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# Analytical and Learning-Based Spectrum Sensing Time Optimization in Cognitive Radio Systems

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## Abstract

In this paper, the average throughput maximization of a secondary user by optimizing its spectrum sensing time is formulated, assuming that a prior knowledge of the presence and absence probabilities of the primary users is available. The energy consumed to find a transmission opportunity is evaluated, and a discussion on the impacts of the number of the primary users on the secondary user throughput and consumed energy are presented. In order to avoid the challenges associated with the analytical method, as a second solution, a systematic adaptive neural network-based sensing time optimization approach is also proposed. The proposed scheme is able to find the optimum value of the channel sensing time without any prior knowledge or assumption about the wireless environment. The structure, performance, and cooperation of the artificial neural networks used in the proposed method are explained in detail, and a set of illustrative simulation results is presented to validate the analytical results as well as the performance of the proposed learning-based optimization scheme.

## Index Terms

Cognitive radio, spectrum handover, artificial neural networks, maximum secondary user's throughput.

## I. INTRODUCTION

**I**NTENSE public interest in new wireless technologies has motivated communication system designers and policy makers worldwide to revolutionize traditional inefficient spectrum management mechanisms and develop advanced flexible scenarios for better spectrum utilization, see [1]. These efforts have revealed that the old strategy of giving the exclusive right of using particular spectrum bands to

some specific users (licensees) makes this valuable resource to be severely under-utilized. Fortunately, the concept of cognitive radio (CR) has emerged to mitigate this issue. In fact, CRs are intended to find transmission opportunities in wireless environment while no particular spectrum has been assigned to them. In order to protect primary users (PUs) from harmful interference, CRs have to be capable of sensing the radio spectrum, learning, and adapting to the wireless environment [2].

Spectrum sensing schemes are of major importance in designing superior CR systems. The average throughput of the secondary users (SUs), their consumed energy, and the amount of interference experienced by PUs are directly related to the effectiveness of the sensing schemes incorporated in CRs. Slotted CRs usually divide their time-slots into two parts; one for sensing and the other for data transmission [3], [4]. Sensing time refers to the portion of time-slots used for sensing the radio spectrum. Generally speaking, increasing the sensing time leads to higher sensing accuracy but decreases the average CR throughput [4], [5]. Hence, it is certainly a challenge to find an optimal value for the spectrum sensing time to have the maximum possible throughput while protecting PUs from harmful interference [3]. On the other hand, due to the dynamic behavior of the PUs, the number and location of the temporarily-available transmission opportunities in the radio spectrum change occasionally. This behavior is modeled as spectrum mobility and when it is taken into account, the aforementioned sensing time optimization problem becomes even more challenging. Since the distribution of white spaces changes due to spectrum mobility, CRs have to handoff spectrums in order to maintain a predefined quality-of-service (QoS) level. In other words, the secondary user (SU) must leave its current spectrum and continue its transmission on another spectrum when the corresponding PU arrives. This process is called spectrum hand-over or simply hand-over (HO).

In recent years, throughput maximization through optimizing spectrum sensing time has gained a lot of interest. In [5], the impact of spectrum sensing time on the overall throughput of an SU is investigated, and the optimum value of the sensing time has been found numerically. In [6], two distributed Q-learning algorithms have been proposed to determine the optimum value of the sensing time. Joint optimizations of sensing time and decision threshold have been addressed in [7] for wideband OFDM-based CRNs.

However, none of these works has considered the effect of spectrum mobility and consequent HOs in their utilized CR system models. In [8]–[10], the problem of sequential channel sensing for an SU has been evaluated. Sequential channel sensing means the SU starts sensing the channels from top of a list (called sensing sequence), and if the considered channel is sensed as occupied, the SU senses the next one and this process is continued until an idle spectrum is found. Based on this assumption, an optimization problem is formulated in [8] in order to minimize the average sensing time. The false detection and spectrum handover effects on the sensing time have been investigated in [8]; however the adverse effect of the handover (the sensing time effect) on the SU throughput has not been considered. The impact of sensing time on the average achievable throughput in sequential sensing scheme has been partially studied in [9], [10].

In this paper, two independent solutions are proposed for this problem. In the first proposed method, spectrum sensing time optimization of a CR system is investigated analytically. Specifically, the throughput of a SU is clearly formulated in terms of the sensing time when the spectrum mobility and consequent HOs are taken into account. Moreover, the energy cost of HOs is considered in the proposed modeling in order to address the energy-throughput tradeoff encountered in designing portable and/or green CR systems. In other words, the tradeoff between the maximum achievable throughput and the sensing energy consumption is explained and a design parameter is introduced to modify the optimization problem to address the consumed energy.

The optimum value of the sensing time derived through conventional analytical optimization procedures depends directly on the models adopted for the channel, the users' traffic, and the PUs' behavior. Despite the increased analytical complexity associated by using more complete modelings, these models are not necessarily consistent with the actual environments in which the CRs work; and therefore the derived values cannot be considered as the perfect optimum ones. Moreover, if any changes occur in the parameters describing the wireless environment and traffic conditions experienced by the SUs, it is required to estimate the new parameters, repeat the analysis, and recalculate the optimum values of the sensing time. In order to deal with these issues appropriately, we propose a second method which is based on systematic

configuration of two kinds of well-known artificial neural networks. Specifically, a multilayer feed-forward (MFF) neural network [11] is used to replace the mathematical modeling, which learns the actual behavior of the secondary link, i.e., the effect of the spectrum sensing time on the average throughput of the SU. Based on the actual (non-analytical) model of the link which is learned by the MFF network, a Kennedy-Chua (KC) neural network [12] is used to find the optimum value of the spectrum sensing time. This learning-based optimization scheme has several advantages over the analytical method. First, no prior knowledge about the link behavior, such as the presence or absence probabilities of primary users are required. Second, the limited consistency of the mathematical models with the real wireless environment does not affect the optimality of the derived spectrum sensing time. Third, using this learning-based optimization scheme, an adaptive system is proposed which is capable of effectively following the variations in the link and keeping the average throughput at the maximum level in non-stationary conditions.

**The main reason for selecting the MFF and the KC networks in our proposed scheme is that these networks can efficiently learn unknown mappings and optimize general nonlinear programming problems. More specifically, Hornik *et al.* have showed that an MFF neural network with as few as a single hidden layer and an appropriately smooth hidden layer activation function is capable of providing arbitrarily accurate approximation of almost any given function and its derivatives [13], [14], which enables the proposed scheme to learn the effect of the spectrum sensing time on the average throughput of the SU. On the other hand, the Kennedy-Chua neural network, which is an advanced version of the classical Hopfield neural network [15], is capable of effectively solving general nonlinear programming problems in a very short period of time, without any need of computationally demanding iterative procedures [12]. This neural network is entirely made of simple electronic devices such as capacitors, resistors, and operational amplifiers, and is also suitable for the implementation in a very large scale integration (VLSI) technology [16]. Furthermore, the stability of its solution is analytically guaranteed [12]. Due to these benefits, it has been widely used in high-performance low-complexity adaptive communication systems, see [16]–[18] and references**

**therein.**

The rest of this paper is organized as follows. In Section II, we describe the considered CR system model and derive the related optimization problem. In Section III, the utilized neural networks as well as the proposed learning-based sensing time optimization scheme are introduced. Numerical results are then presented in Section IV, followed by concluding remarks in Section V.

## II. SYSTEM MODEL AND THE RELATED OPTIMIZATION PROBLEM

### A. System Model

We assume a primary network with  $N_p$  users, each of them with a dedicated channel, and also a single secondary user. The SU utilizes narrow-band spectrum sensing, i.e., it senses only one spectrum (out of  $N_p$  spectrums) at a time. Hence, the maximum possible transmission opportunities obtained after each sensing phase is one. We assume that the SU always has packets to transmit, i.e., the SU starts its transmission when an opportunity is found. The SU senses the channels in an order determined by its sensing sequence. If the sensed channel is busy, the SU reconfigures its sensing circuitry in order to sense the next spectrum indicated in its sensing sequence. Assume that it takes a constant time  $\tau_{ho}$  for the SU to do a HO.  $\tau_{ho}$  does not depend on the amount of frequency shift required by the reconfiguration. The state of channel  $k$  is denoted by  $s_k$ ,

$$s_k = \begin{cases} 1 & : \text{ if channel } k \text{ is occupied , or } \mathcal{H}_1 \\ 0 & : \text{ if channel } k \text{ is idle , or } \mathcal{H}_0 \end{cases} \quad (1)$$

where  $\mathcal{H}_0$  and  $\mathcal{H}_1$  represent the absence and presence hypotheses of the  $k$ -th PU, respectively. Spectrum sensing can be formulated as a binary hypothesis testing problem [5],

$$\begin{cases} \mathcal{H}_0 & : y(n) = z(n) & : \text{ channel is idle} \\ \mathcal{H}_1 & : y(n) = u(n) + z(n) & : \text{ channel is occupied} \end{cases} \quad (2)$$

where  $z(n)$ s denote samples of zero mean complex-valued Gaussian noise with independent and identical distributions (i.i.d),  $u(n)$  denotes the PUs signal which is independent of  $z(n)$ , and  $y(n)$  is the  $n$ -th sample of the received signal.

