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Enabling Cognitive Radio via Sensing, Awareness, and Measurements

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8.1 Introduction

Wireless communications is established through a common medium which is highly dynamic. The elements of wireless communications systems such as nodes in a network, users, and some properties of the wireless devices themselves (e.g. battery) are dynamic as well. In order for wireless communications systems to better perform, adaptation to these dynamic conditions and elements is essential. How well a wireless system adapts to these dynamic conditions depends on the amount of the knowledge of varying parameters. It is clear that the more the knowledge, the better the adaptation.

Recently, wireless communication community meets a new concept called "cognitive radio," which is a radio that can sense, be aware of, learn, and adapt to its surrounding environment [3]. Built on the top of Software Defined Radio (SDR), cognitive radio can adapt the radio parameters with the aid of a special structure called cognitive engine. Cognitive engine can be regarded as the counterpart of human brain in human body, since the brain is the center for intelligence, as described in Chapter 14 with the same analogy.

Cognitive radio is expected to push the concept of adaptation further with the aid of its advanced attributes. The main reason behind this expectation is the fact that cognitive radio is equipped with extended sensing capabilities in addition to Artificial Intelligence (AI) sort of tools that are kept in cognitive engine.

In this chapter, we will discuss how cognitive radio can sense and be aware of major factors that affect its communications. First, we will address sensing and being aware of the wireless channel. Next, we will take network related awareness issues into consideration. In the following, we will discourse user relevant topics along with other possible measurements. Finally, we will address some major challenges and explain future research directions pertinent to the realization of cognitive radio.

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8.2 Wireless Channel Awareness

This section discusses prominent wireless channel characteristics, relevant observable quantities, and some methods to measure them.

8.2.1 Channel Selectivity

Before introducing the channel selectivity in detail, it is appropriate to explain what selectivity means. Selectivity is a measure of how differently a channel behaves over the dimension in which the selectivity is defined. Measuring the selectivity is established by *channel coherence*, which is statistically defined, again, over the same dimension in which the selectivity is measured [8]. More formally, channel coherence over a dimension is the width of the window over which the signal is assumed as invariant. The less the width of the window, the more the selectivity on the dimension of interest. For instance, time selective channel basically means that at time instants that are close to each other, the correlation between the components of the channel is weak. Therefore, the width of the time window (in this case, the duration of the window) formally determines time selectivity. Similar concepts can be deduced by just replacing the dimension with the desired one, such as frequency selectivity and coherence bandwidth; space selectivity and coherence distance. An illustration of the concept of selectivity and coherence is shown in Figure 8.1.

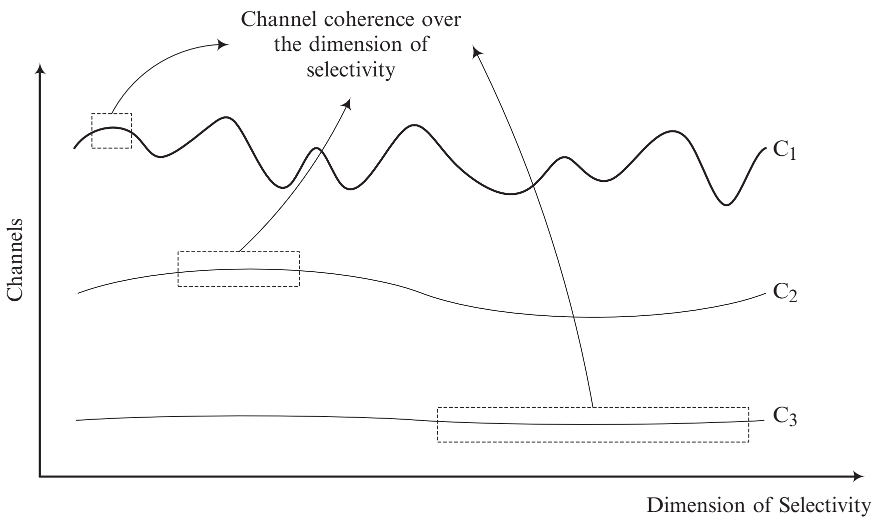

Fig. 8.1. The concept of selectivity and its measurement through channel coherence. The width of the window for $\mathbf{C}_1$ is the narrowest one, whereas that of $\mathbf{C}_3$ is the widest. Thus, for the dimension of interest, the selectivity of $\mathbf{C}_1$ is more than that of $\mathbf{C}_2$ and the selectivity of $\mathbf{C}_2$ is more than that of $\mathbf{C}_3$.

Duality

In this context, it is appropriate to mention a very important notion called *duality.* Fourier[1] transform ($\mathcal{F}\{\cdot\}$) and its inverse ($\mathcal{F}^{-1}\{\cdot\}$) allow one to see time and frequency domain interpretations of the functions as dual of each other. For functions of deterministic type, with the aid of $\mathcal{F}\{\cdot\}$ (and $\mathcal{F}^{-1}\{\cdot\}$), it can be shown that if the width (in time domain, "width" refers to "duration," whereas in frequency domain it refers to "bandwidth") of the function in one domain expands, it shrinks in the dual domain. However, the signals are of stochastic type in wireless communications. Therefore, it is better to investigate the duality in terms of stochastic processes. It is known that, a stochastic process that is defined in one domain automatically has a dual stochastic process in the dual domain with the aid of, again, $\mathcal{F}\{\cdot\}$ or $\mathcal{F}^{-1}\{\cdot\}$ [4]. In order to ease the mathematical tractability, in wireless communications, often, signals are assumed as Wide-Sense Stationary (WSS).

In order to see the connection between selectivity, coherence, and duality, stochastic linear time-varying wireless channels with WSS properties can be considered. If the autocorrelation function of a channel is calculated over one of the three domains (time, frequency, or space), the transform domain can easily be obtained with the aid of Wiener–Khintchine Theorem. A channel that spreads over the transform domain corresponds to a shrinkage in the autocorrelation function because of the duality. Statistically, the shrinkage of the autocorrelation function of a channel implies the decrease of coherence and the increase of selectivity. As can be seen, when selectivity occurs in a domain, the spreading is observed in its dual domain and vice versa. In wireless communications community, the dual domain, namely "spreading" domain, is labeled with its cause. Consider the selectivity in time. Since the dual of time is frequency because of $\mathcal{F}\{\cdot\}$, spreading occurs in the dual domain, namely in frequency. Spreading in frequency is caused by Doppler effect, therefore, selectivity in time corresponds to Doppler spread in frequency. Conversely, selectivity in frequency has its dual in time as a spreading signal. Spreading in time is caused by the delays between multipaths. Therefore, selectivity in frequency corresponds to "delay spread." Duality can be defined over space dimension as well. However, for this case, the space is transformed into a domain called "wavevector" and vice versa.

[1] Jean Baptiste Joseph Fourier, the French mathematician and physicist who was born on March 21, 1768, in Auxerre, France and died on May 16, 1830, in Paris, France. The representation of functions through sum of trigonometric series has been named after him [3], although [3] caused plenty of controversies. Later on, Johann Peter Gustav Lejeune Dirichlet, who was born on February 13, 1805, in Düren, and died on May 5, 1859, in Göttingen, contributed to the Fourier's theory by appending the convergence conditions, which are known as "Dirichlet [Fourier Series] conditions."

