

Review Article

Real-Time Measurements for Adaptive and Cognitive Radio Systems

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Adaptive and cognitive radios (CR) have been becoming popular for optimizing mobile radio system transmission and reception. One of the most important elements of the adaptive radio and CR concepts is the ability to measure, sense, learn about, and be aware of parameters related to the radio channel characteristics, availability of spectrum and power, interference and noise temperature, operational environment of radio, user requirements and applications, available networks and infrastructures, local policies, other operating restrictions, and so on. This paper discusses some of the important measurement parameters for enabling adaptive radio and CR systems along with their relationships and impacts on the performance including relevant challenges.

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1. Introduction

Wireless communication systems have evolved substantially over the last two decades. The explosive growth of the wireless communications market is expected to continue in the future, as the demand for all types of wireless services is increasing. New generations of mobile radio systems aim to provide higher data rates and a wide variety of applications (such as video, data, and positioning) to the mobile users while serving as many users as possible. However, this goal must be achieved under the constraint of limited available resources such as spectrum and power. Given the high price of spectrum and its underutilized use, the systems must provide higher capacity and performance through a better exploitation of all available resources. Therefore, adaptive and cognitive radios (CR) have been becoming popular for optimizing mobile radio system transmission and reception at the physical layer as well as at the higher layers of the protocol stack. Traditional system architectures focus on allocating fixed resources to the mobile users, since the fundamental goal is the simplicity in the design. Adaptive design methodologies, on the other hand, typically identify the users' requirements, and then allocate just enough resources; thus, enabling more efficient utilization of system resources and consequently increasing the capacity.

Considering the escalating demand in use of wireless communications along with the fact that radio spectrum is finite, a straightforward conclusion, which is called as "spectrum scarcity," can be drawn. Contrary to this common reasoning, recent measurements revealed that radio spectrum is actually underutilized rather than being scarce. Cognitive radio (CR) that is based on software-defined radio (SDR) is brought forward to remedy this underutilization problem. Through cognition cycle and SDR, CR is capable of pushing the traditional and limited adaptation concept toward the global adaptation by introducing multi-dimensional awareness, sensing, and learning from its experiences to reason, plan, and decide future actions to meet user needs. Even though there is no consensus on the formal definition of CR as of now, the concept has evolved recently to include various meanings in several contexts. Interoperability across several networks; roaming across borders while being able to stay in compliance with local regulations; adapting the system, transmission, and reception parameters without user intervention; and having the ability to understand and follow actions and choices taken by their users, and learn to become more responsive over time can be considered just to name a few. Since these parameters and notions might tinker over time and over multitude of other dimensions, the radios need to be equipped with proper mechanisms to react these changes.

Including contemporary communication systems, it is not difficult to see that a global adaptation covering the entire protocol stack has not been achieved yet. This stems from the architecture of the protocol stack, which is based on strictly defined individual layers. Furthermore, a global adaptation requires all of the layers to be examined in a combined way leading to a multidimensional problem. However, CR cannot come true without having such a global adaptation which comes at the expense of very challenging tradeoffs in terms of contending goals defined in layers. Hence, by its very definition, being aware of the situation, environment, and many other aforementioned issues will compel CR to find a compromise between many contending objectives. Moreover, it is important to note that CR is also responsible for observing the consequences of its actions to be able to improve the quality of its decisions in the future through its learning ability. Although the contemporary strictly layered protocol structure solves some of the problems to some extent, a conceptual model of CR is required.

In this paper, some of the important parameters for enabling the adaptive radio and CR systems will be discussed along with measurement and estimation techniques including relevant challenges and some sample applications. Desired user's radio channel parameters will be studied in detail. The channel parameters will be grouped under two categories, namely, channel selectivity measurements and channel quality measurements. Interference parameters, which could have also been interpreted as part of the channel parameters, will be treated separately, since for CR, the definition of interference includes concepts beyond what has been interpreted in the past. In addition to the channel and interference parameters, many other parameters that can be useful for CR will be discussed under the concept of external sensing. Based on the traditional channel parameter measurements along with externally obtained ones, a conceptual model of CR is presented as well.

2. Channel Parameters

In wireless radio communication systems, information is transmitted to the receiver through a radio propagation environment. Transmitted signals are typically reflected, diffracted, and scattered, arriving at the receiver along multiple paths with different delays, amplitudes, and phases (see Figure 1). Multipath propagation affects the signal significantly, corrupting the signal, and often placing limitations on the performance of the system.

Depending on the transmission bandwidth (or symbol duration) and the type of environment in which the communication takes place, multipath can cause various problems. When the relative delays are small compared to the transmitted symbol period, different "images" of the *same* symbol arrive at the same time, adding either constructively or destructively. The overall effect is a random fading channel response. When the relative path delays are on the order of a symbol period or more, then images of *different symbols* arrive at the same time causing intersymbol interference (ISI).

In addition, in wireless mobile radio systems, mobility, which includes the mobility of the transmitter, the receiver, and the scattering objects within the propagation environment, causes the channel response to change rapidly in time leading to spectral broadening, which is also referred to as Doppler spread. Impact of Doppler spread depends on the transmission bandwidth. As the transmission bandwidth increases, the relative broadening of the channel with respect to the transmission bandwidth will be insignificant. In other words, the time variation of the channel within the transmission of a symbol will be negligible, since wider transmission bandwidths imply shorter symbol duration. This gives rise to a common tradeoff between high mobility and high data rate.

Finally, the interference conditions in wireless systems change rapidly. Many of the wireless communication systems are interference limited, affecting the performance, capacity, range, data rate, and so on. Since the radio channels of the desired and interfering users are highly random, and the statistical characteristics of the channel are environment-dependent, the effect of interference also varies in time, frequency, and space. As will be discussed subsequently, behavior of interference is also influenced by some other notions such as traffic type and mobility patterns within the propagation environment.

In the following sections, the important measurements related to the radio channel will be discussed. First, channel selectivity measures in different dimensions will be reviewed. Then, various channel quality measures will be studied in detail.

2.1. Channel Selectivity Measurement. Multipath propagation causes the signal to spread in time, frequency, angle, and other possible dimensions (see Table 1). These spreads, which are related to the selectivity of the channel, have significant implications on the received signal. The information about the variation of the channel in multiple dimensions is very crucial in adaptation of wireless communication systems.

2.1.1. Time Selectivity Measure/Doppler Spread. Doppler shift is the frequency shift experienced by the radio signal when there is a relative motion in the propagation environment, and Doppler spread is a measure of the spectral broadening caused by the temporal rate of change of the mobile radio channel. Therefore, time-selective fading and Doppler spread are directly related. The coherence time of the channel can be used for characterizing the time variation of the time-selective channel. It represents the statistical measure of the time window over which the two signal components have strong correlation, and it is inversely proportional to the Doppler spread.

