CHAPTER

Team Methods for Device Cooperation in Wireless Networks

1

David Gesbert[,*] **and Paul de Kerret**[*]
[*]*EURECOM, Communication Systems Department, 450 route des Chappes, Biot* [*]*Corresponding:* {gesbert,dekerret}@eurecom.fr

CHAPTER OUTLINE HEAD

ABSTRACT
Advances in theory, integration techniques and standardization have led to huge progress in wireless technologies. Despite successes with past and current (5G) research, new paradigms leading to greater spectral efficiencies and intelligent network organizations will be in great demand to absorb the continuous growth in mobile data. With few exceptions such as ad-hoc topologies, classical wireless design places the radio device under the tight control of the network. Pure network-centric, centralized, designs, such as optical cloud-supported ones raise cost and security concerns and do not fit all deployment scenarios. Also they make the network increasingly dependent on a large amount of signaling and measurements taken at the network's edge, that must be communicated in real time to a centralized network processing node, which is not always possible or desirable. To circumvent this problem, an alternative (or complementary) system design approach can be imagined in which devices' local computational capabilities are leveraged to a greater extent. Such nodes can for instance be Transmit-

Table 1.1 Summary of notations

Notation	Description
TD	Team Decision
DM	Decision Maker
CSI	Channel State Information
IS	Information Structure
DHIS	Deterministic Hierarchical Information Structure
SHIS	Stochastic Hierarchical Information Structure
TX	Transmitter
RX	Receiver
n	Number of decision makers
$U(\bullet)$	Joint utility function
$\boldsymbol{h}$	Channel state
$\hat{\boldsymbol{h}}^{(j)}$	Estimate of the channel state at node j
$\boldsymbol{w}^{(j)}(\bullet)$	Decision function at node j
K	Number of users
$R(\bullet)$	Sum rate
$Q(\bullet)$	Quantizer
$\boldsymbol{\Sigma}_j$	CSI noise covariance matrix at TX j
$\rho^{(j,j')}$	Correlation factor between the CSI noise at TX j and TX j'
$\mathcal{N}_{\mathbb{C}}(0,1)$	Standard Gaussian distribution with zero mean and unit variance

ters (TXs) trying to coordinate in view of suppressing mutual interference or more generally cooperate in order to maximize a network-level performance. While such wireless nodes are cooperative, they typically act in the face of uncertain (noisy) system/channel state information affecting their own measurements as well as the measurements at other nodes. In addition to measurement noise, decision making is also hindered by limited information exchange capabilities between the nodes. Such impairments prevent perfect coordination and call for robust algorithms.
Deriving the optimal transmission decisions (so-called Team Decisional (TD) methods) at each node under such decentralized information scenario is a difficult problem with interesting connections to fundamental information theoretic, control, signal processing and learning problems. In this chapter we provide a general formulation for TD methods for device cooperation in wireless networks. We introduce relevant decentralized information models and classes of decision making solutions. We illustrate these various approaches through the prism of one specific example, namely the problem of decentralized MIMO beamforming (precoding) in wireless networks.

Keywords: Decentralized systems, Distributed optimization, Coordination, Wireless networks, Team decision theory, MIMO, Beamforming

1.1 INTRODUCTION

1.1.1 DEVICE CENTRIC NETWORK OPTIMIZATION

Tens of billions of machines (sensors, robots, computers, tablets, cars,..) are expected to be connected to the wireless internet within the next five to ten years. In the face of such an unprecedented demand, future mobile networks must deliver on a large number of criteria, such as improved spectral efficiencies, reduced latencies, better and more consistent throughput experience in the cell, as well as extended battery life. From a networking point of view, operators will require highly flexible backhaul architectures that can adapt to large fluctuations in the traffic patterns while maintaining and OPEX (including energy) costs low.

Infrastructure-centric designs have been and –to a large extent– still are the prevailing paradigm in wireless cellular systems such as 4G and 5G. Under this framework, network control and resource optimization tasks are deferred to the infrastructure or *cloud*. One should note the easier path to global network management which stems from such a centralized nature of computations. Nevertheless, pure network-centric designs relying on optical-supported mobile clouds currently envisioned for 5G are powerful yet expensive solutions that come with their own technical and security limitations. Finally, due to cost concerns and the possible lack of efficient pre-existing infrastructures, such designs are difficult to implement precisely in those developing markets where universal broadband access could make the biggest difference. In such cases, the quicker, cheaper installation of heterogeneous wireless networks with less stringent requirement on backhaul communications is appealing. In developed user markets and elsewhere, the use of flying radio access networks, with base stations carried by autonomous drones [1, 2], can provide for an ultra-flexible deployment of network coverage where and when it is needed the most (hot-spots, concerts, sport events) or also help first responders with connectivity needs in disaster recovery scenarios. In all these examples, there is interest in designing a network of devices that can mutually cooperate or self-organize without the help of a centralized architecture and backhaul. Instead, devices should leverage local computing, communication and memory capabilities to interact directly so as to help provide the best service possible. Such a device-centric paradigm renders necessary a system protocol architecture where direct communication between devices (D2D) is made possible.

The notion of cooperation have been heavily studied in the context of wireless network as a tool to extend coverage, improve spectral efficiency, battery autonomy, or manage the interference that stems from frequency reuse [3]. As an example, so-called Coordinated Multi-Point Transmission methods have been proposed for inclusion in the 3GPP standards which feature cooperation algorithms between neighboring base stations based on combinations of multi-user MIMO, power control, and advanced resource allocation methods. Such methods are typically studied under a centralized framework enabled by the so-called Cloud RANs where wireless devices at the edge (terminals, base stations) push their observed data into an optical-backhaul supported cloud where servers run optimization algorithms before optimum decisions are sent back to edge devices for application. Interestingly, the application of such cooperations concepts in a device-centric setup has so far been mostly open, due to the challenge posed by the lack of reliable centralized channel state information in such settings.

