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Multi-Attributes, Utility-Based, Channel Quality Ranking Mechanism for Cognitive Radio Networks

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Abstract: Cognitive radio is an intelligent wireless solution that aims to enhance the access to the radio spectrum. In this technology, secondary users sense the radio spectrum, select the best channel among a pool of free channels, and determine the optimal transmission parameters to meet their quality-of-service requirements while maximizing the spectral efficiency. Over the past decade, several channel-ranking mechanisms have been proposed. However, these mechanisms consider only the remaining idle time of the channel and exclude some crucial parameters. This convincingly demonstrates a strong need for a new channel quality-ranking model that jointly considers several parameters to select the best communication channel for transmission. This paper proposes a utility model that integrates several important parameters for ranking channels. First, we underline the importance of the process of the channel quality ranking. Then, we describe a multi-attributes, utility-based, channel quality-ranking model. Finally, we describe a series of experiments and their results, which show that our model effectively ranks the best communication channels first.

Keywords: cognitive radio; spectrum decision; spectrum sensing; channel ranking; multi-attributes utility function; gradient descent; non-linear regression

1. Introduction

Wireless devices and traffic have been exponentially growing, causing a huge demand for radio frequency channels [1–3]. Current fixed frequency allocation has resulted in an inefficient utilization of radio spectrum resources due to two main reasons: the licensed frequency channels are not or are scarcely used while unlicensed bands, such as Wi-Fi bands, are heavily used. Cognitive radio (CR) technology has been proposed to enhance the access to the radio spectrum and overcome its scarcity by enabling dynamic access. Secondary users (SUs) can perform spectrum sensing and access the free channels while the primary user (PU) is idle.

Cognitive radio systems perform a cycle involving three main processes: spectrum sensing, spectrum analysis, and spectrum decision. During the spectrum sensing, the secondary users identify the state of each frequency channel—free or occupied—using spectrum sensing techniques, such as energy detection [4–9], cyclostationary features detection [10–15], and matched filter detection [16,17].

Energy detection [4–9] computes the energy of the received sample as the squared magnitude of the Fast Fourier Transform (FFT) averaged over the number of samples. Then, this energy is compared to a threshold to decide on the presence or the absence of the primary user. Specifically, if this energy is higher than the threshold, the primary user is declared to be present; otherwise, the primary user is absent. Energy detection is a simple and fast technique that does not require any prior knowledge about the primary user signal, and it is very sensitive to noise, which makes the detection performance of this technique at low signal-to-noise ratio (*SNR)* values unreliable.

Cyclostationary detection [10–15] uses several characteristics of a signal, such as its periodicity, to detect the presence or absence of a primary user signal. Autocorrelation, for instance, is a technique that uses the property of autocorrelation to determine the presence or absence of the primary user signal. This property is based on how the signal is highly correlated while the noise is uncorrelated. An autocorrelation-based sensing technique computes the autocorrelation of the received samples. Then, if the difference between lag 1 and lag 0 is less than the threshold, the primary user is considered present; otherwise, the primary user is declared absent. This technique detects the primary user signal with a high probability.

Matched filter detection [16,17] is an approach that matches the received samples with some saved pilots of the same primary user signal. This technique requires fewer samples to achieve an acceptable probability of detection. However, matched filter detection requires a prior knowledge of the primary user signal characteristics, which is not often available, making this technique unpractical.

During the spectrum analysis, the CR systems estimate several parameters to characterize the quality of each communication channel, such as the estimation of the information capacity of the channel, the bit error rate, the level of noise, and the interference within each communication channel. Then, in the spectrum decision, a decision-making model takes the results of both the spectrum sensing and the spectrum analysis to determine the best channel for transmission. Thus, the channel ranking mechanism is important in the cognitive radio cycle. This mechanism has several objectives: it enables secondary users to maximize the spectral efficiency considering the scarcity of the radio resource, while meeting their requirements regarding quality of service and security.