In CR, Doppler spread information can be used for improving performance or reduce complexity. For example, in channel estimation algorithms, whether using channel trackers or channel interpolators, instead of fixing the tracker or interpolation parameters for the worst-case Doppler spread value (as commonly done in practice), the parameters

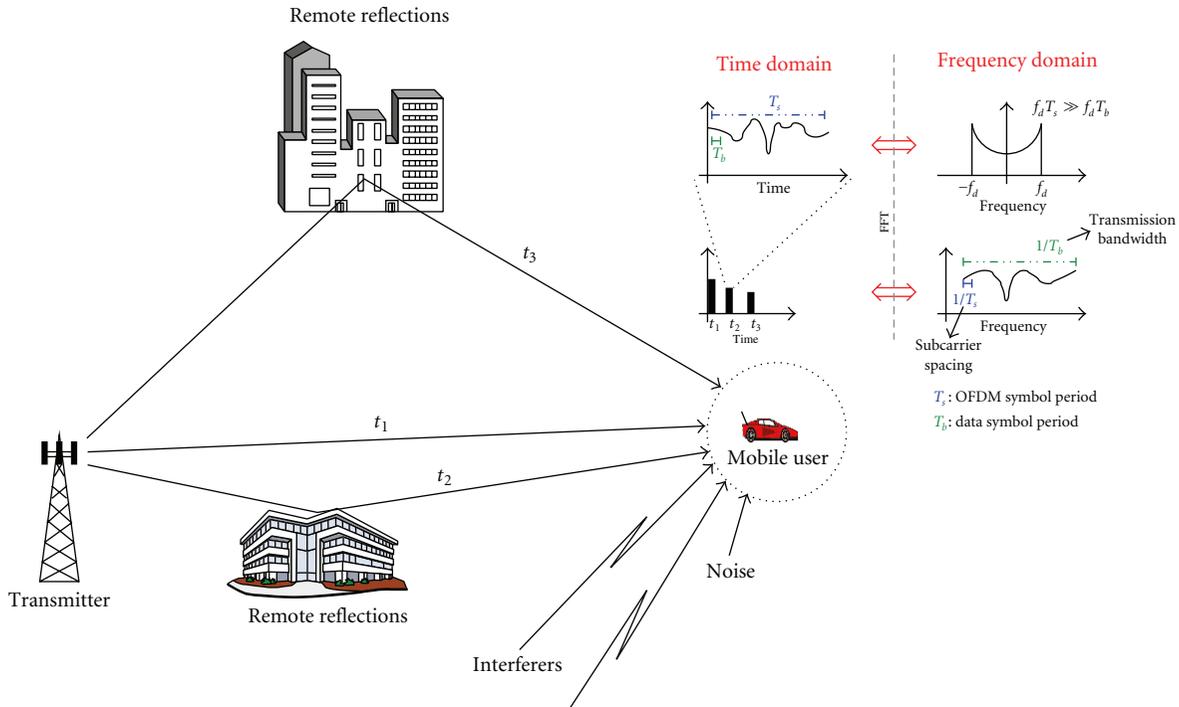


FIGURE 1: Illustration of some of the effects of radio channel: local scatterers cause fading; remote reflectors cause multipath and time dispersion, leading to ISI; mobility of user or scatterers causes time varying channel, leading to frequency dispersion (Doppler spread); reuse of frequencies, adjacent carriers, and so forth, cause interference.

can be optimized adaptively based on the Doppler spread information [1–3]. Similarly, Doppler information could be used for controlling the receiver or the transmitter adaptively under different mobile speeds as in variable coding and interleaving schemes [4] (the direct relationship between mobile speed and Doppler phenomenon is studied broadly in literature as well [5–8]). Also, radio network control algorithms, such as hand-off, cell assignment, and channel allocation in cellular systems, can utilize the Doppler information [9, 10]. For example, in a hierarchical cell structure, the users are assigned to cells based on their speeds (mobility); fast-moving mobiles can be assigned to larger umbrella cells (to reduce the number of hand-offs), while slow-moving mobiles are assigned microcells (to increase capacity).

Doppler spread estimation has been studied for several applications in wireless mobile radio systems. Correlation and variation of channel estimates [11] as well as correlation [12, 13] and variation of the signal envelope have been used extensively [5, 10]. Multiple antennas can also be exploited for Doppler spread estimation [14], where a linear relation between the switching rate of the antenna branches and Doppler frequency can be obtained.

Although the estimation of the Doppler spread information is very useful for adaptive systems, one might wonder if the estimation process brings a heavy burden onto the system. If we consider contemporary wireless receivers, we see that most of them are already accessorized with channel estimation ability. Although the Doppler spread estimation

requires additional effort after the channel estimation process, the gain to be obtained in the long term is encouraging. However, considering the desire of having a mobile device as small as possible such as a cell phone, the use of multiple antennas for this purpose becomes questionable.

2.1.2. Frequency Selectivity Measure/Delay Spread. Delay spread is one of the most commonly used parameters that describe the time dispersiveness of the channel, and it is related to frequency selectivity. Frequency selectivity can be described in terms of coherence bandwidth, which is a measure of range of frequencies over which the two frequency components have a strong correlation. The coherence bandwidth is inversely proportional to the delay spread [15, 16].

Such as time selectivity, the information about frequency selectivity of the channel can be very useful for improving the performance of all types of adaptive wireless radio systems including CR. For example, in a time division multiple access- (TDMA-) based Global System for Mobile (GSM), the number of channel taps needed for equalization might vary depending on the dispersion of the channel. Instead of fixing the number of equalizer taps for the worst case condition, they can be changed adaptively, allowing simpler receivers with reduced battery consumption and improved performance [17, 18]. Dispersion estimation can also be used for other parts of transmitters and receivers. For example, in channel estimation using channel interpolators, instead of fixing the interpolation parameters for the worst

TABLE 1: Dimensions* of channel selectivity and their importance with sample applications.

★	Importance	Sample applications	Illustrations
Time	Indicates how fast the channel is varying in time, and Doppler spread	Receiver optimization (such as channel estimation), adaptation of transmitter and system parameters (such as interleaving length, channel and cell assignment, hand-off optimization)	
			Frequency
Space	Determines how rich the scattering environment and how wide angle spread are	Adaptive multi-antenna system design	
			Interference

expected channel dispersion, the parameters can be changed adaptively depending on the dispersion information [19].

