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E International Journal of Emerging Technology and Innovative Engineering Volume I, Issue 4, April 2015 ISSN: 2394 - 6598

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AN ENERGY SPECTRUM TRADING SCHEME FOR MOBILE TRAFFIC OFFLOADING

V.Nithya¹, Ms.S.Catherin Sonia²

PG Student [Communication Systems], Dept. of ECE, Mahendra Engineering College, Namakkal, Tamilnadu,

India¹

Assistant Professor, Dept. of ECE, Mahendra Engineering College, Namakkal, Tamilnadu, India²

ABSTRACT:

Energy consumption is becoming an increasingly important issue throughout the community. In order to reduce the energy consumption in networks is a crucial to greening mobile networks. In this paper energy spectrum trading (EST) scheme is proposed, which enables the macro Base Stations to offload their mobile traffic to Internet service providers by leveraging cognitive radio techniques. The cognitive radio technique uses a spectrum sharing scheme between wireless networks to improve the efficiency of spectrum usage and thereby alleviates spectrum scarcity due to growing demands for wireless broadband access. However, in the EST achieving optimal scheme. mobile traffic offloading in terms of minimizing the energy consumption of the macro BSs is NP-hard. The power heuristic consumption minimization (HPCM) algorithm to approximate the optimal solution with low computation complexity. The dynamic source routing protocol enables the mobile traffic offloading and significantly enhances the energy and spectral efficiency of mobile networks.

Keywords: Mobile traffic offloading, Cognitive radio, energy efficiency wireless networks.

I.INTRODUCTION

The direct impact of greenhouse gases on the earth environment and the climate changes, the energy consumption of Information and Communication Technology (ICT) is becoming an environmental and economic issues. Mobile networks are among the major energy hoggers of mobile networks [1]. With the rapid development of radio access techniques and mobile devices, a variety of bandwidth-hungry applications and services such as web browsing, video streaming and social networking are gradually shifted to mobile networks, thus leading to an exponential increase of data traffic in mobile networks. The mobile data traffic surges result in a dramatic increase of energy consumption of mobile networks for provisioning higher network capacity. The multicell cooperation solutions for improving the energy efficiency of cellular networks [2]. As cellular network infrastructures and mobile devices proliferate, an increasing number of users rely on cellular networks in their daily lives. As a result, the energy consumption of cellular networks keeps increasing. Therefore, greening cellular networks is attracting tremendous research efforts in both academia and industry. With the aid of multicell cooperation, the performance of a cellular network in terms of throughput and coverage can be enhanced significantly. However, the potential of multicell cooperation on improving the energy efficiency of cellular networks remains to be unlocked. Taking the advantage of multicell cooperation, the energy efficiency of cellular networks can be improved from three aspects [2]. The first one is to reduce the number of active BSs required to serve users in an area. The solutions are to adapt the network layout according to traffic demands. The idea is to switch off BSs when their traffic loads are below a certain threshold for a certain period of time. When some BSs are switched off, radio coverage and service provisioning are taken care of by their neighboring cells. The second aspect is to associate users with green BSs powered by renewable energy. Through multicell cooperation, off-grid BSs enlarge their service area while on-grid BSs shrink their service area. The third aspect is to exploit coordinated

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Volume I, Issue 4, April 2015

ISSN: 2394 - 6598

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multipoint (CoMP) transmissions to improve the energy efficiency of cellular networks. With the aid of multicell cooperation, the energy efficiency of BSs on serving cell edge users is increased.

Mobile traffic offloading, which is referred to as utilizing complementary communication networks to deliver mobile traffic, is a promising technique to improve the energy and spectral efficiency of mobile networks[3]. Content delivery acceleration, whose market is forecasted to grow to \$ 5.5 billion in 2015, attracts tremendous research efforts from both industry and academia [4]. With the rapid development of radio access techniques and mobile devices, Internet applications are gradually moved to mobile networks. As shown in Fig. 1, mobile data traffic is forecasted to increase exponentially, and mobile web and video applications are the major mobile data generators which account for 20% and 70.5% of the total data traffic, respectively [5].