Over the last decade, a few channel-ranking mechanisms have been proposed [18–26]. Most of these mechanisms consider only the remaining idle time of the channel. For instance, the authors of [18] used the availability of the frequency channels and their occupancy to decide whether to access a specific channel or not [18]. The authors of [19] proposed a scheme that continuously monitors the primary user activity of each channel and ranks the sensed channels based on the number of primary user arrivals and the duration of the monitoring. The authors of [20] proposed a scheme in which the channels are rated based on the quality-of-service demand of each secondary user to avoid collisions that might happen as a result of using the frequency channel with the highest availability. The authors of [21–26] performed channel ranking based on the channel state prediction, which is related to the duration of the channel availability. Each secondary user predicts the arrival of the primary users on different communications channels using statistical models, and the secondary user then selects the channel with the least primary user activity to increase its holding time of the communication channel. The authors of [27–31] selected the communication channel based on the availability of the channel using a genetic algorithm. Yet, these schemes consider only a few settings and do not consider the effect of the primary user activity and the quality-of-service parameters of the performance of the channel selection algorithms. The authors of [31] proposed a genetic algorithm-based channel selection and parameter adaptation considering the PU activity, the quality of service of the secondary user, and the channel condition and quality. The proposed scheme performs well under specific settings, but it does not jointly consider these parameters, which may lead to an inefficient solution. In short, even though these techniques rank the channel using some parameters and perform well under specific settings, they consider parameters separately in the ranking, and they exclude critical parameters, which cannot lead to the selection of the best channel. Thus, the channel selection mechanism remains a significant open issue in cognitive radio systems since it has to deal with antagonistic goals: maximizing the spectral efficiency and considering the scarcity of the radio resource, while guaranteeing the quality-of-service requirements.

In this research, we highlight the importance of channel quality ranking. Then, we describe a multi-attributes utility-based model to rank the frequency channels. The model associates a weight to each parameter involved in the ranking mechanism. The weights corresponding to these parameters are determined using a nonlinear regression algorithm.

The main contributions of this paper are as follows:

- Development of a utility ranking-based model for channel quality ranking,
- Use of a nonlinear regression algorithm to determine the weights corresponding to each parameter,
- Validation the proposed model,
- Highlight the challenges and future directions related to channel quality ranking.

The rest of this paper is organized as follows: the second section describes the proposed model, the third section describes the experiments and the results, the fourth section further discusses the proposed model and how it can be extended, and in the last section, conclusions and perspectives are drawn.

2. Methodology

The proposed model involves three main processes: spectrum sensing, channel quality estimation, and channel ranking. As shown in Figure 1, the first step of this model consists of performing spectrum sensing using either energy detection [4–9], cyclostationary features detection [10–15], or matched filter detection [16,17]. This spectrum-sensing process determines the list of free frequency channels. The second process involves the estimation of the parameters related to the quality of each free frequency channel, such as the occupancy of the channel, *SNR*, information capacity of the channel, bit error rate, etc. The channel ranking calculates the global utility of each frequency channel and then ranks all the free channels. The frequency channel with the highest utility value is chosen as the best channel for transmission. In the "ACTION" function, the selected frequency channel is used for communication.

The proposed utility function is described as follows. Let us consider that the radio spectrum is divided into M frequency channels, of which N frequency channels are free. $\mathrm{F} = \{f_1, f_2, \ldots, f_N\}$ denotes the list of these N free channels for which the quality of the channel is increasing as the subscript of the frequency is increasing.

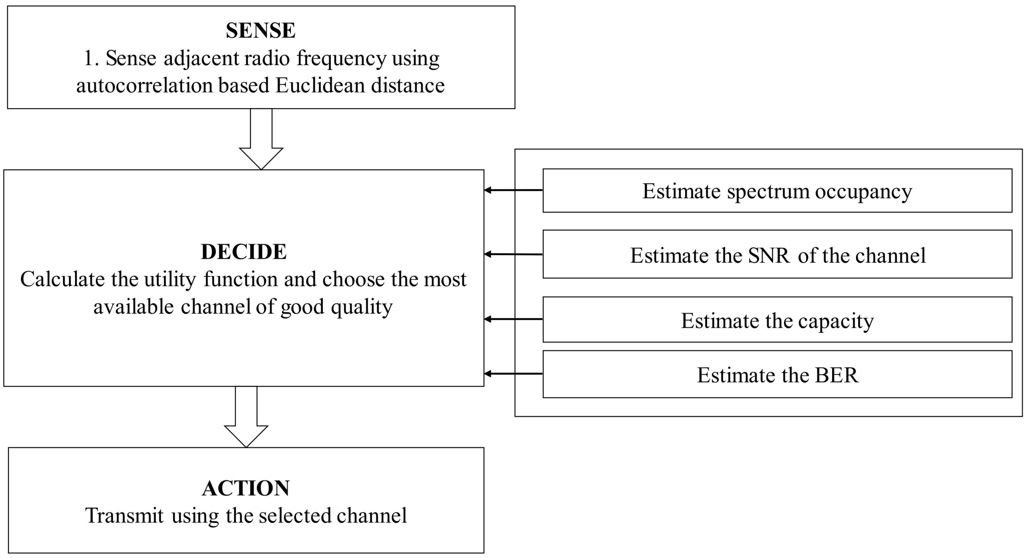

Figure 1. Processes of selecting the best channel.

