Computing and Informatics, Vol. 36, 2017, 1041–1062, doi: 10.4149/cai_2017_5_1041

AGENT-BASED MODEL OF THE SPECTRUM AUCTIONS WITH SENSING IMPERFECTIONS IN DYNAMIC SPECTRUM ACCESS NETWORKS

Juraj Gazda, Slavomír Šimoňák, Emília Pietriková
Martin Chovanec, Eva Chovancová, Norbert Ádám
Csaba Szabó, Anton Baláž, Branislav Madoš

Department of Computers and Informatics
Technical University of Košice
Letná 9
040 01 Košice, Slovakia
e-mail: juraj.gazda@tuke.sk

Abstract. Cognitive radio (CR) is the underlying platform for the application of dynamic spectrum access (DSA) networks. Although the auction theory and spectrum trading mechanisms have been discussed in the CR related works, their joint techno-economic impact on the efficiency of distributed CR networks has not been researched yet. In this paper we assume heterogeneous primary channels with network availability statistics unknown to each secondary user (SU) terminal. In order to detect the idle primary user (PU) network channels, the SU terminals trigger regularly the spectrum sensing mechanism and make the cooperative decision regarding the channel status at the fusion center. The imperfections of the spectrum mechanism create the possibility of the channel collision, resulting in the existence of the risk (in terms of user collision) in the network. The spectrum trading within SU network is governed by the application of the sealed-bid first-price auction, which takes into account the channel valuation as well as the statistical probability of the risk existence. In order to maximize the long-term payoff, the SU terminals take an advantage of the reinforcement comparison strategy. The results demonstrate that in the investigated model, total revenue and total payoff of the SU operator (auctioneer) and SU terminals (bidders) are characterized by the existence of the global optimum, thus there exists the optimal sensing time guaranteeing the optimum economic factors for both SU operator and SU terminals.

Keywords: Cognitive radio, dynamic spectrum access, reinforcement comparison, spectrum auction

1 INTRODUCTION

Dynamic spectrum access (DSA) network promises to revolutionize the way wireless communication operators and networks behave through sophisticated assignment of frequency resources. Currently, the available spectrum is divided into several frequency bands, which are allocated traditionally to a specific operator in return for the monetary gain [1]. However, the recent measurements show that the spectrum utilization in the 0-6 GHz varies from 15 to 85 % depending on the time and geographical location [2]. It implies that the traditional licensing schemes present serious bottleneck for deployment of larger density of wireless devices. We note that the scarcity of RF spectrum is not a result of lack of spectrum but a result of wasteful static spectrum allocations [3]. These observations motivate the researchers and industrial bodies to come up with the solution enabling higher spectrum utilization with only minor requirement changes on the existing operators' infrastructure. The cognitive radio (CR) platform, whereby secondary user (SU) terminals are allowed to access vacant frequency resources of the primary user (PU) network, has a great potential to increase the spectrum efficiency utilization without major changes to the existing PU networks. The major restriction posed on the secondary spectrum access in DSA consists in the fact that the transmission of SU terminals does not cause any measurable interference to the PU network. Therefore, SU terminals must identify possible free and not occupied space-time-frequency slots where the transmission of the PU network is not present [4].

Several methods exist for protecting PU network licensing rights (in terms of the cross-interference due to the SU network), ranging from sensing-only methods [5] to geo-location database techniques [6]. The reliability of these methods is of a major concern of practical applicability of DSA networks. Sensing-only detection methods face challenging performance and design issues, as verified by recent FCC testing of experimental TV white space (TVWS) devices [7, 8]. On the other hand, geo-location database techniques rely on known private information related to the occupancy of the frequency bands, including the exact types of services present and their specific interference requirements. This information is the subject of immediate change and thus, maintaining of the database of such type remains a huge concern [9]. Sensing-only devices do not possess the same level of knowledge about the bands, but have the potential to detect the vacant channels thanks to the cooperative behavior of the SU terminals.

In spectrum sensing, SU terminal analyzes its radio environment, creates a test statistics from the received signal and decides if the transmission of the PU network is present in the received signal. There exist several algorithms of sensing methods in the literature [10]. Matched-filter detection or cyclostationary sensing detection techniques need prior knowledge of the PU network signal. Conversely, the energy detection and interference-based spectrum detection form the group of sensing mechanisms, where no knowledge about the PU network signal is needed prior to the detection. Sensing results can be significantly improved by exploiting the spatial diversity of several spatially distributed SU terminals and making the final sensing decision based on the local sensing results. This is referred to as cooperative spectrum sensing [11].

In cooperative spectrum sensing, multiple SU terminals work together to exchange the information to detect the activity of PU network. This technique exploits the spatial diversity intrinsic to a multiuser network. It can be accomplished in a centralized or distributed fashion. In a centralized manner, each SU terminal reports its spectrum observations to a central controller that processes the information and creates a spectrum occupancy map of the overall network. In a distributed fashion, the SU terminals exchange spectrum observations among themselves and each individually develops a spectrum occupancy map [12, 13, 14]. In our paper we focus on the former approach due to its higher potential to be applied in the networks, where most of the processing capabilities are localized in the secondary operator's base-station (BTS).

The accuracy of the spectrum sensing strongly impacts the economy of DSA networks, mainly operating in the shared-used model. In the shared-used DSA networks, the radio spectrum can be simultaneously shared between PU and SU networks. In this model, SU terminals can opportunistically access the radio spectrum if it is not occupied or fully utilized by PU network, in return for the increased monetary gain of PU operator [15]. On the other hand, the SU network communication in the licensed band of PU network creates the possibility of simultaneous voice/data traffic on the same channel, resulting in the interference. Thus, shared model of DSA is exposed to the performance degradation due to the imperfect spectrum sensing, resulting in the occurrence of a collision. This kind of interference is coined throughout the paper as risk and it reflects the probability of the missed detection of the PU network activity. Nevertheless, most current works on spectrum trading have so far assumed the exclusive-usage model (see e.g. [16, 17] and the references therein). In these kind of models, the spectrum privileges are sold by the PU network to SU operator for a specific period of time and thus, no risk is present in the system. On the other hand, we register only a few papers (e.g. [18]) dealing with both of them, spectrum trading and spectrum sensing mechanisms and their joint optimization. For example, Tehrani et al. in [18] proposed analytical framework allowing the investigation of the mutual impact of spectrum trading and sensing in the shared-used based DSA networks. Many research challenges seen in the shared-used model of DSA networks motivated us to shed more light on the issue of joint optimization of spectrum sensing and trading parameters to improve the measured indicators of both, PU and SU network.