Mobile web applications consume low bandwidth, but are sensitive to network latency. Subscribers usually expect a page to be loaded in less than two seconds, and 40% of subscribers wait for no more than 3 seconds before leaving the web sites. Thus, for a content provider, a one second delay in page load time can result in lost conversions, fewer page views, and a decrease in customer satisfaction [6]. Mobile video applications generate the largest wireless data traffic volume. Different video applications behave differently in term of bandwidth consumption. In order to offload, mobile traffic, mobile network operators usually deploy small cell base stations (BSs), e.g., pico-BSs, femto-BSs and WiFi hot spots, in the area where the mobile traffic intensity is high. Such mobile network deployments, referred as to heterogeneous mobile networks, can efficiently offload mobile traffic from macro BSs, thus reducing the energy consumption of mobile networks. With strong revenue growth in wireless

data markets, internet service providers (ISPs) such as Comcast and Optimum are densely deploying WiFi hot spots to provide WiFi connectivity to their customers in urban and suburban areas. Therefore, it is desirable to utilize the hotspots deployed by ISPs to offload mobile data traffic. A novel mobile traffic offloading scheme by leveraging cognitive radio techniques referred to as energy spectrum trading (EST). The EST scheme exploits the merits of both mobile networks and ISPs' networks. One of the advantages of the mobile networks is that the networks are operating on licensed spectrum, which are not accessed by unlicensed users. Therefore, by proper spectrum management, mobile networks are able to provide their subscribers a variety of services with different QoS levels.

II. RELATED WORKS

Cognitive radio is widely expected to be the next Big Bang in wireless communications [7]. Spectrum sensing, that is, detecting the presence of the primary users in a licensed spectrum, is a fundamental problem for cognitive radio. The issue spectrum underutilization in wireless of communication can be solved in a better way using Cognitive Radio (CR) technology. Cognitive radios are designed in order to provide highly reliable communication for all users of the network, wherever and whenever needed and to facilitate effective utilization of the radio spectrum.

Cognitive radio: It is a radio that can change its transmitter parameters based on interaction with environment in which it operates. Cognitive radio includes spectrum sensing, spectrum management, and spectrum sharing and spectrum mobility.

•Spectrum sensing: Detecting unused spectrum and sharing the spectrum without harmful interference with other users.

•Spectrum management: Capturing the best available spectrum to meet user communication requirements.

•Spectrum mobility: Maintaining seamless communication requirements during the transition to better spectrum.

•Spectrum sharing: Providing the fair spectrum scheduling method among coexisting xG users.

A. Cognitive Radios

Cognitive radios is a new term in wireless communication technology which interacts with real time environment to dynamically alter its operating parameters such as transmit power, carrier frequency, modulation to acclimate itself with the environment whenever there is a statistical change in the incoming radio frequency with the sole purpose to take advantage of the available International Journal of Emerging Technology and Innovative Engineering

Volume I, Issue 4, April 2015

ISSN: 2394 - 6598

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spectrum without causing interference to primary users. Cognitive radio includes intelligent detection by a transreceiver, which checks that which communication channels are in use and which are not, and takes an instant decision of moving to vacant channels while avoiding occupied ones. This optimizes the use of available Radio-Frequency (RF) spectrum while minimizing interference to other users.In practice, the unlicensed users, also called secondary users (SUs), need to continuously monitor the activities of the licensed users, also called Primary Users (PUs), to find the spectrum holes (SHs), which is defined as the spectrum bands that can be used by the SUs without interfering with the PUs. This procedure is called spectrum sensing. There are two types of SHs, namely temporal and spatial SHs, respectively. A temporal SH appears when there is no PU transmission during a certain time period and the SUs can use the spectrum for transmission. A spatial SH appears when the PU transmission is within an area and the SUs can use the spectrum outside that area. To determine the presence or absence of the PU transmission, different spectrum sensing techniques have been used, such as matched filtering detection, energy detection, and feature detection.

