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# Optimization of Spectrum Utilization Parameters in Cognitive Radio Using Genetic Algorithm

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**Abstract**

The dramatically development of wireless technologies in the last few decades, leads to the growth of channel resources demand in a limited spectrum with inextensible character. Cognitive radio network (CR) is a promising technology that provides solutions for the spectrum management and optimization problems via dynamic spectrum management. The spectrum resources management and optimization are an important part of the future network performances. In this paper, we propose an efficient algorithm to examine the design specification issues regarding the choice of optimal power, optimal speed, and optimal amount of information in a wireless network along with studying the effect of different parameters on the obtained results. Our objectives are to guarantee the protection on licensed users (Primary users 'PU') from harmful interference caused by the unlicensed users (Secondary users 'SU'), more especially, to optimize the quality of communication link, Transmission levels, and battery life of the wireless devices. Results show that our proposed work leads to an efficient utilization of radio spectrum and strongly contributes to alleviating the spectrum scarcity problem.



*Keywords:* Optimization, Algorithm Genetic, Cognitive Radio, Adaptive Modulation, Spectrum Sharing.

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## 1. Introduction

Radio spectrum is a natural but limited resource that enables wireless communications. In recent years, the available wireless spectrum resources have gradually decreased, because of the massive emergence of a variety of new wireless communications technologies [1]. Especially, with the emerging of massive connections of internet-of-things (IoT) devices. The spectrum scarcity is mainly due to the legacy command and control regulation rather than due to physical scarcity of spectrum. The traditional way of managing the electromagnetic spectrum is a static spectrum access, in which wireless spectrum resource is allocated to different wireless communication system by the spectrum authorities of each country [2]. Consequently, it is very difficult to allocate new frequencies for the new wireless devices, even if the authorized user (Primary user 'PU') in a certain place and a certain time without using its authorized spectrum. Other unauthorized users (secondary user 'SU') cannot use the frequency spectrum resource, which leads to the waste of time and space and the low spectrum utilization rate. On the other hand, extensive measurements conducted worldwide such as United States [3], Singapore [4], Germany [5], New Zealand [6] and China [7], have revealed that large portions of the allocated radio spectrum are underutilized. This situation does not adapt to the rapid development of wireless communication.

The wireless communication implementation creates many challenges. The first challenge is how to allocate the full range of the radio spectrum, which is very congested and subject to interference. The second challenge of wireless communication is the power consumption. In order to solve the deficient problem of spectrum resources. In this context, dynamic spectrum management (DSM) has been proposed and recognized as an effective approach to mitigate the spectrum scarcity problem. In DSM, the SUs, can access the spectrum of PUs, if the primary spectrum is idle, or can even share the primary spectrum provided that the services of the PUs can be properly protected [8].

According to the way of coexistence between PUs and SUs, there are two basic DSA models: The opportunistic spectrum access model and the concurrent spectrum access model. In our previous works [9]- [11], we have proposed an opportunistic spectrum access model. In which, we have presented a low cost and low power consumption spectrum sensing implementation by using real signals, in the aims to profit from the time slots, frequency bands or spatial directions at which the PU is inactive. Therefore, we assume that the search and detection of vacancies within the licensed spectrum is already carried. In this work, we are interested in the second model of DSA: the concurrent spectrum access model, where the secondary user will compete to share the same primary spectrum with the primary user.

The access to the radio spectrum is under the regulation of government agencies, such as the Federal Communications Commission (FCC) in the United States (US) and Electronic Communications Committee (ECC) in Europe, which have announced rules on the transmission power to limit the interference to an acceptable level for the purpose of protecting the PU service [12] - [13]. FCC adopts a minimum distance between SU and PU service area to guarantee that secondary users do not exceed an interference margin. ECC's restriction requires that the SU adapts its transmission power in order to not violate the interference margin (is known as interference temperature). In this manner, interference control is critical and secondary systems have to determine their optimal transmission power [14]-[19].

