BIUST Research and Innovation Symposium 2019 (RDAIS 2019)
Botswana International University of Science and Technology
Palapye, Botswana, 4 - 7 June 2019

ISSN: 2521-2292

Optimizing Cognitive Radio Deployment in Cooperative Sensing for Interference Mitigation

Temitope Fajemilehin
Department of Electrical Engineering
Pan African University Institute of Basic Sciences, Technology and Innovation
Nairobi, Kenya
fajemilehintope@yahoo.com

Kibet Langat
Department of Telecommunication and Information Engineering
Jomo Kenyatta University of Agriculture and Technology
Juja, Kenya
kibetlp@jkuat.ac.ke

Abid Yahya
Department of Computer, Electrical and Telecommunication Engineering
Botswana International University of Science and Technology
Palapye, Botswana
yahyabid@gmail.com

Jayeola Opadiji
Department of Computer Engineering
University of Ilorin
Ilorin, Nigeria
jopadiji@unilorin.edu.ng

***Abstract*— Cognitive radio system is one of the viable solutions for effective spectrum management. Cooperative spectrum sensing is very often used to mitigate the challenge of interference encountered in single sensing systems. This paper is aimed at developing a model to determine the required number of cognitive radios that would optimize the performance of a communication network with respect to energy utilization and bandwidth requirement. Energy detection was used as the cognitive radio sensing technique due to the limited energy, computational and communication resources required. The noise variance of the channel was set to -25dB. Spectrum sensing was carried out at a frequency of 936MHZ and a bandwidth of 200kHz. Enhancement in specificity of the detection was also explored using machine learning in order to minimize interference. Genetic Algorithm (GA) was used to optimize the number of cognitive radios putting into consideration all constraints in the network. The optimization produced an overall reduction of 59.26% in energy conserved without compromising the detection accuracy.**

Keywords—cognitive radio; energy detection; genetic algorithm; cooperative spectrum sensing

I. INTRODUCTION

Several portions of the radio spectrum (3GHz – 300GHz region) are under-utilized while some portions are overcrowded due to the emergence of more telecommunication applications and services [1]. Spectrum spaces between 30MHz and 3GHz that are not as crowded can therefore be effectively utilized for telecommunication services [2]. If this is not effectively carried out, more of the limited electromagnetic resources required for the increasing wireless devices and services depletes faster [3].

The Radio Communication Sector of International Telecommunications Union (ITU-R) put in place regulations to ensure that the radio spectrum is efficiently allocated to needing sectors. This also helps to avoid interference among various subscribers particularly in the era of increasing bandwidth demanding wireless technologies. In Africa alone, mobile broadband is expected to constitute about 87% of total connections across 690 million smartphones by 2025. The world-wide population of mobile phone subscriptions is already over 7.5 billion with each subscriber individually contributing an average data usage of 2.1GB to worldwide 8.8EB total mobile data traffic [2], [4]. More than 1 million mobile phone subscribers is anticipated to be added to the annual mobile device subscription database by 2022 which would increase the mobile subscribers worldwide to 9 billion [2]. This increases the demand for more telecommunications resources such as bandwidth, power and communicating frequency slots. New radio access technologies are therefore limited by the shortage of the useable available radio spectrum. This limitation is due to fixed radio functions, static spectrum allocation and limited network coordination which still exists in the present spectrum allocation scheme [5]. Improvement is urgently required in form of dynamic spectrum management applications which can accommodate the increased demand for telecommunication resources [6].

Cognitive radio system (CRS) is a dynamic spectrum management technique which is applicable in the GSM white space utilization effort. CRS is a software defined radio which can manage the spectrum by exploiting spectrum holes and permitting the deployment of multiple wireless systems [6]–[8]. It can sense the status of the transmitting channels to determine the occupancy status of such channels. It can tune the usage of the spectrum dynamically based on certain network and environmental related factors such as type of radios in the network, bandwidth required allocation, location of the radios, time of the day etc. [9].

The spectrum sensing function in cognitive radio is required to check if a particular channel is in use by a licensed user a

This research is supported by the African Union through the Pan African University Scholarship.

