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Research Article

SHARP: A JOINT SPECTRUM ALLOCATION, HANDOVER AND ROUTING PROTOCOL FOR COGNITIVERADIO AD-HOC NETWORKS

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ABSTRACT
In this paper, A joint Spectrum allocation, horizontal/vertical Handover and opportunistic multi-hop Routing Protocol (SHARP) is proposed to address a few of the most important challenges of multi-hop ad-hoc, fixed or vehicular cognitive radio networks, such as, maximization of spectrum utilization and throughput. Utilizing the proposed joint velocity and average received power (ARP) estimation algorithms a novel spectrum sensing method is presented that is used for efficient dynamic resource allocation and routing. Numerical evaluation and simulation results, demonstrate that proposed scheme achieves significant improvements over conventional solutions, specifically with the presence of severe AWGN and interference in addition to consideration of a dense urban Manhattan-grid model as a PU/SU environment.

Keywords: *Ad-hoc Networks, Cognitive Radio, Routing, Optimization, Dynamic Spectrum Allocation*

INTRODUCTION

COGNITIVE communication via smart programmable radios promises improvements in the utilization of the currently licensed spectrum and effective reduction of the congestion in the publicly or industrially utilized, valuable ISM band. The concept is emerging from single-hop to multi-hop communication, organizing a cognitive radio network (CRN). It is envisioned for a cognitive radio (CR) to be able to transparently exploit the frequency band of licensed users, either while, they are inactive or through wise control of transmitting power. Making it possible for CR users to get access to the underutilized parts of the frequency band width, opportunistically. It is also envisioned that a heterogeneous wireless network of CRs would provide high bandwidth for fixed and mobile users via dynamic spectrum allocation, resource management and routing [1, 2].

The cognitive channel, enforces an uncertainty in the radio resource management. In other words, the stochastic behavior of the primary users (PUs), imposes unique challenges for CRs. In the activity cycle of any CR, spectrum sensing and detection of the so-called spectrum holes are initial steps to be taken. Spectrum sensing and sharing issues are mainly studied in infrastructure-based networks, which are centrally controlled by an entity, responsible for channel sensing, determination of the best possible portion of the spectrum, and allocation of the available channels among requesting CRs. Such architectures are generally considered as a single-hop, because each CR directly communicates with the central station. It is obvious that resource management and link establishment algorithms that give optimal or suboptimal solutions in a single hop scenario may typically become inefficient in a distributed scenario. Heterogeneous and Multi-hop transmission environment introduces several critical challenges that are open to research [1].

Generally, any network among CRs, may have access to multiple frequency bands with different channel bandwidth and characteristics. Any CR may also have, different QoS requirements or demand certain bearers or applications. Hence, after spectrum hole detection, an efficient channel allocation policy must be implemented. A process called spectrum decision is responsible for determining available resources based on the CR's preferences or requirements of the bearer network. In addition, due to the uncertainty and dynamic nature of the multi-path fading cognitive radio channel, cognitive radios with multi-hop communication and no predefined structure, (i.e., multi-hop cognitive radio ad-hoc networks), essentially require a smart and adaptive routing algorithm.

In fact, in such an environment, spectrum availability and topology depend on instantaneous and spatial variations of PU's activity, interference among primary and secondary users (SUs) also interference among SUs and SUs, signal to noise and interference ratio (SINR) of SUs and PUs, requested bit error rate (BER) by the primary and secondary users and etc. Therefore, in an ad-hoc multi-hop network many frequency handovers may take place at each relay node.

Because of PU or SU mobility, multipath fading and shadowing, the received signal strength (RSS) has fluctuations, which make raw signal strength, unstable criteria for any resource management procedures including, channel allocation, handover and routing. The shadowing, the large-scale variations in path loss, is caused by obstacles in the propagation path. The small-scale variations are due to the Doppler shift along the different signal paths and the time dispersion caused by the multipath propagation delays. As one primary indicator of channel quality, the power of the slowly varying shadow component is important for handoff decisions and power control which are, in turn, essential for any successful route establishment and route maintenance algorithm.

Many of existing cognitive handover algorithms, are based on an assumption that, multipath fluctuations can be efficiently filtered. Consequently, those algorithms based their frequency allocation or frequency handover decisions, on the local mean power estimates [2], [3]. Although these variations bring back uncertainty in the act of PU activity detection and resource management, but those can be utilized for extracting precious information about propagation environment and mobility behavior of PUs and SUs [4]. For mitigating variations of the RS, efficient smoothing techniques must be utilized. If the averaging interval is too short fluctuations may not be effectively removed, or if the interval is too long, it may cause delays in both, cognitive handover and routing. In non-line of sight (NLOS) scenarios this can average out useful information on the corner's positions (in case of mobility). To fully exploit the capacity of the underutilized frequency channels, and to overcome the ping-pong effect in cognitive radio networks, an efficient power estimation method is required [5], [6]. The ping-pong effect occurs if parameters account for frequency handover decisions, change rapidly, thus, a SU performs the handover as soon as it detects a PU activity or a route with better link quality. (e.g. A slow maneuvering PU is bouncing inside and outside of SU sensing range). Due to the fact that several spectrum bands are available for cognitive radios, thus, whenever the traffic load on one band reaches its functional limit, or requested bandwidth by any CR user cannot be supported, by existing spectrum band, a vertical handover should take place for a new band in which requested services are supported. Considering the behavior of PUs, The vertical ping-pong effect occurs, when, requested resources are not available for an active session of a CR user for a stochastic time, and as the CR user opportunistically decides on the working frequency band, several vertical handovers among available spectrum bands, would take place. Due to the heterogeneity, PHY and MAC layer of different integrated heterogeneous wireless networks are different. Thus, a unified approach must be taken into consideration for collecting specific measures from different cognitive and non-cognitive networks. As a result, more sophisticated joint spectrum allocation, handover and routing algorithms are required for the extension of the throughput of multi-layer networks and for increasing the efficiency of resource management for the next generation of wireless cognitive heterogeneous networks.

A cross layer spectrum aware resource management and routing algorithm must be developed to consider all possible interactions between PUs and SUs.

In order to address above-mentioned challenges, this paper proposes a joint cross layer resource management consisting from spectrum allocation, handover and CR routing protocol for ad-hoc networks (SHARP) that specifically addresses the performance concerns of CR communication over an end-to-end path, and the problem of securing the PU communications from the interference generated by SUs specially when they are acting under limited knowledge of the environment and complex and highly stochastic behavior of the multipath fading channel. Our main contributions can be summarized as follows:

• We have proposed a multi-hop joint novel spectrum sensing, spectrum allocation, power control, frequency handover and dynamic routing algorithm for ad-hoc cognitive radio networks in a multipath fading environment. The proposed algorithm gathers several invaluable indicators from the physical layer and addresses the jointly spectrum decision, power control, frequency handover and routing under realistic propagation environment.

- A practical working environment is considered. Multipath channel, in which received signal strength (RSS) is consisted of three different phenomena (path loss, shadow fading, fast fading) is considered as well as AWGN.As a practical measure of interference, signal to interference plus noise ratio (SINR) between SUs themselves in addition to interference between primary and secondary users are considered and analyzed based on the predefined BER limits.
- Opportunistic behavior of the radio spectrum is analyzed through a novel method for joint detection of PU/SU activity and the separations of PU signal from SU signal is presented in this paper which is robust to multipath fading with the presence of severe stochastic additive noise. To our knowledge, no unified framework has been proposed so far in the literature that is able to cover PU/SU activity detection and signal separation for both fixed and mobile PUs and SUs.
- The dynamics of the behavior of the PUs are mathematically and theatrically analyzed and the effect of PU activity is added to different performance metrics utilized for evaluation of the proposed algorithm.
- The ping-pong effect in the cognitive environment is defined. A robust cognitive frequency handover scheme is presented for addressing the challenges imposed because of the uncertainty in the access to the spectrum.
- Utilizing the above mentioned tasks, each CR user can make real-time sessions locally for route establishment and maintenance. The proposed routing algorithm can effectively adapt itself based on PU traffic model and based on the QoS requirement of the CR user offering different classes of functionality for different practical scenarios.

This paper is organized as follows. Section II reviews related work on cognitive resource management. In Section III, network and propagation model is introduced. In Section IV, the proposed PU/SU activity detection and separation, spectrum (SHARP) allocation, frequency handover and routing algorithm are described. The framework for analysis of SHARP algorithm is described in Section V. The performance of the proposed algorithm is evaluated through theoretical model and analyzed by simulations based on proposed performance metrics in Section VI. Finally, paper is concluded in Section VII.

For a successful end-to-end route establishment and route maintenance, clearly in CR networks, several challenges are required to be addressed. This creates a chain of controlling and management functionalities (i.e, spectrum allocation, handover, power-control and routing) that are essential to CR communication. Thus, recent work on each part is reviewed separately.

A. Centrally Managed CR Networks

In [7], dynamic spectrum access protocol (DSAP), as a centralized spectrum sharing algorithm is presented. Similar approach is taken in the central spectrum policy server (SPS) method [32] with an emphasis on intra-network spectrum assignment. The DSAP leases the spectrum for a limited time and to the users in a limited geographical region based on a Radio Map built by the cooperation among SUs.

Graph based analysis of the CR network based on gathering full knowledge of the system via a common control channel (CCC)is another widely presented approach [7]. A CCC based spectrum assignment framework (CogNet) is proposed in [16] that constructs a multi-layered graph of the network, where each layer corresponds to a frequency channel. In either case, all available spectrum is classified to frequency bands, each CR is allowed to have access to the predefined channel as long as it takes. A Dijsktra or Bellman-Fordlike algorithm is utilized for finding the optimal path within the constructed topology graph. Scalability and calculation of route's overhead in addition to the assumption of hard interference makes these algorithms not suitable for routing in ad-hoc CRN. Several other works focused on the CR mesh networks are surveyed in [6-7].

B. Multi-hop Distributed Structure (Ad-hoc)

[9] Proposes multi-hop single-transceiver CR routing protocol, similar to the Ad-hoc On-demand Distance Vector (AODV) routing algorithm, the signaling containing routing request commands are flooded over all the available channels. The channels are defined based on the shortest path, estimates of

the spectrum switching delay, channel contention, and transmission time. Also in [3] the preferred channels are selected based the establishment of the best route. Opportunistic nature of the channel, because of stochastic PU's arrival rate and mean holding time makes above mentioned methods not suitable ways of routing in CRN. Clearly, flooding of signaling messages in all available channels [9] or flooding the CCC [3] increases the interference level of the system, which in turn reduces the throughput and capacity of the system. The protocol proposed in [15] offers a locally calculated cost function based route establishment and scheduling for reduction of frequency channel switching costs. A multi-agent based approach is presented in [13], in which SUs periodically, exchange controlling information, including frequency channel and traffic indicators like delay on a channel basis. Behavior of CR users is learned in a neighboring circle and will be utilized for future decisions. This method suffers from the stochastic and the heterogeneity behavior of PUs. The other relevant literature is reviewed in [6-7].