To design efficient and effective DSA networks, the related technical aspects (e.g. channel detection, power control) as well as economic aspects (e.g. pricing, spectrum auction) need to be considered. In other words, also the economic indicators (retail pricing, operator's profit, etc.) contribute to the overall picture of DSA networks application [19]. Thus, the operators could potentially see DSA networks and underlying CR platform as a threat to their own privilege spectrum rights and regulators are still discussing this complex topic without a clear perspective on their role to facilitate the implementation of DSA networks. Large scale deployment of this technology may be expected in the near future, however meantime the potential economic and social value of such reform should be investigated.

In this paper, we propose an agent-based model of spectrum trading for a shared usage model of DSA. We consider primary network consisting of the PU operator broadcasting in TVWS band and secondary network consisting of secondary BTS and multiple SU terminals. Our intention is to propose the model consistent with any future system using CR technology in the shared-model. For example, in an 802.22 system, agents can be built on base stations, which lease (or sense) the spectrum of VHF/UHF TV bands and serve all its associated Consumer Premise Equipments without any harmful interference to TV receivers [20]. SU network performs cooperative sensing, where the partial SU measurements are processed in the fusion center located at the secondary BTS. We consider two well-known cooperative spectrum sensing rules, namely LOGIC-AND and LOGIC-OR rule. Due to their nature, these rules create different level of the risk in the system, which eventually impacts the investigated metrics, such as SU operator's revenue, SU terminals' payoff, etc. In our case, the presented agent-based model aims to analyze and investigate the impact of the imperfect spectrum sensing determined by the duration of the spectrum sensing itself. For the purpose of the spectrum trading we use well-known auction mechanism. In the auction process, the buyers (SU terminals) submit their spectrum bids and the profit of a spectrum seller (secondary BTS) is maximized by allocating spectrum to the buyer(s) submitting the highest bidding price [21]. In our model we use sealed-bid multiple unit sequential spectrum auction which allows us to create the scenario where SU terminals compete for the block of vacant frequency channels [22]. The auction strategies of the SU terminals are governed by the reinforcement comparison learning, and the knowledge of SU terminals is limited to the instantaneous payoff obtained in each auction round, thus no global environment knowledge is required. Last, the main advantage of the agent-based approach is that it can efficiently simulate the real-world scenario, where the agents (e.g. SU terminals) have only limited knowledge about their environment and distributed intelligence is of more interest.

The rest of the paper is organized as follows. Section 2 describes the system model considered in the paper. The agent-based model and the description of each network entity is described in Section 3. Numerical analysis of the proposed model is pointed out in the Section 4. Finally, conclusion is given in the last Section 5.

2 SYSTEM MODEL

Our model represents a typical IEEE 802.22 system, where the SU network operates in the licensed frequency band of PU network. Here, under the joined term SU network we recognize secondary operator's BTS and N SU terminals (see Figure 1). SU terminals are randomly distributed in the investigated region. Fusion center is physically located on the secondary operators' BTS. Primary user BTS generates the traffic over the dedicated channels, while the vacant channels are allowed to be re-used by SU network. Assuming perfect reporting channels, every SU terminal performs spectrum sensing and reports the sensing result to the fusion center. Eventually the fusion center decides the presence or the absence of PU network. In order to detect idle licensed channels, the cooperative spectrum sensing is performed by SU network. The spectrum auction is eventually recalled in order to assign the channels to respective SU terminals. If all channels are identified as occupied by PU network traffic, no action will be taken and no transmission will take place. Further details regarding the spectrum sensing and spectrum trading schemes will be described in the next sections.

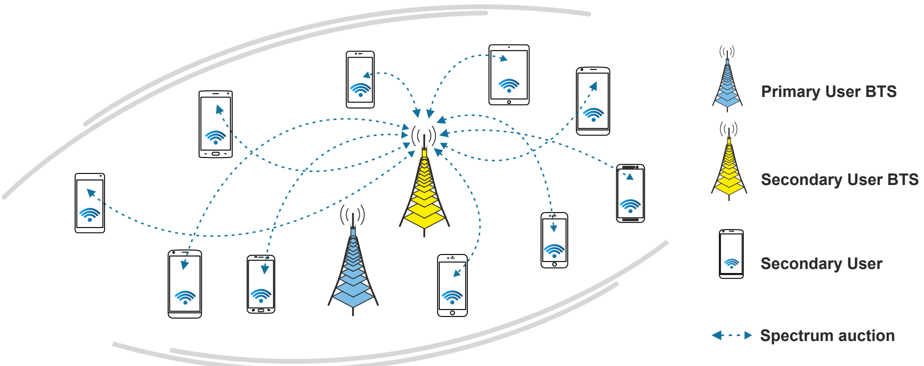


Figure 1. IEEE 802.22 network model with corresponding interacting entities

2.1 Spectrum Sensing

Throughout the paper we take an advantage of the cooperative spectrum sensing, whereby the energy detector provides the local measurements of SU terminals, which are eventually processed in the fusion center. These particular steps are introduced in the following text.

2.1.1 General Model

In this section, spectrum sensing preliminaries that involve multiple SU terminals are discussed. In general, the goal of spectrum sensing is to decide on the hypotheses if the PU network signal is present $\mathcal{H}_1$ or not $\mathcal{H}_0$ as follows [23]:

$$\mathcal{H}_0: \quad y(n) = w(n), \tag{1}$$

$$\mathcal{H}_1: \quad y(n) = h(n)s(n) + w(n) \tag{2}$$

where

- $y(n)$ denotes the signal received by each SU terminal,
- $s(n)$ is the licensed PU network signal,
- $w(n) \sim N(0, \sigma_w^2)$ is the additive while Gaussian noise with zero mean and variance σ_w^2. In turn signal-to-noise ratio (SNR) γ equals: $\gamma = \frac{\sigma_s^2}{\sigma_w^2}$,
- $h(n)$ denotes the Rayleigh fading channel gain of the sensing channel between the PU network and SU terminal,
- the licensed PU network signal $s(n)$ is un-correlated with noise $w(n)$.

The channel considered between the PU network and the SU terminal is the Rayleigh channel. Typically, to specify the channel vacancy, a test statistic $T(y)$ from the received signal is formed. Then the final decision is made by comparing $T(y)$ with a predefined threshold ϵ under certain hypothesis which is expressed as

$$T(y) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \epsilon. \tag{3}$$

The detection performance can be primarily determined on the basis of two metrics: probability of false alarm, which denotes the probability of an SU network declaring that a PU network is present when the spectrum is actually idle, and probability of correct detection, which denotes the probability of an SU network declaring that a PU network is present when the spectrum is indeed occupied by the PU network. Under hypothesis $\mathcal{H}_0$ the probability of false alarm $p_f = Pr(T(y) > \epsilon|\mathcal{H}_0)$ and the probability of correct detection that the channel is idle $p_i = Pr(T(y) < \epsilon|\mathcal{H}_0)$. Similarly, under hypothesis $\mathcal{H}_1$, the probability of correct detection $p_d = Pr(T(y) > \epsilon|\mathcal{H}_1)$ and the probability of missed detection $p_m = Pr(T(y) < \epsilon|\mathcal{H}_1)$. Obviously, our intention is to achieve high probability of detection p_d and low probability of false alarm p_f.

