This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2667882, IEEE Access

Secrecy Energy Efficiency Maximization in Cognitive Radio Networks

Jian Ouyang, *Member, IEEE,* Min Lin, *Member, IEEE,* Yulong Zou, *Senior Member, IEEE,* Wei-Ping Zhu, *Senior Member, IEEE,* and Daniel Massicotte, *Senior Member, IEEE*

***Abstract*—In this paper, we investigate a trade-off between the secrecy rate (SR) and energy efficiency (EE) in an underlay cognitive radio network (CRN) that consists of a cognitive base station (CBS), a cognitive user (CU), a primary user (PU), and multiple eavesdroppers (EDs). By using a so-called secrecy energy efficiency (SEE), which is defined as the ratio of SR to the total power consumption of CBS, as the design criterion, we formulate a secrecy energy efficiency maximization (SEEM) problem for the CBS-CU transmission under the constraints of the transmit power of CBS, the SR of CU and the quality-of-service (QoS) requirement of PU. Since the formulated optimization problem with a fractional objective function is non-convex and mathematically intractable, we first convert the original fractional objective function into an equivalent subtractive form, and then develop a method of combining the penalty function and the difference of two-convex functions (D.C.) approach to obtain an approximate convex problem. Based on this, an optimal beamforming (OBF) scheme is finally proposed to obtain the optimal solution. Furthermore, to reduce the computational complexity, we design a zero-forcing based beamforming (ZFBF) scheme to achieve a sub-optimal solution to the SEEM problem. Simulation results are given to illustrate the effectiveness and advantage of the proposed SEE oriented OBF and ZFBF schemes over conventional secrecy rate maximization (SRM) and energy efficiency maximization (EEM) schemes.**

***Index Terms*—Cognitive radio network, physical-layer security, energy efficiency, zero-forcing beamforming.**

I. Introduction

A cognitive radio network (CRN) is known to be able to significantly improve the spectrum efficiency [1], as it allows its cognitive users (CUs) to share the spectrum licensed to primary users (PUs), such as in cellular network [2] and satellite network [3]. However, the broadcast nature of wireless transmission makes the confidential information transmitted over CRN suffer from potential overhearing attacks from third parties [4], termed as eavesdroppers (EDs). To cope with this threat, some physical-layer security (PLS) technologies have been adopted in CRN to guarantee secure data transmission [5]. The authors of [6] studied the secrecy rate maximization (SRM) problem of multiple-input single-output (MISO) CRNs by optimizing the transmit covariance matrix under interference temperature and transmit power constraints. In [7], the authors presented some multiuser scheduling strategies to improve the PLS of cognitive radio communications against both coordinated and uncoordinated EDs. With the help of a cooperative jammer, two sub-optimal algorithms using a complete or partial orthogonal projection were proposed to maximize the available SR of a CU under an interference power constraint at a primary user (PU) and a global transmit power constraint at transmitters [8]. In addition, by exploiting the mutual interference, the authors of [9] presented a coalition formation game model with nontransferable utility, and a merge and split algorithm to exploit the CU's interference to enhance the PU's SR in CRN. Meanwhile, the authors of [10] employed a terrestrial base station (BS) as a friendly jammer to enhance the PLS for cognitive satellite networks.

Apart from the security, energy efficiency (EE) of CRNs has also been considered as an important issue due to the increasing growth of data traffic and energy cost [11]. In this context, the energy efficiency maximization (EEM) problem constrained by the total transmit power, the interference power and the system throughput was transformed into an equivalent one-dimensional problem and solved by golden section method [12]. In [13], an EE power allocation scheme was proposed to improve the data rate for unit-energy consumption in CRN via the fractional programming. Furthermore, the authors of [14] developed a distributed algorithm to jointly optimize power allocation and transmit beamforming (BF) for a cognitive multiple-input multiple-output (MIMO) channel. To exploit spectrum opportunities, the authors of [15] investigated a cooperative sensing scheduling problem with the objective of maximizing the EE of CRN. Additionally, a chance-constrained subcarrier and power allocation algorithm was proposed in [16] to improve the EE of multicast cognitive orthogonal frequency division multiplexing (OFDM) networks.

Different from the aforementioned literature that focuses only on improving either SR [6]-[10] or EE [12]-[16], the

This work was partially supported by the National Natural Science Foundation of China (61372122, 61401223, 61522109), the China Postdoctoral Science Foundation (2015M571784), the Natural Science Foundation of Jiangsu Higher Education Institutions of China (16KJB510027), the Natural Science Foundation of Jiangsu Province (BK20160911, BK20140887, BK20150040), the Key Project of Natural Science Research of Higher Education Institutions of Jiangsu Province (15KJA510003), and the NUPTSF (NY217001).

J. Ouyang is with the College of Telecommunications and Information Engineering, Nanjing University of Posts and Telecommunications, Nanjing, China (email: ouyangjian@njupt.edu.cn).

M. Lin (Corresponding author) is with the College of Telecommunications and Information Engineering, Nanjing University of Posts and Telecommunications, Nanjing, China, and also with the Nanjing Institute of Telecommunication Technology, Nanjing, China (email: linmin63@163.com).

Y. Zou is with the College of Telecommunications and Information Engineering, Nanjing University of Posts and Telecommunications, Nanjing, China (email: yulong.zou@njupt.edu.cn).

W.-P. Zhu is with the Department of Electrical and Computer Engineering, Concordia University, Montreal, QC, Canada (email: weiping@ece.concordia.ca).

D. Massicotte is with the Department of Electrical and Computer Engineering, Universite du Quebec a Trois-Rivieres, QC, Canada (email: Daniel.Massicotte@uqtr.ca).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2667882, IEEE Access

authors of [17] investigated the impact of multiple EDs on the EE of a CRN, while the authors of [18] investigated a cooperative jamming scheme in CRN to maximize CU's EE subject to the secrecy constraint of PU. To achieve a good trade-off between the SR and EE, secrecy energy efficiency (SEE), defined as the ratio of the SR to the total power consumption, has been proposed in [19] to evaluate the number of available secret bits per unit energy. By using SEE as a design criterion, we have studied the secrecy energy efficiency maximization (SEEM) problem under the constraints of PU's quality-of-service (QoS) requirement and total transmit power limit for CRNs [20] and cognitive relay networks [21], where only a single ED was taken into account. Thus, in this paper, we consider a more general scenario of cognitive radio communications with multiple EDs. Specifically, we make the following major contributions:

- A framework for SEE transmission in an underlay CRN with multiple EDs is established. In particular, we formulate a constrained optimization problem to maximize the SEE, while guaranteeing the CU's SR requirement and limiting the interference received at PU below a predefined threshold. This general framework includes the system model of [20] as a special case where only a single ED is assumed.
- Since the formulated SEEM problem is a max-min fractional optimization problem, which is non-convex and mathematically intractable, we first convert the original problem into an equivalent subtractive counterpart, and then propose an approach of combining the penalty function with the difference of two-convex functions (D.C.) to obtain a further simplified convex optimization problem. Next, an optimal beamforming (OBF) scheme is developed to achieve the optimal solution. Compared with the previous related works only focusing on the maximization of either SR [6] or EE [12], the proposed OBF scheme can achieve a better trade-off between the security and energy consumption, thus extending the previous works to a more general scenario.
- A zero-forcing based beamforming (ZFBF) scheme is also proposed to solve the formulated optimization problem, giving a sub-optimal solution. Since in this case, the normalized BF weight vector and power coefficient are given in analytical expressions, the computational complexity is significantly reduced. On the other hand, it is shown by computer simulations that the performance gap between the optimal and sub-optimal solutions is very small, when a sufficient number of transmit antennas are employed at the cognitive base station (CBS).

The rest of the paper is organized as follows. In Section II, we describe the system model for CRN and formulate the SEE maximization problem. In Section III, we propose an OBF scheme to obtain the optimal solution to the formulated SEEM problem. Section IV presents a sub-optimal scheme using the ZF-based BF. Simulation results and discussions are given in Section V, and conclusions are drawn in Section VI.

Notations: Bold letters denote the vectors or matrices, $(\cdot)^H$ the Hermitian transpose, $|\cdot|$ the absolute value, $\|\cdot\|_F$ the Frobenius norm of a matrix or Euclidean norm of a vector; $\mathrm{E}[\cdot]$ represents the expectation; $\mathbf{I}_N$ the $N \times N$ identity matrix, $\mathbf{0}_N$ the $N \times 1$ vector of all zeros; $\mathbf{A} \succeq \mathbf{0}$ means $\mathbf{A}$ is a Hermitian positive semidefinite matrix, $\mathrm{Tr}(\mathbf{A})$ is the trace of $\mathbf{A}$, $\mathrm{Rank}(\mathbf{A})$ is the rank of $\mathbf{A}$; $\lambda_{\max}(\mathbf{A})$ and $\mathbf{u}_{\max}(\mathbf{A})$ represent the largest eigenvalue and the corresponding eigenvector of $\mathbf{A}$; $\langle \mathbf{A}, \mathbf{B} \rangle = \mathrm{Tr}(\mathbf{AB})$; $[x]^+ = \max\{x, 0\}$; and $\mathcal{CN}(0, \sigma^2)$ stands for the complex Gaussian distribution with zero mean and covariance σ^2.