In this paper, we propose channel allocation algorithm. In which, we consider a general wireless network specification, and we control the spectrum access by secondary users in order to guarantee the protection of the primary users from harmful interference. Therefore, to realize an optimal concurrent spectrum access and to protect the PU services, the genetic algorithm is used to maximize power efficiency of each network users by choosing optimal power, optimal speed, and optimal amount of information.

The rest of this paper is organized as follows. We introduce the proposed system model wireless networks in section 2. Section 3 describes our proposed genetic algorithm model for channel utilization. Section 4 presents the system simulation and evaluates the obtained results of the proposed work. Finally, Section 5 concludes the paper.

## 2. System Model

Our proposed system covers many scenarios, it can be used to model: a cognitive radio system in which the two senders are PU and SU, a multicellular system, a device-to-device system (Fig 1).

Each sender aims to choose the optimal power, optimal speed and optimal amount of information. The transmitted information by each sender is divided into packets. There are M bits per packet. When a sender "i" transmits information, the signal that carries this information is distorted by the medium noise and by the signals of the other senders "j". Therefore, the Information can be delivered with errors because of the existence of noise and interference.

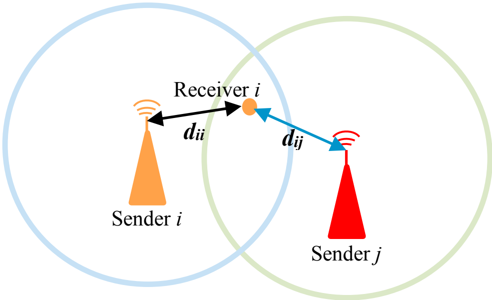


Figure 1. pairs interactions.

Senders are interested in data exchange with their associated receivers by a good quality of services (QoS). In practice, successful reception of a signal depends on the important characteristic of the sender, which is the Signal-to-Interference-plus-Noise Ratio (SINR). Inspired by [20] the SINR model for sender i is modeled as follows:

$$\boldsymbol{\gamma_i(\rho) = \frac{\rho_i G_{ii}}{N_c + \sum_{j \# i} I_{\{d_{ij}<d\}} \rho_j G_{ij}}} \qquad (1)$$

$\rho_i$ the power to noise ratio is denoted: $\rho_i = \frac{p_i}{n_0}$

$p_i$ : the transmit power of the sender i, measured in Watt, [W].

$n_0$ : the power of the additive white Gaussian noise (AWGN), and assumes that all links receive the same noise power, measured in Watt [W].

$G_{ij}$ : represents the channel gain of the sender i sent to the receiver j. Its calculation formula is $G_{ij} = 1/d_{ij}^{\alpha}$.

$d_{ij}$ : the relative distance between receiver i and sender j, in meter (m) (see Figure 1).

$\alpha$ : the path-loss exponent between the (sender, receiver) pair i. varies between 2 for free space to 6 for obstructed in building propagation [21].

$I\{d_{ii} < d\}$ : is the interference function. That is, we assume that sender j interferes receiver i if the distance between them is smaller than d. Where:

$$I = \begin{cases} 1 & \text{if the condition } d_{ij} < d \text{ is satisfied} \\ 0 & \text{otherwise} \end{cases}$$

$N_c$ takes one of two values: 1 if the data rate equals to 1 Mbps (Megabits per second); 2 if the data rate equals 2 Mbps.

We fix the transmit power of sender i and j, and calculate the SINR interference level for two different value 1 Mbps and 2 Mbps (where $N_c = 1$ and $N_c = 2$ respectively), by using (2). The results are illustrated in Fig. 2.

