Discrete Stochastic Optimization Based Parameter Estimation for Modeling Partially Observed WLAN Spectrum Activity

Ioannis Glaropoulos and Viktoria Fodor

***Abstract*—Modeling and parameter estimation of spectrum usage in the ISM band would allow the competing networking technologies to adjust their medium access control accordingly, leading to the more efficient use of the shared spectrum. In this paper we address the problem of WLAN spectrum activity model parameter estimation. We propose a solution based on discrete stochastic optimization, that allows accurate spectrum activity modeling and can be implemented even in wireless sensor nodes with limited computational and energy resources.**

***Index Terms*—cognitive networks, WLAN spectrum activity, discrete stochastic optimization**

I. Introduction

EMERGING wireless technologies for local and personal area communication all use the open Industrial, Scientific and Medical (ISM) band. While the variety of introduced solutions increases, the protocol stacks are usually optimized for a given application area, and at the same time assume the exclusive use of the spectrum space. However, most of the time the different technologies coexist, and communication efficiency and performance guarantees can only be achieved, if the networks have cognitive capabilities [1], that is, they are aware of each other and optimize their transmission parameters and communication protocols accordingly.

Key technologies operating in the ISM band are the IEEE 802.11 wireless local area networks (WLANs). As WLAN carrier sensing is designed to detect WLAN signals, it is *blind* towards the low power, narrow band WSN transmissions. Consequently, if the WSN does not adjust itself to the WLAN operation, it will experience harmful interference from the WLAN, while the WLAN itself is not affected significantly by the narrow band low power WSN interferers.

Previous work in the area of cognitive WSNs includes proposals for novel carrier sensing and medium access control, and the characterization of the channel usage in WLAN cells. In [2] the interfering technology is identified based on spectral signature. In the case of WLAN interferers, the sensors force the WLAN to back off by sending short, high power jamming signals. The POMDP framework [3] introduces the concept of partial channel knowledge and proposes optimal sensing and channel access strategies considering a Markovian channel occupancy model. A Markovian model, however, may lead to suboptimal WSN operation, and therefore several works deal with a more accurate channel characterization, considering sub-geometric [4], hyper-exponential [5] and Pareto [6] idle time distributions.

In [7][8] it is recognized, that the characterization of the idle time can lead to more efficient cognitive access control, if it captures the two basic sources of WLAN inactivity, the short, almost uniformly distributed contention windows and the long, heavy-tailed white space periods, when the WLAN users are inactive. We follow this approach in our previous work, where we propose cognitive medium access control and next hop selection for the WSN [9], given the known WLAN channel idle time distribution. In [10] we define the *Local View* model of WLAN channel activity that extends the solution of [7] and takes into account the limited detection range of the WSN nodes, and propose computationally efficient ways to estimate the model parameters based on time limited continuous sensing at the sensors.

In this paper we provide a deep analysis of the Local View parameter estimation based on discrete stochastic optimization. We follow the approach presented in [11], show that the algorithm converges almost surely to the optimal parameter set, and evaluate how the size of the state space, the size of the sample set and the number of iterations affect the estimation accuracy.

The rest of the paper is organized as follows. Section II defines the considered networking scenario along with the WLAN channel activity models and formulates the parameter estimation as an optimization problem. In Section III we give an overview of the discrete stochastic optimization algorithm proposed in [11]. In Section IV we show that the algorithm converges in the case of the considered parameter estimation problem and in V we evaluate the performance of the algorithm under practical constraints. We conclude the paper in Section VI.

II. WLAN Idle Time Modeling

We consider an IEEE 802.15.4 compliant WSN operating in the transmission area of an IEEE 802.11 WLAN. The transmission power of the WLAN terminals is orders of magnitude higher than that of the coexisting WSN, and the WLAN terminals are *blind* towards the WSN transmissions. The protocol stack of the energy constrained WSN is enhanced by cognitive functionality to optimize the WSN operation. To perform cognitive control, the WSN needs to know the WLAN channel occupancy distribution. For this, the sensors

I Glaropoulos and V. Fodor are with the Access Linnaeus Center, School of Electrical Engineering, KTH Royal Institute of Technology, Stockholm, Sweden. Email: {ioannisg,vfodor}@kth.se.

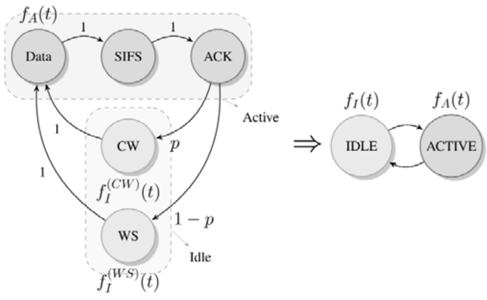

Fig. 1. The Global View model with all channel states and the reduced two-state semi-Markovian model.

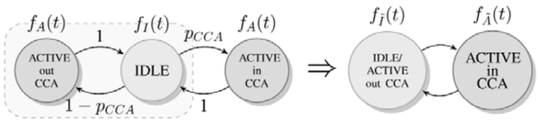

Fig. 2. The 3-state semi-Markovian chain and its 2-state equivalent for the Local View channel activity modeling.

perform continuous sensing and collect samples of busy and idle WLAN period lengths. The sensing is based on the usual Clear Channel Assessment (CCA) process with energy detection, resulting in a limited sensing range.

According to [7][8], the *Global View* of WLAN channel occupancy can be modeled by a semi-Markovian system of Active and Idle periods [12]. Figure 1 depicts all the states of the WLAN channel and their merging into a two-state semi-Markovian chain. The states of Data, SIFS and ACK transmission are grouped together into a single *Active* state, while the states that represent the WLAN Contention Window period (CW) and the WLAN White Space (WS) due to user inactivity are merged into a single *Idle* state. The sojourn times in the Active state can be modeled by the *uniform* distribution $f_A(t)$ within $[\alpha_{\text{ON}}, \beta_{\text{ON}}]$, which denote the minimum and maximum frame-in-the air duration, respectively. The idle period distribution, $f_I(t)$, is a *mixture* distribution with a weight p, that is $f_I(t) \triangleq p \cdot f_I^{CW}(t) + (1-p) \cdot f_I^{WS}(t)$. $f_I^{CW}(t)$ is the distribution of the CW periods, and can be modeled with a *uniform* distribution within $[0, \alpha_{\text{BK}}]$, where α_{BK} denotes the maximum WLAN back-off duration, given by the WLAN specification. The WS periods, however, exhibit a heavy-tailed behavior, and their distribution $f_I^{WS}(t)$ is well approximated by a zero-location *generalized Pareto* distribution with parameters (ξ, σ).