Frequency Selectivity

When electromagnetic waves are released into a physical medium, multiple replicas of the original waves arrive at the destination (or receiver) because of the objects within the environment. The replicas arrive at the receiver with different delays, amplitudes, and phases, which is known as "multipath effect." Depending on the relative distances of the objects that reflect/scatter/refract the electromagnetic waves to the receiver, the replicas spread in time and lead to some important consequences:

1. If the relative delays between multipaths are shorter than (or on the order of) the symbol duration of the transmitted signal, the receiver cannot resolve each separate multipath, therefore, it sees the superposition of the multipaths, which causes a randomly fading channel.
2. If the relative delays of multipaths exceed the symbol duration, the symbols previously transmitted will impinge on other symbols causing Inter-Symbol Interference (ISI). ISI is sometimes described by the analogy of "channel memory," since the channel remembers the previous symbols even in the presence of the new symbols.

Having the knowledge of frequency selectivity provides extremely important performance improvement to the adaptive wireless communication systems including cognitive radio. As a sample application, adaptive channel equalization in single carrier systems can be considered. For example, in Global System for Mobile communications (GSM), channel equalizers are employed to compensate for ISI. However, the number of channel taps needed for equalization might vary depending on the dispersion of the channel. Instead of fixing the number of channel taps for the worst-case channel condition, it can be changed adaptively, allowing simpler receivers with reduced battery consumption and improved performance [8].

Frequency selectivity carries slightly more importance for Orthogonal Frequency Division Multiplexing (OFDM) systems compared to single carrier systems. Even though the symbol duration is prolonged because of the use of multiple orthogonal carriers, there is still partial ISI due to the multipath effect. Therefore, a certain amount of data, which is called Cyclic Prefix (CP), is replicated and added in front of the OFDM symbols to be able to alleviate ISI degradation. Considering the fact that the multipath effect is highly environment dependent, the width of CP is chosen in such a way that it is larger than the maximum excess delay of the channel for the environment in which the wireless system operates.[2] However, alleviating ISI comes at the expense of reducing the spectral efficiency, since a certain amount of the data is repeated.

[2] Since the width of CP is determined by the maximum excess delay of the channel, the maximum excess delay of the channel must be estimated. As a rule of thumb, the maximum excess delay of the channel is computed by multiplying Root-Mean-Squared (RMS) delay spread of that environment by four [5].

Instead of choosing a CP for the worst-case multipath delay spread condition, the size of CP can be adjusted adaptively. Using adaptive CP size increases the spectral efficiency.

Channel selectivity information can be estimated directly from the received signal and/or from channel estimates that are obtained after processing the received signal. However, some other opportunities in estimating the time dispersion of the wireless channel emerge through the use of additional sensing capabilities of cognitive radio. Since time dispersion is highly environment dependent, any tool that can provide cognitive radio with information about the environment plays a crucial role in estimating the selectivity of the channel. For instance, in an indoor environment, it is very likely that the RMS delay spread of the channel is considerably lower than that in a typical outdoor environment [6]. Beside the components that can provide absolute location information such as Global Positioning System (GPS), the peripherals such as light and temperature sensors might be used to characterize whether cognitive radio is in an indoor or outdoor environment [3]. When cognitive radio is in an outdoor environment, a more descriptive sub-class of the environment[3] can be identified via different enabling technologies. For outdoor cases, there are enabling technologies for obtaining the topographical (geomorphological) information about the environment such as Digital Elevation Models (DEMs) and recently becoming popular one, Geographical Information System (GIS). These digital tools allow one to analyze the spatial information. Therefore, these sorts of tools might be very helpful for cognitive radio to comprehend the surrounding environment in terms of its topographical characteristics. Table 8.1 presents some of the techniques that have been proposed for estimating the frequency selectivity of the channel along with new ones that can be used by cognitive radio for the same purpose.

Time Selectivity

When there is a relative motion between transmitter and receiver, a physical phenomenon called Doppler effect[4] occurs. The observed frequency of the

[3] In European Co-operation in the field of Scientific and Technical research (COST) 231, there are four forms for four different environmental classes: Typical urban, bad urban, rural, and hilly terrain [7]. These four types have already been defined in its predecessor, COST 207 for GSM. The Power Delay Profiles (PDPs) of typical urban and rural environments are described via single exponential cluster with different parameters, whereas those of in hilly terrain and bad urban environments are described by two exponential clusters with different parameters. Main parameter differences between environments that have common cluster structure are the arrival times of the clusters.

[4] This phenomenon has been named in the honor of Austrian mathematician and physicist Johann Christian Andreas Doppler who was born on November 29, 1803, in Salzburg, Austria and died on March 17, 1853, in Venice, upon his discovery [8] in 1842.

Table 8.1. Measuring frequency selectivity and some adaptation options.

How To Measure	**What To Adapt**
Frequency domain Level Crossing Rate (LCR)	Number of equalizer taps for single carrier systems
Delay spread and Channel Impulse Response (CIR) estimation	Number of pilots and spacing for multi-carrier systems
Channel frequency correlations	Fast Fourier Transform (FFT) size for multi-carrier systems
Via digital elevation model (DEM) and GIS	Carrier spacing for multi-carrier systems
	Adaptive filtering for channel estimation
	CP length for multi-carrier systems

transmitted signal[5] at the receiver is shifted because of Doppler effect. In wireless communications, Doppler effect describes the time-varying nature of a wireless channel. Generally, impulse response of a wireless channel varies in time rapidly because of the relative motion in the channel. These rapid variations in time cause spectral broadening, which is called "Doppler spread." However, impact of the broadening depends on the bandwidth of the transmitted signal. Under the same conditions, the signals that have wider transmission bandwidths are affected less by this broadening compared to those which have narrower bandwidths. In accordance with earlier discussion about duality, it is concluded that the increase in bandwidth of the transmitted signal corresponds to a shorter symbol duration in which the variation of the channel in time becomes negligible.

Doppler spread information can be very useful in various wireless system improvements. The applications can be investigated from two perspectives: (a) transmitter/receiver improvements and (b) network improvements. For (a), practical channel estimation methods can be examined. Whether channel interpolators or channel trackers are used, contemporary channel estimation algorithms are designed to operate on the worst case Doppler spread value. It is clear that in case of having the Doppler spread information in hand, the parameters of the channel estimation algorithms can be adjusted adaptively rather than adopting a fixed scheme [8, 10]. Variable coding and interleaving schemes can also be employed depending on this information, which is directly related to the speed of the mobile [11]. For (b), the use of Doppler spread information in controlling some network algorithms can be considered.

[5] The application of Doppler effect to the light, which is a sort of electromagnetic wave, was established by the French physicist Armand Hippolyte Louis Fizeau (1819–1896) in 1848 independent of Ernst Mach (1838–1916), who also discovered the same shift in 1860. The effect was first used in calculating the relative speed of the stars by William Huggins [9].

For instance, in cellular systems, hand-off (or handover), cell assignment, and channel allocation can be established efficiently having the Doppler spread estimate [12]. Assignment of fast-moving mobiles to umbrella cells in hierarchical cell structures can be considered as a specific application. The assignment of fast-moving mobiles to umbrella cells reduces the number of hand-offs, whereas the assignment of slow-moving mobiles to microcells increases the capacity [8].

