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Research Article

Dynamic OFDM Transmission for a Cognitive Radio Device Based on a Neural Network and Multiresolution Analysis

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Cognitive radio communications depend on methods for sensing the spectrum as well as adapting transmission parameters to available resources. In this context, this work proposes a novel system that makes use of prediction to dynamically allocate subcarriers to different transmissions in an orthogonal frequency division multiplexing (OFDM) system. To this end, the proposal is comprised of a predictive component which makes use of a neural network and multiresolution analysis and a second component, which uses wavelet analysis and cognitive radio functions to carry out a dynamic allocation of subcarriers in an OFDM system. The use of wavelets allows the system to split the data stream in blocks of information to be transmitted over multiple orthogonal subcarriers. This proposed system makes use of the decision-making functions of a cognitive radio device to select the number and position of the subcarriers used for communications without interference. Although there exist other OFDM systems using wavelets, they are not used in combination with the decision-making functions implemented in cognitive radio devices. In contrast, the proposed OFDM system operates using some of these functions, thus being able to better adapt its operational parameters. The use of wavelets combined with a neural network model improves the prediction of the bandwidth utilization as shown in this work. It is concluded that the proposed system improves spectral efficiency and data rate by using the decision-making functions of cognitive radios to select the appropriate OFDM subcarriers to be used during the data transmissions.

1. Introduction

Cognitive radios must be able to change several of their parameters in order to adapt their operation to the environment where they work and in this way improve spectral usage and enhance communication characteristics (e.g., energy efficiency and data rate). Cognitive radio design makes use of cross-layer and multilayer approaches to face the challenges that opportunistic spectrum allocation poses. For a cognitive radio network to work it is necessary that it be comprised of devices which are both adaptable to the environment (to take advantage of the changing conditions in spectrum availability) and sensitive enough to avoid interference with primary users and other cognitive devices [1, 2]. In the past years several techniques have been proposed to implement dynamic spectrum access (DSA) (e.g., see [3] for a general overview and [4] for the ad hoc networking case), but there are several issues still open to solve. For example, it is necessary to detect and predict spectrum availability quickly enough to avoid interference with licensed users.

Transmissions from cognitive devices can make use of orthogonal frequency division multiplexing (OFDM), which presents several advantages in contrast to the approach of transmitting using a single carrier. For example, OFDM systems can increase spectrum usage and can operate at different frequencies with simple modifications to the frontend radio interface. Furthermore, OFDM can exploit the advantages of diversity by spreading the signal over different subcarriers and improves reception due to the reduction of narrowband noise. However, OFDM is also highly affected by phase noise and it is not suitable for bursty traffic applications.

The inverse fast Fourier transform (IFFT) is commonly used to generate the multiple orthogonal subcarriers that are required for communications in a conventional OFDM system. As an alternative, it is worth mentioning that multiresolution analysis (MRA) using wavelets is able to generate a signal decomposition using different orthogonal frequencies, where each component corresponds to a different resolution [5, 6]. Thus, wavelet-based MRA is able to generate the orthogonal frequencies required by OFDM in order to obtain the set of subcarriers to be used for transmission of a data signal.

A complex synchronization system is required to generate subcarriers of the wavelet-based MRA; however, this approach has the advantage that the wavelet spectral components decay quickly and smoothly, thus favoring the filtering of the signal. Thus, wavelets do not require the use of a significant part of the spectrum in contrast to signal decomposition using sinusoidal functions that have components all over the spectrum, which causes information loss when filtering is applied. The spectral shape of a wavelet offers significant advantages over the noise, as well as the opportunity to increase the bandwidth usage by reducing the need of filtering.

A comparative study between OFDM based on the Fourier transform (FFT-OFDM) and wavelet-based OFDM using the discrete wavelet transform (DWT) is presented in [7]. This study also shows that a system based on DWT-OFDM outperforms the FFT-OFDM in presence of additive white Gaussian noise (AWGN) and Rayleigh fading. Their analysis shows that, under similar conditions, for a channel with AWGN the gain in terms of the ratio between the energy per bit and the average spectral noise density (E_b/N_o) improves when Haar and Daubechies wavelets are used and when it is compared with the FFT-OFDM system. The DWT-OFDM system shows a similar performance when E_b/N_o is less than 10 dB in frequency selective fading; however, DWT-OFDM has a significant improvement in performance when the E_b/N_o is higher than 10 dB. This improvement is a consequence of the wavelet properties where the use of a cyclic prefix for synchronization is not required in contrast to FFT-OFDM systems, where it is used to compensate deviations in the delays due to variations in channel conditions [7]. In addition, wavelet packets offer a better definition in the analysis than a simple signal decomposition using wavelets as it is shown in [7]. A wavelet packet is a generalization of the MRA where particular bands of frequencies are split into narrower bands and these are split again repeatedly into narrower bands using a two-to-one ratio [8]. Thus, the signal to be transmitted can be decomposed into multiple wavelet packets which are orthogonal. Furthermore, the signal can be represented by a selection of wavelet packets without using all wavelet packets for a specific resolution. The decomposition procedure improves operation for systems with OFDM and high data rate operating in fading channels. Studies of the OFDM with wavelets can be found in the literature [9, 10] where its effectiveness to compensate noise and fading is shown. Thus, wavelets can substitute the inverse fast Fourier transform (IFFT) which is simpler to implement but has less accuracy in the reconstruction of the received signal than wavelet packets.

The data stream can be divided into blocks and with the use of wavelets these data can be transmitted over multiple orthogonal subcarriers by using OFDM. To this end, two of the main characteristics of cognitive devices can be incorporated to adapt the parameters for the wavelet-based OFDM transmission. These two characteristics are the cognitive capability and the autoconfiguration. The cognitive capability is mainly related to signal perception in order to get information about the environment, which not only considers received power, but also information extracted with techniques based on expert systems, artificial intelligence and machine learning. This capability is fundamental for the optimal use of the spectral availability since it can take into account variations in both time and frequency of the spectrum characteristics. The autoconfiguration of the radio is crucial to determine how the device should adapt itself to environmental changes and how its parameters (e.g., modulation, medium access, and coding) should be changed accordingly. Cognitive radio devices implement their functions (i.e., sensing, decision making, sharing, and spectral mobility) on flexible hardware platforms based on software defined radio (SDR) [2–4, 11].

