WhiteCell: Leveraging Scant White Space Resource in Dense Area

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***Abstract*—The FCC has reapportioned spectrum from TV white spaces for the purposes of large-scale Internet connectivity via wireless topologies of all kinds. These frequency resource offers additional channel capacity and propagation flexibility for network design. The far greater range of these lower carrier frequencies are especially critical in user mobility adaptation, where high levels of aggregation could dramatically lower the power consumption of network operating. However, the white spaces resource distribution is restricted by FCC contrast to the population density, dense area has few white space channels. Thus, leveraging the range of spectrum across user mobility becomes a critical issue for the operating of heterogeneous data networks with WiFi and limited white space bands. In this paper, we present a feasibility analysis for a heterogeneous network resource allocation to reduce the power consumption via queuing theory approach. In particular, we study the spectrum utility across multi-bands and the user mobility across a weekday in typical environment of the Dallas-Fort Worth metroplex through measurements. Moreover, we propose a Greedy Server-side Replace (GSR) algorithm to reduce the power consumption with white space channels application. In doing so, we find that networks with white space bands reduce the power consumption by up to 512.55% in sparse rural area over WiFi-only solutions via measurements driven numerical simulation. In more populated areas. we find an power consumption reduction on average across 24 hours by 24.57%, 46.27%,67.40% over WiFi only network with one to three white space channels respectively. We further investigate the quality of service requirements impacts on power consumption across the number of channels. We find that the power consumption reduction is up to 150.89% with three white space channels in dense areas with relaxed required waiting time.**

I. Introduction

The FCC has approved the use of broadband services in the white spaces of UHF TV bands, which were formerly exclusively licensed to television broadcasters. These white space bands are now available for unlicensed public use, enabling the deployment of wireless data networks. These white space bands operate in available channels from 54-806 MHz, having a far greater propagation range than WiFi bands for similar transmission power [1]. Thus, white space bands greatly complements the existing WiFi wireless network with their large propagation range for user mobility.

The users in multiple locations under the coverage of both the WiFi and white space have user diversity which represents the difference of transmission qualities due to the variations in channel quality, geographic location, interference, etc. The user diversity mainly comes from two types of reason. One is the temporal diversity which is caused by the environment variation. The other is the spectral diversity which represents the transmission conditions varies across frequencies. In some moderate number of users, the sum capacity of users increase with the diversity in the system [2].

The larger propagation range of white space channels is able to adapt channel association of users located in large area. The white space channels are able to serve the users distributed in a large area. With both WiFi channels and white space channels, the users of an existing WiFi cell have the options to associate with either the WiFi channel assigned to the cell or the large propagation white space channels covering multiple cells. When the users distributed in a large area, the temporal diversity and spectral diversity become key issues in white space wireless network applications. In sparse rural areas, plenty of white space channels are able to deploy new white space network. However, in dense area, the white space channels are restricted by FCC in a small number. For example, there is none white space channel available in New York downtown [3]. Other than the plenty white space channels and none white space channel extreme cases, most areas of major cities in the United States have one to eight white space channels [3]. Since the carrier have deployed WiFi wireless networks in most of the dense areas, the white space channels are able to complement the WiFi wireless networks to achieve better performance in coverage, power consumption, etc. Thus, exploiting these limited white space resource to improve the WiFi network in dense area is a perspective option for wireless networks.

The white space frequencies offer not only more wireless capacity but also the convenience of access across large area for the heterogeneous wireless network structure. A single white space channel is able to satisfy all the users in the area when the total traffic demands of the users in the area are relatively low. The WiFi radios in the heterogeneous structure could be turned off for power saving. While when the total traffic demand of the users in the area is relatively high, all the radios in the wireless network have to operate for the service of users. However, the amount of traffic demands generally come across somewhere between these two extremes. Thus, the question comes out, *in what degree the white space help to reduce the power consumptions of an existing WiFi mesh?* Especially when the WiFi mesh located in dense area with less white space channel availability.

In this work, we study the white space resource impacts on mesh network power consumption via queuing theory model. We describe the heterogeneous wireless network structure with both white space bands and WiFi bands. We perform in-field measurement to leverage the channel utility and mobility footprint of Dallas Fort-worth metroplex. We analyze the heterogeneous structure under the the waiting time constraint for resource allocation in multiple scenarios via the queuing model. We further propose a greedy to find the resource allocation minimizing the power consumption for the heterogeneous network structure. We then evaluate the algorithm, showing the power consumption gains across sparse and dense areas and analyze the impact of the number of white space and WiFi channels in these representative scenarios.

In particular, the main contributions of our work are as follows:

- We perform 24 hours in-field measurements in neighborhoods, campus, downtown business building, and urban business buildings. Through these in-field measurements, we estimate the achieved channel capacity of these typical area in north Texas.
- We leverage the user mobility footprint through in-filed Android based WiEye measurements of Dallas area on weekdays. Through the measurements analysis, we tell the user distribution in multiple types of areas across 24 hours in weekdays.
- We formulate the heterogeneous wireless structure as a queuing system. Based on previous queuing theory works, we analyze the resource allocation of the system quality of service in waiting time. Based on the analysis, we propose a Greedy Server-side Replace (GSR) algorithm to allocate the channel resource to minimize the power consumption.
- We perform measurement-driven numerical simulations to analyze various scenarios of channel resource and users distribution. Our results shows that the white space bands reduce the power consumption in sparse area by up to 512.55% in weekdays.

The rest of the paper is organized as follows. We describe the system and formulate the problem in II. Then, we present the queuing theory analysis and the Greedy Server-side Replace algorithm also in II. The measurements and measurement-driven numerical simulation is discussed in III. Finally, we conclude our article in V.