Thus, the distribution of the sojourn time in the Idle state, $f_I(t)$, is given as:

$$f_I(t) \triangleq \begin{cases} p \cdot \dfrac{1}{\alpha_{\text{BK}}} + (1-p) \cdot \dfrac{1}{\sigma}\left(1 + \xi \dfrac{t}{\sigma}\right)^{\left(-\frac{1}{\xi}-1\right)} & t \leq \alpha_{\text{BK}} \\ (1-p)\dfrac{1}{\sigma}\left(1 + \xi \dfrac{t}{\sigma}\right)^{\left(-\frac{1}{\xi}-1\right)} & t > \alpha_{\text{BK}} \end{cases}$$

This Global View, however, is not fully observable at the individual sensors, that can detect WLAN transmissions only within a given detection range. Therefore, in [10] we define the *Local View*, that describes the WLAN channel occupancy as seen by an individual sensor. Assuming that consecutive WLAN transmissions are not correlated, we introduce a 3-state semi-Markovian system (Figure 2), distinguishing between detected, and un-detected WLAN activity, that occurs with probabilities p_{CCA} and $(1 - p_{\text{CCA}})$, respectively. To model the *observable* sojourn time distributions $f_{\tilde{A}}(t)$ and $f_{\tilde{I}}(t)$ we define the 2-state *Local View* model by merging the states at which the sensor detects an idle channel. It holds that $f_{\tilde{A}}(t) = f_A(t)$, but $f_{\tilde{I}}(t) \neq f_I(t), \quad \forall p_{\text{CCA}} < 1$.

Our objective is to estimate the parameters of $f_A(t)$ and $f_I(t)$ and the *observable load*, p_{CCA}, from a set of samples of $f_{\tilde{A}}(t)$ and $f_{\tilde{I}}(t)$ obtained through channel sensing.

As the active period distribution, $f_{\tilde{A}}(t)$, is uniform, its parameters α_{ON} and β_{ON} are estimated by the lowest and the largest measured active period according to Maximum Likelihood Estimation (MLE). The estimation of the rest of the parameters is more difficult. An idle channel period observed by an arbitrary sensor consists of a random number of WLAN "cycles", that is, consecutive idle and un-detected active periods, followed by an additional idle period. The locally observable idle period distribution, $f_{\tilde{I}}(t)$, is, therefore, a function of the idle and active time distributions $f_I(t)$ and $f_A(t)$, and of the observable load, p_{CCA}, and can not be expressed in a closed form, even if $f_A(t)$ and $f_I^{CW}(t)$ are known.

As we show in [10], closed form expression exists in the Laplace domain and, therefore, we propose to estimate the parameters of $f_{\tilde{I}}(t)$ in the Laplace domain. Since according to the semi-Markovian Local View model the number of consecutive WLAN cycles is geometrically distributed, the Laplace Transform (LT) of $f_{\tilde{I}}(t)$ obtains the following form:

$$f_{\tilde{I}}^*(s) = f_I^*(s)\frac{p_{\text{CCA}}}{1 - (1 - p_{\text{CCA}})f_I^*(s)f_A^*(s)}, \tag{1}$$

where $f_I^*(s), f_A^*(s)$ denote the LT of $f_I(t), f_A(t)$, respectively.

III. An Algorithm for Discrete Stochastic Optimization for Parameter Estimation

In this Section we review the algorithm for stochastic optimization introduced in [11], that we use to estimate the parameters of the Local View model. First we define the necessary notation and then we give the stochastic optimization algorithm, along with the constraint on convergence.

Let us define by $\boldsymbol{\mathcal{K}} \triangleq \{\mathcal{K}_1, \mathcal{K}_2, ..., \mathcal{K}_K\}$ the discrete space of the different alternatives. The number of discrete states, $K = |\boldsymbol{\mathcal{K}}|$, is finite. The optimization problem we aim at solving is of the following form:

$$\mathcal{K}^* = \arg\min_{\mathcal{K}_n \in \boldsymbol{\mathcal{K}}} \{c(n) = E[X_{\mathcal{K}_n}]\}. \tag{2}$$

That is, the function $c(n)$ can not be evaluated analytically and needs to be estimated through a sequence of random samples $\{X_{\mathcal{K}_n}\}$. We denote by:

$$\boldsymbol{\mathcal{L}} = \{\mathcal{L}_1, ..., \mathcal{L}_L\} \subset \boldsymbol{\mathcal{K}} \tag{3}$$

the set of *global* minimizers of the function c, that is:

$$\begin{aligned} &\forall \mathcal{L}_i \in \boldsymbol{\mathcal{L}}, \mathcal{K}_n \in \boldsymbol{\mathcal{K}} \setminus \boldsymbol{\mathcal{L}},\ c(\mathcal{L}_i) < c(\mathcal{K}_n) \text{ and} \\ &\forall i, j = 1, 2, ..., L,\ c(\mathcal{L}_i) = c(\mathcal{L}_j). \end{aligned} \tag{4}$$

In the following we give the original stochastic optimization algorithm as it is proposed in [11] (Algorithm 1). The search process starts from an arbitrary state, $\mathcal{K}_i$. In each iteration step, m, it selects a new state $\mathcal{K}_j$ uniformly at random and obtains the observation of a random variable $Z_{l_m}^{\mathcal{K}_i \to \mathcal{K}_j}$ to compare the two states. $Z_{l_m}^{\mathcal{K}_i \to \mathcal{K}_j}$ is a function of the random variables $\{X_{\mathcal{K}_i}\}_{l_m}, \{X_{\mathcal{K}_j}\}_{l_m}$. Thus, its value can depend on the two states, $\mathcal{K}_i, \mathcal{K}_j$, and on l_m, which is a function of the iteration step m. The algorithm moves to the new state if $Z_{l_m}^{\mathcal{K}_i \to \mathcal{K}_j} > 0$.

