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***Abstract*—In this paper, the aim is to study the robustness against imperfect channel state information (CSI) of the power allocation policies maximizing the constrained and non-convex Shannon rate problem in a relay-aided cognitive radio network. The primary communication is protected by a Quality of Service (QoS) constraint and the relay only helps the secondary communication by performing complex and non-linear operations. First, we derive the optimal power allocation policies under Compress-and-Forward (CF) relaying under perfect CSI. Second, we investigate the robustness of this solution jointly with that of the deep learning existing solution for Decode-and-Forward (DF), which we exploit here for CF as well. For all these solutions that strongly rely on perfect CSI, our numerical results show that errors in the channel estimations have a damaging effect not only on the secondary rate, but most importantly on the primary QoS degradation, becoming prohibitive for poor quality estimations. Nevertheless, we show that the deep learning solutions can be made robust by adjusting the training process to rely on both perfect and imperfect CSI observations. Indeed, the resulting predictions are capable of meeting the primary QoS constraint at the cost of secondary rate loss, irrespective from the channel estimation quality.**

***Index Terms*—Robustness to imperfect CSI, full-duplex relaying, cognitive radio, unsupervised deep learning**

## I. Introduction

The increasing number of connected users and devices coupled with the heterogeneity of mobile applications gives rise to new challenges for future generation wireless networks in terms of throughput target, energy efficiency, spectral efficiency, delay, etc. Various technologies, such as cognitive radio, full-duplexing, cooperative communication and artificial intelligence have hence been proposed to address them, and most likely multiple technologies will have to be cleverly combined for this.

Firstly, cognitive radio and full-duplexing both tackle the spectral scarcity by either allowing an opportunistic use of under-utilized licensed bands, provided that the licensed transmission is not degraded too much [1]–[3]; or by allowing transmission and reception over the same resource block [4], respectively. Secondly, cooperative communications are able to improve the network throughput [5] by exploiting received signals from other users within range. Finally, artificial intelligence and, in particular, deep learning methods have recently been shown to enable smart and efficient resource management for future wireless networks [6].

Based on the above, we consider a relay-aided cognitive radio network, as in [1], [7], and study the maximization of the opportunistic rate when the relay performs either Decode-and-Forward (DF) or Compress-and-Forward (CF) in a full-duplex manner, while ensuring a predefined primary Quality of Service (QoS) constraint. Because of the non-linear and complex operations performed at the relay, the resulting resource allocation problems for cooperative cognitive networks are non-convex ones and cannot be solved in closed-form in general [7].

As opposed to our previous investigations [1], [7], which rely on a perfect and global channel state information (CSI), our main objective in this paper is to relax this assumption. Indeed, perfect CSI can be particularly difficult to obtain in cognitive networks, e.g., when estimating the channels from the secondary to the primary network, the full cooperation of the primary network may not be granted.

*Related works:* In order to solve complex and non convex resource optimization problems, deep neural networks (DNNs) have been recently exploited thanks to their powerful capabilities to learn complex relationships based on relevant training data [8]–[10]. In [8], a DNN has been proposed to maximize the sum rate of a relay-aided non orthogonal multiple access device-to-device network. A convolutional neural network (CNN) solving a non-convex spectral and energy efficiency maximization problem of a non-cooperative multi-users wireless network has been proposed in [9]. In [10], the authors propose an unsupervised method based on DNN for the sum-rate maximization in a fading multi-user interference channel.

More specifically, resource allocation problems for cognitive radio networks have been addressed via DNN-based approaches to maximize the opportunistic spectral efficiency while regulating the interference caused to the primary user, either in a centralized [11], or in a distributed manner [12].

To the best of our knowledge, except for our previous study in [7], DNN-based techniques have not been used for resource allocation problems in cooperative cognitive networks. Compared to [7], in which we only focused on DF relaying, in this paper, we extend our investigation to include CF relaying, for which we derive the analytical solution under perfect CSI. We then shift gears and investigate the robustness of our solutions, either in closed form for CF or via deep learning for DF and CF, to imperfect CSI.

Regarding the robustness to CSI imperfections, the authors of [13] propose a DNN-based autoencoder to improve the channel estimation quality (similarly to [14]), and only afterwards feeding these improved estimations at the input of a second DNN performing the optimal power allocation in the cognitive network under study. In our work, the underlying power allocation problem is different because of the presence of the relay node and we also treat the case of imperfect CSI for the links between the secondary and primary network.