2.1.2 Energy Detection

Energy detection comes under the category of blind spectrum sensing technique and is used to detect the PU network signal [24]. This detection method calculates the energy of the received signal and compares it to a threshold ϵ to take the local decision that the PU network signal is present or absent. Now, let us define τ as the sensing time, f_s as the sampling frequency and L as number of samples used for the sensing purposes. There is a mathematical expression to calculate the energy of any received PU network signal given as

$$T(y) = \frac{1}{L} \sum_{n=1}^{L} |y(n)|^2 \tag{4}$$

where $T(y)$ denotes the energy of the received input signal, which is compared with threshold ϵ to make the final decision.

Assuming the hypothesis $\mathcal{H}_0$, we can characterize the test statistics $T(y)$ as a random variable, which probability density function (PDF) $p_0(x)$ takes the Chi-Square distribution with L degrees of freedom. Considering the detection threshold ϵ, the probability of false alarm p_f can be expressed as

$$p_f(\epsilon, \tau) = Pr(T(y) > \epsilon | \mathcal{H}_0) = \int_{\epsilon}^{\infty} p_0(x)\, \mathrm{d}x. \tag{5}$$

Now considering large number of samples L and using the background idea of the central limit theorem [25], the PDF of $T(y)$ under hypothesis $\mathcal{H}_0$ can be approximated by a Gaussian distribution with mean μ_0 and variance $\sigma_0^2 = \frac{1}{L}[E|w(n)^4 - \sigma_w^4]$. Next, provided $w(n)$ is real-valued Gaussian variable, then $E|w(n)^4 = 3\sigma_w^4$, thus $\sigma_0^2 = \frac{2}{L}\sigma_w^4$, where $E|\cdot|$ is the expected value operator. However in our paper we assume $w(n)$ to be circularly symmetric complex Gaussian (CSCG) variable, thus $E|w(n)|^4 = 2\sigma_n^4$ and consequently $\sigma_0^2 = \frac{1}{L}\sigma_n^4$. Then, the probability of false alarm is given by

$$p_f = \mathcal{Q}\left(\left(\frac{\epsilon}{\sigma_n^2} - 1\right)\sqrt{\tau f_s}\right) \tag{6}$$

where $\mathcal{Q}(\cdot)$ is the Q-function defined as

$$\mathcal{Q}(x) = \frac{1}{\sqrt{2\pi}} \int_1^{\infty} \exp\left(-\frac{t^2}{2}\right) \mathrm{d}x. \tag{7}$$

Under hypothesis $\mathcal{H}_1$, let us denote $p_1(x)$ as the PDF of $T(y)$. For the given threshold ϵ, the probability detection is given by

$$p_d(\epsilon, \tau) = Pr(T(y) > \epsilon | \mathcal{H}_1) = \int_{\epsilon}^{\infty} p_1(x)\, \mathrm{d}x. \tag{8}$$

Further, for sufficiently large L, the PDF of $T(y)$ can be approximated by a Gaussian distribution with mean $\mu_1 = (\gamma + 1)\sigma_n^2$, where $\gamma = \frac{\sigma_s^2}{\sigma_n^2}$ is SNR, and variance [26]

$$\sigma_1^2 = \frac{1}{L}[E|s(n)|^4 + E|w(n)|^4 - (\sigma_s^4 - \sigma_n^4)^2], \tag{9}$$

provided $s(n)$ and $w(n)$ are both circularly symmetric and complex valued. If $s(n)$ is complex PSK modulated and $w(n)$ is CSCG noise, then $\sigma_1^2 = \frac{1}{L}(2\gamma + 1)\sigma_n^4$. For the case of PSK modulated complex-valued signal and CSCG noise, the probability of detection can be approximated as [26]

$$p_d = \mathcal{Q}\left(\left(\frac{\epsilon}{\sigma_n^2} - \gamma - 1\right)\sqrt{\frac{\tau f_s}{2\gamma + 1}}\right). \tag{10}$$

Sensing threshold ϵ can be calculated by evaluating (6) or (10) for given target probabilities $\bar{p}_f$ or $\bar{p}_d$, respectively. The reason why we introduce the analytical formulations of the p_f and p_d probabilities stems from the fact that these quantities control the decisions of SU network in the agent-based model proposed later in the paper. In other words, instead of getting statistics using Monte Carlo simulations, we take advantage of the analytical representations of the sensing statistics.

2.1.3 Cooperative Sensing Data Fusion

When binary local decisions are reported to the fusion center, it is convenient to apply linear fusion rules to obtain the cooperative decision. In our paper, we consider Logic-AND and Logic-OR rules, as these methods are popular due to their relative simpleness. Now, let us suppose there are N SU terminals and define $p_d^{(k)}$ as the probability of detection of the k^{th} SU terminal. The local binary decision of the channel state $D_k \in \{0,1\}$ is calculated by each SU terminal individually and sent to the secondary BTS in each sensing period. The final decision of the channel availability is made by the secondary BTS by using cooperative decision.

- Logic-OR rule; in this case the final decision says that the channel is occupied by a primary signal when one of the local decision declares the channel as busy. Mathematically this relation can be written as $\Lambda = \sum_{k=1}^{N} D_k$. If $\Lambda \geq 1$ then the channel is busy. The final probability of detection, assuming that all local decisions are independent, is given by

$$Q_d = 1 - \prod_{k=1}^{N} \left(1 - p_d^{(k)}\right). \tag{11}$$

- Logic-AND rule; if all local decisions says that the channel is occupied by a primary signal then the final decision declares the channel as busy. Thus we can write $\Lambda = \prod_{k=1}^{N} D_k$. If $\Lambda = 1$ then the channel is busy. Assuming independent local decisions, the final probability of detection can be calculated as

$$Q_d = \prod_{k=1}^{N} p_d^{(k)}. \tag{12}$$

2.2 The Auction Algorithm for the Channel Distribution

There exist several mechanisms used for the spectrum distribution among SU terminals, namely; auction mechanism, direct trading and brokerage mechanism. These mechanisms are discussed in detail in [27]. As the authors suggested in this work, the secondary spectrum usage can increase economic welfare, including SU terminal's payoff and SU operator's profit. In particular, auctions provide higher profits for the service providers than the other mechanisms (see explanation in [27]), and thus we decided to use this mechanism in our model.