Figure 2 shows the expected utility function of the frequency channels. The x-axis represents the list of frequencies from f_1 to f_{100}, and the y-axis represents the expected utility ranging from 0 to 1. The frequency channel f_1 has the lowest quality, and as we increase the subscript of the frequency, the quality of the channel increases until reaching the frequency with the highest frequency that correspond to the channel with the best quality.

The utility function of these parameters can be approximated by a sigmoid function, which is expressed as:

$$U_w(x) = \frac{1}{1 + e^{-\sum_{i=0}^{N} w_i x_i}} \tag{1}$$

where w_i denotes the weight associated with the parameter x_i, and N is the number of features used to estimate the quality of the channel.

Equation (1) can be rewritten as:

$$U_w(x) = \frac{1}{1 + e^{-w^T x}} \tag{2}$$

where x is the N-dimensional vector made of the parameters x_i, w is the N-dimensional vector made of the weights w_i, and T is the transpose operator.

To find the weight w_i corresponding to each utility parameter x_i, we define the cost function as:

$$J(w) = \frac{1}{2m} \sum_{i=1}^{m} \left(U_w\left(x^{(i)}\right) - y^{(i)} \right)^2 \tag{3}$$

where y is the expected global utility and m is the number of training data.

Then, the problem of finding the weights can be solved by minimizing the following cost function:

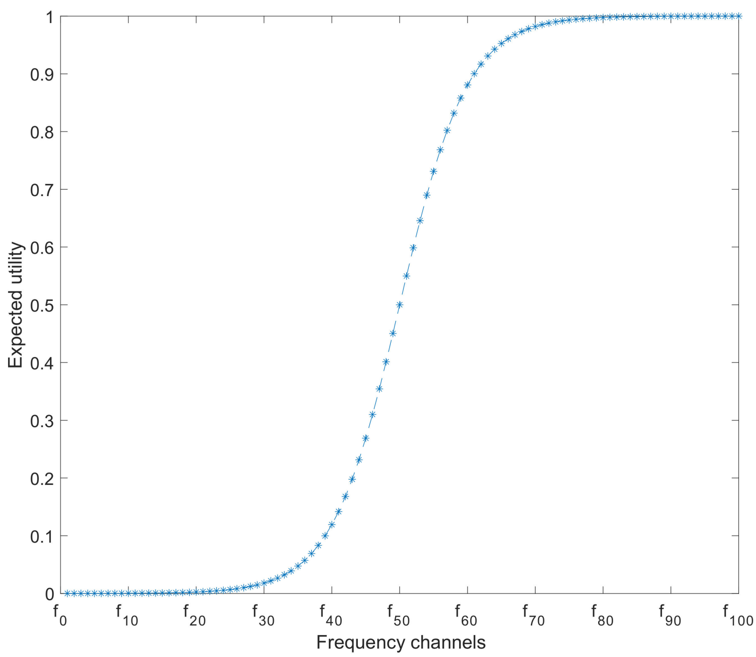

Figure 2. Expected utility of the frequency channels.

$$\min_{w} J(w) \tag{4}$$

To minimize the cost function, we use the Gradient Descent algorithm. This algorithm updates all the weights simultaneously until the convergence to a global minimum. These weights are updated using the following formula:

$$w_j := w_j - \alpha \frac{\partial}{\partial w_j} J(w) \tag{5}$$

where α is the learning rate and $\frac{\partial}{\partial w_j} J(w)$ is the partial derivative regarding the weights w_j.