1.1.2 COOPERATION WITH DECENTRALIZED INFORMATION

In device-centric architectures, wireless devices located at the edge of the network are recast as autonomous agents. These agents run decentralized algorithms that are designed to maximize a global network performance metric, e.g., the average sum throughput or the total user capacity under outage constraints, or minimizing latency towards accessing data contents, to name a few examples. Decentralized decision algorithms are needed so as to guide the devices in their choice of transmission parameters such as power levels, beam design, time frequency resource utilization, routing path, etc. In principle, the coordinated decisions across neighboring devices help overall system performance. A salient feature of device-centric coordination, however, is the lack of reliable observed data (channel measurements, signal to noise ratios,..) at each decision making device and the need to build some robustness with respect to this imperfect knowledge. In particular, an agent must make a transmission parameter decision on the basis of mostly local information, which often takes the form of a noisy and partial estimate of the global system state. Furthermore, devices have limited capability to communicate to each other. This prevents the full sharing (centralization) of system state estimates between the agents. Inevitably, a loss is to be expected in any decentralized setting when compared to the solution that would be obtained in a fully centralized setting with ideal backhaul links. The purpose and challenge behind robust device-centric coordination is exactly to minimize this loss.

Here, the device communication and decision-making capability is geared at enabling a *collective network-friendly intelligence*. As such, these smart devices differ profoundly from previously studied problem in cooperative wireless networks such as those related to frequency agile cognitive radios or (ad-hoc) user mobile relaying. The emphasis on the *network utility* and the taking into account of finite *rate and latency constraints* for inter-device communications also differs sharply from classical device cooperation studies, using ,e.g. , iterative game theoretic approaches [4, 5, 6], although useful connections can be made. More precisely, in our setting, the Decision Makers (DMs) are not conflicting with each other as in a conventional game theoretic sense. In fact it is the decentralized (and noisy) nature of the observed data, based upon which the decisions are made, which hampers the full coordination as opposed to the egoistic nature of the device itself. The theoretical roots behind device-centric coordination are found in the field of Bayesian Game with incomplete information [7] as well as the so-called *team decision theory* [8]. We should however raise to the reader's attention the fact that most of the line of work dealing with the use of game theoretic approaches in decentralized wireless resource allocation problems is related to trying to converge to a game equilibrium via an iterative algorithm. Each such iteration entails a new observations of some utility or price, allowing the players to ultimately converge towards a coordinated decision state. In contrast this work focuses on latency-constrained applications which require robust *single-shot* (Bayesian) decision algorithms.

1.1.3 CHAPTER ORGANIZATION AND OBJECTIVES

This chapter is meant as a brief overview of the challenges and promises related to device centric coordination with application to future wireless networks, especially such networks that will feature one or more decentralized components, i.e. not fully relying on the Cloud-RAN implementation. We first formulate a large class of optimization problems, denoted as "Team Decision (TD) problems", which are well adapted to the context of device-centric coordination. Such problems are hard to crack in their widest generality, as can be inferred from the classical literature on decentralized control [8]. Nevertheless, we point out how the solution to a decentralized coordination problem (and its complexity) critically depends on the associated *Information Structure (IS)*. The latter describes in quantifiable terms the nature and quality of the observations made locally at each Decision Maker (DM) and how such local information relates to the true global system state (correlation or noise level). Wireless networks have the advantage that their design is under human control, hence the IS can be shaped in one of many possible ways, for instance by tuning quantization parameters and feedback rates. Key examples of IS designs are highlighted with their advantages towards the construction of coordination algorithms. In the second part of the chapter, we turn to the application of robust TD methods to the problem of decentralized MIMO precoding in wireless networks. Through the prism of this example, we show various strategies for deriving robust algorithms, several of which are rooted in the principle of exploiting approximation models and/or discretization of the observation and decision spaces. Numerical results highlight the benefits of robust coordination over naive coordination or lack of coordination.

1.2 TEAM DECISIONS FRAMEWORK

1.2.1 GENERAL FORMULATION OF TEAM DECISION

We give here a general formulation for a TD problem for application in a large class of device-centric wireless coordination scenarios. The decentralized network of devices as defined as follows. A network of n Decision Makers (DM) is considered. In some examples of interest here, the DMs are wireless TXs which seek to optimize one (or possibly several) transmission parameters. We assume the n decisions couple into a resulting network performance index which is defined below. The decision space at the k-th DM is d_k dimensional and can cover a variety of domains such as the selection of a power level, a beam in a continuous or discrete grid of beams, usage of a time-frequency resource unit, a message destination (for point to multi-point networks), and many more. The general TD problem can be formulated as follows

$$\left(\boldsymbol{w}_1^\star, \ldots, \boldsymbol{w}_n^\star\right) = \underset{\boldsymbol{w}_1,\ldots,\boldsymbol{w}_n}{\operatorname{argmax}} \, \mathbb{E}_{\boldsymbol{h},\hat{\boldsymbol{h}}^{(1)},\ldots,\hat{\boldsymbol{h}}^{(n)}} \left[U\left(\boldsymbol{h}, \boldsymbol{w}_1(\hat{\boldsymbol{h}}^{(1)}), \ldots, \boldsymbol{w}_n(\hat{\boldsymbol{h}}^{(n)})\right)\right] \quad (1.1)$$