Although dispersion estimation can be very useful for many wireless communication systems, it is particularly crucial for orthogonal frequency division multiplexing-

(OFDM-) based wireless communication systems. OFDM, which is a multicarrier modulation technique, handles the ISI problem due to the high bit rate communication by splitting the high rate symbol stream into several lower rate streams, and transmitting them on different orthogonal

carriers. The OFDM symbols with increased duration might still be affected by the previous OFDM symbols due to the multipath dispersion. Cyclic prefix (CP) extension of the OFDM symbol avoids ISI from the previous OFDM symbols if the CP length is greater than the maximum excess delay of the channel. Since the maximum excess delay depends on the radio environment, the CP length needs to be designed for the worst-case channel condition. This makes CP as a significant portion of the transmitted data, resulting in reduced spectral efficiency. One way to increase spectral efficiency is to adapt the length of the CP depending on the radio environment [20]. The adaptation requires estimation of maximum excess delay of the radio channel, which is also related to the frequency selectivity. A very important statistical parameter that is used to characterize the time dispersiveness of the wireless channel is the root-mean-squared (RMS) delay spread. RMS delay spread is the square root of the second central moment of the power delay profile (PDP) of the channel, and it is generally less than one-fourth of the maximum excess delay. In HIPERLAN/2, which is a wireless local area network (WLAN) standard, a CP duration of 800 nanoseconds, which is sufficient to allow good performance for channels with RMS delay spread up to 250 nanoseconds, is used. Optionally, a short CP with 400 nanoseconds duration may be used for short-range indoor applications. Similarly, the broadband wireless metropolitan area network (WMAN) standard, IEEE 802.16, defines several CP options that can be used in different environments. Delay spread estimation allows adaptation of these various options to optimize the spectral efficiency. Other OFDM parameters that could be changed adaptively using the knowledge of the dispersion are the OFDM symbol duration and OFDM sub-carrier bandwidth.

Characterization of the frequency selectivity of the radio channel is studied extensively using level crossing rate (LCR) of the channel in frequency domain [21–23]. Frequency domain LCR gives the average number of crossings per Hz at which the measured amplitude crosses a threshold level. An analytical expression between LCR and the time domain parameters corresponding to a specific multipath PDP can be easily obtained. LCR is very sensitive to noise, which increases the number of level crossing and severely deteriorates the performance of the LCR measurement. Filtering the channel frequency response reduces the noise effect, but finding the appropriate filter parameters is a challenge. If the filter is not designed properly, one might end up smoothing the actual variation of frequency domain channel response. Channel frequency selectivity and delay spread information can also be calculated using the channel frequency correlation estimates, and analytical expressions between delay spread and coherence bandwidth can be obtained easily [15, 24].

2.1.3. Spatial Selectivity Measure/Angle Spread. Angle spread is a measure of how multipath signals are arriving (or departing) with respect to the mean arrival (departure) angle. Therefore, angle spread refers to the spread of angles of arrival (or departure) of the multipaths at the receiving

(transmitting) antenna array [25]. Angle spread is related to the spatial selectivity of the channel, which is measured by coherence distance. Such as coherence time and frequency, coherence distance provides the measure of the maximum spatial separation over which the signal amplitudes have strong correlation, and it is inversely proportional to angular spread, that is, the larger the angle spread, the shorter the coherence distance. For a given receiver antenna spacing, large angle spread leads to weaker antenna correlations between the signals received by different antenna elements. Note that although the angular spread is described independent of the other channel selectivity values for the sake of simplicity, in reality, the angle of arrival can be related to the path delay. The multipath components that are arriving to the receiver earlier (with shorter delays) are expected to have similar angle of arrivals (lower angle spread values).

Compared to time and frequency selectivity, spatial selectivity has not been studied widely in the past. However, recently, there has been a significant amount of work in multiantenna systems. With the widespread application of multiantenna systems, it is expected that the need for understanding spatial selectivity and related parameter estimation techniques will gain momentum. Spatial selectivity will especially be useful when the requirement for placing antennas close to each other increases, as in the case of multiple antennas in mobile units.

Spatial correlation between multiple antenna elements is related to the spatial selectivity, antenna distance, mutual coupling between antenna elements, antenna patterns and so on [26, 27]. Spatial correlation has significant effects on multiantenna systems. Full capacity and performance gains of multiantenna systems can only be achieved with low antenna correlation values. However, when this is not possible, maximum capacity can be achieved by employing efficient adaptation techniques. Adaptive power allocation is one way to exploit the knowledge of the spatial correlation to improve the performance of multiantenna systems [28]. Similarly, adaptive modulation and coding, which employ different modulation and coding schemes across multiantenna elements depending on the channel correlation, are possible [29, 30]. Multi-input multi-output (MIMO) antenna systems employ adaptive power allocation by exploiting the knowledge of channel matrix estimate and by employing eigenvalue analysis as well [31, 32].

2.1.4. Other Selectivity Measures. Researchers need to explore ways to adaptively access all dimensions associated with the electromagnetic spectrum. The three fundamental dimensions of the channel selectivity (time, frequency, and angle) are well understood in the wireless community (see Table 1). There are other possible dimensions that can be considered as part of channel selectivity. Even though they might not be directly associated with the actual wireless medium, it is possible to consider them within this context. Power, polarization, interference, and coding are some of these dimensions that are really part of the signal space rather than the actual channel space. However, they have strong ties with the channel space.

Code selectivity, like pseudo-noise (PN) codes in direct-sequence spread-spectrum (DSSS) or time hopping codes in ultrawide band (UWB) or frequency hopping (FH) codes in FH systems, could be a strong measure for adaptive system design for future CR systems. Many of the wireless systems are interference-limited. Therefore, the capacity is determined by how much interference the system can tolerate. For example, the self interference (such as ISI) which is caused by the non-zero autocorrelation side lobes, and multiaccess interference (MAI) due to the nonzero cross-correlations are major interference sources that are related to the code design. The effect of interference and near-far problem can be minimized by employing power control [33]. Alternatively, decreasing side lobes of the auto- and crosscorrelation also reduces interference and increases spectral efficiency. Therefore, it is desirable to have sequences with ideal auto- and crosscorrelation properties. However, it is proven that “perfect” sequences do not exist. Also, it is well known that there is a tradeoff between obtaining good auto- and crosscorrelation properties, (i.e., smaller ISI) leading to larger MAI or vice-versa. In addition, the number of possible codes (and hence the capacity) can be increased by allowing some correlation (or interference) in code domain. Being aware of that the number of codes that have good correlation properties is limited, by allowing some correlation adaptively depending on the other system, channel, and transceiver parameters, the overall capacity of the system can be increased. The correlation properties can also be changed adaptively to provide desired properties over a zone depending on other channel selectivity parameters.

