



Robust Energy-Efficient Transmit Design for MISOME Wiretap Channels

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Background

- Physical-layer (PHY) security
 - PHY security can overcome the inherent difficulties of cryptographic methods.
 - Most research activities focussed on the issue of secrecy **rate** maximization.
 - It is also an important problem to characterize the tradeoff between the secrecy performance and the energy consumption.
- PHY security and energy efficiency (EE)
 - Secrecy EE (SEE): the ratio of the achievable secrecy rate to the total power consumption.
 - considered only in a few existing works, with simple system settings (e.g., perfect CSI, one Eve).
- Main contributions
 - More general channel setting: **MISOME** wiretap channel with **imperfect** CSI on **all** links
 - Problem formulation: maximization of the worst-case SEE (WC-SEE) with secrecy rate constraint
 - The optimal covariance matrix is obtained by applying the fractional programming and rank relaxation methods.
 - The rank relaxation is proved to be **tight**.

System Model

- A multi-antenna transmitter (Alice) intends to send confidential information to a single-antenna legitimate receiver (Bob), in the presence of K multi-antenna eavesdroppers (Eves).

$$y_b = \mathbf{h}_b \mathbf{x} + z_b,$$

$$\mathbf{y}_{e,k} = \mathbf{G}_{e,k} \mathbf{x} + \mathbf{z}_{e,k}, \forall k \in \mathcal{K}$$

where $\mathcal{K} \triangleq \{1, 2, \dots, K\}$, $\mathbf{h}_b \in \mathbb{C}^{1 \times N_t}$ is the channel response between Alice and Bob, N_t is the number of transmit antennas employed by the transmitter, $\mathbf{G}_{e,k} \in \mathbb{C}^{N_e \times N_t}$ is the channel response between Alice and Eve k , $N_{e,k}$ is the number of transmit antennas employed by Eve, z_b and $\mathbf{z}_{e,k}$ are AWGN, and \mathbf{x} is the coded confidential information following $\mathbf{x} \sim \mathcal{CN}(0, \mathbf{Q}_c)$.

- Deterministically bounded CSI error model

$$\mathbf{h}_b = \tilde{\mathbf{h}}_b + \Delta \mathbf{h}_b, \|\Delta \mathbf{h}_b\|_F \leq \varepsilon_b$$

$$\mathbf{G}_{e,k} = \tilde{\mathbf{G}}_{e,k} + \Delta \mathbf{G}_{e,k}, \|\Delta \mathbf{G}_{e,k}\|_F \leq \varepsilon_{e,k}, \forall k \in \mathcal{K},$$

- The worst-case secrecy rate

$$R_s^{\text{worst}}(\mathbf{Q}_c) = \min_{\mathbf{h}_b \in B_b} \log(1 + \mathbf{h}_b \mathbf{Q}_c \mathbf{h}_b^H)$$

$$- \max_{k=1, \dots, K} \max_{\mathbf{G}_{e,k} \in B_{e,k}} \log \det(\mathbf{I} + \mathbf{G}_{e,k} \mathbf{Q}_c \mathbf{G}_{e,k}^H)$$

where B_b and $B_{e,k}$ are the sets of all admissible CSI associated with \mathbf{h}_b and $\mathbf{G}_{e,k}$, respectively.

- Power consumption model [Xu et al. '13]

$$P_t = \text{Tr}(\mathbf{Q}_c) + P_c$$

where P_c is a constant transmit independent power.

- Problem Formulation

Our work focuses on the design of \mathbf{Q}_c , to maximize the WC-SEE with QoS and total power constraints.

$$\max_{\mathbf{Q}_c} \frac{R_s^{\text{worst}}(\mathbf{Q}_c)}{\text{Tr}(\mathbf{Q}_c) + P_c} \quad (1)$$

$$\text{s.t. } R_s^{\text{worst}}(\mathbf{Q}_c) \geq \tau_s, \text{Tr}(\mathbf{Q}_c) \leq P, \mathbf{Q}_c \succeq \mathbf{0}.$$

where τ_s is preset requirement of the worst-case secrecy rate.

Problem Solving

- A Dinkelbach Method-based Reformulation

We first define a parametric problem with respect to λ as follow.

$$F(\lambda) = \max_{\mathbf{Q}_c \in \mathcal{F}} R_s^{\text{worst}}(\mathbf{Q}_c) - \lambda(\text{Tr}(\mathbf{Q}_c) + P_c) \quad (2)$$

where \mathcal{F} is the feasible set of problem (1).

Lemma 1 $F(\lambda)$ is a strictly decreasing and continuous function w.r.t. λ , and it has a unique zero solution.

Lemma 2 Assume that λ^* is the unique zero solution to $F(\lambda)$, then $F(\lambda^*)$ and (1) have the same optimal solution, and the optimal objective function value of (1) is λ^* .