where

- $\boldsymbol{h} \in \mathbb{C}^m$ is the state of the system. For instance for a wireless network with n single antenna Transmitters (TXs), K single antenna Receivers (RXs) in a flat-fading propagation scenario, the *instantaneous* system (channel) state is characterized by a random channel matrix of size $K \times n$, or equivalently a vector of $m = K \cdot n$ coefficients.
- $\hat{\boldsymbol{h}}^{(j)} \in \mathbb{C}^m$ is the *local* estimate of the system state $\boldsymbol{h}$ which is available at the j-th DM.
- $\boldsymbol{w}_j : \mathbb{C}^m \to \mathcal{A}_j \subset \mathbb{C}^{d_j}$ is the strategy (or policy) adopted by the j-th DM. Note that the decision is made to be purely a function of what is locally observed by the j-th DM. Hence for an instantaneous observation $\hat{\boldsymbol{h}}^{(j)}$, the decision is $\boldsymbol{w}_j(\hat{\boldsymbol{h}}^{(j)})$.
- $U : \mathbb{C}^m \times \Pi_{j=1}^n \mathbb{C}^{d_j} \to \mathbb{R}$ is the global network *utility* (e.g. throughput) resulting from the policy adopted by the devices.
- $p_{\boldsymbol{h},\hat{\boldsymbol{h}}^{(1)},\ldots,\hat{\boldsymbol{h}}^{(n)}}$ is the *joint probability distribution* of the true system state and all local estimates. Hence $\mathbb{E}_{\boldsymbol{h},\hat{\boldsymbol{h}}^{(1)},\ldots,\hat{\boldsymbol{h}}^{(n)}}$ refers to the expectation operator under the joint probability rule $p_{\boldsymbol{h},\hat{\boldsymbol{h}}^{(1)},\ldots,\hat{\boldsymbol{h}}^{(n)}}$.

Note that while (1.1) describes a decentralized policy search, the centralized design case is simply a particular case where $\hat{\boldsymbol{h}}^{(j)} = \hat{\boldsymbol{h}}^{(1)}, \forall j = 2, \ldots, n$.

There are several reasons which intuitively explain the decentralized and noisy nature of state information which underpins (1.1). First, devices typically have limited sensing and feedback capabilities. They can also be mobile with individual velocities, which tends to add varying levels of outdating to the collected information. Finally, direct exchange of channel state information between devices does not come for free, or if it does the latency related to exchange may induce further outdating to the Channel State Information (CSI), making the CSI degradation fundamentally *device dependent*.

1.2.2 STATIC VERSUS SEQUENTIAL POLICY DESIGN

The TD formulation (1.1) refers to a *static* setting where each of the n DMs designs a policy in order to optimally coordinate with other DMs in the Bayesian sense on the basis of a unique noisy observation of the system state. As predicted by coordination theoretic analysis [9], coordination performance is ultimately limited by the mutual correlation between observations $\hat{\boldsymbol{h}}^{(1)}, \ldots, \hat{\boldsymbol{h}}^{(n)}$ and the correlation between these estimates and the true state $\boldsymbol{h}$. The coordination setup in (1.1) precludes explicit interaction between devices, i.e. no further exchange of information (local estimates or intermediate decisions) is allowed between the devices, an hypothesis that is consistent with low latency application scenarios. In some cases, the low latency condition can be relaxed and multiple rounds of information exchanges are assumed between DMs. This opens the door to family of so-called *sequential* decision algorithms whereby a device can optimize its policy as a function of messages received from other DMs in the previous round. Eventually and under mild conditions, the algorithm will converge towards a solution near to that obtained in the centralized case and rates of convergence can be analyzed. The rest of this chapter is focused on static (single shot) decision making but the reader is referred to [10, 11] for an overview of distributed optimization problems in signal processing and communication and to [4, 5, 6] for game theoretic approaches.

1.2.3 BEST RESPONSE FORMULATION

The above optimization is formulated in a *Bayesian* manner as a joint policy design problem. Note that by virtue of decentralization, no physical entity in the network has access to the full set of instantaneous informations $\hat{\boldsymbol{h}}^{(1)}, \hat{\boldsymbol{h}}^{(2)}, \ldots, \hat{\boldsymbol{h}}^{(n)}$. However the full knowledge of underlying joint distributions is assumed, so that is is possible to compute (and maximize) the network utility in an *expected* sense.

Finding the n policies simultaneously is a daunting task and the complexity of problem (1.1) can be relaxed by adopting the classical Game-theoretic *Best Response* optimization approach [12]. The Best Response optimal policy is denoted by $\boldsymbol{w}_j^{\mathrm{BR}}$ and is obtained by iteratively solving:

$$\boldsymbol{w}_j^{\mathrm{BR}} = \underset{\boldsymbol{w}_j}{\operatorname{argmax}}\, \mathbb{E}_{\boldsymbol{h},\hat{\boldsymbol{h}}^{(1)},\ldots,\hat{\boldsymbol{h}}^{(n)}} \left[U\left(\boldsymbol{h}, \boldsymbol{w}_1^{\mathrm{BR}}, \ldots, \boldsymbol{w}_{j-1}^{\mathrm{BR}}, \boldsymbol{w}_j, \boldsymbol{w}_{j+1}^{\mathrm{BR}}, \ldots, \boldsymbol{w}_n^{\mathrm{BR}}\right)\right], \forall j = 1, \ldots, n \tag{1.2}$$

where for clarity we have omitted to write explicitly the dependency of the functions. This will be done recurrently in the rest of the chapter but it should always be kept in mind that $\boldsymbol{w}_j$ is only a function of $\hat{\boldsymbol{h}}^{(j)}$ and stands for $\boldsymbol{w}_j(\hat{\boldsymbol{h}}^{(j)})$.