II. System, Assumptions and Problem Formulation

A. System and Assumptions

Wireless propagation refers to the signal loss characteristics when wireless signals are transmitted through the wireless medium. The strength of the received signal depends on both the line-of-sight path (or lack thereof) and multiple other paths that result from reflection, diffraction, and scattering from obstacles [4]. The widely-used Friis equation characterizes the received signal power P_r in terms of transmit power P_t, transmitter gain G_t, receiver gain G_r, wavelength λ of the carrier frequency, distance R from transmitter to receiver, and path loss exponent n according to [5]:

$$P_r = P_t + G_t + G_r + 10n \log_{10}\left(\frac{\lambda}{4\pi R}\right) \tag{1}$$

Here, n varies according to the aforementioned environmental factors with a value ranging from two to five in typical outdoor settings [6]. Thus, the channels of low frequency white space bands propagates further than the high frequency WiFi bands with the same RSSI threshold, transceiver settings according to Eq. 1. The propagation range of low frequency white space channels is times of WiFi channels, for instance, 450 MHz channels has more than 12 times propagation range as 5 GHz channels via Friis model. Thus a single white space access point is possible to serve an area up to hundreds times of a WiFi access point. The larger propagation of white space channels is potentially to be applied for reduction of network deployment cost [7], adaptation of vehicular dynamic access [8], and improvement of network capacity [9]. However, previous works focus on the application of plenty white space channels resource or point to point communication require small amount of white space resource.

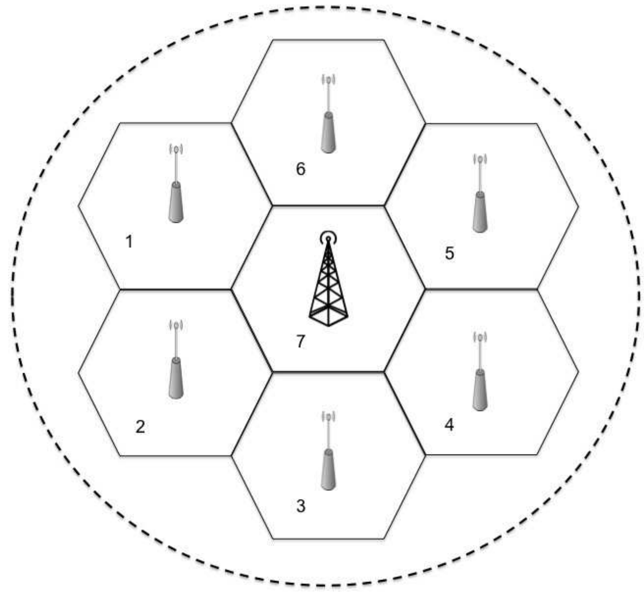

Fig. 1. Heterogeneous WhiteCell Structure

In wireless network design, as discuss in previous works, the more wireless channel resource means the better performance. Unfortunately, FCC restricts the number of white space channels in most dense populated areas due to the existing TV broadcasting application. The minimum number of white space channels in major cities in the U.S is listed in Table I. There are areas has no white space channel available in New York and Los Angeles. Austin has only one white space channel available in downtown area. The other cities in the table have 2 to 7 white space channels. Thus, a heterogeneous network with WiFi channels and few white space channels becomes a practical option for these cities other than a white space wireless network.

Here, we introduce a heterogeneous network named as WhiteCell with existing WiFi cells and an access point with few number of white space channels as shown in Fig. 1. Given a WiFi mesh wireless system with M access points and N users. The users in each WiFi cell of the network have access to the white space channels and the assigned WiFi channel of the cell. The reuse of WiFi channels has been discussed in plenty of previous works and it is out of our scope. There are F_w white space radios is installed on one of the access points to assistant the existing WiFi network. The capacity in clean environment of each radio C is an equally restrict number for all the channels. There are enough buffer store the traffic demand from the users on each radio. The traffic is served in a first-in-first-out (FIFO) scheduling system. In such a network, each user has $1 + F_w$ channels to be scheduled. One is the previous in-cell WiFi channel and the white space channels. We assume the users in the same mesh cell are in a single interference domain. Considering the limited number of white space channels in dense area and the fact spatial reuse of white

City	New York	Log Angeles	San Francisco	Seattle	Houston	Austin	Dallas
White space channels	0	0	2	7	3	1	3

TABLE I
NUMBER OF WHITE SPACE CHANNELS IN MAJOR CITIES

space will make the problem considerably more challenging, we will remains an interesting direction of future research.

Instead of assuming the wireless channels are on-off [10] or equally clean, we apply a measurement method to get the achieved channel capacity. The capacity of the channel between the access points and users is noted as a matrix in Eq. 2

$$H_{i,j}^{f}(t) = G(\zeta, t), i \in M, j \in N, f \in (F_M + F_w) \quad (2)$$

ζ represents the in-field measured historical data and dynamic sensing information. We use a context-aware method to estimate the j user capacity $H_{i,j}^{f}(t)$ to an access point i on channel f. The users in a single cell has the same channel status. We assume the channel capacity is flat during a time slot. The switching time is negligible in the system. The calculation of achieved channel capacity is introduced in III-B. The traffic demand arrive at a user as a Poisson process, with the vector noted as $\boldsymbol{D(t)} = [D_1(t), D_2(t), ...D_N(t)]$ and the sum rate $D(t) = \sum_{i=1}^{N} D_i(t)$. The rate $D(t)$ is the aggregate rate of data generated from all users.

During a time slot, the unscheduled radios remain in sleep mode to save energy. Also we ignore the sleeping energy as well as the amount of energy spent on channel/radio switching. An operating radio will cost equal power in a time unit. Previous work [11] shows a user has a certain patience for waiting. The tolerance time varies across the traffic type, such as text information, voice information. To simply the problem, we assume an average value for W of all the users in the system. The smaller tolerance time of the users, the more channel capacity resource is required. The system applies a first-come-first-serve schedule. The white space channels are able to split for multiple cells.

B. Problem Formulation

We formulate the system introduced in II-A as a discrete-time queuing system as shown in Fig. 2. The channels are represented as servers in the queuing system. Table. II summarizes the notation used in this work. The system has F_w white space channels, F_M WiFi channels in total and N users. Thus, the queuing system has N queues and $F_M + F_w$ servers connecting by time-varying channels $H^*(N, F_M + F_w)$.