Let denote $\mathcal{K}_m$ the state after iteration m and $Q_m(\mathcal{K}_n)$ the "popularity" of state $\mathcal{K}_n \in \boldsymbol{\mathcal{K}}$, i.e. the number of times the algorithm has visited state $\mathcal{K}_n$ until iteration m. The output of the algorithm, $\mathcal{K}^*$, is chosen as the most visited state.

Algorithm 1 A global search for discrete stochastic optimization [11].

Step 0:

Select a starting point $\mathcal{K}_0 \in \boldsymbol{\mathcal{K}}$.
$Q_0(\mathcal{K}_0) \leftarrow 1$ and $Q_0(\mathcal{K}_n) \leftarrow 0, \forall \mathcal{K}_n \in \boldsymbol{\mathcal{K}}, \mathcal{K}_n \neq \mathcal{K}_0$.
$m \leftarrow 0$ and $\mathcal{K}_m^* \leftarrow \mathcal{K}_0$. Go to Step 1.

Step 1:

Generate a uniform random variable $\mathcal{J}_m$ such that for all $\mathcal{K}_n \in \boldsymbol{\mathcal{K}}, \mathcal{K}_n \neq \mathcal{K}_m$, $\mathcal{J}_m \leftarrow \mathcal{K}_n$ with probability $\frac{1}{K-1}$. Go to Step 2.

Step 2:

Generate an observation R_m of $Z_{l_m}^{\mathcal{K}_m \to \mathcal{J}_m}$.
if $R_m > 0$ **then**
  $\mathcal{K}_{m+1} \leftarrow \mathcal{J}_m$.
else
  $\mathcal{K}_{m+1} \leftarrow \mathcal{K}_m$.
end if Go to Step 3.

Step 3:

$m \leftarrow m+1$, $Q_m(\mathcal{K}_m) \leftarrow Q_{m-1}(\mathcal{K}_m)+1$ and $Q_m(\mathcal{K}_n) \leftarrow Q_{m-1}(\mathcal{K}_n)$ for all $\mathcal{K}_n \neq \mathcal{K}_m$.
if $Q_m(\mathcal{K}_m) > Q_m(\mathcal{K}_{m-1}^*)$ **then**
  $\mathcal{K}_m^* \leftarrow \mathcal{K}_m$.
else
  $\mathcal{K}_m^* \leftarrow \mathcal{K}_{m-1}^*$
end if Go to Step 1.

It is shown in [11] that the algorithm converges almost surely to a minimizer, i.e. a member of $\mathcal{L}$, after sufficiently large number of iterations, if the following conditions hold:

Condition 1. *For each $\mathcal{K}_i, \mathcal{K}_j \in \boldsymbol{\mathcal{K}}$ and $l \in \mathbb{N}$, there exists a random variable $Z_l^{(\mathcal{K}_i \to \mathcal{K}_j)}$ such that the limit $\lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_i \to \mathcal{K}_j)} > 0\}$ exists for all $\mathcal{K}_i, \mathcal{K}_j \in \boldsymbol{\mathcal{K}}$ and for all $\mathcal{K}_i \in \mathcal{L}, \mathcal{K}_j \notin \mathcal{L}, \mathcal{K}_n \neq \mathcal{K}_i, \mathcal{K}_j$, and $l \in \mathbb{N}$,*

$$\lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_j \to \mathcal{K}_i)} > 0\} > \lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_i \to \mathcal{K}_j)} > 0\}, \quad (5)$$

$$\lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_n \to \mathcal{K}_i)} > 0\} \geq \lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_n \to \mathcal{K}_j)} > 0\}, \quad (6)$$

$$\lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_i \to \mathcal{K}_n)} \leq 0\} \geq \lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_j \to \mathcal{K}_n)} \leq 0\}. \quad (7)$$

Condition 2. *$\{l_m\}$ is a sequence of positive integers such that $l_m \to \infty$ as $m \to \infty$.*

Condition 3. *The Markov matrix $\mathcal{P}$ defined in the following equations is irreducible.*

$$\mathcal{P}(\mathcal{K}_i, \mathcal{K}_j) = \tfrac{1}{K-1} \lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_i \to \mathcal{K}_j)} > 0\} \quad \forall \mathcal{K}_i, \mathcal{K}_j \in \boldsymbol{\mathcal{K}}, \mathcal{K}_i \neq \mathcal{K}_j,$$

$$\mathcal{P}(\mathcal{K}_i, \mathcal{K}_i) = \tfrac{1}{K-1} \sum_{\mathcal{K}_j \in \boldsymbol{\mathcal{K}} \setminus \{\mathcal{K}_i\}} \lim_{l\to\infty} P\{Z_l^{(\mathcal{K}_i \to \mathcal{K}_j)} \leq 0\} \quad \forall \mathcal{K}_i \in \boldsymbol{\mathcal{K}}.$$

IV. Local View Parameter Estimation

A. The Estimation Process

We apply Algorithm 1 to estimate the parameters of $f_{\tilde{I}}(t)$. We discretize the model parameters ξ, σ and p within the reasonable intervals, and define the state $\mathcal{K}_n$ as the set of model parameters:

$$\mathcal{K}_n \triangleq (\xi_n, \sigma_n, p_n).$$

Since the value of these model parameters give, together with p_{CCA}, the estimated average observable idle period length, we do not include p_{CCA} directly in the algorithm state space, but determine it through Moment Evaluation (ME), considering the sample mean of the measured observable idle period lengths, μ, and the rest of the parameters, i.e.

$$p_{\text{CCA}} = \frac{\frac{p\alpha_{\text{BK}}}{2} + \frac{(1-p)\sigma}{1-\xi} + \frac{\alpha_{\text{ON}}+\beta_{\text{ON}}}{2}}{\bar{\mu} + \frac{\alpha_{\text{ON}}+\beta_{\text{ON}}}{2}}.$$