In this work combining wavelet-based MRA for detection and adaptive OFDM transmission is proposed where the dynamic selection of subcarriers is controlled by the decision-making function of the cognitive device. The purpose is to adapt the operational parameters of the radio in order to appropriately select the subcarriers to be used for communication. Thus, the proposed system is intended to improve both spectral efficiency and data rate. Although in the literature it is possible to find studies of OFDM systems using wavelets, none of them is used in combination with the decision-making functions of the cognitive radio as proposed in this work.

It is important to mention that the use of wavelets helps to accurately detect time-scale relationships for signal transmission and improves the spectral usage by detecting discontinuities in available bandwidth. This information is used in the proposed system to implement a predictive approach where wavelet-based analysis can implement transmission, signal perception, and effective reconstruction of signal patterns. The use of wavelets combined with a neural network increases the prediction capabilities of bandwidth usage [12]. The dynamic spectrum allocation is leveraged by the cognitive radio functions, where the communication between cognitive devices improves the spectral use and minimizes interference to licensed users. This is achieved by accessing the medium opportunistically, which optimizes bandwidth utilization by opportunistically occupying white spaces. This opportunistic approach for using white spaces is known as overlay and allows the coexistence of licensed users and cognitive devices in contrast to the underlay approach which requires that the cognitive devices operate at lower levels of power than the licensed users [13].

The rest of the document is organized as follows. For the sake of clarity Section 2 gives a brief overview on wavelet theory and multiresolution analysis. Section 3 describes

the proposed system, Section 4 presents the simulation characteristics and results for the predictive neural network system and wavelets for the decomposition of the power signal, as well as the simulation characteristics and results for the proposed DWT-OFDM system for cognitive radio. Finally, some conclusions are provided in Section 5.

2. Background Concepts on Wavelets and Multiresolution Analysis

Wavelets, which are denoted by $\psi_{a,b}(t)$, represent an ensemble of functions obtained from a time-shift by b and a dilation (scale) a of an initial function called mother wavelet $\psi(t)$; i.e., $\psi_{a,b}(t) = (1/\sqrt{a})\psi((t-b)/a)$. These functions exhibit fast oscillations and decay quickly in a finite time period [14]. The decomposition of a signal $x(t)$ with this family of functions yields the continuous wavelet transform (CWT), thus creating the so-called time-scale plane, i.e., $CWT_x(a,b)$. This time-scale plane allows a representation of $x(t)$ at multiple scales or resolutions. There is an inverse relationship between scale and frequency (a pseudo frequency to be more precise) which allows a time-frequency representation associated with the $CWT_x(a,b)$. The discrete wavelet transform (DWT) is obtained by discretization of the time-scale plane at values $a = 2^j$, $b = k2^j$; for $k, j \in \mathbb{Z}$, i.e., $DWT_x(j,k) = CWT_x(2^j, k2^j)$. From this sampling, the ensemble $\psi_{j,k}$ becomes a wavelet basis (not necessarily orthonormal).

Due to the multiresolution analysis (MRA), developed by Mallat [15, 16], it is possible to construct a wavelet basis (e.g., Daubechies, Symlets, and Discrete Meyer) using a filter bank. Basically, the MRA consists of a low-pass filter and high-pass filter with a recursive decomposition on the low-pass element as it is depicted in Figure 1. Resulting filtered signals correspond to the so-called approximation ($a_j(n)$) and detail coefficients ($d_j(n)$). The approximation is just a coarse version of the analyzed signal $x(n)$. The details, besides adding finer information of the signal, correspond to the DWT. These coefficients allow a representation of signal $x(n)$ as

$$\begin{aligned} x(n) &= approx_L(n) + \sum_{j=1}^{L} detail_j(n) \\ &= a_L(n) + \sum_{j=1}^{L} d_j(n) = \langle x, \phi_{L,n} \rangle + \sum_{j=1}^{L} \langle x, \psi_{j,n} \rangle \end{aligned} \tag{1}$$

where $\langle x, \phi_{L,n} \rangle$ is the projection in the time domain of $x(n)$ over the orthonormal base $\{\phi_{j,n}\}_{n\in\mathbb{Z}}$ of the approximation space $\mathbf{V}$ at level L and $\langle x, \psi_{j,n} \rangle$ is the projection over the orthonormal base $\{\psi_{j,n}\}_{n\in\mathbb{Z}}$ of the wavelet spaces $\mathbf{W}_j$. Embedded spaces $\mathbf{V}_j$ and $\mathbf{W}_j$ (complementary and orthogonal to $\mathbf{V}_j$) are the fundamental idea behind the MRA. The initial functions $\phi_{1,0} = \phi(t)$ and $\psi_{1,0} = \psi(t)$ are called the *scaling* function and the *wavelet* function, respectively. These functions, generating these spaces, are linked to a bank of digital filters by a two-scale relationship given by [16]

$$\begin{aligned} &\frac{1}{\sqrt{2}}\phi\left(\frac{t}{2}\right) = \sum_{n=-\infty}^{\infty} h(n)\,\phi(t-n) \\ &\qquad \text{with } h(n) = \left\langle \frac{1}{\sqrt{2}}\phi\left(\frac{t}{2}\right), \phi(t-n) \right\rangle; \\ &\frac{1}{\sqrt{2}}\psi\left(\frac{t}{2}\right) = \sum_{n=-\infty}^{\infty} g(n)\,\phi(t-n) \\ &\qquad \text{with } g(n) = \left\langle \frac{1}{\sqrt{2}}\psi\left(\frac{t}{2}\right), \phi(t-n) \right\rangle. \end{aligned} \tag{2}$$

It turns out that $g(n) = (-1)^{1-n}h(1-n)$, where $g(n)$ is a low-pass filter and $h(n)$ is the corresponding mirror filter, i.e., a high-pass filter. This two-scale relationship is implemented through a low-pass filter and a high-pass filter in conjunction with decimators by a factor of 2 (see Figure 1).

In Figure 2 it is shown how these coefficients (approximation and details) are linked to the frequency content of the decomposed signal. In this figure the exemplified decomposition level is $L = 4$ and f_s represents the sampling frequency of the decomposed signal.