We consider energy detector (ED) method for the PU detection in which the energy of the received signal is computed during a sensing time  $\tau$ , and then the result is compared with a predefined threshold to make the decision [3]. Let  $N$  denote the number of samples of the received signal, i.e.,  $N = \tau f_s$ , where  $\tau$  is the sensing time and  $f_s$  is the sampling frequency. By defining  $X$  as a decision metric for the ED scheme, we have,

$$X = \sum_{n=1}^N |y(n)|^2 \quad (3)$$

Let  $\lambda$  denote the threshold of the ED decision rule. Then,

$$\begin{cases} X < \lambda \equiv \mathcal{H}_0 \\ X \geq \lambda \equiv \mathcal{H}_1 \end{cases} \quad (4)$$

If  $N$  is large enough,  $X$  can be described by a Gaussian distribution [5]. Assume that  $P_{fa}$ ,  $P_d$ , and  $P_d^{min}$  denote the false alarm probability, detection probability, and minimum allowable detection probability (i.e., we must have  $P_d \geq P_d^{min}$ ), respectively. Then [5]:

$$P_{fa} = Q \left[ \left( \frac{\lambda}{\sigma_u^2} - 1 \right) \sqrt{\tau f_s} \right], \quad (5)$$

$$P_d = Q \left[ \left( \frac{\lambda}{\sigma_u^2} - 1 - \gamma \right) \sqrt{\frac{\tau f_s}{1 + 2\gamma}} \right] \quad (6)$$

where  $\sigma_u^2$  is the received energy of the PU signal and  $\sigma_z^2$  is the noise variance. The received signal to noise ratio due to the PU activity is  $\gamma = \frac{\sigma_u^2}{\sigma_z^2}$ .

Taking (5) and (6) into account, for  $P_d = P_d^{min}$  we have,

$$P_{fa} = Q \left[ \beta + \gamma \sqrt{\tau f_s} \right] \quad (7)$$

where  $\beta = Q^{-1}(P_d^{min}) \sqrt{1 + 2\gamma}$ .

### B. Sensing Time Optimization Problem

We consider a sequential HO method [8] as described in the introduction. Based on the energy detection scheme assumed, the  $i$ -th channel is sensed as occupied with probability,

$$\begin{aligned} q_i &= \Pr \{ED_i = 1 | s_i = 0\} P_{i,0} + \Pr \{ED_i = 1 | s_i = 1\} P_{i,1} \\ &= P_{fa} P_{i,0} + P_d P_{i,1}, \end{aligned} \quad (8)$$

where  $ED_i$  is the output of the ED due to sensing the  $i$ -th channel.  $ED_i = 1$  means that the CR has detected a PU on the  $i$ -th channel whereas  $ED_i = 0$  means that no PU has been detected.  $P_{i,0}$  and  $P_{i,1}$  are the absence and presence probabilities of the  $i$ -th PU, respectively.

Let  $\alpha$  denote the maximum number of allowed HOs.  $\alpha$  is limited by two constraints. First, the number of sensed channels which cannot exceed the number of the PUs. Second, the elapsed time for both sensing and HO procedures that cannot exceed the time slot duration,  $T$ . Therefore,

$$\alpha = \min \left( \left\lfloor \frac{T - \tau}{\tau + \tau_{ho}} \right\rfloor, N_P - 1 \right) \quad (9)$$

Using the sequential spectrum sensing scheme, the SU transmits on channel  $i$  when  $i - 1$  consecutive handoff events occur, i.e., when  $ED_k = 1$  for all  $k < i$  and  $ED_i = 0$ . Clearly, due to possible sensing errors, the SU might mistakenly decide to transmit on a channel which has already been occupied by a PU. Therefore, two maximum throughput levels are expected for a SU depending on the presence or absence of a PU on the adopted channel. We denote these two maximum throughput levels by  $C_1$  and  $C_0$  for the occupied and free channels, respectively. Using these definitions, the contribution of the  $i$ -th channel on the overall maximum achievable throughput of the SU can be expressed as,

$$\begin{aligned} \bar{R}_i = & C_0 T_i \Pr \{ ED_i = 0 \text{ and } ED_k = 1 \text{ for } k < i \text{ and } s_i = 0 \} + \\ & C_1 T_i \Pr \{ ED_i = 0 \text{ and } ED_k = 1 \text{ for } k < i \text{ and } s_i = 1 \} \end{aligned} \quad (10)$$

where  $C_0 = \log_2(1 + \gamma_s)$  and  $C_1 = \log_2\left(1 + \frac{P_s}{N_0 + P_p}\right) = \log_2\left(1 + \frac{\gamma_s}{1 + \gamma_p}\right)$  respectively are the SU's capacities under the hypotheses  $\mathcal{H}_0$  and  $\mathcal{H}_1$ .  $\gamma_s$  and  $\gamma_p$  are the received SNRs due to the secondary and primary users' signals at the SU receiver, respectively.  $T_i$  is the fraction of time-slots remained for data transmission after sensing  $i - 1$  channels occupied and is calculated as,

$$T_i = T - \tau - (i - 1)(\tau + \tau_{ho}) \quad \text{for } i = 1, 2, \dots, N_p \quad (11)$$

While the random variables  $ED_i, i = 1, 2, \dots, N_p$ , are mutually independent, each pair  $ED_i$  and  $s_i$  (the state of channel  $i$ ) are related to each other based on the incorporated spectrum sensing algorithm

which is characterized by  $P_{fa}$  and  $P_d$ . Hence, (10) can be restated as,

$$\begin{aligned}\bar{R}_i &= (C_0 T_i \Pr\{ED_i = 0 \text{ and } s_i = 0\} + C_1 T_i \Pr\{ED_i = 0 \text{ and } s_i = 1\}) \prod_{k=1}^{i-1} \Pr\{ED_k = 1\} \\ &= (C_0 T_i \Pr\{ED_i = 0 | s_i = 0\} + C_1 T_i \Pr\{ED_i = 0 | s_i = 1\}) \prod_{k=1}^{i-1} \Pr\{ED_k = 1\} \\ &= (C_0 T_i (1 - P_{fa}) P_{i,0} + C_1 T_i (1 - P_d) P_{i,1}) \prod_{k=1}^{i-1} q_k\end{aligned}\quad (12)$$

where  $q_i$ ,  $P_{i,0}$ , and  $P_{i,1}$  are as defined in (8). Finally, the aggregate maximum achievable throughput of the SU is derived by summing over all  $\bar{R}_i$ , i.e., for  $i = 1, 2, \dots, \alpha$ . Hence, the following proposition has been proved.