Consider n parameters that are encompassed in the global utility function. All of these parameters are updated simultaneously, and Equation (5) can be rewritten as:

$$\begin{aligned} w_1 &:= w_1 - \alpha \frac{\partial}{\partial w_1} J(w) \\ w_2 &:= w_2 - \alpha \frac{\partial}{\partial w_2} J(w) \\ &\vdots \\ w_n &:= w_n - \alpha \frac{\partial}{\partial w_n} J(w) \end{aligned} \tag{6}$$

The partial derivative $\frac{\partial}{\partial w_j} J(w)$ becomes the following:

$$\frac{\partial}{\partial w_j} J(w) = \frac{1}{m} \sum_{i=1}^{m} \left(U_w \left(x^{(i)} \right) - y^{(i)} \right) x_j^{(i)} \tag{7}$$

where m is the number of element in the training set.

Thus, Equation (5) above can be rewritten as:

$$w_j := w_j - \alpha \frac{1}{m} \sum_{i=1}^{m} \left(U_w \left(x^{(i)} \right) - y^{(i)} \right) x_j^{(i)} \tag{8}$$

The performance of the gradient descent is related to two main parameters: the learning rate and the number of iterations. When the learning rate is smaller, the chance that the gradient descent converges to a global minimum of the cost function is higher. As we increase the value of the learning rate, the gradient descent can miss the global minimum and can diverge. With a small learning rate value, the gradient descent runs for a large number of iterations to find the global minimum. As we increase the number of iterations, the convergence time increases as well. Finding the optimal values of the learning rate and the number of iterations is necessary for the convergence of this algorithm in an acceptable time.

3. Results

To validate the proposed model, we consider a scenario in which the quality of frequency channels is determined using two parameters: the information capacity and the availability of the channel. However, more parameters can be easily included to evaluate the quality of the channel without any change in the proposed model. These two parameters are important in channel ranking. To illustrate the importance of the first parameter in channel ranking, we consider a scenario in which a secondary user has to choose between two channels: channel one, with a capacity C_1, and channel two, with a capacity C_2. If C_1 is more significant than C_2, the secondary user will choose the first channel since it allows him to transmit at a higher data rate. To illustrate the importance of the second parameter, let us take, for instance, two channels with occupancies of 10% and 90%. A secondary user, who has to choose between these channels, will select the first one as it is less occupied.

The information capacity, C, refers to the maximum rate at which data can be transmitted across the channel without errors. This parameter can be determined based on the bandwidth of the channel and the received signal-to-noise ratio, as given by:

$$C = B \, * \, \log_2(1 + SNR) \tag{9}$$

where C is measured in bits per second or bits per transmission, B is the bandwidth, and SNR is the signal-to-noise ratio.

The Shannon information capacity theorem states that for a prescribed channel bandwidth B and a received SNR, a signal can be transmitted without error even when the channel is noisy, provided that the actual signaling rate R in bits per second, at which data is transmitted through the channel, is less than the information capacity C.

The availability of the channel refers to the holding time or the time that a secondary user can benefit from using a channel until the arrival of the primary user signal. The availability of a specific channel can be derived from its occupancy. The frequentist method [32], for instance, gives a simple statistical computation of the channel occupancy as:

$$occupancy = \frac{N_0}{N} \tag{10}$$

where N_0 denotes the number of observations in which the frequency channel is occupied, and N denotes the total number of observations.

The first step of this experiment was the determination of the weights w_1 and w_2 corresponding to each parameter of the utility. For this reason, a dataset has to be generated to train our model and determine the optimal value of these weights. To generate this dataset, we considered a list of 100 frequency channels with different values of capacity and occupancy. For each frequency channel, we computed its corresponding utility; we then calculated the capacity of each frequency channel considering the SNR value and the bandwidth B using the Shannon formula given in Equation (9). Different values of bandwidth are considered in this experimental setup depending on the bands. For instance, for Wi-Fi 2.4 GHz, a bandwidth of 20 MHz is considered. Then, according to the standard IEEE 802. 11ac, we selected a combination of a modulation and a coding rate that allow secondary users to achieve a maximum data rate less or equal to the capacity of this channel, i.e., $R \leq C$. To illustrate this process, we consider an example of a channel that has a capacity of 80 Mbps, and then, according to Table 1, we can achieve a data rate of 78 Mbps, if we select QPSK modulation with a coding rate of 3/4. Once we determined the data rate that can be achieved by each frequency channel with the modulation technique and coding rate, we used the maximum data rate in addition to the holding time to rank these 100 frequency channels. For instance, the frequency channel that has a high data rate and a higher holding time is ranked first, and the frequency channel that has a low data rate and short holding time is ranked last. Finally, we attributed a utility value to each frequency channel that reflects its ranking. Channels ranked on the top of the list have high values of the utility, while the channels ranked last have small values of the utility.