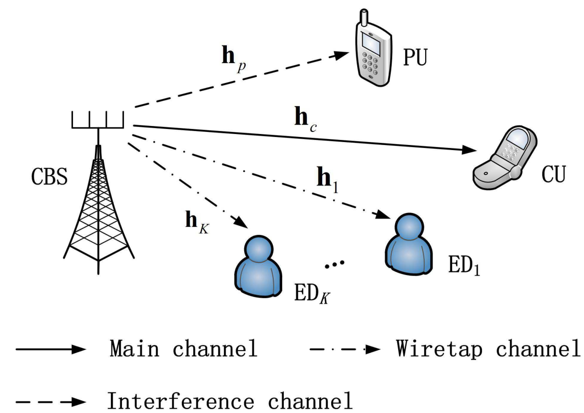


Fig. 1. System model of the underlay CRN with multiple EDs.

II. System Model and Problem Formulation

As illustrated in Fig.1, an underlay CRN consisting of one CBS, one CU and K EDs utilizes the spectrum assigned to the PU. Here, we assume that CBS is equipped with N_c antennas, while CU, PU and ED each have a single antenna. The CBS intends to deliver its signal $x_c(t)$ with $\mathrm{E}\left[|x_c(t)|^2\right] = 1$ to CU, thus the signal received at CU can be expressed as

$$y_c = \sqrt{\vartheta_c}\mathbf{h}_c^H \mathbf{w}_c x_c(t) + n_c(t) \tag{1}$$

where $\mathbf{w}_c$ is the downlink BF vector, $\mathbf{h}_c$ is the fading channel vector between CBS and CU, ϑ_c is the corresponding path loss, and $n_c(t)$ is the additive white Gaussian noise (AWGN) with zero mean and variance σ_c^2. Meanwhile, each ED attempts to independently overhear the confidential messages transmitted from CBS to CU. Due to the broadcast nature of the wireless communication, the signal received by the k-th ED can be written as

$$y_k = \sqrt{\vartheta_k}\mathbf{h}_k^H \mathbf{w}_c x_c(t) + n_k(t), \quad k \in \mathbb{K} \tag{2}$$

where $\mathbf{h}_k$ and ϑ_k are the fading channel vector and the path loss between CBS and ED_k, and $n_k(t) \sim CN(0, \sigma_k^2)$ is the AWGN, $k \in \mathbb{K} = \{1, 2, \cdots, K\}$. Hence, the output signal-to noise ratios (SNRs) at CU and ED_k can be, respectively, expressed as

$$\gamma_c(\mathbf{w}_c) = \frac{\vartheta_c \left|\mathbf{h}_c^H \mathbf{w}_c\right|}{\sigma_c^2} \tag{3}$$

$$\gamma_k(\mathbf{w}_c) = \frac{\vartheta_k \left|\mathbf{h}_k^H \mathbf{w}_c\right|}{\sigma_k^2}, \quad k \in \mathbb{K} \tag{4}$$

According to the definition of the PLS [4], the available worst-case SR for CU is given by

$$R_{sec} = \left[\log_2\left(1+\gamma_c\left(\mathbf{w}_c\right)\right) - \max_{k\in\mathbb{K}} \log_2\left(1+\gamma_k\left(\mathbf{w}_c\right)\right)\right]^+ \tag{5}$$

In addition, the total power consumption at CBS can be modelled as [16]

$$P_{tot} = \zeta \left\|\mathbf{w}_c\right\|_F^2 + N_c P_A + P_B \tag{6}$$

where $\zeta \geq 1$ denotes the power amplifier inefficiency coefficient, P_A the circuit power consumption of each transmit antenna at CBS, and P_B the basic power consumed by CBS. To balance the SR and the total power consumption of the considered CRN, we adopt SEE as the performance metric in unit bit/Joule/Hz, which is given by [19]

$$\eta = \frac{R_{sec}}{P_{tot}} \tag{7}$$

Meanwhile, to protect the PU's QoS, the interference temperature I_p from CBS should be limited below a predefined threshold I_p^{th}, namely,

$$I_p = \vartheta_p \left|\mathbf{h}_p^H \mathbf{w}_c\right|^2 \leq I_p^{th} \tag{8}$$

where $\mathbf{h}_p$ denotes the fading channel vector of the CBS-PU link and ϑ_p the corresponding path loss.

We now formulate a constrained maximization problem for SEE under three constraints: the secure transmission requirement, the transmit power limit of CBS and the interference control for PU, namely,

$$\max_{\mathbf{w}_c} \min_{k\in\mathbb{K}} \frac{\log_2\left(1+\gamma_c\left(\mathbf{w}_c\right)\right) - \log_2\left(1+\gamma_k\left(\mathbf{w}_c\right)\right)}{\zeta\|\mathbf{w}_c\|_F^2 + N_c P_A + P_B} \tag{9a}$$

$$\text{s.t.} \quad \log_2\left(1+\gamma_c\left(\mathbf{w}_c\right)\right) - \log_2\left(1+\gamma_k\left(\mathbf{w}_c\right)\right) \geq R_{sec}^{\min}, k \in \mathbb{K} \tag{9b}$$

$$\vartheta_p \left|\mathbf{h}_p^H \mathbf{w}_c\right| \leq I_P^{th} \quad \text{and} \quad \|\mathbf{w}_c\|_F^2 \leq P_c^{\max} \tag{9c}$$

where $R_{sec}^{\min} \geq 0$ denotes the minimum acceptable SR which guarantees the secure transmission for CU, and $P_c^{\max}$ the maximum allowed transmit power of CBS. Note that there could be feasibility issue with the above optimization problem due to the constraints of CU's SR requirement and transmit power limit. Throughout this paper, however, we assume that the SR requirement of CU is feasible and our focus is on solving the formulated problem (9).

III. Proposed OBF Scheme

In this section, we propose an OBF scheme to obtain the optimal solution to the problem (9). First of all, we introduce an auxiliary variable $\varphi \geq 1$ and reformulate the SEEM problem (9) as

$$\max_{\mathbf{w}_c, \varphi\geq 1} \frac{\log_2\left(1+\gamma_c\left(\mathbf{w}_c\right)\right) - \log_2\varphi}{\zeta\|\mathbf{w}_c\|_F^2 + N_c P_A + P_B} \tag{10a}$$

$$\text{s.t.} \quad \log_2\left(1+\gamma_k\left(\mathbf{w}_c\right)\right) \leq \log_2\varphi, \quad k \in \mathbb{K} \tag{10b}$$

$$\log_2\left(1+\gamma_c\left(\mathbf{w}_c\right)\right) - \log_2\varphi \geq R_{sec}^{\min} \tag{10c}$$

$$\vartheta_p \left|\mathbf{h}_p^H \mathbf{w}_c\right| \leq I_P^{th} \quad \text{and} \quad \|\mathbf{w}_c\|_F^2 \leq P_c^{\max} \tag{10d}$$

Obviously, problem (10) is non-convex due to the fractional form of the objective function (10a). To tackle this difficulty, we transform problem (10) into an equivalent subtractive one through the following Proposition.

Proposition 1: Let η_{OBF}^* be the maximum SEE. The optimization problem (10) is equivalent to the following subtractive form problem,

$$g(\eta_{OBF}) = \max_{\mathbf{w}_c, \varphi\geq 1} \log_2\left(1+\gamma_c\left(\mathbf{w}_c\right)\right) - \log_2\varphi - \eta_{OBF}\left(\zeta\|\mathbf{w}_c\|_F^2 + N_c P_A + P_B\right) \tag{11a}$$

$$\text{s.t.} \quad \text{(10a)-(10d)} \tag{11b}$$

if and only if $g(\eta_{OBF}^*) = 0$ holds.