Let matrix $\{A_{i,j}(t), i \in (F_M + F_w), j \in N\}$ denote the associate meets the tolerance constraint as shown in Eq. 3.

$$A_{i,j}(t) = \begin{cases} 1 & if\ D_{j \in N},\ is\ associated\ with \\ & channel\ i \in (F_M + F_w) \\ 0 & Otherwise \end{cases} \quad (3)$$

The queuing system keeps the expected waiting time of the system w less than the tolerance threshold W as shown in Eq. 4

$$E[w] \leq W \quad (4)$$

With the intuition, when the total traffic demand of the users in the system are relatively small, a single white space channel could achieve the quality of service for the users. Thus all the

t	Time slot
N	Set of users
M	Set of WiFi cells
H_{ij}^{f}	Measurement based Capacity between AP i and user j on channel f
F_m	WiFi Channels in the cells
F_w	Set of White Space Channels
$A(t)$	User access channel schedule
C	Clean Radio Capacity
R	Operating Radio
ζ	In-Field Measurements
W	User Tolerance time window
μ	Channel capacity assigned for a cell

TABLE II
TABLE OF NOTATIONS

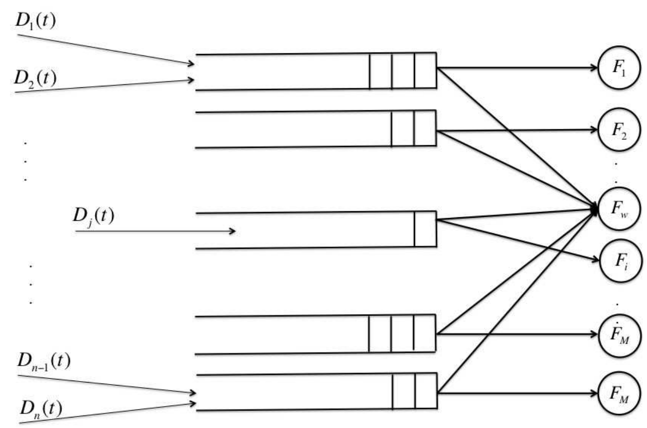

Fig. 2. System Model

WiFi radios could be turned into sleep mode for power saving. On the other side, as the traffic demand increase with the number of users or the demand per user, we need to increase the channel resource as servers in the system to qualify the user waiting time tolerance requirements. Moreover, when the users are distributed non-uniformly, the white space channels are able to deliver more capacity for the cells with more users to balance the system load without new infrastructure. The flexibility of white space channels offers new opportunity for network design. To apply these white space advantages, the question *how much power we could save via dividing the white space capacity into the WiFi cells?* has to be addressed in this system.

In this work, we focus on the analysis on the power consumption saving of the heterogeneous wireless system. To model the power consumption of the system, we count the power consumption of each operating radio via standby and transmitting power consumption. We assume the sleeping standby power consumption is negligible. We define R_i represents the radios status in the system, $i \in F_w, F_M$. When R_i is working in WiFi channels F_M or white space channels F_w, R_i denotes the power consumption with the standby and transmitting cost. Otherwise, $R_i = 0$. The definition is as shown in Eq. 5

$$R_i(t) = \begin{cases} P_s + P_t \cdot \mu & \sum_{j=1}^{N} A_{i,j}(t) \geq 1 \\ 0 & Otherwise \end{cases} \quad (5)$$

P_s is the constant standby power consumption of a radio, P_t is the transmit power for the channel capacity assigned of the radio. μ is the total assigned channel capacity of the radio. $R_i(t)$ is the power consumption of the radio in the time slot.

Thus, to reduce the power consumption, we need to minimize R_i for all the radios under the quality of service constraints. Our goal, to minimize the power consumption is represented in Eq. 6:

$$R^*(t) = \min\{\sum_{i=1}^{(F_M+F_w)} R_i(t)\} \quad (6)$$

R^* represent the minimum operating radios power consumption required for the system.

C. Challenges And Analysis

Prior works formulate similar multi-channel system as $M/M/m$ queuing system for analyzing [10]. However, this system is not able to be formulated as a $M/M/m$ queuing system due to the non-equal capacity of the assigned channel capacity across white space and WiFi channels. Thus we first analyze the queuing system and apply previous work in $M/M/m$ queuing theory to generate the solution for such system.

Without the white space channels, the users in a cell can only access to the WiFi channel assigned for the cell to get service. The large propagation of white space channels offers more options for all the users. The user could either associate with the white space channels or the WiFi channels. Thus, the white space channels could be slitted into several cells. The splitting of the white space channels brings more capacity variation of the servers. The white space channel splitting capacity variation and the spectrum capacity variation of cells might remove the equal service capacity assumption of the system in most scenarios. However, the equal server capacity is the pre-request for a general $M/M/m$ queuing system analysis. Thus, the $M/M/m$ queuing system of a multi-channel version is not directly applicable for this system model.

In the design of the wireless system, the response time W constraints have to be satisfied to keep the quality of service. The users in this system can only be served by the large propagate white space channels or the WiFi channels assigned in the cell. The users located in multiple cells have different channel status in the same white space channels, which is mentioned as part of the multi-user diversity in previous works. Multi-user diversity is a form of diversity inherent in a wireless network, provided by independent time-varying channels across the different users [12]. The diversity could be generated by the interference from device inside the network or out of the network, the environmental variations. The variation among users make the channel capacity among all the cells for white space channels. Thus, some cells may have clean white space channels in the air while the other cells may suffer worse white space channel performance. To address the variation, instead of holding the on-off channel assumption, we implement an in-field measurements based channel capacity estimation approach in this work.