*Main contributions:* In this paper, we derive the optimal power allocation policy for full-duplex CF relaying under individual power constraints and a primary QoS constraint, assuming perfect and global CSI. Then, we investigate the robustness to imperfect CSI of this solution coupled with that of our existing DNN solution for DF in [7], which we exploit here also for CF. The training of the DNN is performed with perfect CSI as in [7]. The resulting deep learning predictions perform just as poor as the ideal benchmarks (i.e., the brute force for DF, and our closed-form analytical solution for CF) when tested with imperfect CSI and lead to prohibitive primary QoS degradation levels. Indeed, the training with perfect CSI conveys no information about channel estimation errors and results in an unfit prediction in the case of imperfect CSI. This is precisely the issue of our closed-form solution that strongly relies on the perfect CSI assumption.

We further provide an easy fix to increase the robustness of our deep learning methods, which is not the case for the closed-form solution. We propose to use a new training dataset composed of pairs of perfect channel estimations jointly with their noisy versions. This enables the neural network to learn when imperfect CSI is available at its input and to perform much better by avoiding the prohibitive primary QoS violations, even when only poor channel estimations are available.

## II. System model and problem formulation

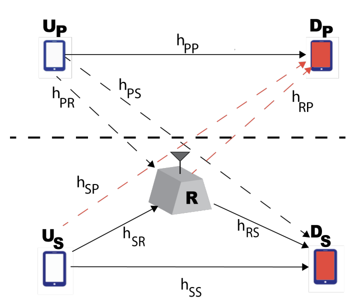


Fig. 1. Cognitive relay-aided network under study.

We study the network illustrated in Fig. 1, consisting of a primary link: transmitter $U_P$ – destination $D_P$, and a secondary link: transmitter $U_S$ – destination $D_S$ aided by a full-duplex relay node, as in [1], [7]. The received signals at the relay, the primary and secondary destinations write as

$$Y_R = h_{PR}X_P + h_{SR}X_S + Z_R \tag{1}$$

$$Y_i = h_{Ri}X_R + h_{ii}X_i + h_{ji}X_j + Z_j, \tag{2}$$

where $i, j \in \{P, S\}, i \neq j$; $X_P, X_S$ and $X_R$ are the messages sent by $U_P$, $U_S$ and the relay, of average power $P_P$, $P_S$ and $P_R$ respectively; $Z_R$ and $Z_i$ represent the additive white Gaussian noise (AWGN) at the relay and at destination $D_i$, of variance $N_R$ and $N_i$ respectively. Without loss of generality, we assume that all noises are of unit variance such that $N_R = N_S = N_P = 1$; or equivalently assume that the channel gains are normalized by the received noise variance, i.e., $g_{ij} = \frac{h_{ij}^2}{N_j}$. We let $\mathbf{h} = \{\sqrt{g_{ij}}, \forall i, j\}$ represent the collection of all normalized network channels.

Furthermore, we consider a full-duplex relay which is assumed to cancel out any self-interference. Both messages sent from the secondary network are treated as additional noise at the primary destination; and the primary message is treated as additional noise for all secondary receivers (relay and destination $D_S$). Hence, we can consider equivalent correlated Gaussian noises at the relay and secondary destination of variance $\widetilde{N}_R = g_{PR}P_P+1$ and $\widetilde{N}_S = g_{PS}P_P+1$ respectively; where the correlation coefficient equals $\rho_Z = \frac{\sqrt{g_{PR}g_{PS}}P_P}{\sqrt{\widetilde{N}_R\widetilde{N}_S}}$.

The achievable rate of the primary and secondary transmitters are denoted by $R_i, i \in \{P, S\}$; and $\overline{R_P}$ is the single-user primary rate in the absence of the secondary network: $\overline{R_P} = 1/2\log_2(1 + g_{PP}P_P)$.

As in our previous studies [1], [7], the opportunistic network is allowed to access the licensed resources provided that the primary minimum QoS constraint is met in terms of achievable primary rate degradation: $R_P \geq (1-\tau)\overline{R_P}$, $\tau \in [0, 1]$.