Proof. To show the equivalence of problems (10) and (11), we need to prove that they have the same optimal solution when $g(\eta_{OBF}^*) = 0$. Since problems (10) and (11) have the same constraints (10b)-(10d), we can define $\mathcal{R}_1$ as the set of feasible solutions for both of them. By assuming $(\hat{\mathbf{w}}_c^*, \hat{\varphi}^*)$ to be the optimal solution to problem (10), for any feasible solution $(\hat{\mathbf{w}}_c, \hat{\varphi}) \in \mathcal{R}_1$, we have

$$\begin{aligned}\eta_{OBF}^* &= \frac{\log_2\left(1+\gamma_c\left(\hat{\mathbf{w}}_c^*\right)\right) - \log_2\hat{\varphi}^*}{\zeta\|\hat{\mathbf{w}}_c^*\|_F^2 + N_c P_A + P_B} \\ &= \max_{(\hat{\mathbf{w}}_c, \hat{\varphi})\in\mathcal{R}_1} \frac{\log_2\left(1+\gamma_c\left(\hat{\mathbf{w}}_c\right)\right) - \log_2\hat{\varphi}}{\zeta\|\hat{\mathbf{w}}_c\|_F^2 + N_c P_A + P_B} \\ &\geq \frac{\log_2\left(1+\gamma_c\left(\hat{\mathbf{w}}_c\right)\right) - \log_2\hat{\varphi}}{\zeta\|\hat{\mathbf{w}}_c\|_F^2 + N_c P_A + P_B}\end{aligned} \tag{12}$$

Due to the fact that $\zeta\|\hat{\mathbf{w}}_c\|_F^2 + N_c P_A + P_B > 0$, we can further obtain the following equality and inequality,

$$\log_2\left(1+\gamma_c\left(\hat{\mathbf{w}}_c^*\right)\right) - \log_2\hat{\varphi}^* - \eta_{OBF}^*\left(\zeta\|\hat{\mathbf{w}}_c^*\|_F^2 + N_c P_A + P_B\right) = 0 \tag{13}$$

$$\log_2\left(1+\gamma_c\left(\hat{\mathbf{w}}_c\right)\right) - \log_2\hat{\varphi} - \eta_{OBF}^*\left(\zeta\|\hat{\mathbf{w}}_c\|_F^2 + N_c P_A + P_B\right) \leq 0 \tag{14}$$

Combining (13) and (14), we find that the maximum value of problem (11) equals zero at the optimal solution $(\hat{\mathbf{w}}_c^*, \hat{\varphi}^*)$. Next, let $(\check{\mathbf{w}}_c^*, \check{\varphi}^*)$ be the optimal solution of problem (11) and assume $g(\eta_{OBF}^*) = 0$. Then, we can obtain

$$\log_2\left(1+\gamma_c\left(\check{\mathbf{w}}_c^*\right)\right) - \log_2\check{\varphi}^* - \eta_{OBF}^*\left(\zeta\|\check{\mathbf{w}}_c^*\|_F^2 + N_c P_A + P_B\right) = 0 \tag{15}$$

For any solution $(\check{\mathbf{w}}_c, \check{\varphi}) \in \mathcal{R}_1$, we have

$$\begin{aligned}&\log_2\left(1+\gamma_c\left(\check{\mathbf{w}}_c\right)\right) - \log_2\check{\varphi} - \eta_{OBF}^*\left(\zeta\|\check{\mathbf{w}}_c\|_F^2 + N_c P_A + P_B\right) \\ &\leq \max_{(\check{\mathbf{w}}_c, \check{\varphi})\in\mathcal{R}_1} \log_2\left(1+\gamma_c\left(\check{\mathbf{w}}_c\right)\right) - \log_2\check{\varphi} - \eta_{OBF}^*\left(\zeta\|\check{\mathbf{w}}_c\|_F^2 + N_c P_A + P_B\right) \\ &= \log_2\left(1+\gamma_c\left(\check{\mathbf{w}}_c\right)\right) - \log_2\check{\varphi} - \eta_{OBF}^*\left(\zeta\|\check{\mathbf{w}}_c\|_F^2 + N_c P_A + P_B\right) \\ &= 0\end{aligned} \tag{16}$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2667882, IEEE Access

which yields

$$\frac{\log_2\left(1+\gamma_c\left(\check{\mathbf{w}}_c\right)\right)-\log_2\check{\varphi}}{\zeta\|\check{\mathbf{w}}_c\|_F^2+N_cP_A+P_B} \leq \eta_{OBF}^*=\frac{\log_2\left(1+\gamma_c\left(\check{\mathbf{w}}_c^*\right)\right)-\log_2\check{\varphi}^*}{\zeta\|\check{\mathbf{w}}_c^*\|_F^2+N_cP_A+P_B} \tag{17}$$

From (17), it is obvious that $(\check{\mathbf{w}}_c^*,\check{\varphi}^*)$ is also the optimal solution of problem (10). Hence, problems (10) and (11) have the same optimal solution when $g(\eta_{OBF}^*)=0$, completing the proof of Proposition 1. □

In what follows, we focus on the constrained optimization problem (11). By defining $\mathbf{W}_c=\mathbf{w}_c\mathbf{w}_c^H$ and $\mathbf{H}_\alpha=\mathbf{h}_\alpha\mathbf{h}_\alpha^H$ with $\alpha=\{c,p,k|k\in\mathbb{K}\}$, we can rewrite problem (11) as

$$\begin{aligned}\max_{\mathbf{W}_c\succeq\mathbf{0},\varphi\geq1}\ &\log_2\left(1+\frac{\vartheta_c\mathrm{Tr}\left(\mathbf{H}_c\mathbf{W}_c\right)}{\sigma_c^2}\right)-\log_2\varphi\\ &-\eta_{OBF}\left(\zeta\mathrm{Tr}\left(\mathbf{W}_c\right)+N_cP_A+P_B\right) &(18a)\\ \text{s.t.}\quad &\vartheta_c\mathrm{Tr}\left(\mathbf{H}_k\mathbf{W}_c\right)/\sigma_k^2-\varphi+1\leq0,\quad k\in\mathbb{K} &(18b)\\ &\vartheta_c\mathrm{Tr}\left(\mathbf{H}_c\mathbf{W}_c\right)/\sigma_c^2-2^{R_{sec}^{\min}}\varphi+1\geq0 &(18c)\\ &\vartheta_p\mathrm{Tr}\left(\mathbf{H}_p\mathbf{W}_c\right)\leq I_p^{th} &(18d)\\ &\mathrm{Tr}\left(\mathbf{W}_c\right)\leq P_c^{\max} &(18e)\\ &\mathrm{Rank}\left(\mathbf{W}_c\right)=1 &(18f)\end{aligned}$$

In (18f), the non-convex constraint $\mathrm{Rank}\left(\mathbf{W}_c\right)=1$ is due to the fact $\mathbf{W}_c=\mathbf{w}_c\mathbf{w}_c^H$, which makes problem (18) difficult to solve. In many previous works, optimization problems with rank-one constraint were widely handled by the randomization method [22], which first ignores the rank-one constraint to simplify the original optimization problem and then select the best solution from a large number of randomly generated rank-one candidates as an approximate optimal solution. As the candidates from the random space do not ensure a final optimal solution for the original optimization problem, the chosen rank-one solution may be sub-optimal or ineffective. To overcome this drawback, the penalty function approach is adopted in this paper to find the optimal solution of problem (18).

Motivated by the fact that

$$\mathrm{Rank}\left(\mathbf{W}_c\right)=1\Longleftrightarrow\mathrm{Tr}\left(\mathbf{W}_c\right)-\lambda_{\max}\left(\mathbf{W}_c\right)=0 \tag{19}$$

the rank-one constraint (18f) can be replaced by a penalty term $\mathrm{Tr}\left(\mathbf{W}_c\right)-\lambda_{\max}\left(\mathbf{W}_c\right)$ with the penalty coefficient $\rho\geq1$. Then, problem (18) is further reformulated as

$$\begin{aligned}\max_{\mathbf{W}_c\succeq\mathbf{0},\varphi\geq1}\ &\log_2\left(1+\frac{\vartheta_c\mathrm{Tr}\left(\mathbf{H}_c\mathbf{W}_c\right)}{\sigma_c^2}\right)-\log_2\varphi\\ &-\eta_{OBF}\left(\zeta\mathrm{Tr}\left(\mathbf{W}_c\right)+N_cP_A+P_B\right)\\ &-\rho\left(\mathrm{Tr}\left(\mathbf{W}_c\right)-\lambda_{\max}\left(\mathbf{W}_c\right)\right) &(20a)\\ \text{s.t.}\quad &\text{(18b)-(18e)} &(20b)\end{aligned}$$

Remark 1: Problem (20) is to maximize the original objective function (18a) and minimize the value of $\mathrm{Tr}\left(\mathbf{W}_c\right)-\lambda_{\max}\left(\mathbf{W}_c\right)$, simultaneously. Once $\mathrm{Tr}\left(\mathbf{W}_c\right)-\lambda_{\max}\left(\mathbf{W}_c\right)\approx0$, it means that $\mathbf{W}_c$ has only one non-zero eigenvalue, and the rank-one constraint in problem (18) is satisfied.