There are several approaches to estimate Doppler spread. Examining the variation and autocorrelation of channel estimates are two fundamental methods in measuring the Doppler spread. Instead of channel estimates, the envelope of the signal can also be used [13]. When the channel estimates are of interest, the variation is calculated by *differentials*. However, the results obtained after differentials are generally noisy and low-pass filtering is required for smoothing. The bandwidth of the low-pass filter depends on Doppler spread too. Therefore, in essence, this method relies on changing the bandwidth of the filter adaptively. Apart from variation of the channel estimates, the autocorrelation of the channel estimates can be used in Doppler spread estimation as well. The autocorrelation of the channel is computed over the known part of the received data. Some examples of Doppler spread estimation that use the autocorrelation of the channel estimations can be found in [13, 14]. A brief list of quantifying time selectivity and some relevant adaptation options is given in Table 8.2.

As in time dispersion, Doppler spread estimation can also be improved by additional capabilities of cognitive radio. Since Doppler shift is a function of the speed of the mobile and Angle-of-Arrival (AoA), a sensor that provides the absolute location information improves the Doppler spread estimation. GPS is one of the prominent candidates for this sort of sensing applications for cognitive radio. After several consecutive measurements,[6] the speed and angle-of-arrival (AoA) can be obtained in case the position of the base station is known.

Table 8.2. Measuring time selectivity and some adaptation options.

How To Measure	What To Adapt
Correlation of channel estimates	Channel tracker step size
Correlation of signal envelope	Coding and interleaving schemes
Variation of channel estimates	Hand-off management
Variation of signal envelope	Frequency allocation
Multiple antennas	
Positioning methods such as GPS	

[6] This can be seen with the fact that $v = d\mathbf{r}(t)/dt$, where $\mathbf{r}$ is the position vector (such as $\mathbf{r}(t) = [x\ y\ z]^T$, $(\cdot)^T$ denotes the transpose operation) and v is the speed of the mobile. Note that transmission frequency and speed of light are assumed as known quantities.

Space Selectivity

Space selectivity is caused by the arrivals (or departures) of different multipaths at the receiver (from the transmitter) at different angles. When the power of arriving (or departing) multipaths is considered over angle domain, a spread is observed. The amount of spread is directly related to the richness of the scatterers within the environment. The more the scatterers, the larger the spread. Such as in time and frequency selectivity, coherence distance is a measure of the selectivity over space. Coherence distance is inversely proportional to angular spread. Hence, the shorter the coherence distance in the space, the larger the spread over angle domain.

Although space selectivity is not studied as much as time and frequency selectivity, there is a significant interest on space selectivity in multi-antenna systems. Adaptive wireless systems and cognitive radio can make use of the information about space selectivity in several ways. For instance, the information about space selectivity can be used in adaptive multi-antenna system design. Adaptive power allocation is another method in which space selectivity is used to improve the performance [15]. Adaptive modulation and coding across multi-antenna elements are also possible depending on the channel correlations. Some other options are presented in Table 8.3.

Interference Selectivity

Apart from the three basic wireless channel dimensions (time, frequency, and space) and related selectivity issues, several other dimensions can also be discussed [see Chapter 9 in this book]. Dimension of interference and selectivity over which it is defined can be considered as one of them. However, unlike the three basic dimensions, the selectivity cannot be defined solely over interference dimension. Interference selectivity becomes clearer when it is considered along with the basic dimensions. For instance, interference can be selective over frequency. It can be either Narrow Band Interference (NBI) or Wide Band Interference (WBI) depending on the bandwidth of the interferer as illustrated in Figure 8.2. Similarly, interference conditions may change in time resulting "time selective interference," whereas change of interference conditions in space causes "space selective interference."

Table 8.3. Measuring space selectivity and some adaptation options.

How To Measure	**What To Adapt**
Antenna arrays	Beamforming
Environmental characterization	Smart antenna
(such as indoor/outdoor)	Adaptive Multiple-Input Multiple-Output
	(MIMO) systems
	Interference management
	Frequency allocation

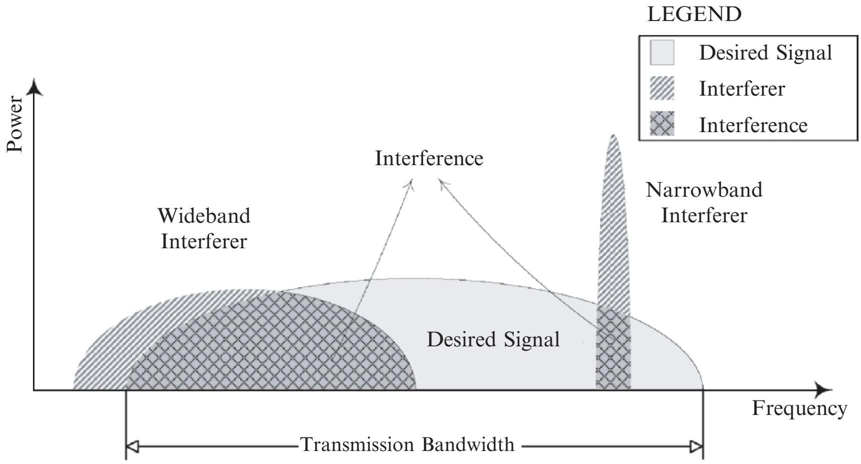

Fig. 8.2. Interference selectivity can be described via three basic dimensions: time, frequency, and space. Here, an example of interference selectivity is shown over frequency dimension. Note that the interference characteristics vary in frequency.

A cognitive radio, with enough knowledge of interference selectivity, can adapt its radio parameters to have a better transmission. As an example, a cognitive radio that uses Ultra Wide Band (UWB) scheme with OFDM can be considered. The information about the frequency selectivity of interference can be used to avoid NBI by de-activating the carriers corresponding to the interfering bands [16]. Similarly, being aware of the time selectivity of interference will give cognitive radio a chance to schedule its transmission accordingly in time as well.

Code Selectivity

Toward the latest steps of the evolution of the wireless communication systems, we witness the emergence of *code* as an extension to the basic dimension set. Therefore, selectivity over code dimension can be considered as well. Code selectivity could be a very important measure for cognitive radio systems that use codes in accessing the channel such as Direct-Sequence Spread-Spectrum (DSSS) systems using Pseudo Noise (PN) codes, Frequency Hopping (FH) systems using FH codes, and UWB systems using Time Hopping (TH) codes. Since most of the wireless systems are interference limited, the interference that is caused by statistical properties of the codes (e.g. ISI, which is caused by non-zero autocorrelation sidelobes of the codes or Multi Access Interference (MAI), which is caused by non-zero cross-correlation sidelobes of the codes) can be controlled by designing the codes appropriately. Beside interference, spectral efficiency can also be achieved by adjusting the statistical properties of the codes such as suppressing the sidelobes of auto- and cross-correlation. However, it is impossible to have codes that have both perfect auto- and cross-correlation properties. Furthermore, there is a trade-off between having sidelobes suppressed and the amount of interference created. Suppressing the sidelobes of the autocorrelation of the codes reduces ISI and increases MAI, and vice versa. Therefore, taking all these concerns into account, cognitive radio systems can increase the overall system capacity by adjusting the statistical properties of the codes adaptively depending on other system, channel, and transceiver parameters.