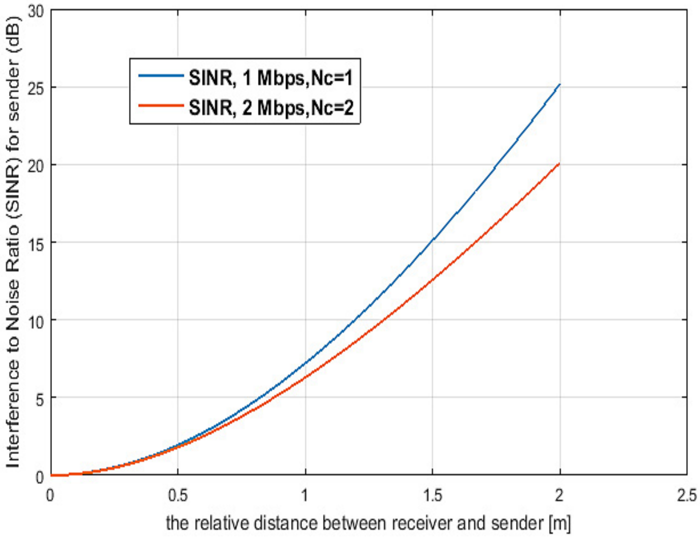

Figure 2. SINR as a function of relative distance $d_{ij}$.

From this figure we can see that the SINR increases with the distance $d_{ij}$. But the increasing of the distance does not achieve an optimal channel organization. However, achieving a high SINR level often requires the (sender, receiver) pair to transmit at a high power, which in turn results in a high-power consumption and decreases the SINR of the other pairs. Therefore, the other pairs would increase their power levels too. Senders do not want to waste power; they want to be as efficient as possible in the transmission of information. The efficiency of each sender is determined by a utility function, which is the ratio of its throughput to its transmit power.

Efficiency is measured in terms of bits that can be transmitted per joule of energy consumed. It leads to the model of efficiency described in (2), It is clear that a higher efficiency level output of the receiver will result in a lower used power and hence higher throughput.

$$u_i(p, M, R) = \frac{T_i(p, M, R)}{\mathrm{p}_i}, \qquad \left[{}^{bit}/_{Joule}\right] \qquad (1)$$

In this formula, $M = (M_1, \dots, M_n)$ is the vector containing the (sender, receiver) pair packet sizes, $R = (R_1, \dots, R_n)$ is the vector containing the (sender, receiver) pairs data rates, and $T_i(p, M, R)$ is the throughput, which is the expected number of information bits that are transmitted correctly per unit time. The throughput is modeled as follows:

$$T_i(p, M, R) = I_i(p_i, M_i, R_i) H\big(\gamma_i(p)\big), \quad [bps] \qquad (2)$$

Where, $I_i(p, M, R)$ is the average data rate for the pair i, it is measured in bits per second [bps]. The relation between the average data rate $Ii$, the data rate $Ri$, and the packet size $Mi$ is as follows:

$$I_i(p, M, R) = \frac{R_i}{1 + \frac{R_i}{M_i} t_{interval}} \qquad (3)$$

Where, $t_{interval}$ is the time needed to send two packets on the same data channel.
$H(\gamma_i(p)) = \left(1 - e^{-\gamma_i(p)}\right)^{M_i}$ is the probability that the packet is sent without an error.

In Table 1, we provide the values of the two data rates and the values of the three packet sizes that are used in our applications. The throughput function takes one of four shapes depending on the combinations of the data rate and the packet size.

Table 1. The used values of the data rates and the values of the three packet sizes

| Data Rate ($R_i$) | Packet size ($M_i$) |
|---|---|
| 1 Mbps | 100 bytes |
| | 255 bytes |
| 2 Mbps | 100 bytes |
| | 255 bytes |

In Figure 3, we plot the shapes of the throughput function with respect to the dimensionless power $\boldsymbol{\rho}$ on a dB scale. The used network consists of two (sender, receiver) pairs with $\alpha = 1$, $\boldsymbol{d_{ii} = 0.2}$, $\boldsymbol{d_{ij} = 3}$. Figure 3 shows the highest throughput that can be achieved by each (data rate, packet size) combination.