Our work, focuses on a cross-layer approach that is fully suitable for heterogeneous ad-hoc multi-hop CRNs. As a result, the proposed algorithm must have a high level of adaptability to PHY and MAC structures of various types of telecommunication systems. A set of sophisticated and yet practically implementable solutions for spectrum sensing, PU/SU separation, frequency allocation are offered in this paper that will fully adapt to heterogeneous cognitive radio network. Several works have been proposed so far, that addresses spectrum sensing [6-7].Those approaches are divided into four different categories: use of a broker between PU and SU networks, energy detection algorithms, advanced signal processing techniques such as cycle-stationary feature detection or blind source separation of radio signals in the presence of AWGN, or leverage cooperation for increasing accuracy [6-7]. However, mentioned methods often cover a part of CRN requirements including:

(i) Simplified system model (free space propagation) without consideration of multipath fading and shadowing, (ii) detection of PU transmitters and lack the ability to detect the PU receivers,

(iii) No ability to cope with mobility of the PU and SU subscribers and (V) high rate of false alarms. Thus, an effective and easy to implement frequency-hole detection method is proposed.

If the existing frequency channel become not useable (according to predefined QoS measures), or the PU activity appears reclaiming owned, licensed channel(s), SUs are required to immediately back off and evacuate the channel simultaneously take control of another channel to seamlessly continue of the communication. We call this kind of a frequency handover, a cognitive handover (CHO). Since the transmissions of SUs are suspended during a CHO they will experience a longer packet delay or a possible loss of a session. In order to address this aspect, [97] offered a channel reservation algorithm. In the mentioned algorithm, a certain number of channels are reserved for future CHO. Due to the stochastic behavior of PUs such an approach will result in a severe throughput reduction. A location-assisted CHO algorithm is proposed in [98], where the SUs benefit from location information. In such CHO, the frequency channels are assigned from the geographically available channels. A joint spectrum handoff scheduling and routing protocol in multi-hop multi-radio CR networks is proposed in [99], the main contribution of this work is to extend CHO of a single link to that of multiple links [102]. Ideas like switching spectrum bands for CHO is offered in [100], [101] with the assumption that PUs in different bands may have different behaviors. In the abovementioned literature, no attention has been made on the system performance measures, such as the blocking probability of originating sessions in CR network and the forced termination probabilities of CHO. To our knowledge, the concept of ping-pong effect in CR networks has not been addressed so far. Thus, a sophisticated frequency handover mechanism is essential for SUs with seamless frequency shift.

In a fixed heterogeneous CR environment, the ping-pong effect is a phenomenon that rapidly repeats CHOs between two SUs because of rapid changes in PU activity or error (false alarm) in the PU activity detection due to the time based fluctuations of RSS in multipath fading channel.

In a scenario that PUs are mobile but, SUs are fixed, the ping-pong effect is a phenomenon that rapidly repeats CHOs between two SUs because of changes in PU location or behavior plus false alarms. Extensive maneuvers of PUs can also trigger the unnecessary handovers. In this scenario CR users face another challenge, which is caused by mobility of the PUs and hidden node problem. When mobile PU turns at the corners or loses LOS, RSS drastically decreases (between 20 to 40 dB) [103].

Remark: RS is affected by fast fluctuations caused by multi-path and fast fading, thus, apparently, the probability of false alarm in the spectrum sensing phase will be increased. In a scenario that PUs and SUs are mobile, the ping-pong effect is a phenomenon that rapidly repeats CHOs between two SUs because of mobility of both PUs and SUs. In this case the act of spectrum hole detection and CHO cannot rely on RSS. Also, time varying nature of the dynamics of the system like velocity, acceleration and location of the PUs and SUs demands for efficient cross-layer approach for more effective mitigation of RSS instability, this is done by utilizing an efficient average received power (ARP) estimator which will be discussed in section. V.

Network and Propagation Model

A. Network Model

The CR network architecture is assumed to be a multi-hop wireless ad-hoc network, consisted of two integrated heterogeneous primary and secondary networks. The primary or licensed network is referred to as an existing network, where the PUs own license(s) for any specific band(s).

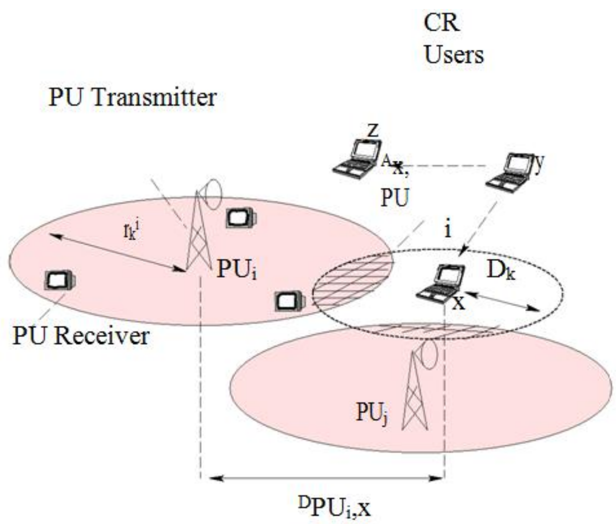

Figure 1: Typical cognitive radio network structure

The SUs, in the secondary network does not own any frequency license to operate. The SUs will take advantage of the frequency holes in the licensed band(s) for communication. Let the CRN be modeled by a general connectivity map $\Psi(\kappa,\upsilon)$, where κ represents a finite set of live users, including N primary users and M secondary users. Each primary user is listed in the subset $PU=\{\kappa_1,\dots,\kappa_L\}$ and each secondary user is listed in the subset $SU=\{\kappa_{L+1},\dots,\kappa_{M+L}\}$.ν denotes active links between κ_i and κ_j user for any $(i,j)\in\upsilon$. All of the SUs are assumed to be equipped with cognitive spectrum sensors and transceivers similar to the implemented prototypes GENI and KNOWS [20]. Each CR can choose its frequency band from a set of regulated bands by Federal Communications Commissions (FCC) including 54-72MHz, 76-88MHz, 174-216 MHz, 470-806MHz and ISM 2.4GHz/5.4GHz subject to different channel bandwidth in each frequency band. Thus, any CR transceiver selects its maximum bandwidth ΔBW from the k^{th} available bands [f_k ;$f_k+\Delta BW_k$].Note that assignable ΔBW in each of the k^{th} bands are different and may not be contiguous, due to the diverse characteristics of the different frequency bands. The physical layer (PHY) is considered to be generic for better compatibility and applicability. However, multi-carrier code division multiple access (MC-CDMA) and orthogonal frequency division multiplexing (OFDM) based transmission are promising methods for CR networks. Utilizing the different spreading codes with different code lengths, softens the interference level (i.e. multiple transmissions can simultaneously occur between SUs) and explicitly protects PUs from any SU communication. Among others, by using OFDM, the cognitive users can manipulate the heterogeneous spectrum bands with a flexible sub-carrier pool. To increase the capacity of the CR network, efficient adaptation to the stochastic behavior of the PUs is required. In addition to the above, supporting different bearer services with different bandwidth requirements, multiple non-contiguous and heterogeneous spectrum bands (i.e. VHF, UHF, ISM, etc.) can also be concurrently utilized. This procedure is triggered and controlled by proposed joint spectrum sensing and handover algorithms.

In this scenario, we discuss both vertical (VHOs) and horizontal cognitive handovers (CHOs). The proposed algorithms are described in section. V.

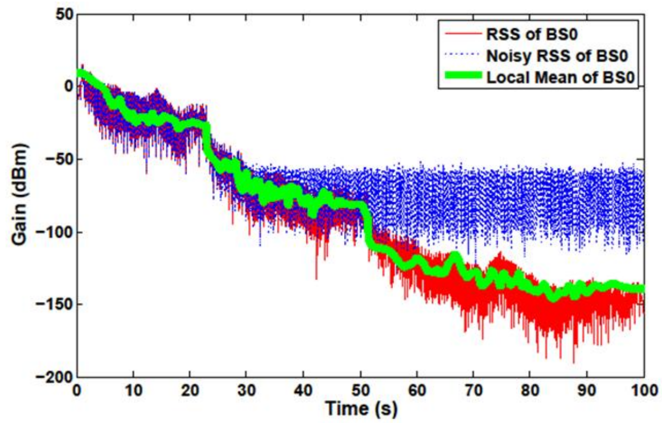

Figure 2: Simulated RSS for variable mobile speed, long term SNR = 20 dB for noisy RSS

The proposed algorithm, can explicitly protect the PUs from SU's interference, in addition to an enhancement in throughput. Let the ω^k be the bandwidth in i^{th} channel of the k^{th} spectrum and let the ω_D^k be the requested bandwidth that corresponds to requested bearer by κ^{th} CR user, the number of concurrent available channels are $\lceil \omega^k / \omega_D^k \rceil$.In general, data traffic flows are, carried over multi-hop ad-hoc routes. The demanded traffic flow is assumed to be consisted of a set data streams DS = {1, 2, …;dS_P}, where dS_p=|DS| for a uni cast session. Each session $dS_p \in DS$ is defined by source-destination, relay pairs. Let the arrival rate of traffic stream dS_p at the n^{th} time slot, for the κ^{th} CR user over the k^{th} spectrum band be $\lambda^{\kappa}_{k,dS_p}[n]$.

Each pair of the source-destination/relay CRS maintains a queue for each session dS_p. The number of queued packets of $dS_p{}^{th}$ session for κ^{th} CR user over the k^{th} spectrum at the n^{th} time slot, is represented by $Q^{\kappa}_{k,dS_p}[n]$. The queue length is affected by several network characteristics (e.g. (r^{κ}_{ji}) link rate measured in bit/s, traffic arrival rate ($\lambda^{\kappa}_{k,dS_p}[n]$) measured in packet/sec), thus, we propose a classic definition of the queue length of as

$$Q^{\kappa}_{k,dS_p}[n] = \left[Q^{\kappa}_{k,dS_p}[n-1] + \left[\frac{r^{\kappa}_{ji}}{\sum_{z \in SU, z \neq i}^{|SU|} r^{\kappa}_{zi}} - \frac{r^{\kappa}_{ij}}{\sum_{x \in SU, x \neq i}^{|SU|} r^{\kappa}_{ix}} \right] \bar{L}^{\kappa}_{k} + \lambda^{\kappa}_{k,dS_p}[n] \right] \tag{1}$$

***B.** Propagation Model*

The propagation model discussed here takes into account the correlated multipath fading, the correlated lognormal shadowing and a distance dependent trend [13]. A discrete model (with the sampling rate of 1/2BW) for the received signal (RS), γ[n] is given by

$$\gamma[n] = \sqrt{s[n]}r[n] + \eta[n] \tag{2}$$

Where r[n] is the complex envelops due to multipath propagation and user mobility, which contains the mobile's Doppler amplitude information, s[n] is ARP (local mean) at the user and η[n] is AWG noise with zero mean and variance of σ_n^2. r[n], s[n] and η[n] are mutually independent .r[n] is defined by

$$r[n] = \frac{1}{\sqrt{k}} \sum_{i=1}^{k} a_i e^{j(2\pi f_d \cos(\theta_i)\frac{n}{2BW} + \varphi_i)} \tag{3}$$

Where f_d is the Doppler frequency, θ_i and φ_i are mutually independent random variables, uniformly distributed over $(-\pi, \pi]$, a_i is the gain of i^{th} scatter and k is the number of independent scatters (usually k=20 is sufficient to provide good approximation). The process s[n] is a wide-sense stationary lognormal random process, which contains a distance dependent trend and lognormal shadowing with mean and variance, μ_s and σ_s^2, respectively. The Shadow-fading process is assumed to have an exponential correlation function model proposed by [14] based on the measured auto-covariance function s[n] in the urban environments. Path-loss (μ_s), the mean of s[n], decreases monotonically with the increasing distance from the transmitter. The propagation model utilized in this paper, is based on the Manhattan model, therefore, corner effect is fully manifested in the model. We believe that complex propagation model is essential for evaluation of any CR resource management and controlling algorithm because it is completely covering the complexities of practical communication for a heterogeneous CR system. Let d_c be the distance between BS and intersection at which user makes a turn. Following [4], dimensionless parameter x_0, the distance parameters x_c, y_0, y_c and exponents ζ, η, χ are introduced. Corner effect could cause ΔSdB signal drop, in y_0 meters. P_0 is a constant that accounts for transmitted power and antenna gain. Path loss for microcellular structure, at position d is modeled by:

$$\mu_s(d) = \begin{cases} P_0 - 20\log_{10}(d/x_0) \\ -\frac{10}{x}\log_{10}(1+(1+(d/x_0)^{(\zeta-2)\chi})), & 0 < d_1 < d_c \\ P_L(d_1)10^{\frac{-\Delta S \cdot d}{10 y_0}}, & d_c < d < y_0 \\ P_L(d_1) - 20\log_{10}(d/y_0) \\ -\frac{10}{x}\log_{10}(1+(1+(d/y_c)^{(\eta-2)\chi})), & d_2 < y_0 \end{cases} \tag{4}$$

To suppress noise and interference terms, γ[n] is passed through a low-pass filter with a BW>f_{max}; since we are only interested in the narrow band Doppler power spectrum, which is variable (0-f_{max} (Hz)), in the femto or micro-cellular system. $f_{max}$is the maximum possible channel Doppler frequency. Note that, the shadow fading s[n] varies very slowly in comparison with r[n]. An example of the RSS in a microcellular environment is plotted against 100 seconds of observation in Figure 2, for variable speed while the long-term SNR is 20 dB. As it is seen, the short term SNR is high near the transmitter.

