A Spectral Opportunities Forecasting Method in a Mobile Network Based on the Integration of COST 231 Walfisch-Ikegami and Wavelet Neural Models

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Abstract

The forecast of radioelectric spectrum occupancy is useful in the design of wireless systems that profit the opportunities in the spectrum as in the cognitive radio. In the current paper, the development of a method is proposed, that through the forecast of the reception power, identifies the spectral opportunities in a channel of a mobile cellular network for an urban environment. The proposed method integrates the COST 231 Walfisch-Ikegami (C231-W-I) large-scale propagation model with a wavelet neural model. The method results, obtained through simulations, are consistent with the observed behavior in experiments of this kind of wireless systems.

Keywords: Radioelectric Spectrum, COST 231 Walfisch-Ikegami Model, Wavelet Neural Model, Reception Power, Cognitive Radio, Duty Cycle
1 Introduction

The radioelectric spectrum is perceived as a scarce resource, currently the use of a great percentage of the licensed bands is low, and typically, frequency bands very congested and other underused bands can be found. The cognitive radio (CR) has become one of the most researched paradigms in the radio communications in order to optimize the use of the radioelectric spectrum [1, 2]. A CR is an intelligent radio aware of the context, which is able to reconfigure itself in an autonomous way to learn and adapt to the radio environment around it [3]. The research in CR has been motivated by the results of the spectrum measurement campaigns around the world [4-14]. These measurement campaigns show that the radioelectric spectrum is underused in terms of frequency, time and geographical space [5, 7-9, 11, 14].

The principle for CR performance is based on that the unlicensed users do not interfere with the licensed users and one way to deal with this problem is that the unlicensed users must detect spectrum occupancy in different locations as a function of the considered environment and the propagation conditions, which gives a valuable tool for the design, dimensioning and evaluation of the performance in CRs networks [15].

The propagation models started being formulated at the end of the 1960s, with the aim of estimating with precision the propagation losses in an environment. Initially, empirical and statistical propagation models were designed in urban areas [16, 17] then with the unfold of mobile communications in the 1980s, propagation models were designed to microcells and macrocells scenarios [18-20]. From this, several efforts to understand and predict the characteristics of the channels in mobile communications have been developed [21].

Time series have been used in some cases as a mechanism for the forecast of propagation losses. For example, neural networks have been employed to forecast the field strength [22], and the average propagation losses [23, 24]. Besides, fuzzy logic has been employed for this same purpose [25].

Hence, in this paper a forecast of the reception power to identify the spectral opportunities in a licensed mobile network is developed, which integrates the C231-W-I propagation model with the wavelet neural model in an urban environment.

The paper is structured as follows. In section 2 the proposed method is presented. In section 3 the results of the reception power and the duty cycle for the developed model are submitted and discussed. Finally, in section 4 conclusions are exhibited.

2 Proposed Method

Firstly, the design of the wavelet neural model is carried out. Secondly, the C231-W-I propagation model is adjusted from the sensed measurements around the urban environment. Finally, the proposed methodology to forecast the spectral opportunities is presented.
2.1 Wavelet Neural Model

For cognitive systems in [26] a backpropagation neural network is used in order to predict the state of the spectrum, and in [27, 28] the neural network is optimized with a genetic algorithm. Also, in [29] a neural network is used to forecast the power in the television and GSM900 bands. The aforementioned and presented in [30] show the promising character of the neural networks in the reception power forecast in wireless channels, above models such as Markov and empirical mode decomposition-support vector regression. Therefore, in this paper the use of a theory which combines the wavelets and neural networks subjects is proposed [31] to forecast the reception power in a channel of the Global System for Mobile Communications (GSM) technology.

The input signal to the model, which corresponds to the reception power in a GSM channel for the carried out measurements in [32] and analyzed in [30], is decomposed using the Discrete Meyer (dmey) mother wavelet, which shows an error lower than Daubechies, Coiflets and Symlets mother wavelets [33]. The results are two levels that contained in total four coefficients.