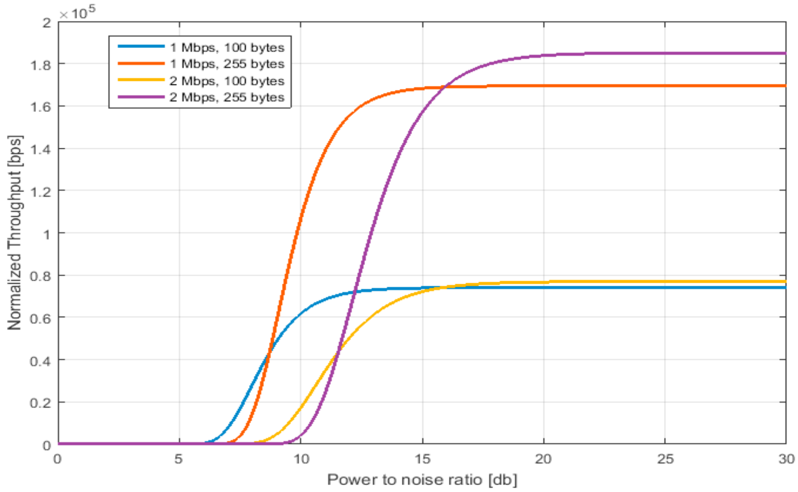


Figure 3. Throughput as a function of power to noise ratio.

We normalize the efficiency function in the same manner as in [20]. We divide the efficiency function $u_i(p_i)$ by the maximum average data rate $Imax$ and multiply by the noise $N$. Thus, the normalized utility function is expressed as follows:

$$\tilde{u}(\rho, M, R) = \frac{I_i(M_i, R_i) \,.\, \left(1 - e^{-\gamma_i(p)}\right)^{M_i}}{I_{max} \cdot \rho_i} \qquad (4)$$

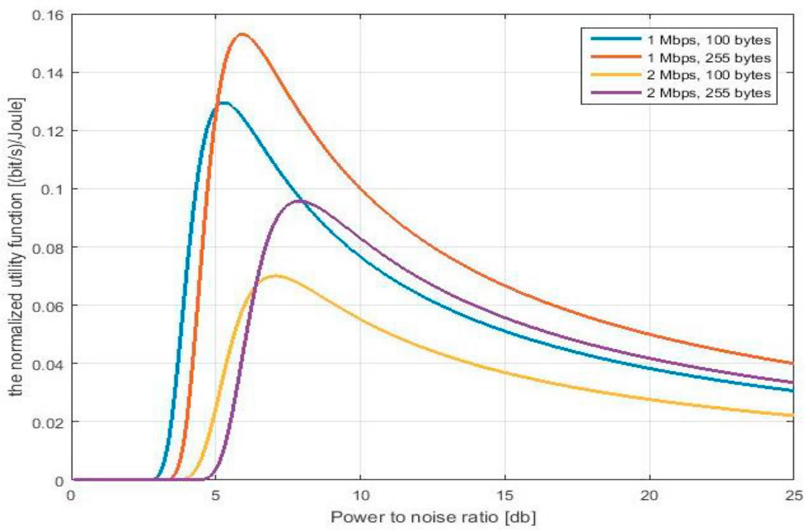


Figure 4. Normalized efficiency function.

Similarly, to the throughput function, the normalized efficiency function has four shapes shown in Figure 4. The main objectives are to find the optimal power, optimal data rate and optimal packet size such that the efficiency function is maximized [22]-[24].

## 3. Spectrum Allocation and Power Control Based on Genetic Algorithm

In this section, we first introduce genetic algorithm. Then we present the details of how we implement and apply the GA to the interference and power control problems.

### *3.1. Genetic Algorithm*

A genetic algorithm is a classic algorithm, which is a biologically inspired heuristic (inspired by the evolution of populations from natural genetics) search technique that solves a highly complex computational problem by finding optimal solutions. An initial population of individual solutions can be combined to make fitter solutions. At each step, the GA uses three main types of rules to create the next generation from the current population: selection rules, crossover rules, and mutation rules.

