.

The sensing methods can be categorized in three methods: i) Energy Detection, ii) Matched Filter, and iii) Feature Detection. The spectrum sensing method considered for this paper is Energy Detection. Since, it is particularly suitable for multiband sensing because of its low computational and implementation complexities [8-9]. We presume using OFDM modulation with M sub carriers with bandwidth W. In this paper we premised the IEEE 802.22 as it has developed air interface for opportunistic SU access to the TV spectrum in which PUs change slowly [10].

The timing model for spectrum sensing is shown in Fig. 2.a and spectrum mobility model for SUs is depicted in Fig. 2.b. The required time for channel estimation, spectrum sensing and sharing is indicated by τ. According to the [11] the given channel estimation delay is for WCDMA/HSDPA, so the scaled delay for a shorter sub-frame length in UTRAN LTE is considered for this paper. For each Resource Block (RB), there are 7 frames in time frame and 12 subcarriers and each square in Fig .2.b is called Resource Element (RE In Fig. 2.a. T is time length of each frame and K is number of frames. Supposed that received signal at SUs sampled at f_s over i*th* sub channel where values of discretized samples at $t = n\ T_s$, which T_s is $0.1\mu s$ in our framework. In discrete form, when the primary user is active, we define two hypotheses as follow:

$$\begin{cases} y_i(n) = h_i x_i(n) + u_i(n) & ,\mathcal{H}_{1,i} \\ y_i(n) = u_i(n) & ,\mathcal{H}_{0,i} \end{cases} \quad (1)$$

That h_i is the subchannel gain between PU transmitter and SU receiver with variance $E(|h_i|^2) = \sigma_{h,i}^2$. The signal transmitted,

x_i, by PU is assumed to be independent and identically distributed (*i.i.d*), $\mathcal{CN}(0, \sigma_s^2)$, and u_i, the noise, is circularly symmetric complex Gaussian (CSCG) noise.

B. Energy Detection

In order to detect the RF energy in the certain subcarrier for a given PU, the CR service residing in the WCD samples on-the-air signal constructs the following test statistics as the observed energy summation within *N* samples to decide on the presence of the active users in targeted subcarrier [12].

$$\mathcal{U}_i = \begin{cases} \frac{1}{N_i}\sum_{n=1}^{N_i} |h_i x_i(n) + u_i(n)|^2 & ,\mathcal{H}_{1,i} \\ \frac{1}{N_i}\sum_{n=1}^{N_i} |u_i(n)|^2 & \mathcal{H}_{0,i} \end{cases} \tag{2}$$

N_i is number of samples transmitted on duration τ_i which is equal to $N_i = \tau_i f_s$. The PDF of $\mathcal{U}_i$ is Central Chi Square

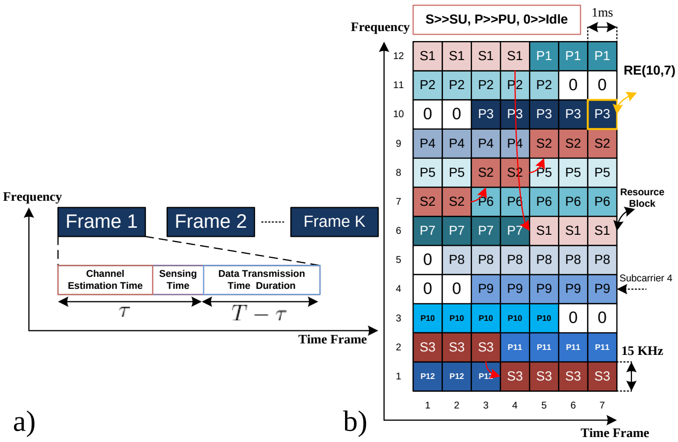

Fig. 2. a)Timing Model, b)Resource Block & Dynamic Resource Management

N_i is number of samples transmitted on duration τ_i which is equal to $N_i = \tau_i f_s$. The PDF of $\mathcal{U}_i$ is Central Chi Square distribution with $2N_i$ degrees of freedom, $\mathcal{X}^2_{2N_i}$, for when no PU exists and on Central Chi Square distribution with $2N_i$ degrees of freedom and non-centrality parameter $2\gamma_i$, $\mathcal{X}^2_{2N_i}(2\gamma_i)$, for the state that PU exists. So:

$$\mathcal{F}_{\mathcal{U}_i}(\mathcal{U}_i) = \begin{cases} \mathcal{X}^2_{2N_i} = \frac{1}{2^{2N_i}\,\Gamma(N_i)}\mathcal{U}_{i,1}^{N_i-1} e^{-\frac{\mathcal{U}_{i,1}}{2}} & ,\mathcal{H}_{1,i} \\ \mathcal{X}^2_{2N_i}(2\gamma_i) = \frac{1}{2}\left(\frac{\mathcal{U}_{i,0}}{2\gamma_i}\right)^{\frac{N_i-1}{2}} e^{-\frac{2\gamma_i+\mathcal{U}_{i,0}}{2}} & \\ I_{N_i-1}(\sqrt{2\gamma_i \mathcal{U}_{i,0}}) & ,\mathcal{H}_{0,i} \end{cases} \tag{3}$$

where the signal to noise ratio (SNR) is depicted by $\gamma_i = \frac{\sigma^2_{x_i}\sigma^2_{h,i}}{\sigma^2_{u_i}}$, $\Gamma(.)$ denotes the gamma function, $I_\alpha(.)$ is the first kind modified Bessel function of degree α.

Two performance parameters for spectrum sensing are probability of detection, P_d, and probability of false alarm, P_f, which is probability of when the frequency is unoccupied but we get alarm that the frequency is used. Hence, Higher P_d protects PU from interfering with SUs and smaller P_f causes better band usage efficiency. To calculate probability of detection [13]:

$$P_{d,i}(\epsilon_i, \tau_i, \gamma_i) = Pr(\mathcal{U}_i > \epsilon_i | \mathcal{H}_1) = \int_{\epsilon_i}^{\infty} p_1(x)dx \tag{4}$$

where ϵ_i is threshold and τ_i is denoted sensing time for *i*th subchannel.

$$P_{d,i}(\epsilon_i, \tau_i, \gamma_i) = \mathcal{Q}\left(\left(\frac{\epsilon_i}{\sigma^2_{u_i}} - \gamma_i |h_i|^2 - 1\right)\sqrt{\frac{\tau_i f_s}{2\gamma_i |h_i|^2+1}}\right) \tag{5}$$

Now the probability of missed detection can be defined as:

$$P_{m,i}(\epsilon_i, \tau_i, \gamma_i) = 1 - P_{d,i}(\epsilon_i, \tau_i, \gamma_i) \tag{6}$$

we have following equations for probability of false alarm,

$$P_{f,i}(\epsilon_i, \tau_i) = Pr(\mathcal{U}_i > \epsilon_i | \mathcal{H}_0) = \int_{\epsilon_i}^{\infty} p_0(x)dx \tag{7}$$

$$P_{f,i}(\epsilon_i, \tau_i) = \mathcal{Q}\left(\left(\frac{\epsilon_i}{\sigma^2_{u_i}} - 1\right)\sqrt{\tau_i f_s}\right) \tag{8}$$

Usually to evaluate the performance of energy detection, the goal is to minimize P_f for a target P_d or to maximize P_d for a target P_f. At first we assume $P_{d,i,target}$ is our target probability of detection ,

$$\epsilon_i(P_{d,i,terget}) = \left(\frac{\mathcal{Q}^{-1}(P_{d,i,target})}{\sqrt{\frac{\tau_i f_s}{2\gamma_i |h_i|^2}}} + \gamma_i |h_i|^2 + 1\right)\sigma^2_{h_i} \tag{9}$$

$$P_{f,i}(\epsilon_i(P_{d,i,terget}), \tau_i) = \mathcal{Q}(\mathcal{Q}^{-1}(P_{d,i,terget}) \sqrt{2\gamma_i |h_i|^2 + 1} + \gamma_i |h_i|^2 \sqrt{\tau_i f_s}) \tag{10}$$