The coefficients are sent to the input of the wavelet multi-layer neural network of backpropagation developed, which is shown in Figure 1 and expressed as:

\[
f[n] = g \sum_{i=1}^{n} \left[ \frac{1}{\sqrt{M}} \sum_{k} W_\psi[j_0,k] \Phi[j_0,k][n] \right] + \frac{1}{\sqrt{M}} \sum_{j=j_0}^{j_\infty} \sum_{k} W_\psi[j,k] \psi[j,k][n]
\]  

(1)

where g is the activation function of the neural network, which for this case contains 2 inputs, 2 outputs, and 2 hidden layers. The network was trained in the beginning with about five days of continuous measurements, and the number of training pattern was increased until the error diminished and it was relatively constant, this was reached for 1000 training patterns. Finally, the output of the neural network is rebuilt using a wavelet analysis to obtain the forecasted power, whose training time is enough of one day to obtain an acceptable error, as indicated in [30].

![Fig. 1. Wavelet neural network](image-url)
2.2 COST 231 Walfisch-Ikegami Model

Figure 2 presents the surroundings of the base station (BS) used to make measurements with the spectrum analyzer in the north of Bogotá-Colombia. The six measurement spots correspond to the covering sites of the cell, located at different distances of the BS, in order to evaluate and adjust the C231-W-I propagation model [20]. The period of the measurement was of one hour approximately. The environment is plane and consists mainly of an important concentration of buildings; also, green zones and trees are present, as it can be seen in the measure spot D.

![Fig. 2. Measurement spots in north Bogotá-Colombia](image)

Table 1 presents the parameters of the transmitter and receiver employed to evaluate the C231-W-I propagation model. The model is then adjusted using the sensed powers in the spots seen in Figure 2.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>BS Transmission power ($P_{Tx}$)</td>
<td>26 dBm</td>
</tr>
<tr>
<td>BS Height</td>
<td>26 m</td>
</tr>
<tr>
<td>BS Antenna Gain ($G_{BS}$)</td>
<td>16.5 dBi</td>
</tr>
<tr>
<td>BS Combiner Losses ($L_{co}$)</td>
<td>4 dB</td>
</tr>
<tr>
<td>BS Cable Losses ($L_c$)</td>
<td>4 dB</td>
</tr>
<tr>
<td>Analyzer Antenna Gain ($G_{An}$)</td>
<td>3 dBi</td>
</tr>
<tr>
<td>Analyzer Cable Losses ($L_{ca}$)</td>
<td>0.72 dB</td>
</tr>
<tr>
<td>Low-noise Amplifier Gain ($G_{LNA}$)</td>
<td>11 dB</td>
</tr>
<tr>
<td>Analyzer Height ($A_{H}$)</td>
<td>1.5 m</td>
</tr>
<tr>
<td>GSM Channel Transmission Frequency ($f_c$)</td>
<td>828.93 MHz</td>
</tr>
</tbody>
</table>
Through Equation (2) the theoretical average propagation losses ($\bar{L}$) are obtained of the C231-W-I model for each measuring spot in non-line-of-sight conditions, as observed in Table 2,

$$
\bar{L}(dB) = 32.4 + 20 \log d + 20 \log f_c - 16.9 - 10 \log w + 10 \log f_c + 20 \log \Delta h_m + L_{ori} + L_{bsb} + K_a + K_d \log d + K_f \log f_c - 9 \log b
$$

(2)

where $d$ is the distance between the transmitter and the receiver in km, $f_c$ is the carrier frequency in MHz, $w$ is the width of the street in m, $\Delta h_m$ is the difference between mean height of the buildings ($h_{Roof}$) and the height of the antenna of the mobile device ($A_H$) in m, $L_{ori}$ is a factor of empirical correction that counts the losses due to the orientation of the street, and $b$ is the mean separation among buildings in m [20]. The rest of factors employed are expressed in Equations (3), (4), (5) and (6).

$$
L_{ori} = -10 + 0.354\phi \quad \text{for} \quad 0^\circ \leq \phi < 35^\circ
$$

(3)

Here, $\phi$ is the angle between street orientation and the direction of propagation in degrees.

$$
L_{bsb} = -18 \log (1 + \Delta h_b) \quad \text{for} \quad h_b > h_{Roof}
$$

(4)