In this section, we first discuss the background of GA and then the implementation of the proposed solution model on the channel allocation in CR.

The mixture of selected chromosomes from the population is carried out by crossover and mutation function. The genetic algorithm procedure applied in our work is shown in figure 5.

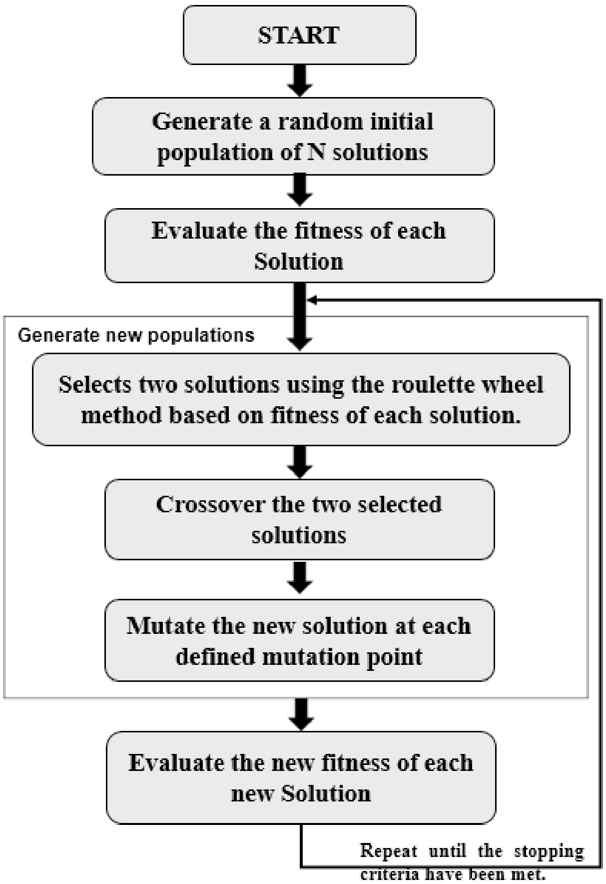


Figure 5. Genetic Algorithm

### *3.2. Chromosome Structure*

The three parameters to be are arranged in the Chromosome in the following order: 1) the data rate 2) the packet size and 3) the used power. However, mutation process requires the binary form of any value encoding adopted. Table 2 shows the configuration of the chromosome in decimal and the number of bits used for the binary representation of each of the genes.

Table 2. The proposed chromosome configurations.

| Gene | Decimal Values | Number of Bits |
|---|---|---|
| Packet size *Mi* | [60 120 180 255] | 2 bits (00 01 10 11) |
| Data rate *Ri* | [1 2] | 1 bit (0 1) |
| The power to noise ratio *(SNR)* | [2 : 2 : 32] | 4 bits (0000 … 1111) |

### *3.3. Fitness Function*

According to the power and interference control optimization described above, we define the fitness function as $\tilde{\boldsymbol{u}}(\boldsymbol{\rho}, \boldsymbol{M}, \boldsymbol{R})$ Eq. (5).

## 4. Simulation and Results

In this paper, we use the MATLAB software to simulate our proposed algorithm to obtain the simulation results. And, we consider just two players (N=2), we use $M = \{30,100,180,255\}$ as a number of bits per packet (in bytes), $R = \{1,2\}$ as a data rate (in Mbps), we choose $2 \leq \alpha \leq 4$, and we use the power to noise ratio interval $\rho_i = [0,25]$ (in dB). For genetic algorithm, the population size is set to 50. The crossover rate and the mutation rate are set to 0.60 and 0.001, respectively.

The average data rate $I_i(p, M, R)$ can takes one of eight shapes depending on the combinations of the data rate *R* and the packet size $M$. Using (4) and $t_{interval} = 1ms$, we obtain the following values (Table 3).