We define an activity level to estimate the achieved channel capacity. We perform measurements to sense the activities in the air through our portable spectrum analyzer. The percentage of sensing samples (S_θ) above an interference threshold (θ) over the total samples (S) in a time unit is the activity level (A):

$$A = \frac{S_\theta}{S_a} \quad (7)$$

The capacity of a clean channel is denoted by C. With the protocol model, the achieved capacity of a channel C_r could be represented as the remaining free time of the channel capacity according to Eq. 8:

$$C_r = C * (1 - \bar{A}) \quad (8)$$

Other than the achieved channel capacity, we also perform in-field measurements of the user mobility footprint. When the total number of the users is a certain value, the user distribution becomes important for wireless network operating. We analyze the data set from WiEye, an Android application reports the location, velocity and signal information to leverage the mobility pattern of users during week days. The setup and results are shown in Section III.

With these measurements information, we further analyze the channel capacity allocation for such a system. We first investigate the channel capacity allocation in a single cell. The users of the the same WiFi cell are in a heterogeneous queuing system with server of WiFi channels and white space channels with service rate $\mu_1, \mu_2, ...\mu_{(F_w+1)}$. μ denote the capacity allocated for this cell. The white space channel capacity is slitted into multiple WiFi cells, thus, the capacity of the white space is usually the minimum channel capacity in a cell. Thus, there are three cases of the channel capacity in a single cell. The first scenario is several channels of both WiFi and white space works for the cell and the capacity of some white space channel is several time less than other channel capacity since white space channels are slitted for many cells. An example here is in a single cell, the white space channel assigned is equally distributed to two cells, while the WiFi channel works in this cell, thus, the capacity of the WiFi channel is about twice of the white space channel capacity in this cell. The second scenario is only the WiFi channel or only part of a single white space channel works for the cell. The third scenario is several channels work for this cell with around equal capacity. The fist case is a heterogeneous server queuing system with unequal capacity servers. The second case is simplified as a $M/M/1$ queuing system. The third case is converted into a $M/M/m$ queuing system.

For the first case heterogeneous server queuing system, we apply the transformation model in [13] to estimate the response time $\bar{w}$. In the transformation model, the actual arrival rate for one specific server λ_s is defined as in Eq. 9

$$\lambda_s = D_{cell}/(F_w + 1) \quad (9)$$

D_{cell} is the traffic aggregated from the users in the cell.

The other parameters are noted from Eq. 10 to 12.

$$\mu_{min} = \min(\mu_1, \mu_2, ...\mu_{(F_w+1)}) = \bar{\mu} \quad (10)$$

$$\mu_{max} = \max\left(\mu_1, \mu_2, ...\mu_{(F_w+1)}\right) \tag{11}$$

$$k = \lfloor \frac{\mu_{max}}{\mu_{min}} \rfloor \tag{12}$$

When $k = 1$, the system becomes a homogeneous queuing system as in case three. Otherwise, $k \geq 2$ the average response time of such heterogeneous system [13] could be represented as in Eq. 13:

$$\bar{w} = \frac{1}{\frac{1}{3}\bar{\mu}(2k+1) - \lambda_s} \tag{13}$$

Through the transformation model, we could further calculate the channel capacity required for response time constraints. Further, the power consumption could be calculated for the system. When the traffic could be served by part of a single white space channel or the WiFi channel, as the second scenario, the system converge into a $M/M/1$ queue. The response time $\bar{w}$ could be estimated from Eq. 14 [14].

$$\bar{w} = \frac{1}{\mu^+ - D} \tag{14}$$

μ^+ is the channel capacity of the single channel capacity in queuing system.

In the third scenario, the system could be treated as a $M/M/m$ queuing system. The average response time is calculated as in Eq. 15 [14].

$$\bar{w} = \frac{1}{\mu^*}(1 + \frac{c(m,\rho)}{m(1-\rho)}) \approx \frac{1}{\mu^*}\frac{1}{1-\rho^m} \tag{15}$$

μ^* is the average capacity of channels in the $M/M/m$ queuing system. $\rho = \frac{\lambda}{m\mu^*}$ is the traffic density, and $c(m, \rho)$ is the Erlang-C formula [14].

In this model, the less radio in operation and the less power consumption will be cost in the system according to Eq. 5. The basic idea of power reduction for this heterogeneous system is to replace the WiFi radios via white space channel capacity. To implement the division of the white space capacity we propose a Greedy Server-side Replace(GSR) algorithm to approach the minimize power consumption in the system as shown in Algorithm 1.

The algorithm input the measurement-based achieved channel capacity, the number of white space channels and the WiFi cells. The white space channels are employed for the cell with less traffic demand to reduce the standby power. The algorithm compare the three configurations of channel capacity and tell the setup with the best power consumption. Further, the process is repeat till all the traffic demand are served or the channel resource has been used up. Then output the power consumption and channel allocation of the system.

III. Experiment and Analysis

In this section, we introduce the in-field measurements experiments , the evaluation of the heterogeneous wireless system and analysis of the results.

Algorithm 1 Greedy Server-side Replace

Input:
- N: Users
- $H^f_{i,j}$: Vector of channel capacity
- D: Traffic Rate
- M: WiFi Cells

```
Find the WiFi cell with the lowest traffic rate D,break the tie with index
Calculate the power consumption according to Eq. 13 14 15
if If channel resource feasible and exist unserved traffic demand then
    List available options
    if Single channel is the best then
        Apply half-interval search to find the minimum capacity for the users
    else if Homogeneous is the best then
        Allocate the resource for the cell
        Keep the WiFi channel and find the minimum capacity for the users
    else if Heterogeneous is best then
        Adding white space resource to the cell
    end if
else
    Get the waiting time of the cell with all available resource
end if
Update the system information
Repeat the process for all the cells
Calculate the power consumption
```

Output:
The power consumption, resource allocation and the maximum waiting time

A. In-field Measurements

We perform in-field measurements in typical areas to find the channel state variation across time and the user mobility patterns among the areas. We chose neighborhoods, campus, downtown business office and urban business office to perform long term 24 hours measurements on weekdays. The locations we chosen are located in Downtown Dallas, a university campus in Dallas, a business in Dallas urban area and an apartment on north Dallas. The locations where we collected measurements are shown in Fig. 3.