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Fig.2 shows the principle of spectrum sensing. In the fig. the PU transmitter is sending data to the PU receiver in a licensed spectrum band while a pair of SUs intends to access the spectrum. To protect the PU transmission, the SU transmitter needs to perform spectrum sensing to detect whether there is a PU receiver in the coverage of the SU transmitter. Dynamic spectrum access (DSA) enables the implementation of cognitive radio (CR). Cognitive technology allows nodes to adapt to the radio environment by tuning their communication parameters. These parameters include operating frequency, power transmission and modulation scheme. In the cognitive network, secondary users (SUs) can access the free spectrum using overlay and underlay approaches, and by renting the free spectrum. In the overlay approach, SUs detect the existence of PUs and specify the unused spectrum accurately. Developing an efficient scheme for utilizing spectrum using overlay approach faces many challenges. These challenges include: detecting PUs signals, exchanging spectrum data, coordinating among SUs, accessing unused spectrum, assigning the unused spectrum to the SUs, and evaluating the available spectrum. Using underlay approach, SUs are constrained to operate below the noise threshold of PUs. Protecting the PUs against interference and supporting OoS for SUs are the main challenges for this approach. In this approach, there is no need to detect PUs signals or to specify the unused spectrum. SUs may also buy the right to access free spectrum temporarily from PUs. Specifying the size and the price of the offered spectrum for renting is the main challenge for PUs in the trading approach. PUs are required to maintain their OoS while simultaneously satisfying SUs.

III. SYSTEM MODEL

Consider an area consisting of one PBS and several SBSs from various ISPs as shown in Fig. 3. The PUs are randomly distributed in the area. Denote U and S as the set of Pus and SBSs, respectively. The PBS provides data service to the PUs within its coverage area via licensed spectrum. SBSs are randomly deployed in the area. We assume that SBSs are able to dynamically access the licensed spectrum by utilizing cognitive radio techniques



Fig 3: Illustration of the energy spectrum trading scheme.

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International Journal of Emerging Technology and Innovative Engineering

Volume I, Issue 4, April 2015

ISSN: 2394 - 6598

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The proposed scheme is illustrated in Fig. 3, where the primary BS (PBS) is defined as the macro BS owned by the mobile network operator while the secondary BSs (SBSs) are referred to as the hotspots owned by ISPs. We assume both the PBS and SBSs are able to dynamically access the spectrum by leveraging cognitive radio techniques. There are two types of users: primary users (PUs) and secondary users (SUs). PUs are subscribers of the mobile networks while SUs are subscribers of ISPs. Different SUs may subscribe to different ISPs. The energy spectrum trading server manages the spectrum sharing and mobile data offloading between the mobile networks and ISPs' networks. The PBS has the exclusive access to the licensed band. However, owing to the wireless channel fading between the PBS and PUs, providing high data rates to the PUs, especially to those located at the cell edge, is both bandwidth and power consuming. As compared with the PBS, the SBSs which are closer to the PUs may experience less wireless channel fading and have higher spectral and energy efficiency in providing data services to the PUs. In the EST scheme, the PBS shares a certain amount of licensed bandwidth with SBSs while SBSs provide data services to PUs within their coverage area using the allocated bandwidth. Since SBSs are close to PUs, the SBSs can satisfy PUs' QoS requirements by utilizing only a portion of the allocated bandwidth. For example, in Fig. 3, if PU 1 is associated with the PBS, the PBS should allocate 2 MHz bandwidth to the PU to satisfy its minimum data rate requirement. If associated with the SBS, PU 1 may only require 1 MHz to ensure its minimum data rate. If the PBS offloads PU 1 to the SBS and grants the SBS 2MHz bandwidth, then the SBS spends 1 MHz bandwidth to serve PU 1, and the other 1MHz bandwidth can be utilized to enhance QoS of its SUs. Therefore, the EST scheme enables the PBS to reduce its power consumption by offloading some of the PUs to SBSs, and allows the SBSs to enhance their QoS to SUs by utilizing the licensed bandwidth. Since SBSs usually have a low transmit power, the power consumption and the spectrum usages of mobile networks in providing data