Table 3. The used average data rate $I_i(p, M, R)$ values

| data rate *R* $(bps)$ | packet size *M* *(bits)* | The average data rate *I* *(*$10^6$*bps)* |
|---|---|---|
| $10^6$ | $30 \times 8$ | 0.1935 |
| $10^6$ | $100 \times 8$ | 0.4444 |
| $10^6$ | $180 \times 8$ | 0.5902 |
| $10^6$ | $255 \times 8$ | 0.6711 |
| $2.10^6$ | $30 \times 8$ | 0.2143 |
| $2.10^6$ | $100 \times 8$ | 0.5714 |
| $2.10^6$ | $180 \times 8$ | 0.8372 |
| $2.10^6$ | $255 \times 8$ | 1.0099 |

From the above table, we can conclude that the maximum obtained value of the average data rate is $I_{max}$ =1,0099.$10^6$bps.

After the initialization of the all parameters, in the next step, we study the effect of the distance between the pairs $d_{ij}$, the distance between (sender, receiver) pair $d_{ii}$ and finally the path-loss exponent $\alpha$ on the obtained results of: Fitness, the used power, the throughput and the SINR values.

### *4.1. Effect of the distance between the pairs*

We fix the distance between the (sender, receiver) pair at $d_{ii} = 0.4m$, the path-loss exponent at $\alpha = 2$, and we vary the distance between the pairs $d_{ij}$. The following figures (Figures 6, 7, 8 and 9) illustrate the effect of the distance $d_{ij}$ on the optimal Fitness, the optimal used power, the optimal throughput and the optimal SINR.

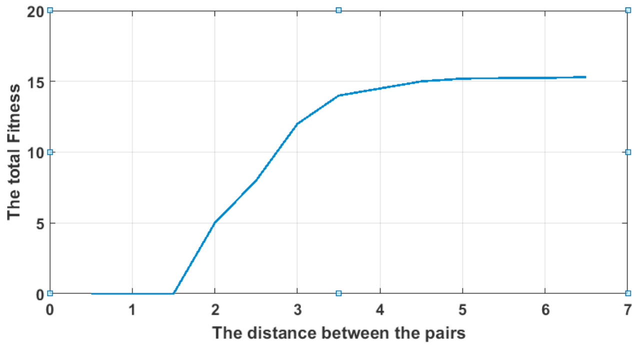


Figure 6. The effect of distance between pairs on the total Fitness

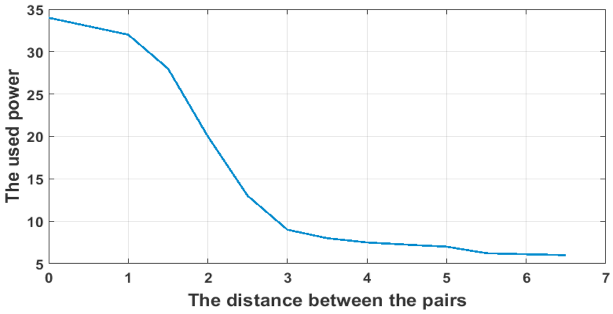


Figure 7. The effect of distance between pairs on the used power


Figure 8. The effect of distance between pairs on the Throughput

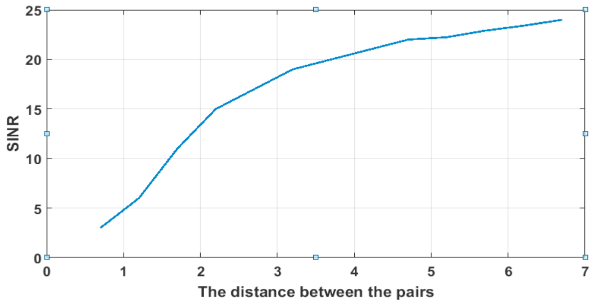


Figure 9. The effect of distance between pairs on SINR value

*4.2. Effect of the distance between (sender, receiver) pair:*

In this case we fix the distance between the users at $d_{ij} = 3\text{m}$ and the path-loss exponent at $\alpha = 2$, we change the distance between pair $d_{ii}$. The following Figures 10, 11, 12 and 13 illustrate the obtained results. As we can see from these results, the effect of the path-loss exponent on GA results is similar to the effect of distance between pairs.