In each of the location, we left our equipment running to measure the channel state for 24 hours during weekdays. We employ a Rohde & Schwarz FSH8 portable spectrum works from 100 KHz to 8 GHz. The portable spectrum analyzer is controlled by a Python script on a laptop to measure the received signal strength. To the best of our knowledge, there is no readily available mobile, multiband antenna from 450 MHz to 5.2 GHz on the market. Thus, we use a 700-MHz mobile antenna to perform in-field measurements. We then normalize the mobile antenna performance across bands with indoor experimentation. To do so, we use a Universal Software Radio Peripheral (USRP) N210 to generate signals at 450 MHz, 800 MHz, and 2.4 GHz. We feed the USRP signals directly to a spectrum analyzer and adjust the configuration of USRP to make the received signal strength the same as the 5.2 GHz signal from Gateworks 2358 with a XR5 radio. Then, we connect the signal source to a fixed multiband antenna (QT 400 Quad Ridge Horn Antenna) and measure the received signal at a fixed distance with the 700 MHz antenna and antennas for different bands to obtain the antenna loss for each band. We adjust the received signal strength collected via the 700-MHz mobile antenna according to the normalization. We use

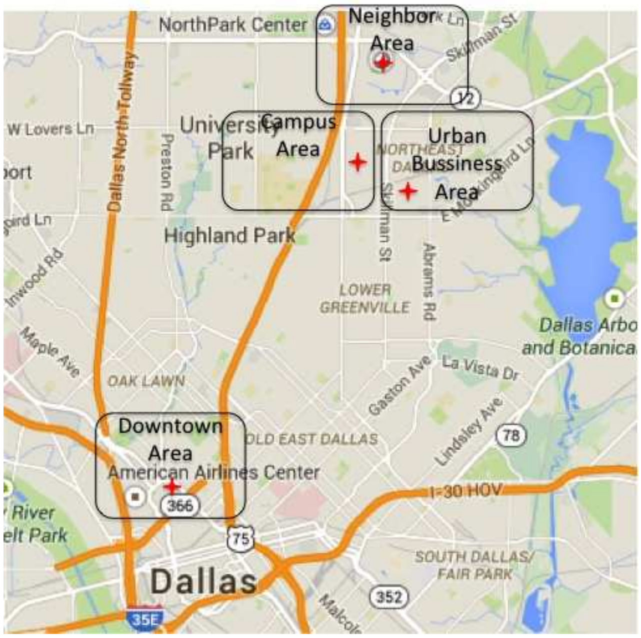

Fig. 3. Long Term Measurements Locations

$-85dBm$ as a threshold in the activity level calculation for the normalized data.

When wireless devices operate in WiFi bands, the channel separation is relatively small (e.g., 5 MHz for the 2.4 GHz band). As a result, many works assume that the propagation characteristics across channels are similar. However, with the large frequency differences between WiFi and white space bands (e.g., multiple GHz), propagation becomes a key factor in the deployment of wireless networks with both bands. Here, a frequency band is defined as a group of channels which have little frequency separation, meaning they have similar propagation characteristics. In this work, we consider the diverse propagation and activity characteristics for four total frequency bands: 450 MHz, 800 MHz, 2.4 GHz, and 5.2 GHz. We refer to the two former frequency bands as white space bands and the two latter frequency bands as WiFi bands. The differences in propagation and spectrum utilization create opportunities for the joint use of white space and WiFi bands in wireless access networks according to the environmental characteristics (e.g., urban or rural and downtown or residential) of the deployment location.

Through the measured data set, we calculate the activity level via Eq. 7. The activity level is calculated in one minute time window. We average the activity level in 30 minutes across 24 hours.

Through the activity level results, we observe that the activities of 450 MHz in the air has almost the same patterns across all the four measured areas. The large propagation area of 450 MHz influence the areas simultaneous and the 450 MHz activities are perform regularly on weekdays. Neighborhood area has more activity in 800 MHz than other types of areas. But the 800 MHz activity levels are relatively lower than other bands in all the areas. The WiFi 2.4 GHz channel of neighborhoods has more activity in the night while the downtown area has more activity in the day time. The campus has more WiFi activities in the morning than the afternoon and night. Part of the measurements results are list in Table III.

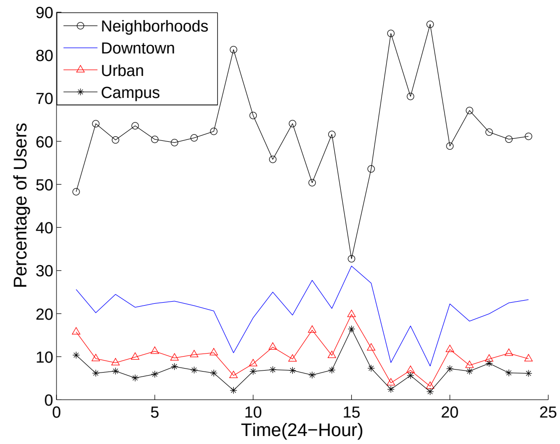

Fig. 4. User Distribution across Time

Due to the limited space, the full list of measurements are available upon request. We integrate the measurements result into our numerical simulation of GSR algorithm later in this section.

To identify the user mobility pattern, we leverage the data from WiEye database and find the user locations across time. WiEye application created for the data collection is currently available for download and usage via the Google Android Market under the name WiEye. The application offers WiFi access points connection quality in both graphical and tabular form. All data collection is done in the background, either continuously while the user is running the application or periodically if the user has opted in to background data collection to SMU research. The data collected has been approved by the Southern Methodist University Institutional Review Board, a human subjects research committee,ensuring that all ethical precautions have been taken in collecting data from the users of our application.