Other Selectivities

In this sequel, we must state that, wireless communications is not limited to the aforementioned dimensions and selectivities. There are some other aspects of wireless communications that need to be examined such as polarization, signal, and power. Although these dimensions might not be directly related to the actual wireless medium and can be regarded as elements of signal space, they have strong connections with channel space.

8.2.2 Link Quality

First and foremost condition of having a communication is to make sure that the information reaches at the receiver in a form that the receiver can reconstruct what is transmitted. As discussed in Section 8.1, the communication link exhibits different behaviors over several dimensions because of the dynamic nature of wireless communications. Thus, sensing the communication link is regarded as one of the most important tasks of cognitive radio in order to be aware of the wireless channel. In this regard, this subsection reviews some popular link quality measurement methods from the perspective of cognitive radio.

Path-Loss

Path-loss is the measure of the difference between transmitted and received power [6]. It is known that this loss increases with the transmitter–receiver separation in distance and depends on the environment, which is represented by the path-loss exponent.[7,8]

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[7] Here, it must be stated that path-loss includes the antenna gains of the transmitter and receiver as well as the wavelength (or frequency) of the transmitted electromagnetic wave. However, the average large-scale path-loss can be approximated with the use of a function of both transmitter–receiver separation and a path-loss exponent that takes different values for different environments [6].

[8] There is also another type of path-loss, which is called frequency dependent path-loss, that manifests itself in UWB communications systems.

Path-loss information can be used in a very well-known application: adaptive power control [17]. In Code Division Multiple Accessing (CDMA) systems, when power control is not employed, all the users transmit with the same power level. Hence, the users closer to the base station cause a very high level of interference to the users which are far away from the base station. Therefore, power control algorithms are applied to adjust power levels of the users [8, and references therein]. Similar to adaptive power control, interference management based on sensing the path-loss is also possible. Apart from transmitter–receiver centric applications, path-loss information is useful for the network control. In cellular systems, hand-off (or handover) can be managed with the aid of path-loss information. As a direct consequence of the use of this information in hand-offs, adaptive channel allocation schemes can be employed, which increase the channel utilization and decreases the probability of call blocking [6]. As stated, path-loss highly depends on the environment. Therefore, the performance of the aforementioned applications can be improved in case of having information about the path-loss exponent.

In order to be able to make use of path-loss information as explained above, it must be measured. Received Signal Strength (RSS) is one of the simplest tools serving this purpose. In order to get RSS, the receiver samples the channel and averages them out.[9]

At this point, it must be stated that being aware of the location, cognitive radio can better estimate the path-loss by taking advantage of statistical propagation models. Before getting into the details of this discussion, it is appropriate to review the statistical propagation models briefly.

Statistical Propagation Models for Path-Loss – It is known that the profile of the terrain in which the communication is established has a significant impact on path-loss [6]. Various statistical propagation models for different terrain profiles are available in the literature. These models, which are based on extensive field measurements, can provide quite simple formulae for path-loss estimation in connection with the terrain of interest. For instance, the path-loss model for "urban" areas can be considered. According to Hata's model [18], the median path-loss in "urban" areas is given by the following formula:

$$\begin{aligned} L_{\text{urban}}(\text{dB}) &= 69.55 + 26.16 \log\left(\frac{f_c}{\text{MHz}}\right) - 13.82 \log\left(\frac{h_{\text{BS}}}{\text{m}}\right) - a(h_{\text{MS}}) \\ &\quad + \left(44.9 - 6.55 \log\left(\frac{h_{\text{BS}}}{\text{m}}\right)\right) \log\left(\frac{d}{\text{km}}\right), \end{aligned} \tag{8.1}$$

where

$$a(h_{\text{MS}}) = \left(1.1 \log\left(\frac{f_c}{\text{MHz}}\right) - 0.7\right) \frac{h_{\text{MS}}}{\text{m}} - \left(1.56 \log\left(\frac{f_c}{\text{MHz}}\right) - 0.8\right), \tag{8.2}$$

[9] RSS can be obtained by processing pilot signals (as in Wide Band CDMA (WCDMA)) or link layer beacon (as in IEEE 802.11). However, the duration of averages depends on many things such as system itself (having single or multiple antennas), variation of the channel, application, and so on.

and MS stands for "mobile station;" BS stands for "base station;" f_c denotes the transmission frequency; h_i denotes the effective antenna height ($i \in \{\text{MS, BS}\}$); d is the distance between MS and BS; and $a(\cdot)$ represents the correction factor. In (8.2), the correction factor is defined for small to medium scaled city.[10]

In Hata's model, we can model path-loss for other propagation environment classes as well. If one wants to estimate the path–loss for "suburban" area, (8.1) becomes

$$L_{\text{suburban}}(\text{dB}) = L_{\text{urban}}(\text{dB}) - 2\left(\log\left(\frac{f_c}{28\text{MHz}}\right)\right)^2 - 5.4, \tag{8.3}$$

whereas for "open rural" area, (8.1) becomes

$$\begin{aligned} L_{\text{open rural}}(\text{dB}) = L_{\text{urban}}(\text{dB}) - 4.78\left(\log\left(\frac{f_c}{\text{MHz}}\right)\right)^2 \\ + 18.33\left(\log\left(\frac{f_c}{\text{MHz}}\right)\right) - 40.94. \end{aligned} \tag{8.4}$$

As can be seen from (8.1), (8.3), and (8.4), obtaining the path–loss depends only on choosing the correct environmental index such as "urban," "suburban," or "open rural."[11] In conventional systems, there is no method, infrastructure, or device that can distinguish the propagation environments from each other. However, with the emergence of cognitive radio, the use of auxiliary sensing methods are brought forward to fill this gap. Hence, cognitive radio can take advantage of these extra sensing capabilities to distinguish the propagation environments from each other. In this sequel, one might wonder how cognitive radio can establish the distinguishing process. The answer of this question requires the formal definition of each propagation environment. Unfortunately, there is no formal definition for propagation environments. Nonetheless, a coarse classification of the propagation environments can still be established. In Figure 8.3, very frequently used propagation environments in the literature and their classification are shown.

Having a classification such as in Figure 8.3 will definitely be useful for cognitive radio to employ the corresponding path-loss formula. However, there is still a missing link in the chain: "How can cognitive radio understand that which of the propagation environments presented in Figure 8.3 corresponds to its surrounding environment?" Now, we are going to search for an answer to this question.

[10] There are several correction factors further to represent other sort of environments such as large city for different transmission frequencies, f_c.

[11] In COST 231, the extension of Hata's model is provided as well [7]. Here, the details of the specifications of Hata's model such as the limits for h, d, and f_c are not discussed. However, interested readers may refer to [6, 7, and references therein] for further details.