To sum up, our objective is to maximize the achievable secondary rate $R_S$, when the relay and secondary transmitter are also subject to maximum power budgets given as $\overline{P_R}$ and $\overline{P_S}$, which writes as

$$
\begin{aligned}
(\mathbf{OP})\ &\max_{P_R, P_S} R_S(P_S, P_R)\\
&\text{s.t. } R_P \geq (1-\tau)\overline{R_P},\\
&\quad 0 \leq P_S \leq \overline{P_S}, \quad 0 \leq P_R \leq \overline{P_R}.
\end{aligned}
$$

*Notations:* $A = \frac{g_{PP}P_P}{(1+g_{PP}P_P)^{1-\tau}-1} - 1$, $C(x) = \frac{1}{2}\log_2(1+x)$, $x^+ = \max\{0, x\}$.

In the following, we focus on two relaying schemes, namely Compress-and-Forward (CF) and Decode-and-Forward (DF).

### A. Compress-and-Forward (CF)

For CF, the relay sends a compressed version of it's received signal. To simplify the presentation, we use the notations

$$
\begin{aligned}
K_1 &= g_{SR}\widetilde{N}_S + g_{SS}\widetilde{N}_R - 2\rho_Z\sqrt{g_{SR}g_{SS}\widetilde{N}_S\widetilde{N}_R},\\
K_2 &= (1-\rho_Z^2)\widetilde{N}_R\widetilde{N}_S.
\end{aligned}
$$

Replacing the achievable rate region obtained with CF in [1] into our optimization problem $(\mathbf{OP})$, leads to

$$
\begin{aligned}
(\mathbf{OCF})\ &\max_{P_R, P_S} \frac{K_1 g_{RS}P_SP_R + g_{SS}P_S(K_1P_S + K_2)}{K_2 g_{RS}P_R + \widetilde{N}_S(K_1P_S + K_2)},\\
&\text{s.t. } g_{SP}P_S + g_{RP}P_R \leq A, && \text{(QoS)}\\
&\quad 0 \leq P_S \leq \overline{P_S}, \quad 0 \leq P_R \leq \overline{P_R}. && \text{(TP)}
\end{aligned}
$$

*B. Decode-and-Forward (DF)*

For DF, the relay decodes first the message send by the secondary transmitter and then re-encodes it before being forwarded to the destination. Replacing the resulting achievable rate region in [1] into our optimization problem $(\mathbf{OP})$ leads, as in our previous work [7], to

$$
\begin{aligned}
(\mathbf{ODF}) \max_{P_R, P_S, \alpha} \; & R_S(\mathbf{h}, \alpha, P_S, P_R) \\
\text{s.t. } & Q(\mathbf{h}, \alpha, P_S, P_R) \leq A, && (\text{QoS}') \\
& 0 \leq P_S \leq \overline{P_S}, \quad 0 \leq P_R \leq \overline{P_R}, && (\text{TP}) \\
& 0 \leq \alpha \leq 1, \text{ with} && (\text{ADF})
\end{aligned}
$$

$$
\begin{aligned}
R_S(\mathbf{h},\alpha,P_S,P_R) &= C(\min\{f_R(\mathbf{h},\alpha,P_S,P_R), f_S(\mathbf{h},\alpha,P_S,P_R)\}) \\
Q(\mathbf{h},\alpha,P_S,P_R) &= g_{SP}P_S + g_{RP}P_R + 2\alpha\sqrt{g_{SP}g_{RP}P_S P_R}, \\
f_R(\mathbf{h},\alpha,P_S,P_R) &= \frac{g_{SR}(1-\alpha^2)P_S}{\widetilde{N}_R}, \\
f_2(\mathbf{h},\alpha,P_S,P_R) &= \frac{g_{SS}P_2 + g_{RS}P_R + 2\alpha\sqrt{g_{RS}g_{SS}P_S P_R}}{\widetilde{N}_S},
\end{aligned}
$$

where the additional optimization parameter $\alpha \in [0,1]$ follows from the use of superposition coding.

## III. Perfect CSI

We start by investigating the two optimization problems $(\mathbf{OCF})$ and $(\mathbf{ODF})$ when the secondary network has access to perfect and global channel state information (CSI), before delving into the robustness of our solutions in the more realistic case of imperfect CSI.