services to PUs is reduced. Thus, the EST scheme enhances both the energy efficiency and the spectral efficiency of mobile networks. In order to minimize the power consumption, the PBS has to maximize the number of users offloading to SBSs. Meanwhile, since the total amount of licensed spectrum is limited, the PBS aims to minimize the amount of bandwidth allocated to SBSs because the less bandwidth allocated to SBSs, the more bandwidth is reserved for the PUs associated with the PBS, and therefore the PBS consumes less power. On the other hand, the PBS has to give the SBS sufficient incentives in term of the amount of licensed spectrum to incentivize SBSs to provide data services to the PUs. Therefore, solving the power consumption minimization (PCM) problem is to find user-BS associations and bandwidth allocations to minimize the power consumption of the PBSs while satisfying PUs' minimum data rates and SBS's bandwidth requirements. Therefore, we propose a heuristic algorithm to approximate the optimal solution achieved by the brute force search. The heuristic algorithm first finds the PUs whose user-BS associations are not determined, and then iteratively associates the PU, whose power-bandwidth ratio is the largest, with SBSs.

A. User-BS Associations in Heterogeneous Mobile Networks

Heterogeneous network is a promising network architecture which may significantly enhance the spectral and energy efficiency of mobile networks. Thus, mobile users are more likely associated with the macro BS based on the strength of their received pilot signal. As a result, small cell BSs may be lightly loaded, and do not contribute much on traffic offloading. To address this issue, many user-BS association algorithms have been proposed [8]-[11]. Kim et al. [8] proposed a framework for the user-BS association in cellular networks to achieve flow level load balancing under spatially heterogeneous traffic distribution. Jo et al. [9] proposed cell biasing algorithms to balance traffic loads among macro BSs and small cell BSs. The cell biasing algorithms perform user-BS association according to the biased measured pilot signal strength, and enable the traffic to be offloaded from macro BSs to small cell BSs. Corroy et al. [10] proposed a dynamic user-BS association algorithm to maximize the sum rate of the network and adopted cell biasing to balance the traffic load among BSs. Fooladivanda et al. [11] studied the joint resource allocation and user-BS association in heterogeneous mobile networks. They investigated the problem under different channel allocation strategies, and the proposed solution achieved global proportional fairness among the users. Madan et al. [12] studied the user-BS association and interference coordination in heterogeneous mobile networks, and proposed heuristic algorithms to maximize the sum utility of average rates. The existing mobile traffic offloading scheme does not consider the traffic offloading among different service providers. In addition, the available user-BS association algorithms in heterogeneous networks usually assume that the

IJETIE International Journal of Emerging Technology and Innovative Engineering

Volume I, Issue 4, April 2015

ISSN: 2394 - 6598

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macro BS and small cell BSs belong to the same service provider.

B. Communications Model

In the EST scheme, the PBS aims to offload data traffic to SBSs to reduce its energy consumption, and is willing to grant a portion of the licensed spectrum to incentivize SBSs to allow PUs to access their networks. Meanwhile, SBSs aim to dynamically utilize the licensed spectrum to enhance QoS of data services to their subscribers. Thus, SBSs are willing to allow PUs to access their networks in exchange for the access of the licensed spectrum. We assume the total amount of licensed spectrum is W which can be split into orthogonal channels, e.g., OFDMA, with variable amount of bandwidth to avoid interference. Each channel is allocated to an individual PU as needed. For simplicity, we assume both PUs and SUs experience frequency flat fading. Therefore, we focus on the amount of bandwidth allocated to PUs and SBSs instead of specifying which part of the spectrum to be allocated. Users' locations are assumed to be static during an EST procedure. We assume the channel fading changes slowly and can be considered as a constant within the duration. Therefore, the wireless channel is modeled as a slow-fading channel which reflects the large-scale fading between BSs and users. At the beginning of an EST procedure, the kth SBS calculates its bandwidth requirements, denoted as $\varphi_{k,i}$, for serving the *i*th PU. The calculation of φ_{ki} consists of two steps. First, the kth SBS calculates the required bandwidth, $\varphi_{k,i}^{P}$, to satisfy the *i*th PU's minimum data rate, r_i^{min} . Assuming the kth SBS's transmit power-spectral density is p^s , and the channel fading between the kth SBS and the *i*th PU is h_{ki}^{s} , φ_{ki}^{P} can be derived by solving