Our strategy is to optimize (2) and obtain $F(\lambda)$ with a given λ , and employ the *Dinkelbach method* to seek the optimal λ .

Introducing a slack variable β , one can check that (2) is equivalent to the following problem (3).

$$F(\lambda) = \max_{\mathbf{Q}_c, \beta} \left\{ \log(\beta^{-1} + \beta^{-1} \min_{\mathbf{h}_b \in B_b} \mathbf{h}_b \mathbf{Q}_c \mathbf{h}_b^H) - \lambda(\text{Tr}(\mathbf{Q}_c) + P_c) \right\}$$

$$\text{s.t. } \log \det(\mathbf{I} + \mathbf{G}_{e,k} \mathbf{Q}_c \mathbf{G}_{e,k}^H) \leq \log \beta, \forall k \in \mathcal{K}, \mathbf{G}_{e,k} \in B_{e,k} \quad (3)$$

$$\log(1 + \mathbf{h}_b \mathbf{Q}_c \mathbf{h}_b^H) - \log \beta \geq \tau_{cs}, \forall \mathbf{h}_b \in B_b,$$

$$\text{Tr}(\mathbf{Q}_c) \leq P, \mathbf{Q}_c \succeq \mathbf{0}$$

- A tight rank relaxation

Lemma 3 The following inequality holds, $\det(\mathbf{I} + \mathbf{A}) \geq 1 + \text{Tr}(\mathbf{A})$ for any PSD matrix \mathbf{A} . Moreover, the equality holds if and only if $\text{rank}(\mathbf{A}) \leq 1$.

By applying Lemma 3, problem (3) can be relaxed as

$$F_{\text{relax}}(\lambda) = \max_{\mathbf{Q}_c, \beta} \left\{ \log(\beta^{-1} + \beta^{-1} \min_{\mathbf{h}_b \in B_b} \mathbf{h}_b \mathbf{Q}_c \mathbf{h}_b^H) - \lambda(\text{Tr}(\mathbf{Q}_c) + P_c) \right\}$$

$$\text{s.t. } 1 + \text{Tr}(\mathbf{G}_{e,k} \mathbf{Q}_c \mathbf{G}_{e,k}^H) \leq \beta, \forall k \in \mathcal{K}, \mathbf{G}_{e,k} \in B_{e,k} \quad (4)$$

$$\log(1 + \mathbf{h}_b \mathbf{Q}_c \mathbf{h}_b^H) - \log \beta \geq \tau_{cs}, \forall \mathbf{h}_b \in B_b,$$

$$\text{Tr}(\mathbf{Q}_c) \leq P, \mathbf{Q}_c \succeq \mathbf{0}$$

with $F_{\text{relax}}(\lambda) \geq F(\lambda)$.

- A two-stage reformulation of (4)

Outer problem

$$F_{\text{relax}}(\lambda) = \max_{\eta} \left\{ \log \gamma(\lambda, \eta) - \eta \right\} \quad (5)$$

$$\text{s.t. } \lambda(\eta_{\min} + P_c) \leq \eta \leq \lambda(P + P_c),$$

slack variable η introduced

The inner problem

$$\begin{aligned} \gamma(\lambda, \eta) = \max_{\mathbf{Q}_c, \beta} \beta^{-1} (1 + \min_{\mathbf{h}_b \in B_b} \mathbf{h}_b \mathbf{Q}_c \mathbf{h}_b^H) \\ \text{s.t. } \lambda(\text{Tr}(\mathbf{Q}_c) + P_c) \leq \eta, \end{aligned} \quad (6)$$

constraints in (4) satisfied.

SDP-based Reformulation of the Inner Problem

Step 1: variable transformation

Introduce the transformation $\alpha = 1/\beta$, $\mathbf{Z} = \mathbf{Q}_c/\beta$ to rewrite (6) as

$$\begin{aligned} \gamma(\lambda, \eta) = \max_{\mathbf{Z}, \alpha} \min_{\mathbf{h}_b \in B_b} \alpha + \mathbf{h}_b \mathbf{Z} \mathbf{h}_b^H \\ \text{s.t. } \lambda(\text{Tr}(\mathbf{Z}) + \alpha P_c) \leq \alpha \eta, \\ \alpha + \text{Tr}(\mathbf{G}_{e,k} \mathbf{Z} \mathbf{G}_{e,k}^H) \leq 1, \forall k \in \mathcal{K}, \mathbf{G}_{e,k} \in B_{e,k} \\ \alpha + \mathbf{h}_b \mathbf{Z} \mathbf{h}_b^H \geq 2^{\tau_{cs}}, \forall \mathbf{h}_b \in B_b, \\ \text{Tr}(\mathbf{Z}) \leq P\alpha, \mathbf{Z} \succeq \mathbf{0}. \end{aligned} \quad (7)$$