*A. Closed-form solution for CF*

For CF relaying, in spite of $(\mathbf{OCF})$ not being a convex problem, we provide below its closed-form analytical solution. To simplify its derivation, we will use the following notations:

$$
\begin{aligned}
C_1 &= K_1 g_{RP}(g_{SS}g_{RP} - g_{RS}g_{SP}) \\
C_2 &= K_1 g_{RS}g_{SP}A - 2K_1 g_{SS}Ag_{RP} - g_{SS}g_{RP}g_{SP}K_2 \\
C_3 &= g_{SS}A(K_1 A + g_{SP}K_2) \\
C_4 &= K_2 g_{RS}g_{SP}^2 - \widetilde{N}_S K_1 g_{RP}g_{SP} \\
C_5 &= \widetilde{N}_S g_{SP}(K_1 A + K_2 g_{SP})
\end{aligned}
$$

The objective function of the optimization problem $(\mathbf{OCF})$ can be shown to be monotonically increasing unilaterally w.r.t. $P_S$ for fixed $P_R$, and w.r.t. $P_R$ for a fixed $P_S$. This implies that the optimal power allocation lies on the Pareto boundary of the feasible set. Now, regarding the specific shape of the feasible set defining the solution of $(\mathbf{OCF})$, five cases can arise as depicted in Fig. 2, depending on the relative position of the QoS curve and the total power constraints:

**[H1]** if $\frac{A}{g_{RP}} < \overline{P_R}$ and $\frac{A}{g_{SP}} < \overline{P_S}$, (aside from positivity) only the QoS constraint restricts the feasible set;

**[H2]** if $\frac{A}{g_{RP}} < \overline{P_R}$ and $\frac{A}{g_{SP}} > \overline{P_S}$, the QoS constraint intersects the secondary user power constraint;

**[H3]** if $\frac{A}{g_{RP}} > \overline{P_R}$ and $\frac{A}{g_{SP}} < \overline{P_S}$, the QoS constraint intersects the relay's power constraint;

**[H4]** if $\frac{A}{g_{RP}} > \overline{P_R}$ and $\frac{A}{g_{SP}} > \overline{P_S}$ and $g_{SP}\overline{P_S} + g_{RP}\overline{P_R} < A$, the QoS constraint intersects both total power constraints;

**[H5]** if $\frac{A}{g_{RP}} > \overline{P_R}$ and $\frac{A}{g_{SP}} > \overline{P_S}$ and $g_{SP}\overline{P_S} + g_{RP}\overline{P_R} \geq A$, only the total power constraints define the feasible set.

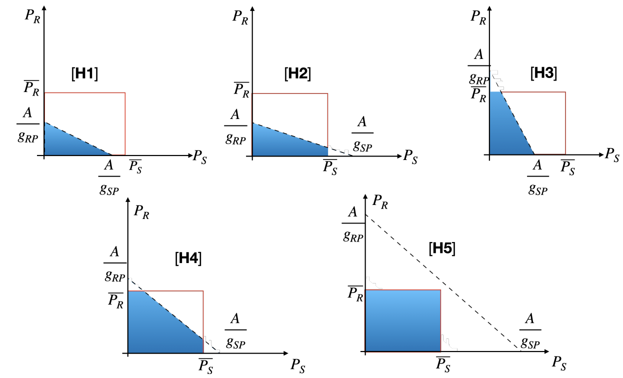


Fig. 2. Feasible set of $(\mathbf{OCF})$.

A close analysis of these five cases and, since the optimal solution lies on the Pareto boundary of the feasible set, leads us to the following result.

**Theorem 1** *When the relay employs CF over the cooperative cognitive radio network, the solution to $(\mathbf{OCF})$ can be found analytically in closed form. Indeed, when **[H5]** is met, the QoS constraint is not restrictive and the solution is simply $P_R^* = \overline{P_R}, P_S^* = \overline{P_S}$. In all other cases, **[H1]–[H4]**, the solution to $(\mathbf{OCF})$ lies on the QoS constraint such that $P_R^* = x^*$, $P_S^* = \frac{A - g_{RP}\ x^*}{g_{SP}}$, where $x^*$ is the closed-form solution to the following single-value optimization problem*

$$
\begin{aligned}
(\mathbf{OCF_x}) \quad \max_{x} \quad & f(x) \triangleq \frac{C_1 x^2 + C_2 x + C_3}{C_4 x + C_5}, \\
\text{s.t. } & x \in [x_\ell;\ x_u]. && (3)
\end{aligned}
$$

*The values of $x_\ell$ and $x_u$ defining the box-type constraints depend on the system parameters and the specific case.*

*Proof:* In **[H1]–[H4]**, the search for the optimal solution is reduced to the candidate points meeting the QoS constraint with equality. Hence, by setting $P_R^* = x, P_S^* = \frac{A - g_{RP}\ x}{g_{SP}}$, the original problem $(\mathbf{OCF})$ is reduced to $(\mathbf{OCF_x})$.