Joint Spectrum Allocation, Handover and Routing Protocol

In this section, the distributed joint Spectrum allocation, Handover and Routing Protocol (SHARP) is presented. We start by introducing the proposed ARP and velocity estimator which are utilized in the process of spectrum sensing, handover and routing in section IV.A. Notions of the joint spectrum hole detection and differentiation of PU'sRS from SU'sRS are presented in Sections IV.B. IV.C summaries calibrated metrics for route(s) establishment and maintenance. Then, in Section IV.D the distributed cognitive vertical and horizontal handover algorithms are outlined. Finally, the cognitive routing algorithm (SHARP) based on the proposed dynamic spectrum allocation and handover algorithms is presented in Section IV.E.

A. The Proposed Framework for Joint Velocity and ARP Estimator

A wealth of literature on spectrum sensing focuses on PU downlink activity detection. SUs, locally detect PU activity based on RSS measurements. Generally, existing approaches lack the ability to distinguish between PU and SU activity. Complexity, accuracy and applicability of spectrum sensing techniques are fully studied in [4].A simple type of window-based ARP estimator (WBEs), namely weighted sample average estimators of local mean power, is currently deployed in many commercial communication systems and various other WBEs have been proposed in [16]. These WBEs, work well under the assumption that the shadowing is constant over the duration of the averaging window and in this case their performance improves as the window size increases. In practice, however, the shadow process varies with time (albeit slowly relative to the fast-fading process), and this variation should be taken into consideration since both analyses (developed herein) and experiment shows that the mean square error (MSE) performance of these WBEs deteriorate severely when the window size increases beyond a certain value. For variable speed, the observation window must be adapted constantly, and the rate of adaptation depends not only on the user speed, but also on the sampling period and shadow fading characteristics. In particular, errors in the estimates could propagate due to suboptimal observation windows. Valuable information about the dynamics of the behavior of PUs and SUs are extracted from raw RS, and then it is used for ARP estimation. Utilizing an accurate joint velocity and ARP estimation algorithm and by using the proposed recursive matched filtering of the estimated power density spectrum (PSD) of the RS, unique spectrum sensing and PU/SU activity detection algorithms are introduced for heterogeneous cognitive environment. Naturally, wireless communication is a non-stationary environment. The signal properties include amplitude, frequency, and phase (AFP) are time-variant. In cases where the signal can be modeled by the sum of sinusoids (i.e. received band-pass signal at fixed or mobile radio station) the Fourier transforms of finite-length segments of the RS, yields valuable information about user and channel characteristics. Thus, periodogram analysis is used to estimate the PSD of RS. The DFT of finite-length time segments of RS obtained by a bank of rectangular temporal filters. In which, each filter has different temporal duration. The N point DFT of windowed RS from κ^{th} user over the j^{th} spectrum band is:

$$V_{i,j}^{\kappa}[k]=\sum_{n=0}^{N-1} w_i[n]\,\gamma_j^{\kappa}[n]\,e^{-j\frac{2\pi n}{N}k} \tag{5}$$

where $w_i[n]$ is the ith window with the length L_i. An estimate of the PSD (called periodogram) is

$$PSD_{i,j}^{\kappa}(\omega_k)\approx\frac{1}{L_i\,\Delta tF}E\left\{\left|V_{i,j}^{\kappa}[K]\right|^2\right\} \tag{6}$$

Where the constant $\omega_k=2\pi K/N$ for $k=0,1\ \ldots,N-1$, Δt is the sampling interval and F anticipates a need for normalization for removing the bias in the process of spectral estimation [10]. This approximation is valid for large L_i. It is well known that a fast movement, causes high Doppler spread in the RS, while a slow movement, brings about a low Doppler spread. Therefore, the shift in the local maximum of the estimated PSD is related to the maximum Doppler frequency, which is proportional to the user velocity ($\hat{v}\propto\hat{f}_d\cdot\lambda$).Where λ is the wavelength. Under the ith window, user velocity estimation problem can be formulated as follows

$$\hat{v}_{i,j}^{\kappa}\propto\arg\underset{\omega}{Max}\left\{PSD_{i,j}^{\kappa}(\omega_k)\right\} \tag{7}$$

In Figure 3 estimated PSD for two different speeds is plotted versus the Doppler spread. As it is seen, any increase in the velocity would increase the Doppler spread ($\hat{f}_d$) in the frequency domain. Due to the symmetry of the Doppler PSD, one-half of Doppler PSD is plotted in Figure 3. The relative velocity of any active user can be estimated using the Doppler spread estimation and classification. If the user's

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mobility model is classified into two distinctive classes, pedestrian and fast, the relative velocity of mobile user can be extracted for proposed method. To increase the speed and the accuracy of user mobility model detection, only two segments (subsets) of frequency domain of the estimated PSD, is going to be considered as the regions of interest and $\hat{f}_d$ estimation algorithm is performed only in these two segments. In the proposed algorithm, the maximum of PSD is searched only in pedestrian subset, which limits search space and as a result increases estimation speed.

The ARP (RS local mean) is estimated based on the fact that slow fading and path loss have slow variations in comparison to the envelope of RS, while a mobile user is maneuvering in the coverage area, therefore; information of slow fading and path loss are present, only in the DC component of the estimated PSD of the RS. For variable mobile speed, the duration of the observation window ($w_i[n]$) L_i should be constantly adapted and the rate of adaptation is a critical factor that directly affects the performance of the speed and the power estimators [9]. The DC component of estimated PSD is adaptively extracted based on the following:

$$\hat{S}_{i,j}^{\kappa} \approx \frac{1}{L_i \Delta tF} \left| V_{i,j}^{\kappa}(e^{j\omega}) \right|^2 \Bigg|_{\omega=0} \approx \frac{1}{L_i \Delta tF} \left| \sum_{n=0}^{L_i-1} w_i[n]\, \gamma_j^{\kappa}[n] \right|^2 \tag{8}$$

In order to improve robustness of the proposed method against severe distortion caused by AWGN, a bank of matched filter(s) in the frequency domain is utilized, before the estimation of the velocity and ARP. Figure 4, Demonstrates, the block diagram of the proposed estimator. Due to additive noise, in the coverage border areas, where the SNR is at the lowest level, or in scenarios that sudden loss of LOS would suddenly decrease the SNR, the maximum of Doppler PSD, may be shifted. In other words, the Doppler PSD will have a maximum in a frequency different than the maximum Doppler frequency).

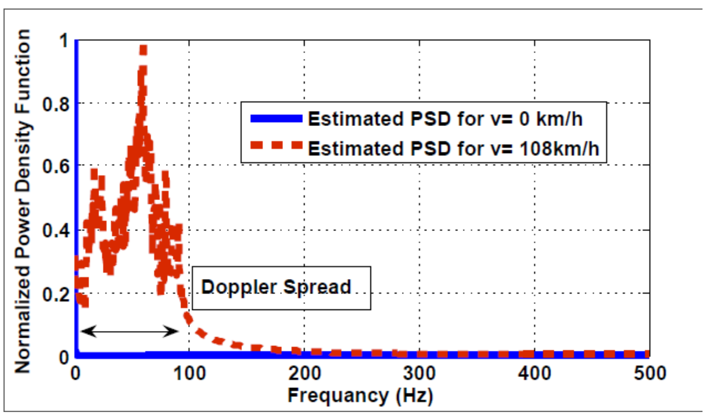

Figure 3: Folded PSD and Doppler spread for minimum and maximum possible velocities in the Manhattan area model

This adds a severe bias to the estimated velocities. Utilizing a unique matched filtering technique in the frequency domain, effects of AWGN can be efficiently mitigated, ensuring a maximum output SNR in the presence of the stochastic AWGN.

In the proposed unique method, each CR user matches its estimated PSD to itself. In other words, each CR will match the estimated Doppler PSD to a calculated obviously not exposed to noise, PSD of its own. Since the noise is non-cyclostationary signal, after a few iterations, the effect of AWGN is efficiently mitigated. The performance of proposed Velocity and ARP detector is analyzed in section.VI. The concept of unique recursive matched filtering based on the expectation maximization technique is mathematical evaluated in Annex. B.