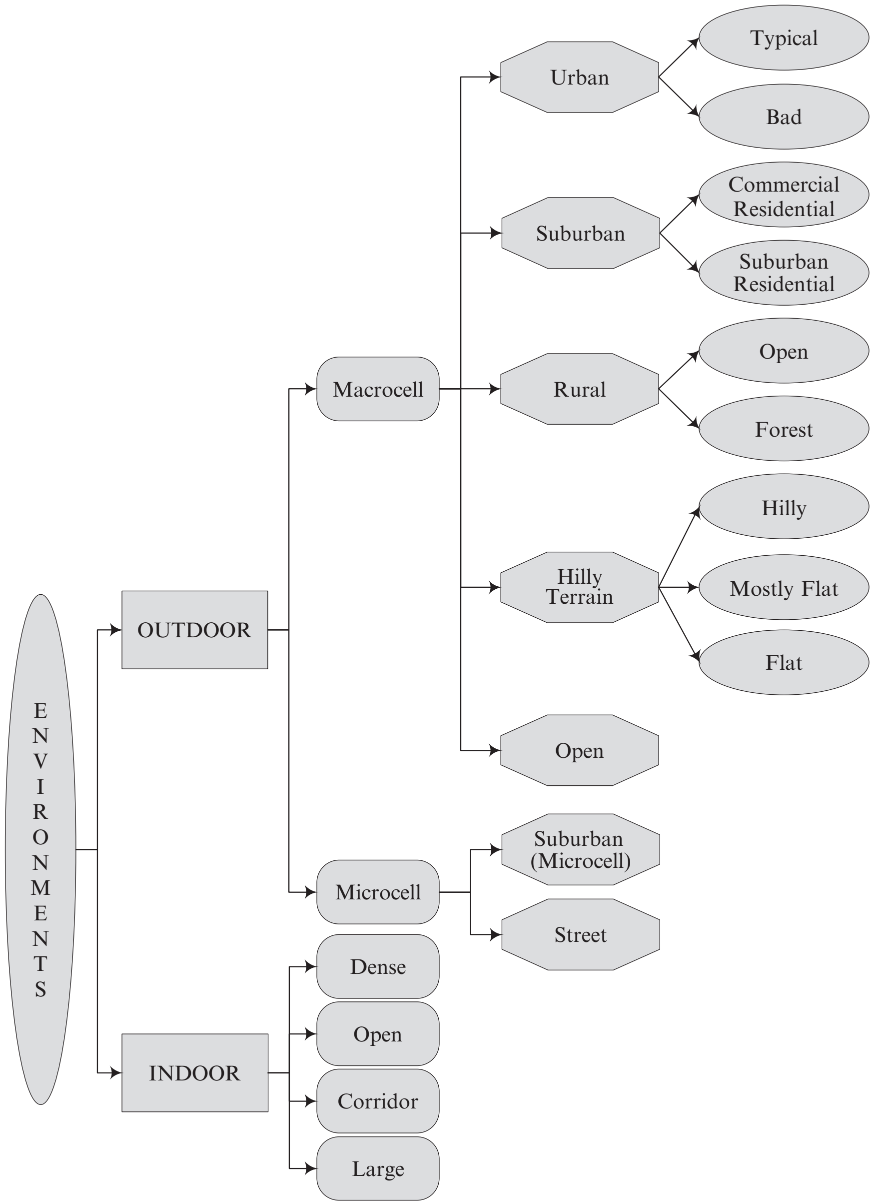

Fig. 8.3. Some popularly used propagation environments in the literature and their classification.

Environmental Characterization – In Longley–Rice model, which is one of the earliest propagation models, there are two operation modes defined depending on the availability of the terrain profile: "point-to-point mode" and "area mode" [19, 20]. Although this model is for point-to-point communication, its significance lies beneath the use of terrain profiles in estimating the path-loss. Similar to [19, 20], [21, 22] make use of a topographical database to estimate the field strength. In light of this approach, it can be said that cognitive radio can take advantage of terrain profile data to characterize the topography of its surrounding environment. Some of the basic topographical databases such as DEMs – i.e. digital representations of a topographic surface, which is used for determining properties of terrain in terms of elevation at any point, slope, aspect and extracting features of it, such as peaks, pits, and other landforms – are already available. GIS is also another very popular application which can be used for the same purpose.[12] In fact, GIS is more promising than DEMs, because it can be queried by several methods one of which is the position vector $\mathbf{r}(t) = [x, y, z]^T$. Recall that global positioning system (GPS) can provide the position vector. Thus, cognitive radio that can be provided with position information by a network or a positioning capable sensor (such as GPS) can easily extract the topographical information. Then, the digital data is processed with the aid of Spatial Interpolation Method (SIM) to obtain characteristics of the local physical environment [21, 22, 24]. The remaining part is just to find the best match for the extracted topographical data among environmental classes. As stated above, matching the data can be handled via pattern recognition and/or parallel processing capable tools that cognitive radio possesses. Upon finding the best match, a statistical model related to the matched environmental class is chosen and adaptation stage is initiated. The algorithm for this process is presented in Figure 8.4. Besides, Table 8.4 presents the possible ways of quantifying the path-loss along with adaptation options.

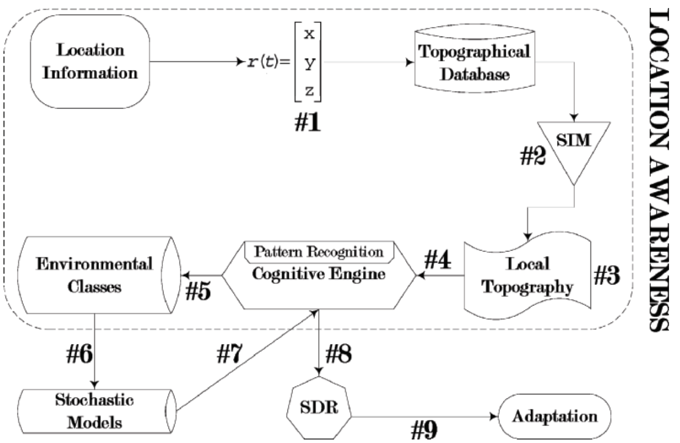

Fig. 8.4. The algorithm of location awareness and environmental characterization for cognitive radio. #is represent the steps of the algorithm.

[12] Note that, there are already some products in the market for mobile version of GIS applications [23].

Table 8.4. Measurement of path-loss and some adaptation options.

How To Measure	What To Adapt
RSS	Link adaptation via adaptive coding/modulation
	Hand-off (handover)
Geolocationing Methods	Channel allocation
	Interference management
	Simple distant–based power control algorithm

The impact of noise upon communications systems is known very well [34]. Noise is also taken into account in statistical wireless channel models. In order to improve the performance of wireless systems, characterizing the behavior of noise is very important. As will be shown subsequently, environments can provide some hints about the statistical behavior of noise. Hence, cognitive radio can make use of the relationship between environment and corresponding statistical behavior of the noise for its adaptation.

Noise

In most of the wireless channel models, noise is assumed as white and Gaussian distributed because of its mathematical tractability. However, in practice, several other types of noise behaviors exist too. In the literature, several studies show that offices, factories, and hospitals have impulsive noise [26]. Similarly, in outdoor environments such noise sources are observed. Thus, the performance of a system designed under the assumption of white and Gaussian distributed noise will be affected in the presence of an impulsive noise. Moreover, it is also reported that some diversity schemes such as maximal ratio combining, equal gain combining, and selection diversity are not effective in impulsive noise environments [27].

If cognitive radio knows the characteristics of the ambient noise, some of the system parameters such as coding requirements can be adjusted accordingly [26]. Besides, information about noise can be very useful in designing transceivers via adaptive modulation, optimal soft information calculation, and improved channel estimation [28,29]. From the network perspective, noise information can be used in improving several applications such as hand-off, power control, and channel allocation techniques [8].