$\Delta h_b$ is the difference between antenna height of the base station ($h_b$) and $h_{Roof}$ in m.

$$
K_a = 54 \quad \text{and} \quad K_d = 18 \quad \text{for} \quad h_b > h_{Roof}
$$

(5)

$$
K_f = -4 + 1.5 (\frac{f_c}{925} - 1)
$$

(6)

Table 2. Propagation losses of the C231-W-I model for the measurement spots in Figure 2

<table>
<thead>
<tr>
<th>Spot</th>
<th>$L$ GSM channel (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>F(58m)</td>
<td>82.62</td>
</tr>
<tr>
<td>C(152m)</td>
<td>93.409</td>
</tr>
<tr>
<td>D(226m)</td>
<td>98.841</td>
</tr>
<tr>
<td>B(287m)</td>
<td>102.294</td>
</tr>
<tr>
<td>E(290m)</td>
<td>102.447</td>
</tr>
<tr>
<td>A(328m)</td>
<td>104.27</td>
</tr>
</tbody>
</table>

The results of Table 2 and parameters in Table 1 give the theoretical average reception power ($\bar{P}_{RX}$) [34]:

$$
\bar{P}_{RX} = P_{TX} + G_{BS} + G_{An} + G_{LNA} - \bar{L} - L_c - L_{co} - L_{ca}
$$

(7)
Figure 3 depicts $\overline{P_{RX}}$ found through Equation (7) for the C231-W-I model in comparison to the range of the sensed reception power with its respective average values. Figure 3 reveals a significant difference between the theoretical data and the ones sensed.

$$\overline{L}(dB) = 47.1435 - 612.156 \log d + 20 \log f_c - 16.9 - 10 \log w + 10 \log f_c + 20 \log \Delta h_m + L_{ori} + L_{bsh} + K_a + K_d \log d + K_f \log f_c - 9 \log b$$

(8)

where,

$$L_{ori} = -10 + 0.0162 \varphi \quad \text{for} \quad 0^\circ \leq \varphi < 35^\circ$$

(9)

and,

$$K_d = 622.4238 \quad \text{for} \quad h_b > h_{Roof}$$

(10)

Figure 4 presents the reception power of the model C231-W-I adjusted by Equation (8) with respect to the average of the sensed reception power. The Figure 4 presents the approximation between the sensed values and the adjusted model, which has a mean squared error of 1.5456.
2.3 Methodology Proposed

In the following we describe the methodology to develop the proposed method and the general equation to forecast reception power through the wavelet neural model and the C231-W-I propagation model previously adjusted. The general procedure to obtain the forecasting method of spectral opportunities in an unknown environment is shown below:

1. Sensing
   In this step the time-variant(s) channel(s) of the radioelectric spectrum are sensed during a day, as described in [32].
2. Adjusting the propagation model
   The C231-W-I propagation model is adjusted using, for example, the least squares method according to the mean values of the measurements.
3. Training of the wavelet neural model
   The measurements developed in a minimum time of 24 hours serve to train the wavelet neural model designed.
4. Integration of models
   Extrapolate the adjusted C231-W-I propagation model to the wavelet neural model, thus integrating average propagation losses with instantaneous losses.
5. Forecasting reception power
   Along the analyzed urban environment, reception power is forecast during a specified period of time using the compound model in step 4.

Therefore, the model that takes into consideration both instantaneous and average propagation losses can be described as:

\[ L = \Delta L + \bar{L} \]  \hspace{1cm} (11)
where $\Delta L = f(f[n]) | f[n] = \Delta PRX$ represent the instantaneous propagation losses according to the reception power obtained using Equation (1), and $\bar{L}$ are the average propagation losses obtained from the adjustment of Equation (2) of the C231-W-I model. Thus, at combining Equations (1) and (7) the reception power is obtained as a function of the C231-W-I model:

$$P_{RX} = g \sum_{i=1}^{n} \left[ \frac{1}{\sqrt{M}} \sum_{k} W[k, j] \Phi(j, k) [n] + \frac{1}{\sqrt{M}} \sum_{j=0}^{n} \sum_{k} W[j, k] \psi[j, k][n] \right] + P_{RX}\bar{L}$$

(12)

where $P_{RX}\bar{L} = f(\bar{L})$. Equation (12) is represented in Figure 5.