By defining

$$\begin{aligned}g_1\left(\mathbf{W}_c,\eta_{OBF}\right)=&\log_2\left(1+\frac{\vartheta_c\mathrm{Tr}\left(\mathbf{H}_c\mathbf{W}_c\right)}{\sigma_c^2}\right)-\rho\mathrm{Tr}\left(\mathbf{W}_c\right)\\ &-\eta_{OBF}\left(\zeta\mathrm{Tr}\left(\mathbf{W}_c\right)+N_cP_A+P_B\right)\end{aligned} \tag{21}$$

and

$$g_2\left(\mathbf{W}_c,\varphi\right)=\log_2\varphi-\rho\lambda_{\max}\left(\mathbf{W}_c\right) \tag{22}$$

we can rewrite the optimization problem (20) as

$$\begin{aligned}\max_{\mathbf{W}_c\succeq\mathbf{0},\varphi\geq1}\ &g_1(\mathbf{W}_c,\eta_{OBF})-g_2(\mathbf{W}_c,\varphi) &(23a)\\ \text{s.t.}\quad &\text{(18b)-(18e)} &(23b)\end{aligned}$$

Since the logarithmic function is concave and $\lambda_{\max}\left(\mathbf{W}_c\right)$ is convex, $g_2\left(\mathbf{W}_c,\varphi\right)$ is a concave function, which makes the objective function (23a) with the subtractive form of two logarithmic functions non-convex. To tackle it, we apply the D.C. approach [23] to transform the objective function (23a) into a convex one. Assuming $(\bar{\mathbf{W}}_c,\bar{\varphi})$ is a feasible solution to problem (23), $g_2\left(\mathbf{W}_c,\varphi\right)$ can be approximated by its first-order Taylor series expansion, i.e.,

$$\begin{aligned}g_2\left(\mathbf{W}_c,\varphi\right)\leq&g_2(\bar{\mathbf{W}}_c,\bar{\varphi})\\ &+\langle\nabla g_2(\bar{\mathbf{W}}_c,\bar{\varphi}),(\mathbf{W}_c,\varphi)-(\bar{\mathbf{W}}_c,\bar{\varphi})\rangle\end{aligned} \tag{24}$$

where $\nabla g_2(\bar{\mathbf{W}}_c,\bar{\varphi})$ is the gradient of $g_2\left(\mathbf{W}_c,\varphi\right)$ at $(\bar{\mathbf{W}}_c,\bar{\varphi})$, which is given by

$$\nabla g_2(\bar{\mathbf{W}}_c,\bar{\varphi})=\begin{bmatrix}-\rho\mathbf{u}_{\max}(\bar{\mathbf{W}}_c)\mathbf{u}_{\max}^H(\bar{\mathbf{W}}_c)\\ 1/(\bar{\varphi}\ln2)\end{bmatrix} \tag{25}$$

Here, we have employed the fact that the sub-gradient of $\lambda_{\max}(\mathbf{W}_c)$ is $\mathbf{u}_{\max}(\mathbf{W}_c)\mathbf{u}_{\max}^H(\mathbf{W}_c)$. Substituting (25) into (24) yields

$$\begin{aligned}g_2\left(\mathbf{W}_c,\varphi\right)\leq&g_2(\bar{\mathbf{W}}_c,\bar{\varphi})+\frac{\varphi-\bar{\varphi}}{\bar{\varphi}\ln2}\\ &-\rho\mathrm{Tr}(\mathbf{u}_{\max}(\bar{\mathbf{W}}_c)\mathbf{u}_{\max}^H(\bar{\mathbf{W}}_c)(\mathbf{W}_c-\bar{\mathbf{W}}_c))\end{aligned} \tag{26}$$

Finally, by employing (26), the optimal solution to problem (23) can be obtained through the following iterative procedure,

$$\begin{aligned}&(\bar{\mathbf{W}}_c^{i+1},\bar{\varphi}^{i+1})=\\ &\max_{\mathbf{W}_c\succeq\mathbf{0},\varphi\geq1}\ g_1(\mathbf{W}_c,\eta_{OBF})-g_2(\bar{\mathbf{W}}_c^i,\bar{\varphi}^i)-\frac{\varphi-\bar{\varphi}^i}{\bar{\varphi}^i\ln2}\\ &\qquad+\rho\mathrm{Tr}(\mathbf{u}_{\max}(\bar{\mathbf{W}}_c^i)\mathbf{u}_{\max}^H(\bar{\mathbf{W}}_c^i)(\mathbf{W}_c-\bar{\mathbf{W}}_c^i)) &(27a)\\ &\qquad\text{s.t.}\quad\text{(18b)-(18e)} &(27b)\end{aligned}$$

where $(\bar{\mathbf{W}}_c^{i+1},\bar{\varphi}^{i+1})$ and $(\bar{\mathbf{W}}_c^i,\bar{\varphi}^i)$ are the optimal solutions at the i-th and $(i+1)$-th iterations, respectively. Since the objective function is concave and all constraints are linear, problem (27) is convex and can be efficiently solved by standard optimization packages, such as CVX [24].

Proposition 2: The iterative procedure in (27) generates a sequence of improved solutions which converge to the optimal solution of problem (23).

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2667882, IEEE Access

Proof. Following the iterative procedure in (27), one can obtain

$$\begin{aligned} g_1(\bar{\mathbf{W}}_c^{i+1}, \eta_{OBF}) &- g_2(\bar{\mathbf{W}}_c^{i}, \bar{\varphi}^i) - \frac{\bar{\varphi}^{i+1} - \bar{\varphi}^i}{\bar{\varphi}^i \ln 2} \\ &+ \rho \mathrm{Tr}(\mathbf{u}_{\max}(\bar{\mathbf{W}}_c^i)\mathbf{u}_{\max}^H(\bar{\mathbf{W}}_c^i)(\bar{\mathbf{W}}_c^{i+1} - \bar{\mathbf{W}}_c^i)) \\ = &\max_{(\mathbf{W}_c, \varphi)\in\mathcal{R}_2} g_1(\mathbf{W}_c, \eta_{OBF}) - g_2(\bar{\mathbf{W}}_c^{i}, \bar{\varphi}^i) - \frac{\varphi - \bar{\varphi}^i}{\bar{\varphi}^i \ln 2} \\ \geq & g_1(\bar{\mathbf{W}}_c^{i}, \eta_{OBF}) - g_2(\bar{\mathbf{W}}_c^{i}, \bar{\varphi}^i) \end{aligned} \tag{28}$$

where $\mathcal{R}_2$ is the feasible set of problem (27). Furthermore, with the help of (26), we have

$$\begin{aligned} g_2(\bar{\mathbf{W}}_c^{i+1}, \bar{\varphi}^{i+1}) \leq & g_2(\bar{\mathbf{W}}_c^{i}, \bar{\varphi}^i) + \frac{\bar{\varphi}^{i+1} - \bar{\varphi}^i}{\bar{\varphi}^i \ln 2} \\ & - \rho \mathrm{Tr}(\mathbf{u}_{\max}(\bar{\mathbf{W}}_c^i)\mathbf{u}_{\max}^H(\bar{\mathbf{W}}_c^i)(\bar{\mathbf{W}}_c^{i+1} - \bar{\mathbf{W}}_c^i)) \end{aligned} \tag{29}$$

By substituting (29) into (28), we can further obtain

$$\begin{aligned} g_1(\bar{\mathbf{W}}_c^{i+1}, &\eta_{OBF}) - g_2(\bar{\mathbf{W}}_c^{i+1}, \bar{\varphi}^{i+1}) \\ & \geq g_1(\bar{\mathbf{W}}_c^{i+1}, \eta_{OBF}) - g_2(\bar{\mathbf{W}}_c^{i}, \bar{\varphi}^i) - \frac{\bar{\varphi}^{i+1} - \bar{\varphi}^i}{\bar{\varphi}^i \ln 2} \\ & \quad - \rho \mathrm{Tr}(\mathbf{u}_{\max}(\bar{\mathbf{W}}_c^i)\mathbf{u}_{\max}^H(\bar{\mathbf{W}}_c^i)(\bar{\mathbf{W}}_c^{i+1} - \bar{\mathbf{W}}_c^i)) \\ & \geq g_1(\bar{\mathbf{W}}_c^{i}, \eta_{OBF}) - g_2(\bar{\mathbf{W}}_c^{i}, \bar{\varphi}^i) \end{aligned} \tag{30}$$

Now, it can be observed that the proposed iterative procedure (27) constructs a series of non-decreasing solutions to increase the objective function (27a). In addition, by applying the Cauchy-Schwarz inequality $\mathrm{Tr}(\mathbf{AB}) \leq \mathrm{Tr}(\mathbf{A})\mathrm{Tr}(\mathbf{B})$ and the transmit power constraint of CBS, $\mathrm{Tr}(\mathbf{W}_c) \leq P_c^{\max}$, we can obtain the upper bound of the objective function as

$$\begin{aligned} g_1(\mathbf{W}_c, &\eta_{OBF}) - g_2(\mathbf{W}_c, \varphi) \\ & \leq \log_2\left(1 + \frac{\vartheta_c \mathrm{Tr}(\mathbf{H}_c \mathbf{W}_c)}{\sigma_c^2}\right) \\ & \leq \log_2\left(1 + \frac{P_c^{\max}\vartheta_c \mathrm{Tr}(\mathbf{H}_c)}{\sigma_c^2}\right) \end{aligned} \tag{31}$$

Combining (30) and (31), the convergence of the iterative procedure in (27) is guaranteed. □

By combining Proposition 1 with the penalty function and D.C. approaches, we present an iterative algorithm to search for the optimal solution $(\mathbf{W}_c^*, \varphi^*)$ that satisfies the rank-one constraint $\mathrm{Rank}(\mathbf{W}_c^*) = 1$, and thereby obtain the corresponding optimal solution $\mathbf{w}_c^* = \sqrt{\lambda_{\max}(\mathbf{W}_c^*)}\mathbf{u}_{\max}(\mathbf{W}_c^*)$ for problem (9). The overall OBF scheme is described in Algorithm 1. The outer iteration is to find η_{OBF} satisfying $g(\eta_{OBF}) = 0$ with the Dinkelbach's method [25], while the inner iteration is to obtain the rank-one solution for a given η_{OBF} at each iteration.