In extracting the characteristics of the ambient noise, Signal-to-Interference Ratio (SIR) (or Signal-to-Noise Ratio (SNR) or Signal-to-Interference-plus-Noise Ratio (SINR)) are popularly used during or right after the demodulation process at the receiver. Unlike Received Signal Strength Indicator (RSSI), these quantifiers need to wait for the completion of the demodulation process.[13] However, the estimates are more reliable at this

[13] It must be stated that because these quantifiers can be read during or right after the demodulation procedure, they introduce additional complexity to the system compared to RSSI.

stage. As their names imply, these quantifiers are based on the ratio between the power level of the desired signal (S), and the power level of the unwanted signal(s) (I and/or N), where $\frac{S}{I}$, $\frac{S}{N}$, and $\frac{S}{I+N}$ denote SIR, SNR, and SINR, respectively. They can be obtained in several ways. In many new–generation wireless systems, coherent detection is employed. Since coherent detection requires estimation of channel parameters, estimated parameters can be used in calculating the signal power as well. The use of training sequences and data symbols are other two options of signal-to-interference ratio (SIR) estimation.[14] SNR (or SIR, or signal-to-interference-plus-noise ratio (SINR)) is formed by estimating the desired received signal and the impairment separately. Hence, estimation of SNR provides information about the noise. In OFDM based systems, noise power estimation is often based on the difference between the noiseless and noisy samples in frequency domain, which assumes the noise is white and Gaussian distributed. However, as stated above, noise in frequency domain can sometimes have a different power spectrum from a flat power spectrum. In such cases, looking at the estimate of the noise variance in frequency domain provides beneficial information about the noise color [28, 29]. Some of the parameters in measuring the noise and relevant adaptation options are given in Table 8.5.

There are further link quality measurements on the physical and Medium Access Control (MAC) layers too. These measurements such as Bit-Error-Rate (BER), Frame-Error-Rate (FER), and Cyclic Redundancy Check (CRC) become available after the decoding process and their reliabilities are improved significantly compared to the aforementioned ones. However, one should keep in mind that, having information at this stage comes at the expense of larger processing delays and additional computational complexity. Furthermore, some of them such as BER and FER require excessive amount of time to attain a reliable quantification.

Table 8.5. Measurement of noise and some adaptation options.

How To Measure	What To Adapt
SNR	Link adaptation via adaptive coding/modulation
SIR	Transmission frequency
SINR	Transmit power
	Hand-off
	Receiver algorithm parameters
	Bandwidth
	OFDM carriers
	Carrier assignment in OFDM Access (OFDMA)

[14] For further information, the interested readers may refer to [8, and references therein].

Network and Transport Layer Measurements

When network and transport layer are considered, observing and quantifying the wireless communication link brings about different perspectives. In these layers, transceivers perceive the communication link as a whole that includes other transceivers. Therefore, in these layers, transceivers take into account the status of other nodes in the network as well.

Packet loss is one of the basic and simple quantifier that can be used in these layers. Transceivers can get information about the quality of the link by simply counting the packets which could not be acknowledged. Similarly, Round-Trip Time (RTT) can be used in estimating the quality of the link to some extent. The buffer status of the nodes can be used in determining the congestion level of the link, which can also be regarded as a measure of link quality. Particularly in ad hoc networks, being aware of other nodes become prominent. For instance, a quantifier that indicates the power level of the other nodes introduces another metric for routing, which is known as “power aware routing” [30]. In connection with power aware routing, being aware of the locations (or relative positions) of the nodes will definitely provide these layers with an extra and very important quantifier.

With the aid of these quantifiers, cognitive radio can adjust its transmission rate to avoid congestion, increase efficiency, save energy, and so on. In addition, cognitive radio can contribute to the network optimization by combining many of them. For instance, combination of power aware routing and being aware of the locations of other nodes will provide a superior routing scheme compared to those which make use of only one routing metric. Some of the quantification parameters and related adaptation options are presented in Table 8.6.

Upper Layers

After passing through session and application layers, cognitive radio reaches at the user even though the user by itself is not a layer in the protocol stack. From the perspective of cognitive radio, the user carries a significant importance

Table 8.6. Measurement of the quality of the communication link in network and transport layer and some adaptation options.

How To Measure	What To Adapt
Packet Loss	Routing Algorithm
Routing Table Change Rate	Routing Metric
Congestion Level	Clustering Parameters
Positions of Nodes	Network Scheduling Algorithm
Power Level of Nodes	Congestion Control Parameters
RTT	Rate Control Parameters

because of its place in the cognition cycle. Therefore, cognitive radio can perceive the user as another layer that is placed on top of the traditional protocol stack and sense it. These issues will be discussed in Section 8.4 in detail.

8.2.3 Other Wireless Channel Characteristics

In addition to the topics discussed in Sections 8.2.1 and 8.2.2, there are some further parameters that have significant impact on the transmission such as being in Line-of-Sight (LOS)/Non-Line-of-Sight (NLOS).

LOS/NLOS

When the field measurements are established in order to have a statistical channel model, it is extremely important to distinguish the measurements as for LOS and NLOS. This stems from the fact that LOS channels will behave very differently compared to NLOS channels because of the presence of the direct component. LOS/NLOS distinction is very important in terms of the operation band as well, since the behavior of propagation differs in LOS and NLOS. For instance, in order to be able to establish a communication with electromagnetic waves that have wavelengths on the order of millimeters (the bands above 10 GHz), LOS is required as in 10–66 GHz portion of the physical layer part of IEEE 802.16 [31]. However, the necessity of having LOS is not required for sub-10 GHz bands. In addition, being in LOS/NLOS is very important for positioning algorithms. The error characteristics change drastically depending on being in LOS or NLOS [32].

The knowledge of being in LOS or NLOS allows cognitive radio to have some adaptation options. Cognitive radio can easily switch to an appropriate upper frequency band to achieve higher data rates in case of being in LOS or switches back to the band in which it was previously operating when there is no LOS. Ranging and positioning algorithms can be selected by cognitive radio adaptively, depending on the status of the transmission in terms of being in LOS or NLOS as well.

In order to determine whether the status of the communication is LOS or NLOS, hypothesis test is applied. Hypothesis test makes use of the mutually exclusive relationship between LOS and NLOS [32–35]. Considering the fact that the channel amplitudes of the first tap in narrowband systems follow Ricean distribution in LOS and Rayleigh distribution in NLOS, a comparison between the reference (theoretical) distributions and values observed can be established before the hypothesis test [36].[15] However, a reliable decision for the comparison approach, *a priori* knowledge about the noise level of the system is required [32]. Apart from these methods, autocorrelation characteristics of multiple channel taps have also been proposed [31].

[15] In comparing the statistics obtained to a reference one, some statistical tests such as Pearson's test statistics [36] or Kolmogorov–Smirnov test [37] can be employed.

Table 8.7. Measuring LOS/NLOS and some adaptation options.

How To Measure	What To Adapt
Channel Estimates	Transmission frequency
Geolocationing Methods	Power adjustment
	Locationing algorithms for improved accuracy
	Receiver algorithm parameters

Quantifying the transmission status in terms of being LOS or NLOS becomes possible through the use of additional sensing capabilities of cognitive radio. A list of quantification options and relevant adaptation parameters for LOS/NLOS is given in Table 8.7. As discussed in detail in Section 8.2.2, the use of DEMs is a very promising candidate for this purpose. In fact, previously, DEMs have already been used in digital domain to determine the status of being LOS or NLOS [21, 22].