ISSN: 2521-2292

specific point in time [10]. It is crucial to avoid interference and channel misallocation. One of the commonly used spectrum sensing techniques is Energy detection-based sensing. It requires minimal resources to detect the occupancy status of the channel and is not as computationally demanding as the other techniques [11], [12]. But it has several limitations such as multipath fading, shadowing and consequently, the hidden terminal problem. It also cannot discriminate between the type of user occupying the channel (i.e. differentiating between Primary User (PU), Secondary User (SU) or Interfering User (IU)).

Cooperative sensing is often utilized to overcome several of the shortfalls. But it increases the communication overhead of the network and is usually also not able to determine the type of user occupying the channel particularly if the cooperating cognitive radios are sensing through energy detection technique.

Researchers have worked on improving detection sensitivity of energy detection-based spectrum sensing using several techniques using the concept of an adaptive threshold[13]. Several combining techniques for the cognitive radio users in cooperative spectrum sensing were considered while utilizing different modulation schemes. Significant improvements were recorded but the technique was not fully predictable in noisy channels.

Authors in [14], also proposed a method of improvement that enhanced the classical energy detection scheme and maintained a similar level of computational complexity and cost. Detection time was also reduced in comparison to other more sophisticated methods of sensing. But it could not differentiate between the type of users in the network. [15] used an augmented spectrum sensing algorithm where the energy detector's detection is augmented by cyclostationary detection. However, the technique requires information about the primary users' transmission characteristics which is not always available.

Multiple antenna techniques to improve the performance of energy detection and cyclostationary feature detection-based was used in [13]. This was implemented in a cooperative spectrum sensing scheme using Equal Gain Combining (EGC). It improved the detection sensitivity but was not focused on interference mitigation.

Authors in [16], used different channels without any information about the environment to improve on the usage of idle spectrum with due consideration for fairness in channel selection. This was improved upon by authors in [17] with the aid of a p-norm energy detector. The performance of the cooperative spectrum sensing was improved alongside improved gain in κ-μ fading channels. These improvements are the foundations on which the current paper is building on to increase the capacity of the cognitive radio identify the user occupying the channel.

More recently, [18] proposed a two-stage reinforcement learning approach to improve the performance of the cooperative sensing. The method minimized the number of sensing operations and reduced the energy required in the sensing operation. The channel sensing and allocation was improved, but demanded computational resources and learning time.

[19] further explored optimal threshold selection at low SNR to improve sensing performance. Better sensing performance was obtained compared to previous approaches which used constant false-alarm rate and constant detection rate threshold selection. However, there was no provision made for instantaneous SNR drop which sometimes occur.

[20] used an adaptive simulated annealing particle swarm optimization (ASASPSO) to improve cognitive radio power allocation. Parameters considered were the interference power threshold of the primary user, transmission rate limitation of secondary users and the signal to interference and noise ratio (SINR). Thus, the power consumed was reduced was reduced and an improved SINR and transmission rate was achieved.

The addition of more cognitive radios in the cooperative sensing scheme increases energy consumption and general communication overhead. What would therefore be the optimum number of cognitive radios in a communication network to ensure high quality performance in terms of interference mitigation and resource conservation? This paper seeks to find a solution to this salient question by developing a model to identify the required number of cognitive radios that would fulfil the objective of optimum performance.

II. SYSTEM MODEL

A. Theoretical Background

Energy detection is a non-coherent detection method which detects the operation of a licensed user within a particular communication channel [21]. In energy detection, the energy detected in the channel being sensed is measured and compared with a predefined threshold to determine the presence or absence of the primary user (PU) signal [7]. Energy detector is largely employed in ultra-wideband communication to utilize an idle channel when not in use by a licensed user.

In the implementation of the energy detector, the received signal $x(t)$ is filtered by a band pass filter (BPF) in line with the bounds of the frequency channel being sensed. This signal detected is then squared with a square law device. The band pass filter serves to reduce the noise bandwidth. Hence, noise at the input to the squaring device has a band-limited flat spectral density. The output of the integrator is the energy of the input to the squaring device over the time interval T. Afterwards, the output signal from the integrator (the decision statistic), Y, is compared with a threshold to decide whether a primary (licensed) user is present or not. Decision regarding the usage of the band will be made by comparing the detection statistic to a threshold [22].