Fig. 5. Scheme of the proposed method to forecast the spectral opportunities

3 Results and Discussion

In this section we present and discuss the results of the proposed method for different occupancy levels of channels. Figure 6 shows the working of the proposed method. In this example the CR user perceives the power of a primary BS and may move over the cell coverage in the direction of the arrows. The CR user may forecast the power level that will be sensed from the primary BS at different distances, bearing in mind the environment propagation losses.

The results were analyzed using Matlab® software in a dual core 2.4GHz computer with a RAM of 4GB.

The evaluation of the proposed method covers the forecasting of up to one hour of received power, with a maximum distance 328m. The duty cycle over the analyzed environment is also presented.

Fig. 6. Application of the proposed method
By applying Equation (12), the equation of the method in the proposed environment of the Figure 2 is:

\[
P_{RX} = g \sum_{j=1}^{n} \left[ \frac{1}{\sqrt{M}} \sum_{k} W_{\phi}[j_0,k] \phi_{j_0,k}[n] + \frac{1}{\sqrt{M}} \sum_{j=j_0}^{n} \sum_{k} W_{\psi}[j,k] \psi_{j,k}[n] \right] + f[47.1435 - 612.156 \log d + 20 \log f_c - 16.9 - 10 \log w + 10 \log f_c + 20 \log \Delta h_m + L_{ori} + L_{bsh} + K_a + K_d \log d + K_f \log f_c - 9 \log b]
\]

(13)

Figure 7 depicts Equation (13):

![Figure 7. Forecast reception power for the proposed method](image)

In Figure 7, the spectral opportunities that would be perceived and profited by CR users are observable in orange color, though to be more precise would depend on the selected threshold. These are obtained from the one-hour power forecast based on the historical information of one day. The Figure 7 also shows the tendency of the power level to decrease as the distance augments, according to the found losses.

In the example of Figure 6 the analysis of the proposed method is done by developing the power forecast from the CR user, using a similarity with the spectrum analyzer in which measurements were made. However, such similarity depends on the CR architecture deployed in the environment. Considering that the processor and the power consumption are more limited in the device of the CR user, it is recommended the use of an architecture with infrastructure that develops the forecast since the CR BS. The CR BS is equipped with a better processor than the CR user and has no limitations regarding power consumption.

Nevertheless, a period of time between the data collection in the environment and the processing adds a delay in the response that should not be ignored; the forecast helps to reduce the negative impact of the delay in the response. Figure 8 presents an architecture with infrastructure [3].
For a CR system, the developed modeling in the channel of the GSM band may help improve the use of spectral efficiency, as it allows CR users to share channels and to avoid collisions with primary users in the found opportunities.

### 3.1 Duty Cycle

The forecast of the duty cycle can be found using Equation (14) [15, 36]:

$$
\psi = (1 - \sum_{k=1}^{K} \alpha_k)P_{fa} + \sum_{k=1}^{K} \alpha_k \cdot Q \left( -\frac{1}{\sigma_{Sk}} \left( \frac{P_{RXk} - P_{N}}{\gamma_k} \right) \right)
$$

(14)

where $K>0$ represents the number of power levels of transmission that can be present in the channel. In this case, in the measurements of each spot of Figure 2 there exists one single transmission power. $0 < \alpha_k \leq 1$ is the activity factor of the k-th power level, which can be obtained from the average value of the use of the analyzed GSM channel. $P_{fa}$ is the target probability of false alarm considered for the selection of the energy decision threshold, which in this case is of 1%. $\gamma_k = P_{RXk} - P_N$ is the signal to noise ratio resulting from the k-th average transmission power level. $\sigma_{Sk}$ and $\sigma_N$ represent the standard deviation in decibels of the k-th signal and noise power levels respectively. These values were obtained experimentally using the spectrum analyzer and are presented in Table 3. $Q(\cdot)$ is the Gaussian Q-function and $Q^{-1}(\cdot)$ is the inverse of $Q(\cdot)$.