The merit of matched filtering is the short time it requires to achieve a certain detection performance, such as a low probability of missed detection and false alarm [48], since a matched filter needs less received signal samples. However, the required number of signal samples also grows as the received SNR decreases, so there exists a SNR wall [27] limiting the performance of a matched filter. It is essential to come up with an idea to cover the minimum SNR requirements of the system. In addition, implementation complexity and power consumption of matched filter is too high when it is performed in the time domain [49]. Generally the matched filter needs receivers for all types of signals and corresponding receiver algorithms to be executed. In the previous works that offered matched filtering for PU activity detection, perfect knowledge of the primary user's signal, such as the operating frequency, bandwidth, modulation type and order, pulse shape, packet format, etc. are required. If wrong information is fed to the matched filter, the performance will be degraded, extensively. On the other hand, many of the wireless communication systems, exhibit certain patterns, such as pilot tones, preambles, mid-ambles, spreading codes, and etc., which are used to assist control, equalization, and synchronization, continuity, or reference purposes. Even though perfect information about a primary user's signal may not be attainable, if a certain pattern is known from the received signal, coherent detection (a.k.a. waveform-based sensing) can be used to decide whether a primary user is transmitting or not [50]. In this paper, we have proposed a recursive matched filtering of estimated Doppler PSD in the frequency domain to itself, which will effectively increase the performance of proposed PU/SU signal differentiation and frequency hole detection algorithm. The contributions of our work can be listed as follows:

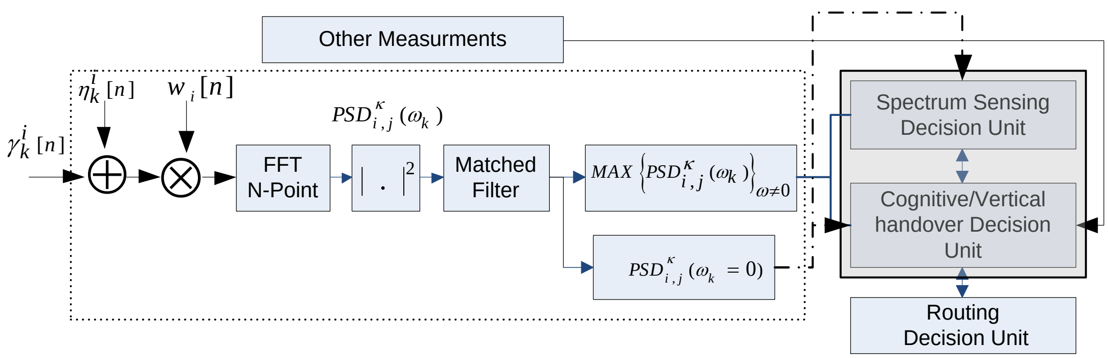

Figure 4: Block Diagram of proposed velocity and ARP estimation and spectrum decision

- Calculation of the N-DFT of the RS is an essential and built-in part of PHY's of many of the current and future wireless systems. Thus, the generic PHY of wireless system does not require a major change. In the proposed algorithm, temporal windowing technique is utilized. The window length is adjusted proportional to the dynamics of the mobility behavior of mobile user. The approach is efficient both in fixed and mobile scenarios.
- Due to the low computational burden of the approach monitoring of the k^{th} different spectrum band is feasible.
- Matched filtering is utilized in frequency domain based on the available information on each user. The aim of matched filtering to differentiate the PU signal from the SU signal.
- PU activity can be precisely differentiated from SU activity which is invaluable information for better load balancing and resource management in the CR network.
- The proposed approach does not require noise variance estimation.
- The main input for the algorithm is raw RS, thus no specific information on PUs are required.

B. Proposed Framework for Spectrum Decision and Differentiation of PU Transmission from SU's

For frequency f_k, the κ^{th} SU must (i) avoid raising the maximum tolerable interference level for PUs (ii) satisfy the required BER when it transmits to $\kappa+1^{th}$ SU, and (iii) avoid raising the maximum tolerable interference level of the system (i.e. not interfering with ongoing SU communication). Let $SINR_{SU}^{th}$ be the minimum level of allowed SINR that can support the required BER for achieving a certain bitrate, respectively, for any primary (BER_{PU}^{th}) and any secondary (BER_{SU}^{th}) subscribers. It should be noted that typically SU do not have access to $SINR_{PU}^{th}$ and BER_{PU}^{th}, unless a broker would be present for signaling exchange or SUs utilize a prior knowledge regarding PHY and MAC of the PUs. In order to detect frequency hole SINR for each CR user is going to be calculate SINR from estimated ARP with is much less sensitive to the AWGN in comparison with RS. For a link between (i,j)∈ν links, we have our first constraint similar to [25] as

$$\frac{\hat{S}_k^{ij}}{\eta_k^j + \sum_{m\in\upsilon, m\neq i}^{L} \hat{S}_k^{mj}} \geq SINR_{SU}^{th} \text{ for } BER_{SU}^{\text{target}} \tag{9}$$

The term $\sum_{m\in\upsilon, m\neq i}^{L} \hat{S}_k^{mj}$ denotes interference estimated at the j[th] CR user in the k[th] band. Equation (8), demonstrates that, for a successful transmission among SUs, the achieved SINR must be better than a predefined threshold. The second constraint highlights the maximum tolerable interference in the presence of AWGN for the receiver u. Let u∈ν,u≠j, the estimated ARP at the user u from i[th] user (i.e. additional interference at the node u enforced by thei's user transmission) are expressed by $\hat{S}_k^{iu}$ and $SINR_{k,\text{ available}}^{\text{neighbouring of } u}$ denotes for SINR at the user u before i[th] user transmission, which is

$$\hat{S}_k^{i,u} + SINR_{k,\text{ available}}^{\text{neighbouring of u}} \leq SINR_k^{\text{critical}} \text{ for } BER_{\min}^{\text{target}} \tag{10}$$

By assuming that the demanded bandwidth (ω_D^k) is supported for u∈SU, the lower band in (8) and upper band in (9) assures the SU operability in case of no PU transmission. As it is shown in figure 4, each the SU matches the output of the periodogram estimator to itself, at this point SU have a full knowledge of its own MAC and PHY. Therefore, if the output of the matched-filter is compared to a threshold. This can easily, pinpoint that we are dealing with, SU or PU activity. Algorithm. I summarize the PU/SU detection algorithm. In case of the SU activity, the algorithm, exhibits an output higher than the threshold. In case of the PU activity, the output is going to be less than the predefined threshold. The threshold will be defined based on the characteristics of the system prior to the start of the algorithm and it will be calibrated with the gathered information, constantly.

The essence of spectrum sensing is widely considered to be a binary hypothesis-testing, modeling only presence or absence of PU activity [26-27]. In the ad-hoc CR network, the uplink interference caused by SUs activity in a neighboring is as challenging and as bounding as the PU activity, if the ultimate goal of the CR network is considered to be CR communication. If the available SINR ratio at each CR user do not satisfy the minimum requirements of the SINR required for target BER enforced by its PHY, still no communication will be feasible. Further descriptions will be given at the end of this section.

Inability of the SUs to opportunistically use the chance of absence of PUs activity can also occur, when the requested bandwidth ω_D^k is not supported by the available spectrum. It seems that monitoring only the PU activity will not cover all the possible scenarios essential for a successful communication in CR environment, due to the interference.

In order to address this, a ternary hypothesis-testing can be utilized. As the PUs and SUs, stochastically change their state of activity, a Markov model is useful for analysis and calculation of probability of transition for each state. It should be noted that all the SUs are considered to be backlogged and they are in sensing mode (i.e. not already transmitting). For the given system model of Figure 5 we have

H_0: PUs are absent and SUs cannot operate;

H_1: PUs are active and SUs cannot operate;

H_2: PUs are absent and SUs can operate;

The output of the spectrum sensing algorithm will decide on the above mentioned hypothesis,

Algorithm I: PU/SU Signal Differentiation

1: **loop**
2: for **k = 1 to |**{supported bandwidths}**|**
3: if **k∈**{supported bandwidths}**then**
4:calculate $PSD_{i,j}^{\kappa}(\omega_k)$ **then**
5:calculate Matched$_{\text{filtered}}$($PSD_{i,j}^{\kappa}(\omega_k)$) **then**
6: **if** Matched$_{\text{filtered}}$($PSD_{i,j}^{\kappa}(\omega_k)$) ≤ SU detection Threshold **then**
7: **if there is no activity on CCC then**
8: **"PU activity is detected" enable backlogging function**
9: else
Repeat the calculation (Go to step 6)
9: **end if**
10:**else if** Matched$_{\text{filtered}}$($PSD_{i,j}^{\kappa}(\omega_k)$) > SU detection Threshold **then**
11: **if there is activity on CCC then**
12: **"SU activity is detected" enable frequency hole detection function**
13: **else** declare detection error
14: **end if**
14: **end if**
15: **end if**
16**:** end
17**: end loop**

$$\gamma_k^i[n] = \begin{cases} \eta_k^i[n], \text{ if constraints (8 \& 9) are not fullfilled,} & H_0 \\ \sqrt{S_k^{PU}[n]} \cdot r_k[n] + \eta_k^i[n], & H_1 \\ \sqrt{S_k^{SU}[n]} \cdot r_k[n] + \eta_k^i[n], & H_2 \end{cases} \quad (11)$$

The structure of the proposed estimator, is as follows. First, the RS is segmented using temporal window banks. Then, the modulus-squared of the discrete Short Time Fourier transform of the windowed RS is calculated, this will prepare a measure of the PSD of RS. The output is adaptively matched to itself in order to maximize the SNR. The squared RS acts as a test statistic for ternary hypotheses evaluation H0, H1 and H2. As the raw signal is the least information that and a CR user can gather about the surrounding environment. Following [26], the probability density function of squared RS, is presented in the appendix. B. For the κ^{th} CR user, the average probability of false alarm is $P_f^{\kappa} = \Pr(|RS|^2 \succ \xi | H_0).p_i^k + \Pr(|RS|^2 \succ \xi | H_2)$.

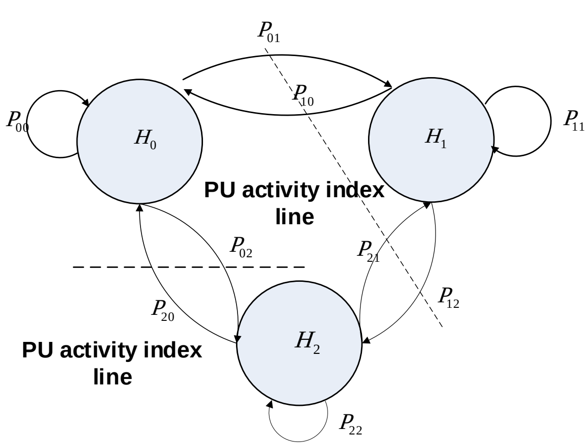

Figure 5: The State Transition diagram

Here, p_i^k is calculated by equation (14) and the average probability of PU detection is defined by $P_D^\kappa = \Pr\left(|RS|^2 \succ \xi | H_1\right).(1-p_i^k)$ .The average probably of missed detection of PU is defined by $P_M^\kappa = 1 - P_D^\kappa$. With the presence of stochastic AWGN, the closed form for probability of false alarm is

$$P_f^\kappa = \frac{\Gamma(m/2, \xi/2)}{\Gamma(m/2)}.p_i^k + Q_{m/2}\left(\sqrt{2SNR^\kappa}, \sqrt{\xi}\right).p_i^k, \kappa \in SU \tag{12}$$

where ξ stands for the detection threshold, Γ(a,b) is the incomplete gamma function, m denotes product of the window length and the bandwidth. Let the $Q_{m/2}$(a,b) be the generalized Marcum –function. The probability of the PU detection is

$$P_D^\kappa = Q_{m/2}\left(\sqrt{2SNR^\kappa}, \sqrt{\xi}\right)\cdot\left(1-p_i^k\right), \tag{13}$$

The analysis of the spectrum sensing problem in PHY and MAC layers, shows different characteristics of the PU activity. In order to come up an efficient routing algorithm in a CR network, it is essential to look at the statistics of the PU activity, from the MAC layer's point of view. As it is demonstrated in (10), the actual energy, present or detected in the channel is hardly binary.

Focusing on the nature of the PUs activity, it can easily be concluded that their behavior is a renewal process (a.k.a generalized Poisson process). In essence, the Poisson process is a continuous-time Markov process on the positive integers which has exponentially distributed, i.i.d. (independent identically distributed) holding times before any change in the state of the current CR user.

The PU traffic is assumed to be a stationary Poisson process over a sufficiently large observation window with an exponentially distributed off-and on-times [3], [10], [17]. The probability density function of an exponentially distributed random variable, x, is given as $f_\lambda(x) = \lambda e^{-\lambda x}$ for $x \geq 0$. Let the λ_{on} and λ_{off} be the average on (i.e. PU activity) and off (i.e. spectrum hole) times for the i^{th} channel from k^{th} spectrum. u_i^k denotes the duty cycle (i.e. PU channel utilization) of PU activity $u_i^k = \lambda_{on} / (\lambda_{on} + \lambda_{off})$.