Remark 2: According to the procedure of Algorithm 1, the overall computational complexity to compute the optimal solution of problem (9) is determined by the iteration number, the variable size and the number of constraints at the outer and inner loops. For a given convergence tolerance ϵ, the iterations excluding convex programming can be written as $O(\log(\eta_{OBF}^{up}/\epsilon)\log(g_{OBF}^{up}/\epsilon))$, where $\eta_{OBF}^{up} = \log_2(1 + P_c^{\max}\vartheta_c\mathrm{Tr}(\mathbf{H}_c)/\sigma_c^2)/(N_cP_A + P_B)$ and $g_{OBF}^{up} = \log_2(1 + P_c^{\max}\vartheta_c\mathrm{Tr}(\mathbf{H}_c)/\sigma_c^2)$. Since problem (27) has one $N_c \times N_c$ matrix variable and one scalar variable, the interior point method needs at most $O((N_c+1)^{3.5}\log(1/\epsilon))$ calculations at each inner iteration [22]. As a result, the overall computational complexity can be roughly given by

$$O\left(\log\left(\frac{1}{\epsilon}\right)\log\left(\frac{\eta_{OBF}^{up}}{\epsilon}\right)\log\left(\frac{g_{OBF}^{up}}{\epsilon}\right)(N_c+1)^{3.5}\right) \tag{32}$$

Algorithm 1: The proposed OBF scheme to obtain the optimal solution for problem (9).

Function *Outer_Iteration*
- Initialize $i = 0$ and $\eta_{OBF}^0 = 0$.
- **repeat**
  - (i) Call **Function** *Inner_Iteration* with η_{OBF}^i to obtain the optimal solution $(\mathbf{w}_c^i, \varphi^i)$.
  - (ii) Update $\eta_{OBF}^{i+1} = \frac{\log_2(1+\gamma_c(\mathbf{w}_c^i)) - \log_2\varphi^i}{\zeta\|\mathbf{w}_c^i\|_F^2 + N_cP_A + P_B}$.
  - (iii) Set $i = i + 1$.
- **until** $|\eta_{OBF}^i - \eta_{OBF}^{i-1}| \leq \epsilon$, *where ϵ is the tolerance*;
- Obtain the maximum SEE $\eta_{OBF}^* = \eta_{OBF}^i$ and the optimal solution $\mathbf{w}_c^* = \mathbf{w}_c^i$ for problem (9).

end

Function *Inner_Iteration(η_{OBF})*
- Initialize $i = 0$ and the penalty coefficient ρ.
- Find a feasible solution $(\mathbf{W}_c^0, \varphi^0)$ for problem (27) and calculate $g^0 = g_1(\mathbf{W}_c^0, \eta_{OBF}) - g_2(\mathbf{W}_c^0, \varphi^0)$ for given η_{OBF}.
- **repeat**
  - (i) Find the optimal solution $(\mathbf{W}_c^{i+1}, \varphi^{i+1})$ of problem (27) for obtained $(\mathbf{W}_c^i, \varphi^i)$ and η_{OBF} by using CVX.
  - (ii) Compute $g^{i+1} = g_1(\mathbf{W}_c^{i+1}, \eta_{OBF}) - g_2(\mathbf{W}_c^{i+1}, \varphi^i)$.
  - (iii) Set $i = i + 1$.
- **until** $|g^i - g^{i-1}| \leq \epsilon$, *where ϵ is the tolerance*;
- Set the optimal rank-one solution $\mathbf{W}_c = \mathbf{W}_c^i$, and calculate the corresponding optimal beamformer through eigenvalue decomposition $\mathbf{w}_c = \sqrt{\lambda_{\max}(\mathbf{W}_c^i)}\mathbf{u}_{\max}(\mathbf{W}_c^i)$ and set optimal $\varphi = \varphi^i$.
- **return** $\mathbf{w}_c$ and φ.

end

IV. Proposed ZFBF Scheme

In the previous section, we have obtained an optimal solution to maximize SEE for the considered CRN. However, the high computational complexity makes it difficult to be applied in real-time scenarios. To overcome this problem, here we propose a sub-optimal solution via ZF-based BF. By assuming $N_c > K$, the beamformer $\mathbf{w}_c$ of CBS can be designed such that all confidential signals leaked to EDs are completely eliminated, namely,

$$\mathbf{H}_e^H \mathbf{w}_c = \mathbf{0}_{K\times 1} \tag{33}$$

where $\mathbf{H}_e = [\mathbf{h}_1, \cdots, \mathbf{h}_K]$. By denoting $\mathbf{w}_c = \sqrt{P_c}\mathbf{v}_c$ with $\|\mathbf{v}_c\|_F^2 = 1$, the original SEE maximization problem (9) can

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2667882, IEEE Access

be reformulated as

$$\max_{\mathbf{v}_c, P_c} \quad \frac{\log_2(1 + P_c\vartheta_c \left|\mathbf{h}_c^H \mathbf{v}_c\right|^2 / \sigma_c^2)}{\zeta P_c + N_c P_A + P_B} \tag{34a}$$

$$\text{s.t.} \quad P_c\vartheta_c \left|\mathbf{h}_c^H \mathbf{v}_c\right|^2 / \sigma_c^2 \geq 2^{R_s^{\min}} - 1 \tag{34b}$$

$$P_c\vartheta_p \left|\mathbf{h}_p^H \mathbf{v}_c\right|^2 \leq I_p^{th} \tag{34c}$$

$$\mathbf{H}_e^H \mathbf{v}_c = \mathbf{0}_{K\times 1} \tag{34d}$$

$$P_c \leq P_c^{\max} \quad \text{and} \quad \|\mathbf{v}_c\|_F^2 = 1 \tag{34e}$$

As that the objective function in (34a) monotonously increases with $|\mathbf{h}_c^H \mathbf{v}_c|^2$ and the corresponding constraints must be satisfied, the normalized BF vector $\mathbf{v}_c$ can be designed to maximize $|\mathbf{h}_c^H \mathbf{v}_c|^2$ and lie in the null-space of $\mathbf{H}_e$, as given by [26]

$$\mathbf{v}_c = \frac{\left(\mathbf{I}_{N_c} - \mathbf{H}_e^{\perp}\right)\mathbf{h}_c}{\|\left(\mathbf{I}_{N_c} - \mathbf{H}_e^{\perp}\right)\mathbf{h}_c\|_F} \tag{35}$$

where $\mathbf{H}_e^{\perp} = \mathbf{H}_e\left(\mathbf{H}_e^H\mathbf{H}_e\right)^{-1}\mathbf{H}_e^H$ is the orthogonal projection matrix of $\mathbf{H}_e$. By employing (35), problem (34) can be further simplified as the following optimization problem over P_c,

$$\max_{P_c} \quad \frac{\log_2(1 + P_c\vartheta_c \left|\mathbf{h}_c^H \mathbf{v}_c\right|^2 / \sigma_c^2)}{\zeta P_c + N_c P_A + P_B} \tag{36a}$$

$$\text{s.t.} \quad P_c^{low} \leq P_c \leq P_c^{up} \tag{36b}$$

where $P_c^{low} = (2^{R_{sec}^{\min}} - 1)\sigma_c^2/(\vartheta_c \left|\mathbf{h}_c^H \mathbf{v}_c\right|^2)$ and $P_c^{up} = \min\{I_p^{th}/(\vartheta_p \left|\mathbf{h}_p^H \mathbf{v}_c\right|^2), P_c^{\max}\}$. Due to the fractional form in the objective function, it is difficult to directly obtain optimal P_c in (36). To tackle this problem, we assume η_{ZF}^* to be the maximum SEE of the problem (36) and consider a non-fractional form as

$$g(\eta_{ZF}) = \max_{P_c} \quad \log_2(1 + P_c\vartheta_c \left|\mathbf{h}_c^H \mathbf{v}_c\right|^2 / \sigma_c^2) - \eta_{ZF}(\zeta P_c + N_c P_A + P_B) \tag{37a}$$

$$\text{s.t.} \quad (36b) \tag{37b}$$

Proposition 3: The optimization problem (36) and (37) are equivalent if and only if $g(\eta_{ZF}^*) = 0$.