We choose the data from WiEye database according to the GPS location. The data we chosen from Dallas area, including downtown, urban, SMU campus and neighborhood area. We note the SMU campus area size as the unit, find the same size of downtown area and urban area. The rest of the chosen locations are counted as neighborhoods. The size of neighborhoods area is about 2.8 of campus area. The data set is generated from Oct. 1st 2014 to March 20th 2015. We track the identified 538 users from the data set in different types of areas. The number of users located in these area are counted according to the GPS and further converted into the percentage each hour. The percentage distribution of users across these areas during a weekday is shown in Fig. 4

From the measurements results, we could find the distribution increase from 9:00 AM in the morning till 3:00 PM in the afternoon in downtown, urban business area and campus. This match the most of the work schedule. The peak of neighborhoods is around 6:00 PM in the afternoon and 9:00 AM in the morning. The reason could be the users are looking for breakfast in the morning before go to work. We input the user mobility pattern into our power consumption numerical simulation.

Downtown 450 MHz	0:00-11:00	22.09	21.27	22.28	22.47	21.65	21.68	22.37	22.16	23.12	22.73	22.01	22.54
	12:00-23:00	21.80	20.86	21.80	22.54	22.35	22.61	22.45	21.58	22.18	23.09	22.11	22.09
Campus 450 MHz	0:00-11:00	20.29	21.56	21.41	22.52	23.12	21.97	21.65	21.63	21.87	21.22	21.17	21.39
	12:00-23:00	22.33	22.88	22.28	21.65	22.49	22.16	21.32	22.35	21.56	21.75	21.75	20.45
Neighborhoods 800 MHz	0:00-11:00	15.72	16.30	16.33	15.72	16.54	14.48	14.62	14.48	15.68	15.03	15.60	16.33
	12:00-23:00	15.72	14.74	14.74	14.38	15.41	15.00	15.84	16.25	14.84	14.69	15.51	14.93

TABLE III
PART OF ACTIVITY LEVEL IN MULTIPLE LOCATIONS

B. Experiments, Results and Analysis

We apply our GSR algorithm with the measurements in a virtual city to investigate white space band impacts on power consumption. The virtual city in our experiment includes a downtown area, a school campus area, two urban business areas and three neighborhood areas. All the areas are in the same size with a single WiFi cell. The white space channels has more than 3 times propagation range than WiFi channels even with the lowest frequency WiFi channel and the highest white space channel. The white space radios are located in the center of the virtual city cover all the users in the four types of areas. We assume the residents in the city is a constant number which could be calculated through the population distribution according to the 2010 U.S. Census [15]. The channel variation of spectrum is setup according to the channel state measurements and the user mobility from the measurements results of WiEye introduced in Subsection III-A.

The transmit power of radios are equal and with the same clean channel capacity. The standby power consumption of a radio is 500 watt and transmit power is 1 watt per Mbps. We lookup population distribution from the US census 2010 to calculate the users in the virtual city. We set the demand requested per user as 0.5 Mbps and assume 30% of the users will activate their device (ie. the take rate is 30). The tolerance time of users is $30\ ms$ in most of the simulations. We adopt an 802.11n maximum data rate of 600 Mbps for all the radios. For the single white space channel setup, the channel is from the 800 MHz. For two white space channels, one is 450 MHz, the other one is from 800 MHz. For three white space channels setup, two of them are from 800 MHz and one from 450 MHz.

We first investigate the power consumption variation across time with the population distribution as $2000 ppl/km^2$ with the measurements setup. The results across 24 hours of the virtual city is shown in Fig. 5

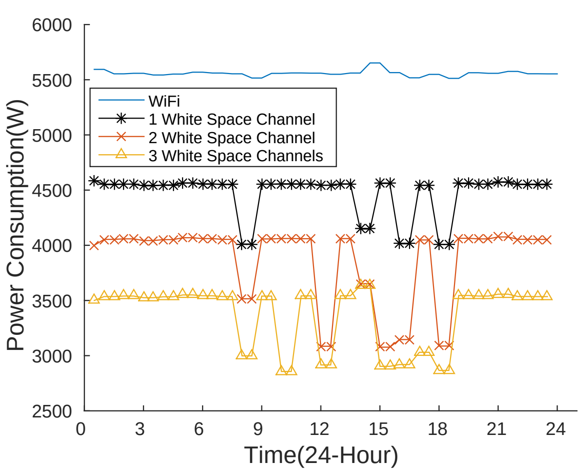

Fig. 5. Power Consumption across Time

We observe that the WiFi power consumption keeps constant in most case. That because the WiFi propagation range restrict all the radios have to be on operating to serve the users. While the white space radios could adapt the user non-uniform distribution or user mobility better. When the user distribution changes fast at 9:00 AM, the white space configurations could reduce the power consumption by about 20% of the previous user distribution. Three white space channels could reduce almost half of the power consumption in the simulation. The power consumption gain is mainly from turning off the radios. When the users are uniform distributed, the power consumption may increase due to the splitting of white space channels. The queuing theory concludes that a single faster server is better than multiple slower server have the same capacity. When the users are uniform like distributed, the white space channels may be divided into several sub-channels which lower the performance. From the measurements numerical simulation, one white space channel could reduce the power consumption by 24.57% during 24 hours. Two white space channels could reduce by 46.27% and three white space channels could reduce by 67.40% relatively. As the number of white space channel increase, the power consumption gains per channel will become a constant since there is enough channel capacity to satisfy the users. Thus, according to the result, we could design the network with white space channels to adapt the user mobility patterns with affordable power consumption as well as apply the white space channels as complement resource for the existing WiFi infrastructure.

Further, we study the tolerance waiting time W of users impacts on the power consumption. We keep the population distribution as $2000\ ppl/km^2$ and 11:00 AM channel state and user distribution. The tolerance waiting time is set from $5\ ms$ to $90\ ms$ with $5\ ms$ steps. The results are shown in Fig. 6.