A typical structure of CR network is shown in Figure 1. It is assumed that each CR performs the spectrum sensing separately. The probability of no PU activity over the i^{th} channel is

$$1 - u_i^k = p_i^k = \frac{\lambda_{off}}{\lambda_{off} + \lambda_{on}} \tag{14}$$

We will calculate the probability of transition between states, to demonstrate how the channel states follow the renewal process. The process can be characterized by a set of conditional probabilities $\Pr_{i,j}^\kappa(\Delta t),\ i,j \in \{0,1,2\}$ with the observation interval $\Delta t \geq 0$, defined as the probability that given CR user in the state i^{th} at Δt time unit, before it changes state to j^{th} at the present moment. Based on the Figure 5, the transition probabilities can be

simplified, due to the PU inactivity in the H_0 and H_2 states. Thus,

$$\begin{aligned} \Pr_{i,j}^\kappa(\Delta t)\Big|_{i,j\neq 2} &= \mathrm{u}^j (1-u)^{1-j} + (-1)^{j+i}\, \mathrm{u}^{1-j} (1-u)^i e^{-(\lambda_{off}+\lambda_{on})\Delta t} \\ \Pr_{0,2}^\kappa(\Delta t) = \Pr_{2,0}^\kappa(\Delta t) &= \Pr_{2,2}^\kappa(\Delta t) = \Pr_{0,0}^\kappa(\Delta t), \\ \Pr_{1,2}^\kappa(\Delta t) &= \Pr_{1,0}^\kappa(\Delta t), \\ \Pr_{2,1}^\kappa(\Delta t) &= \Pr_{0,1}^\kappa(\Delta t) \end{aligned} \tag{15}$$

It should be noted that the channel utilization factor, U_i^k can be estimated through the mean of m successive estimates of the PU activity obtained from the proposed sensing algorithm for a specific temporal observation time defined by Δt. Let $\mathrm{H}^\kappa = \{h_t^\kappa, h_{t+\Delta t}^\kappa, \ldots, h_{t+m\Delta t}^\kappa\}$, where $h_t^\kappa \in \{0,1\}$:

$$\widehat{U}_i^k = \frac{1}{m}\sum_{i=1}^{m} h_i^\kappa \tag{16}$$

C. Proposed Metrics for Routes Establishment and Maintenance

C.1 CR Link Capacity

The SUs are backlogged at the beginning of their life cycle (i.e. are not allowed to communicate in order to pass the sensing period). This on-off change in the status of the CR's transmission and backlogs in the SU transmission make a periodic transmission pattern. Note that, the sensing-transmission period can play an important role in the success of the frequency hole detection algorithm. Therefore, the sensing efficiency factor (ς^{κ}) is added to the analysis based on [8].The link capacity in CR network is widely modeled by the Shannon capacity law that reflects the maximum achievable bit rate. But due to the cognitive nature of the channel, this definition should be revised [3-4]. Effective parameters can be listed as

- Statistics of the PU activity
- Spectrum sensing efficiency [8]
- Spectrum switching delay
- Handover delay (between available channels and available spectrums)
- Noise variance
- Available bandwidth
- Interference level
- Efficiency factor of modulation and coding schemes
- Delay caused by backlogging

In a fast-fading channel, the latency requirement is greater than the channel coherence time and typically the length of the codeword(s) spans many channel coherence periods. Thus, we propose the following formula as a closed form for calculation of frequency selective, fast-fading wireless cognitive channel. Since the link capacity in CR network demonstrates a stochastic characteristic, the expected capacity of a specific link (i,j) for k^{th} spectrum and κ^{th} user is

$$c_{i,j}^{\kappa}(F_k)=$$

$$E\left[cp_{i,j}^{\kappa}(F_k)\right]=\sum_{f\in F_k=[f_k;f_k+\Delta BW]}\sum_{n=0}^{N_C-1}\frac{\hat{\lambda}_{off}^{k}}{\hat{\lambda}_{off}^{k}+\tau_k}\cdot\varsigma^{k}\cdot\omega_n^{k}\cdot\chi_n^{k}$$

$$\times\log_2\left[1+\frac{\hat{S}_{n,k}^{ij}}{\eta_k^{j}+\sum_{m\in\upsilon,m\neq i}\hat{S}_{n,k}^{mj}}\right] \tag{17}$$

where $\hat{\lambda}_{off}^{k}$ is the mean of estimated PU inactivity time, τ_k represents the spectrum sensing, spectrum switching and backlogging delays in the system, ς^{k} denotes sensing efficiency factor, χ_n^{k} stands for the modulation and coding efficiency factor and ω_n^{k} is the total available bandwidth of n^{th} sub-channel. The total capacity of the system for κ^{th} user, over k^{th} spectrum is

$$C_{CR}^{\kappa}=\sum_{k=1}^{N_{spectrum}}\sum_{l=1}^{N_{ch}}c_{i,j}^{\kappa}(F_{l,k}) \tag{18}$$

C.2 The Proposed Cost Function

Dynamic backpressure routing, has several useful characteristics for multi-hop, blind source routing in CR environment, such as per-packet next-hop route computations without a full knowledge of the topology and characteristics of the system. Such a blind decision making method, promises a greater adaptability and responsiveness to the channel temporal variations, opportunistic/stochastic nature of accessing to the media for CR users, CR user mobility and queue hotspots; this substantially enhances the through put efficiency of the whole CRN. In this paper, back pressure routing refers to a stochastic network optimization algorithm also referred to as Utility Optimal Lyapunov Networking algorithm [22-25]. Due to the instable nature of the channel for SUs, SUs may establish large queue sizes, which in turn can provide the required gradient for data flow. Therefore, by nature, backpressure is a promising technique for CR communication. Using the information about queue backlogs and link states, each CR is able to make a decision on maximum transmitting power, best route, achievable transmission rates, suitable coding rates, buffering requirements and etc, decisions without the notion of end-to-end routes. Previous studies demonstrate that the back pressure and queue management techniques, offers a near optimal performance in terms of the spectrum-utilization and the achieved-through put. Despite the theoretical capability of the backpressure mechanism, practical implementation of this technique mainly for routing in cognitive channel faces a few challenges. These challenges are listed as follows:

- If the cost function is not carefully defined, backpressure routing can either excessively select high hop-counts or low-hop counts, each one in turn can result in high channel utilization but with an infinite loop of packets or wasted transmissions and link-layer packet losses respectively.
- Large queues are required to be maintained to provide a gradient for the data packet flow, therefore, any routing algorithm with backpressure kernel can experience excessive stochastic delays.
- Queue length grows proportionally to the increase in the distance between CR users. This problem shows itself more vividly when large-scale networks are to be deployed. The limitations in the size of buffers in resource-constrained devices, have a direct impact on the queue length and consequently the network size.

Note. The idea of using differential backpressure as the kernel of routing scheme in CR networks is currently described in [24-25], several key elements are not considered in their utilized routing cost functions that make those algorithms, powerless for addressing the abovementioned challenges. Using the backpressure in the routing algorithm, although it guaranties the maximum achievable throughput for any available channel, but it fails to weight and prioritize the routs based on the measurements done in PHY. Considering the fact that we are dealing with an ad-hoc multi-hop multi-channel cognitive radio network; due to the stochastic change in the network topology, temporal and spatial variation of the RS and route diversity, an advanced measure for prioritizing routes is essential.

As it has been mentioned before, the CCC is assumed to be slotted. At each slot, the differential backlog is utilized in order to push the packets in the correct routes. The routing cost function between (i,j) link, dS_p^{th} session of κ^{th} CR user over the k^{th} spectrum is calculated and optimized as follows

$$\Phi_{ij,dS_p}^{\kappa} = \left[\Delta Q_{ij,dS_p}^{\kappa} - \Upsilon \cdot \Theta_{ij,dS_p}^{\kappa}\right] \cdot C_{CR}^{\kappa} \tag{19}$$

where $\Delta Q_{ij,dS_p}^{\kappa} = Q_{i,dS_p}^{\kappa} - Q_{j,dS_p}^{\kappa}$ is the queue differential length over (i,j) link, $\Theta_{ij,dS_p}^{\kappa}$ represents the cost of using the (i,j) link and Υ denotes a step function that trades off the system queue occupancy(better differential backlog pressure and as a result higher throughput) for the cost minimization. We have offered a unique elimination mechanism in order to enrich the cost function by adding several heterogeneous elements, as follows

$$\Upsilon \cdot \Theta_{ij,dS_p}^{\kappa} = \sum_{i=1}^{N_{\text{cost elements}}} \Upsilon_i \, {}^{i}\Theta_{ij,dS_p}^{\kappa} \tag{20}$$

C.3 Proposed Routing Metrics for Multi-Path Fading, Cognitive Channel

Due to the nature of CR channel, every CR user is subjected to the stochastic noise and severe interference, therefore, a specific quality parameter is required to be taken into consideration in addition to other measures that previously discussed inside the goal function. A textbook requirement for defining routing metrics is that any chosen metric should not change the routes a lot and guaranteeing route stability. This basic requirement is hard to achieve in a CRN. When the mobility is also an issue, a hybrid measure should be used for better adaptation of the measures proportional to the dynamic behavior of CR users. Several factors including load balancing, interference, link quality, Isotonicity, overhead, mobility and agility are required to be carefully considered for specification of routing metric(s).

In the reactive routing algorithms, several routing metrics are proposed for wireless ad-hoc multi-hop networks, (e.g. hop-count, expected number of transmissions (ETX)and expected transmission time (ETT)as the key measures for route selection in DSR and AODV algorithms [9, 38, 4, 15]). These measures clearly have several weaknesses, especially, when they are used in wireless fixed or mobile, ad-hoc CRN. e.g., the hop-count, does not cover the interference, channel diversity, load balancing, link quality, link capacity requirements (all the links are treated identically and distance is only weighed by hop-count) or the ETX, although effectively considers the link quality and the packet loss rate for each route, but it does not consider the effect of interference, it does not capture the variations in the rates of transmission and it cannot differentiate the heavily loaded links.

In our proposed routing algorithm, a unique cost function is introduced, which selects the best route covering all the above mentioned requirements. The route switching cost is another factor which represents the cost of cognitive handover or the cost of transferring an active session from one route over the same frequency to another due to link quality considerations. It is clear that a route that cannot support the requested bandwidth by CR user is a route that should not be assigned. The proposed penalty function is as follows

$$ {}^{1}\Theta_{ij,dS_p}^{\kappa} = \sum_{i\in\kappa}\sum_{j\in N_{\text{neighbors}}} \theta_{ij,dS_p}^{\kappa}\cdot\hat{\Psi}_{ij,dS_p}^{\kappa} + \sum_{r\in\text{channel list}}^{\text{k}\in\text{spectrum list}} \Xi_r^{\kappa,k} \tag{21} $$

Here, CR users, each have an out of bound link with their neighbors $N_{\text{neighbors}}$, dS_p^{th} session of κ^{th} CR user over the k^{th} spectrum, $\theta_{ij,dS_p}^{\kappa}$ is the forwarded packet count and Ξ_r^{κ} denotes channel switching cost (i.e. cognitive horizontal and vertical handover costs).Utilizing, measurements form PHY including estimated ARP and a few MAC functionalities of a cognitive radio, a Cognitive Expected Delay Estimate (CEDE) is developed. $\hat{\Psi}_{ij,dS_p}^{\kappa}$ denotes the estimated of CEDE. It is demonstrated through extensive simulations that, CEDE will achieve better results in multipath fading, multi-channel, cognitive network. This measure is planned to estimate the delay for transmission each packet by SUs. Following the ternary Markov model proposed in (11), the expected link delay for ad-hoc fixed or mobile CRN is a stochastic process of weighted sum of four delay terms: i) the delay of spectrum sensing and PU/SU differentiation.; ii) the delay of packet transmission (i.e. a function of packet length and link capacity); iii) the delay imposed by PU activity, which depends on the PU statistics calculated in (15) and (16).We assumed that over each spectrum at least of PU is active for time Δt .iv) the delay introduced by unwanted retransmissions cause by interference that SUs are producing for their neighbors. In this scenario the system works similar to ad-hoc routing mechanisms, focusing only on the link quality. In which, packet error rate is considered as a main factor for calculation of the link delay. Due to the fact that, delay increases proportional to the increase in the packet error rate.