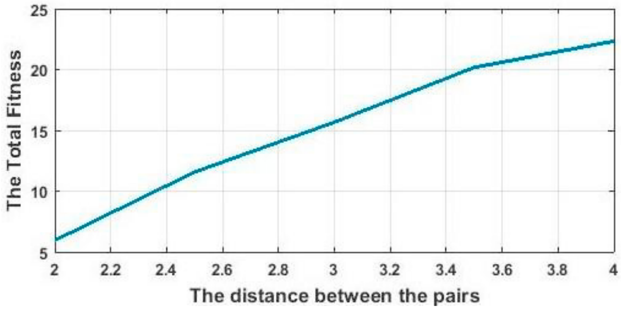


Figure 10. The effect of distance between pairs on the total Fitness

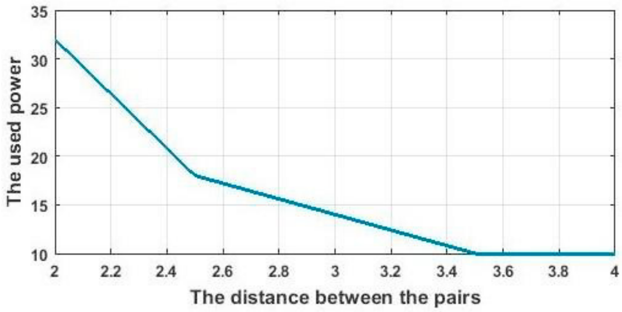


Figure 11. The effect of distance between pairs on the used power

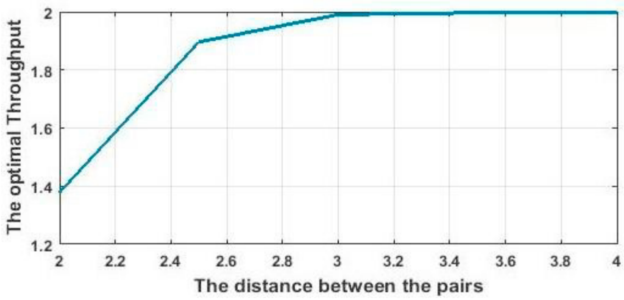


Figure 12. The effect of distance between pairs on the Throughput

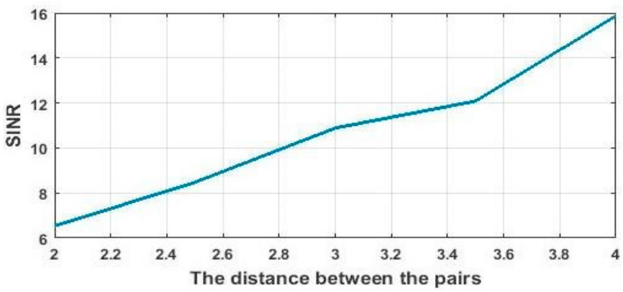


Figure 13. The effect of distance between pairs on SINR value

## 5. Conclusion

The spectrum utilization and power control are two of the main tasks in resource allocation in cognitive radio networks. The optimization of these two tasks is a great challenge to improve the global spectral efficiency. In this paper, a genetic algorithm was developed and used to find good solutions to the problem of interference and power consumption in a wireless network. Considering the optimal: throughput, the optimal power to noise ratio, the optimal distances between the pairs, and the (receiver sender) distance that maximize the efficiency function. We have proposed a genetic algorithm to solve the problem of interference and power consumption in wireless network.

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