$P_{RXk}$ is the sensed received power by the user, which has already been found for the proposed method, whereas $P_N$ represents the CR terminal noise floor created from the sum of all the noise sources in the receiver (including thermal noise), and can be expressed as:

$$
P_N(dBm) = -174 \frac{dBm}{Hz} + 10 \log B \ (Hz) + NF \ (dB)
$$

(15)

where -174 dBm/Hz is the thermal noise power spectral density at 290 °K, $B$ is the band width of the sensed channel, and $NF$ is the total noise figure of the receiver. The NF of the low noise amplifier is 4dB with a gain of 11dB, cable losses
are of 0.72dB. The NF of the analyzer is 16dB for the implemented configuration. Thus, total NF can be found by the total noise factor ($F_T$) [37]:

$$F_T = F_{ca} + \frac{F_{LNA}-1}{G_{ca}} + \frac{F_{An}-1}{G_{ca}G_{LNA}} = 3.266$$ (16)

$F_{ca}$ is the noise factor of the cable, $F_{LNA}$ is the noise factor of the low noise amplifier, $F_{An}$ is the noise factor of the spectrum analyzer, $G_{ca}$ is the gain of the cable and $G_{LNA}$ is the gain of the low noise amplifier. Therefore, the total NF is 5.14dB.

Table 3. Experimental values of $\sigma_{Sk}$ and $\sigma_N$ for GSM

<table>
<thead>
<tr>
<th>Band</th>
<th>B(kHz)</th>
<th>$\sigma_{Sk}$(dB)</th>
<th>$\sigma_N$(dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GSM</td>
<td>200</td>
<td>1.816</td>
<td>0.8785</td>
</tr>
</tbody>
</table>

The duty cycle resulting from Equation (14) for the proposed method in the sector of the BS cell of the external environment in Figure 2 is seen below:

![Fig. 9. Duty cycle for the proposed method in the GSM channel.](image)

Figure 9 shows that as a result of the approach employed in Equation (14) the scenario reveals different occupancy levels, and not only busy or idle. For example, the probability of channel occupancy can be low or high, but not equal to zero or one. This way the modeling affords a realistic characterization of the spectrum occupancy forecast according to the considered propagation scenario, which constitutes a major aspect in the design and dimensioning of CR systems for real implementations.

Figure 9 warns that the maximum occupancy levels fluctuate about 0.3. These values correspond to localizations close to the BS and appear in red tones. In general, occupancy values decrease and therefore the spectral opportunities for CR users increase, as the signal moves away from the BS; such values are represented
by the range of blue colors. This is consistent at a practical level and strengthens the proposed method. However, some low occupancy levels appear in places close to the BS. This is because at these locations the $\phi$ angle of the Equation (3) is greater than 35°, and for this reason there it was necessary to use values predefined by the C231-W-I model; this responds to the fact that in the model the only $\phi$ value adjusted was less than 35°, as a consequence of the small $\phi$ angles formed in the six measuring spots in Figure 2.

4. Conclusions

In this study a method to forecast the spectral opportunities was developed. First, from the adjustment of the propagation model C231-W-I with the measurements developed in an urban environment. Then, given the approximation of the adjustment and the average of the measured data, the integration with a wavelet neural model was proposed.

The spectral opportunities were set through the forecast the received power in a determined time and the duty cycle within an urban environment. These results show the consistency with the practical behavior of the mobile communication systems.

The proposed methodology presents a novel and practical approach to forecasting the spectrum occupancy that would be perceived by CR users in real settings. The forecast of received power through propagation models is relevant as it allows CR users to access to benefits like: saving energy in the spectrum sensing process, taking advantage of spectral opportunities by increasing the rate of successful transmission as well as the transmission opportunities, reducing the time to find available channels, and adjust the transmission power levels to protect primary users from collisions and interferences.

Another advantage and difference is that, whereas most of the forecast schemes is based on determining spectrum holes, the proposed methodology in this paper is based on an a-priori knowledge of the received power by a channel of primary users, which allows to avoid selecting noisy channels and entails a better sharing of the spectrum among CR users. This leads to superior quality of service parameters involving less radio resources.

References


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