Note. The expected numbers of the allowed MAC-layer retransmissions are limited. The maximum number of retransmissions of SUs (Max-Retry) before MAC outage, (i.e. the number of retransmissions exceed the Max-Retry) should be considered in the routing metric, as any routing method must ????? the MAC outage. The probability of SU-MAC outage, in (i,j) link, for κ^{th} CR user over the k^{th} spectrum is

$$ \begin{aligned} &\mathrm{P}_{outage\,ij}^{\,k,\kappa}(\Delta t) = \Pr(P_{SU}(x) > 1/Max\_\text{Retry}) \\ &= \Pr\left((\hat{S}_k^{i,\kappa}(\Delta t) + SINR_k^{\kappa\,\text{neighbour}}(\Delta t)) > (SINR_k^{\kappa\,\text{critical}}(\Delta t) \text{ for } SINR_{\min}^{\text{target}}) \right) \end{aligned} \tag{22} $$

CEDE Definition. The expected hop-to-hop delay ($D_{i,k}(\Delta t)$) for link (i,k), κ^{th} CR user from the neighboring $\mathrm{K} = \{user_\kappa\}_{\kappa=1}^{n}$, over the k^{th} spectrum, in the time interval Δt is given by:

$$ D_{i,k}(\Delta t) = \frac{1}{1-q_{i\kappa}^{N_{ch}}} \left(\left(\sum_{j=1}^{\kappa} \sum_{k=1}^{K_{spectrum}} \sum_{l=1}^{N_{ch}^{k}} q_{i\kappa}^{l-1}(\Delta t) p_{i\kappa}^{l}(\Delta t) \cdot \left(\frac{L}{c_{i,j}^{\kappa}(F_k)} + D_{i,k}(\Delta t) \right) + q_{i\kappa}^{N_{ch}} \cdot \Delta t + p_{suc\ i\kappa}^{N_{ch}} \cdot \Delta t \right) \right) \tag{23} $$

where $c_{i,j}^{\kappa}(F_k)$ is defined in (17), L is the packet length, $p_{i\kappa}^{l}$ is defined in (14), $D_{i,k}$ denotes the minimum expect delay for intermediating-destination node, $P_{Suc} = 1-[1-BER_{\min}]^{L}$ and $q_{i\kappa}^{l}$ is given by:

$$q^{l}_{i\kappa} = \begin{cases} 1 & if \quad l=0 \\ \prod_{m=1}^{N_{spectrum}} \prod_{n=1}^{N^{m}_{ch}} \left(1-p^{n}_{ik}\right) & else \end{cases} \tag{24}$$

Proof is presented in Annex. C

The final cost function is the modified version of (20)

$$\Upsilon \cdot \Theta^{\kappa}_{ij,dS_p} = u\left(I - I_{th}\right) \cdot {}^{1}\Theta^{\kappa}_{ij,dS_p} + \ln\left(u\left(\omega - \omega_D\right)\right) \tag{25}$$

Where I stand for the availability of CEDE estimate. In CR network, an estimate of CEDE cannot be provided in the early stages of the network, at least one successful communication must have happened, and therefore the moment CEDE estimates are available, I would be equal to I^{th} and the CEDE factor will play its role on minimization of the number of transmissions required for routing. The step function assures if the specific conditions are not fulfilled the cost element is eliminated. Therefore, if the requested bandwidth is not required by link (i,j), the natural log makes sure that such route is not going to be selected. This practice can be used in CRNs as well. In the proposed algorithm the estimated velocity (estimated mobility state of the user fixed or mobile) of any CR user is utilized for adaptively calibration of the cost function with user mobility behavior. This will be fully evaluated in the numerical results. The routing algorithm must choose a route that its retransmitted packets are less than the previously defined.

Further discussion over the proposed method of reducing the delay in the route establishment is described in section. IV.E.

D. Proposed Cognitive Horizontal and Vertical Handover Algorithm

Based on the proposed joint velocity and power estimator mobility behavior of maneuvering PU and SU user in dense urban area is estimated. This is further utilized to mitigate fluctuations of RSS in order to minimize the number of CHOs and simultaneously assigns different service requests and CR user's efficiently to different spectrums in a cognitive heterogeneous network (CHN). This in turn can minimize the probability of blocking and probability of false vertical handover, having a direct influence on the performance of the proposed algorithm.

D.1. Cognitive Horizontal Handover and Vertical Handover Algorithms

As it is mentioned in the previous section, due to heterogeneity of different integrated networks (PU and SU PHY can be heterogeneous) and available spectrum bands, the measurements of each network/band cannot be compared directly to other networks so hysteresis method [9], [10] cannot be used in the CHO algorithm. Hence, using a pre-defined threshold is considered here. In CHN structure shown in Figure 2.

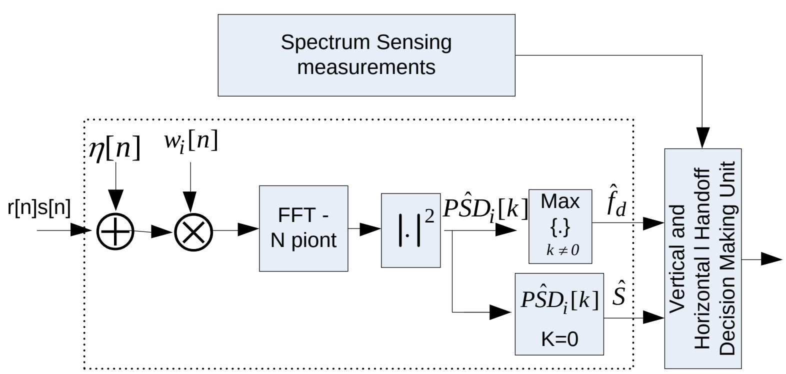

Figure 6: Block Diagram of proposed load balancing algorithm

Each network shall have its own threshold(s). There is a difference between requirements of load balancing in the secondary and primary networks. Thus, the proposed algorithm is divided into 2 sections, 1) CHO between available frequency channels in k^{th} spectrum band and 2) Vertical handover among available spectrum bands. Which can change PHY and MAC layer characteristics, as well.

CHO algorithm utilizes joint velocity and ARP estimator in the act of CHO decision making. Proposed CHO is based on using the hysteresis margin method [17] in addition to Dwell Timer (DT), which is calculated based on the inverse of velocity estimates.

Figure 6 shows a block diagram of the proposed CHO algorithm. First velocity and RS local mean is estimated from raw RSS. Values and thresholds used in the CHO decision making are also calculated and updated periodically. The proposed load balancing algorithm selects a network based on the specifications of each network.

Algorithm. II illustrates CHO algorithm. According to algorithm II in order to reduce the effect of velocity estimation error on the accuracy of CHO decision making, average of all the velocity estimates during the dwell time period, is considered as a velocity estimate to classify user as pedestrian or fast. Based on the result of spectrum sensing and CCC activity, The SU user detects and possible PU activity cause by new arrival or PU movement within their primary network, therefore a horizontal frequency handover is triggered based on the PU activity. False alarms (P_f^{κ}) and misdetections ($1-P_D^{\kappa}$) influences the performance of handover and upcoming routing algorithms. Therefore, effective measures are required to be defined to overcome this challenge. The idea of utilizing 2 thresholds for adding the user to the list of CHO candidates solves the problem of lack of accuracy in scenarios that slow maneuvering PUs are bouncing inside and outside of sensing boundaries of SUs.

Benefits gained from knowledge of PU/SU velocity, estimates of PU/SU ARP (i.e. mitigation of the ping-pong effect caused by fluctuations and RS due to sever fading and noise) and spectrum sensing are elimination of the ping-pong effect, reducing the probability of SU blocking, reducing the probability of horizontal and vertical resource consuming Hanover, effective routing and importantly enhancing the achievable throughput. Last but not the least, increasing the utilization of the available frequency channels. The idea of using an adaptive dwell timer ($t_{DT} \propto 1/\hat{v}$) compensates the lack of ability to use hysteresis methods for such a CHNs.

The ping-pong effect occurs if parameters account for frequency handover decisions, change rapidly, thus a SU performs the handover as soon as it detects a PU activity or a route with better link quality. Due to the fact that several spectrum bands are available for cognitive radios, thus, whenever the traffic load on one spectrum reaches its functional limit, or requested bandwidth by the CR user cannot be supported by the existing spectrum band, a vertical handover should take place for a band in which requested services are supported. The vertical ping-pong effect occurs, when, due to the PU behavior, for a stochastic time, the requested resources are not available for an active session of a CR user. Therefore, as the CR user opportunistically makes its decision, several vertical handovers among the available spectrum bands are triggered. Because of heterogeneity, PHY and MAC layer of different integrated heterogeneous wireless networks are different, thus, a unified approach is essential for collecting specific measures from different networks. As a result more sophisticated joint spectrum allocation, handover and routing algorithms are required to extend the throughput of multi-layer network and to increase efficiency of resource management for the next generation of wireless cognitive heterogeneous networks.

D.2. Cognitive Horizontal and Vertical Handover Algorithm Analysis

Due to the fact that CHO algorithm, is highly influenced by the present and previous states of PUs activity, thus the Markov model can be used for modeling and calculation of probability of transition in each state. For the given system model of Figure 5, a user in the system can be in one of the following states

• State0) PUs have no active sessions in progress and SUs cannot operate due to channel characteristics or insufficient available spectrum (i.e., the PUs and SUs are idle),

• State1) there is a PU activity and SUs are not allowed to access to the occupied channel/spectrum.

• State2) PUs are idle and SUs are functional.

(**P**) is given by

$$\begin{bmatrix} P_{s_0}[k] \\ P_{s_1}[k] \\ P_{s_2}[k] \end{bmatrix} = \begin{pmatrix} p_{00}[k] & p_{01}[k] & p_{02}[k] \\ p_{10}[k] & p_{11}[k] & p_{12}[k] \\ p_{20}[k] & p_{21}[k] & p_{22}[k] \end{pmatrix} \cdot \begin{bmatrix} P_{s_0}[k-1] \\ P_{s_1}[k-1] \\ P_{s_2}[k-1] \end{bmatrix} \tag{26}$$

Figure 7 shows the user state transition diagram for the CR network system model, where $P_{si}[k]$ shows i^{th} steady-state probability at k^{th} moment and $P_{ij}[k]$ denotes the transition probability from state ito state j, i, j $\in\{0, 1, 2\}$ and state transition probability matrix. Based on the algorithm. II, a user can change state from state0 to any nonzero state when a new connection is made. If a session is completed while a user is currently in a nonzero state, the user changes to state 0. The Markov chain depicted in Figure 5 is irreducible and a periodic, and all the states are recurrent non-null, so that the equilibrium state probabilities can be determined by solving the (11), subject to the normalization condition $\sum_{i=0}^{N_{state}} P_{si} = 1$, however, the expressions for the transition probabilities remain to be determined; this form the topic of discussion in the succeeding sections.