8.3 Network Awareness

This section outlines what and how cognitive can sense, be aware of, and consequently adapt the network related issues. The following two perspectives are considered: being aware of the same network and other network structures.

8.3.1 Being Aware of the Same Network

This sort of awareness is necessary while cognitive radio is already communicating with some other nodes. From this point of view, being aware of its own network and its other members (nodes) will definitely improve the quality of overall network communications. However, being a member of the same network does not necessarily require that all the nodes have cognitive capabilities. Therefore, it can be said that being "entirely" aware of the same network is only possible when all the nodes in that network are cognitive radio.

As discussed in Section 8.2.2, being aware of the same network can be extended by using conventional and advanced methods such as the use of packet loss quantifiers, routing algorithms, and some other additional capabilities which are introduced by cognitive radio such as location sensing.

8.3.2 Being Aware of Other Networks

Before cognitive radio begins to communicate, it can sense not only the unoccupied bands in the spectrum, but also the signaling schemes over the air. For instance, cognitive radio can sense unoccupied slots for Time Division Multiple Accessing (TDMA)–based signaling, and furthermore, it can be aware of the network type by using several methods such as cyclostationary-based detection. This is very important for cognitive radio, since it can easily change its transmission parameters such as employing valid waveforms and relevant policies for the network sensed with the aid of SDR.

This type of sensing and awareness carries a great importance especially for emergency, disaster relief, and rescue operations. The transmission of other devices can be observed by sensing the spectrum, extracting the data from other users' transmission, processing it, comparing it with some *a priori* information (such as standard information), and making a decision about the existence of a possible network. Thus, in such an environment, cognitive radios can establish a network and connectivity for the devices which cannot easily be detected by first responders [39].

8.4 User Awareness

When cognitive radio has first been brought forward [3, 19], beside its advanced properties such as the capability of sensing the spectrum, adjusting the transmission parameters via software (or software defined radio (SDR)), the concept of "*user dimension*" has been pulled inside the radio communication domain entirely. Here, the word "entirely" is preferred, because, there are already some earlier attempts. However, these attempts are limited compared to that of cognitive radio, because, they mostly require user's intervention. Some advanced cell phones, Personal Digital Assistants (PDAs), and laptops can define several user profiles as options, but, these options are not automated. In addition, once the user chooses any of the options provided, the device cannot make modifications on the options depending on the changing conditions.

However, cognitive radio, beside the aforementioned capabilities, can learn and even make predictions about the user. One of the interesting awareness topic about the user is being aware of user's perception. When a simple voice conversation over phone is considered, some sort of adaptations become clearer depending on the environment and/or who the user is. For instance, if the user is in a crowded and noisy environment such as a stadium, the intelligibility of the voice decreases drastically. In the conventional way, the user intervention is required by just choosing the loudest voice level of the phone or warning the other party to raise his/her voice. However, cognitive radio can reduce or totally remove the user intervention by sensing the environment with the aid of its additional sensing and advanced recognition capabilities. Detecting the crowd via visual sensing and picking the phrases such as "I did not hear you," "Can you repeat it?" "Can you raise your voice?" cognitive radio is aware of the user's perception (as well as the environment) and adapts to satisfy its user's needs. Another interesting user awareness and adaptation scenario can occur while driving a car. Driving car inherently limits some of the abilities of the user such as reading and/or using the keypad of the communication device. When a text message (such as Short Message Service (SMS) or e-mail) arrives, cognitive radio can convert the text to speech without requiring user intervention. When the user wants to reply, it can do the process in reverse direction, in other words it can convert speech to text, and send the text message. In case the user wants to call the sender, it can initiate an ordinary phone conversation by recognizing the user's speech and command (such as "Call him!"). Another very important application area of user oriented sensing occurs in emergency related events. Cognitive radio that is aware of physiological state of its user can immediately establish a 911 call in case of an emergency.

Because humans have many aspects in terms of their perceptions, psychological status, and some other further characteristics, the items to be included into the list in user dimension are numerous. However, possessing very powerful abilities such as learning and sensing beside awareness and adaptation, cognitive radio can have various sensing options for other aspects of human, which have very stong relations with AI.

8.5 Other Possible Awareness Scenarios

It is certain that wireless communications cannot be limited to the topics mentioned throughout this chapter. Although a wide perspective is tried to be established, it is very difficult to put all possible aspects of the communications into text, since most of them evolve in time. However, some of the topics that are and will be of interest can still be discussed.

The security is one of the most important aspects in all types of communications. In this manner, cognitive radio can decide the appropriate security level without requiring any external intervention. Here, the discussion excludes the use of the safest level, because it comes at the expense of delay, overhead, and so on. These concerns force cognitive radio to optimize (deciding the appropriate level) the security level. In connection with optimization, cognitive radio itself can be considered as another dimension (or entity) to be sensed and aware of in the communications domain. Cognitive radio cannot attain a global optimization unless it is aware of itself. In this regard, being aware of its resources such as battery level and hardware limitations (e.g. the limits of Analog-to-Digital Converter (ADC), processor speed, memory size, and so on), the operational status such as being in hibernation, in-charge mode, communication mode, learning mode can be considered just to name few.

8.6 Challenges and Future Directions

So far, it is discussed that the capabilities of cognitive radio enable many new sensing options providing alternatives to already existing ones. A hierarchical list of some major items to be sensed by cognitive radio is presented in