Proof. It can be proved in a similar manner as Proposition 1. □

The above proposition shows that if we can find a value of η_{ZF} in (37) that satisfies $g(\eta_{ZF}) = 0$, the optimal solution P_c^* is also the optimal solution of (36). In what follows, we present a method to obtain the analytical solution for η_{ZF} such that $g(\eta_{ZF}) = 0$.

By differentiating the objective function in (37) with respect to P_c, and setting it to zero, the saddle point can be obtained as

$$P_c = \frac{1}{\eta_{ZF}\zeta \ln 2} - \frac{\sigma_c^2}{\vartheta_c \left|\mathbf{h}_c^H \mathbf{v}_c\right|^2} \tag{38}$$

Proposition 4: Let $\eta_{ZF}^i = \frac{\log_2(1+P_c^{i-1}\vartheta_c\left|\mathbf{h}_c^H\mathbf{v}_c\right|^2/\sigma_c^2)}{\zeta P_c^{i-1}+N_cP_A+P_B}$ at the i-th iteration, P_c^i calculated by (38) is always non-negative.

Algorithm 2: The proposed ZFBF scheme to find the sub-optimal solution for problem (9).

1 Initialize $i = 0$ and $P_c^0 = P_c^{up}$.
2 Calculate $\mathbf{v}_c$ using (34).
3 **repeat**
    (i) Update $\eta_{ZF}^{i+1} = \frac{\log_2(1+P_c^i\vartheta_c\left|\mathbf{h}_c^H\mathbf{v}_c\right|^2/\sigma_c^2)}{\zeta P_c^i+N_cP_A+P_B}$ and compute P_c^{i+1} through (39).
    (ii) Set $i = i + 1$.
    (iii) Calculate $g(\eta_{ZF}^i) = \log_2\left(1 + P_c^i\vartheta_c\left|\mathbf{h}_c^H\mathbf{v}_c\right|^2/\sigma_c^2\right) - \eta_{ZF}^i(\zeta P_c^i + N_cP_A + P_B)$.
  until $|g(\eta_{ZF}^i)| \leq \epsilon$, *where* ϵ *is the tolerance*;
4 Obtain the optimal transmit power $P_c^* = P_c^i$ and the corresponding ZF-based beamformer of problem (9) as $\mathbf{w}_c^* = \sqrt{P_c^*}\mathbf{v}_c$.

Proof. Since $\log_2(1+x) \leq x/\ln 2$, for a given P_c^{i-1} resulting from the $(i-1)$-th iteration, we have

$$\begin{aligned} P_c^i &= \frac{1}{\eta_{ZF}^i\zeta\ln 2} - \frac{\sigma_c^2}{\vartheta_c\left|\mathbf{h}_c^H\mathbf{v}_c\right|^2} \\ &\geq \frac{\zeta P_c^{i-1} + N_cP_A + P_B}{\log_2(1 + P_c^{i-1}\vartheta_c\left|\mathbf{h}_c^H\mathbf{v}_c\right|^2/\sigma_c^2)}\frac{1}{\zeta\ln 2} - \frac{\sigma_c^2}{\vartheta_c\left|\mathbf{h}_c^H\mathbf{v}_c\right|^2} \\ &\geq \left(\frac{\zeta P_c^{i-1} + N_cP_A + P_B}{\zeta P_c^{i-1}} - 1\right)\frac{\sigma_c^2}{\vartheta_c\left|\mathbf{h}_c^H\mathbf{v}_c\right|^2} \geq 0 \end{aligned} \tag{39}$$

This completes the proof of Proposition 4. □

By jointly using Proposition 4 and the power constraint (36b), the optimal transmit power P_c^* to problem (37) can be calculated by the following iterative procedure,

$$P_c^i = \begin{cases} P_c^{low} & \eta_{ZF}^i > \frac{1}{\zeta\ln 2(P_c^{low}+\alpha^{-1})} \\ \frac{1}{\eta_{ZF}^i\zeta\ln 2} - \frac{1}{\alpha} & \frac{1}{\zeta\ln 2(P_c^{up}+\alpha^{-1})} < \eta_{ZF}^i \leq \frac{1}{\zeta\ln 2(P_c^{low}+\alpha^{-1})} \\ P_c^{up} & \eta_{ZF}^i \leq \frac{1}{\zeta\ln 2(P_c^{up}+\alpha^{-1})} \end{cases} \tag{40}$$

where $\alpha = \vartheta_c\left|\mathbf{h}_c^H\mathbf{v}_c\right|^2/\sigma_c^2$. Finally, we present a ZFBF scheme to solve the SEE maximization problem (9) as summarized in Algorithm 2. At the i-th iteration, for a given η_{ZF}^i, we employ (40) to obtain P_c^i, which is used to update η_{ZF}^{i+1} for the next iteration. The iteration is stopped when $g(\eta_{ZF}) \approx 0$ is satisfied and the corresponding optimal transmit power is set to $P_c^* = P_c^i$. Therefore, the sub-optimal ZF-based solution of the SEE maximization problem (9) is obtained as $\mathbf{w}_c^* = \sqrt{P_c^*}\mathbf{v}_c$ with $\mathbf{v}_c$ given by (35).

Remark 3: The proposed ZFBF scheme consists of only one loop, which has a linear time complexity only, i.e. $O(\log(g_{ZF}^{up}/\epsilon))$, where $g_{ZF}^{up} = \log_2(1 + P_c^{\max}\vartheta_c\|\mathbf{h}_c\|_F^2/\sigma_c^2)$. Hence, the proposed algorithm is of low complexity and suitable for real-time implementation.

V. Simulation Results

This section provides some simulation results to confirm the validity of the proposed OBF and ZFBF schemes. Here, we assume that each fading channel $\mathbf{h}_\alpha$ ($\alpha = \{c, p, k | k \in \mathbb{K}\}$)

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2667882, IEEE Access

TABLE I
SYSTEM PARAMETERS

Parameters	Values
Path loss model, $\log_{10}(\vartheta)$	$22\log_{10}(d[\mathrm{m}]) + 42$ $+20\log_{10}(f_c[\mathrm{GHz}]/5)$ [27]
Carrier Frequency, f_c	1.9 GHz
Bandwidth, Δf	5 MHz
Noise spectral density, N_0	-116 dBm/Hz
Inefficiency power coefficient, ζ	2.6
Power consumed by each antenna, P_A	30 dBm
Basic power consumption of CBS, P_B	40 dBm
Minimum acceptable SR, $R_{sec}^{\min}$	0.5 bit/s/Hz
Interference threshold, I_p^{th}	-60 dBm

follows Rayleigh distribution and the covariance of AWGN is set to $\sigma_\alpha^2 = \Delta f N_0$ with Δf and N_0 being the system bandwidth and the single-sided noise spectral density, respectively. The distance from CBS to CU and that to PU are set as $d_c = d_p = 500$m, and the ratio of the CBS-CU distance to the CBS-ED$_k$ distance is denoted as $\delta_d = d_c/d_k$ with $\delta_d = 1$ except for Fig.4. Other system parameters are summarized in Table I. In addition, the convergence tolerance ϵ for the proposed algorithms 1 and 2 is set to 10^{-3}. All of the simulation curves are calculated by averaging over 1000 random channel realizations.

Fig.2 shows the average SEE of the proposed OBF and ZFBF schemes versus the maximum transmit power of CBS $P_c^{\max}$. The number of transmit antennas at CBS is $N_c = 6$ and the number of EDs is $K = 3$. It is observed that the OBF scheme outperforms the ZFBF scheme in all transmit power regions. This is because the optimal beamformer obtained by OBF scheme has more intelligent interference management than the sub-optimal beamformer calculated by ZFBF scheme for the legitimate CU. Meanwhile, the gap between the two proposed schemes is very small, implying that the ZFBF scheme is effective. Here, the results of the SRM [6] and the EEM [12] schemes are also provided for comparison. It is observed that the proposed OBF scheme achieves the same performance as that of the SRM scheme when $P_c^{\max} \leq 32$dBm, since both schemes use full transmit power $P_c^{\max}$ to obtain the maximum SEE. After achieving the maximum SEE, the proposed OBF scheme remains the same whille the SRM scheme is degraded drastically as $P_c^{\max}$ increases. The performance gain of OBF scheme is kept becasuse it ceases allocating more transmit power to avoid sacrificing the achieved SEE. However, the SRM scheme continues to employ full transmit power to obtain higher SR. Finally, both of the proposed schemes give a significant improvement in SEE as compared with the EE maximization scheme, which focuses only on the EE and ignores the existence of the multiple EDs.