The mathematical model for energy detection is given by the following two hypotheses [8]:

H_0: PU absent

$$y(n) = u(n) \quad n = 1,2, \dots N \tag{1}$$

H_1: PU present

ISSN: 2521-2292

$$y(n) = s(n) + u(n) \quad n = 1,2, \dots N \tag{2}$$

where $u(n)$ is noise and $s(n)$ is the PU's signal

Energy detector performs optimally in spectrum sensing if the noise variance is known. This is required to define the threshold which helps in deciding spectrum is occupied or not [23]. The challenge with the spectrum sensing of the energy detector is that it is unable to accurately detect the PU when the signal is weak i.e. at low SNR. The detection accuracy further deteriorates when the noise characteristics cannot be defined due to varying noise uncertainties [24], [25].

This study is aimed at managing interference which may occur in energy-detection based cognitive radio by introducing supervised machine learning. This is expected to help the cognitive radio system (CRS) learn the patterns in the unknown noise characteristics through a clustering algorithm. The specific properties of the PU were used as training data in a supervised learning technique to serve a feature detection algorithm in the CRS. This scheme intends to improve the detection accuracy of the energy detector in scenarios when the SNR falls to the SNR wall level.

Equation (3) shows the normalized test (decision) statistic for the detector and this was developed based on [26] as:

$$T' = \left(\frac{1}{N_{02}}\right) \int_0^T y^2(t)dt \tag{3}$$

where:

T'= test statistic in during sensing session

y = received signal input

T = sampling instant

N_{02} = two-sided noise power density spectrum

If the test statistics exceeds a fixed decision threshold then it results in H_1 hypothesis. However, when the test statistics is less than the decision threshold then H_0 hypothesis occurs.

As shown in [14], λ is the decision threshold which in the number of samples $N \gg 1$, can be expressed as a Gaussian distribution:

$$\lambda = \sqrt{\frac{2}{NQ^{-1}}} (P_{fa}^{CED} + 1) \tag{4}$$

where:

$$P_{fa}^{CED} = Q\left(\frac{\lambda - 1}{\sqrt{\frac{2}{N}}}\right) \tag{5}$$

$$P_d^{CED} = Q\left(\frac{\lambda - (1+\gamma)}{\sqrt{\left(\frac{2}{N}\right)(1+\gamma)^2}}\right) \tag{6}$$

$$\gamma = \frac{\sigma_s^2}{\sigma_w^2} \tag{7}$$

σ_s^2 is the received average primary signal power

σ_w^2 is the noise variance.

B. Optimization Model

The operating characteristics in the network can be assessed in frames (N). Energy test statistic ($Y_{p|s|x,i}^{\alpha}$) at the i^{th}frame of the user's transmission operations can be extracted as input data. Similarly, $Y_{p|s|x,i}^{\beta}$ and $Y_{p|s|x,i}^{\gamma}$can be extracted at specific points in the channel and receiver respectively.

Energy test statistics for the primary user ($Y_{p,i}$) is represented as:

$$Y_{p,i} \in (Y_{p,i}^{\alpha}, Y_{p,i}^{\beta}, Y_{p,i}^{\gamma}) \tag{8}$$

Energy test statistics for a secondary user ($Y_{s,i}$) is represented as:

$$Y_{s,i} \in (Y_{s,i}^{\alpha}, Y_{s,i}^{\beta}, Y_{s,i}^{\gamma}) \tag{9}$$

Energy test statistics for an interfering user ($Y_{x,i}$) is represented as:

$$Y_{x,i} \in (Y_{x,i}^{\alpha}, Y_{x,i}^{\beta}, Y_{x,i}^{\gamma}) \tag{10}$$

The labels identifying these input data in specific frames as primary user (U_p), secondary user (U_s) or interfering user (U_x) based on their respective energy test statistics can be represented as decisions (d_i).