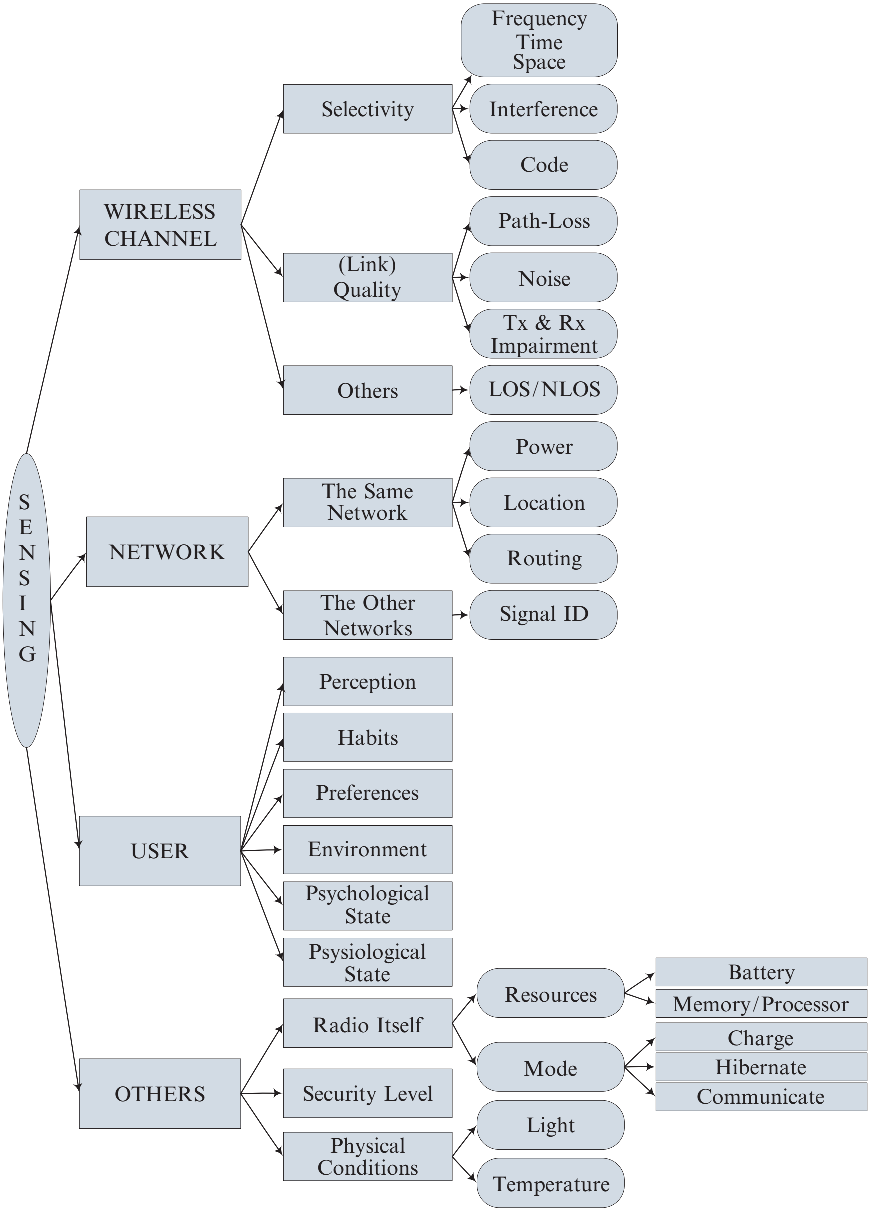

Fig. 8.5. Some major items to be sensed by cognitive radio. Please note that this represents a limited list that only provides some of the key measurements. As the cognitive radio evolves, this list will certainly evolve as well.

Figure 8.5. However, there are many challenges related to these enabling approaches. In this section, the prominent challenges and hurdles regarding to these approaches will be outlined.

First, the challenge with the general architecture of cognitive radio needs to be addressed. In order for cognitive radio to attain the point that has been discussed so far, a design, which integrates SDR and tools that handle artificial intelligence (AI) sort of operations, is required. This can be considered as the most challenging issue for cognitive radio.

Assuming that such an architecture or design is established, the complexity of the procedures in sensing mentioned throughout this chapter is quite overwhelming. Therefore, cognitive radio needs to find ways of handling this complexity issue. Cognitive radio makes use of not only existing methods and approaches, but also the new opportunities of sensing with the aid of additional sensors and devices to improve the adaptation process. Since the information traffic will increase considerably, controlling, processing, and therefore managing the resources automatically become a major concern.

Apart from general challenges, there are some other challenges peculiar to sensing, being aware, and adaptation for each topic discussed up until now. In Section 8.2.2, determining the path-loss through the use of external sensors has been discussed. The main challenge here is to find how cognitive radio can identify the environment in order to use the appropriate path-loss exponent. As explained in [3], distinguishing indoor from outdoor is a simple job by just using light and thermal sensor. However, distinguishing several indoor environments from each other, such as LOS and NLOS indoor communications requires additional effort.

In Section 8.2.3, extracting time dispersion parameters of the wireless channel with the aid of DEMs and GIS has been discussed as well. However, digital information provided by these sorts of tools must be interpreted by cognitive radio in such a way that it can understand the geomorphological characteristics of the environment and classify them as hilly terrain, urban, and so on. As can be seen, the interpretation process requires the use of advanced pattern recognition algorithms. Another aspect of geomorphological characterization is that it may require the classification of the propagation environments for cognitive radio to choose an appropriate model as discussed earlier. There are extensive statistical channel models in the literature to include various possible propagation environments. If cognitive radio can match the surrounding environment with an existing statistical model in its memory, it can easily adjust a few relevant parameters to adapt the environment. However, in order for cognitive radio to choose one of the statistical models among many of them, it should store the statistical models in a hierarchical way. Unfortunately, there is no clear-cut definition for types of propagation environments in the literature. Cognitive radio may suffer from lack of these definitions.

In quantifying time selectivity, apart from the conventional way of extracting the parameters, cognitive radio can make use of its location sensors such as GPS. However, it is not known how frequently cognitive radio must refer to the sensors to obtain the information. In addition, the capabilities of the sensors (such as acquisition time, precision, and so on) must also be taken into account.

In time selective interference, characterizing the pattern of the interference that changes in time for adapting purposes may require long observation durations. This hurdle becomes clearer in channels that are randomly accessed. Similar to interference, the relationships between code dimension and three basic dimensions need to be studied to have a comprehensive understanding of the selectivity.

The inclusion of aforementioned and possible future dimensions into the universe of cognitive radio will force researchers to examine the relationships between these dimensions. The entangled structures of these dimensions must be investigated throughly to realize the ultimate cognitive radio, which is a very challenging task.

Considering the complete adaptation and global optimization jointly unveils one of the biggest challenges in realizing cognitive radio. In order for cognitive radio to achieve both complete adaptation and global optimization, the complex nature of complete adaptation needs to be scrutinized. The analysis must encompass both already existing and recently emerging sensing options and their relevance. Upon this analysis, which is very likely to provide a very comprehensive list, the ways of attaining global optimization must be researched. Global optimization through additional sensing capabilities along with the already existing ones can be achieved by AI structure, which is, generally, referred as cognitive engine. Thus, cognitive engine must be capable of "understanding," "interpreting," and even "reasoning" via the input provided by layers, sensors, and even by its own hardware. In order for cognitive engine to "think" taking into account all input, a descriptive language, Radio Knowledge Representation Language (RKRL), is proposed in [3]. Hence, already existing and recently emerging options must be included into the knowledge space of cognitive radio in connection with the analysis.

The interactions, applications, and algorithms in a network that include both cognitive and non-cognitive radios need to be studied as well. In this regard, networks in which all the nodes are cognitive radios form another field of study.

Especially in sensing other networks, cognitive radio is challenged by technological limitations. Currently, sensing other types of networks and signaling schemes is carried out by huge devices. Beyond that, the techniques that are employed for that purpose require computationally very complex signal processing operations which are power hungry. Thus, in order for cognitive radio to have these abilities, practically simple and less complex algorithms that can perform the same operations must be developed.

Considering the fact that sensing, learning, being aware, and adaptation capabilities make cognitive radio more personal, the characterization of the user can be examined in detail. Especially sensing the user's psychological and physiological status and act on accordingly will be an interesting research for the sake of becoming more personal.

8.7 Conclusion

Cognitive radio provides new horizons to the radio communications with its advanced capabilities such as sensing, learning, being aware of, and adaptation to its surrounding environment. These advanced capabilities improve almost every aspect of wireless communications. In this chapter, some major items to be sensed by cognitive radio are discussed. It is certain that the things that cognitive radio can sense, be aware of, and measure are not limited to the items discussed here. As cognitive radio evolves, the list of the things that cognitive radio can sense, be aware of, and measure will evolve as well. However, in order for cognitive radio to come true, the hurdles in front of the new methods of sensing and measuring processes must be overcome.

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