Note however that both in the cases of (1.2) and (1.1), the formulation calls for an optimization within the space of n functions $\boldsymbol{w}_j(\bullet)$, $j = 1, \ldots, n$. In fact, just like the original formulation in (1.1)), the problem in (1.2) is to be solved in a central computing location on the basis of probability density information $p_{\boldsymbol{h},\hat{\boldsymbol{h}}^{(1)},\ldots,\hat{\boldsymbol{h}}^{(n)}}$ alone. Yet the *application* of the policies $\boldsymbol{w}_j^{\mathrm{BR}}(\hat{\boldsymbol{h}}^{(j)})$, $j = 1, \ldots, n$, is carried out at each DM and remains fundamentally decentralized.

Although simpler than (1.1), the problem in (1.2) is generally quite difficult to solve from an algorithm design and complexity point of view. Furthermore, the coordination performance (i.e. the network utility) which can be attained under a decentralized information setting is bound to be less than what can be achieved under a centralized information scenario. The loss of performance due to imperfect sharing of the noisy channel state information among the DMs is referred to as the *price of distributedness*. In practice this loss depends on the quality of the channel state estimates made available to the devices. How information about channel states is allocated among the DMs is captured by the notion of *Information Structure* (IS) which is covered in more details in Section 1.2.5.

1.2.4 NAIVE AND LOCALLY ROBUST COORDINATION

The original TD problem in (1.1) seeks robustness with respect to uncertainties along two ways. First, DM j needs to be robust with respect to uncertainties related to its own local information $\hat{\boldsymbol{h}}^{(j)}$. Secondly, as a multi-agent problem, this device ought to take into account uncertainties at other DMs with which it seeks to coordinate. Ignoring both local and global uncertainties leads to the following *naive* policy denoted by $\boldsymbol{w}_j^{\mathrm{nv}}$ and obtained from:

$$\left(\boldsymbol{v}_1, \ldots, \boldsymbol{v}_{j-1}, \boldsymbol{w}_j^{\mathrm{nv}}(\hat{\boldsymbol{h}}^{(j)}), \boldsymbol{v}_{j+1}, \ldots, \boldsymbol{v}_n\right) = \operatorname*{argmax}_{\boldsymbol{w}_1,\ldots,\boldsymbol{w}_n} U\left(\hat{\boldsymbol{h}}^{(j)}, \boldsymbol{w}_1(\hat{\boldsymbol{h}}^{(j)}), \ldots, \boldsymbol{w}_n(\hat{\boldsymbol{h}}^{(j)})\right)$$

where decisions $\left(\boldsymbol{v}_1, \ldots, \boldsymbol{v}_{j-1}, \boldsymbol{v}_{j+1}, \ldots, \boldsymbol{v}_n\right)$ are only auxiliary variables and will not be used in the actual transmission. In the above optimization, DM j optimistically assumes that (i) his local information $\hat{\boldsymbol{h}}^{(j)}$ is perfect (equal to $\boldsymbol{h}$) and (ii) that *all other DMs* have identical information. Interestingly, it is possible to relax the robustness with respect to the distributed nature of information while retaining robustness with respect to *local* uncertainties. Doing so, the following *Locally Robust* (LR) policy $\boldsymbol{w}_j^{\mathrm{LR}}$ is obtained at DM j:

$$\left(\boldsymbol{v}'_1, \ldots, \boldsymbol{v}'_{j-1}, \boldsymbol{w}_j^{\mathrm{LR}}, \boldsymbol{v}'_{j+1}, \ldots, \boldsymbol{v}'_n\right) = \operatorname*{argmax}_{\boldsymbol{w}_1,\ldots,\boldsymbol{w}_n} \mathbb{E}_{\boldsymbol{h},\hat{\boldsymbol{h}}^{(j)}}\left[U\left(\boldsymbol{h}, \boldsymbol{w}_1(\hat{\boldsymbol{h}}^{(j)}), \ldots, \boldsymbol{w}_n(\hat{\boldsymbol{h}}^{(j)})\right)\right]$$

where this time $\mathbb{E}_{\boldsymbol{h},\hat{\boldsymbol{h}}^{(j)}}$ accounts for noise in the local information at the j-th DM. Here, the DM accounts for local estimation noise, yet *erroneously* assumes that the noise is the same everywhere else. This approach corresponds in fact to a conventional robust design in a centralized setting. The performances of naive and LR strategies vary strongly depending on the scenarios. Yet, they are often building blocks of more advanced schemes, as it will be seen later on.

1.2.5 INFORMATION STRUCTURES

The Information Structure (IS) underpinning the TD problem in (1.1) and (1.2) describes how the local information $\hat{\boldsymbol{h}}^{(j)}$ available at the j-th DM relates to local estimates at other DMs $\hat{\boldsymbol{h}}^{(j')}$, $j' \neq j$ as well as to the true global state information vector $\boldsymbol{h}$. Ultimately the IS is characterized by the joint distribution $p_{\boldsymbol{h},\hat{\boldsymbol{h}}^{(1)},\ldots,\hat{\boldsymbol{h}}^{(n)}}$ which in turns governs the price of distributedness.

1.2.5.1 Additive White Gaussian Noise Model

An intuitive and mathematically tractable model for the decentralized information structures consists in considering that the nodes receive global information that are corrupted by an arbitrarily shaped, device dependent, Gaussian noise. In this case, the estimate at the j-th DM is modeled as:

$$\hat{\boldsymbol{h}}^{(j)} \triangleq \sqrt{1-(\boldsymbol{\Sigma}^{(j)})^2}\boldsymbol{h} + \boldsymbol{\Sigma}^{(j)}\boldsymbol{\delta}^{(j)} \tag{1.3}$$

where $\boldsymbol{\Sigma}^{(j)} \in \mathbb{R}^{m\times m}$ is the covariance matrix of the CSI noise at TX j. Furthermore, the CSIT noise error terms $\boldsymbol{\delta}^{(j)} \in \mathbb{C}^m$ have their elements i.i.d. $\mathcal{N}_{\mathbb{C}}(0,1)$, are independent of the true channel, and are jointly distributed such that

$$\mathbb{E}\left[\boldsymbol{\delta}^{(j)}(\boldsymbol{\delta}^{(j')})^{\mathrm{H}}\right] = (\rho^{(j,j')})^2\mathbf{I}_m \tag{1.4}$$

with the parameters $\rho^{(j,j')} \in [0,1]$ being the *CSI noise correlation factor*.