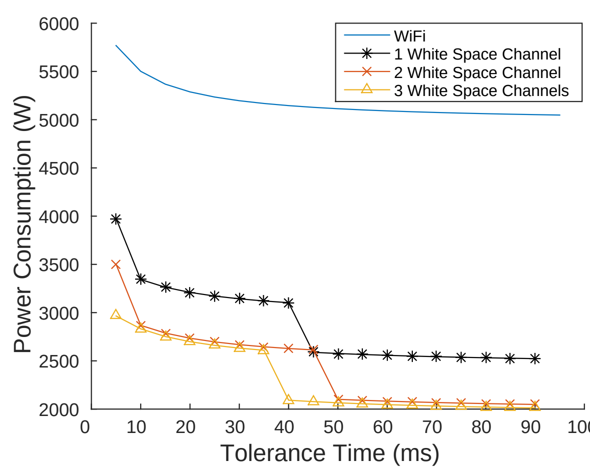

Fig. 6. Power Consumption across Delay Tolerance

The results that the less quality of service in waiting time, the less power consumption is required. As the tolerance waiting time increase, the power consumption of both WiFi and heterogeneous configuration gains power saving. The WiFi configuration gains the power saving mainly from the reduction of channel capacity delivery. The white space configuration gains the power saving from both the reduction of channel capacity delivery and the sleeping radios. Thus, there are some sharp reduction in the white space setup in the numerical simulation results due to the radio turning off. The power consumption could be reduced by 170.24% with three white space channels under the tolerance waiting time $90\ ms$. When the tolerance waiting time is more than $50\ ms$ there is no great difference between the two white space channels setup and three white space channels setup. As discussed in previous section, most of the major cities in the U.S. has restriction of white space channels. Thus, the network carriers is able estimate the quality of service they can offer according to the resource they own, such as the number of white space channels, the power supply, etc.

We involve the previous measurement work of channel state in multiple cities in DFW metroplex area to study the population density variation in white space network design [7]. We choose the The achieved channel capacity is mapping to the population distribution as in [7]. The user distribution is set as our measurements in 11:00 AM with $30\ ms$ tolerance waiting time. The results are shown in Fig. 7.

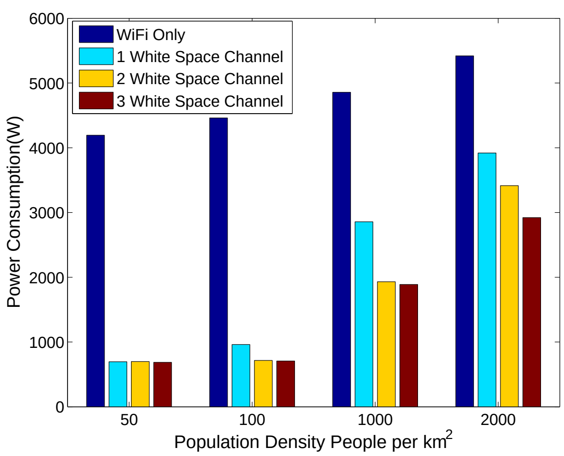

Fig. 7. Power Consumption across Population Distribution

As the population increase, all the configuration of network cost more power to serve the users. The gains of a single white space channel reach the peak in 50 ppl/km^2 as 512.55%. And the users are able to be satisfied by only one white space channel, the increasing of white space channels does not gains in power consumption. The same result happens for 100 ppl/km^2 with more than two white space channels. The number of white space channels reaches the constant power consumption increase with the population. For 50 ppl/km^2 is one white space channel while 100 ppl/km^2 needs two white space channels. Also, the gain of a single white space channels decrease as the number of white space channels increase. Such as in 1000 ppl/km^2, the first white space channel gains 70% of power consumption, the second channel adding to the system gains only 47.98% and the third one gains only 2.26%. Thus, when the white space channels are limited, split them into multiple combination of WiFi cells could increase the power consumption other than put them in one WiFi virtual city.

We study the white space impacts on the WiFi mesh networks. The application of white space channels reduce the power consumption of the system most of the time. The white space channels are good at adapting user mobility with less power consumption. Through the numerical simulation, putting the limited white space channels as complementary resource for the existing wireless network is able to reduce the power consumption of the system or increase the quality of service. When the wireless resource is above a threshold, the gain of white space becomes relatively small in the system.

IV. Related Work

Since white space bands were free for wireless communication, many efforts have been put in the area for the application of white space bands. [16] In [9]. the author considered a cognitive method to avoid collision between white space communication and TV broadcasting. Many works increasing the convenience of using white space databases have been published (e.g., Microsoft's White Space Database [17]). Google has even visualized the licensed white space channels in US cities with an API for research and commercial use [18]. Previous work discussed the point to point communication with white space bands [19], and the wireless network deployment with plenty white space channels [7]. However, many of the major cities in the US do not have plenty white space channels, such as most area of Austin, TX has only one white space channel. As far as we know, there is no work discuss these scenarios.

Applying white space in wireless network is similar to the previous multi-channel works other the propagation variation. In [10] a multi-channel system is formulated as a queuing system and Server Side Greedy algorithm is proposed to optimize the throughput with low complexity. In [20], Delay-based Queue-Side-Greedy algorithm is proposed with low complexity for optimal throughput and near-optimal delay. [21] develop a multi-objective optimization framework to minimal energy consumption in a multi-channel multi-radio system. However, these works do not address minimizing the resource for certain quality of service and assume an on-off channel model.

Previous work studied the multi user setting with a single channel [22]. Spectral diversity is isolated for a single user in [23]. In [24], multi-user dynamic channel access is proposed jointly consider the temporal and spectral diversity in a multichannel model. However, none of these works address the channel association problem in multiband scenario. Previous work [7] studied the white space application in access network deployment with spectral diversity. However, these works fails to leverage the white space frequency in multi-user diversity in both spectral and temporal scenarios.

Previous works in real time systems put many efforts to minimize the resources, such as processors [25]. In [26], the author proves the capacity augmentation bounds for schedulers of parallel tasks. However, these works assume the parallel tasks have uniform servers. Previous work [8] investigate the white space in a queuing system without considering the heterogeneous topology. In contrast, we study the performance of a heterogeneous network with both white space channels and WiFi channels in channel utilization.