$$r_i^{min} = \phi_{k,i}^P \log\left(1 + \frac{p^s |h_{k,i}^s|^2}{\mathcal{N}_0}\right).$$
(1)

Second, the *k*th SBS calculates the required bandwidth, $\varphi_{k,i}^{S}$, to compensate for its cost in serving the *i*th PU. The *k*th SBS's cost includes the SBS's energy consumption and backhaul usages for serving the *i*th PU. The cost may be different for different ISPs. For example, in Fig. 3, the second ISP utilizes green energy powered access point, which may reduce the energy cost. Thus, as compared with other ISPs, the second ISP may incur a smaller cost in serving one PU. However,

how to calculate $\varphi_{k,i}^{S}$ is beyond the scope of the paper. We assume $\varphi_{k,i}^{S}$ is a constant. Then,

(2)

+

The energy spectrum trading server collects $\varphi_{k,i} \forall k \in S$, $\forall i \in U$, and optimizes the user-BS associations and bandwidth allocations to minimize the energy consumption of the PBS.

IV. POWER MODEL

This section provides a power model for various types of Base Stations. The power model constitutes the interface between component and system level, which allows quantifying how energy savings on specific components enhance the energy efficiency at the node and network level [13]. A. Base Station Power Consumption Breakdown



Fig 4.Block diagram of a base station transceiver

Fig.4 shows a simplified block diagram of a complete BS that can be generalized to all BS types, including macro, micro, pico and femto BSs. A BS consists of multiple transceivers (TRXs), each of which is serving one transmit antenna element. A TRX comprises a Power Amplifier (PA), a Radio Frequency (RF) small-signal transceiver section, a baseband (BB) interface including a receiver (uplink) and transmitter (downlink) section, a DC-DC power supply, an active cooling system, and an AC-DC unit (mains supply) for connection to the electrical power grid. In the following the various TRX parts are analyzed. Antenna Interface: The influence of the antenna type on power efficiency is modeled by a certain amount of losses, including the feeder, antenna band-pass filters, duplexers, and matching components. Since macro BS sites are often situated at different physical locations as the antennas a feeder loss of about σ feed=3 dB needs to be added. The feeder loss of a macro BS may be mitigated

by introducing a remote radio head (RRH), where the PA is mounted at the same physical location as International Journal of Emerging Technology and Innovative Engineering

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ISSN: 2394 - 6598

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the transmit antenna. Likewise, feeder losses for smaller BS types are typically negligible.

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Power Amplifier (PA): Typically, the most efficient PA operating point is close to the maximum output power (near saturation). Unfortunately, non-linear effects and OFDM modulation with non-constant envelope signals force the power amplifier to operate in a more linear region, i.e., 6 to 12 dB below saturation. This prevents Adjacent Channel Interference (ACI) due to non-linear distortions, and therefore avoids performance degradation at the receiver. However, this high operating back-off gives rise to poor power efficiency _PA, which translates to a high power consumption PPA.

The Small-Signal RF Transceiver (RF-TRX) comprises a receiver and a transmitter for uplink (UL) and downlink (DL) communication. The linearity and blocking requirements of the RF-TRX may differ significantly depending on the BS type, and so its architecture. Typically, low-IF (Intermediate-Frequency) or super-heterodyne architectures are the preferred choice for macro/micro BSs, whereas a simpler zero-IF architecture are sufficient for pico/femto BSs [10].