The main interest of this model is that it allows to model *partially centralized CSIT*, thus bridging the gap between fully distributed configuration with *independent* CSIT errors and centralized CSIT. Indeed, the CSIT configuration where

$$\boldsymbol{\Sigma}^{(j)} = \boldsymbol{\Sigma}^{(j')},\ \rho^{(j,j')} = 1, \qquad \forall j, j' = 1, \ldots, n \tag{1.5}$$

corresponds to the conventional centralized CSIT configuration [13, 14] while taking

$$\rho^{(j,j')} = 0, \qquad \forall j, j' = 1, \ldots, n \tag{1.6}$$

corresponds to the distributed CSIT configuration with independent CSIT noise [15].

1.2.5.2 Deterministic Hierarchical Information Structure

In some network setups, some wireless nodes may be endowed with greater information gathering capabilities (e.g. high-end devices) either due to practical connectivity constraint (e.g., better connectivity to some devices) or due to a protocol design aiming at minimizing backhaul load by sharing the information only to some devices.

A so-called *Deterministically Hierarchical* Information Structure (DHIS) is obtained when the DMs can be ordered by increasing quality of CSI with DM j having access to the information at DM $j-1$ in addition to some local information. This implies that DM 1 is the least informed one while DM n is the most informed one and knows the information at all preceding DMs. Mathematically, it means that there exists some functions $f_{j,j'}$ such that

$$\hat{\boldsymbol{h}}^{(j')} = f_{j,j'}(\hat{\boldsymbol{h}}^{(j)}), \qquad \forall j' < j. \tag{1.7}$$

The advantage of the DHIS is that akin to the information chain in (1.7), DMs can follow a chain of policies where a better informed DM j can *adapt* its own policies by relying on its knowledge of the decision at the lesser informed DM j' for $'j' < j$. This allows an increased coordination between the DMs and simplifies strongly the optimization problem. A remaining difficulty resides in the fact the DM j cannot safely predicts the behavior of a better informed devices j' with $j' > j$. Suboptimal solutions exist however where for instance DM j may conservatively assume that better informed ones only have access to the same information $\hat{\boldsymbol{h}}^{(j)}$ that it has itself. This method is discussed in a practical case in Section 1.3.4.

The Two Nodes Case

An interesting subcase of the hierarchical structure above is the two DMs scenario where the first DM has zero prior information (other than the common statistical knowledge). This case is referred to as *Master Slave* information structure. Here, the first DM is the slave: Being deprived of any real time information, its strategy consists in taking a fixed decision which maximized the network utility in an *average sense*. In this setting, we will apply the previous heuristic which consists in letting DM 1 solve the optimization by assuming that DM 2 has received the same channel information, i.e., no information. DM 1 then solves:

$$(\boldsymbol{w}_1^{\text{stat}}, \boldsymbol{v}_2) = \underset{\boldsymbol{w}_1, \boldsymbol{w}_2}{\operatorname{argmax}} \, \mathbb{E}_{\boldsymbol{h}} \left[U\left(\boldsymbol{h}, \boldsymbol{w}_1, \boldsymbol{w}_2\right) \right]$$

where $\boldsymbol{w}_1^{\text{stat}}$ is no longer a policy but a fixed deterministic (yet statistically optimal, hence the subscript "stat") decision. Note that $\boldsymbol{v}_2$ is an auxiliary variable and will not be used in practice: it corresponds to the erroneous estimation at DM 1 of the policy used at DM 2.

Turning to the second DM, his best option is to *adapt itself* to the decision made by the first DM. As such the second DM is a *master* as it attempts to control the situation. The policy is adapted at the second DM as follows:

$$\boldsymbol{w}_2^{\star} = \underset{\boldsymbol{w}_2}{\operatorname{argmax}} \, \mathbb{E}_{\boldsymbol{h}, \hat{\boldsymbol{h}}^{(2)}} \left[U\left(\boldsymbol{h}, \boldsymbol{w}_1^{stat}, \boldsymbol{w}_2(\hat{\boldsymbol{h}}^{(2)})\right) \right]$$

Note that the above optimization is meaningful because the second DM has access to the same underlying statistical information as the first DM such that it can also compute $\boldsymbol{w}_1^{\text{stat}}$ before solving for 1.2.5.2. Hence the master-slave information structure allows to nicely decouple the multi-agent coordination problem into a sequence of separated single-agent problems.

1.2.5.3 Stochastically Hierarchical Information Structure

The deterministic notion of hierarchy above imposes strong constraints on feedback (or information exchange) mechanisms between DMs, which not all practical network scenarios will be compatible with. Interestingly, the restrictive inclusion relation shown in (1.7) may be relaxed by adopting a stochastic notion of hierarchy. Referring back to the Gaussian information model shown in (1.3), a *Stochastically Hierarchical* Information Structure (SHIS) is one whereby the following relation holds:

$$\boldsymbol{\Sigma}^{(1)} \geq \boldsymbol{\Sigma}^{(2)} \geq \ldots \geq \boldsymbol{\Sigma}^{(n)}.$$

In other words, there exists a ranking between DMs in terms of the *quality* with which they observe the channel state $\boldsymbol{h}$. The SHIS model is also called *physically degraded* configuration in the Information Theory community [16]. Because the stochastic hierarchy does not remove the fundamental uncertainties related to local observations at the DM, this information structure does not directly lead to a strong simplification of the optimization problem (1.1). Nevertheless, if exploited properly, it can lead to an improved coordination between DMs. In [17, 18], considering decentralized network MIMO precoding with SHIS, a transmission scheme is developed to exploit the stochastic hierarchical structure so as to improve the coordination between the TXs, and hence the performance.