**Proposition 1** *By studying the different cases in Fig. 2, the values of $x_\ell$ and $x_u$ defining the feasible set of $(\mathbf{OCF_x})$ are*

$$
[x_\ell;\ x_u] = \begin{cases}
\left[0;\ \frac{A}{g_{RP}}\right], & \textit{if [H1] is met}, \\
\left[\frac{A - g_{SP}\overline{P_S}}{g_{RP}};\ \frac{A}{g_{RP}}\right], & \textit{if [H2] is met}, \\
\left[0;\ \overline{P_R}\right], & \textit{if [H3] is met}, \\
\left[\frac{A - g_{SP}\overline{P_S}}{g_{RP}};\ \overline{P_R}\right], & \textit{if [H4] is met}.
\end{cases}
$$

Now, the derivation of the closed-form solution $x^*$ to the reduced problem $(\mathbf{OCF_x})$ amounts simply to the analysis of the first order derivative of the objective, denoted by $f'(x)$, and the critical points, which are the solutions to $f'(x) = 0$. The latter reduces to a second-order equation, whose roots are given by $\frac{-C_1 C_5 \pm \sqrt{\Delta'}}{C_1 C_4}$, where $\Delta' = C_1^2 C_5^2 - C_1 C_4 (C_2 C_5 - C_3 C_4)$ represents the corresponding reduced discriminant. Ultimately, the analytical expression of $x^*$ depends on the sign of the dominant coefficient $C_1 C_4$ (of $f'(x) = 0$), the sign of $\Delta'$, and on the relative position of the critical points (when they exist) w.r.t. the feasible set $[x_\ell;\ x_u]$ given in Proposition 1. The full details are somewhat tedious and will be omitted here. ■

### B. Deep learning for DF and CF

Solving the optimization problem $(\mathbf{ODF})$ is very challenging because of the non convexity of both the objective function and the QoS constraint. Hence, we proposed in [7] a new approach based on unsupervised deep neural networks (DNN), which exploits a customized loss function and for which the training dataset contains only channel samples, i.e., $\mathbf{h}$, without ground truth data. For the sake of completeness, we briefly present our proposed DNN-based method but kindly refer the reader to [7] for complete details.

Since the non-convex QoS constraint is a requirement rather than a physical hard constraint, we propose to relax it and minimize the following customized loss function instead of optimizing solely the secondary rate:

$$\mathcal{L} = \sum_{\ell=1}^{N} \left(-R_S(\mathbf{h}_\ell, \alpha, P_S, P_R) + \lambda[Q(\mathbf{h}_\ell, \alpha, P_S, P_R) - A]^+\right),$$

where $N$ is the number of channel realizations $\mathbf{h}_\ell$, $\ell \in \{1, \ldots, N\}$ in the training dataset. Large values of $\lambda$ turn the optimization problem $(\mathbf{ODF})$ into a QoS driven one, at the cost of the secondary rate; whereas small values of $\lambda$ turn $(\mathbf{ODF})$ into a rate driven one, at the cost of QoS violation.

Based on extensive numerical simulations [7], we propose to use a DNN architecture composed of four fully connected hidden layers with $M - 2M - 2M - 2M$ neurons, where $M = 128$, followed by a rectified linear unit (ReLU) activation function and a hyperparameter $\lambda = 10^{0.5}$. The final layer is followed by sigmoid activation functions to ensure that the outputs, i.e., the predicted values of $\alpha$ and powers $P_R$ and $P_S$ satisfy the box-type constraints of $(\mathbf{ODF})$.

Now, regarding CF relaying, our analytical solution in Sec. III-A greatly relies on perfect CSI. In order to investigate the robustness to imperfect CSI, we further exploit the deep learning approach above to solve $(\mathbf{OCF})$, using the same neural network architecture and $\lambda = 10^{0.5}$ as for DF, by simply removing the output $\alpha$ (specific to DF) and then retraining the network with the corresponding CF loss function.