The generated dataset was divided into two parts: training and testing data. The training dataset represented 75% of the overall data, and the testing data represented 25%. The Gradient Descent algorithm determines the optimal values of weights corresponding to each parameter by solving the optimization problem, given by Equation (7). To find the appropriate learning rate and the number of iterations to use with the Gradient Descent algorithm, we varied the learning rates and compared the outputs of the Gradient Descent in terms of error function and convergence time. The learning rate and the number of iterations that have a low error function and a short convergence time are chosen for the Gradient Descent setting.

Once the weight corresponding to each parameter is determined, the model can predict the utility function of each channel frequency, and this predicted utility is used to rank the list of frequency channels, which are given in Table 2. This list considers four bands from Global System for Mobile (GSM) and Wi-Fi: GSM 850 MHz, GSM 1900 MHz, Wi-Fi 2.4 GHz, and Wi-Fi 5.8 GHz. This table also gives the list of frequency ranges, the channel spacing, and the number of channels for each band. These frequency channels are considered because they are the most used ones in wireless communication. It is worth mentioning that the experiments have been carried out on Matlab (R2016a, MathWorks corporate, Natick, MA, USA) running on a machine with a processor intel(R) Core (TM) i7-6700 CPU 3.40 GHz.

Table 1. List of bands and channels.

Modulation Technique	Coding Rate	Data Rate (Mbits/s)
BPSK	1/2	26.0
QPSK	3/4	78.0
16-QAM	1/2	104.0
64-QAM	5/6	260.0

Table 2. List of bands and channels.

Band	Start Frequency (MHz)	Stop Frequency (MHz)	Channel Spacing (MHz)	Number of Channels
GSM850 (U/L)	824	849	0.2	126
GSM1900(U/L)	1850	1910	0.2	301
2.4 GHz	2402	2497	5	20
5.8 GHz	5725	5875	5	31

Examples of results are given in Figures 3–6. Figure 3 shows the error function, or the cost function, of the Gradient Descent algorithm versus different values of the learning rate α . As it can be observed, the error function is minimal (0.04) for a value of learning rate of 0.01. As we increase the learning rate, the error function increases to reach a value of 0.07 when the learning rate is 0.028.

Figure 4 shows the convergence time of the gradient descent as a function of the number of iterations for a learning rate equal to 0.01. As observed, the convergence time increases as the number of iterations increases. The convergence time for 20,000 iterations is equal to 0.26 s.

Figure 5 shows the error function as a function of the number of iterations for a learning rate equal to 0.01. As one can see, the cost function or the error function decreases as the number of iterations increases. For a number of iterations greater than 20,000, the error function remains constant.

Based on the results of Figures 3–5, we have chosen a learning rate of 0.01 and a number of iterations equal to 20,000 to determine the weights of our model.

Figure 6 shows both the experimental and the calculated global utility using the testing dataset. The x-axis represents the list of frequencies from f_1 to f_{100}. The y-axis represents the utility function. From this figure, one can see that the calculated utility with the estimated weights using the proposed model fits the experimental utility.

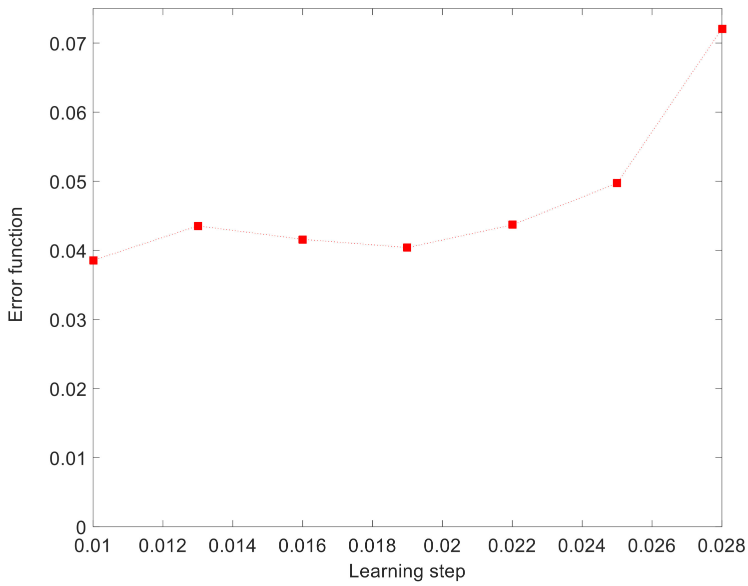

Figure 3. Error function as a function of the learning rate.