In our proposal, wavelet decomposition and its corresponding reconstruction path (i.e., the inverse discrete wavelet transform, IDWT), via a MRA, are exploited in two different ways. First, the DWT is used for sensing (detection of primary users) along with a neural network whose purpose is to improve performance. Second, the IDWT is used for transmission (i.e., dynamic allocation) of secondary users. The following section elaborates on these ideas.

3. Proposed System

The overall goal of the proposed system is to optimize the use of white spaces found in specific frequency bands and, in this way, to improve bandwidth usage and data rate performance. The main purpose of the system is to take advantage of available frequencies, which are not necessarily contiguous (i.e., discontinuities are possible due to the presence of signals belonging to licensed users), unifying them as a single white space. Wavelet-based MRA combined with a predictive neural network (a concept described in [5]) allows the detection of present and future transmission opportunities, thus extending the sensing capabilities of the radio [17]. This enhancement in perception is combined with the decision-making functions of a cognitive radio as follows. The system constructs the signal to be transmitted by using multiple subcarriers dynamically selected by means of the decision-making function of a cognitive device. In this way, available transmission opportunities, found not only in the frequency domain, but also in the time domain (i.e., sensing is carried out in the frequency-time space), are selected by means of cognitive radio techniques. These techniques selectively change the OFDM subcarriers for transmission by analyzing the characteristics of the spectral conditions.

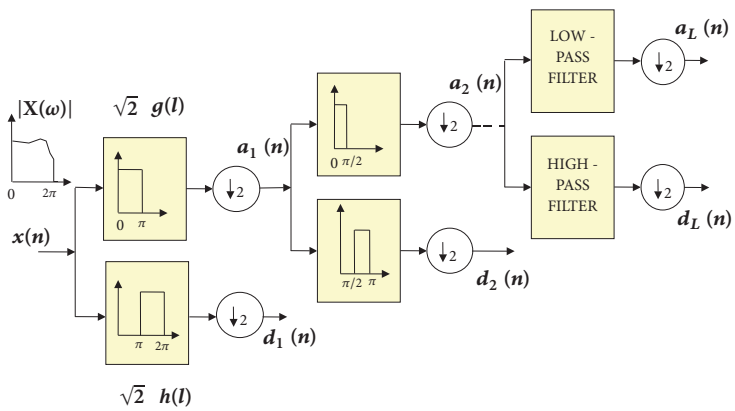


Figure 1: Implementation of the MRA based on a filter bank.

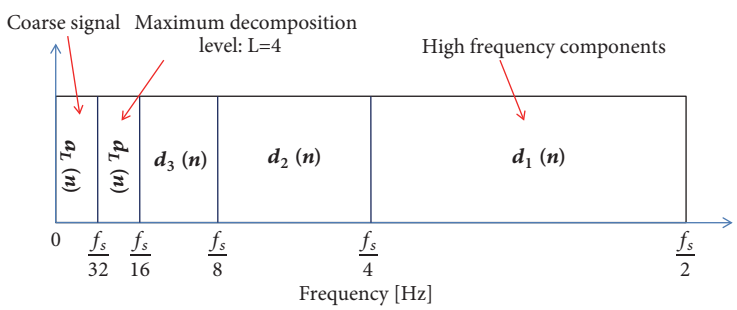


Figure 2: Frequency content of the approximation and detail coefficients.

The neural network assesses the error found by comparing the received power with what was previously obtained by wavelet decomposition. Error analysis is used to predict the spectral behavior and thus, to make decisions about which white spaces to occupy for future transmissions with OFDM subcarriers. The same wavelet module is used to decompose the received signal and extract the information that is distributed across the orthogonal components of the wavelet used for transmission. The OFDM subcarriers are controlled by a system which either activates or switches off the subcarriers to be used considering the information gathered and analyzed by the decision-making function. This function includes the analysis carried out by the neural network used for predicting available spectrum white spaces. In the cognitive radio context this is known as a proactive decision-making function. In general, proactive systems utilize the acquired information and statistical techniques (or other analytical methods) to predict the spectral behavior. In contrast, there are reactive systems, which command the device to change the transmission frequency to a new available place when the presence of licensed users is detected. Both techniques imply coordination between transmitter and receiver to carry on with the communication.

In the following subsection the two main elements of the system are detailed, namely, the neural predictive system and the dynamic wavelet-based OFDM. Both are related to the decision-making function of the cognitive radio device.

3.1. Neural Predictive System. A neural network based approach is used to predict spectral behavior and dynamically allocate OFDM subcarriers to the cognitive radio device. This system implements a practical approach to predict spectral usage and to incorporate this idea into cognitive radio devices. The decision-making function considers the predictive analysis and other attributes (i.e., bandwidth, noise, and white space availability) and, with this information, it selects the appropriate frequency bands for transmission. With this information, the appropriate subcarriers are generated in order to produce an OFDM symbol. The decision-making function uses statistical data with a proactive approach and a tree structure where different weights are assigned to the attributes to be measured, according to a specific application. Figure 3 shows a block diagram that illustrates the proposed decision-making function. Our previous work, reported in [18], introduces and evaluates the decision-making technique used for spectral handoff.

The predictive model decomposes the received power of the signal by using wavelets and the result is assessed by the neural network system which aims to minimize the error; this information is sent to the decision-making function of the radio. This predictive model is shown in Figure 4 which illustrates the neural network adopted and studied in a previous work reported in [12].