## IV. Robustness to imperfect CSI

In this section, we investigate via extensive numerical simulations the robustness of our solutions to errors in the channel estimations of the links related to the primary network: $h_{PP}$ (direct primary link); $h_{SP}$, and $h_{RP}$ (interfering links from the secondary network to the primary receiver); $h_{PR}$ and $h_{PS}$ (interfering links from the primary transmitter to the secondary network). We assume that the estimations are corrupted by additive Gaussian noise: $\widehat{h}_{ij} = h_{ij} + \varepsilon_{ij}$, $\forall (i,j) \in \{(P,P), (S,P), (R,P), (P,R), \text{ and } (P,S)\}$ such that $\varepsilon_{ij} \sim \mathcal{N}(0, \sigma_{ij}^2)$, as per usual in the related literature [13], [14]. The estimation error variance is such that $\sigma_{ij}^2 = \mathrm{Var}[h_{ij}]/\mathrm{SNR}$, where $\mathrm{Var}[h_{ij}]$ represents the empirical variance of the true channels $h_{ij}$ in the datasets (train and test) and SNR $\in [-10, 20]$ dB represents the signal-to-noise ratio (SNR) of the estimator. The imperfect channel gains become $\widehat{g}_{i,j} = (\widehat{h}_{ij})^2/N_j$. We henceforth denote by $\widehat{\mathbf{h}} = \{\widehat{h}_{ij}, \forall i,j\}$ the vector collecting the imperfect channel estimations ( the secondary channel links are assumed perfectly known: $\widehat{h}_{ij} = h_{ij},\ \forall (i,j) \in \{(S,S), (S,R), \text{ and } (R,S)\}$).

*Dataset:* The simulation setup is the same as in [7] described in details at https://github.com/yacine074/Robustness_SPAWC22, where all source codes can be found. The majority of related works exploiting DNNs use simulated data given the lack of real data available and in open access. Our train (containing $10^6$ samples), validation (20% of train) and test ($2 \times 10^5$ samples) datasets are disjoint and generated as follows. The channel gains follow a common fading and pathloss model: $h_{ij} \sim \frac{\mathcal{N}(0,\sigma_g^2)}{\sqrt{1+d_{ij}^\gamma}}$, where $d_{ij}$ is distance between nodes $i$ and $j$, the pathloss is $\gamma = 3$. The nodes' positions are generated uniformly within a 10 m square cell. The primary QoS primary is $\tau = 25\%$ and the maximum powers are $P_P = \overline{P}_S = \overline{P}_R = 10$ W.

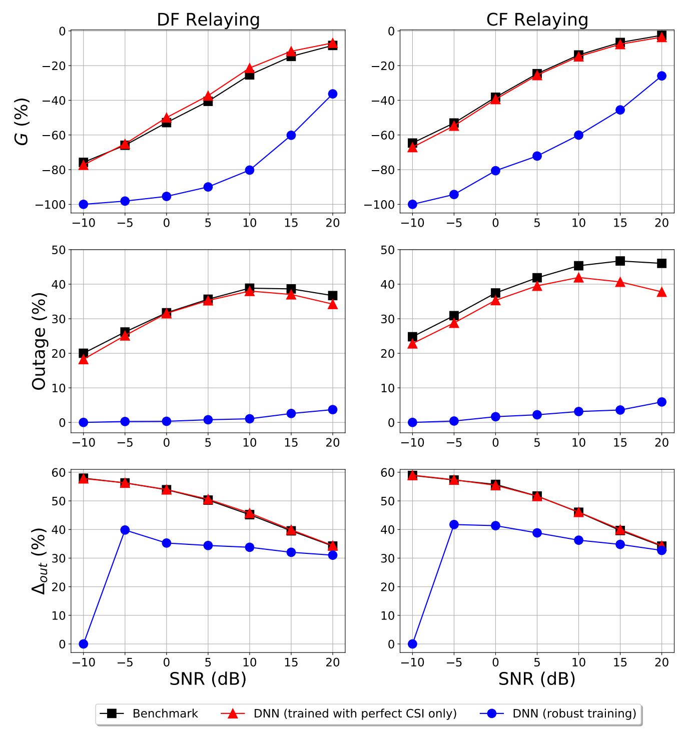


Fig. 3. Impact of imperfect CSI on our proposed solutions (via deep learning and in closed form for CF) for DF and CF relaying over the test set.