*Proposition 1:* The overall average throughput of a CR system which incorporates the energy detection and sequential spectrum sensing schemes to find transmission opportunities among  $N_p$  primary channels is,

$$R = \sum_{i=0}^{\alpha} q_0 q_1 \cdots q_i (C_1 P_{i+1,1} (1 - P_d) + C_0 P_{i+1,0} (1 - P_{fa})) \left(1 - \frac{\tau + i(\tau + \tau_{ho})}{T}\right) \quad (13)$$

where  $q_0 \triangleq 1$ . ■

Considering (13), the optimum throughput can be obtained by solving the following optimization problem  $P1$ :

$$P1 : \quad \max_{\tau, \lambda} \quad R$$

$$s.t. \quad \begin{cases} P_{fa} \leq P_{fa}^{\max} \\ P_d \geq P_d^{\min} \\ 0 < \tau < T \end{cases} \quad (14)$$

The derived optimization problem cannot be simplified to a one-dimensional one, as [5], without any preassumptions on  $P_{fa}$  or  $P_d$ . However, we can convert our two-dimensional optimization problem to a one-dimensional one by using an acceptable value for the detection probability imposed by standards like *IEEE 802.22*. Supposing  $P_d = P_d^{\min}$ , the optimization problem is converted to:

$$P2 : \quad \max_{\tau, \lambda} \quad R$$

$$s.t. \quad \begin{cases} P_{fa} \leq P_{fa}^{\max} \\ P_d = P_d^{\min} \\ 0 < \tau < T \end{cases} \quad (15)$$

Note that, under the assumption  $P_d = P_d^{\min}$  and using (6),  $\lambda$  can be expressed in terms of  $\tau$  and as a result, the throughput of the SU derived in (13) only depends on  $\tau$ . Moreover, based on the first constraint of (15) and from (7), we have  $Q[\beta + \gamma\sqrt{\tau f_s}] \leq P_{fa}^{\max}$  which in turn leads to  $\tau \geq \frac{1}{f_s} \left( \frac{Q^{-1}(P_{fa}^{\max}) - \beta}{\gamma} \right)^2$ .

Therefore,  $P2$  can be simplified as,

$$P3 : \max_{\tau} R \quad (16)$$

$$s.t. \quad \tau_{\min} < \tau < T$$

$$\text{where } \tau_{\min} = \frac{1}{f_s} \left( \frac{Q^{-1}(P_{fa}^{\max}) - \beta}{\gamma} \right)^2.$$

### C. Energy-Throughput Tradeoff

Recall that as defined in (8),  $q_i$  denotes the probability that the channel  $i$  is sensed busy. Thus, the probability of occurring just one HO in the system equals to  $q_1(1 - q_2)$ . In the same way, the probability of performing exactly two HOs by the system equals to  $q_1q_2(1 - q_3)$  and so on. In other words, for the sequential handover method described, the probability of having  $i$  consecutive handovers and transmitting on the  $(i + 1)$ -th channel is equal to  $(1 - q_{i+1}) \prod_{k=1}^i q_k$ . Hence, if we denote the average number of HOs required for finding a free transmission opportunity by  $\bar{g}$ , we have,

$$\bar{g} = q_1(1 - q_2) + 2q_1q_2(1 - q_3) + \dots + (\alpha - 1)(1 - q_\alpha) \prod_{j=1}^{\alpha-1} q_j + \alpha \prod_{j=1}^{\alpha} q_j \quad (17)$$

where  $\alpha$  is defined in (9). Clearly, the average number of sensed channels equals to  $1 + \bar{g}$ .

Assume that  $E_c(\tau)$  and  $E_c(\tau_{ho})$  denote the consumed energies for sensing of each primary channel and for each HO, respectively. Hence, the average consumed energy for finding a transmission opportunity is computed,

$$E = (1 + \bar{g}) E_c(\tau) + \bar{g} E_c(\tau_{ho}) \quad (18)$$

The processes of channel sensing and signal transmission consume more energy compared with the HO [19]. Therefore, it is reasonable to ignore the second term  $\bar{g} E_c(\tau_{ho})$  in (18) compared with the first one.

When the number of PUs increases,  $\alpha$  in (9) increases, and thus  $R$  and  $(1 + \bar{g})$  in (13) and (17) raise, consequently. Therefore, increasing the number of PUs increases both the maximum achievable throughput

and the number of sensed channels (equivalently the consumed energy). But, among these two metrics, the consumed energy increases more rapidly than the maximum throughput. To illustrate this phenomenon, in the following we consider a numerical example.

Fig. 1 shows the plot of the normalized energy consumed for finding a transmission opportunity (i.e.,  $\frac{E}{E_c}$  which is equal to the number of sensed channels) versus the maximum achievable throughput assuming  $P_{fa}^{\max} = 0.1$ ,  $P_d^{\min} = 0.9$ ,  $T = 100$  ms,  $\tau_{ho} = 0.1$  ms, and  $f_s = 6$  MHz. Simulation setup procedure is described in Section IV. As illustrated, for high throughput values, increasing the consumed energy cannot improve the data rate significantly. In fact, since increasing the number of HOs reduces the time duration left for the transmission, the achievable data rate is not substantially improved. For instance, for  $N_p = 4$  with the average number of sensed channels equal to 1.8757, the maximum data rate is 0.8544, while for  $N_p = 15$  with the average sensed channels of 3.398, the maximum data rate is 0.8809. As a result, increasing the average number of sensed channels by 81% only leads to near 3% increase in the maximum data rate. Therefore, at the cost of small reduction of the maximum throughput, the consumed energy can be substantially decreased. To take into account the energy consumption, in the following, we reformulate the optimization problem.

At first, we show that  $R$  in (13) does not depend on the number of the PUs for sufficiently large  $N_p$ . If we rewrite  $R$ , from (13) we have,

$$R(\tau, \lambda, N_P) = \sum_{m=0}^{\alpha(\tau, N_P)} A_m(\tau, \lambda) B_m(\tau, \lambda) \quad (19)$$

$$\text{where } \begin{cases} A_m(\tau, \lambda) = C_1 P_{m+1,1} (1 - P_d) + C_0 P_{m+1,0} (1 - P_{fa}) \\ B_m(\tau, \lambda) = q_0 q_1 \cdots q_m \left( 1 - \frac{\tau + m(\tau + \tau_{ho})}{T} \right) \\ \alpha(\tau, N_P) = \min \left( \left\lfloor \frac{T - \tau}{\tau + \tau_{ho}} \right\rfloor, N_P - 1 \right) \end{cases}$$

$R(\tau, \lambda, N_P)$  is the throughput as a function of  $\tau$ ,  $\lambda$ , and  $N_p$ . Considering the constraint of derived optimization problem imposed by sensing time, i.e.,  $\tau_{min} < \tau < T$ , if  $N_p \geq \left\lfloor \frac{T - \tau_{min}}{\tau_{min} + \tau_{ho}} \right\rfloor + 1$ , we have,

$$\alpha(\tau, N_P) = \left\lfloor \frac{T - \tau}{\tau + \tau_{ho}} \right\rfloor = \alpha(\tau) \quad (20)$$

so

$$R(\tau, \lambda, N_p)_{|N_p \geq \lfloor \frac{T - \tau_{min}}{\tau_{min} + \tau_{ho}} \rfloor + 1} = R(\tau, \lambda) \quad (21)$$

If we indicate the maximum achievable throughput of the SU by  $L$ , from (21) we have,

$$L = \max_{\tau} R\left(\tau, \lambda, N_P = \left\lfloor \frac{T - \tau_{min}}{\tau_{min} + \tau_{ho}} \right\rfloor + 1\right) = R(\tau, \lambda) \quad (22)$$

*s.t.*  $\tau_{min} < \tau < T$

To take into account the energy consumption, we define

$$\tau_{opt} = \arg \max_{\tau} R\left(\tau, \lambda, N_P = \left\lfloor \frac{T - \tau_{min}}{\tau_{min} + \tau_{ho}} \right\rfloor + 1\right) \quad (23)$$

*s.t.*  $\tau_{min} < \tau < T$

and the corresponding optimum number of HO is:

$$\alpha_{opt} = \alpha|_{\tau=\tau_{opt}} \quad (24)$$

As stated above, at the throughput close to the maximum achievable one, i.e.,  $L$ , defined in (22), by a small reduction of the throughput, the average energy consumption is substantially reduced. Now, let us define  $TF$  ( $0 \leq TF \leq 1$ ) as a Tradeoff Factor indicating the amount of the throughput reduction considered. That is the target throughput is set as  $R_{TF} = TF \times L$ . Then, from (22), the maximum number of HOs  $\bar{\alpha}$  ( $\bar{\alpha} \leq \alpha_{opt}$ ) considering the energy consumption concern (reflected in the parameter  $TF$ ) is obtained by solving the following equation:

$$TF = \frac{\sum_{m=0}^{\bar{\alpha}} A_m(\tau, \lambda) B_m(\tau, \lambda)}{L} \quad (25)$$

That is from (22),  $L$  is calculated and by choosing a value for  $TF$ ,  $\bar{\alpha}$  is obtained from (25). Finally a new optimization problem considering the consumed energy is formulated as:

$$\max_{\tau} R_{TF} = \sum_{m=0}^{\bar{\alpha}} \left( (C_1 P_{m+1,1} (1 - P_d) + C_0 P_{m+1,0} (1 - P_{fa})) \times \right. \\ \left. q_0 q_1 \cdots q_m \left( 1 - \frac{\tau + m(\tau + \tau_{ho})}{T} \right) \right) \quad (26)$$

*s.t.*  $\tau_{min} < \tau < T$

This new derived optimization problem enables the SU to have control on the consumed energy and the achieved average throughput by the parameter  $TF$ .