We propose the spectrum trading algorithm based on the sealed-bid first-price auction [28][1]. Thus, the highest bidder gets the chance to acquire the channel. In our model, secondary BTS has a role of an auctioneer and SU terminals send theirs bids with aim to get the channel auctioned at the auction.

We define the payoff of the i^{th} SU terminal in the t^{th} time frame $R(i,t)$ as

$$R(i,t) = \begin{cases} V(i,t) - b(i,t), & \text{SU terminal wins the auction,} \\ 0, & \text{SU terminal loses the auction,} \end{cases} \tag{13}$$

where $V(i,t)$ is a spectrum valuation of the i^{th} bidder in the t^{th} time frame and $b_{i,t}$ is a bid of the i^{th} bidder in the t^{th} time frame. We define $V(i,t)$ as

$$V(i,t) = \omega[1 - r(t)](T - \tau)\frac{C(i,t)}{C_{ref}} \tag{14}$$

where $r(t)$ is the risk associated with getting the channel in the t^{th} time frame, T is the duration of the time frame, τ is the sensing time, $C(i,t)$ is the channel capacity between the i^{th} SU terminal and secondary BTS in the t^{th} time frame, C_{ref} is the reference channel capacity and ω is a scaling parameter.

The probability that the i^{th} bidder wins the auction can be expressed as [18]

$$P(i^{\text{th}} \text{ bidder winning}) = \left(\frac{b(i) - b_{min}}{V_{max} - b_{min}}\right)^{(N-1)} \tag{15}$$

where b_{min} is the minimum bid, V_{max} is the maximum spectrum valuation and N is the number of bidders (i.e. number of SU terminals participating at the auction). The expected payoff of the i^{th} bidder can be then expressed as:

$$E(i) = (V(i) - b(i)) \times P(i^{\text{th}} \text{ bidder winning}). \tag{16}$$

Optimal bid can be determined by substituting $P(i^{\text{th}}$ bidder winning$)$ from (15) into (16) and maximizing the resulting $E(i)$ by getting the first derivative of $E(i)$ to 0. Thus, the optimal bid $b(i)^*$ for the i^{th} bidder can be expressed as:

$$b(i)^* = \frac{(n-1)V(i) + b_{min}}{n}. \tag{17}$$

Obviously, this is a pure theoretical concept as the minimum bid b_{min} is generally not known for the SU terminals. Instead the SU terminal needs to approximate optimal bid $b(i)^*$. As long as we assume bounded rationality of the agents in the model, the learning algorithms with limited information are of our interest. Reinforcement

[1] Although there exist numerous papers dealing with sealed-bid second price auction, this type of auction is rarely used in practice because of the possibility of cheating by the seller [29]. With the fear of cheating, a second price auction may become less profitable than a first price auction for non-cheating and fair seller (operator).

comparison, which belongs to the broad group of the reinforcement learning based algorithms [30], seems to be the suitable candidate to be used in our model. In order to determine the SU terminal decision about their bids in each auction round, we have employed the reinforcement comparison algorithm. When creating secondary spectrum market, we decided to look for the inspiration in the smart grid electricity systems. The authors in [31] used reinforcement learning allowing the service providers to learn the behavior of the electricity network and the change of retail price to make an optimal pricing decision in the retail market. However it should be noted when dealing with the secondary spectrum market model there are certain differences that should be emphasized:

1. spectrum goods have a non-storable character;
2. postponing its consumption is impossible (consumption runs in real time).

These facts make the situation with the secondary spectrum trading more simplified compared to the traditional wholesale electricity market. The traditional Markov decision problem (MDP) could be successfully reduced to one state (under the assumption that the spectrum consumption cannot be postponed), which resembles typical multi-armed bandit problem. In our model the particular arms of the bandit are represented by the possible choices of SU terminals' bids. Thus, the algorithm governs the SU terminals to choose those bids, which would maximize their long-term payoffs. Therefore, we propose an algorithm based on the reinforcement comparison algorithm in order to determine the optimal bid locally for each bidder (SU terminal).

2.2.1 Reinforcement Comparison Learning

Let us define a vector of the available bids for the i^{th} bidder in the t^{th} time frame $\mathbf{b}(i,t)$ with elements $b_j(i,t)$, which can be expressed as

$$b_j(i,t) = V(i,t)\frac{j}{N_b} \tag{18}$$

where $j = 1, 2, \ldots, N_b$ and N_b is the number of the possible bid options, i.e., the set of available bids $\mathcal{B}$ is defined as

$$\mathcal{B} = \left\{0, V(i,t)\frac{1}{N_b - 1}, V(i,t)\frac{2}{N_b - 1}, \ldots, V(i,t)\frac{N_b - 1}{N_b - 1}\right\}. \tag{19}$$

Each bid has its corresponding selection probability $p_j(i,t)$. To increase the readability of the text, we ignore the index i in the following expressions, however note that the probability vector is unique for each bidder. Bid valuation adaptation for the j^{th} bid choice can be expressed as

$$\pi_j(t+1) = \pi_j(t) + \alpha(\rho(t) - \pi(t)) \tag{20}$$

where $\pi_j(t)$ is a valuation of the j^{th} bid choice in the current time frame, $\pi_j(t+1)$ is a valuation of the j^{th} bid choice in the next time frame, $\rho(t)$ is the reference payoff and α is an adaptation parameter. Adaptation of the $\rho(t)$ can be expressed as

$$\rho(t+1) = \rho(t) + \beta(R(t) - \rho(t)) \tag{21}$$

where $\rho(t)$ is the reference payoff in the current time frame, $\rho(t+1)$ is the reference payoff in the next time frame and β is the adaptation parameter. Normalized probability of the j^{th} bid selection in the $(t+1)^{\text{th}}$ time frame is calculated as follows:

$$p_j(t+1) = \frac{\exp\left(\frac{\pi_j(t+1)}{\delta}\right)}{\sum_{l=1}^{N_b} \exp\left(\frac{\pi_l(t+1)}{\delta}\right)} \tag{22}$$

where δ is the cooling parameter that controls the convergence speed of the algorithm. Eventually, the bid $b_j(t+1)$ is computed according to the bid probabilities vector $\mathbf{p}(t)$.