Genetic Algorithm (GA) was selected as a suitable tool to optimize the number of cognitive radios putting into consideration constraints such as the spatial distribution of the cognitive radios, sensing time and noise characteristics. These are crucial to identify the optimal number of cognitive radios that would minimize resource consumption while ensuring interference mitigation in the system. This objective is achieved by the following function:

$$\min_n Y(n) = n_1 Y_{p,i}^{\alpha} + n_2 Y_{p,i}^{\beta} + n_3 Y_{p,i}^{\gamma} + n_4 Y_{s,i}^{\alpha} + \cdots$$

$$n_5 Y_{s,i}^{\beta} + n_6 Y_{s,i}^{\gamma} + n_7 Y_{x,i}^{\alpha} + n_8 Y_{x,i}^{\beta} + n_9 Y_{x,i}^{\gamma} \tag{11}$$

Subject to

$$n_1, n_2, n_3, n_4, n_5, n_6, n_7, n_8, n_9 \geq 0 \tag{12}$$

$$n_1 + n_2 + n_3 \geq 3 \tag{13}$$

$$n_4 + n_5 + n_6 \leq 3 \tag{14}$$

$$n_7 + n_8 + n_9 \leq 3 \tag{15}$$

Based on previous studies [27], cooperative sensing aids more accurate detection. The first constraint in (12) is therefore essential to ensure that sufficient cognitive radios operate cooperatively to minimize missed detections and false alarms.

RESEARCH & INNOVATION SYMPOSIUM 2019
ISSN: 2521-2292

The critical nature of primary user detection makes it imperative to include not less than 3 cognitive radios to cover every zone of operation. This is represented in the second constraint in (13).

An assumption made is that 3 cognitive radios are sufficient to monitor operations of potential secondary users and interfering users. This is based on previous studies [28] where the provision of an extra cognitive radio for monitoring other non-PU operations produces a more accurate sensing outcome.

C. Simulation Setup

The model implemented with MATLAB Simulink on MATLAB 2017a software. The model consisted of transmitters with an energy detector based cognitive radio through an additive white gaussian noise (AWGN) channel. The noise variance of the channel was set to -25dB. The sensing technique was employed using a frequency of 936MHZ and a bandwidth of 200 kHz and the threshold set to 0.2. Setting up the cognitive radio spectrum sensor (energy detector) in Simulink. Details of the simulation parameters are presented in **Error! Reference source not found.**.

TABLE I. SIMULATION PARAMETERS

Parameters	**Value**
SNR	-25dB
Pf	0.05
Operating frequency	936 MHz
Observation time	2×10^{-4}
Variance of the noise (σ^2n)	1×10^{-12}
Threshold	0.2
Operating power	40 mW
Bandwidth	200 kHz
Population type	Double vector
Population size	200
Scaling function	Rank
Selection function	Stochastic uniform
Crossover fraction	0.8
Crossover function	Constraint dependent
Generations	900

The sensitivity of the cognitive radio system was first improved using ML to ensure that the sensing accuracy is not compromised as the optimization is done. Tree algorithms and KNN were selected based on a previous study [29] which revealed that the algorithms performed reliably. After ensuring the accuracy of the CRS through ML, GA was then utilized to obtain the optimum number of cognitive radios that would minimize the energy consumption.

III. RESULTS AND DISCUSSION

The quick-to-train classification algorithms used to train the data were Complex Tree, Fine KNN, Weighted KNN, Cubic KNN and Medium KNN. Table 2 shows the accuracy for the different classifiers considered at -25dB. The receiver operating characteristics (ROC) for the CRS at -25dB to compare the accuracy of the ML-improved cognitive radio to the conventional version is presented in Fig. 1.

TABLE II. ACCURACY OF CLASSIFIERS AT -25DB

	PU		SU		IU		
CM	TPR (%)	FNR (%)	TPR (%)	FNR (%)	FNR (%)	TPR (%)	OA[1] (%)
WKNN	93	7	89	11	91	9	91.1
FKNN	91	9	89	11	92	8	90.8
MKNN	95	5	88	12	89	11	90.7
CKNN	95	5	88	12	89	11	90.4
CTree	>99	<1	85	15	87	13	90.5

OA[1]: Overall accuracy
CM: Classification methods
WKNN: weighted KNN
FKNN: fine KNN
MKNN: medium KNN
CKNN: cubic KNN
CTree: Complex tree
TPR: True positive rate
FNR: False negative rate

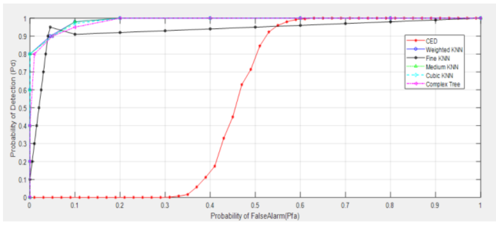

Fig. 1:ROC curve comparing five classifiers at -25dB

The results reveal the ML-improved cognitive radio operated at a higher accuracy level than the conventional cognitive radio. Using complex tree, as one of the most accurate algorithms in this context, accurate detection of PU was >99%. The detection accuracy for the SU and IU were 85% and 87% respectively with an overall detection accuracy of 90.5%. These results were obtained with the assumption that 9 cognitive radios monitoring each category of users (PU, SU, IU) would give more accurate results.