### III. NEURAL NETWORK-BASED OPTIMIZATION SCHEME

#### A. Learning and Optimization

To recast the aforementioned optimization problem in a suitable form for the learning-based optimization scheme, first note that the proposed optimization problem can be divided into two distinct parts. First, obtaining the mappings between  $\tau$  and  $R$  described by (13). Second, from (16), finding the optimum value for  $\tau$  using the derived mapping. In the proposed learning-based optimization scheme, both of these parts are performed effectively using Kennedy-Chua (KC) and Multilayer Feed-Forward (MFF) neural networks.

To restate the spectrum sensing time optimization problem suitable for the Kennedy-Chua neural network, we define our adaptable parameter  $x$ , the cost function  $\varphi$ , and the constraint functions  $f_1$  and  $f_2$  as

$$\begin{aligned} x &\triangleq \tau \\ \varphi(x) &\triangleq 1/R(x) \\ f_1(x) &\triangleq T - x \\ f_2(x) &\triangleq x - \tau_{\min} \end{aligned} \tag{27}$$

Hence, from (16) and (27), the optimization problem can be rewritten as:

$$x^{opt} = \arg \min_x \varphi(x) \tag{28}$$

$$\text{s.t. } f_1(x) \geq 0 \tag{29}$$

$$f_2(x) \geq 0 \tag{30}$$

We collect the constraint functions and their derivatives in a matrix named  $\mathbf{F}$  and defined as:

$$\mathbf{F} = \begin{bmatrix} f_1(x) & f_2(x) \\ f_1'(x) & f_2'(x) \end{bmatrix} \tag{31}$$

**The exploited MFF network has three layers, i.e., one input layer, one hidden layer, and one output layer. There is one neuron at the input layer,  $K$  neurons at the hidden layer, and one neuron at the output layer. The proper value of  $K$  will be discussed in Section IV. The network input and**

output are  $x$  and the learned version of  $\varphi(x)$  defined in (27), respectively. There is also one extra output corresponding to the sensitivity of the cost function, i.e.,  $\partial\varphi/\partial x$ , [20].

The output of the  $i$ -th neuron at the  $l$ -th layer is described as,

$$u_i(l) = \sum_{j=1}^{N_{l-1}} w_{ij}(l)a_j(l-1) + b_i(l) \quad (32)$$

$$a_i(l) = h_l(u_i(l)), \quad 1 \leq i \leq N_l, \quad l = 1, 2 \quad (33)$$

where  $N_l$  is the number of neurons at the  $l$ -th layer; and  $u_i(l)$  and  $a_i(l)$  are the activation and output values of the  $i$ th neuron at the  $l$ -th layer.  $w_{ij}(l)$  refers to the weight connecting the output from the  $j$ -th neuron at the  $(l-1)$ -th layer to the input of the  $i$ th neuron at the  $l$ -th layer.  $b_i(l)$  refers to the bias associated with the  $i$ -th neuron at the  $l$ -th layer. The utilized transferring function  $h_l(\cdot)$  in (33) is logistic sigmoid at hidden layer ( $l=1$ ) and is hyperbolic tangent sigmoid at output layer ( $l=2$ ), i.e.,

$$h_l(x) = \begin{cases} (1 + e^{-x})^{-1}, & l = 1 \\ 2(1 + e^{-2x})^{-1} - 1, & l = 2 \end{cases} \quad (34)$$

The input unit is demonstrated by  $a_i(0)$  and the output unit by  $a_i(2)$ , so we have,

$$x = a_1(0) \quad (35)$$

$$\hat{\varphi}(x) \triangleq a_1(2)$$

where  $\hat{\varphi}$  is the learned version of the cost function. We denote the set of weights and biases by the matrix  $w$ . The MFF network can be trained to model the function  $\varphi$ , by recursively adjusting  $w_{ij}(l)$  and  $b_i(l)$  to minimize the mean-squared error (MSE) between the MFF network output  $\hat{\varphi}$  and our cost function  $\varphi$ ,

$$d = \frac{1}{2} \sum_{m=1}^M |\hat{\varphi}_m - \varphi_m|^2 \quad (36)$$

where  $M$  is the number of teacher patterns.

The first order output derivative of the MMF networks, i.e.,  $\partial a_1(2)/\partial a_1(0)$ , can be calculated by

applying a backward chaining partial differentiation rule that is described in detail in [20]:

$$\begin{aligned}
& \frac{\partial a_j(2)}{\partial a_i(0)} \\
&= \sum_{k=1}^{N_1} \frac{\partial a_j(2)}{\partial a_k(1)} \cdot a_k(1) [1 - a_k(1)] \cdot w_{ki}(1) \\
&= \sum_{k=1}^{N_1} \frac{\partial a_j(2)}{\partial u_j(2)} \cdot \frac{\partial u_j(2)}{\partial a_k(1)} \cdot a_k(1) [1 - a_k(1)] \cdot w_{ki}(1) \\
&= [1 - a_j(2)^2] \cdot \sum_{k=1}^{N_1} w_{jk}(2) \cdot a_k(1) [1 - a_k(1)] \cdot w_{ki}(1)
\end{aligned} \tag{37}$$

The KC neural network has one output voltage corresponding to the adaptable parameter  $x$ . This network calculates the optimum sensing time based on the cost function learned by the MFF network. Now, if there exist a training process to adjust the weight and bias values of the MFF network appropriately and if the learned mapping approximates the actual cost function closely, then the KC network output is equal to the optimum value of  $x$  (i.e., the sensing time).

The dynamic equation implemented by the KC neural network is [12], [21],

$$C \frac{dx}{dt} = -\frac{\partial \hat{\varphi}}{\partial x} - \sum_{j=1}^2 i_j \frac{\partial f_j}{\partial x} - Gx \tag{38}$$

where  $i_j = g_j(f_j(x))$ , and  $C$  and  $G$  are the output capacitor and the parasitic conductance of the KC network, respectively, and  $g_j(\cdot)$  is defined as [12]:

$$g_j(v) = \begin{cases} 0, & v \geq 0 \\ \frac{1}{R}v, & v \leq 0 \end{cases}, \quad R \rightarrow 0 \tag{39}$$

**The proper values for  $C$  and  $G$  will be discussed later in Section IV.**

### B. Proposed Scheme

Fig. 2 demonstrates the proposed neural network-based optimization scheme. It consists of a KC neural network cooperating with an MFF neural network in a feedback loop, a training process which calculates and updates the weight and bias values of the MFF network, and a throughput estimator (TE).

The TE estimates the SU throughput and calculates the value of  $\varphi(x)$ . This estimation can be performed by inspecting the packets and their acknowledgments (ACKs) at the secondary transmitter for a period of

time equal to  $T_{ep}$  (estimation period) [22].  $T_{ep}$ , as a design parameter, depends on the PUs activity and link behavior.

As mentioned before, the KC neural network has one output corresponding to  $x = \tau$ . It calculates the optimum value for  $\tau$  based on the cost function provided by the MFF network  $\hat{\varphi}(x)$ . Its output, even though not necessarily optimal at first, is always used by the ED as the channel sensing time. The learned mapping of the MFF network is considered as the cost function by the KC network. Specifically, this learned function, i.e.,  $\hat{\varphi}(x)$ , and its derivative are used by the KC network to establish its dynamic equation (38). Thus, the KC network output  $x$  will be sufficiently close to the optimum value provided that the function learned by the MFF network can model the link behavior sufficiently accurate, i.e.,  $\hat{\varphi}(x) \approx \varphi(x)$ . Once the KC network output  $x$  is applied to set the spectrum sensing time of the ED, the TE estimates the throughput obtained by this setting and calculates  $\varphi(x)$  within  $T_{ep}$  seconds. Then, the training process uses  $x$  as the input and the estimated  $\varphi(x)$  as the target to adjust the weight and bias values of the MFF network by the well-known backpropagation algorithm [11]. Having its weight and bias values modified, the MFF network models the link more accurately, and therefore the KC network output takes a new value closer to the optimal point  $x^{opt}$ . By iterating this learning and optimization cycle, we observe a joint convergences in the weight and bias values  $\mathbf{w}$  and more importantly in the KC network output  $x$ . That is,  $\mathbf{w}$  converges to  $\mathbf{w}^{opt}$  by which the learned mapping fits the cost function  $\varphi(x)$  appropriately and  $x$  converges to  $x^{opt}$  which denotes the optimum value for  $\tau$ , thanks to the universal approximation theorem [14].