Step 2: S-procedure

$$\alpha + \text{Tr}(\mathbf{G}_{e,k} \mathbf{Z} \mathbf{G}_{e,k}^H) \leq 1, \forall k \in \mathcal{K}, \mathbf{G}_{e,k} \in B_{e,k} \Leftrightarrow$$

$$\mathbf{X}_k(\rho_k, \alpha, \mathbf{Z}) = \begin{bmatrix} \rho_k \mathbf{I}_{N_r N_{e,k}} - (\mathbf{Z}^T \otimes \mathbf{I}_{N_{e,k}}) & -(\mathbf{Z}^T \otimes \mathbf{I}_{N_{e,k}}) \tilde{\mathbf{g}}_{e,k} \\ -\tilde{\mathbf{g}}_{e,k}^H (\mathbf{Z}^T \otimes \mathbf{I}_{N_{e,k}})^H & -\rho_k \varepsilon_{e,k}^2 - \tilde{\mathbf{g}}_{e,k} (\mathbf{Z}^T \otimes \mathbf{I}_{N_{e,k}}) \tilde{\mathbf{g}}_{e,k}^H + 1 - \alpha \end{bmatrix} \succeq \mathbf{0}$$

in which $\tilde{\mathbf{g}}_{e,k} = \text{vec}(\tilde{\mathbf{G}}_{e,k})$, please refer to our paper for details.

$$\begin{aligned} \alpha + \mathbf{h}_b \mathbf{Z} \mathbf{h}_b^H \geq 2^{\tau_{cs}}, \forall \mathbf{h}_b \in B_b, \Leftrightarrow \\ \mathbf{U}(t, \alpha, \mu, \mathbf{Z}) = \begin{bmatrix} t\mathbf{I} + \mathbf{Z} & \mathbf{Z} \tilde{\mathbf{h}}_b^H \\ \tilde{\mathbf{h}}_b \mathbf{Z} & -\mu \varepsilon_b^2 + \tilde{\mathbf{h}}_b \mathbf{Z} \tilde{\mathbf{h}}_b^H - v + \alpha \end{bmatrix} \succeq \mathbf{0} \end{aligned}$$

in which $v \triangleq \max\{2^{\tau_{cs}}, \mu\}$.

Then problem (7) can be transformed into an SDP problem given in (8), which can be efficiently solved via CVX. The outer problem can be handled via a **one-dimensional search**.

$$\begin{aligned} \gamma(\lambda, \eta) = \max_{\mathbf{Z}, \alpha, \mu, t, \{\rho_k\}_{k \in \mathcal{K}}} \mu \\ \text{s.t. } \lambda(\text{Tr}(\mathbf{Z}) + \alpha P_c) \leq \alpha \eta, \\ \mathbf{X}_k(\rho_k, \alpha, \mathbf{Z}) \succeq \mathbf{0}, \rho_k \geq 0, \forall k \in \mathcal{K} \\ \mathbf{U}(t, \alpha, \mu, \mathbf{Z}) \succeq \mathbf{0}, t \geq 0, \\ \text{Tr}(\mathbf{Z}) \leq P\alpha, \mathbf{Z} \succeq \mathbf{0}, \end{aligned} \quad (8)$$

Overall Algorithm

Algorithm 1 Dinkelbach Algorithm for Solving the WC-SEE Maximization Problem (3)

- 1: Initiate $n = 0$, $\epsilon > 0$ and λ_n such that $F(\lambda_n) \geq 0$.
- 2: **Repeat**
- 3: Perform a one-dimensional line search over η to get $(\eta^*, \gamma(\lambda_n, \eta^*))$, wherein each $\gamma(\lambda_n, \eta)$ is returned by solving the problem (8);
- 4: Retrieve the corresponding \mathbf{Q}_c^* via the variable transformation;
- 5: Compute $F(\lambda_n) = R_s^{\text{worst}}(\mathbf{Q}_c^*) - \lambda_n(\text{Tr}(\mathbf{Q}_c^*) + P_c)$;
- 6: Update $\lambda_{n+1} = \frac{R_s^{\text{worst}}(\mathbf{Q}_c^*)}{\text{Tr}(\mathbf{Q}_c^*) + P_c}$;
- 7: Update $n = n + 1$;
- 8: **until** $|F(\lambda_{n-1})| \leq \epsilon$
- 9: Output λ_n as the maximum WC-SEE.

Tightness proof of the relaxation

Proposition 1 There exist an optimal solution (\mathbf{Q}_c^*, η^*) of problem (4), for which $\text{rank}(\mathbf{Q}_c^*) \leq 1$, and the optimal \mathbf{Q}_c^* can be constructed by solving a power minimization problem (9).