The result presenting the minimization of the number of cognitive radios using GA is presented in Fig.2. The results revealed that with 6 cognitive radios at various locations monitoring the PU, less resources would be incurred without compromising the detection accuracy. The results also show that 5 cognitive radios are sufficient to sensing the activities of the SU and the IU. Using this number, the detection accuracy would be optimum, with resource utilization minimized. The overall reduction in energy conserved based on the minimization of the cognitive radios is 59.26%.

ISSN: 2521-2292

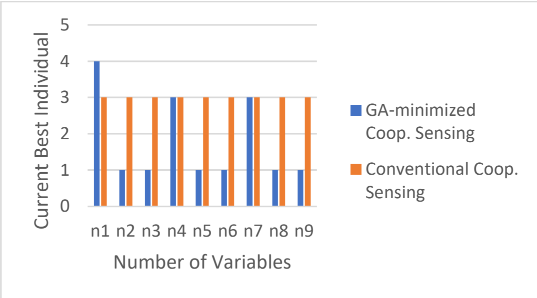

Fig. 2:Best Individual versus Number of Variables

IV. CONCLUSION

The results presented reveal that the use of GA optimized the number of cognitive radios used per sensing period. The ML introduced before the optimization helped in the reduction of the probabilities of false alarm and misdetections. Thus, enhancing the overall sensing outcomes of cooperative spectrum sensing in cognitive radio systems and conserving resources.

ACKNOWLEDGMENT

This research is supported by the African Union through the Pan African University Scholarship. Temitope Fajemilehin thanks Samuel Olatunji for his help, review and invaluable comments to help this paper better.

REFERENCES

[1] T. Chiwewe and G. Hancke, "A look at spectrum management policies for radio spectrum," *EngineerIT*, no. March, 2015.

[2] Ericsson, "Mobility Report," *White Paper*, no. May, pp. 7–8, 2016.

[3] S. Chaudari, *Spectrum Sensing for Cognitive Radios: Algorithms, Performance, and Limitations*, Aalto Univ. School of Electrical Engineering, Department of Signal Processing and Acoustics, 2012.

[4] S. Kemp, "Digital in 2017 Southeast Asia : A Study of Internet, Social Media, and Mobile Use Throughout the Region," *We Are Social*, p. 197, 2017.

[5] S. Haykin, D. J. Thomson, and J. H. Reed, "Spectrum sensing for cognitive radio," *Proceedings of the IEEE*, vol. 97, no. 5, pp. 849–877, 2009.

[6] G. S. A. K. Reddy, U. G. Raju, P. Aravind, and D. Sushma, "Intelligent Wireless Communication System of Cognitive Radio," no. 5, pp. 78–82, 2013.

[7] C. Mmary, "Cognitive Radio for Broadband Access in Rural Africa and other Developing Countries," *MSc. Thesis, University of York, UK*, no. December, 2011.

[8] S. Sudeep and K. Nirajan, "Energy detection based techniques for Spectrum sensing in Cognitive Radio over different fading Channels," *Journal of Selected Areas in Telecommunications*, vol. 4, no. 2, pp. 15–22, 2014.

[9] M. Marcus, J. Burtle, N. Mcneil, A. Lahjouji, and N. McNeil, "Report of the Unlicensed Devices and Experimental Licenses Working Group," *FCC, Spectrum Policy Task Force*, pp. 1–24, 2002.

[10] R. Mittal and E. D. Garg, "A Review on : Spectrum Sensing Techniques," *International Journal of Advanced Research in Computer Science and Software Engineering*, vol. 5, no. 5, pp. 1187–1192, 2015.

[11] M. Lakshmi, R. Saravanan, and R. Muthaiah, "Energy Detection Based Spectrum Sensing for Cognitive," *International Journal of Engineering and Technology (IJET)*, vol. 5, no. 2, pp. 963–967, 2013.