To sum up, the proposed adaptive system works according to the following three-steps algorithm:

- Step 1) *Setting*: The KC network output  $x$  is applied to the ED to set its sensing time duration.
- Step 2) *Throughput Estimation*: The average throughput is estimated by inspecting the packets and their ACKs for  $T_{ep}$  seconds, and accordingly  $\varphi(x)$  is calculated.
- Step 3) *Training*: The KC network output  $x$  and the TE outputs  $\varphi(x)$  are used as an input-target pair to adjust the weights and biases of the MFF network, and then the process returns back to *Step 1*).

Computational complexity of the proposed system is due to the backpropagation algorithm, which its order is  $\mathcal{O}(N)$ , where  $N$  is the number of weights and biases of the MFF network [11]. For the examples considered in numerical result section, 9 hidden neurons have been enough to well model the relationship between sensing time and SU's throughput. The MFF network with 9 hidden neurons can be considered equivalently as an adaptive filter with  $N = 1 \times 9 + 1 \times 9 + 10 = 28$  weights which are being updated by the LMS algorithm.

**It is worth noting that the proposed learning-based optimization scheme adapts the sensing time of the spectrum sensing according to the variations in the statistics associated with the wireless environment. More specifically, the optimization is based on the link throughput estimated by the TE, which according to the presented analysis is directly related to the average SNR, experienced by the CR nodes (see (5)-(8) and (13)), instead of instantaneous variations of the wireless media. That is, in the proposed scheme, the weights change according to variations of a) average channel SNRs, which change far more slowly than the instantaneous values of the SNRs, and b) primary users presence probabilities, which do not change or changes slowly. Therefore, considering its considerably low update rate, even though the proposed system is designed for links with a non-stationary behavior, the computational complexity of the backpropagation algorithm, i.e.,  $\mathcal{O}(N)$ , is not very substantial in overall.**

#### IV. NUMERICAL RESULTS

**In this section, we evaluate the performance of the proposed schemes considering various parameters introduced throughout the paper. To this end, first an SU performing sequential channel sensing is simulated, and then by the implementation of the MFF and KC networks, the performance of the proposed learning-based approach is evaluated.** For numerical evaluations, the parameters are set according to Table I. The values of SNR and sampling frequency are adopted from [5], and  $P_d^{\min}$  and  $P_{fa}^{\max}$  are chosen according to *IEEE 802.22* standard [23]. In simulation evaluations, the average throughput has been computed after simulating the scenario for 100 time slots.

As stated previously, the MFF network, exploited in the learning-based scheme, has three layers with one neuron at the input layer,  $K$  neurons at the hidden layer, and one neuron at the output layer. As shown in [24], increasing the number of hidden neurons in an MFF network promotes its learning capability, and once the satisfactory performance is obtained, further increasing the number of hidden neurons does not degrade the performance. Therefore, as in [24] and [25], the value of  $K$  ( $= 9$ ) is chosen in our simulations as the minimum value which leads to a satisfactory performance (see Figs. 4-6). Moreover, to build a KC network, first, it must be noted that the values of  $C$  (capacitances) and  $G$  (conductances) do not prevent KC network outputs from the convergence to the optimum point<sup>1</sup>, provided that  $C$  is strictly positive and  $G$  is very small. In practice, those very small conductances are realized using op-amps based active elements with high input impedances [12]. In the following numerical evaluations, the values of  $C$  and  $G$  are adopted from [16].

Fig. 3 verifies our analysis and depicts the achievable data rate versus the normalized sensing time (i.e.,  $\frac{\tau}{T}$ ) for various values of  $N_p$  assuming that the presence probabilities of all the PUs are equal to 0.65. As observed, for large normalized sensing time, the plots for different values of  $N_p$  coincide. This behavior is expected due to our previous discussions on the constraints which affect the number of possible HOs for an SU. As stated previously in Section II, the number of possible HOs is dictated by two factors; namely,  $N_p$ , and the ratio  $(T - \tau) / (\tau + \tau_{ho})$ . Therefore, as  $\tau$  increases, we observe that the second factor dominates and regardless of the number of available primary channels  $N_p$ , the achieved throughput becomes limited to a value corresponding to a lower  $N_p$ . The throughput of the SU where there are 10 primary channels equals the throughput of the SU with 3 primary channels for approximately  $\tau > 1/4T$ . Other important observations can be made through Fig. 3. First, there exists an optimum value for the spectrum sensing time. Second, as the number of primary channels increases, the SU throughput increases as well, but in

<sup>1</sup>From the analyses provided in [12], it can be concluded that the values of  $C$  and  $G$  only affect the convergence speed of the KC network, which is negligible compared to the throughput estimation period and MMF training phases (see Fig. 6). Therefore, those values have no considerable effects on the performance of the proposed system.

a saturating manner. This is due to the fact that as the number of primary channels increases, though the average number of obtained transmission opportunities increases, the average time duration in which the SU transmits data reduces. Third, the importance and efficiency of having multiple handovers can be observed; the improvement in the throughput when using multiple handovers, i.e.,  $N_p \geq \left\lfloor \frac{T - \tau_{min}}{\tau_{min} + \tau_{ho}} \right\rfloor + 1$ , is about 44.5% compared with the case of  $N_p = 1$ , with no handover capability.

The effectiveness of the discussed energy-throughput tradeoff on the proposed sensing time optimization scheme is demonstrated by Table II. In this table, two design sets are presented namely *Design 1* and *Design 2*. *Design 1* is referred to the analytical optimization that does not consider the energy consumed by the SU, whereas in *Design 2*, the sensing time is optimized using the  $TF$  factor to obtain an energy-efficient sensing scheme. This table illustrates that considering energy-throughput tradeoff provides near maximum throughput for each  $N_p$  with much lower consumed energy (compared to *Design 1*). It is worth noting that the SU consumed energy can be very high when  $N_p$  is large. From Table II, the proposed energy-efficient sensing time optimization procedure reduces the consumed energy dramatically when the consumed energy concern is more serious, i.e., when the number of primary channels is large. See the 65% reduction in consumed energy for *Design 2* compared to *Design 1* at the expense of only 2% reduction in the throughput when  $N_p = 12$ .

Figs. 4 and 5 demonstrate the performance of the proposed learning-based optimization scheme. They compare the maximum normalized throughputs and the optimum sensing times of the learning-based optimization scheme and the analytical modeling. This comparison is performed for various number of primary channels, for the presence probabilities of the PUs given in Table III. Results labeled as *Analysis* depict the maximum normalized throughput and optimum sensing time obtained by the analytical modeling and results labeled as *Learning-based* are the ones obtained through the neural network-based optimization. As can be realized from Fig. 4, the average throughput values obtained by the proposed neural network-based optimization method are very close to those obtained through the the mathematical analysis. Moreover, Fig. 5 shows that optimum sensing times calculated through our learning-based optimization method are very close to the results obtained by the analysis.

Fig. 6 depicts the KC network output convergence to the optimal sensing time corresponding to secondary links with  $N_p = 3$  and  $N_p = 5$  primary channels. As shown in this figure, using the learned cost function provided by the MFF network, the KC output converges to the optimal sensing time very fast. Therefore, we observe that if the learned function well-approximates the actual link model, the KC output represents the optimal value of the sensing time.

## V. CONCLUSION

In this paper, we considered the problem of channel sensing time optimization for a secondary user which senses the primary channels sequentially. Maximizing the average throughput of the secondary user by optimizing the spectrum sensing time was formulated assuming that a prior knowledge of the presence and absence probabilities of the primary users are available. Then, the energy-throughput tradeoff of a CR system was discussed using the derived expressions. Moreover, a learning-based sensing time optimization approach was proposed using a novel and effective combination of two powerful and well-organized artificial neural networks. Finally, the validity of the analytical results as well as the capability of the proposed adaptive system in finding the optimal spectrum sensing time were demonstrated by a set of illustrative simulation results.