Interference selectivity can be considered how the interfering sources (such as the cochannel interference (CCI) and adjacent channel interference (ACI)) are affecting the desired signal in different dimensions of electospace. For example, interference can be a strong narrowband interference or wideband interference indicating the selectivity of the interference in spectrum, as presented in Table 1. Similarly, interference can hop across the spectrum over time which might correspond the time selectivity of interference. Interference might also be selective over other dimensions such as space or code as discussed earlier.

2.2. Channel Quality (Link Quality) Measurement. Channel quality estimation, by far, is the most important measure that can be used in adaptive receivers and transmitters [34]. Different ways of measuring quality of the radio channel exist and many of them are done in the physical layer using baseband signal processing techniques. In most of the adaptation algorithms, the target quality measure is either frame-error-rate (FER) or bit-error-rate (BER), where FER (or BER) is the ratio of the erroneous frames (or bits) relative to the total number of frames (or bits) received during the transmission. FER and BER are closely related to higher level quality of service parameters such as speech and video quality. However, reliable estimation of these qualities requires numerous measurements and this causes delays in the adaptation as the process can be very long. Therefore, other types of channel quality measurements,

which are related to FER and BER, might be preferred. When the received signal is impaired only by white Gaussian noise, analytical expressions can be found relating the BER to other measurements. For other impairments such as colored interferers, numerical calculations, and computer simulations that relate these measurements to BER can be performed. Hence, depending on the system, the channel quality is related to the BER. Then, for a target BER (or FER), a required signal quality threshold can be calculated to use it with the adaptation algorithm.

The measurements can be performed at various points of a receiver or protocol stack, depending on the complexity, reliability, and delay requirements. There are trade-offs in achieving these requirements simultaneously. Figure 2 shows a simple example where some of these measurements can take place. In the following sections, these measurements will be discussed briefly.

2.2.1. Measures Before Demodulation. Received signal strength (RSS) estimation provides a simple indication of the fading and path loss, and provides the information about how strong the signal is at the receiver front end. If the RSS exceeds a threshold, then the link is considered as “good.” Measuring the signal strength of the available radio channels can be used as a part of the scanning and intelligent roaming process in cellular systems. Also, other adaptation algorithms, such as power control and hand-off can use this information. The RSS measurement is simply done by reading samples from a channel and averaging these samples [35]. Compared to other measurements, RSS estimation is simple and computationally less complex, as it does not require processing and demodulation of the received samples. However, the received signal includes noise, interference, and other sorts of channel impairment. Therefore, observing a good signal strength does not tell much about the channel and signal quality. Instead, it indicates whether a strong signal is present or not in the channel of interest.

2.2.2. Measures During and After Demodulation. Signal-to-interference ratio (SIR), signal-to-noise ratio (SNR), and signal-to-interference-plus-noise ratio (SINR) are the most common ways of measuring the channel quality during (or just after) the demodulation of the received signal. SIR (or SNR, or SINR) provides information about how strong the desired signal is compared to the interferer (or noise, or interference plus noise). Most wireless communication systems are interference limited; therefore, SIR and SINR are more prevalent. Compared to RSS, these measurements provide more accurate and reliable estimates at the expense of computational complexity and additional delay.

There are many adaptation schemes where these measurements can be exploited. Link adaptation (adaptive modulation and coding, rate adaptation, etc.), adaptive channel assignment, power control, adaptive channel estimation, and adaptive demodulation are only a few from countless applications [34, 36–38].