3 AGENT-BASED IMPLEMENTATION OF THE MODEL

The application of the principles of techno-economic analysis (technological in terms of the spectrum sensing and learning, and economic in terms of the spectrum auction) opens up the possibility of using a wide variety of research approaches. In general, several simulation models that describe techno-economic analysis have been introduced lately, such as game theory [16], evolutionary game theory [32, 33] and bargaining theory [34]. In general, most of these models impose unrealistic assumptions regarding the interactions of agents. For example, the interacting agents in the game theory based models have perfect knowledge of the payoffs of the opponents, i.e., full rationality is considered. However, we claim that this information is private and thus, the agents with limited knowledge are of more interest in these scenarios. Thus, the agents should be uncertain about the spectrum demand (bounded rationality) and may act opportunistically. Provided the bounded rationality of the market participants is assumed, an agent-based modeling & simulation (ABMS) approach seems to be very effective tool for analyzing the interactions of the market agents [35, 36].

Thus, in order to analyze an impact of the risk caused by imperfect spectrum sensing on the spectrum trading, we propose an agent-based model consisting of three types of agents; PU network, secondary operators' BTS and multiple SU terminals. Our fundamental goal is to analyze the revenue of the secondary operator's BTS and the payoff of the SU terminals in the relation with the risk due to the imperfect spectrum sensing.

3.1 Primary-User Network

PU network is represented by a simple agent entity in our model. It takes on the role of the two states, which are directly related to its activity: *ACTIVE* or *IDLE*. The role of this agent is to simulate the PU network traffic, which, in turn, is detected by SU network.

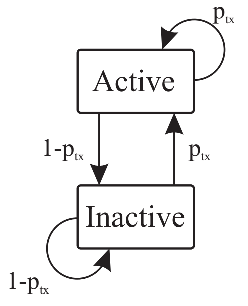


Figure 2. Traffic model of the PU network. The probability p_{tx} is related to the transition probabilities between the PU network states.

3.2 Secondary-User BTS

Secondary BTS agent makes the global sensing decision based on the local decisions from the SU terminals, it calculates the risk r, which is associated with purchasing the spectrum band and it determines the winner of the auction. The global probability of correct detection Q_d is calculated using (11) or (12) based on which decision fusion scheme is applied. If the channel is identified as idle, auction is being held, and risk r is calculated as follows:

$$r = 1 - Q_d. \tag{23}$$

Risk r is sent to each SU terminal over a dedicated channel. SU terminal computes the corresponding valuation of the channel and sends the corresponding bid to the secondary BTS. When all bids are collected, the winning SU terminal is determined and all SU terminals are notified about the auction results.

3.3 Secondary-User Terminal

The agent carries out four typologically different actions contributing the overall DSA functionality. Here we introduce them in the order in which they are initialized in the agent based model:

1. spectrum sensing,

2. auction participation,
3. reinforcement comparison learning for choosing the optimum bid,
4. data transmission.

Each SU terminal regularly triggers the spectrum sensing based on the energy detection of the signal. The local sensing results are then processed in the fusion center and global decision is reached. Provided the channel is identified as idle, SU terminal chooses bid b_j with the probability p_j and sends it to the secondary operator's BTS. Based on the auction results, SU terminal calculates its payoff from the current auction round according to (18) and (22). Then it adapts its bidding choices and their corresponding probabilities using the reinforcement comparison algorithm.

4 NUMERICAL RESULTS

4.1 Simulation Setup

The network model considered throughout the simulation scope consists of the PU network, one secondary operator's BTS and 10 SU terminals. The area under investigation has a square shape of size 1 km × 1 km. The SU terminals follow the random walk with constant speed in the model. We assume the Rayleigh channel, i.e., no line of sight is considered in the model, which fits the investigated scenario mainly to the urban area. The model parameters used throughout the simulation runs are depicted in Table 1. We analyze both the single-unit and multi-unit spectrum auctions. In multi-unit, multiple frequency channels are auctioned at the same time, in order to increase its network throughput. We use three figures of merits determining the mutual impact of the cooperative spectrum sensing mechanisms and spectrum auction, namely – development of the risk over time, normalized revenue of SU operator and normalized payoff of SU terminal.

4.2 Results

In Figure 3 we illustrate risk r in terms of the sensing time. Here we can see monotonic dependence of the risk on the sensing time. Obviously, the larger the sensing time is, the less risk is present in the system. On the other hand, the average risk is significantly higher for LOGIC-OR fusion rule for both investigated cases of the spectrum auction. That observation can be explained in such way that the risk of purchasing the spectrum in the scenario with the LOGIC-OR fusion rule is lower, than in the case of the LOGIC-AND fusion rule and therefore the SU terminals are willing to pay more for the same spectrum resource.

Figure 4 shows the normalized revenue of secondary operator's BTS in terms of sensing time τ for both LOGIC-OR and LOGIC-AND fusion rules. Normalized revenue is the crucial parameter for the secondary BTS as if it does not excess

Parameter	**Value**
Number of iterations	10 000
Number of time frames per iterations	100 000
Time frame length	$T = 80\,\mathrm{ms}$
Sampling frequency	$fs = 400\,\mathrm{kHz}$
Carrier frequency	$fc = 800\,\mathrm{MHz}$
Transmit power of the PU BTS	$P_{tx,PU} = 60\,\mathrm{dB}$
Transmit power of the SU BTS	$P_{tx,BTS} = 80\,\mathrm{dB}$
Velocity of the SU terminals	$v_{SU} = 3\,\mathrm{m/s}$
PU network; probability of transmission	$p_{tx} = 0.5$
Variance of the noise on the SU terminal	$\sigma_n^2 = 1$
Target probability of false alarm	$\bar{p}_f = 0.1$
Parameter of the learning algorithm α	$\alpha = 0.1$
Parameter of the learning algorithm β	$\beta = 0.1$
Parameter of the learning algorithm δ	$\delta = 10$
Number of bid choices	$M = 10$
Reference channel capacity	$C_{ref} = 660\,\mathrm{kbps}$