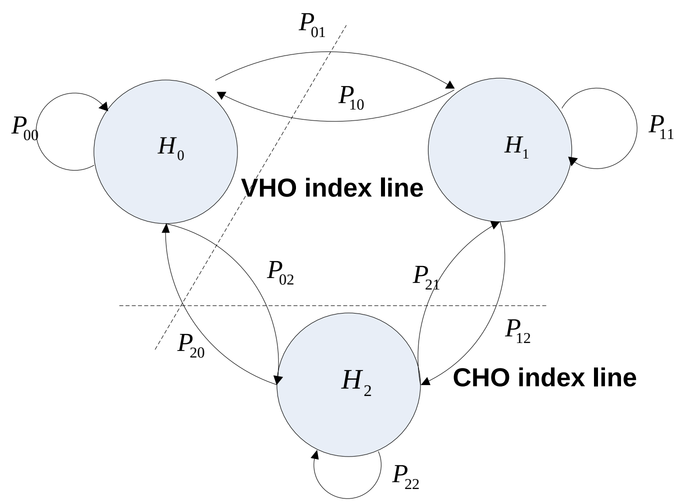

Figure 7: State transition map for cognitive handover algorithm,

D.2.1. Service Model

The service model relies on six assumptions.

1) It is assumed that the probability of SU being inside the coverage area of PU, is $P_{PU\ coverage}=1$ and because the coverage area of SU is a subset of PU coverage it is clear that $P_{SU\ coverage}<1$.

2) Horizontal cognitive handovers are triggered by PU activity/mobility and mobility of SUs.

3) Cognitive vertical handovers are triggered by the lack of available frequency channel in the current spectrum band because of PU activity or SU demand.

4) New calls arrive at the primary and secondary networks are Poisson processes with mean arrival rate λ_{PU} and λ_{SU} respectively. A new session is randomly determined as the Real Time (RT) and Non-RT (NRT) sessions with probabilities Prt and Pnrt, respectively. Similarly, a call is also independently determined as a low (high) bandwidth application with probability Pbwl (Pbwh). Clearly $P_{rt}+P_{nrt}=1$ and $P_{bwl}+P_{bwh}=1$

5) Session duration T_{dSP} is exponentially distributed with a mean of $1/\mu$, where μ is the average session completion rate. Hence, the session completion (termination) probability Pterm= P ($T_{dSP}\leq$ Tth), where T this the time unit for the user state transition diagram, as shown in Figure 5.

Algorithm. II. Proposed CHO/VHO Algorithm

1: **loop**
2: **For** spectrum k=1: |k|
3:**if** $USER_i \in$ {SU}**then**
3: **if** PU activity is detected and conditions (9) and (10) are fulfilled
4: **if** there is any available channel on k^{th} spectrum
5: Let $USER_i \in$ { CHO Active Set }**then**
6: CHO to target frequency; CHO($target_{frequency}$)
7: **else if** $\hat{v}_{PU}$ **≥**$\mathbf{V_{th}}$ and $\hat{v}_{SU}$ **≤**$\mathbf{V_{th}}$ **then** PU ∉∈ {MSconnectedtoWWAN}{Pedestrian Class}
8: Start(t_{DT});{ $t_{DT} \propto 1/\hat{v}$ PU}
9: **if term 5 is valid** until the timer expires **then**
10: at the end of t_{DT} $\hat{v} = (1/n)\sum_{i=1}^{n}\hat{v}_i^{PU}(t) \quad 0 \le t \le t_{DT}$
11: $USER_i \in$ { CHO Active Set }**then**
12: CHO to target frequency; CHO($target_{frequency}$)
13: **else**
14: Reset Dwell Timer {Reset(t_{DT})}
15: $USER_i \notin$ { CHO Candidate Set}⇒ Unbeneficial CHO
16:$USER_i$ Stay in Current Serving channel
17: **end if**
18:**end if**
Drop the SU session
End if
19:**elseif**PU activity is NOT detected but conditions (9) is fulfilled **then**
20: **if** there is **no** available channel on k^{th} spectrum
21:$USER_i \in${VHO Active Set }**then**
22: **if** $\hat{v}_{SU}$ **≤**$\mathbf{V_{th}}$ **and** the condition in equation (10) is **not** fulfilled
23: VHO to target frequency; VHO($target_{frequency}$)
24: **end if**
25: **end if**

26: **else if** PU activity is NOT detected and conditions (9) is fulfilled
27: **if** there is **no** available channel on k^{th} spectrum
28:$USER_i \in$ { VHO Active Set }**then**
29: **if** $\hat{v}_{SU}$ **≥**$\mathbf{V_{th}}$ **and** the condition in equation (10) is **not** fulfilled
30: SU ∉∈ {MSconnectedtoWWAN}{ PedestrianClass}**then**
31: Start(t_{DT});{ $t_{DT} \propto 1/\hat{v}$ PU}
32: **if term 22 is valid** until the timer expires **then**
33: at the end of t_{DT} $\hat{v} = (1/n)\sum_{i=1}^{n}\hat{v}_i^{PU}(t) \quad 0 \le t \le t_{DT}$
34: VHO to target frequency; CHO($target_{frequency}$)
35: **else**
36: Reset Dwell Timer {Reset(t_{DT})}
37: $USER_i \notin${VHO Candidate Set}⇒ Unbeneficial VHO
38: $USER_i$ Stay in Current Serving channel
39: **end if**
40:**end if**
41:**end if**
42: **end if**

43**: end**
44**: end loop**

6) The transition probabilities are calculated based on (15).
For exponentially distributed interarrival times, T_{ar} with a mean of $1/\lambda_n(\lambda_n = \lambda_{PU} + \lambda_{SU})$, the new session arrival probability within the next time unit is $P_{new} = P(T_{ar} \leq T_{th})$.
The probability of a new session arrival in the secondary network P_{new_SU} and the probability of a new session arrival in the primary P_{new-PU} can be given by $P_{new\_SU} = P_{new}.P_{SUcoverage}$ and $P_{new\_PU} = P_{new}.P_{PUcoverage}$.
D.2.2. State Transition Probabilities for CHO
As it is shown in Figure 5 CHO probability can be determined by state probabilities crossed by CHO index line

$$P_{CHO}[k] = P_{s_0}[k-1]P_{02}[k] + P_{s_1}[k-1]P_{12}[k] + P_{s_2}[k-1]P_{20}[k] + P_{s_2}[k-1]P_{23}[k] \quad (27)$$

According to the list of states, each state consists of a set of events (S_i) (e.g. each network have N_{celli} BSs therefore, probability of being in any state can be determined based on the traffic model and the SINR criteria discussed in (9) and (10)). Hence, the probability i^{th} set of events can be written as follows

$$P_{s_i}[k] = \sum_{l=1}^{N_{States}} P_{s_{il}}[k], \qquad S_i = \{S_{i1}, ..., S_{iN_{states}}\} \quad (28)$$

$P_{s_{il}}[k]$ is the probability of κ^{th} user changes state from i^{th} to the l^{th} based on the SINR requirements and PU and SU activity. State transition probabilities can be calculated from (15).
E. Proposed Cognitive Power Allocation and Routing Algorithm
Any stable multi-hop, ad-hoc network has a queue backlog that follow the rule below [27]

$$\lim_{T\to\infty} \sup \frac{1}{T} \sum_{\tau=0}^{T-1} E\left[Q_{dSp}(\tau)\right] \prec \infty \text{ for all } dSp \in Q \quad (29)$$

The main constraint in CR network is the fact that any efficient routing algorithm needs to be able to perform in a distributed fashion and to overcome the instability of the radio channels. The Utility Optimal Lyapunov Networking theoretical framework ([14], [22], [23], [26]) has the following general form. Given a series of penalties x(t)and a series of rewards y(t) incurred by network control decisions, each non-negative for all time and upper bounded, let $\bar{x}$ and $\bar{y}$ be the long term average values. Provided non-negative, continuous, convex and entry wise non-decreasing ($f(x) - f(\bar{y})$ whenever $x - \bar{y}$ entry-wise) penalty functions f(x) and l(y), and likewise utility functions g(y) and h(y), Utility Optimal Lyapunov Networking solves the following stochastic optimization problem:

$$\begin{aligned} &\text{Minimize}: f(\bar{x}) - g(\bar{y}) \\ &\text{subject to}: l(\bar{x}) \leq L \\ &\qquad h(\bar{x}) \leq H \quad \text{strongly stable} \end{aligned} \quad (30)$$

Especially the problem of routing can be formulated in the above form by assuming that f(x) is some cost metric for routing.
The proposed joint smart handover, spectrum allocation and routing algorithm (SHARP), aims at maximizing the throughput through joint opportunistic routing, dynamic spectrum allocation, transmit power control and handover while performing scheduling in a distributed way. Every backlogged node i, once it senses an idle CCC, performs the following joint routing and scheduling algorithm:

1) Find the set of feasible next hops $\{n_1^{dSp}, n_2^{dSp}, \cdots, n_\kappa^{dSp}\}$ for the backlogged sessions, which are neighbors with a positive advance towards the destination of session dSp. Node n has positive advance with respect to i if n is closer to the destination than i. Calculate $c_{i,j}^{\kappa}(F_k)$ for each link (i;j), where $j \in \{n_1^{dSp}, n_2^{dSp}, \cdots, n_\kappa^{dSp}\}$ using Algorithm.III.

2) Schedule dSp with the next hop j such that

$$(dSp, j) = \arg\max\left(\Phi^{\kappa}_{ij,dS_p}\right) \quad (31)$$

Note that Φ^{κ}_{ij,dS_p} depends on the link capacity, available bandwidth, CEDE and the differential backpressure of link (i; j). Hence, routing is performed in such a way that lightly backlogged queues with more spectrum resource receive most of the traffic.

ALGORITHM. III. SHARP ALGORITHM

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loop
for **i∈**{backlogged Secondary Users}
Let the $\Phi^{\kappa}_{i,dS_p} = 0$, [$f_k$; ΔBW_k]=0, Γ_i=0.
for s=1: |dSp| “number of backlogged sessions”
for**j = ∈** $\{n_1^{dSp}, n_2^{dSp}, \cdots, n_\kappa^{dSp}\}$
Calculate $c^{\kappa}_{i,j}(F_k)$**,** f_k based on the spectrum sensing mechanism and calculated maximum allowed Γ_i based on constraints (9&10)
Calculate Goal function $\Phi^{\kappa}_{Temp} = \Phi^{\kappa}_{i,dS_p}$
if $\Phi^{\kappa}_{Temp} > \Phi^{\kappa}_{i,dS_p}$ **then**
$\Phi^{\kappa}_{i,dS_p} = \Phi^{\kappa}_{Temp}$
Estimate [j, Φ^{κ}_{ij,dS_p} , f_k , ΔBW_k , Γi]
end if
end for
end for
end **for**
end loop

---

3) Once spectrum selection, ARP estimation and next hop have been determined, the probability of accessing the medium is calculated based on the value of goal function Φ^{κ}_{ij,dS_p}. Each CCR user that achieves higher Φ^{κ}_{ij,dS_p} with higher probability has a chance to access the spectrum. Obviously, the higher any node has traffic to send, the higher the backlog pressure would be. This may result higher probability of transmission. In the cost function, a fairness factor can be introduced. This fairness factor can in turn adjust the backlog pressure between neighboring CR nodes by sending null packets. Hence, we can be assured that nodes have an equal chance of winning the spectrum. This mechanism can adjust the chance for spectrum access between CR nodes.