Sketch of proof: Suppose that we have solved (6) with the optimal value E_η . Then, we study the power minimization problem below.

$$\begin{aligned} \min_{\mathbf{Q}_c \succeq \mathbf{0}} \text{Tr}(\mathbf{Q}_c) \\ \text{s.t. } \min_{\mathbf{h}_b \in B_b} 1 + \mathbf{h}_b \mathbf{Q}_c \mathbf{h}_b^H \geq \beta E_\eta, \\ \lambda(\text{Tr}(\mathbf{Q}_c) + P_c) \leq \eta, \\ 1 + \text{Tr}(\mathbf{G}_{e,k} \mathbf{Q}_c \mathbf{G}_{e,k}^H) \leq \beta, \forall k \in \mathcal{K}, \mathbf{G}_{e,k} \in B_{e,k} \\ \log(1 + \mathbf{h}_b \mathbf{Q}_c \mathbf{h}_b^H) - \log \beta \geq \tau_{cs}, \forall \mathbf{h}_b \in B_b. \end{aligned} \quad (9)$$

Problem (9) can be converted into an SDP problem via S-procedure. The remaining proof consists of two steps:

Step 1: It can be proved, by contradiction, that the optimal solution of (9) is bound to be optimal to (6). Hence, it suffices to prove that the optimal \mathbf{Q}_c of (9) is of rank one.

Step 2: By checking the Karush-Kuhn-Tucker (KKT) conditions of (9), one can verify that the optimal \mathbf{Q}_c of (9) is of rank one. The details are omitted here. Similar proof can be found in [Li et al.'13].

Numerical Results

Benchmark scheme (worst-case secrecy rate maximization, WC-SRM)

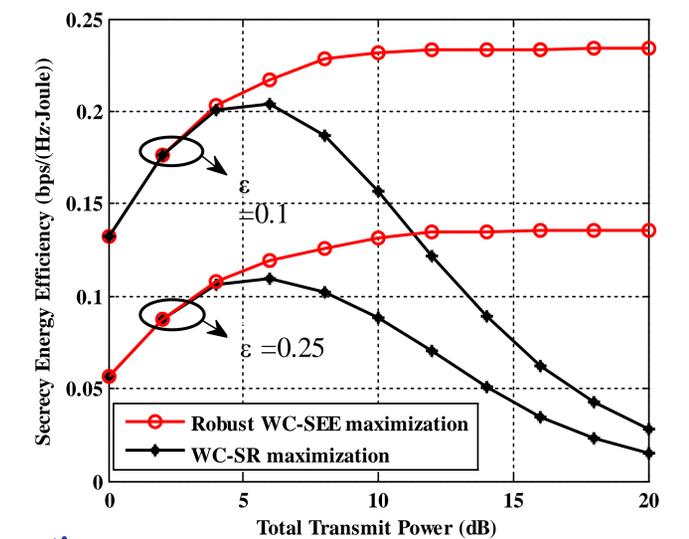
$$\begin{aligned} \hat{\mathbf{Q}}_c = \arg \max_{\mathbf{Q}_c \succeq \mathbf{0}, \text{Tr}(\mathbf{Q}_c) \leq P} R_s^{\text{worst}}(\mathbf{Q}_c) \\ \text{s.t. } R_s^{\text{worst}}(\mathbf{Q}_c) \geq \tau_s. \end{aligned} \quad (10)$$

the resultant SEE

$$SEE_{\text{SRM}} = \frac{R_s^{\text{worst}}(\hat{\mathbf{Q}}_c)}{\text{Tr}(\hat{\mathbf{Q}}_c) + P_c} \quad (11)$$

Simulation setting

- Transmit antenna#: $N_t=6$
- Eves#: $K=2$
- Eves' antennas#: $N_{e,k}=3$ for all k
- Transmit independent power $P_c=7\text{dB}$
- Required secrecy rate $\tau_s=1.5\text{bps/Hz}$
- Channel uncertainty $\varepsilon_b = \varepsilon_{e,k} = \varepsilon$
- Average of 100 channel trials



Observations:

- ✓ When $P \leq 4\text{dB}$, both schemes increase with the transmit power and achieve **identical** SEE performance.
- ✓ After that, the performance achieved by the WC-SRM scheme degrades significantly, since it has used up all power budget.

Concluding Remarks

- The input transmit covariance was optimized to maximize the WC-SEE with constrained QoS.
- By resorting to the fractional programming theory and introducing a tight convex relaxation, we manage to recast the primal fractional optimization problem as a sequence of SDP problems.
- We proved that our obtained method can admit a rank-one solution, which guarantees the tightness of the convex relaxation.
- Numerical results showed that our proposed WC-SEE maximization optimal strategy achieves SEE no less than that achieved by the WC-SR maximization optimal strategy.