The proposed predictive system used in this work utilizes a multilayer backpropagation neural network architecture where the error is propagated backwards to adjust the weights

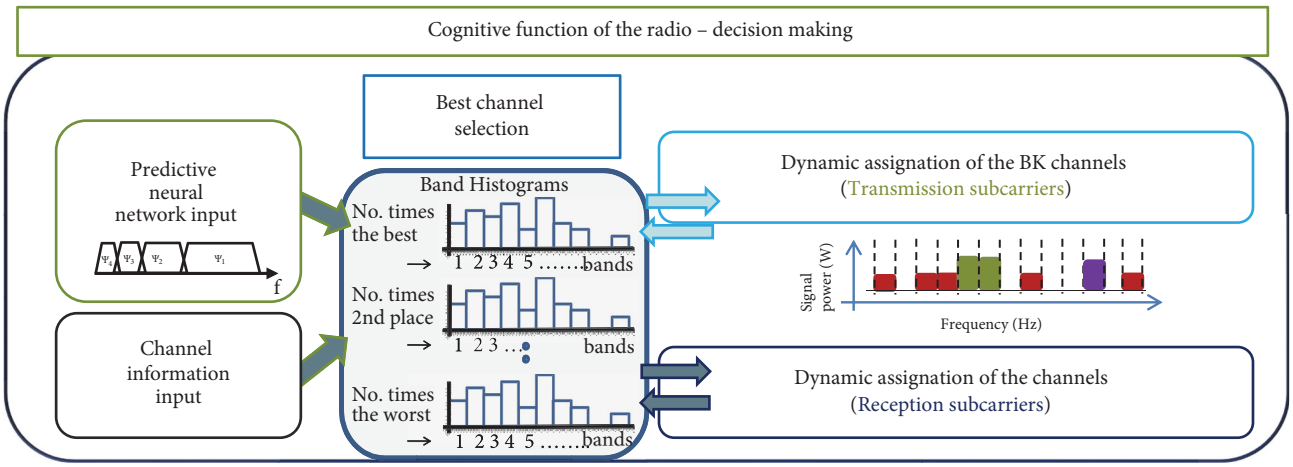


Figure 3: Diagram of the proposed function for decision making in the cognitive radio.

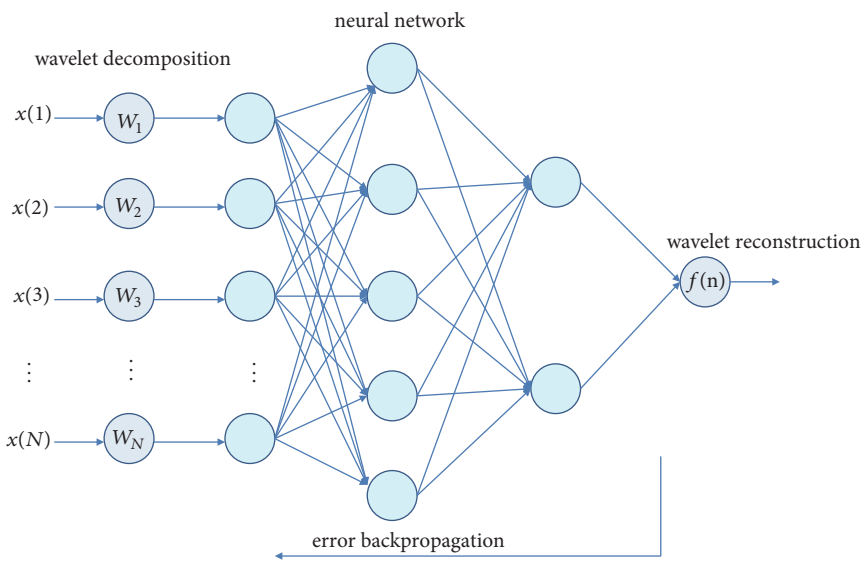


Figure 4: Decomposition of the signal with wavelets for the predictive analysis using a neural network.

allowing the minimization of the error. The backpropagation neural network makes use of the gradient descent method which defines a function $E(W)$ that provides information about the error as a function of a set of weights W. The learning objective of the neural network is to find the weight configuration which corresponds to the global minimum of the error function. The method starts with an initial set of weights $W(0)$ and determines the direction of the maximum variation of the error. For the proposed model, the neural network and the wavelet analysis are separated. First, the input signal is decomposed using a MRA to get the wavelet coefficients which are sent to the input of the backpropagation neural network. Thereafter, the output of the neural network is reconstructed using the wavelet analysis to obtain the forecast of signal power of the available frequency bands.

3.2. Dynamic Wavelet-Based OFDM. The characteristics of the other main element of the model, that is the dynamic OFDM with wavelet packets, considers a coordination control for the communication, which includes a proposed data frame structure. This data frame specifies the required information to establish the communication between devices and to coordinate the communication by means of acknowledgements in order to know whether a data packet was successfully received or not.

The proposal considers the scalability of the network. As a consequence, a modified version of the CSMA/CA protocol for cognitive radio (CR) is implemented and based on our previous work reported in [19]. The frame is comprised of blocks of information that can be used for the communication between devices as shown in Figure 5.

The first field (i.e., Control) includes the information necessary to start the handshaking process and for knowing whether a packet was successfully sent or not. Then, the idSource field is the identification of the CR caller device and the idTarget field is the identification of the CR device to

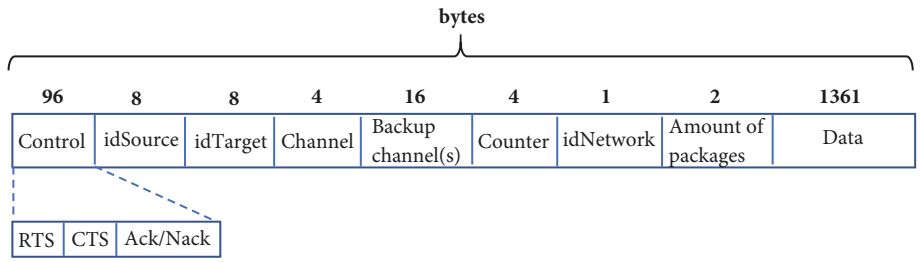


Figure 5: Proposed data frame structure.

be called. The Channel field specifies the channel where the pair of devices must communicate. The next field indicates the list of backup (BK) channels. The Counter field is used to count the number of attempts to find a free channel to communicate; its value is set to a number greater than the number of BK channels. Once the counter expires, the CR device has to wait until a free channel is available. The idNetwork field is a parameter which identifies a communication in progress. This field is also used when the CR device wants to call another CR device. Then, a communication signal with idTarget and idNetwork is sent through some available channels until the intended CR device receives this signal and answers. This establishes the communication in the available channel. During the handshaking there are two possible situations, when the CR devices move to a free BK channel, if available, or when they search for a new channel to communicate and have to wait. The purpose of using the idNetwork field is inspired by wireless LAN technology implemented by the IEEE802.11b standard. In fact, idNetwork is an identifier number, which corresponds to the signal of the CR device trying to communicate, so that the called device is able to know by scanning the spectrum, who is calling and is also able to acquire the list of available channels for both devices. Thanks to the idNetwork field, the transmitting CR can identify whether the accessing device is a primary user (PU) or another CR. The "Amount of packets" field indicates how many packets have been successfully sent to the receiver. Finally, the payload is incorporated in the last part of the frame, where the information is divided into packets of fixed size. The system coordination requires to identify which channels a pair of radios have in common to establish the communication using available channels for the OFDM system. The system uses the BK channels to distribute the orthogonal subcarriers of the OFDM system until the sensing part detects a new distribution of available channels for communication.