Table 1. Simulation parameters

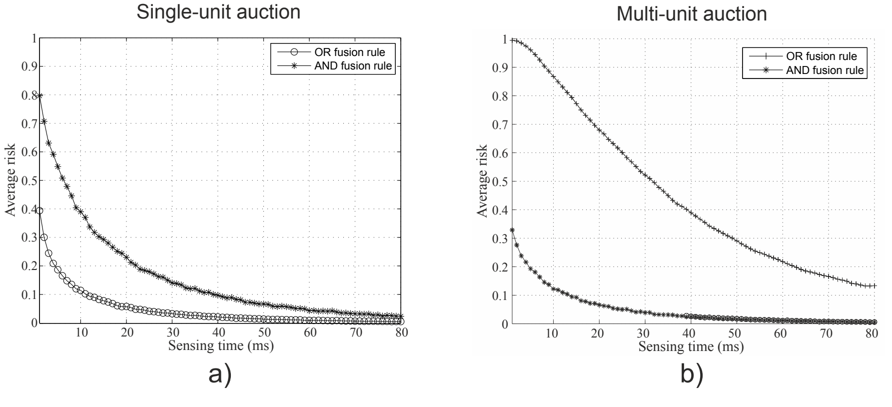
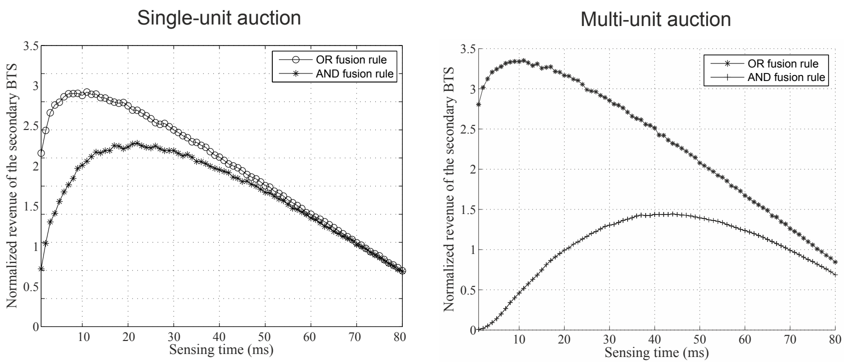


Figure 3. Development of the risk vs. sensing time

the critical level, the secondary operator's BTS becomes unprofitable (considering the fixed and variable cost) and its deployment becomes not feasible. In general, we can see that the normalized revenue (normalized to the one auction round) is higher for the LOGIC-OR fusion rule. This observation is more remarkable for the scenario when multi-unit auction is applied. On the other hand, the dependence of the revenue is not monotonic and we can see the global optimum ensuring the highest revenue for both LOGIC-AND and LOGIC-OR rules. In general we can claim that the LOGIC-AND rule needs higher sensing time in order to achieve its optimum performance in term of revenue.

Figure 5 illustrates the average payoff of the SU terminal in terms of sensing time τ. Here we depict only the scenario with single-unit spectrum auction. Based on our extensive simulations we can claim that the results are overlapping with those representing multi-unit spectrum auction. In general, the aim of SU is to get the highest normalized average payoff (e.g. the lowest price entering the spectrum auction paid for the highest utility when it succeeds in the spectrum auction round). Here the results are again in accordance with previous results and LOGIC-OR fusion rule significantly outperforms the LOGIC-AND fusion rule for the relatively short sensing time. However, the longer the sensing time is, the more the differences among the investigated fusion rules diminish. Again, we observe the global optimum which ensures the highest payoff for the SU terminal (i.e. $\tau = 20\,\mathrm{ms}$ for LOGIC-AND rule and $\tau = 10\,\mathrm{ms}$ for LOGIC-OR rule).



a) b)

Figure 4. Total revenue of the secondary BTS with respect to the sensing time

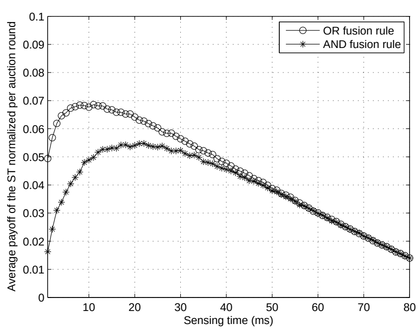


Figure 5. Average payoff of the SU terminal with respect to the sensing time

5 CONCLUSION

The aim of this paper was to propose the techno-economic model of the secondary spectrum sharing, whereby the focus is paid on the mutual impact of the technological and economical aspects of the spectrum sharing. Spectrum sensing is a crucial component of the spectrum sharing and thus we decided to take it under our investigation. The economical aspects in our model are represented by the dynamic spectrum auction. Reinforcement comparison algorithm is considered in the model in order to introduce the intelligence to the autonomous agents which take on the role of the SU terminals. Initially, we proved the relevance of the model as we showed that the probability of the risk existence decreases with the spectrum sensing, as expected. Then we analyzed the average revenue of the secondary operator's BTS. As the simulation results suggested the LOGIC-OR fusion rule outperforms the LOGIC-AND fusion rule over the entire spectrum sensing time parameter space. Obviously there is the clear trade-off between the probability of the risk in the system and the revenue of the secondary BTS. While in the former scenario, risk existence is higher when LOGIC-OR fusion rule is applied, the latter shows clear dominance of the LOGIC-OR fusion rule compared to the LOGIC-AND fusion rule. When discussing the average payoff of the SU terminal, we have got an agreement with the previous results as the LOGIC-OR fusion rule again provides better results that LOGIC-AND fusion rule.

In our follow up research, we aim to apply more sophisticated spectrum sensing mechanisms (e.g. cyclostacionary detection), which should be capable to provide a higher revenue for the secondary BTS at the expense of increased cost of the SU terminals (e.g. battery life). As these aspects are somehow contradictory, there should be some agreement among the SU terminals and secondary BTS, allowing to be beneficial for both sides. A good example would be for instance a reduced price for the wireless services offered towards potential SU terminals.

Acknowledgement

This work was supported by the Slovak Research and Development Agency, project number APVV-15-0055, and by European Intergovernmental Framework COST Action CA15140: Improving Applicability of Nature-Inspired Optimisation by Joining Theory and Practice. This work was also supported by KEGA Agency of the Ministry of Education, Science, Research and Sport of the Slovak Republic under Grant No. 077TUKE-4/2015 "Promoting the Interconnection of Computer and Software Engineering Using the KPIkit" and Grant No. 003TUKE-4/2017 "Implementation of Modern Methods and Education Forms in the Area of Security of Information and Communication Technologies towards Requirements of Labour Market".

REFERENCES

[1] Zhang, W.—Wang, Y.—Xu, M.—Shi, C.—Zhang, P.: Optimization of Layer Selection with Unreliable RI in LTE Systems. Computing and Informatics, Vol. 33, 2014, No. 2, pp. 431–445.

[2] Cabric, D.—O'Donnell, I. D.—Chen, M.-W.—Brodersen, R. W.: Spectrum Sharing Radios. IEEE Circuits and Systems Magazine, Vol. 6, 2006, No. 2, pp. 30–45, doi: 10.1109/MCAS.2006.1648988.

[3] Yrjola, S.—Matinmikko, M.—Ahokangas, P.—Mustonen, M.: Licensed Shared Access to Spectrum. Spectrum Sharing in Wireless Networks: Fairness, Efficiency, and Security, 2016, p. 139.