Baseband (BB) Interface: The baseband engine (performing digital signal processing) carries out digital up/down-conversion, including filtering, FFT/IFFT for OFDM, modulation/demodulation, digital-pre-distortion (only in DL and for large BSs), signal detection (synchronization, channel estimation, equalization, compensation of RF nonidealities), and channel coding/decoding. For large BSs the digital baseband also includes the power consumed by the serial link to the backbone network. Finally, platform control and MAC operation add a further

power consumer (control processor).

Power Supply and Cooling: Losses incurred by DC-DC power supply, mains supply and active cooling scale linearly with the power consumption of the other components, and may be approximated by the loss factors $\sigma_{\rm DC}$, $\sigma_{\rm MS}$, and $\sigma_{\rm cool}$, respectively. Note that active cooling is only applicable to macro BSs, and is omitted in smaller BS types. Moreover, for RRHs active cooling is also obsolete, since the PA is cooled by natural air circulation, and the removal of feeder losses $\sigma_{\rm feed}$ allow for a lower PA power consumption, $P_{\rm PA} = \frac{P_{\rm out}}{\eta_{\rm PA} \cdot (1 - \sigma_{\rm feed})}$, where $\eta_{\rm PA}$ denotes the PA power efficiency.

A. Energy Consumption Model

The PBS's power consumption consists of two parts: the static power consumption and the dynamic power consumption. The static power consumption is the power consumption of a BS without any traffic load. The dynamic power consumption refers to the additional power consumption caused by traffic load on the BS. We consider the PBS's static power consumption, p^{fix} , as a constant, and focus on reducing the dynamic power consumption of a PBS by offloading its traffic to SBSs. The dynamic power consumption of a macro BS depends on the traffic load on the BS and can be expressed as a linear function of the BS's transmit power [13]. Therefore, we model the PBS's power consumption as

$$C = \sum_{i \in \mathcal{U}} \alpha \mu_i p_i w_i + p^{fix}$$
(3)

Here, α is a coefficient which reflects the relationship between the PBS's dynamic energy consumption and the summation of the PBS's transmit power toward its associated PUs.

The value of α depends on the characteristic of the BS [17]. μ_i is an indicator function. If PU is associated with the PBS, $\mu_i = 1$; otherwise, $\mu_i = 0$. w_i is the amount of bandwidth allocated to the ith PU, and p_i is the transmit power-spectral density in w_i .

V. A HEURISTIC POWER CONSUMPTION MINIMIZATION ALGORITHM

In this section, we propose a heuristic power consumption minimization (HPCM) algorithm to approximate the optimal solution of the PCM problem with low computational complexity, and prove that the maximum power savings achieved by the HPCM algorithm is at least 50% of that achieved by the brute force search.

A. The HPCM Algorithm

For the PCM problem, if user-BS associations are determined, then μ_i and $\beta_{k,i}$ are known. The amount of available bandwidth in the PBS can be derived as

$$W^{P} = W - \sum_{i \in \mathcal{U}} \sum_{k \in \mathcal{S}} \beta_{k,i} \phi_{k,i}.$$
(4)

Define $U^P = \{i | \mu_i = 1, \forall i \in U\}$ as the set of PUs associated with the PBS. Then, the PCM problem becomes a bandwidth allocation (BA) problem as follows:

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International Journal of Emerging Technology and Innovative Engineering Volume I, Issue 4, April 2015

ISSN: 2394 - 6598

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 $\min_{w_i} \qquad \sum_{i \in \mathcal{U}^P} \alpha p_i w_i + p^{fix}$ subject to : $\sum_{i \in \mathcal{U}^P} w_i = W^P$ $w_i \ge w_i^{min}, \forall i \in \mathcal{U}^P$ (5)