The medium access protocol processes the information to coordinate the communication between devices. For the communication, the interaction between CR devices assumes two possible roles, a caller CR, i.e., the CR source device (Cs) and a called CR, i.e., the targeted CR device (Ct). Then, if a CR device wants to communicate with other CR devices, the Cs establishes a connection on a free channel using idNetwork. Meanwhile, all CR devices are sensing the spectrum and the Ct detects when it is being called, by reading the idNetwork field created by the Cs. The devices continue sensing the medium during communication to verify if either the channel is still free or PUs have arrived. If a PU is detected, i.e., a collision takes place, the CR devices already know where to move as soon as possible by using the information of the BK channels. In case that they do not find a new common free channel, the Cs aborts the call and initiates the process again. Otherwise, the Cs verifies whether the Ct is communicating in the new acquired free channel to continue with the previously interrupted communication. If the Ct does not communicate on the channel, a counter is incremented until it reaches the maximum number of attempts. The counter is compared to the maximum number of attempts and if this value is less than the maximum, the Cs refreshes the idNetwork and waits for a response from Ct. In other case, the communication process starts from the beginning. The proposed MAC can operate with or without BK channels. For the latter scenario, the performance of the control mechanism depends only on the speed of the sensing function in order to avoid interference to the PUs. Figure 6 illustrates the medium control access used for the dynamic allocation of the BK channels that are utilized by the OFDM subcarriers.

The BK channel allocation for the communication through subcarriers must be done dynamically, changing from time to time depending on spectrum availability. Communication takes place by distributing data signals across the subcarriers; this strategy allows a cumulative increase of bandwidth by using frequency bands that may not be contiguous, as illustrated in Figure 7. This figure shows an example with four subcarriers allocated according to the available frequency bands to form a unified white space.

The proposed OFDM system based on wavelets is shown in Figure 8(a) (transmitter) and Figure 8(b) (receiver).

The IDWT substitutes the IFFT in the traditional OFDM transmitter and at the receiver side the DWT substitutes the FFT. The output of the IDWT can be expressed as [7]

$$s(k) = \sum_{m=0}^{\infty} \sum_{n=0}^{\infty} S_m^n 2^{m/2} \psi\left(2_k^m - n\right) \tag{3}$$

where $\{S_m^n\}$ is the set of wavelet coefficients, $\psi(t)$ is the wavelet function whose arguments are the compression factor m, the time shift parameter n, and k takes on values in the interval $0 \le k \le N-1$, where N represents the number of subcarriers.

The output of the DWT is represented by

$$S_m^n = \sum_{k=0}^{N-1} s(k)\, 2^{m/2} \psi\left(2_k^m - n\right) \tag{4}$$

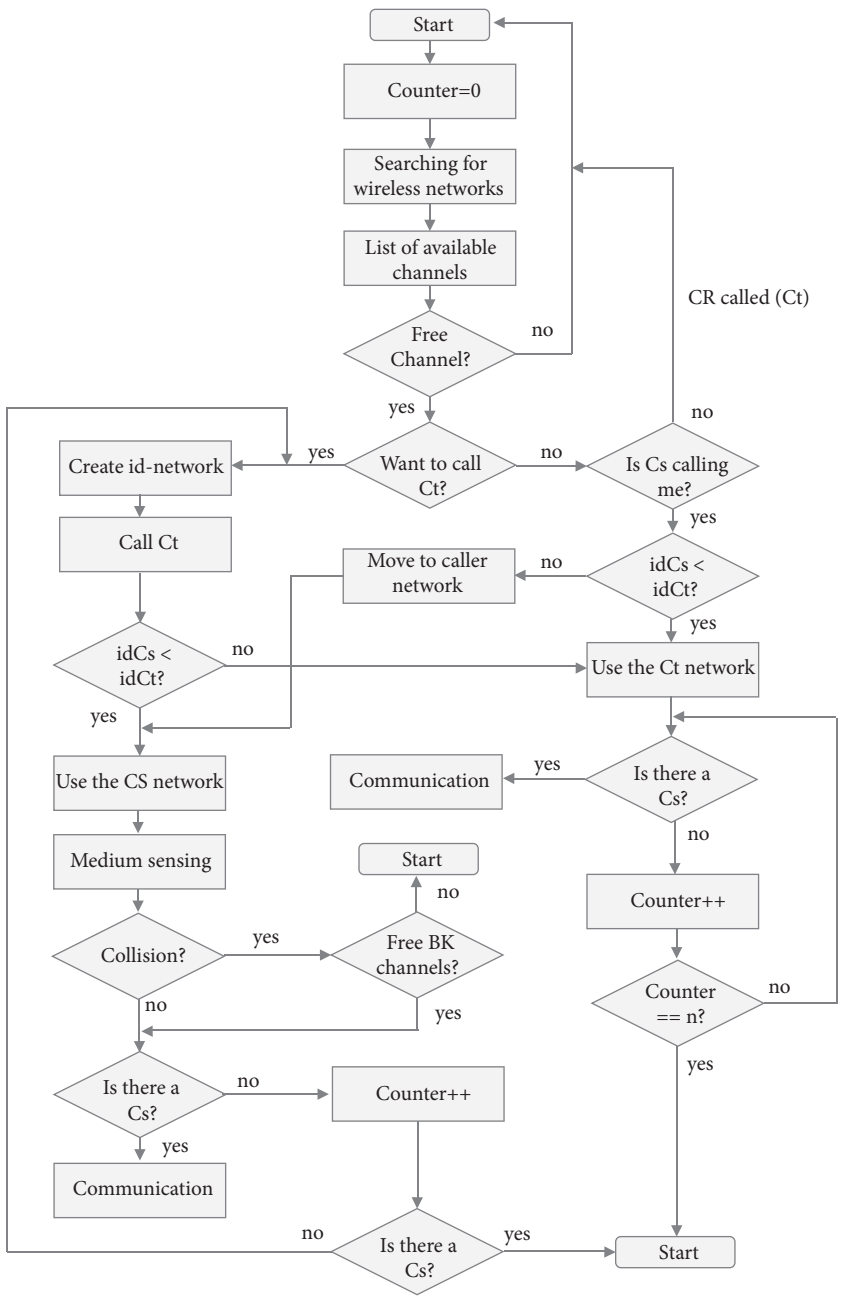


Figure 6: Flow chart of media control implemented on the CR devices.