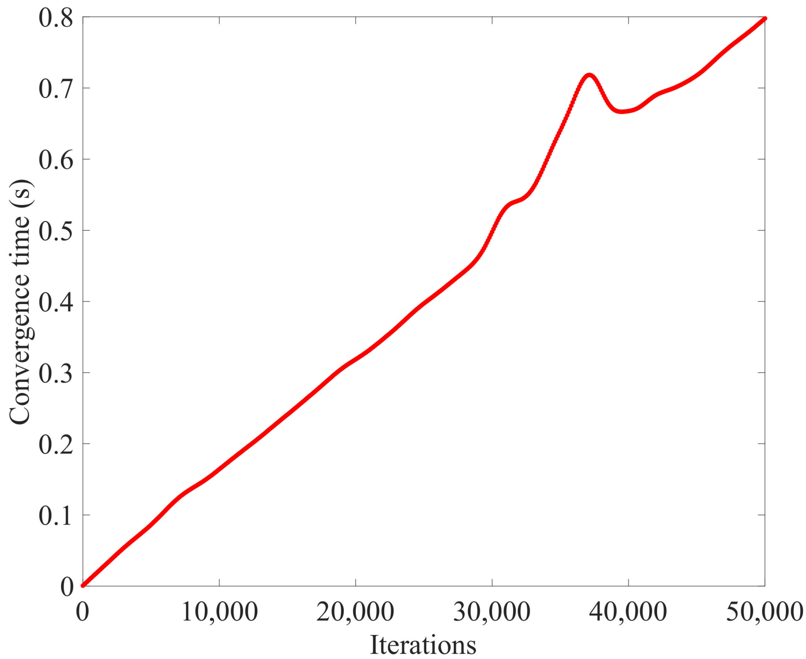

Figure 4. Convergence time as a function of the number of iterations.

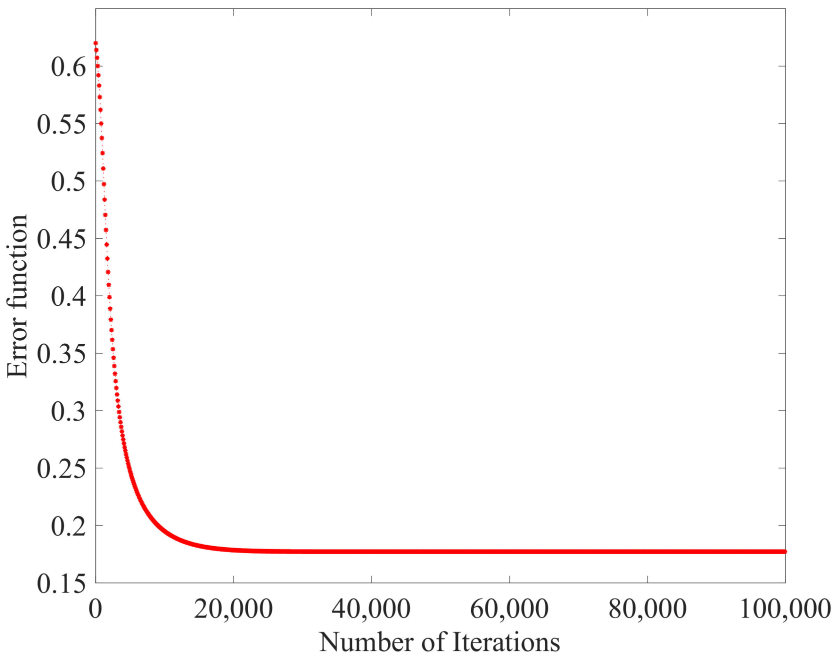

Figure 5. Error function as a function of the number of iterations.