. Let $f(w) = \sum_{i \in \mathcal{U}^P} \alpha p_i w_i + p^{fix}$ and w = $(w_1, w_2, \cdots, w|UP|)$. When w > 0,

$$\frac{d^2 f(\boldsymbol{w})}{dw_i^2} = \frac{\alpha \mathcal{N}_0 \mu_i (r_i^{min})^2 (\ln 2)^2 2^{r_i^{min}/w_i}}{|h_i^P|^2 w_i^3} > 0$$

Thus, f(w) is a convex function of w. Therefore, the objective function of the BA problem is convex. The constraints of the BA problem satisfy the Slater's conditions, and therefore the Karush-Kuhn-Tucher (KKT) conditions provide necessary and sufficient conditions for the optimality of the BA problem [19]. Hence, we can derive optimal bandwidth allocations by solving the KKT conditions of the BA problem. The PCM problem, thus, can be solved in two steps. In the first step, the user-BS associations are determined. Then, the PCM problem is reduced to the BA problem. In the second step, the BA algorithm is solved by solving its KKT conditions. Since the BA problem can be easily solved, the major difficulty of solving the PCM problem is to optimize the user-BS associations.

VI. SIMULATION RESULTS

The simulation scenarios are set up to evaluate the performance of the proposed Energy Spectrum Trading scheme and the Heuristic power consumption minimization algorithm. In the simulation, fig 5 the EST scheme enables mobile network to offload data traffic to ISPs' network to improve energy and spectral efficiency. There are two types of users: primary users (PUs) and secondary users (SUs). PUs are subscribers of the mobile networks while SUs are subscribers of ISPs. Different SUs may subscribe to different ISPs.

The energy spectrum trading server manages the spectrum sharing and mobile data offloading

between the mobile networks and ISPs' networks. The PBS has the exclusive access to the licensed band. As compared with the PBS, the SBSs which are closer to the PUs may experience less wireless channel fading and have higher spectral and energy efficiency in providing data services to the PUs.









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Fig: 7 The graph of Time versus Delay

In the EST scheme, the PBS shares a certain amount of licensed bandwidth with SBSs while SBSs provide data services to PUs within their coverage area using the allocated bandwidth. By using this technique, we thus propose a heuristic algorithm to approximate the optimal solution with low computation complexity. We have proved that the energy savings achieved by the proposed heuristic algorithm is at least 50% of that achieved by the brute-force search. By using this technique, we have minimize the power consumption of base station at least 50% and maintain the network performance, delay, packet loss and throughput. The graph of packet loss is shown in fig: 6

In fig 6 time is plot on the x-axis and packet loss is plot on the y-axis. If PU 1 is associated with the PBS, the PBS should allocate 2 MHz bandwidth to the PU to satisfy its minimum data rate requirement. If associated with the SBS, PU 1 may only require 1 MHz to ensure its minimum data rate.

If the PBS offloads PU 1 to the SBS and grants the SBS 2 MHz bandwidth, then the SBS spends 1 MHz bandwidth to serve PU 1, and the other 1MHz bandwidth can be utilized to enhance QoS of its SUs. Therefore, the EST scheme enables the PBS to reduce its power consumption by offloading some of the PUs to SBSs, and allows the SBSs to enhance their QoSs to SUs by utilizing the licensed bandwidth. Since SBSs usually have a low transmit power, the power consumption and the spectrum usages of mobile networks in providing data services to PUs is reduced. Thus, the EST scheme enhances both the energy efficiency and the

spectral efficiency of mobile networks. Throughput of the network also maintained.



Fig: 8 The graph of Time versus Throughput

VII. CONCLUSION

In this paper, we have proposed a novel energy spectrum trading(EST) scheme which enables the mobile traffic offloading between the mobile networks and the ISPs' network by leveraging cognitive radio techniques. The HPCM algorithm enables the mobile traffic offloading, and significantly enhances the energy and spectral efficiency of mobile networks. The heuristic power consumption minimization (HPCM) algorithm to approximate the optimal solution with low computation complexity. The dynamic source routing protocol enables the mobile traffic offloading and significantly enhances the energy and spectral efficiency of mobile networks.

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