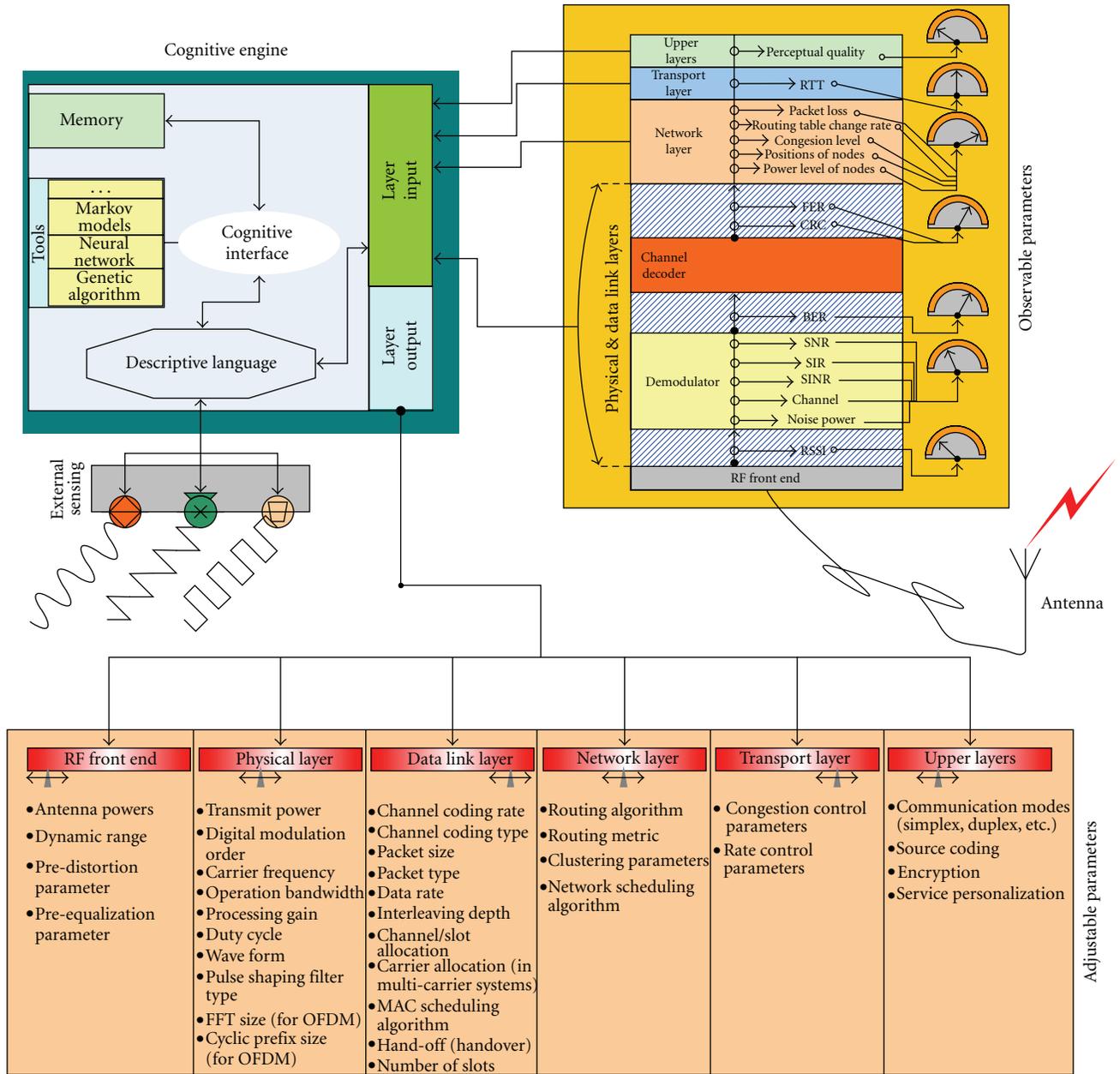


FIGURE 2: A conceptual model of CR including external sensing capabilities to improve estimations and to attain global adaptation along with observable and adjustable parameters across the protocol stack.

SIR estimation can be employed by estimating the signal power and the interference power separately, and then by taking the ratio of these two. In many new generation wireless communication systems, coherent detection, which requires estimation of channel parameters, is used. These channel parameter estimates can also be used to calculate the signal power. The training (or pilot) sequences can be used to obtain the estimate of SIR. Instead of using a training sequence, the data symbols can also be used for this purpose. For example, in [34, 39], where SNR information is used as a channel quality indicator for rate adaptation, the cumulative

Euclidean metric corresponding to the decoded trellis path is exploited for channel quality information. There are several other SNR measurement techniques available in the literature, which can be found in [40] and references therein.

Note that since both channel of the desired signal and conditions of the interferer change rapidly, depending on the application, both short- and long-term estimates would be desirable. Long-term estimates provide information on long-term fading statistics due to shadowing and log-normal fading as well as average interference conditions. Short-term measurements, on the other hand, provide measurements of

instantaneous channel and interference conditions. Applications such as adaptive channel assignment and hand-off prefer long-term statistics, whereas applications such as adaptive demodulation and adaptive interference cancellation prefer short-term statistics.

For some applications, a direct measure of the channel quality from channel estimates would be sufficient for adaptation. As mentioned earlier, channel estimates only provide information about the power of the desired signal. It is a much more reliable estimate than RSS information, as it does not include the other sorts of impairment as part of the desired signal power. However, it is less reliable than SNR (or SINR) estimates, since it does not provide information about the levels of noise and/or interference power with respect to the power level of the desired signal.

Channel estimation for wireless communication systems has a very rich history. Significant amount of work has been done for various systems. For the details of channel estimation for wireless communication systems, the readers may refer to [41, 42] and references therein.

2.2.3. Measures After Channel Decoding. Channel quality measurements can also be based on post-processing of the data (after demodulation and decoding). BER, symbol-error-rate (SER), FER, and cyclic redundancy check (CRC) information are some of the examples of the measurements falling in this category. CRC indicates the quality of a frame, which can be calculated using parity check bits through the use of a known cyclic generator polynomial. FER can be obtained by averaging the CRC information over a number of frames. In order to calculate the BER, the receiver needs to know the actual transmitted bits, which is not possible in practice. Instead, BER can be calculated by comparing the bits before and after the decoder. Assuming that the decoder corrects the bit errors that appear before decoding, this difference can be related to BER. Note that the comparison makes sense only if the frame is error-free (good frame), which is obtained from the CRC information.

Although these estimates provide excellent link quality measures, reliable estimates of these parameters require observations over a large number of frames. Especially, for low BER and FER measurements, extremely long transmission intervals will be needed. Therefore, for some applications these measures might not be appropriate. Note also that these measurements provide information about the actual operating condition of the receiver. For example, for a given RSS or SINR measure, two different receivers which have different performances will have different BER or FER measurements. Therefore, BER and FER measurements also provide information on the receiver capability as well as the link quality.

2.2.4. Measures After Speech or Video Decoding. The speech and video quality, the delays on data reception, and network congestion are some of the parameters that are related to user's perception. Essentially, these are the ultimate quality measures that need to be used for adaptive algorithms. However, these parameters are not easy to measure, and

in many cases, measurements in real-time might not be possible. On the other hand, these measures are often related to the other measures mentioned in the previous subsections. For example, speech quality for a given speech coder can be related to FER of a specific system under certain assumptions [43]. However, as discussed in [43], some frame errors cause more audible damage than others. Therefore, it is still desired to find ways to measure the speech quality more reliably (and timely), and to adapt the system parameters accordingly. Speech (or video) quality measures that take the human perception of the speech (or video) into account would be highly desirable.

Perceptual speech quality measurements have been studied in the past. Both subjective and objective measurements are available [44]. Subjective measurements are obtained from a group of people who rate the quality of the speech after listening to the original and received speech. Then, a mean opinion score (MOS) is obtained from these feedbacks. Although these measurements reflect the exact human perception that is desired for adaptation, they are not suitable for adaptation purposes as the measurements are not obtained in real-time. On the other hand, the objective measurements can be implemented at the receiver in real-time [45]. However, these measurements require sample of the original speech at the receiver to compare the received voice with the undistorted original voice. Therefore, they are not applicable for many scenarios either.

3. Interference Parameters

In communications system design, dealing with interference is one of the main considerations. Interference can be defined as any kind of signal received beside the desired signal and noise. Interference may occur in the following two ways depending on its origin:

(1) *Self-interference*, which is caused by the own transmitted signal due to the improper system design. Examples include ISI, intercell interference (ICI), interframe interference (IFI), interpulse interference (IPI), and crossmodulation interference (CMI). Self-interference can be handled by properly designing the system and transceivers.

(2) *Interference from other users*, which can be further categorized as follows.

- (i) Multiuser interference, which is the interference from users using the same system or a similar technology. CCI and ACI belong to this category. It can be overcome by proper multiaccess design and/or employing multiuser detection techniques.
- (ii) Interference from other types of technologies, which is a sort of interference that mostly requires interference avoidance or cancellation. It is more difficult to handle compared to multiuser interference and often it cannot be suppressed completely. Narrow-band interference (NBI) is a well-known example for this type of interference.