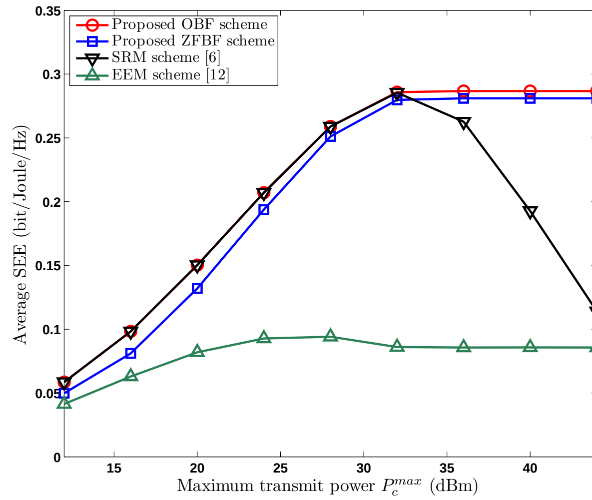


Fig. 2. Average SEE versus $P_c^{\max}$ with $N_c = 6$, $K = 3$ and $\delta_d = 1$.

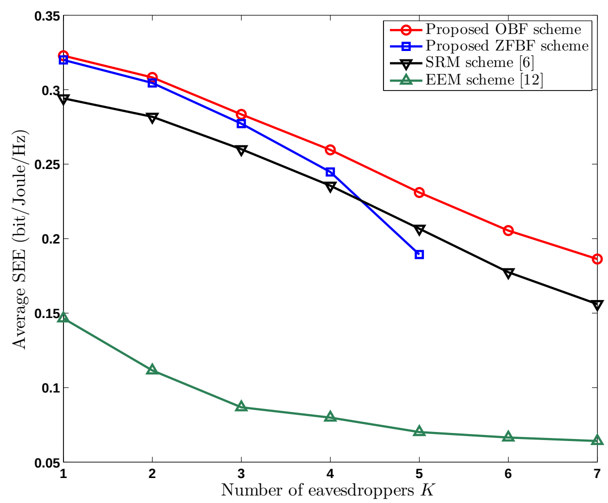


Fig. 3. Average SEE versus K with $N_c = 6$, $P_c^{\max} = 36$dBm and $\delta_d = 1$.

Fig. 3 illustrates the average SEE against the number of EDs. Here, the CBS has $N_c = 6$ transmit antennas and the maximum transmit power is $P_c^{\max}$ =36dBm. It is seen that as the number of ED increases, the SEE reduces for both proposed schemes. The performance degradation is due to the proposed schemes trying to null out the signals leaked to all the EDs to satisfy the secrecy rate constraint, leaving little room to improve the CU's channel. We can also observe that the proposed OBF scheme achieves a better SEE performance than the EE maximization and SR maximization schemes. However, the SEE performance of ZFBF scheme drops quickly and cannot guarantee the secrecy of the cognitive transmission when the number of EDs $K > 5$, while the OBF scheme can still satisfy the SEE requirement. This is because for the ZF-based solution obtained by the ZFBF scheme, there is no degree-of-freedom (DoF) to generate the null-spaces to all EDs.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2667882, IEEE Access

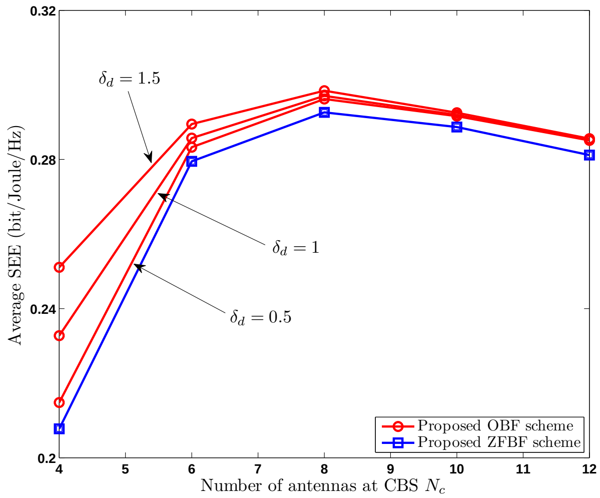


Fig. 4. Average SEE versus N_c at CBS with $K = 3$ and $P_c^{\max} = 36$dBm.

Fig. 4 depicts the average SEE versus the number of transmit antennas on the CBS for the values of the distance ratio of the main channel and the wiretap channel $\delta_d = 0.5, 1, 1.5$. Here, we suppose there are $K = 3$ EDs and the maximum transmit power is $P_c^{\max} = 36$dBm. It can be seen that increasing the number of transmit antennas from 4 to 8 can enhance the SEE for both OBF and ZFBF schemes, owing to the sufficient number of transmit antennas ($N_c > K + 1$) that can completely eliminate the confidential signals leaked to EDs. Specially, the ZFBF scheme achieves a significant performance improvement due to the increased DoF which helps the ZF-based sub-optimal beamformer not only null out the signals received by all EDs but also allocate more power to CU, resulting in a reduced gap between two proposed schemes. Furthermore, we can also observe that the SEE performance of the considered CRN is enhanced when δ_d increases, which corresponds to the case of CU being closer to CBS than EDs. In addition, we can also observe that CRN achieves a higher SEE with transmit antennas $N_c = 8$ than $N_c > 8$. This is because the CBS equipped with more transmit antennas results in increasing circuit power consumption of CBS and thus degrading the SEE value for CRN. Therefore, from the EE perspective, the CBS equipped with a large number of antennas may decrease the SEE of CRN.

VI. Conclusion

In this paper, we have studied the SEEM problem in an underlay CRN in the presence of multiple EDs. As the originally formulated optimization problem is in the max-min fractional form, we have transformed it into an equivalent problem with an additional rank-one constraint and then simplified the equivalent problem to a convex one by jointly applying the penalty function and D.C. approaches. Based on this special effort, an OBF scheme has then been proposed to find the optimal solution to the SEEM problem. Furthermore, a ZFBF scheme has also been proposed, which achieves a sub-optimal solution with a significantly reduced computational complexity. Simulation results have been provided to show the effectiveness and advantage of the proposed schemes.

References

[1] Y.-C. Liang, K. C. Chen, G. Y. Li, et al., “Cognitive radio networking and communications: An overview,” *IEEE Transactions on Vehicular Technology*, vol. 60, no. 7, pp. 3386-3407, Sep. 2011.
[2] J. Zhu and Y. Zou, “Cognitive network cooperation for green cellular networks,” *IEEE Access*, vol. 4, pp. 849-857, 2016.
[3] K. An, M. Lin, W.-P. Zhu, et al, “Outage performance of cognitive hybrid satellite terrestrial networks with interference constraint,” *IEEE Transactions on Vehicular Technology*, vol. 65, no. 11, pp. 9397-9404, Nov. 2016.
[4] Y. Zou, J. Zhu, X. Wang, et al., “A survey on wireless security: Technical challenges, recent advances and future trends,” *Proceedings of the IEEE*, vol. 104, no. 9, pp. 1727-1765, Sep. 2016.
[5] Y. Zou, J. Zhu, L. Yang, et al., “Securing physical-layer communications for cognitive radio networks,” *IEEE Communications Magazine*, vol. 53, no. 9, pp. 48-54, Sep. 2015.
[6] Y. Pei, Y.-C. Liang, L. Zhang, et al., “Secure communication over MISO cognitive radio channels,” *IEEE Transactions on Wireless Communications*, vol. 9, no. 4, pp. 1494-1502, Apr. 2010.
[7] Y. Zou, X. Li, and Y.-C. Liang, “Secrecy outage and diversity analysis of cognitive radio systems,” *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 11, pp. 2222-2236, Nov. 2014.
[8] T. Chen, H. Q. Yuan, T. Z. Zhao, et al., “Joint beamforming and power allocation for secure communication in cognitive radio networks,” *IET Communications*, vol. 10, no. 10, pp. 1156-1162, Jul. 2016.
[9] H. Zhang, T. Y. Wang, L. Y. Song, et al., “Interference improves PHY security for cognitive radio networks,” *IEEE Transactions on Information Forensics and Security*, vol. 11, no. 3, pp. 609-620, Mar. 2016.
[10] K. An, M. Lin, J. Ouyang and W.-P. Zhu, “Secure transmission in cognitive satellite terrestrial networks,” *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 11, pp. 3025-3037, Oct. 2016.
[11] H. Shokri-Ghadikolaei, I. Glaropoulos, V. Fodor, et al., “Green sensing and access: Energy-throughput trade-offs in cognitive networking,” *IEEE Communications Magazine*, vol. 53, no. 11, pp. 199-207, Nov 2015.
[12] J. Mao, G. Xie, J. Gao, et al., “Energy efficiency optimization for cognitive radio MIMO broadcast channels,” *IEEE Communications Letters*, vol. 17, no. 2, pp. 337-340, Feb. 2013.
[13] M. Naeem, K. Illanko, A. Karmokar, et al., “Optimal power allocation for green cognitive radio: Fractional programming approach,” *IET Communications*, vol. 7, no. 12, pp. 1279-1286, Aug. 2013.
[14] X. Zhang, H. Li, Y. Lu, et al., “Distributed energy efficiency optimization for MIMO cognitive radio network,” *IEEE Communications Letters*, vol. 19, no. 5, pp. 847-850, May 2015.
[15] T. Zhang, and D. H. K. Tsang, “Cooperative sensing scheduling for energy-efficient cognitive radio networks,” *IEEE Transactions on Vehicular Technology*, vol. 64, no. 6, pp. 2648-2662, Jun. 2015.
[16] L. Xu, and A. Nallanathan, “Energy-efficient chance-constrained resource allocation for multicast cognitive OFDM network,” *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 5, pp. 1298-1306, May 2016.
[17] S. Althunibat, V. Sucasas, H. Marques, et al., “On the trade-off between security and energy efficiency in cooperative spectrum sensing for cognitive radio,” *IEEE Communications Letters*, vol. 17, no. 8, pp. 1564-1567, Aug. 2013.
[18] F. Gabry, A. Zappone, R. Thobaben et al., “Energy efficiency analysis of cooperative jamming in cognitive radio networks with secrecy constraints,” *IEEE Wireless Communications Letters*, vol. 4, no. 4, pp. 437-440, Aug. 2015.
[19] M. El-Halabi, T. Liu, and C. N. Georghiades, “Secrecy capacity per unit cost,” *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 9, pp. 1909-1920, Sep. 2013.
[20] J. Ouyang, M. Lin, W.-P. Zhu, D. Massicotte, and A. L. Swindlehurst, “Energy efficient beamforming for secure communication in cognitive radio networks,” *In Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 3496-3500, 2016.
[21] J. Ouyang, W.-P. Zhu, D. Massicotte, and M. Lin, “Energy efficient optimization for physical layer security in cognitive relay networks,” *In Proc. IEEE International Conference on Communications (ICC)*, 2016.
[22] Z.-Q. Luo, W.-K. Ma, A. M.-C. So, et al., “Semidefinite relaxation of quadratic optimization problems,” *IEEE Signal Processing Magazine*, vol. 27, no. 3, pp. 20-34, May 2010.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2017.2667882, IEEE Access