## REFERENCES

- [1] B. Wang and K. J. R. Liu, "Advances in cognitive radio networks: A survey," *IEEE J. Sel. Topics Signal Process.*, vol. 5, no. 1, pp. 5–23, January 2011.
- [2] A. He, K. K. Bae, T. R. Newman, J. Gaeddert, K. Kim, R. Menon, L. Morales, J. Neel, Y. Zhao, J. H. Reed, and W. H. Tranter, "A survey of artificial intelligence for cognitive radios," *IEEE Trans. on Vehicular Technology*, vol. 59, no. 4, pp. 1578–1592, May 2010.
- [3] I. F. Akyildiz, B. F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," *Physical Communication*, vol. 4, no. 1, pp. 40–62, December 2010.
- [4] H. Shokri-Ghadikolaei and M. Nasiri-Kenari, "Sensing matrix setting schemes for cognitive networks and their performance analysis," *accepted in IET Commun.*, July 2012.
- [5] Y. C. Liang, Y. Zeng, E. C. Y. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," *IEEE Trans. Wireless Communication*, vol. 7, no. 4, pp. 1326–1337, Apr. 2008.
- [6] O. van den Biggelaar, J. M. Dricot, P. D. Doncker, and F. Horlin, "Sensing time and power allocation for cognitive radios using distributed q-learning," *EURASIP J. on Wireless Commun. and Networking*, pp. 1–40, April 2012.

- [7] J. He, C. Xu, and L. Li, "Joint optimization of sensing time and decision thresholds for wideband cognitive ofdm radio networks," *IET ICWMNN*, pp. 230–233, September 2010.
- [8] D. J. Lee and M. S. Jang, "Optimal spectrum sensing time considering spectrum handoff due to false alarm in cognitive radio networks," *IEEE Commun. Letters*, vol. 13, no. 12, pp. 899–901, December 2009.
- [9] X. Zhang, Q. Wu, and J. Wang, "Optimization of sensing time in multichannel sequential sensing for cognitive radio," *Int. J. Commun. Syst.*, pp. 230–233, July 2011.
- [10] H. Shokri-Ghadikolaei and R. Fallahi, "Intelligent sensing matrix setting scheme in cognitive networks," *accepted in IEEE Commun. Letter*, Sept. 2012.
- [11] T. L. Fine, *Feedforward Neural Network Methodology*, 1st ed. New York: Springer, 1999.
- [12] M. P. Kennedy and L. O. Chua, "Neural networks for nonlinear programming," *IEEE Trans. Circuits Syst.*, vol. 35, no. 5, pp. 554–562, May 1988.
- [13] K. Hornik, M. Stochcombe, and H. White, "Multilayer feedforward networks are universal approximators," *Neural Netw.*, vol. 2, pp. 359–366, 1989.
- [14] ———, "Universal approximation of an unknown mapping and its derivatives using multilayer feedforward networks," *Neural Netw.*, vol. 3, pp. 551–560, 1990.
- [15] J. E. Dayhoff, *Neural Network Architectures*. New York: Van Nostrand Reinhold, 1990.
- [16] R. Fantacci, D. Tarch, M. Marini, and A. Rabbini, "A neural network approach to MMSE receivers in a DS-CDMA multipath fading environment," *IEEE Trans. Commun.*, vol. 54, no. 5, pp. 778–782, May 2006.
- [17] J. M. Zurada, *Introduction to Artificial Neural Systems*. Boston, MA: Van Nostrand Reinhold, 1995.
- [18] C. Maa and M. Shanblatt, "Linear and quadratic programming neural network analysis," *IEEE Trans. Neural Netw.*, vol. 3, no. 4, pp. 580–594, Jul. 1992.
- [19] Monica and A. K. Sharma, "Comparative study of energy consumption for wireless sensor networks based on random and grid deployment strategies," *International Journal of Computer Applications IJCA*, vol. 6, no. 1, pp. 28–35, September 2010.
- [20] S. Hashem, "Sensitivity analysis of feedforward artificial neural networks with differentiable activation functions," in *Proc. IEEE IJCNN*, vol. 1, Baltimore, MD, June 1992, pp. 419–424.
- [21] A. Abdi and P. Azmi, "Intelligent cross-layer adaptation scheme for wireless links with QoS-guaranteed traffic," in *Proc. 5th International Symposium on Telecommunications (IST)*, vol. 1, Tehran, Dec. 2010, pp. 419–424.
- [22] S. H. Park, H. Yoon, and J. W. Kim, "A cross-layered network adaptive HD video steaming in digital A/V home network: Channel monitoring and video rate adaptation," *IEEE Trans. on Consum. Electron.*, vol. 52, no. 4, pp. 1245–1252, Nov. 2006.
- [23] C. R. Stevenson, G. Chouinard, W. H. Z. Lei, and S. J. Shellhammer, "IEEE 802.22: The first cognitive radio wireless regional area network standard," *IEEE Comm. Mag.*, vol. 47, no. 1, pp. 130–138, Jan 2009.
- [24] R. Caruana, S. Lawrence, and L. Giles, "Overfitting in neural nets: Backpropagation, conjugate gradient, and early stopping," in *Proc Neural Inf. Process. Syst.*, pp. 402–408, Dec. 2001.

- [25] L. Jiao, L. Bo, and L. Wang, "Fast sparse approximation for least square support vector machine," *IEEE Trans. Neural Net.*, vol. 18, no. 3, pp. 685–697, May 2007.

TABLE I  
SIMULATION PARAMETERS

Parameter	Description	Value
$P_d^{\min}$	Minimum allowable detection probability	0.9
$P_{fa}^{\max}$	Maximum allowable false alarm probability	0.1
$f_s$	Receiver sampling frequency	6 MHz
$T$	Time-slot duration	100 ms
$\tau_{ho}$	Required time for handover	0.1 ms
$N_p$	Number of primary users	15
$K$	Number of hidden neurons	9
$C$	Capacitances of Kennedy-Chua network	10nF
$G$	Conductances of Kennedy-Chua network	$0.001\Omega^{-1}$

TABLE II

THE SU'S AVERAGE THROUGHPUT AND NORMALIZED CONSUMED ENERGY (NCE) FOR  $TF = 1$  IN *Design 1* (WITHOUT CONSIDERING ENERGY-THROUGHPUT TRADEOFF) AND  $TF = 0.98$  IN *Design 2*

	Design 1		Design 2	
	Throughput	NCE	Throughput	NCE
$N_p = 2$	0.775	1.3186	0.775	1.3186
$N_p = 6$	0.8723	2.3909	0.8660	2.1397
$N_p = 12$	0.8807	3.3080	0.8660	2.1397

TABLE III

PRIMARY FREE PROBABILITIES

$k$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$P_{k,0}$	0.71	0.46	0.34	0.72	0.66	0.72	0.76	0.35	0.25	0.70	0.37	0.23	0.72	0.24	0.43