We would like to determine the optimal state, $\mathcal{K}^* \in \boldsymbol{\mathcal{K}}$, that is the optimal model parameter set $\mathcal{K}^* \triangleq (\xi^*, \sigma^*, p^*)$, that minimizes the Mean Square Error (MSE) between the Laplace transform of the idle distribution, $f_{\tilde{I}}^*(s)$, and the LT given by the system state, $f_{\tilde{I}}^*(s; \mathcal{K}_n)$, over $\mathcal{S} = \{s_1, s_2, \dots s_S\}$, the finite discrete subset of the s-domain, that is,

$$(\xi^*, \sigma^*, p^*) = \arg\min_{\mathcal{K}_n \in \boldsymbol{\mathcal{K}}} \frac{1}{S} \sum_{k=0}^{S} (f_{\tilde{I}}^*(s_k) - f_{\tilde{I}}^*(s_k; \mathcal{K}_n))^2. \quad (8)$$

As $f_{\tilde{I}}^*(s)$ is not known, it needs to be evaluated through the idle period samples obtained by channel sensing.

To ensure fast parameter estimation, we propose to run the estimation process, that is, Algorithm 1 parallel to the channel sensing. That is, in each iteration step, m, n_m new idle period samples are integrated in the empirical LT. The total number of samples integrated up to iteration m is $N_m = \sum_{k=0}^{m} n_m$. We define the *empirical* LT, $f_{\tilde{I}e}^*(s; N_m)$, of the observable idle time distribution directly from a set of N_m measured idle period samples, $(t_1, ..., t_{N_m})$ as:

$$f_{\tilde{I}e}^*(s; N_m) = \frac{1}{N_m} \sum_{i=1}^{N_m} e^{-st_i}. \quad (9)$$

Comparing the general expression in (2) and the Mean Square Error minimization problem in (8) we have:

$$X_{\mathcal{K}_n} = \text{MSE}_n^{(N)} = \frac{1}{S} \sum_{k=0}^{S} \left[f_{\tilde{I}e}^*(s_k; N) - f_{\tilde{I}}^*(s_k; \mathcal{K}_n)\right]^2, \forall \mathcal{K}_n, \quad (10)$$

where $\mathrm{MSE}_n^{(N)}$ denotes the MSE calculated with the N samples, and, consequently,

$$\begin{aligned} c(n) = E\left[\tfrac{1}{S}\sum_{k=0}^{S}[(f_{Ie}^*(s;N) - f_I^*(s;\mathcal{K}_n))^2]\right] = \\ = \tfrac{1}{S}\sum_{k=0}^{S} E[(f_{Ie}^*(s;N) - f_I^*(s;\mathcal{K}_n))^2]. \end{aligned} \tag{11}$$

Accordingly, for Algorithm 1 we select $l_m = N_m$ and define:

$$Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)} \triangleq X_{\mathcal{K}_i} - X_{\mathcal{K}_j} = \mathrm{MSE}_{\mathcal{K}_i}^{(l_m)} - \mathrm{MSE}_{\mathcal{K}_j}^{(l_m)},\ \forall \mathcal{K}_i, \mathcal{K}_j \in \boldsymbol{\mathcal{K}}. \tag{12}$$

That is, the observation of variable $Z_{l_m}^{\mathcal{K}_i \to \mathcal{K}_j}$, generated at step m in our algorithm, is the difference between the mean square errors evaluated at states $\mathcal{K}_i, \mathcal{K}_j$ and over N_m total idle period samples. The process moves to the new state $\mathcal{K}_j$ if the MSE is decreased this way.

B. On the Convergence of the Estimation Process

To prove that the proposed parameter estimation algorithm solves the optimization problem in (8), we proceed as follows. The proof that Condition 2 holds is trivial; since $\{l_m\}$ defines the number of samples that are integrated in the empirical LT calculation until step m, it is a sequence of integers that tends to ∞ as $m \to \infty$. With Lemma 1 we prove that $f_{\tilde{I}e}^*(s;N)$ is an unbiased estimator of $f_{\tilde{I}}^*(s)$, and converges to $f_{\tilde{I}}^*(s)$ as $N \to \infty$. Based on Lemma 1, we prove with Corollary 1 that the minimization of $c(n)$ solves the original problem in (8). Lemma 2 proves that the particular selection of the random variable $Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)}, \forall \mathcal{K}_i, \mathcal{K}_j \in \boldsymbol{\mathcal{K}}$ satisfies Condition 1. Lemma 3 shows that in our problem Algorithm 1 converges to the optimal state, bypassing the requirement for Condition 3 to hold.

Lemma 1. *The empirical Laplace Transform as a function of N i.i.d. samples $\{t_1, ..., t_N\}$ can be approximated as*

$$f_{Ie}^*(s;N) = \frac{1}{N}\sum_{l=1}^{N} e^{-st_l}.$$

and is an unbiased estimator of $f^*(s)$, converging to $f^*(s)$ as $N \to \infty$.

Proof: We, first, generate the empirical distribution function, $F_e(t;N)$ based on the N collected time period samples, $T = \{t_1, ..., t_N\}$,

$$F_e(t;N) = \frac{\#\text{samples in } T \le t}{N}.$$

It is known that $F_e(t;N)$ converges almost surely to the actual CDF, $F(t)$, as $N \to \infty$, based on the strong law of large numbers. In addition, $F_e(t;N)$ is an unbiased estimator of $F(t)$, i.e. $E[F_e(t;N)] = F(t)$. $F_e(t_l) - F_e(t_{l-1})$ is, then, an unbiased estimator for $P\{t \in (t_{l-1}, t_l)\} = F(t_l) - F(t_{l-1}),\quad l = 1, 2, ..., N$. We define the empirical density function, $f_e(t;N)$ being non-zero only on the set T, as follows:

$$f_e(t;N) = \sum_{l=1}^{N} [F_e(t_l;N) - F_e(t_{l-1};N)]\, \delta(t - t_l),$$

where $\delta(t)$ is the Dirac function and by convention $t_0 = 0, F_e(t_0) = 0$. Clearly,