1.3 TEAM DECISION METHODS FOR DECENTRALIZED MIMO PRECODING

In this section, we show how the TD formulation (1.1) unfolds in a particular practical scenario. In this chapter, we illustrate these methods through the prism of the example of *decentralized MIMO precoding*. We first define formally the setting considered and shows how it fits in the TD framework introduced earlier. We then present three different methods to tackle the TD problem formulated.

1.3.1 SYSTEM SETTING

We study a so-called network MIMO transmission from n TXs to K RXs where the j-th TX is equipped with M_j antennas, while the i-th RX equipped with N_i antennas. The i-th RX is sent d_i streams *jointly* from all the TXs. The total number of RX antennas, the total number of TX antennas and the total number of streams are respectively given by

$$N_{\text{tot}} \triangleq \sum_{i=1}^{K} N_i, \quad M_{\text{tot}} \triangleq \sum_{i=1}^{K} M_i, \quad d_{\text{tot}} \triangleq \sum_{i=1}^{K} d_i. \tag{1.8}$$

We always consider that $M_{\text{tot}} \geq K$ such that in a perfect coordination setting (i.e. with ideal Channel State Information (CSI)) a precoding solution exists which allows for all users to be served at the same time, e.g. via zero-forcing precoding [19, 20]. We further assume that the RXs have perfect CSI and that linear filtering is used on both the TX and the RX side, and that the RXs treat interference as noise. The channel from the n TXs to the K RXs is represented by the multi-user channel matrix $\mathbf{H} \in \mathbb{C}^{N_{\text{tot}} \times M_{\text{tot}}}$ where $\mathbf{H}_{i,j} \in \mathbb{C}^{N_i \times M_j}$ denotes the channel matrix from TX j to RX i. For the sake of exposition, we consider in the numerical evaluations that the channel elements are distributed following a standard Rayleigh fading with unit variance.

The transmission is then described as

$$\begin{bmatrix} \boldsymbol{y}_1 \\ \vdots \\ \boldsymbol{y}_K \end{bmatrix} = \mathbf{H}\mathbf{x} + \boldsymbol{\eta} = \begin{bmatrix} \mathbf{H}_1\mathbf{x} \\ \vdots \\ \mathbf{H}_K\mathbf{x} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\eta}_1 \\ \vdots \\ \boldsymbol{\eta}_K \end{bmatrix} \tag{1.9}$$

where $\boldsymbol{y}_i \in \mathbb{C}^{N_i}$ is the signal received at the i-th RX, $\mathbf{H}_i \in \mathbb{C}^{N_i \times M_{\text{tot}}}$ the channel from all TXs to the i-th RX, and $\boldsymbol{\eta} \triangleq [\boldsymbol{\eta}_1, \ldots, \boldsymbol{\eta}_n]^{\mathrm{T}} \in \mathbb{C}^{N_{\text{tot}}}$ the normalized Gaussian noise with its elements i.i.d. as $\mathcal{CN}(0,1)$.

Information Structure

TX j receives the channel estimate $\hat{\mathbf{H}}^{(j)} \in \mathbb{C}^{N_{\text{tot}} \times M_{\text{tot}}}$ and designs its transmit coefficient $\mathbf{x}_j \in \mathbb{C}^{M_j}$ as a function of $\hat{\mathbf{H}}^{(j)}$, *without any form of information exchange with the other TXs*. To keep the notations consistent with Section 1.2, we use the vectorized version

$$\hat{\boldsymbol{h}}^{(j)} \triangleq \text{vect}\left(\hat{\mathbf{H}}^{(j)}\right) \tag{1.10}$$

and accordingly $\boldsymbol{h} = \text{vect}(\mathbf{H})$ where vect($\bullet$) denotes the vectorization operation. For convenience, we will use both $\hat{\boldsymbol{h}}^{(j)}$ and $\hat{\mathbf{H}}^{(j)}$ with the implicit reference to equation (1.10).

We will consider in the following the noisy Gaussian CSI model introduced in Section 1.2.5. The estimate at TX j is hence given by

$$\hat{\boldsymbol{h}}^{(j)} \triangleq \sqrt{1-(\mathbf{\Sigma}^{(j)})^2}\boldsymbol{h} + \mathbf{\Sigma}^{(j)}\boldsymbol{\delta}^{(j)} \tag{1.11}$$

where $\mathbf{\Sigma}^{(j)} \in \mathbb{R}^{N_{\text{tot}}M_{\text{tot}} \times N_{\text{tot}}M_{\text{tot}}}$ is the covariance matrix of the CSIT noise at TX j.