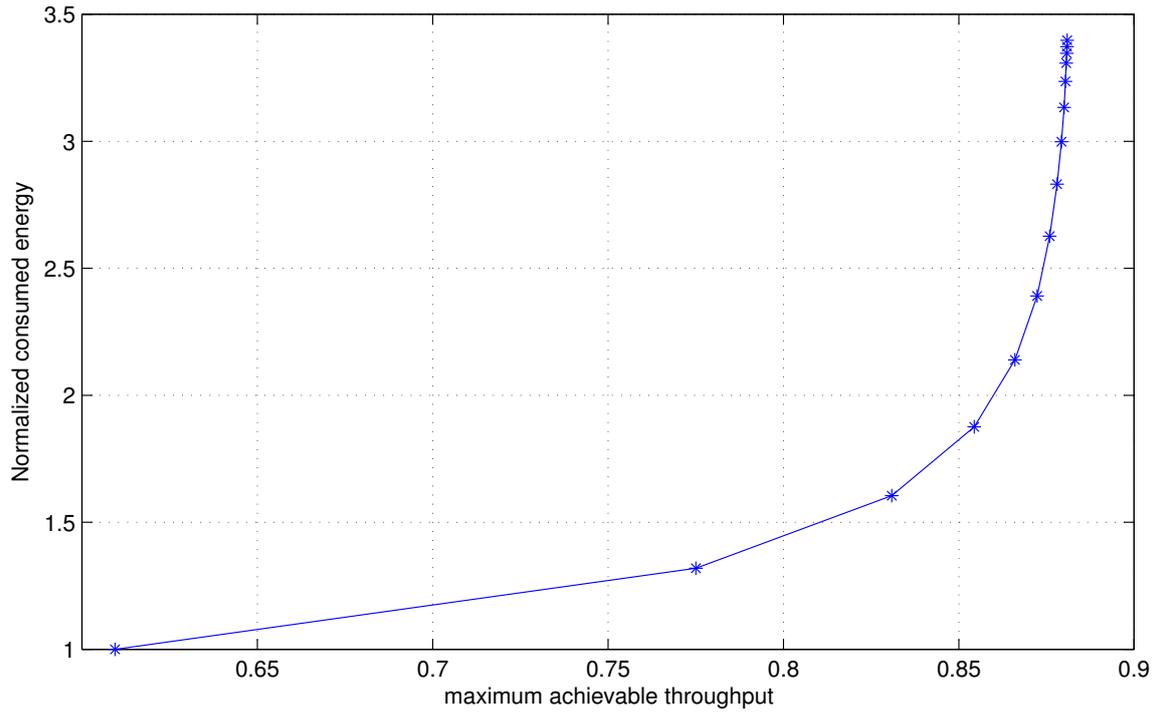


Fig. 1. The relationship between the normalized consumed energy of an SU and its maximum achievable throughput.

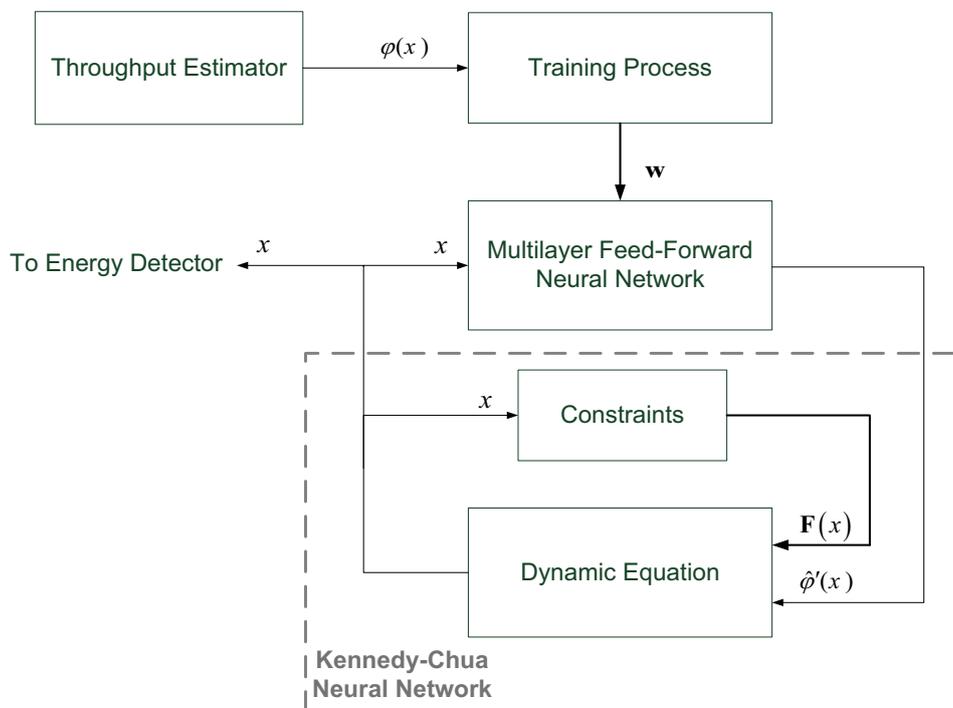


Fig. 2. Block diagram of the proposed neural network-based sensing time optimization scheme.

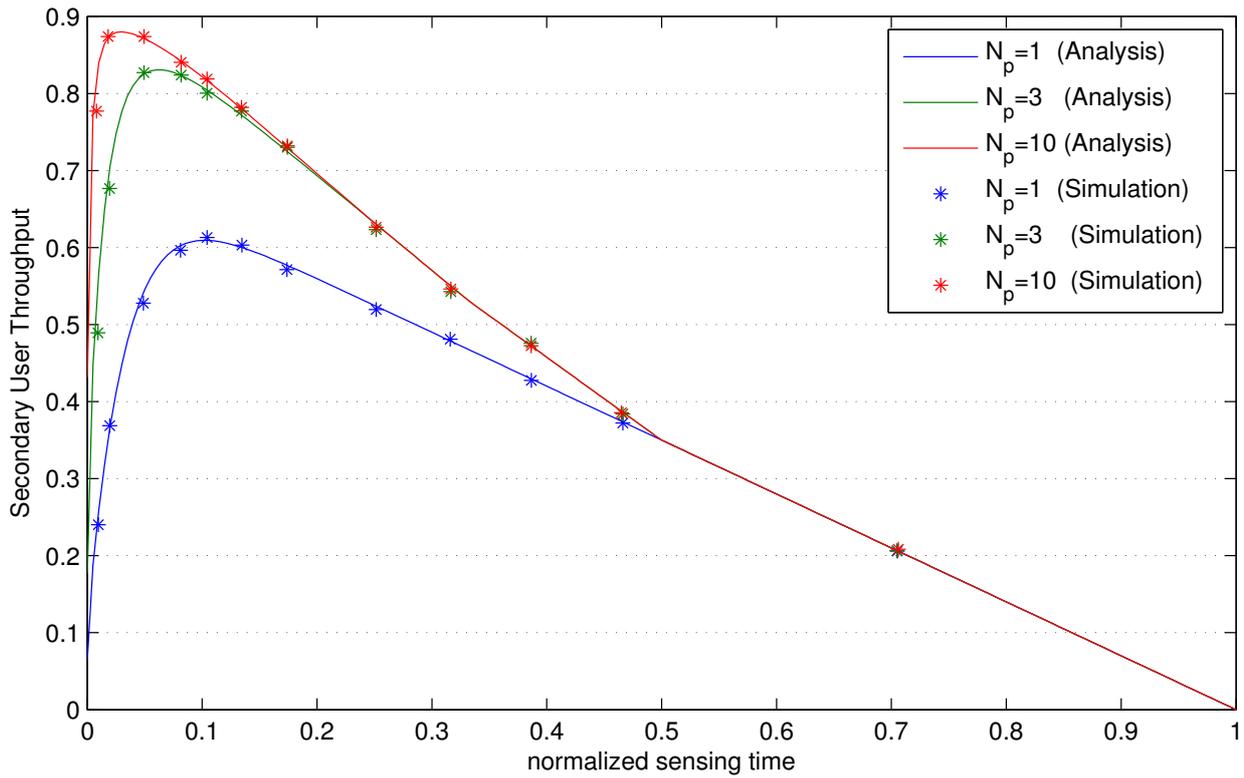


Fig. 3. Secondary user throughput versus normalized sensing time.