*DNN training:* For the training phase, we assume that we have access to a dataset containing perfect or high quality channel samples $\{\mathbf{h}_\ell\}_\ell$ obtained offline, but that in the running or test phase we only have access to erroneous channel estimations. First, our training is done solely by exploiting this perfect CSI dataset, as in [7]. Second, we propose a different training process to improve the robustness of our predictions to imperfect CSI. To this aim, we build a different training dataset containing pairs of perfect and imperfect channel estimations: $(\widehat{\mathbf{h}}_\ell, \mathbf{h}_\ell)_\ell$, obtained simply by adding Gaussian noise to the initial samples. The perfect channels $\mathbf{h}_\ell$ are exploited in the loss function $\mathcal{L}$, whereas the imperfect ones $\widehat{\mathbf{h}}_\ell$ are used as inputs to the DNN.

To avoid overfitting effects, an early-stopping method is adopted for both CF and DF with a patience parameter of 20 epochs.

*Benchmarks and performance metrics:* Our comparison benchmarks are: the brute force or exhaustive search for DF (due to its' implementation simplicity), and our closed-form solution for CF (due to its' minimal computational cost).

The *relative gap* between the predicted achievable rate with imperfect CSI and the achievable rate obtained by the benchmark with perfect CSI, as follows:

$$\mathrm{G} = \frac{\frac{1}{N}\sum_{\ell=1}^{N} \hat{R}_{S,\ell} - R^*_{S,\ell}}{\frac{1}{N}\sum_{\ell=1}^{N} R^*_{S,\ell}} \tag{4}$$

where $\hat{R}_{S,\ell}$ denotes the secondary rate achieved by either our DNN or the benchmark when the corresponding power allocation policy relies on imperfect CSI and $R^*_{S,\ell}$ denotes the ideal optimal rate via the benchmark obtained with perfect CSI, both for the $\ell$-th sample in the dataset.

The *degradation of the primary rate* caused by the opportunistic interference is defined as: $\Delta_\ell = 1 - \hat{R}_{P,\ell}/\overline{R}_{P,\ell}$, where $\hat{R}_{P,\ell}$ is the primary rate achieved by either our DNN or the benchmark when the corresponding power allocation policy relies on imperfect CSI. Based on this metric, we define the *empirical outage* as the proportion of samples in the dataset for which the target primary QoS constraint is not met, and the *average primary rate degradation* when in outage:

$$\mathrm{Outage} = \frac{1}{N}\sum_{\ell=1}^{N} \mathbb{I}\left[\Delta_\ell > \tau\right], \quad \Delta_{\mathrm{out}} = \frac{\sum_{\ell=1}^{N}\mathbb{I}\left[\Delta_\ell > \tau\right] \times \Delta_\ell}{\sum_{\ell=1}^{N}\mathbb{I}\left[\Delta_\ell > \tau\right]},$$

where $\mathbb{I}\left[x\right]$ equals $1$ when $x$ is true and $0$ otherwise.

*Robustness analysis over the test set:* We now evaluate the performance over new data samples that have not been seen during the training phase and that are imperfect, i.e., $\{\widehat{\mathbf{h}}_\ell\}_\ell$. In Figure 3, we plot: the relative secondary rate gap $G$ (top sub-figures), empirical outage (middle) and average primary rate degradation $\Delta_{\mathrm{out}}$ (bottom) as functions of the quality of the channel estimator $\mathrm{SNR} \in [-10, 20]$ dB and for both DF (left sub-figures) and CF (right) relaying schemes. In each sub-figure we evaluate and compare the robustness to imperfect CSI of the power allocation policy obtained by the benchmark (i.e., brute force for DF, our closed-form solution for CF), by our DNN trained with perfect CSI only, and by our DNN trained with both perfect and imperfect CSI, i.e., our robust training described above.