$$\lim_{N\to\infty, t_l - t_{l-1} \to dt_l} F_e(t_l;N) - F_e(t_{l-1};N) = f(t_l)dt_l$$

and so

$$\begin{aligned} \lim_{N\to\infty} \textstyle\sum_{l=1}^{N} [F_e(t_l;N) - F_e(t_{l-1};N)]\, \delta(t - t_l) = \\ = \textstyle\int_{t_l} f(t_l)\delta(t - t_l)dt_l = f(t), \end{aligned}$$

consequently $f_e(t;N)$ converges to the actual pdf. The empirical Laplace Transform is defined as

$$f_e^*(s;N) \triangleq \int_0^\infty f_e(t;N)e^{-st}dt.$$

Since $F_e(t_l) - F_e(t_{l-1}) = 1/N$, the above becomes

$$\begin{aligned} f_e^*(s;N) = \textstyle\int_0^\infty \sum_{l=1}^{N} \frac{1}{N}\delta(t - t_l)e^{-st}dt = \\ = \textstyle\sum_{l=1}^{N} \frac{1}{N}\int_0^\infty \delta(t - t_l)e^{-st}dt = \frac{1}{N}\sum_{l=1}^{N} e^{-st_l}. \end{aligned}$$

The convergence of $f^*(s;N)$ is ensured due to the convergence of $f_e(t;N)$. Finally,

$$E[f_e^*(s;N)] = \sum_{l=1}^{N} \frac{1}{N} E[e^{-st_l}] = E[e^{-st}] = f^*(s), \tag{13}$$

so $f^*(s;N)$ is an unbiased estimator of the LT transform. ■

Corollary 1. *The minimization of $c(n)$ in (11) solves the original problem in (8).*

Proof: We have:

$$\begin{aligned} c(n) &= \tfrac{1}{S}\textstyle\sum_{k=0}^{S} E\left[\left(f_{\tilde{I}e}^*(s_k;N) - f_{\tilde{I}}^*(s_k;\mathcal{K}_n)\right)^2\right] = \\ &= \tfrac{1}{S}\textstyle\sum_{k=0}^{S} E\left[\left(f_{\tilde{I}e}^*(s_k;N)\right)^2 - 2f_{\tilde{I}e}^*(s_k;N)f_{\tilde{I}}^*(s_k;\mathcal{K}_n)\right] + \\ &+ \left(f_{\tilde{I}}^*(s_k;\mathcal{K}_n)\right)^2 = \\ &= \tfrac{1}{S}\textstyle\sum_{k=0}^{S} E\left[\left(f_{\tilde{I}e}^*(s_k;N)\right)^2\right] - 2f_{\tilde{I}}^*(s_k)f_{\tilde{I}}^*(s_k;\mathcal{K}_n) + \\ &+ \left(f_{\tilde{I}}^*(s_k;\mathcal{K}_n)\right)^2. \end{aligned}$$

For $N \to \infty$ it holds from Lemma 1 that $\mathrm{Var}\left[f_{\tilde{I}e}^*(s_k;N)\right] = 0$, and consequently, $E\left[\left(f_{\tilde{I}e}^*(s_k;N)\right)^2\right] = E\left[f_{\tilde{I}e}^*(s_k;N)\right]^2$, so $c(n)$ converges to $\frac{1}{S}\sum_{k=0}^{S}(f_{\tilde{I}}^*(s_k) - f_{\tilde{I}}^*(s_k;\mathcal{K}_n))^2$. ■

Let us now prove, that Condition 1 is satisfied.

Lemma 2. *Let us select a random variable $Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)}$ as follows:*

$$Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)} = MSE_{\mathcal{K}_i}^{(l_m)} - MSE_{\mathcal{K}_j}^{(l_m)}.$$

The variable $Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)}$ satisfies Condition 1.

Proof: We start with showing that (5) is satisfied. Let $\mathcal{K}_i \in \mathcal{L}$, $\mathcal{K}_j \notin \mathcal{L}$, so that

$$\frac{1}{S}\sum_{k=0}^{S}(f_I^*(s_k) - f_I^*(s_k;\mathcal{K}_i))^2 < \frac{1}{S}\sum_{k=0}^{S}(f_I^*(s_k) - f_I^*(s_k;\mathcal{K}_j))^2 \tag{14}$$

We show, first, by direct computation that the mean of $Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)}$, defined in (12) is negative.

$$\begin{aligned}
&E[Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)}] = \\
&= E[\mathrm{MSE}_{\mathcal{K}_i}^{(l_m)} - \mathrm{MSE}_{\mathcal{K}_j}^{(l_m)}] = \\
&= E[\tfrac{1}{S}\textstyle\sum_{k=0}^{S} (f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_i))^2 - \\
&\quad -\tfrac{1}{S}\textstyle\sum_{k=0}^{S} (f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_j))^2] \\
&= \tfrac{1}{S}E[\textstyle\sum_{k=0}^{S} (f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_i))^2 - \\
&\quad - (f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_j))^2] \\
&= \tfrac{1}{S}E[\textstyle\sum_{k=0}^{S} (2f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_i) - f_I^*(s_k; \mathcal{K}_j)) \cdot \\
&\quad \cdot (f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_i))] \\
&= \tfrac{1}{S}\textstyle\sum_{k=0}^{S} (f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_i)) \cdot \\
&\quad \cdot E\left[2f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_i) - f_I^*(s_k; \mathcal{K}_j)\right] \\
&\overset{(13)}{=} \tfrac{1}{S}\textstyle\sum_{k=0}^{S} (f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_i)) \cdot \\
&\quad \cdot (2f_I^*(s_k) - f_I^*(s_k; \mathcal{K}_i) - f_I^*(s_k; \mathcal{K}_j)) \\
&= \tfrac{1}{S}\textstyle\sum_{k=0}^{S} (f_I^*(s_k) - f_I^*(s_k; \mathcal{K}_i))^2 - (f_I^*(s_k) - f_I^*(s_k; \mathcal{K}_j))^2 \\
&\overset{(14)}{<} 0.
\end{aligned}$$