[12] P. Kumar Verma, S. Taluja, and R. Lal Dua, "Performance analysis of Energy detection, Matched filter detection & Cyclostationary feature detection Spectrum Sensing Techniques," *International Journal Of Computational Engineering Research (ijceronline.com)*, vol. 2, no. 5, pp. 2250–3005, 2012.

[13] R. F. Ustok, "Spectrum Sensing Techniques for Cognitive Radio Systems With Multiple Antennas," Izmir Institute of Technology, 2010.

[14] M. López-Benítez and F. Casadevall, "Improved energy detection spectrum sensing for cognitive radio," *IET Communications*, vol. 6, no. 8, p. 785, 2012.

[15] M. Kanti, D. Barma, H. Singh, S. Roy, and S. K. Sen, "Augmented Spectrum Sensing in Cognitive Radio Networks," *IJCSN International Journal of Computer Science and Network*, vol. 4, no. 6, 2015.

[16] J. Zhu, Y. Song, D. Jiang, and H. Song, "Multi-armed bandit channel access scheme with cognitive radio technology in wireless sensor networks for the Internet of Things," *IEEE Access*, vol. 4, pp. 4609–4617, 2016.

[17] M. Jain, V. Kumar, R. Gangopadhyay, and S. Debnath, "Cognitive Radio Oriented Wireless Networks," in *CROWNCOM 2015*, 2015, vol. LNICST 156, pp. 225–234.

[18] V. Raj, I. Dias, T. Tholeti, and S. Kalyani, "Spectrum Access in Cognitive Radio Using a Two-Stage Reinforcement Learning Approach," *IEEE Journal on Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 20–34, 2018.

[19] A. Kumar, P. Thakur, S. Pandit, and G. Singh, "Analysis of optimal threshold selection for spectrum sensing in a cognitive radio network: an energy detection approach," *Wireless Networks*, vol. 0123456789, no. 1, 2019.

[20] H. Wang, F. Jiang, and M. Zhou, "Cognitive radio power allocation algorithm based on improved particle swarm optimization," in *IEEE International Conference on Communication Systems (ICCS)*, 2018, pp. 354–359.

[21] E. Union, "West African Common Market Project : Harmonization of Policies," 2008.

[22] K. Nirajan, S. Sudeep, S. Suman, and B. Lamichhane, "Performance Comparison of Energy Detection Based Spectrum Sensing for Cognitive Radio Networks," *International Refereed Journal of Engineering and Science (IRJES) ISSN*, vol. 4, no. 8, pp. 2319–183, 2015.

[23] E. Axell, G. Leus, E. G. Larsson, and H. V. Poor, "Spectrum sensing for cognitive radio : State-of-the-art and recent advances," *IEEE Signal Processing Magazine*, vol. 29, no. 3, pp. 101–116,

ISSN: 2521-2292

2012.

[24] N. Hoven, R. Tandra, and A. Sahai, “Some fundamental limits on cognitive radio,” *Wireless Foundations EECS, University of California at Berkeley*, 2005.

[25] E. Axell and E. G. Larsson, “Optimal and Sub-Optimal Spectrum Sensing of OFDM Signals in Known and Unknown Noise Variance Optimal and Sub-Optimal Spectrum Sensing of OFDM Signals in Known and Unknown Noise Variance,” *IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS*, vol. 29, no. 2, pp. 290–304, 2011.

[26] H. Urkowitz, “Energy Detection of Unknown Deterministic Signals,” *Proceedings of the IEEE*, vol. 55, no. 4, pp. 523–531, 1967.

[27] T. O. Fajemilehin, S. A. Olatunji, and J. F. Opadiji, “Improved Energy Detection Algorithm for Cognitive Radios in Cooperative Spectrum Sensing,” *International Journal of Information Processing and Communication (IJIPC)*, vol. 7, no. 1, pp. 148–163, 2019.

[28] J. F. Opadiji, S. A. Olatunji, and T. O. Fajemilehin, “On Energy Detection of Cognitive Radios in Cooperative Spectrum Sensing,” in *URSI-NG Conference Proceedings*, 2015, pp. 29–36.

[29] A. M. Mikaeil, *Machine Learning Approaches for Spectrum Management in Cognitive Radio Networks*. Rijeka: IntechOpen, 2018.