[23] H.H. Kha, H.D. Tuan and H.H. Nguyen, “Fast global optimal power allocation in wireless networks by local DC programming,” *IEEE Transactions on Wireless Communications*, vol. 11, no.2, pp. 510-515, Feb. 2012.

[24] M. Grant and S. Boyd, “CVX: Matlab Software for Disciplined Convex Programming, version 2.1,” [Online:] http://cvxr.com/cvx, Mar. 2014.

[25] W. Dinkelbach, “On nonlinear fractional programming,” *Management Science*, vol. 13, pp. 492498, Mar. 1967.

[26] B. Friedlander and B. Porat, “Performance analysis of a null-steering algorithm based on direction of arrival estimation,” *IEEE Transactions on Acoustics Speech and Signal Processing*, vol. 37, no. 4, pp. 461-466, Apr. 1989.

[27] M. Lin, J. Ouyang, and W.-P. Zhu, “Joint beamforming and power control for device-to-device communications underlaying cellular networks,” *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 1, pp. 138-150, Jan 2016.

Jian Ouyang (M’15) received the B.S., M.S. and Ph.D. degrees from Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 2007, 2010 and 2014, respectively. Since July 2014, he has been a full-time faculty member with the College of Telecommunications and Information Engineering, Nanjing University of Posts and Telecommunications, Nanjing, China. From 2015 to 2016, he was a Postdoctoral Fellow with the Department of Electrical and Computer Engineering, Concordia University, Montreal, Canada. His research interests are cooperative and relay communications, physical layer security and green communications.

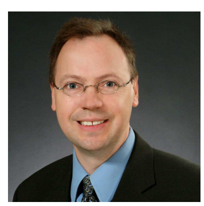
Min Lin (M’13) received the B.S. degree from the National University of Defense Technology, Changsha, China, in 1993, the M.S. degree from the Nanjing Institute of Communication Engineering, Nanjing, China, in 2000, and the Ph.D. degree from Southeast University, Nanjing, in 2008, all in electrical engineering. He is currently a Professor with Nanjing University of Posts and Telecommunications, Nanjing, China. He has authored or co-authored over 100 papers. His current research interests include wireless communications and array signal processing. Dr. Lin has served as the TPC member of many IEEE sponsored conferences, such as IEEE ICC and Globecom.

Yulong Zou (SM’13) is a Professor at the Nanjing University of Posts and Telecommunications (NUPT), Nanjing, China. He received the B.Eng. degree in information engineering from NUPT, Nanjing, China, in July 2006, the first Ph.D. degree in electrical engineering from the Stevens Institute of Technology, New Jersey, USA, in May 2012, and the second Ph.D. degree in signal and information processing from NUPT, Nanjing, China, in July 2012.

His research interests span a wide range of topics in wireless communications and signal processing, including the cooperative communications, cognitive radio, wireless security, and energy-efficient communications. Dr. Zou was awarded the 9th IEEE Communications Society Asia-Pacific Best Young Researcher in 2014. He has served as an editor for the IEEE Communications Surveys & Tutorials, IEEE Communications Letters, IET Communications, and China Communications. In addition, he has acted as TPC members for various IEEE sponsored conferences, e.g., IEEE ICC/GLOBECOM/WCNC/VTC/ICCC, etc.

Wei-Ping Zhu (SM’97) received the B.E. and M.E. degrees from Nanjing University of Posts and Telecommunications, and the Ph.D. degree from Southeast University, Nanjing, China, in 1982, 1985, and 1991, respectively, all in electrical engineering. He was a Postdoctoral Fellow from 1991 to 1992 and a Research Associate from 1996 to 1998 with the Department of Electrical and Computer Engineering, Concordia University, Montreal, Canada. During 19931996, he was an Associate Professor with the Department of Information Engineering, Nanjing University of Posts and Telecommunications. From 1998 to 2001, he worked with hi-tech companies in Ottawa, Canada, including Nortel Networks and SR Telecom Inc. Since July 2001, he has been with Concordias Electrical and Computer Engineering Department as a full-time faculty member, where he is presently a Full Professor. Since 2008, he has been an Adjunct Professor at Nanjing University of Posts and Telecommunications, Nanjing, China. His research interests include digital signal processing fundamentals, speech and statistical signal processing, and signal processing for wireless communication with a particular focus on MIMO systems and cooperative communication.

Dr. Zhu served as an Associate Editor for the IEEE Transactions on Circuits and Systems Part I: Fundamental Theory and Applications during 2001-2003, an Associate Editor for Circuits, Systems and Signal Processing during 2006-2009, and an Associate Editor for the IEEE Transactions on Circuits and Systems Part II: Transactions Briefs during 2011-2015. He was also a Guest Editor for the IEEE Journal on Selected Areas in Communications for the special issues of: Broadband Wireless Communications for High Speed Vehicles, and Virtual MIMO during 2011-2013. Currently, he is an Associate Editor of Journal of The Franklin Institute. Dr. Zhu was the Secretary of Digital Signal Processing Technical Committee (DSPTC) of the IEEE Circuits and System Society during June 2012-May 2014, and the Chair of the DSPTC during June 2014-May 2016.



Daniel Massicotte (S’91-M’94-SM’08) received the B.Sc.A. and M.Sc.A. degrees in electrical engineering and industrial electronics in 1987 and 1990 respectively from the Universit du Qubec Trois-Rivires (UQTR), Qc, Canada. He obtained the Ph.D. degree in electrical engineering in 1995 at the cole Polytechnique de Montral, Qc, Canada. In 1994, he joined the Department of Electrical and Computer Engineering, Universit du Qubec Trois-Rivires, where he is currently a Full Professor. He is Founder of the Laboratory of Signal and Systems Integration. Since 2001, he has been Founding President and Chief Technology Officer of Axiocom Inc. He has been Head of the Industrial Electronic Research Group, since 2011 and Head of the Electrical and Computer Engineering Department, since 2014. He received the Douglas R. Colton Medal for Research Excellence awarded by the Canadian Microelectronics Corporation, the PMC-Sierra High Speed Networking and Communication Award and the Second place at the Complex Multimedia/Telecom IP Design Contest from Europractice in 1997, 1999 and 2000 respectively. His research interests include advanced VLSI implementation, digital signal processing for wireless communications, measurement, medical and control problems for linear and nonlinear systems. He has proposed many methods based on modern signal and biosignal processing such as neural networks, fuzzy logic, wavelet transform, and metaheuristics. He is the author or co-author of more than 150 technical papers in international conferences and journals, as well as author or co-author of 6 inventions. He was also a Guest Editor of the Springer Analog Integrated Circuits and Signal Processing for the special issues of NEWCAS 2013.

Dr. Massicotte is also member of the ”Ordre des Ingnieurs du Qubec”, ”Groupe de Recherche en lectronique Industrielle” (GREI), and ”Microsystems Strategic Alliance of Quebec” (ReSMiQ).