The proposed goal function opportunistically chooses the best route (i.e. next hop) based on queuing, spectrum utilization, requested and the supported bandwidth. Consequently, different route is selected for each packet depending on the dynamics of the channel and the traffic. (i.e. packets from the same session may follow different paths). In the proposed goal function, each selected path considering the backpressure with an eye on maximization of channel utilization and throughput has its own cost. The cost of selection of each route is calculated using an appropriate cost function. The combination of next hop, leads to a multi-hop path. The multi-hop path discovery terminates when the destination is selected as the next hop. If the destination is in the transmission range of the transmitter (either a source or an intermediate relay node for that session), the differential back log between the transmitter and the destination is not less than the differential backlogs between the transmitter and any other nodes, because the queue length of the destination is zero. Hence, the destination has a higher probability of being selected as next hop than any other neighboring node of the transmitter. Note that the transmitter may still select anode other than the destination as the next hop even if the destination is in the transmission range.

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Research Article

This can happen, for example, if there is no available low interference frequency channel between the transmitter and receiver, or if the interference on all not interfering channels at that time is high, which results in low link capacity between the transmitter and the destination.

RESULTS AND DISCUSSION

Results

Appendix

A. Derivation of Bias and MSE of Proposed ARP Estimator

Shadowing is assumed to be independent from multipath fading and constant over the length of temporal windows (LTWs), window magnitude is normalized (F=1) and let $\Psi = s[n]s^*[m],\ E\{\Psi\} = \sigma_s$ and $W = w[n]w^*[n]$. From (7)

$$\hat{S}_i = \sum_{n=0}^{L_i-1}\sum_{m=0}^{L_i-1}\sum_{i=0}^{k-1}\sum_{z=0}^{k-1} \frac{W\Psi}{L_i\Delta t} e^{j(\omega_d cos\theta_i n+\varphi_i)} e^{-j(\omega_d cos\theta_z m+\varphi_z)}$$
$$= \sum_{i=0}^{k-1}\sum_{z=0}^{k-1} e^{j(\varphi_i-\varphi_z)} \underbrace{\sum_{n=0}^{L_i-1}\sum_{m=0}^{L_i-1} \frac{W\Psi}{L_i\Delta t} e^{j(\omega_d cos\theta_i n)} e^{-j(\omega_d cos\theta_z m)}}_{A} \quad (32)$$

if n-m = q then $\begin{cases} \text{begining of period} & 0 < q < L_i - 1 \\ \text{end of period} & -(L_i-1) < q < 0 \end{cases}$ thus $-m \le q \le L_i - m - 1$ after substitution in (20)

$$A = \sum_{m=0}^{L_i-1}\sum_{q=-(L_i-1)}^{L_i-1} w[m+q]\,w^*[m]\,e^{j\omega_d(cos\theta_i - cos\theta_z)m} e^{j\omega_d cos\theta_i q}$$

From (4) a closed form for ARP estimator bias is given by

$$E\left[\hat{S}_i\right] = \lim_{L_i\to\infty} \frac{1}{L_i\Delta tF} E\left\{V_i(e^{j\omega})\times V_i^*(e^{j\omega})\right\}\Big|_{\omega=0}$$
$$= \lim_{L_i\to\infty} \sum_{n=0}^{L_i-1}\sum_{m=0}^{L_i-1} \frac{W}{L_i\Delta tF} e^{-j\omega(n-m)} E\left\{s[n]\,s^*[m]\right\}$$
$$\times E\left\{\sum_{i=0}^{k-1}\sum_{z=0}^{k-1} e^{j(\omega_d cos\theta_i n+\varphi_i)} e^{-j(\omega_d cos\theta_z m+\varphi_z)}\right\}\Bigg|_{\omega=0}$$
$$= \lim_{L_i\to\infty} \sum_{n=0}^{L_i-1}\sum_{m=0}^{L_i-1} \frac{\sigma_s}{L_i\Delta tF} J_0(\omega_d(n-m))We^{-j\omega(n-m)}\Bigg|_{\omega=0}$$
$$= \lim_{L_i\to\infty}\left(G_i(\omega)*\left|w_i(\omega)\right|^2\right)\Big|_{\omega=0} \quad (33)$$

Where $G_i(0)$ and $W_i(0)$ are DC component of RSS PSD and rectangular window respectively and"*" refers to convolution. Equation (23), shows that if LTW approaches to infinity in time domain, in frequency domain it approaches to Kronecker delta function δ[.] and as a result the PSD estimation error based on peridogram approaches zero. Following (21)

$$E\left[\hat{s}_i\right] = \frac{\sigma_s}{L_i\Delta t}\sum_{m=0}^{L_i-1}\sum_{q=-(L_i-1)}^{L_i-1} w[m+q]\,w^*[m] J_0(q\Delta t\omega_d)$$
$$= \frac{\sigma_s}{L_i\Delta t}\sum_{q=-(L_i-1)}^{L_i-1} J_0(q\Delta t\omega_d) \underbrace{\sum_{m=0}^{L_i-1} w[m+q]\,w^*[m]}_{C_{ww}[q]} \quad (34)$$

Where $C_{WW}[m]$ is autocorrelation function (ACF) of rectangular window. Hence, window ACF can be determined as

$$C_{ww}[q]=\begin{cases} L-|q| & |q|\le(L-1) \\ 0 & \text{elsewhere}\end{cases} \text{ then } C_{ww}(e^{j\omega})=\left(\frac{\sin(\omega L/2)}{\sin(\omega/2)}\right)^2 \quad (35)$$

After substitution in (22)bias can be calculated as follows

$$E\left[\hat{s}_i\right]=\sigma_s\sum_{q=-(L_i-1)}^{L_i-1}\left(\frac{L_i-|q|}{L_i}\right)J_0(q\Delta t\omega_d)$$
$$=\sigma_s\left[\frac{1}{L_i}+2\sum_{q=1}^{L_i-1}\left(\frac{L_i-|q|}{L_i}\right)J_0(q\Delta t\omega_d)\right] \quad (36)$$

In order to calculate variance of local mean estimates, 4th moment of RSS is calculated. When LTW approaches infinity, the 4th moment of most of stochastic processes will approach to Gaussian process and for a Gaussian process, the 4th moment can be calculated based on ACF [18]. Let X be the square of RSS with ACF equal to $J_0^2(\omega_d K\Delta t)$ [11]. Due to the fact that RSS is Gaussian process, it can be shown that

$$E\left[\left(\hat{S}-E[\hat{s}_i]\right)^2\right]=$$
$$\underbrace{E\left[\left(\sum_{i=0}^{k-1}\sum_{z=0}^{k-1}\sum_{n=q}^{L_i-1}\frac{\sigma_s^2}{L_i\Delta t}e^{j(\varphi_i-\varphi_z)}e^{j\omega_d n(\cos\theta_i-\cos\theta_z)}e^{j\omega_d\cos\theta_z q}\right)^2\right]}_{A}$$
$$-\underbrace{\left(\sigma_s\left[\frac{1}{L_i}+2\sum_{q=1}^{L_i-1}\left(\frac{L_i-|q|}{L_i}\right)J_0(q\Delta t\omega_d)\right]\right)^2}_{B}$$
$$A=\frac{R_{|s|^2|s|^2}(0)}{L_i^2\Delta t^2}+\frac{2\sigma_s^2}{L_i^2\Delta t^2}\sum_{q=1}^{L_i-1}\left(L_i-|q|\right)^2J_0^2(\omega_d q\Delta t)$$
$$B=4\sigma_s^2\sum_{q=0}^{L_i-1}\frac{(2L_i^2-3L_i+1)}{6L_i}J_0^2(q\Delta t\omega_d)$$

A lower band for proposed local mean power estimator variance can be determined as follows (from (24))

$$Var(\tilde{S})\le\sigma_s^2\left[\left(\frac{R_{|s|^2|s|^2}(0)-1}{L_i^2\Delta t^2}\right)+\sum_{q=1}^{L_i-1}J_0^2(\omega_d q\Delta t)\left(\left(\frac{L_i-|q|}{L_i}\right)^2\right.\right.$$
$$\left.\left.-\frac{2(2L_i^2-3L_i+1)}{3L_i}\right)-4\sum_{q=1}^{L_i-1}\left(\frac{L_i-|q|}{L_i^2}\right)J_0(\omega_d q\Delta t)\right] \quad (37)$$

B. Derivation of Conditional PDF of RS

Due to the fact that RS estimates $\hat{S}$ have Gaussian distribution, joint and conditional PDF of each event is also Gaussian. Let $VAR\left\{\hat{S}[k]\right\}=\sigma_{\hat{S}[k]}$ and $E\left\{\hat{S}[k]\right\}=\mu_{\hat{S}[k]}$ therefore conditional PDF of RSS is given by

$$f_{\hat{S}_k|\hat{S}_{k-1}}(\hat{S}_k\,|\,\hat{S}_{k-1})=\frac{\exp\left(-\left(\hat{S}_k-\mu_{k|k-1}\right)\Big/2\sigma^2_{\hat{S}_k|\hat{S}_{k-1}}\right)^2}{\sqrt{2\pi}\sigma_{\hat{S}_k|\hat{S}_{k-1}}} \quad (38)$$

where $\mu_{k|k-1}=\mu_k+\rho_{\hat{S}\hat{S}}\frac{\sigma_{\hat{S}_k}}{\sigma_{\hat{S}_{k-1}}}\left(\hat{S}_{k-1}-\mu_{k-1}\right)$, $\sigma^2_{\hat{S}_k\,|\,\hat{S}_{k-1}}=\sigma^2_{\hat{S}_k}\left(1-\rho^2_{\hat{S}\hat{S}}\right)$ and

$$\rho_{\hat{S}\hat{S}}=\frac{\left[X_0\exp\left(-|vt_s|/X_0\right)-X_{av}\exp\left(-|vt_s|/X_{av}\right)\right]}{X_{av}+X_0}$$

Where X_0 is correlation distance of local mean power and X_{av} is smoothing window length. From above, transition probabilities can be determined, for instance $p_{23}[k]$ is:

$$p_{23}[k]=Q\left(\frac{Tr_{WWAN}-\mu_{WWAN[k]}}{\sigma_{WWAN[k]}}\right)\Big/Q\left(\frac{Tr_{WLAN}-\mu_{WLAN[k-1]}}{\sigma_{WLAN[k-1]}}\right)\times$$
$$\left[\int_{Tr_{WLAN}}^{\infty}f_{\hat{S}_{k-1}}(\hat{S})\left[1-Q\left(\frac{T_{Add,WLAN}-\mu_{k|k-1}}{\sigma_{\hat{S}_k|\hat{S}_{k-1}}}\right)\right]d\hat{S}\times P\{V[k]\succ V_{th}\}\right.$$
$$\left.+\int_{Tr_{WLAN}}^{\infty}f_{\hat{S}_{k-1}}(\hat{S})\left[1-Q\left(\frac{T_{rDrop,WLAN}-\mu_{k|k-1}}{\sigma_{\hat{S}_k|\hat{S}_{k-1}}}\right)\right]d\hat{S}\times P\{V[k]\le V_{th}\}\right] \quad (39)$$

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