We now show that $\lim_{l_m\to\infty} Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)}$ is symmetric around its mean. We write:

$$\begin{aligned}
&Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)} = \\
&= \tfrac{1}{S}\textstyle\sum_{k=0}^{S} (f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_i))^2 - \\
&\quad -\tfrac{1}{S}\textstyle\sum_{k=0}^{S} (f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_j))^2 \\
&= \tfrac{1}{S}\textstyle\sum_{k=0}^{S} (2f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_i) - f_I^*(s_k; \mathcal{K}_j)) \cdot \\
&\quad \cdot (f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_i)) \\
&= \tfrac{1}{S}\textstyle\sum_{k=0}^{S} 2f_{Ie}^*(s_k; l_m)\,(f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_i)) - \\
&\quad -\tfrac{1}{S}\textstyle\sum_{k=0}^{S} (f_I^*(s_k; \mathcal{K}_j) + f_I^*(s_k; \mathcal{K}_i)) \cdot \\
&\quad \cdot (f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_i)).
\end{aligned}$$

The second term is deterministic and, thus, excluded from the calculations. We concentrate on the first term.

$$W_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)} = \frac{1}{S}\sum_{k=0}^{S} 2f_{Ie}^*(s_k; l_m)\,(f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_i)) \tag{15}$$

As shown above the empirical LT is generated as $f_{Ie}^*(s_k; l_m) = \frac{\sum_{l=1}^{l_m} e^{-s_k t_l}}{l_m}$. We rewrite (15) as

$$\begin{aligned}
&W_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)} = \\
&= \tfrac{1}{S}\textstyle\sum_{k=0}^{S} 2f_{Ie}^*(s_k; l_m)\,(f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_i)) \\
&= \tfrac{1}{S}\tfrac{1}{l_m}\textstyle\sum_{k=0}^{S}\sum_{l=1}^{l_m} 2e^{-s_k t_l}\,(f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_i)) \\
&= \tfrac{1}{S}\textstyle\sum_{l=1}^{l_m}\left[\tfrac{1}{l_m}\sum_{k=0}^{S} 2e^{-s_k t_l}\,(f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_i))\right].
\end{aligned}$$

Since the variables t_l are i.i.d. so are the variables

$$g_l^{ji} = \sum_{k=0}^{S} \frac{2}{S} e^{-s_k t_l}\,(f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_i)). \tag{16}$$

As a result, the variable $\frac{1}{l_m}\sum_{l=1}^{l_m} g_l^{ji}$ approaches a Gaussian distribution, due to the Central Limit Theorem, and becomes, thus, symmetric around its mean value. Consequently, $\lim_{l_m\to\infty} W_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)}$ is symmetric around its mean, and so does $\lim_{l_m\to\infty} Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)}$. Since, additionally, $E\left[Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)}\right] < 0$, it follows that

$$P\{Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)} < 0\} > P\{Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)} > 0\}. \tag{17}$$

From the last equation, along with $P\{Z_{l_m}^{(\mathcal{K}_i \to \mathcal{K}_j)} < 0\} = P\{Z_{l_m}^{(\mathcal{K}_j \to \mathcal{K}_i)} > 0\}$, follows Eq. (5).

We proceed with showing that (6) is satisfied. For that, we need to show, first that the variance of $Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_j)}$ is finite. By direct computation we obtain:

$$\begin{aligned}
&\mathrm{Var}\left[Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_j)}\right] \\
&= \mathrm{Var}\left[\mathrm{MSE}_{\mathcal{K}_n}^{(l_m)} - \mathrm{MSE}_{\mathcal{K}_j}^{(l_m)}\right] \\
&= \mathrm{Var}[\tfrac{1}{S}\textstyle\sum_{k=0}^{S} (f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_n))^2 \\
&\quad - (f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_j))^2] \\
&= \mathrm{Var}[\tfrac{1}{S}\textstyle\sum_{k=0}^{S} (2f_{Ie}^*(s_k; l_m) - f_I^*(s_k; \mathcal{K}_n) - f_I^*(s_k; \mathcal{K}_j)) \cdot \\
&\quad \cdot (f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_n))]
\end{aligned}$$

We neglect the deterministic term in $Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_j)}$, resulting in the expression

$$\begin{aligned}
&\mathrm{Var}\left[\tfrac{1}{S}\textstyle\sum_{k=0}^{S} 2f_{Ie}^*(s_k; l_m)\,(f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_n))\right] \\
&= \mathrm{Var}\left[\tfrac{2}{l_m S}\textstyle\sum_{k=0}^{S}\sum_{l=1}^{l_m} e^{-s_k t_l}\,(f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_n))\right] \\
&= \left(\tfrac{1}{l_m}\right)^2 \mathrm{Var}\left[\textstyle\sum_{l=1}^{l_m} g_l^{nj}\right],
\end{aligned}$$

where g_l^{nj} is given as in (16). For the time distribution that we consider in [10], $\mathrm{Var}[t_l]$ is finite, as a result $\mathrm{Var}[e^{-s_k t_l}]$ is finite. Consequently, the variance of g_l^{nj} is finite as as summation over non-independent variables indexed by s_k:

$$g_l^{nj}(s_k) = \frac{2}{S} e^{-s_k t_l}\,(f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_n))$$

where

$$\begin{aligned}
&\mathrm{Var}\left[g_l^{nj}(s_k)\right] = \\
&\quad = \tfrac{4}{S^2}\,(f_I^*(s_k; \mathcal{K}_j) - f_I^*(s_k; \mathcal{K}_n))^2\,\mathrm{Var}[e^{-s_k t_l}] < \infty,
\end{aligned}$$

$$\mathrm{Var}\left[g_l^{nj}\right] = \sum_{s_k=0}^{S}\sum_{s_o=0}^{S} \mathrm{Cov}\left[g_l^{nj}(s_k), g_l^{nj}(s_o)\right] < \infty.$$

Since $\mathrm{Var}[g_l^{nj}] < \infty$, and the g_l^{nj} are i.i.d., it is clear that

$$\lim_{l_m\to\infty} \frac{1}{l_m^2}\mathrm{Var}\left[\sum_{l=1}^{l_m} g_l^{nj}\right] = 0.$$