The signal obtained from (4) must be decoded before the demodulation to obtain the data.

The DWT-OFDM transmitter and receiver are controlled by the decision-making function of the radio and once the number of subcarriers is selected by the medium access control, the subcarriers are activated and deactivated to transmit and receive depending on the availability of the BK channels.

4. Simulations and Results

The performance evaluation of the system is presented considering the previously described medium access control, which coordinates the allocation of the backup channels to transmit. The backup channels are distributed through the subcarriers to transmit aggregate throughput. In turn, the aggregate throughput is evaluated to show the performance achieved when multiple subcarriers are dynamically used. The system is also evaluated when the availability of white spaces randomly changes. This evaluation scenario considers the sensing and decision-making functions of cognitive radio devices in overlay transmission mode for dynamic spectrum access and to improve bandwidth usage by considering the discontinuities in white spaces.

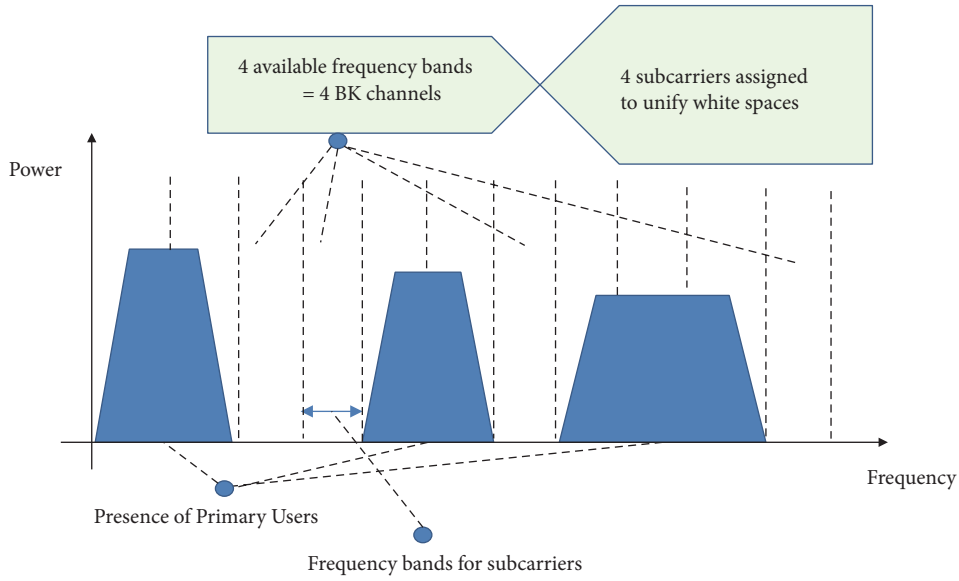
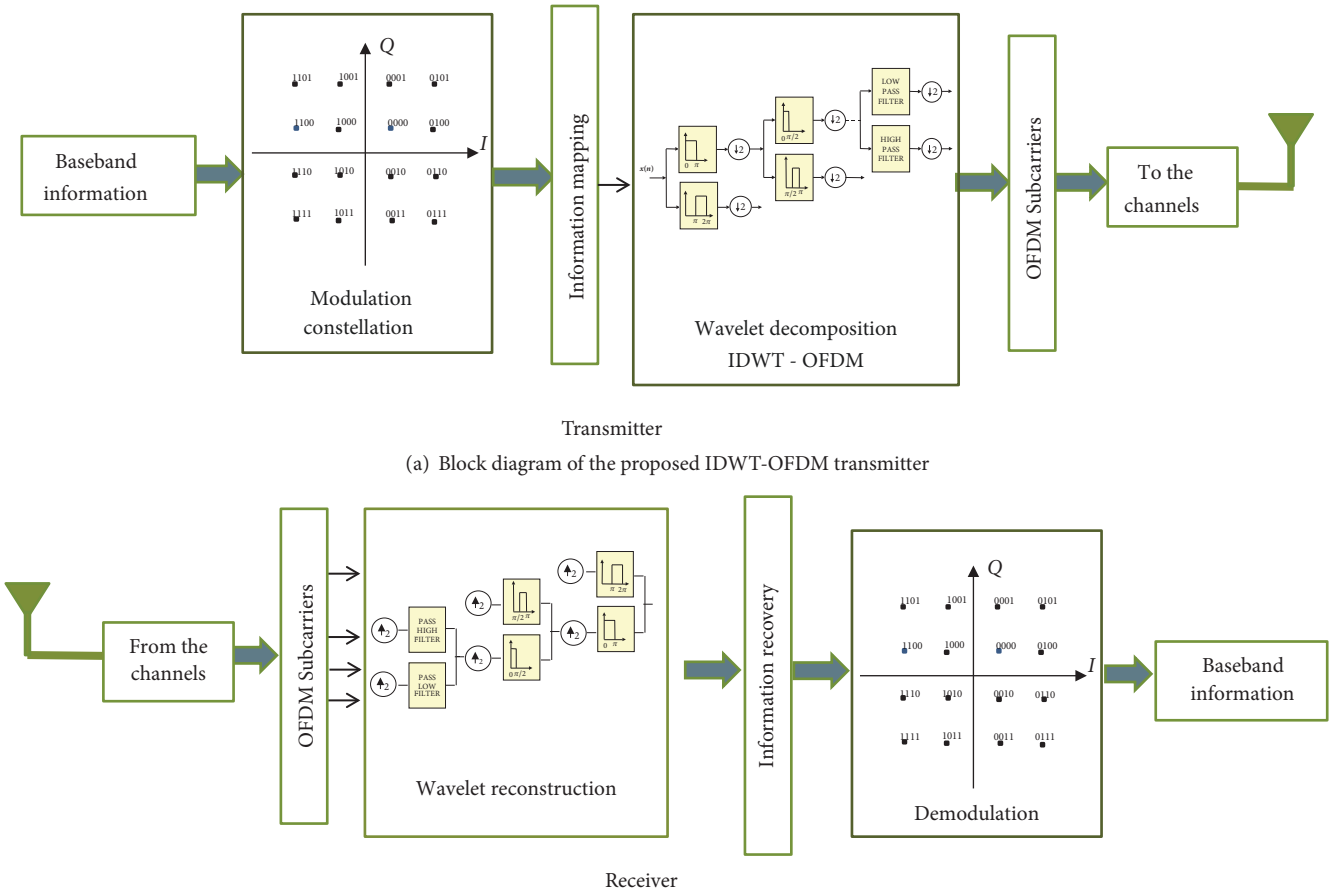