Among the two types of interference listed above, the latter one (and especially CCI) draws more attention

especially with the increasing demand and services in wireless communications. Emanating from the underutilization concern mentioned earlier, next-generation wireless networks (NGWNs) focuses on frequency reuse of one (FRO) schemes in order to avoid arduous and expensive system-wise planning step. However, FRO comes at the expense of dramatic CCI levels especially for the user equipments (UEs) in the vicinity of cell borders. This fact obligates nodes in NGWNs and CRs to be aware of many factors influencing interference to better perform under such conditions.

From the perspective of traditional protocol stack, there are some factors that affect CCI but cannot be populated in any of the layers, since they cannot be measured (therefore, controlled) in real-time in an adaptive manner. Weather and seasonal variations would be one of the most interesting “non-layer factors” influencing interference falling into this category. Due to the presence of high pressure air sometimes, signals can be reflected to the distances to which they are not intended [46, 47] (for even derivations of models such as two-ray round reflection model, readers can refer [47, Section 3]). Since the signal over the same channel is able to reach the other terminal, CCI occurs.

Although cellular systems are deployed according to the theoretical models such as the use of hexagonal shape cells, in practical cases, coverage and propagation are not as regular as in the theory. Since coverage and propagation is governed by the physical environment (local topography can result in large attenuation changes over quite short distances), namely, topographical and even demographical characteristics, and the traffic distribution depends also on the same factors [48, 49], “indirectly,” it can be concluded that CCI is affected by physical environment as well. However, it is very difficult to model these effects, since they are mathematically intractable. Statistically speaking, one can still observe more severe in urban areas due to large number of base stations and mobiles [50] and references therein. In indoor environments, depending on the use of devices, CCI is more likely to occur, since there are many devices (e.g., microwave ovens, telephone handsets, etc.) operating on the similar bands. Especially in-indoor environments, in conjunction with propagation channel properties, non-line-of-sight (NLOS) cases experience more severe interference compared to line-of-sight (LOS) cases [51]. Many possible combinations of the propagation effects of several environmental characteristics with respect to interference conditions are investigated in detail in [52], and references therein.

In cellular systems, sectorization is established by replacing omnidirectional antennas with narrower beam width antennas (e.g., six-sector antennas of 60° or three-sector antennas of 120° openings), the capacity increases and CCI is reduced [16, 53–55].

Beamforming methods perform spatial filtering by placing comparatively sharp nulls in the direction of the interfering mobile stations, which is again related to the impact of antennas. Therefore, the interference level can be reduced significantly [56–58]. If beamforming is quantified

by the directivity ratio, say d and $0 \leq d \leq 1$, it is reported that CCI is minimized when $d = 1$. However, the relationship between the CCI reduction and d is not linear. Results are generally based on simulations [56]. Yet, it is possible to see the impact of beamforming on CCI when free-space is of interest with $P_{rx} = P_{tx}d/4r^2$, where r denotes the distance between transmitter and receiver, P_{tx} is the transmit power, and P_{rx} is the received power.

Similar to antenna radiation patterns, in literature, it is also reported that the polarization affects CCI [59]. Polarization can be used as a tool to reduce CCI relying on a method known as cross polarization discrimination (XPD). Because of XPD, when a horizontally polarized antenna receives a co-channel signal sent from a vertically polarized antenna (and the other way around), the effective signal strength is reduced by several decibels. It is also reported that the amount of XPD is reduced if the signal undergoes extensive scattering. Hence, this relationship is somehow connected to surrounding physical environment as well.

In contrast to non-layer parameters, there are many parameters that can be populated in the protocol stack. In conjunction with the discussion in Section 2.2, interference power is one of the fundamental measurement items falling into physical layer. With the emergence of CR, the term interference power gains additional concepts which have not existed before in previous communication systems such as “interference temperature” and “primary user.” Interference temperature is a sort of measure of radio frequency (RF) power that includes power of ambient noise and other interfering signals per unit bandwidth for a receiver antenna. Primary users can be defined as the users who have the higher priority or legacy rights on the usage of a specific part of the spectrum. On the other hand, secondary users are defined as those who (have lower priority) exploit this spectrum in such a way that they do not cause interference to the primary users. Therefore, secondary users need to have the capabilities of CRs, such as sensing the spectrum reliably to check whether it is being used by a primary user and to change the radio parameters to exploit the unused part of the spectrum. Sensing the spectrum for the opportunity is, therefore, one of the most important attributes of CR. Although spectrum sensing is traditionally understood as measuring the spectral content or measuring the interference temperature over the spectrum, when the ultimate CR is considered, it refers to a general term that also involves obtaining the spectrum usage characteristics in multiple dimensions (including time, space, and frequency) (When multihop systems are considered, all of these dimensions merge on transmission paths of routing which is also very important from the network layer stand point. In such scenarios, some routes might observe more interference than others [60], which carries significant importance. Note that this option is not valid in single-hop systems.) And determining what type of signal is occupying the spectrum (including the modulation, waveform, bandwidth, and carrier frequency). However, this requires more powerful signal analysis techniques with additional computational

complexity. Some of the current challenges for spectrum sensing include the following:

(i) *Difficulty and complexity of wideband sensing*, which requires high sampling rate and high-resolution analog to digital converter (ADC) or multiple analog front end circuitry, high-speed signal processors and so on. Estimating the noise variance or interference temperature over the transmission of narrowband desired signals is not new. Such noise variance estimation techniques have been popularly used for optimal receiver designs (such as channel estimation and soft information generation), as well as for improved hand-off, power control, and channel allocation techniques. The noise/interference estimation problem is easier for these purposes as the receiver is tuned to receive the signal that is transmitted over the desired bandwidth anyway. Also, the receiver is capable of processing the narrowband baseband signal with reasonably low complexity and low power processors. However, CRs are required to process the transmission over a much wider band for sensing any opportunity.

(ii) *Hidden primary user problem* (such as the hidden node/terminal problem in carrier sense multiple accessing (CSMA)), which can be caused by many reasons including severe multipath fading or shadowing that the secondary user observes in scanning the primary user's transmission. The hidden terminal problem can be avoided by incorporating distributed sensing, where the information sensed between multiple terminals is shared, rather than each terminal makes the decision based on its local measurement. One of the examples of distributed sensing is known as spectrum pooling. In this technique [61], cooperative sensing decreases the probability of miss-detections and false alarms considerably. The rental users who are the users that—in case of having spectral opportunities—rent the licensed band temporarily until the licensed user emerges, send their results to a base, which makes a decision and sends the final decision back to the rental users. In this type of scheme, throughout exchanging the sensing information between the base station, the mobile units may create interference to the primary users around. However, this can be overcome by a special signaling scheme which attain a reliable result very fast so that the interference to the primary users can be neglected [61]. Besides, it is again reported in [61] that, since this special signaling scheme is not involved with the medium access control (MAC) layer and directly operates on physical layer, the overhead problem on the network is minimized.