Consequently,

$$\lim_{l_m\to\infty} \mathrm{Var}\left[Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_j)}\right] = 0. \tag{18}$$

For $i, n \in \boldsymbol{\mathcal{L}}$ it, then, holds

$$\lim_{l_m\to\infty} P\{Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_i)} > 0\} \geq \lim_{l_m\to\infty} P\{Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_j)} > 0\} = 0,$$

since

$$E[Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_j)}] < 0.$$

For $n \notin \boldsymbol{\mathcal{L}}$

$$\lim_{l_m \to \infty} P\{Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_i)} > 0\} = 1 \geq \lim_{l_m \to \infty} P\{Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_j)} > 0\}, \tag{19}$$

since

$$E[Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_i)}] > 0.$$

This proves statement (6). Finally, the proof of (7) follows from the proof of (6) and from

$$\begin{aligned} &P\{Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_j)} \leq 0\} = \\ &= P\{\mathrm{MSE}_{\mathcal{K}_n}^{l_m} - \mathrm{MSE}_{\mathcal{K}_j}^{l_m}\} P\{Z_{l_m}^{(\mathcal{K}_j \to \mathcal{K}_n)} > 0\}, \\ &\forall j, n \in \boldsymbol{\mathcal{K}}. \end{aligned} \tag{20}$$

■

Lemma 3. *Algorithm 1 converges almost surely to a minimizer state.*

Proof: Consider, first, the case when Condition 3 holds. Since Conditions 1,2 hold as well, the requirements for convergence, according to Theorem 3.1 in [11] are satisfied and Algorithm 1 leads to mean square error minimization. Consider, now, the case when Condition 3 does not hold. Assume $\mathcal{K}_n \notin \boldsymbol{\mathcal{L}}$. If $\mathcal{K}_n$ is transient, then with probability one the sequence $\{\mathcal{K}_m\}$ of visited states will not converge to $\mathcal{K}_n$ as $m \to \infty$. Assume now that $\mathcal{K}_n$ is positive recurrent. By (19) in Lemma 2 we have that $\lim_{l_m \to \infty} P\{Z_{l_m}^{(\mathcal{K}_n \to \mathcal{K}_i)} > 0\} > 0, \forall \mathcal{K}_i \in \boldsymbol{\mathcal{L}}$. Consequently, $\{\mathcal{K}_m\}$ and all states of $\boldsymbol{\mathcal{L}}$ belong to the same communicating class, denoted by $\boldsymbol{\mathcal{K}^I}$, as well as all the other positive recurrent $\mathcal{K}_i \notin \boldsymbol{\mathcal{L}}$ states. The system is thus reduced to a set of states $\boldsymbol{\mathcal{K}^I}$. Clearly, Condition 1 holds for all states in $\boldsymbol{\mathcal{K}^I}$, and a result, the requirements for Theorem 3.1 in [11] are fulfilled. ■

V. Performance evaluation

The performance of the discrete stochastic optimization based parameter estimation depends on the granularity of the discretization for each dimension of the state space, $\boldsymbol{\mathcal{K}}$, and on the number an the location of the s-domain points, on which the empirical and the analytic LTs are compared, for the MSE calculation. These parameters affect the accuracy of the parameter estimation, even if the optimal parameter vector is determined by exhaustive search.

In addition, we consider a limited idle period sample size, and terminate the algorithm when all idle period samples are integrated. This on one hand minimizes the time spent for parameter estimation, but on the other hand, does not ensure that the algorithm finds the optimal parameter vector. To evaluate the achievable estimation performance, we perform parameter estimation with exhaustive search and with early termination, considering a large set of model compliant traffic traces. We select 10^4 $(\xi, \sigma, p, p_{\mathrm{CCA}})$ parameter vectors, generate a sequence of idle and active periods for each vector, and run the estimation algorithms. The parameters are randomized according to Table I, to cover a wide range of traffic patterns. For the evaluations presented here we fix $S = 10^3, s_k \in (10^0, 10^5), 1 \leq k \leq S$, and integrate one new idle period sample in each iteration step.

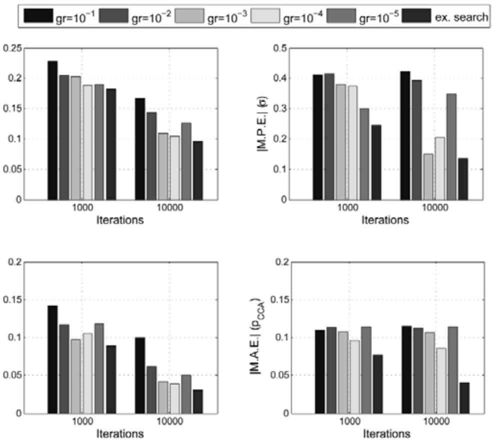

Fig. 3. The accuracy of the LT-based estimation with respect to the number of iterations, and the granularity of the state space. Exhaustive search results are shown for comparison.

TABLE I
MODEL PARAMETERS

Parameter	Distribution	Min	Max	Mean	StdDev
ξ	Truncated Gaussian	0.1	0.4	0.3095	0.1
σ	Truncated Gaussian	1e-4	0.1	0.02	0.2
p	Uniform	0.1	1.0		
p_{CCA}	Uniform	0.1	1.0		
α_{ON}	Uniform	0.0008	0.001		
β_{ON}	Uniform	α_{ON}	0.0015		
α_{BK}	Deterministic			0.0007	

As stated in Section II it is assumed that the $f_A(t)$ parameters can be estimated correctly and α_{BK} is known. We measure the estimation accuracy by calculating the mean absolute error (MAE) of the p and p_{CCA} and the mean percentage error (MPE) of the ξ and σ estimation.

As the number of idle period samples affects the time needed for continuous sensing and in our case even gives the number of iterations of the optimization algorithm, it is one of the main design parameters to be considered. Therefore we evaluate the parameter estimation performance for 10^3 and 10^4 idle period samples and iteration steps. In addition, to evaluate the effect of the size of the state space of the discrete optimization we alter the granularity of the discretization of the state parameters $\{\xi_i, \sigma_i, p_i\}$ between 10^{-1} and 10^{-5}, while bounding them within the respective intervals given in Table I.