[4] Liang, B.—Huang, H.—Jing, X.: Dynamic Power Allocation for Spectrum Sharing in Interference Alignment (ia)-Based Cognitive Radio. 2016 16th International Symposium on Communications and Information Technologies (ISCIT). IEEE, 2016, pp. 646–650, doi: 10.1109/ISCIT.2016.7751713.

[5] Khan, A. A.—Rehmani, M. H.—Reisslein, M.: Cognitive Radio for Smart Grids: Survey of Architectures, Spectrum Sensing Mechanisms, and Networking Protocols. IEEE Communications Surveys & Tutorials, Vol. 18, 2016, No. 1, pp. 860–898, doi: 10.1109/COMST.2015.2481722.

[6] Zhu, H.—Fang, C.—Liu, Y.—Chen, C.—Li, M.—Shen, X. S.: You Can Jam but You Cannot Hide: Defending Against Jamming Attacks for Geo-Location Database Driven Spectrum Sharing. IEEE Journal on Selected Areas in Communications, Vol. 34, 2016, No. 10, pp. 2723–2737, doi: 10.1109/JSAC.2016.2605799.

[7] Flores, A. B.—Guerra, R. E.—Knightly, E. W.—Ecclesine, P.—Pandey, S.: IEEE 802.11 af: A Standard for TV White Space Spectrum Sharing. IEEE Communications Magazine, Vol. 51, 2013, No. 10, pp. 92–100.

[8] Kriska, M.—Janitor, J.—Fecilak, P.: Dynamic Routing of IP Traffic Based on QoS Parameters. International Journal of Computer Networks & Communications, Vol. 6, 2014, No. 4, p. 11.

[9] Gao, Z.—Zhu, H.—Liu, Y.—Li, M.—Cao, Z.: Location Privacy in Database-Driven Cognitive Radio Networks: Attacks and Countermeasures. INFOCOM, 2013 Proceedings IEEE, IEEE, 2013, pp. 2751–2759, doi: 10.1109/INFCOM.2013.6567084.

[10] Sun, H.—Nallanathan, A.—Wang, C.-X.—Chen, Y.: Wideband Spectrum Sensing for Cognitive Radio Networks: A Survey. IEEE Wireless Communications, Vol. 20, 2013, No. 2, pp. 74–81.

[11] Ganesan, G.—Li, Y.: Cooperative Spectrum Sensing in Cognitive Radio, Part I: Two User Networks. IEEE Transactions on Wireless Communications, Vol. 6, 2007, No. 6, pp. 2204–2213, doi: 10.1109/TWC.2007.05775.

[12] Ganesan, G.—Li, Y.: Cooperative Spectrum Sensing in Cognitive Radio Networks. 2005 First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN 2005), IEEE, 2005, pp. 137–143, doi: 10.1109/DYSPAN.2005.1542628.

[13] Kleinová, K.—Feciľak, P.: New Approach to Remote Laboratory in Regard to Topology Change and Self-Repair Feature. Central European Journal of Computer Science, Vol. 2, 2012, No. 3, pp. 344–353, doi: 10.2478/s13537-012-0026-4.

[14] Kovalčík, M.—Feciľak, P.—Jakab, F.—Dudiak, J.—Kolcun, M.: Cost-Effective Smart Metering System for the Power Consumption Analysis of Household. International Journal of Advanced Computer Science and Applications (IJACSA), Vol. 5, 2014, No. 8, pp. 135–144.

[15] Ji, Z.—Liu, K. R.: Cognitive Radios for Dynamic Spectrum Access – Dynamic Spectrum Sharing: A Game Theoretical Overview. IEEE Communications Magazine, Vol. 45, 2007, No. 5, pp. 88–94.

[16] Niyato, D.—Hossain, E.: Spectrum Trading in Cognitive Radio Networks: A Market-Equilibrium-Based Approach. IEEE Wireless Communications, Vol. 15, 2008, No. 6, pp. 71–80.

[17] Maharjan, S.—Zhang, Y.—Gjessing, S.: Economic Approaches for Cognitive Radio Networks: A Survey. Wireless Personal Communications, Vol. 57, 2011, No. 1, pp. 33–51, doi: 10.1007/s11277-010-0005-9.

[18] Tehrani, M. N.—Uysal, M.: Auction Based Spectrum Trading for Cognitive Radio Networks. IEEE Communications Letters, Vol. 17, 2013, No. 6, pp. 1168–1171, doi: 10.1109/LCOMM.2013.043013.130371.

[19] Nekovee, M.—Anker, P.: Regulatory Policy and Economics of Cognitive Radio for Secondary Spectrum Access. Cognitive Communications: Distributed Artificial Intelligence (DAI), Regulatory Policy & Economics, Implementation, Wiley, 2012, pp. 283–317.

[20] Qian, L.—Ye, F.—Gao, L.—Gan, X.—Chu, T.—Tian, X.—Wang, X.—Guizani, M.: Spectrum Trading in Cognitive Radio Networks: An Agent-Based Model Under Demand Uncertainty. IEEE Transactions on Communications, Vol. 59, 2011, No. 11, pp. 3192–3203.

[21] Jia, J.—Zhang, Q.—Zhang, Q.—Liu, M.: Revenue Generation for Truthful Spectrum Auction in Dynamic Spectrum Access. Proceedings of the Tenth ACM International Symposium on Mobile Ad Hoc Networking and Computing, ACM, 2009, pp. 3–12, pp. 5761–5766, doi: 10.1145/1530748.1530751.

[22] Ausubel, L. M.: An Efficient Ascending-Bid Auction for Multiple Objects. The American Economic Review, Vol. 94, 2004, No. 5, pp. 1452–1475, doi: 10.1257/0002828043052330.

[23] Ghasemi, A.—Sousa, E. S.: Collaborative Spectrum Sensing for Opportunistic Access in Fading Environments. First IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks (DySPAN 2005), IEEE, 2005, pp. 131–136, doi: 10.1109/DYSPAN.2005.1542627.

[24] Zhang, W.—Mallik, R. K.—Letaief, K. B.: Optimization of Cooperative Spectrum Sensing with Energy Detection in Cognitive Radio Networks. IEEE Transactions on Wireless Communications, Vol. 8, 2009, No. 12, pp. 5761–5766.

[25] Dudley, R. M.: Uniform Central Limit Theorems. Cambridge University Press, Cambridge Studies in Advanced Mathematics, Vol. 63, 1999, doi: 10.1017/CBO9780511665622.

[26] Liang, Y.-C.—Zeng, Y.—Peh, E. C.—Hoang, A. T.: Sensing-Throughput Tradeoff for Cognitive Radio Networks. IEEE Transactions on Wireless Communications, Vol. 7, 2008, No. 4, pp. 1326–1337.