(iii) *Primary users that use FH and spread spectrum signaling*, where the power of the primary user signal is distributed over a wider frequency even though the actual information bandwidth is much narrower. Especially, FH based signaling creates significant problems regarding spectrum sensing. If one knows the hopping pattern, and also perfect synchronization to the signal is achieved, then the problem can be avoided. However, in reality, this is not practical. Approaches based on exploiting the cyclostationarity of the signal have recently been studied to avoid these requirements. The cyclostationary based techniques exploit the features of the received signal caused by the periodicity in the signal or in its statistics (mean, autocorrelation, and so on).

(iv) *Traffic type* is another factor that affects the interference. Statistical characteristics of the traffic type determines the evolution of interference in several dimensions such as time and frequency and helps in determining crucial quality of service (QoS) parameters such as link capacity and buffer size and in predicting bandwidth requirements. It is known that different types of traffics exhibit different statistical characteristics. Having the knowledge about the traffic type helps nodes avoid/cancel/minimize interference by different methods such as employing intelligent scheduling. However, it is worth mentioning that with the increasing services and applications, nodes in NGWNs are expected to be exposed to interference composed of several types of traffic rather than of a single type, which includes voice, multimedia, and gaming whose statistical characteristics are different from each other. Furthermore, in order to reliably characterize the network traffic, sufficient statistics need to be accumulated in real time.

(v) *Mobility* is crucial for wireless radio communications [62, 63]. From the perspective of interference, mobility introduces further concerns such as mobility behavior [64]. When an MAI environment is of interest, the overall interference becomes a function of mobility behavior of all of the mobile sources within the environment, which can be of individual or of group form. In case victim nodes can extract or are provided with the pattern of the mobility behavior of interfering sources, they can make use of it and improve their performances. Decentralized sensing seems to be a plausible approach for this concern which combines speed and direction information for multiple interference sources.

4. Other Parameters

The parameters that have been discussed so far are measured using the received signal and in many cases, these parameters are obtained using baseband signal processing techniques of the signal over the transmission bandwidth. Therefore, from the CR perspective, we can classify the methods to evaluate the parameters mentioned up to this point as “internal sensing.” However, the sensing and measurement capabilities should not be limited to the internal sensing, or in other words, to the parameters that can be obtained from the received signal. Because, there are some other parameters that cannot be quantified solely by internal sensing such as measuring the light intensity and the temperature of the environment to understand if the device is inside or outside a building [65]. For these sorts of measurements, CR needs “external sensing” capabilities as well. Recently, we see that many wireless devices come along with some stand alone sensing capabilities embedded. Therefore, the devices such as camera/video phones, voice recognition capable wireless units, geolocation capable terminals can be used to obtain additional information about the users' perception and even about the environment on which the device is operating. In other words, through external sensing, CR takes advantage of the additional capabilities to improve its adaptation.

In this sequel, we must state that there are some types of measurements that can be counted in both internal and

external sensing. For instance, estimation of the location of a mobile device can be established through base stations depending on internal sensing parameters such as RSS. On the other hand, a Global Positioning System- (GPS-) embedded device can do the same thing, which is counted in external sensing.

One of the prominent adaptation parameter of CR is the characteristics of the environment, which can be obtained through external sensing. It is known that the wireless channel is highly dependent on the environment. Environmental dependency manifests itself in terms of previously discussed statistical parameters of the wireless channel. Under different geographical environments, delay spread statistics change drastically such as in hilly terrain area and rural area. Also, some of the environments inherently have less mobility as compared to the others, which determines the crucial factor for Doppler spread. It is not very likely to have users with very high speed mobility in an indoor environment. On the contrary, in rural areas, the mobility of the users can be much more than that in indoor. Similarly, angle spread highly depends on the surrounding environment of the wireless device in connection with the number of scatterers around. Considering that there are numerous statistical models related to almost every sort of environment in literature, CR can take advantage of these models by choosing the one which fits the best. However, selecting the best model includes a major challenge: classification of the propagation environment. This challenge stems from the following two facts: (i) obtaining the topographical characteristics of the surrounding environment and (ii) absence of the formal descriptions of the environments presented in the literature. However, (i) can be overcome through the use of digital elevation models (DEMs) (and recently Geographical Information System (GIS)) of the geographical area of interest. These are easy to be processed data and when combined with spatial interpolation methods, they can provide CR with some hints about the topographic characteristics of its surrounding environment.

In (i), CR faces a sort of pattern recognition problem. Because, CR needs to match the characteristics of the environment with the environmental classification. Unfortunately, there is not any formal definition for propagation environments in literature. However, there are some properties peculiar to each environment to some extent. For instance, as stated in [65], distinguishing indoor from outdoor is possible, through light and temperature. Similarly, for outdoor environments, the topographical characteristics of a hilly terrain can be used to distinguish it from rural area.

Another challenge hidden in both (i) and (ii) is to represent the raw data obtained through external sensing and to classify them in a formal way for matching operation, respectively. This is established with the aid of a special descriptive language that allows CR to represent entire universe through semantics [65]. With the aid of this language, CR is able to not only deduct information in the presence of several external data source such as GPS and DEMs but also adjust its parameters through SDR.

Since CR can represent the raw data and characteristics in a semantic way, by using its formal tools such as neural

network and hidden Markov models, the characteristics of the environment can be selected appropriately [66]. In this sequel, it must be mentioned that the additional sensing capabilities come at the expense of additional hardware and processing, which also means power consumption as well. Besides, the tools with which CR is equipped and cognition cycle bring additional burden onto the system in terms of delay, power consumption, and overhead.

As a final remark, we can state that it is possible for CR to combine internal and external sensing to improve the reliability of the estimates. In light of these pieces of information, a conceptual model of CR including external sensing capabilities is shown in Figure 2.

In accordance with the discussion here, some of the important measurements for future CR applications are briefly discussed in what follows.

(i) *Geolocation Information for CR.* Geolocation and GPS are becoming popular due to the low power and low complexity implementation of these services, which can be embedded into other wireless devices. Beside providing the physical coordinates of the mobile user (or terminal), the geolocation (or GPS) information can also be used to improve the wireless communication systems in many layers. Even though the use of the GPS in improving the communication functionalities does not have a long and rich history, recently many researchers started integrating the GPS information to enhance other various aspects of wireless systems. For example, some studies for GPS-aided services in cellular networks (such as the traffic and navigation services, improved hand-off, channel, and cell assignment techniques); improved MAC layer protocols in an ad-hoc networks, which eliminates the hidden terminal and exposed terminal problems; efficient multi-hopping scheme in ad-hoc cellular networks by broadening the coverage area of the base station by means of exploiting the location information of mobile devices are some samples from the previous studies that show how the GPS information can be incorporated into the wireless systems.