$P_{f,i}(\epsilon(P_{d,i,target}), \tau_i)$ is the probability of false alarm regard to target $P_{d,i}$, and $\mathcal{Q}^{-1}$ is the inverse of complementary error function. For a target $P_{f,i,target}$ we have:

$$\epsilon_i(P_{f,i,terget}) = \left(\frac{\mathcal{Q}^{-1}(P_{d,i,target})}{\sqrt{\tau_i f_s}} + 1\right)\sigma^2_{h_i} \tag{11}$$

$$P_{d,i}(\epsilon_i(P_{f,i,terget}), \tau_i) = \mathcal{Q}\left(\frac{\mathcal{Q}^{-1}(P_{f,i,terget}) - \gamma_i |h_i|^2 \sqrt{\tau_i f_s}}{\sqrt{2\gamma_i |h_i|^2+1}}\right) \tag{12}$$

$P_{d,i}(\epsilon(P_{f,i,target}), \tau_i)$ is the probability of detection when $P_{f,i}$ is targeted. As a result, in this part, probability of false alarm and detection based on $P_{d,i,target}$ and $P_{f,i,target}$, respectively, are calculated.

C. Primary User Activity Model

In this section, we present a model for primary users' activities which is directly proportional to CR network performance. In our Markov chains model, we consider two states (Busy by PU and Idle) for each subcarrier. The Poisson distribution is considered in the modelling with arrival rate, α, and departure rate, β:

$$N_{tot}(nT_s) = N_{tot}(n(T_s - 1)) + \alpha(nT_s) - \beta(nT_s) \tag{13}$$

as a result, the existing users in a cell is equivalent to total existing users on previous time period added to arrival rate at current time and subtracted by current departure time as mentioned in equation (13). The transition probabilities are $p^T$and q^T as illustrated in Fig. 3 and the calculated steady probabilities are depicted below [14]:

$$P_{i,BUSY} = \frac{p^T}{p^T + q^T}, \quad P_{i,Idle} = \frac{q^T}{p^T + q^T}, \tag{14}$$

Eq. (14) is applied to analyze the model for identifying subcarriers states (i.e. busy or idle).

D. *Optimum Sensing Time*

The throughput of SU is calculated as follows [15],

$$C_i = W\log_2(1+\frac{P_{i,SU}|h_{i,SU}|^2}{\mathcal{N}_0}) \quad (15)$$

where W is bandwidth, $P_{i,SU}$ is the power of transmitter SU and $\mathcal{N}_0$ is the noise power and $h_{i,SU}$ is the gain channel between *i*th SU's transmitter and receiver with variance $E(|h_{i,SU}|^2)=\sigma^2_{h_{i,SU}}$.

Considering probabilities for different states gives us achievable throughput, $R_i(\tau_i)$, calculated by,

$$R_i(\tau_i) = (1-\frac{\tau_i}{T})(1-P_{f,i})\ P_{i,Idle}C_i \quad (16)$$

where $(1-P_{f,i}(\epsilon_i,\tau_i))\ P_{i,Idle}$ is the probability of absence of PU when we detect correctly. $(1-\frac{\tau_i}{T})$ is the entire data transmission. Following equations can be derived,

$$\lim_{\tau_i\to 0^+}\frac{d\ R_i(\tau_i)}{d\ \tau_i}\to +\infty > 0 \quad (17)$$

$$\lim_{\tau_i\to T}\frac{d\ R_i(\tau_i)}{d\ \tau_i} < 0 \quad (18)$$

Thus, there is a τ_i between 0 and T that gives us maximum $R_i(\tau_i)$. The Fig. 4 shows the optimum sensing time based on equation (16). By Fig. 4, it can be denoted that the optimum sensing time in regard to technology limits and optimum sensing time is approximated between 3ns and 1μs.