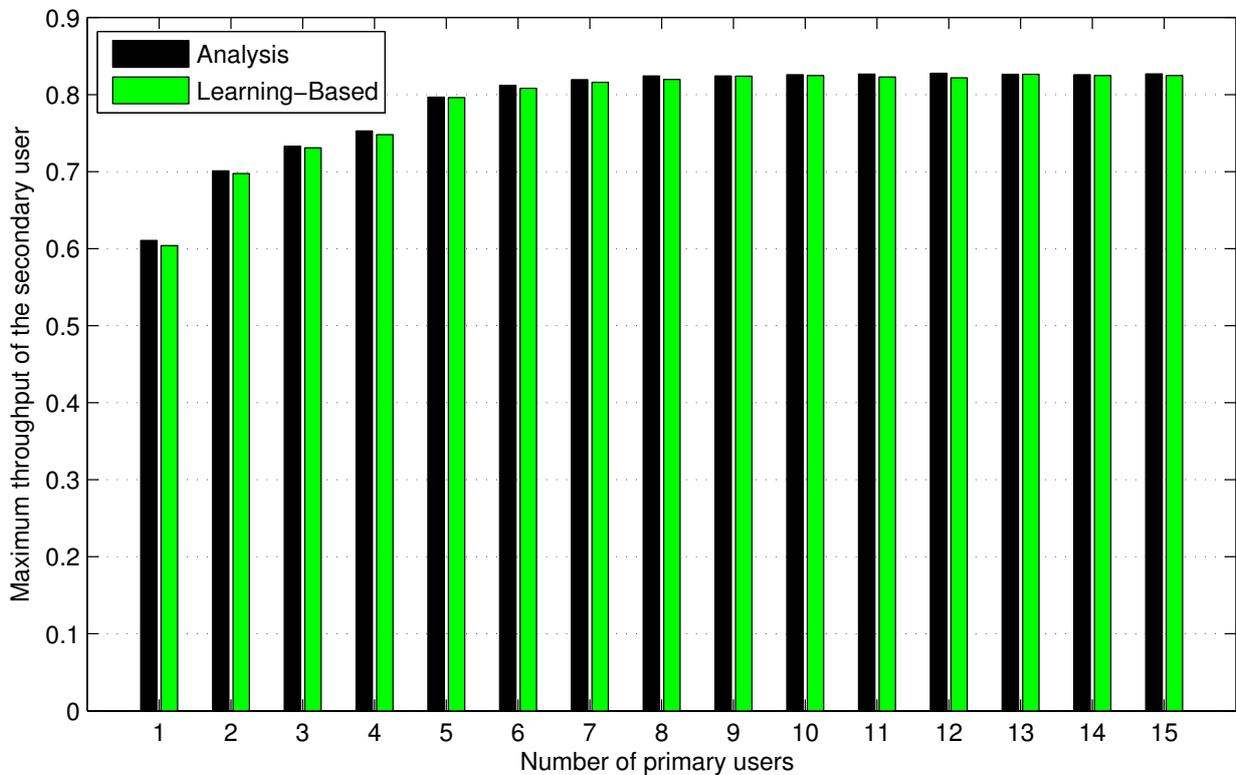


Fig. 4. Maximum normalized throughput of the secondary user versus the number of channels.

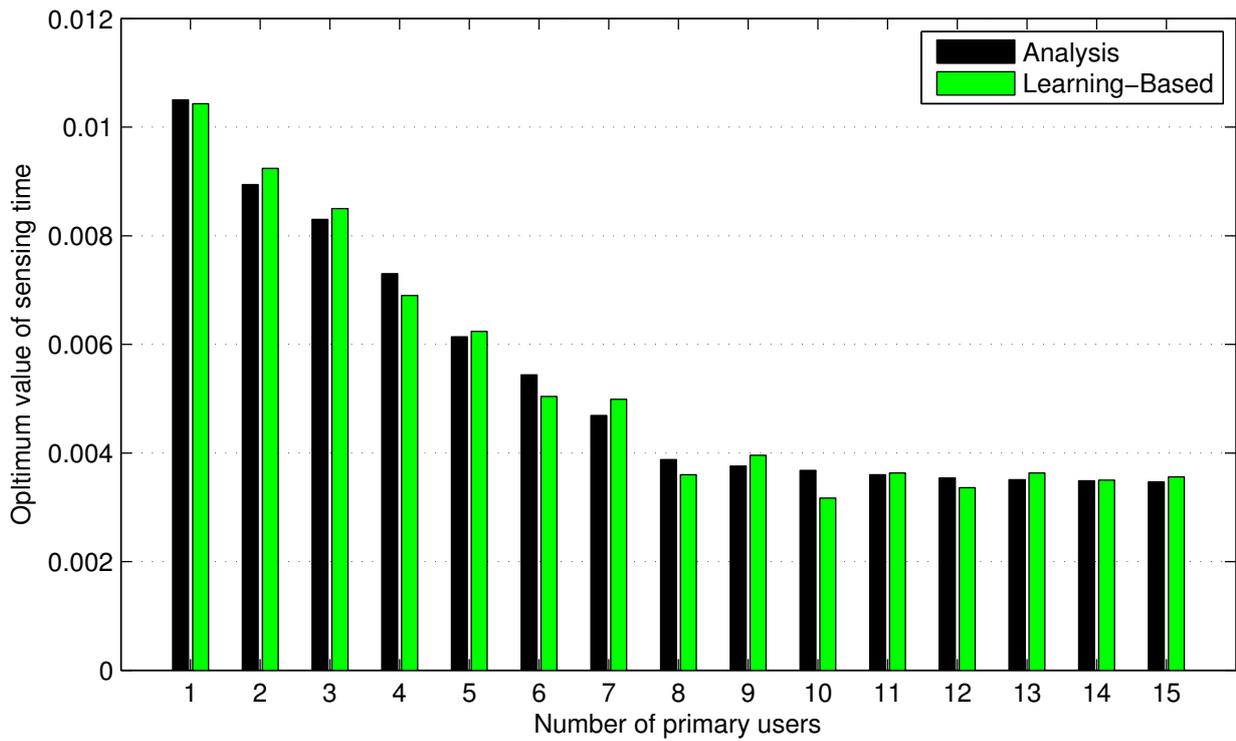


Fig. 5. Optimal value of the sensing time obtained by the two methods.

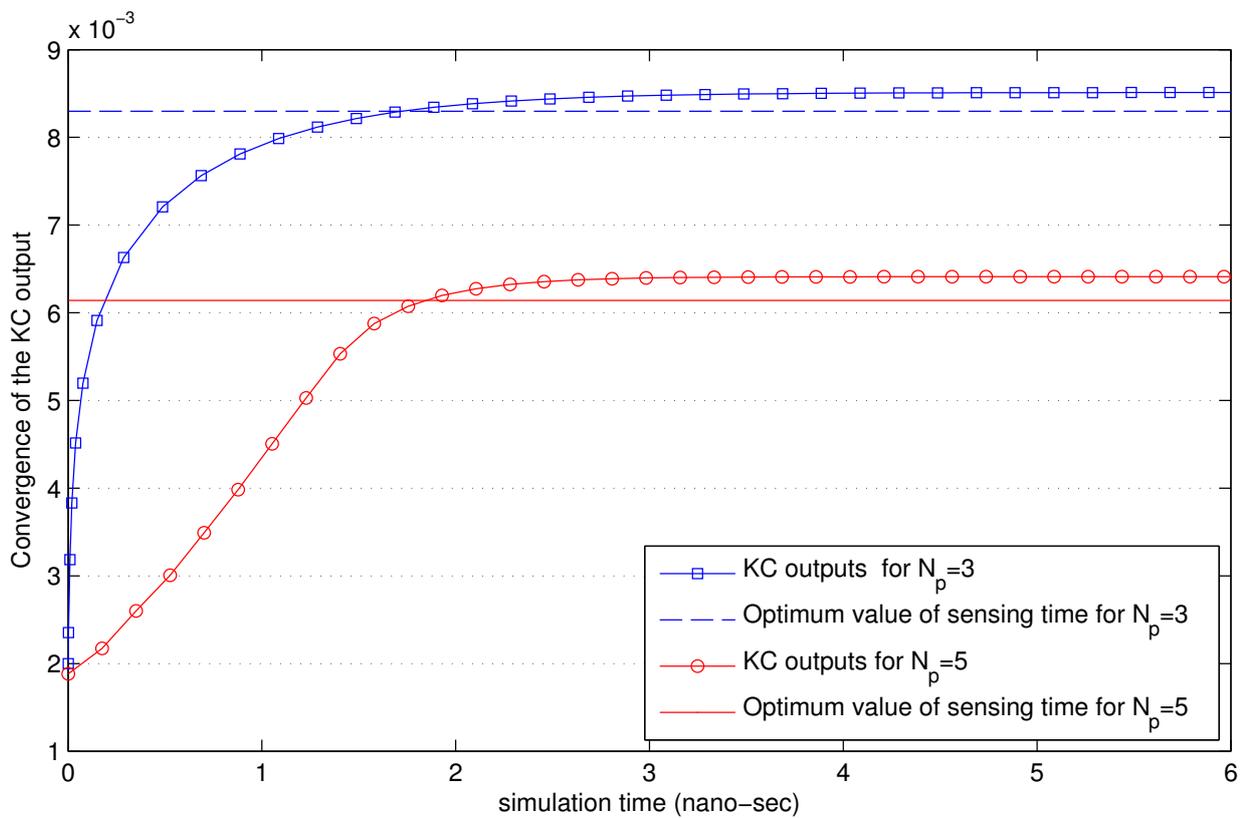


Fig. 6. Convergence of the output of the KC neural network to optimal sensing time using a learned model for secondary links with  $N_p = 3$  and  $N_p = 5$  primary channels.