[27] Yoon, H.—Hwang, J.—Weiss, M. B.: An Analytic Research on Secondary-Spectrum Trading Mechanisms Based on Technical and Market Changes. Computer Networks, Vol. 56, 2012, No. 1, pp. 3–19.

[28] Badica, C.—Ilie, S.—Muscar, A.—Badica, A.—Sandu, L.—Sbora, R.—Ganzha, M.—Paprzycki, M.: Distributed Agent-Based Online Auction System. Computing and Informatics, Vol. 33, 2014, No. 3, pp. 518–552.

[29] Krishna, V.: Auction Theory. Academic Press, San Diego, USA, 2002.

[30] Mingo, J. M.—Aler, R.—Maravall, D.—de Lope Asiaín, J.: Investigations into Lamarckism, Baldwinism and Local Search in Grammatical Evolution Guided by Reinforcement. Computing and Informatics, Vol. 32, 2013, No. 3, pp. 595–627.

[31] Nanduri, V.—Das, T. K.: A Reinforcement Learning Model to Assess Market Power under Auction-Based Energy Pricing. IEEE Transactions on Power Systems, Vol. 22, 2007, No. 1, pp. 85–95, doi: 10.1109/TPWRS.2006.888977.

[32] Niyato, D.—Hossain, E.—Han, Z.: Dynamics of Multiple-Seller and Multiple-Buyer Spectrum Trading in Cognitive Radio Networks: A Game-Theoretic Modeling Approach. IEEE Transactions on Mobile Computing, Vol. 8, 2009, No. 8, pp. 1009–1022.

[33] Gao, L.—Wang, X.—Xu, Y.—Zhang, Q.: Spectrum Trading in Cognitive Radio Networks: A Contract-Theoretic Modeling Approach. IEEE Journal on Selected Areas in Communications, Vol. 29, 2011, No. 4, pp. 843–855.

[34] Pan, M.—Liang, S.—Xiong, H.—Chen, J.—Li, G.: A Novel Bargaining Based Dynamic Spectrum Management Scheme in Reconfigurable Systems. International Conference on Systems and Networks Communications (ICSNC '06), IEEE, 2006, pp. 54–54, doi: 10.1109/ICSNC.2006.10.

[35] Noble, J.—Franks, D. W.: Social Learning in a Multi-Agent System. Computing and Informatics, Vol. 22, 2004, No. 6, pp. 561–574.

[36] Blecic, I.—Cecchini, A.—Trunfio, G. A.: Multi-Agent Based Modelling of an Endogenous-Money Economy. Computing and Informatics, Vol. 34, 2015, No. 6, pp. 1234–1256.

Juraj Gazda has been working as Associate Professor at the Faculty of Electrical Engineering of the Technical University of Košice, Slovakia. In the past, he acted as Guest Researcher at the Ramon Llull University and the Technical University of Harburg. He was also involved in the development activities of the telecommunication broadband companies (Nokia, Ericsson). His research interests include spectrum pricing, techno-economic aspects of the cognitive networks and artificial markets.

Slavomír Šimoňák received his M.Sc. degree in computer science in 1998 and Ph.D. degree in computer tools and systems in 2004, both from the Technical University of Košice, Slovakia. He is currently Assistant Professor at the Department of Computers and Informatics, Faculty of Electrical Engineering and Informatics of the Technical University of Košice, Slovakia. His research interests include formal methods integration and application, communication protocols, algorithms, and data structures.

Emília Pietriková is Assistant Professor at the Department of Computers and Informatics, Technical University of Košice, Slovakia. She received her M.Sc. in 2010 and Ph.D. in 2014 in informatics from Technical University of Košice. In 2010 she spent 1 month at the Department of Telematics at Norwegian University of Science and Technology, Norway. In 2011 she spent 1 semester at the Department of Computer Architecture at University of Málaga, Spain. The subject of her research is abstraction and generation in programming languages, and quality of education.

Martin Chovanec received his Master's degree in informatics in 2005 from the Faculty of Electrical Engineering and Informatics, Technical University of Košice. In 2008 he received his Ph.D. degree from the Department of Computers and Informatics, Faculty of Electrical Engineering and Informatics of the Technical University of Košice and his scientific research has focused on network security and encryption algorithms. Currently, he is Director of the Computer Technology Centre at the Technical University of Košice.

Eva Chovancová graduated (Ing.) in 2009 from the Department of Computers and Informatics, Faculty of Electrical Engineering and Informatics of the Technical University in Košice, Slovakia. She received her Ph.D. in computers and computer systems in 2012; her thesis title was "Specialized Processor for Computing Acceleration in the Field of Computer Vision". Since 2012, she has been working as Assistant Professor at the Department of Computers and Informatics. Her scientific research is focused on multicore computer architectures and security.

Norbert Ádám received his M.Sc. in 2003 with distinction from the Department of Computers and Informatics, Faculty of Electrical Engineering and Informatics of the Technical University of Košice. He received his Ph.D. in computers and computer systems in 2007; his thesis title was "Contribution to the Simulation of Feed-Forward Neural Networks on Parallel Computer Architectures". Since 2006, he has been working as Lecturer at the Department of Computers and Informatics. Since 2008, he is Head of the Computer Architectures and Security Laboratory at the Department of Computers and Informatics. His scientific research is focused on parallel computers architectures.

Csaba Szabó received his M.Sc. with distinction from the Department of Computers and Informatics, Faculty of Electrical Engineering and Informatics (FEI) of the Technical University of Košice in 2003. He received his Ph.D. in program and information systems from the FEI of the Technical University of Košice in 2007. Since 2006 he is affiliated with the Department of Computers and Informatics, FEI, Technical University of Košice. Currently he is involved in research in the field of behavioral description of software, information systems and web services, software and test evolution, and testing and evaluation of software.

Anton Baláž received his Master's degree in informatics in 2004 from Faculty of Electrical Engineering and Informatics, Technical University of Košice. In 2008 he received Ph.D. in area of computer security. Since 2007 he is working as Assistant Professor at the Technical University of Košice.

Branislav Madoš graduated (Ing.) in 2006 from the Department of Computers and Informatics, Faculty of Electrical Engineering and Informatics of the Technical University of Košice. He defended his Ph.D. in the field of computers and computer systems in 2009; his thesis title was "Specialized Architecture of Data Flow Computer". Since 2010 he is working as Assistant Professor at the Department of Computers and Informatics. His scientific research is focused on the parallel computer architectures and architectures of computers with data driven computational model and computer security using cryptographic and steganographic methods.