Figure 7: An example of four subcarriers allocated according to the available frequency bands to unify white spaces.



(a) Block diagram of the proposed IDWT-OFDM transmitter

(b) Block diagram of the proposed DWT-OFDM receiver

Figure 8

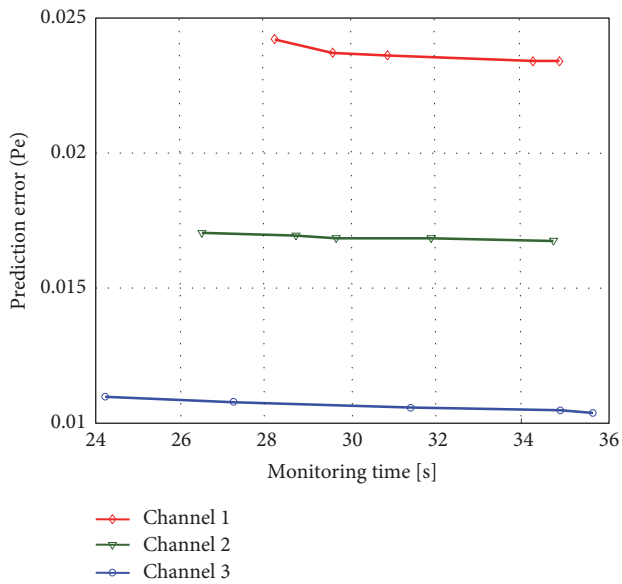


Figure 9: Prediction error versus monitoring time for the proposed neural network model with wavelets.

4.1. Simulation Results for the Predictive Neural Network System and Wavelets for the Decomposition of the Power Signal. The evaluation of the prediction of the channel conditions was performed by computer simulations. Statistics regarding the following performance variables were collected: channel availability, time occupancy of the channel, monitoring time (i.e., time spent monitoring the channel for forecasting), and mean error.

The decomposed power signal was the input to the neural model shown in Figure 4. The corresponding received power was simulated by using a uniform distribution for channel activity and was normalized for the analysis of the collected data. The data signal was decomposed by using the discrete Meyer mother wavelet due to the fact that it is reported in the literature [7, 20] with less error than other mother wavelets such as Daubechies, Coifman, and Symlets. This process consisted of two levels with four coefficients. The proposed backpropagation neural network shown in Figure 4 can be represented by

$$\begin{aligned} f(n) &= g\left[a_L(n) + \sum_{j=1}^{L} d_j(n)\right] \\ &= g\left[\langle x, \phi_{L,n}\rangle + \sum_{j=1}^{L} \langle x, \psi_{j,n}\rangle\right] \end{aligned} \tag{5}$$

where $g(\cdot)$ is the activation function for the neural network, which for our case study has two inputs and two outputs. The neural network was trained with data from the input signal (i.e., received power) and the number of training patterns was increased until the error decreased significantly and was relatively constant. Finally, the output of the neural network was reconstructed using wavelet analysis to obtain the power forecasting.

The prediction error versus the corresponding monitoring time for the proposed neural network model with wavelets is shown in Figure 9. The obtained results show that the prediction is about 99% accurate and the monitoring time is suitable for practical applications for cognitive radio with a monitoring time of about 30 s. This allows the system to determine with accuracy the received power for a network training time of one day. The proper utilization of available channels, the increase in bandwidth, and the decrease in error probability can be achieved if the forecast is accurate and fast enough to predict the availability of the channels.

4.2. Simulation Results for the Proposed DWT-OFDM System for Cognitive Radio. Figure 10 depicts the elements of the proposed decision-making function which considers the input of received power from the frequency bands. In order to determine the spectral opportunities, two methods are possible. One of them is based on the analysis of the received power, which corresponds to a reactive policy for spectral mobility. The other one, which is proactive, consists of analyzing the data using the neural network included in the diagram. The decision-making function shown in Figure 10 takes into account the prediction about channel occupancy. As previously mentioned, the purpose is to detect bands of frequencies which are not necessarily contiguous to unify them as a single white space. The decision-making function shown in Figure 10 considers the predictive analysis and other attributes (i.e., bandwidth, noise, and availability of white spaces) and, with this information, it selects the appropriate frequency bands for transmission and consequently the selection of the adequate OFDM subcarriers to be used.

In the test scenario the presence and absence of primary users are simulated with a uniform distribution function, i.e., the availability of the channels is random. For the simulation if two cognitive radios are communicating and a primary user occupies the same channel (or the same channels), the cognitive radio has to move to another set of available channels by means of the decision-making function, which adapts the allocated OFDM subcarriers. The simulation parameters consider a 5 Mb/s data transfer rate per channel and the transfer of data files of 30 packets of 1500 bytes each. The purpose of fragmenting the file into packets is to have a flow control implemented by acknowledgements (ACK) for each received packet and to control interruptions of a continuous transmission, which is considered as a characteristic of cognitive radio environments. At the end of each simulation, the number of successfully transmitted bits is counted; the results show the goodput (i.e., without considering the overhead). Figure 11 shows the results of the simulation where the data rate varies depending on the number of BK channels used for the transmission.

The results obtained with proposed system show the bandwidth increment by adaptively using the BK channels for transmission. If more BK channels are used, then the total bandwidth increases. In addition, the proposed system improves accuracy in the prediction of available channels and then the interference is reduced to increase the total signal to noise ratio per channel.