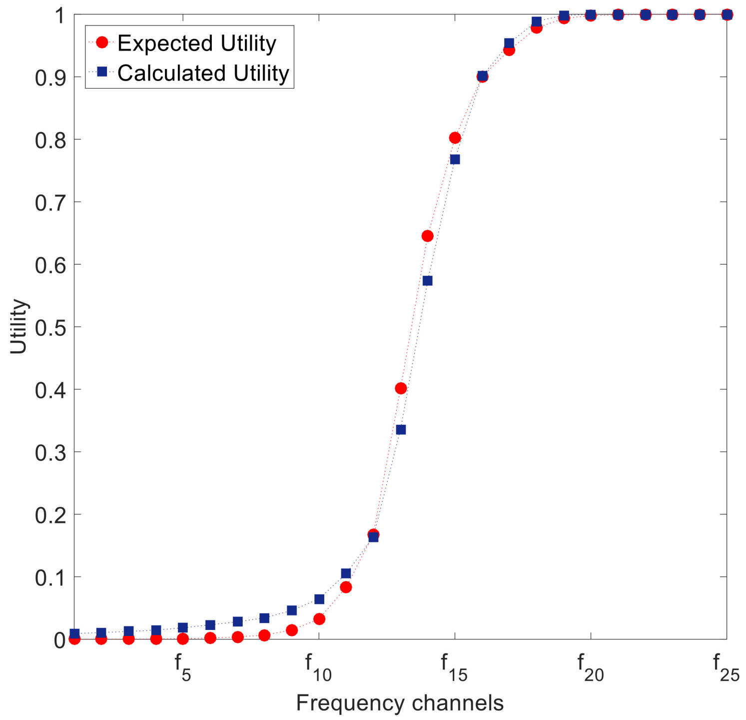

Figure 6. Experimental and calculated utilities.

Table 3 shows the obtained values of the global utility for several values of the capacity and the occupancy. As one can see, the utility function tends toward zero with increasing values of the occupancy and decreasing values of the capacity. Thus, based on the obtained ranking, the best channels are the desirable ones. For instance, the 1850 MHz frequency with a capacity of 0.14 and an occupancy of 34% is better than 1856.4 MHz with a capacity of 0.14 and an occupancy of 37%. In addition, the first ranked channel 5725 MHz has the highest capacity and the lowest occupancy. In contrast, the last channel in the ranking is 5815 MHz, which has the lowest capacity and the highest occupancy.

Table 3. Global utilities for frequency channels with several values of the capacity and occupancy.

Channels	Capacity (Mbps)	Occupancy	Global Utility
5725 MHz	266.32	0%	99
2472 MHz	81.49	60%	80
5775 MHz	82.29	73%	70
2482 MHz	31.65	21%	65
824 MHz	0.41	4%	45
827.2 MHz	0.75	9%	40
1882 MHz	0.36	15%	33
2402 MHz	4.24	28%	25
830.4 MHz	0.69	30%	20
1850 MHz	0.14	34%	17
1856.4 MHz	0.14	37%	15
833.6 MHz	0.75	39%	14
1907.6 MHz	0.94	46%	11
840 MHz	0.23	49%	9
2412 MHz	11.72	67%	7
1901.2 MHz	0.75	58%	6
5805 MHz	0.57	66%	4
2462 MHz	9.66	90%	2
5815 MHz	4.41	96%	1

According to the results obtained in Table 3, a secondary user can use the channel frequency of 5725 MHz to achieve a higher data rate and a high holding time for the frequency channel, which minimizes the number of switching from a channel to another, therefore reducing the power consumption from the process of sensing and ranking. The channel 5725 MHz has a capacity of 266.32 Mbps, and according to the standard IEEE 802.11ac, if we use a modulation 64-QAM with a coding rate of 3/4, the secondary user can achieve a data rate of up to 243 Mbps. In contrast, the algorithms that rank the channels using only the remaining idle time, i.e., the channel with the lowest occupancy, which gives the secondary user a high holding time of the channel, are selected. However, selecting the channel with the lowest occupancy does not mean necessarily that this channel has the highest capacity, which makes the secondary users unable to transmit with a high data rate to meet their requirements in terms of quality of service.

4. Discussion

The proposed model was evaluated experimentally using two parameters: the information capacity and the occupancy of the free channel, which was determined by using spectrum sensing. These two parameters involve several other parameters. For instance, the capacity in its calculation involves two main parameters, which are the bandwidth of the channel and the level of noise represented by the signal-to-noise ratio. The data rate is also considered, which involves a modulation and coding techniques. One of the advantages of the proposed model is its modularity as one can easily include as many parameters as needed to evaluate the quality of the channel. For instance, one crucial parameter that can be included in the channel quality ranking is the bit error rate. In the case of the communication systems, the reliability is commonly expressed using the bit error rate (BER). The BER can be defined as the ratio between the number of corrupted bits and the total number of transmitted bits during a period of time. The knowledge of the BER associated with each channel at any time can help to evaluate the quality of the channel, and thus, can improve the quality of service by enabling the selection of a channel with a minimum BER for transmission. Clearly, the smaller the BER, the more reliable the communication system is. To measure the BER, several techniques have been proposed [33]. For instance, the authors of [34] have proposed a technique that measures the BER in the Additive White Gaussian Noise (AWGN) channel using as few as 32 pilot samples to estimate the BER with an error of 0.00066.