E. *Scheduling algorithms for CR users*

We consider the downlink of N_{su} secondary users are serviced by a base station within a cell. The base station allocates *RE(i,j)* among the N_{su} SUs. At each frame multiple REs can be assigned to a single user, although each RE can be allocated to only one SU.

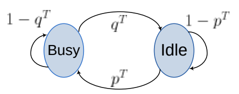

Fig. 3. Markov Chains Model

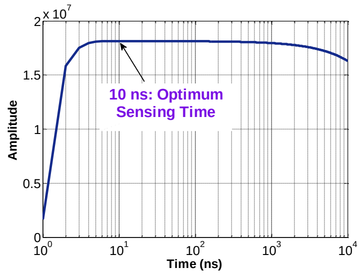

Fig. 4. Optimum Sensing Time

We assume that channel conditions vary across the subcarriers as well as secondary users. The channel conditions typically depend on the channel frequency, so they may be different for different channels. We presume typical urban area model. Moreover, scheduling of SUs also depend on the user location and the time frame. However, in our context the AMI meters are geographical stationary leading to constant SINR values. We also define capacity of secondary user in presence of loss,

$$C = \int \sum_{SINR}(1-\rho)(1-\delta)\beta.W_{eff}.\eta\ .log_2(1+\frac{\frac{|h|^2 S}{N+I}}{SNR_{eff}})dt \quad (21)$$

ρ is detection probability parameter and calculated by addition of false alarm detection probability (Pf) and detection probability (Pd). δ is primary user spectrum usage and we presume a average of 80% loading. β is a correction factor which nominally should be equal to one and it is discussed more detailed in. η is the spectrum sensing efficiency. The scheduler decides which SU to transmit the information at each time frames, based on the request rates the base station.

Scheduling the user with the instantaneously best link conditions is often referred as max rate scheduling. The max rate can be expressed as $k = \arg\ \max_i R_i$ for i^{th} user.

Proportional fair (PF) scheduler is designed to meet the challenges of delay and fairness constraints while harnessing multi user diversity. PF scheduler tracks the average throughput, $T_k[nT_s]$, for each SU delivered in the past over sliding window of size t_c. In the time frame [τ], the base station receives rates $R_k[nT_s]$, k=1...N_{su} from all the active SUs and scheduler basically schedules the SU with highest PF metric value, γ that is defined as $\gamma = \frac{R_k[nT_s]}{T_k[nT_s]}$.

The average throughputs $T_k[nT_s]$ are updated using an exponentially weighted low pass-filter :

$$T_k[nT_s+1] = \begin{cases}(1-\frac{1}{t_c}T_k[nT_s]+(\frac{1}{t_c})T_k[nT_s] & k=\gamma\\(1-\frac{1}{t_c}T_k[nT_s] & k=\gamma\end{cases} \quad (22)$$

Based on the Eq. (21) and (22) we can write as the following

$$\gamma = \frac{C=\int\sum_{SINR}(1-\rho)(1-\delta)\beta.W_{eff}.\eta\ .log_2(1+\frac{\frac{|h|^2 S}{N+I}}{SNR_{eff}})dt}{T_k[nT_s]} \quad (23)$$

As a result, unlike PF scheduling, the users having low throughput but high PF metric, γ, that had been chosen to access frequency will have lower priority than users with enough PF metric and higher throughput.