Decentralized Precoding

In this distributed CSIT setting, the DM is the TX and the precoding function of TX j is denoted by

$$\boldsymbol{w}_j : \mathbb{C}^{N_{\text{tot}}M_{\text{tot}}} \to \mathbb{C}^{M_j \times d_{\text{tot}}} \tag{1.12}$$

such that the transmit signal $\mathbf{x}_j$ at TX j, for a given received estimate $\hat{\boldsymbol{h}}^{(j)}$, is equal to

$$\mathbf{x}_j = \boldsymbol{w}_j(\hat{\boldsymbol{h}}^{(j)})\boldsymbol{s} \tag{1.13}$$

with $\boldsymbol{s} \triangleq [\boldsymbol{s}_1^{\text{T}}, \ldots, \boldsymbol{s}_K^{\text{T}}]^{\text{T}} \in \mathbb{C}^{d_{\text{tot}}}$ containing the d_{tot} data symbols to be transmitted to the K users and distributed as i.i.d. $\mathcal{N}_{\mathbb{C}}(0,1)$. Upon concatenation of all TX's precoding decisions, the multi-user joint precoder $\mathbf{T} \in \mathbb{C}^{M_{\text{tot}} \times d_{\text{tot}}}$ used for the transmission for a given channel realization is equal to

$$\mathbf{T} \triangleq \begin{bmatrix} \boldsymbol{w}_1(\hat{\boldsymbol{h}}^{(1)}) \\ \boldsymbol{w}_2(\hat{\boldsymbol{h}}^{(2)}) \\ \vdots \\ \boldsymbol{w}_n(\hat{\boldsymbol{h}}^{(n)}) \end{bmatrix}. \tag{1.14}$$

We consider a per-TX power constraint such that $\|\boldsymbol{w}_j(\hat{\boldsymbol{h}}^{(j)})\|^2 \leq P_j, \forall j$, with P_j being the power constraint at TX j. It is also useful to introduce the *precoder to user k*,

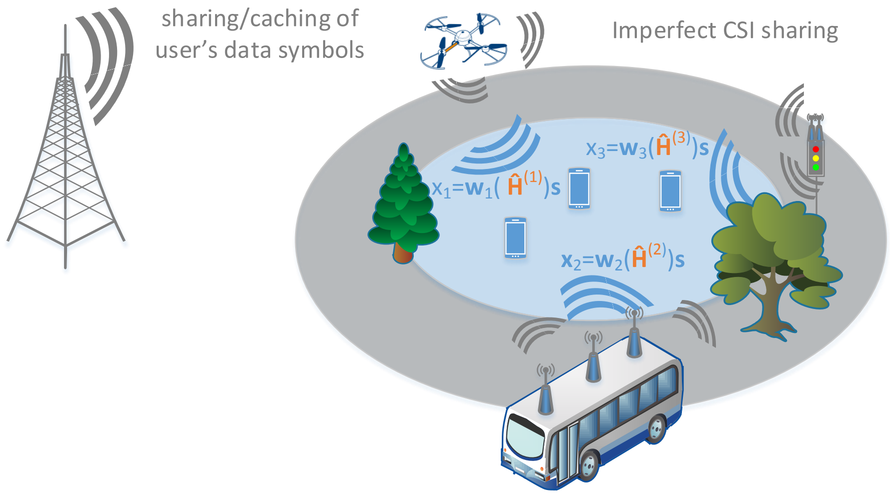

FIGURE 1.1 Decentralized MIMO precoding with distributed CSIT.

Due to imperfect and heterogeneous backhaul, the transmitting devices receive imperfect *and unequal* channel estimates based on which they design their transmit coefficients.

denoted by $\mathbf{T}_k \in \mathbb{C}^{M_{\text{tot}} \times d_k}$, such that

$$\mathbf{x} = \sum_{k=1}^{K} \mathbf{T}_k \boldsymbol{s}_k. \tag{1.15}$$

The decentralized joint MIMO precoding with distributed CSIT setting is illustrated in Fig. 1.1.

Network utility

We are interested in the particular example where the network utility of (1.1) represents the sum of all users' rates.

As stated earlier, the received signal at RX k is assumed to be linearly filtered by $\mathbf{G}_k^{\mathrm{H}} \in \mathbb{C}^{d_k \times N_k}$. Due to the assumption of Gaussian signaling, the rate of user k can be written as

$$R_k \triangleq \log_2 \left| \mathbf{I}_{d_k} + \mathbf{T}_k^{\mathrm{H}} \mathbf{H}_k^{\mathrm{H}} \left(\mathbf{I}_{N_k} + \sum_{\ell=1, \ell \neq k}^{K} \mathbf{H}_k \mathbf{T}_\ell \mathbf{T}_\ell^{\mathrm{H}} \mathbf{H}_k^{\mathrm{H}} \right)^{-1} \mathbf{H}_k \mathbf{T}_k \right|. \tag{1.16}$$

Finally, we introduce the average sum rate $\mathbb{E}[R]$ as

$$\mathbb{E}[R] \triangleq \sum_{k=1}^{K} \mathbb{E}[R_k]. \quad (1.17)$$

Team Decision Formulation

With distributed CSIT, the TD problem of (1.1) applied to the case of rate maximizing decentralized precoding can be written as:

$$(\boldsymbol{w}_1^\star, \ldots, \boldsymbol{w}_n^\star) = \operatorname*{argmax}_{(\boldsymbol{w}_1,\ldots,\boldsymbol{w}_n)\in\mathcal{W}} \mathbb{E}[\mathrm{R}(\boldsymbol{w}_1(\hat{\boldsymbol{h}}^{(1)}), \ldots, \boldsymbol{w}_n(\hat{\boldsymbol{h}}^{(n)}))] \quad (1.18)$$

where $\mathcal{W}$ is defined as

$$\mathcal{W} \triangleq \{(\boldsymbol{w}_1, \ldots, \boldsymbol{w}_n) \big| \boldsymbol{w}_j : \mathbb{C}^{N_{\text{tot}}M_{\text{tot}}} \to \mathbb{C}^{M_j \times d_{\text{tot}}}, \forall \mathbf{x} \in \mathbb{C}^{N_{\text{tot}}M_{\text{tot}}}, \|\boldsymbol{w}_j(\mathbf{x})\|^2 \leq P_j, \forall j\}. \quad (1.19)$$