V. Conclusion

In this paper, we considered the use of few white space channel resource for improving the power consumption across a broad range of user mobility, population densities. To consider the power consumption of a system, we formulate the heterogeneous wireless network as a queuing system. We then analyze the heterogeneous queuing system based on previous queuing theory work. To address the resource allocation of white space channels, we proposed a Greedy Server-side Replace algorithm to find the resource allocation with minimum power consumption. We then perform spectrum utilization measurements in the typical areas of downtown, urban, campus, neighborhoods to drive the algorithm. We also leverage the user mobility pattern from WiEye measurements. Through extensive analysis across the spectrum utilization and user mobility, we show that white space bands can reduce the average of power consumption by 64.70% on average over 24 hours. We also integrated previous measurements work in north Texas and find the power consumption is reduced by white space bands by 512.55% in sparse area. In the future, we will consider to propose the heterogeneous wireless network deployment with large scale user mobility patterns.

References

[1] C. A. Balanis, *Antenna theory: analysis and design*. John Wiley & Sons, 2012.

[2] Y. Gan and Y. Wu, "Multiple rayleigh fading channels modeling based on sum-of-sinusoids model," *International Journal of Communication Systems*, vol. 27, no. 11, pp. 2997–3012, 2014.

[3] Google, "Spectrum database," http://www.google.org/spectrum/whitespace/, 2013.

[4] J. B. Andersen, T. S. Rappaport, and S. Yoshida, "Propagation measurements and models for wireless communications channels," *IEEE Communications Magazine*, vol. 33, no. 1, pp. 42–49, 1995.

[5] H. T. Friis, "A note on a simple transmission formula," vol. 34, no. 5, pp. 254–256, May 1946.

[6] T. Rappaport, *Wireless Communications, Principles & Practice*. Prentice Hall, 1996.

[7] D. R. Pengfei Cui, Hui Liu and J. Camp, "A measurement study of white spaces across diverse population densities," *IEEE 10th WiNMeE*, 2014.

[8] S. Chen, A. M. Wyglinski, S. Pagadarai, R. Vuyyuru, and O. Altintas, "Feasibility analysis of vehicular dynamic spectrum access via queueing theory model," *Communications Magazine, IEEE*, vol. 49, no. 11, pp. 156–163, 2011.

[9] P. Bahl, R. Chandra, T. Moscibroda, R. Murty, and M. Welsh, "White space networking with WiFi like connectivity," *ACM SIGCOMM*, vol. 39, no. 4, pp. 27–38, 2009.

[10] S. Bodas, S. Shakkottai, L. Ying, and R. Srikant, "Low-complexity scheduling algorithms for multichannel downlink wireless networks," *Networking, IEEE/ACM Transactions on*, vol. 20, no. 5, pp. 1608–1621, 2012.

[11] S. Niida, S. Uemura, and H. Nakamura, "User tolerance for waiting time," *IEEE Vehicular Technology Magazine*, vol. 5, no. 3, pp. 61–67, 2010.

[12] P. Viswanath, D. N. C. Tse, and R. Laroia, "Opportunistic beamforming using dumb antennas," *Information Theory, IEEE Transactions on*, vol. 48, no. 6, pp. 1277–1294, 2002.

[13] S. Yu, R. Doss, T. Thapngam, and D. Qian, "A transformation model for heterogeneous servers," in *High Performance Computing and Communications, 2008. HPCC'08. 10th IEEE International Conference on*. IEEE, 2008, pp. 665–671.

[14] E. Gelenbe, G. Pujolle, and J. Nelson, *Introduction to queueing networks*. Citeseer, 1998.

[15] "People and households," http://www.census.gov/people/, 2014.

[16] "Fcc white space," http://www.fcc.gov/topic/white-space, 2012.

[17] "Microsoft research white space database," http://whitespaces.cloudapp.net/Default.aspx, 2013.

[18] "Google spectrum database," http://goo.gl/NnIFXQ, 2013.

[19] P. Cui, H. Liu, J. He, O. Altintas, R. Vuyyuru, D. Rajan, and J. Camp, "Leveraging diverse propagation and context for multi-modal vehicular applications," in *IEEE WiVeC*, 2013.

[20] B. Ji, G. R. Gupta, X. Lin, and N. B. Shroff, "Performance of low-complexity greedy scheduling policies in multi-channel wireless networks: Optimal throughput and near-optimal delay," in *INFOCOM, 2013 Proceedings IEEE*. IEEE, 2013, pp. 2589–2597.

[21] L. Liu, X. Cao, Y. Cheng, L. Du, W. Song, and Y. Wang, "Energy-efficient capacity optimization in wireless networks," in *INFOCOM, 2014 Proceedings IEEE*. IEEE, 2014, pp. 1384–1392.

[22] S.-S. Tan, D. Zheng, J. Zhang, and J. Zeidler, "Distributed opportunistic scheduling for ad-hoc communications under delay constraints," in *Proceedings of the 29th conference on Information communications*. IEEE Press, 2010, pp. 2874–2882.

[23] T. Shu and M. Krunz, "Throughput-efficient sequential channel sensing and probing in cognitive radio networks under sensing errors," in *Proceedings of the 15th annual international conference on Mobile computing and networking*. ACM, 2009, pp. 37–48.

[24] Y. Liu and M. Liu, "To stay or to switch: Multiuser dynamic channel access," in *INFOCOM, 2013 Proceedings IEEE*. IEEE, 2013, pp. 1249–1257.

[25] G. Nelissen, V. Berten, J. Goossens, and D. Milojevic, "Techniques optimizing the number of processors to schedule multi-threaded tasks," in *Real-Time Systems (ECRTS), 2012 24th Euromicro Conference on*. IEEE, 2012, pp. 321–330.

[26] J. Li, J. J. Chen, K. Agrawal, C. Lu, C. Gill, and A. Saifullah, "Analysis of federated and global scheduling for parallel real-time tasks," in *Real-Time Systems (ECRTS), 2014 26th Euromicro Conference on*. IEEE, 2014, pp. 85–96.