Algorithm: Opportunistic scheduling

1) for n=1 to N_T (simulation time)
2)Update SU profile, Update γ
3)Let S be the set of secondary users
4)Let RE(i,j) where i=1 to M subcarriers and j=1 to K be the total time frames.
5)for i=1 to M, for j=1to K
6)Select the secondary user l ϵ S with highest γ(l)
7)If $R_l[nT_s] \geq \bar{R}_l[nT_s]$
8) Update the SU profile with S=S-{l}
9)Allocate RE(i,j) to lth secondary user from S
10)Else
11)Update the SU profile with S=S-{l}
12)End if, End for j, i, n

IV. Analysis & Simulation Results

To evaluate the performance of CR system model, system level simulations have been conducted based on 3GPP LTE system model. Table [see 16] shows the simulation parameters used for the simulations. We analyze the performance of the scheduling in terms of throughput and fairness. We first evaluate the system throughput for algorithms with varying the primary user loading within a cell. In this case, the primary user average loading is around 80% and total number of users is 500 in a cell. Over the period of time that spectrum sensing reports the number of idle resource blocks, scheduler allocates the idle REs with SUs. The Fig. 5 illustrates average capacity for three aforementioned algorithms.

Max-rate results in highest average capacity among three algorithms are followed by opportunistic and fairness algorithms. In proportional fair algorithm the users compete for resources not directly based on the requested rates but based on the rates normalized by their respective average throughputs, PF metrics. In OS the users having low request rate but high PF metric, γ, will have less chance to be scheduled. OS objective is to achieve higher average capacity compared to PF, while achieving decent fairness among the SUs.

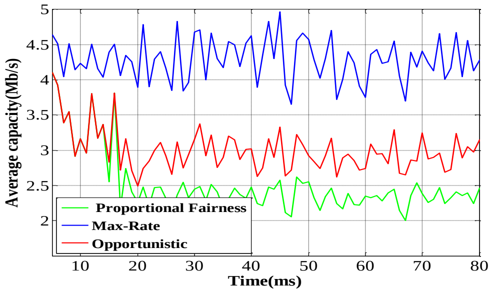

Fig. 5 Average Capacity over Time

In Fig. 6, we analyze the scheduled SUs average capacity of each algorithm in each scenario when number of active PUs varies. Based on goals of each algorithm they indicate respective positions in the results. It can be seen that the solution obtained using the proposed algorithm (OS) is quite close to the PF specifically when the active PUs are less.

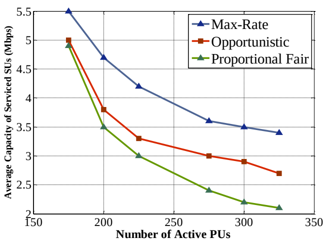

Fig. 7 Max-Rate average capacity

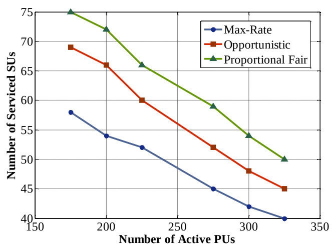

Fig. 8 Average No. of scheduled SUs

We note that the less PUs scheduled yields to high availability of idle REs. Therefore, higher number of SUs scheduled results in larger average capacity in the CR network. When the numbers of PUs are increased, the advantage of the OS algorithm over PF is more obvious (i.e. Fig.6) due to more sparse SUs. Sparse implies large variability in SUs profile (i.e. SINR, fading channel, physical location).

In Fig. 7, we analyze the average number of scheduled SUs in each scenario when number of active PUs varies. We note that the more PUs scheduled yields to less availability of idle REs and therefore less number of SU scheduled.

In Fig. 6 the Max-Rate average capacity is much higher than average capacity of PF; on the contrary, Fig. 7 shows the more scheduled SUs by PF algorithm compared to Max-Rate algorithm. As a result, the OS algorithm can balance both the performance of the cognitive radio networks in terms of achieving acceptable average capacity of secondary users and the fairness.

V. CONCLUSION

In this paper, we have analyzed the potential 4G CR network framework in context of smart grid information systems. Our system level simulation results show that the 4G CR network can achieve an average capacity of 3.5Mbs in a 3Km cell radius under the constraint of an average primary user network usage of 80%. Finally, we present that the CR capacity of a 20% usage model meets the smart grid protocols requirements for a multi-user CR network of smart meters.

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