(ii) *Line-of-Sight (LOS) and NLOS Measure of the Channel.* LOS and NLOS measures can be very useful for the future wireless communication systems. The radio signal transmission for LOS and NLOS is different. For example, radio transmission over millimeter waves (above 10 GHz) requires LOS. However, in microwave bands LOS is not necessary. Similarly, radio channel model will be different in both LOS/NLOS scenarios, which affects the performance of the overall network [16, 50, 67, 68]. Therefore, the transceiver performances will be highly dependent on the knowledge about the existence of LOS.

The LOS measurement can be obtained from the received signal by looking at the first-order channel statistics and finding the likelihood of whether these statistics fit the LOS or NLOS channel [69, 70] as well as examining the second-order statistics of the channel [71, 72]. Also, this information can be obtained by using additional sensing capabilities that are discussed above. As mentioned earlier, the estimation of LOS/NLOS needs a great deal of research.

(iii) *Network Measurements.* There are several measures in the network layer that can be used for improved adaptive systems design and crosslayer adaptation. Automatic repeat request (ARQ) rate for non-real time data communication, mean and peak packet delay, routing table and routing path change rate for wireless ad-hoc and sensor networks, absolute and relative locations of nodes (location awareness), velocity of nodes, and direction of movement are some of the important measurements that can be used for improving the network performance.

Note that the parameters that are measured in different layers can affect the adaptation parameters across several layers. This can be considered part of the crosslayer adaptation. For example, physical layer estimated parameters are often related to the adaptation parameters in physical, MAC, and other layers of the protocol stack. Therefore, the network layer measurements discussed earlier should not be perceived as the measurements to improve only the network performance. They can also be used to improve the performance across many layers.

Note also that often one parameter, say about the channel, can affect more than one adaptation parameter. For example, SNR (or link quality) measure can be used for adapting the modulation, coding, transmitted power, or other adaptation parameters such as the packet delay in networking layer. Therefore, several adaptation parameters should not be changed independently based on the (single) quality measure, as the change of one adaptation parameter might effect the measured value. Hence, the adaptation of the system parameters should be done in a global manner by considering the relation among them, leading to the cross-layer design approaches. In this regard, some of the adjustable parameters according to the layers in which they are defined are presented in Figure 2.

Another important issue related to the network measurements is the awareness of the user's terminal about the possible networks and other wireless terminals around it. This is very critical for many applications, especially for emergency, disaster relief, and rescue operations. The transmission of other possible devices can be observed by sensing the spectrum, extracting the data from the 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. Currently, high-end signal analyzers designed by measurement companies are capable of doing this kind of measurements, but, with extremely expensive, power hungry, and bulky measurement devices. However, the goal is to implement such capabilities in wireless terminals with reasonable hardware and signal processing complexities. Hence, this area needs a significant amount of research as well.

(iv) *Situation (Context) Awareness.* This includes determining (measuring) the user's needs, preferences, activity, circumstances, and user's behavior (e.g., tasks, habits). The previously discussed user's perception of the services can also be included into user's awareness. Even the user mobility, geographical location, and some other measurements

discussed earlier can be considered within this context, as well. These measures often can not be obtained from the received signal. Therefore, additional sensing and learning capabilities are needed. As mentioned earlier, the evolution of mobile devices and networks will allow additional sensing capabilities that will make estimation of physical environment (e.g., geographical location, ambient conditions) as well as other possible user contexts possible. Various sensor technologies can be included in the mobile terminal that can sense things like who the user is, where he/she is, what the environmental conditions (such as the temperature, the noise level, or the illumination conditions) are, and what the user is doing, what the mood of the user is, and so forth. All these estimates would be very useful to improve the network and service performance. The wireless networks and services can use these measures to adapt themselves to the user's needs, preferences and circumstances, and cooperate with their environment to provide an optimal user experience.

5. Discussion and Future Directions

In this paper, several measurement approaches for adapting and improving the radio network and transceiver performances are presented. These measurements and possible future extensions of the list will allow the CR concept to become a reality. The wireless communications community have already started seeing some partial adaptive and cognitive features integrated into the current generation wireless standards. There is no doubt that the future standards will include more cognitive capabilities.

In many wireless standards, some of the parameters discussed here are measured by the network terminals. For instance, received signal strength indicator (RSSI), CPICH Ec/No, and CPICH RCSP are some of the items to be measured by UEs in Universal Mobile Telecommunications System (UMTS), whereas Ec/Io is one of the parameters to be measured in $1 \times$ EV-DO. In Worldwide Interoperability for Microwave Access (WiMAX), carrier-to-interference-plus-noise ratio (CINR)/SINR is measured for the same purpose by mobile stations (MSs). In Third Generation Long Term Evolution (3GLTE), reference signal received power (RSRP) is measured by UEs as a counterpart of RSSI measurements in some other standards [73], and references therein. Also, SINR sort of measurements are available in 3GLTE for the purpose of network management [74]. The recent 802.11k standard defines some radio resource measurement parameters to facilitate network management and performance enhancement. Several parameters are listed and defined as mandatory and optional radio measurements within all of these standards. However, these defined parameters are still very limited, and only aimed for a specific standard, even though the list is more enhanced compared to the other earlier standards [75], and references therein. It is expected that as wireless standards evolve further, some other parameters that need to be measured will emerge and such lists need to be extended accordingly.

In parallel to these measurement parameters and relations between them, relevant challenges from the perspective

of adaptive radio systems pushes the research toward the realization of CR. In this aspect, there is a strong urge in the wireless community toward the cooperative sensing that facilitates nodes which have CR capabilities [76]. For instance, CR capability nodes are employed in [77] in order to establish cognitive sensing tasks. Furthermore, in [78], the evaluation of the pieces of information gathered through sensing operation is established by the manager nodes (peculiar to [78], these manager nodes are assumed to be base stations (BSs)) with a certain protocol (a detailed discussion pertaining cooperative sensing with CRs is given in [79], whereas a survey that is devoted to cognitive sensing can be found in [80]). Thus, it is easy to conclude that some of the promising research topics regarding measurements of CR include cooperative sensing using multiple devices that communicate each other via networks which could be assisted by a manager node in the network side and opportunistic spectrum usage in the presence of primary users in orthogonal frequency division multiple access (OFDMA-) based technologies.

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