Figure 3 compares the estimation accuracy of $\{\xi, \sigma, p, p_{\mathrm{CCA}}\}$ under exhaustive search and with stochastic optimization with early termination. Considering the number of integrated samples, we can see that the increased number of samples improves the estimation accuracy under exhaustive search. At the same time, an increased state space does not necessarily lead to better estimation accuracy. The estimation accuracy may increase with increased state space for a while, in this interval the minimizer is found, and the increased granularity means lower MSE. However, as the state space is further increased, the minimizer can not anymore be discovered in the limited number of iterations, and therefore the estimation accuracy drops. Therefore, the state space size has to be selected carefully, taking the expected number of samples into account.

The results show that the performance of the proposed algorithm is comparable to the one of the exhaustive search. A number of samples in the range of 10^4 and parameter granularity of $10^{-3} - 10^{-4}$ gives an estimation accuracy that is sufficient for the cognitive control as it was shown in [9], while it allows acceptable sensing times, and a state space size that is implementable on sensor devices with limited memory.

VI. DISCUSSION

In the heterogeneous networking environment of the the open ISM band the prediction of the availability of the wireless resources is a key enabler for the design of energy efficient wireless networks. In this paper we considered the issue of WLAN and WSN coexistence. In this case WSN transmissions suffer from WLAN interference, because the WLAN carrier sensing does not detect the low power, narrow band WSN transmissions. The sensor network can avoid this interference, if it can characterize the channel occupancy, and tune its transmission parameters accordingly.

We described a semi-Markovian model of the WLAN channel occupancy, as observed by the individual sensor nodes and proposed a discrete stochastic optimization based algorithm to estimate the parameters of the idle time distribution in the Laplace domain. We showed that the proposed solution can achieve the required estimation accuracy by sequentially integrating the measured idle period samples and by simultaneously searching for the optimal parameter vector. We can conclude that the required idle time sample size allows limited sensing times and the parameter granularity can be low enough for the algorithm to be implemented in resource limited sensor nodes. Therefore the proposed algorithm can support the development of cognitive medium access control and routing in WSNs.

REFERENCES

[1] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *IEEE Journal on Selected Areas in Communications*, vol. 23, pp. 201 – 220, February 2005.

[2] K. Chowdhury and I. Akyildiz, "Interferer classification, channel selection and transmission adaptation for wireless sensor networks," in *Proceedings of IEEE ICC'09*, pp. 1 –5, June 2009.

[3] Q. Zhao, L. Tong, A. Swami, and Y. Chen, "Decentralized cognitive MAC for opportunistic spectrum access in ad hoc networks: A POMDP framework," *IEEE Journal on Selected Areas in Communications*, vol. 25, pp. 589 –600, April 2007.

[4] J. Misic and V. Misic, "Characterization of idle periods in IEEE 802.11e networks," in *Proceedings of IEEE Wireless Communications and Networking Conference (WCNC)*, pp. 1004 –1009, March 2011.

[5] L. Stabellini, "Quantifying and modeling spectrum opportunities in a real wireless environment," in *Proceedings of Wireless Communications and Networking Conference (WCNC)*, pp. 1 –6, April 2010.

[6] J. Huang, G. Xing, G. Zhou, and R. Zhou, "Beyond co-existence: Exploiting WiFi white space for Zigbee performance assurance," in *Proceedings of 18th IEEE International Conference on Network Protocols*, ICNP 2010, pp. 305–314, Oct. 2010.

[7] S. Geirhofer, L. Tong, and B. Sadler, "Cognitive medium access: Constraining interference based on experimental models," *IEEE Journal on Selected Areas in Communications*, vol. 26, pp. 95–105, Jan. 2008.

[8] S. Geirhofer, J. Z. Sun, L. Tong, and B. M. Sadler, "Cognitive frequency hopping based on interference prediction: theory and experimental results," *ACM SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 13, pp. 49–61, September 2009.

[9] I. Glaropoulos, V. Fodor, L. Pescosolido, and C. Petrioli, "Cognitive WSN transmission control for energy efficiency under WLAN coexistence," in *2011 Sixth International ICST Conference on Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM)*, pp. 261 –265, June 2011.

[10] M. Lagana, I. Glaropoulos, V. Fodor, and C. Petrioli, "Modeling and estimation of partially observed WLAN activity for cognitive WSNs," in *IEEE Wireless Communications and Networking Conference (WCNC), 2012*, pp. 1526 –1531, April 2012.

[11] S. Andradottir, "A global search method for discrete stochastic optimization," *SIAM Journal on Optimization*, vol. 6, no. 2, pp. 513–530, 1996.

[12] A. Papoulis and S. U. Pillai, *Probability, Random Variables and Stochastic Processes*. USA: McGrawHill, 4th ed., 2002.

Ioannis Glaropoulos received his Diploma in Electrical & Computer Engineering from the School of Engineering at the Aristotle University of Thessaloniki in 2005 and his MSc in Electrical Engineering with specialization in Wireless Systems at the Royal Institute of Technology (KTH) in Stockholm. As of October 2008 he is with the Laboratory for Communication Networks at the School of Electrical Engineering at KTH. His research interests include dimensioning and routing in wireless sensor networks, cognitive radios and dynamic spectrum access technologies.

Viktoria Fodor Viktoria Fodor received her M.Sc. and Ph.D. degrees in computer engineering from the Budapest University of Technology and Economics in 1992 and 1999, respectively. In 1994 and 1995 she was a visiting researcher at Politecnico di Torino and at Boston University, where she conducted research on optical packet switching solutions. In 1998 she was a senior researcher at the Hungarian Telecommunication Company. In 1999 she joined the KTH, Royal Institute of Technology, where she now acts as assistant professor in the Laboratory for Communication Networks. Her current research interests include multimedia and peer-to-peer communication, sensor network and cognitive radio network protocol design and performance analysis.