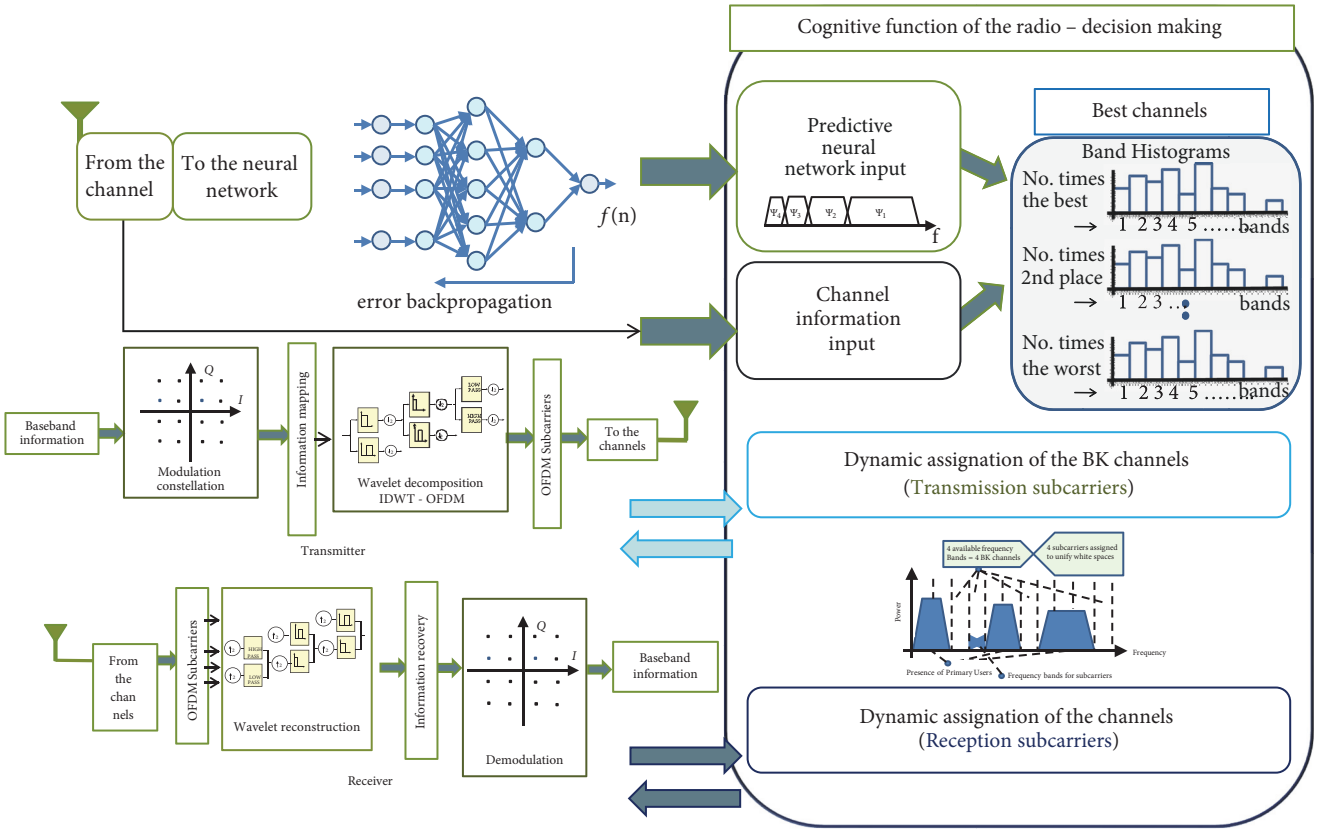


Figure 10: Elements of the proposed decision-making function.

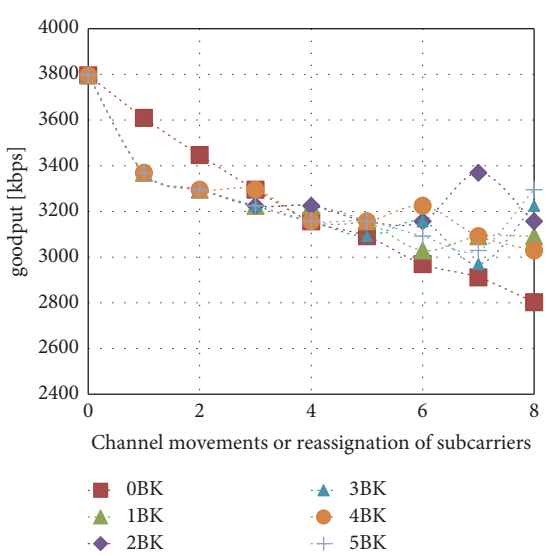


Figure 11: Data rate (goodput) varying the number of available channels used for the OFDM subcarriers, i.e., BK channels.

5. Conclusions

This work presents a novel system to solve some open issues in cognitive radio systems with the use of wavelet analysis to detect and use available frequency bands, prediction by using a neural network, and dynamic allocation of OFDM subcarriers to use white spaces scattered across the spectrum for transmission. We show the advantages of using an adaptive OFDM system for the communication based on wavelet decomposition.

The major contribution of this work is related to two basic improvements for the decision-making function of a cognitive radio device, a predictive system based on a neural network, and dynamic channel allocation for a wavelet-based OFDM transmission. The results for the predictive neural model show that the accuracy and monitoring time of 30 seconds are suitable for practical applications with 99% accuracy in prediction of the received power signal. The improvement in the data rate of the system reduces the error probability. The proposed decision-making function of the radio dynamically allocates the OFDM subcarriers for transmission according to the availability of the channels improving the use of available noncontiguous bands of the spectrum.

There are OFDM systems using wavelets; however, these approaches do not dynamically allocate the subcarriers for an adaptive response to the spectrum opportunities as the proposed system in this work, which uses cognitive radio techniques. Additionally, the sensing capabilities are extended by the prediction based on the neural network that uses multiresolution analysis. Future research will address issues to be taken into account towards a real implementation with emphasis on studying the spectrum sensing component.

Data Availability

The availability of the data supporting the results of the article can be provided upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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