The signal-to-interference-plus-noise-ratio (SINR) is another crucial parameter in channel quality ranking, especially in cognitive radio networks [35], since interference is one of the critical factors that affects the performance of communication in these networks. The SINR is the relative ratio between the power of the transmitted signal and the interference power added to the noise power. This parameter is affected by several parameters such as shadowing and path loss.

Another aspect that has to be considered in channel quality ranking is the security risk associated with each specific channel. The cognitive radio network is subject to several attacks that can create a denial of service [36–38]. For instance, if a channel is jammed, the communication is interrupted. To avoid jamming attacks, it is possible to calculate, for instance, the probability that a channel will be jammed. A secondary user can choose the channel with a lower attack probability.

Another advantage of the proposed model is that it involves several parameters in the process of the selection of the best communication channel, which contrasts to other models that consider only one parameter, such as the occupancy of the channel. The selection of the best channel based on the occupancy can lead to the selection of a channel with a high remaining idle time, but this channel can have a low bandwidth or can experience a high level of noise, which does not allow secondary users to achieve a high data rate. This clearly show the outperformance of the proposed model compared with other techniques.

Once the selection of the best channel is done, secondary users can choose the optimal parameters of transmission such as the modulation technique, the coding rate, and the power of transmission that allow them to achieve the maximum data rate. Several algorithms can be applied in this stage, such as genetic algorithms discussed in the introduction section.

Table 4 gives a comparison between ranking mechanisms. This table shows that our algorithm ranks the channels based on the capacity that involves in its calculation the bandwidth, level of noise within a channel, and the occupancy. A machine-learning model is used to predict the utility value of each frequency channel. The model involves several parameters jointly in the process of the channel ranking. The selection of the channel with the lowest occupancy and the highest capacity enables secondary users to transmit with a high data rate during a long period. However, most of the existing algorithms rank channels based only on the availability, which can lead to the selection of a channel with low occupancy, but it can be of low quality. Some other algorithms such as the one given in [27–31] consider the quality of the channel, but this occurs only after the selection of the channel to adapt the parameters of transmission according to the condition of the selected channel.

Table 4. Comparison of channel-ranking algorithms in cognitive radio networks.

Channel Ranking Algorithm	Concept	Advantages	Disadvantages
[18–20]	• Rank channels based on availability of the channel	• Selection of the channel with the highest holding time	• No estimation of the quality of the channels
[21–26]	• Rank channels based on the prediction of their state	• Selection of the channel with the highest holding time	• No estimation of the quality of the channels
[27–31]	• Rank channels based on their availability	• A few parameters have been used to determine the transmission parameters	• The quality of the channels is not involved in channel selection
The proposed model	• Rank channels based on the capacity • A machine-learning model is used to predict the utility value of each frequency channel	• Involves several parameters jointly in the process of the channel ranking • Selection of the channel with lowest occupancy and the highest capacity, allowing high data rate and high holding time	• The algorithm does not involve security parameters.

5. Conclusions

In cognitive radio, secondary users have to sense and select the best frequency channel that meets their requirements regarding the quality of service and security before transmitting data. Several channel quality ranking mechanisms have been proposed for helping secondary users in their choice. Nevertheless, most of these ranking mechanisms include the occupancy as a parameter and exclude other key parameters such as channel capacity. In addition, most of these existing ranking techniques consider parameters separately in ranking. In this paper, we have proposed an aggregate utility function of several parameters. The weight associated with each parameter is determined using the nonlinear regression. Our findings demonstrate that the proposed model produces good results and can help secondary users in selecting the best channel for communication. To further improve our research, we plan to investigate the validity of our model with other important parameters, especially those related to security.

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Author Contributions: Y.A., Z.E.M. and N.K. conceived the model, designed the experiments, performed the experiments, analyzed the data, and wrote the paper.

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