Notice that the performance of the DNN trained with perfect CSI only matches almost perfectly that of the benchmark in all plots. This shows the high generalization capability of our DNN approach, which was tuned for DF relaying (its architecture and choice of $\lambda$) and can be exploited with almost no change for CF relaying as well. Nevertheless, having imperfect CSI reduces the secondary rate and, most critically, it highly damages the primary communication: the primary QoS is violated in $20-40$ % of cases (the $\mathrm{Outage}$) and the average degradation when in outage is of $35-60$ % (the $\Delta_{\mathrm{out}}$). Finally, the outage of the DNN approach trained in a robust manner is much improved and stays below $5\%$. At the same time, the average degradation $\Delta_{\mathrm{out}}$ is also reduced (in between $0-40\%$). All this comes at the cost of secondary rate, which is acceptable in cognitive radio settings, in which the primary communication must be protected.

## V. Conclusions

In this work, we have analyzed the robustness to CSI imperfections of two different solutions to the power allocation problem in a relay-aided cognitive radio network: our closed-form solution obtained for CF relaying, and a deep learning method previously proposed for DF, which is also exploited here for CF. The closed-form solution strongly relies on perfect CSI, leading to prohibitive primary communication degradation and is unfit in cognitive radio settings. At the opposite, the deep learning methods can be easily rendered robust to errors in channel estimations by cleverly adjusting the training phase to exploit some information about the channel estimation quality.

## References


[1] A. Savard and E. V. Belmega, "Full-duplex relaying for opportunistic spectrum access under an overall power constraint," *IEEE Access*, vol. 8, pp. 168 262–168 272, 2020.

[2] D. Giral, C. Hernández, and C. Salgado, "Spectral decision in cognitive radio networks based on deep learning," *Expert Systems with Applications*, vol. 180, p. 115080, 2021.

[3] D. Xu, X. Yu, Y. Sun, D. W. K. Ng, and R. Schober, "Resource allocation for IRS-assisted full-duplex cognitive radio systems," *IEEE Trans. Commun.*, vol. 68, no. 12, pp. 7376–7394, 2020.

[4] A. Nasser, H. Al Haj Hassan, J. Abou Chaaya, A. Mansour, and K.-C. Yao, "Spectrum sensing for cognitive radio: Recent advances and future challenge," *Sensors*, vol. 21, no. 7, p. 2408, 2021.

[5] Y. Lu, P. Cheng, Z. Chen, Y. Li, W. H. Mow, and B. Vucetic, "Deep autoencoder learning for relay-assisted cooperative communication systems," *IEEE Trans. Commun.*, vol. 68, no. 9, pp. 5471–5488, 2020.

[6] B. Brik, K. Boutiba, and A. Ksentini, "Deep learning for B5G open radio access network: Evolution, survey, case studies, and challenges," *IEEE Open Journal of the Communications Society*, 2022.

[7] Y. Benatia, A. Savard, R. Negrel, and E. V. Belmega, "Unsupervised deep learning to solve power allocation problems in cognitive relay networks," in *IEEE ICC Workshop*, 2022.

[8] Z. Ali, G. A. S. Sidhu, F. Gao, J. Jiang, and X. Wang, "Deep learning based power optimizing for NOMA based relay aided D2D transmissions," *IEEE Trans. on Cogn. Commun. Netw.*, vol. 7, no. 3, pp. 917–928, 2021.

[9] W. Lee, M. Kim, and D.-H. Cho, "Deep power control: Transmit power control scheme based on convolutional neural network," *IEEE Commun. Lett.*, vol. 22, no. 6, pp. 1276–1279, 2018.

[10] F. Liang, C. Shen, W. Yu, and F. Wu, "Power control for interference management via ensembling deep neural networks," in *IEEE ICCC*, 2019, pp. 237–242.

[11] W. Lee, "Resource allocation for multi-channel underlay cognitive radio network based on deep neural network," *IEEE Commun. Lett.*, vol. 22, no. 9, pp. 1942–1945, 2018.

[12] W. Lee and K. Lee, "Deep learning-aided distributed transmit power control for underlay cognitive radio network," *IEEE Trans. Veh. Technol.*, vol. 70, no. 4, pp. 3990–3994, 2021.

[13] X. Zong, X. Zhu, A. Zhu, and J. O. Byrne, "Optimization and transmit power control based on deep learning with inaccurate channel information in underlay cognitive radio network," in *Journal of Physics: Conference Series*, vol. 1746, no. 1. IOP Publishing, 2021, p. 012090.

[14] V. Rizzello and W. Utschick, "Learning the CSI denoising and feedback without supervision," in *IEEE SPAWC*, 2021, pp. 16–20.