As discussed in Section 1.2.3, it is often interesting to consider the best-response optimization problem (1.2), which in the case of (1.18) is written as

$$\boldsymbol{w}_j^{\mathrm{BR}} = \operatorname*{argmax}_{\boldsymbol{w}_j} \mathbb{E}\left[\mathrm{R}\left(\boldsymbol{h}, \boldsymbol{w}_1^{\mathrm{BR}}, \ldots, \boldsymbol{w}_{j-1}^{\mathrm{BR}}, \boldsymbol{w}_j(\hat{\boldsymbol{h}}^{(j)}), \boldsymbol{w}_{j+1}^{\mathrm{BR}}, \ldots, \boldsymbol{w}_n^{\mathrm{BR}}\right)\right]. \quad (1.20)$$

In the following, we present three different methods to deal either directly with (1.18), or with its best-response formulation (1.20).

1.3.2 MODEL-BASED APPROACH

Principle

Our first approach is called *model-based* and consists in restricting the space of the precoding functions by introducing a model using some parameters $\boldsymbol{\theta} \in \mathbb{C}^p$ which should typically be optimized in order to maximize the value of the joint utility achieved. How one reduces the infinite dimensional functional space to a finite parametrized space is naturally crucial. Often, the performance of this approach heavily depends on the existence of a good model that governs the devices's optimal decision. Good heuristics can hence emerge from the analysis of the problem in some limiting regimes (e.g., high/low SNR, large antenna settings).

We consider here the model of *regularized Zero-Forcing (ZF)* which has been shown to be an efficient and robust scheme in the centralized CSIT configuration. In this model, the precoding function at TX j takes the form [19, 20]:

$$\boldsymbol{w}_j^{\mathrm{rZF}}(\hat{\boldsymbol{h}}^{(j)}) \triangleq \mathbf{E}_j^{\mathrm{H}} \left((\hat{\mathbf{H}}^{(j)})^{\mathrm{H}}\hat{\mathbf{H}}^{(j)} + \theta_j \mathbf{I}_{M_{\text{tot}}}\right)^{-1} (\hat{\mathbf{H}}^{(j)})^{\mathrm{H}} \frac{\sqrt{P_j}}{\sqrt{\Psi^{(j)}}} \quad (1.21)$$

with parameter $\theta_j > 0$ and where $\mathbf{E}_j^{\mathrm{H}} \in \mathbb{C}^{M_j \times M_{\text{tot}}}$ allows to select the precoding coefficients effectively used to transmit at TX j and is defined as

$$\mathbf{E}_j^{\mathrm{H}} \triangleq \left[\mathbf{0}_{M_j \times \sum_{j'=1}^{j-1} M_j} \quad \mathbf{I}_{M_j} \quad \mathbf{0}_{M_j \times \sum_{j'=j+1}^{n} M_j}\right]. \tag{1.22}$$

The scalar $\Psi^{(j)}$ corresponds to the power normalization at TX j. Hence, it holds that

$$\Psi^{(j)} \triangleq \|\mathbf{E}_j^{\mathrm{H}} \left((\hat{\mathbf{H}}^{(j)})^{\mathrm{H}}\hat{\mathbf{H}}^{(j)} + \theta_j \mathbf{I}_{M_{\mathrm{tot}}}\right)^{-1} (\hat{\mathbf{H}}^{(j)})^{\mathrm{H}}\|_{\mathrm{F}}^2. \tag{1.23}$$

With this parametrization, the TD optimization problem (1.18) simplifies to

$$(\theta_1^\star, \dots, \theta_n^\star) = \operatorname*{argmax}_{(\theta_1,\dots,\theta_n)} \mathbb{E}[\mathrm{R}(\boldsymbol{w}_1^{\mathrm{rZF}}(\hat{\boldsymbol{h}}^{(1)}), \dots, \boldsymbol{w}_n^{\mathrm{rZF}}(\hat{\boldsymbol{h}}^{(n)}))]. \tag{1.24}$$

Through this model, the TD optimization reduces to the optimization with respect to a vector of deterministic scalars $\theta_1 \dots \theta_n$. The model can be further simplified by parameterizing using a single common parameter θ. This forces all TXs to use the same regularization coefficient. The simplified optimization then reads as

$$\theta^\star = \operatorname*{argmax}_{\theta} \mathbb{E}[\mathrm{R}(\boldsymbol{w}_1^{\mathrm{rZF}}(\hat{\boldsymbol{h}}^{(1)}), \dots, \boldsymbol{w}_n^{\mathrm{rZF}}(\hat{\boldsymbol{h}}^{(n)}))], \qquad \text{subject to } \theta_j = \theta, \forall j. \tag{1.25}$$

With single-antennas users and in the regime of large number of antennas where the number of antennas at each TX grows at the same rate as the number of users, *and when the TXs use the precoding model* (1.21), it is possible to accurately approximate the expectation inside (1.25) by a deterministic equivalent R_0 [21]. This deterministic equivalent depends only on the statistical information and is obtained from a fixed-point equation [20]. The optimal parameters $\theta_j^\star$ can then be obtained using any non-convex optimizer. In particular, in the simplified problem with a single parameter (1.25), $\theta^\star$ can be obtained via a simple linear search. We omit the deterministic equivalent expressions which require heavy notations and we refer to [21] for more details.

Note that using deterministic equivalent is a method to transform the stochastic optimization problem (1.24) into a deterministic one. Yet, it would also have been possible to apply any standard method of stochastic optimization to tackle directly (1.24) [See [22] for an overview of stochastic optimization].

Performance Evaluation and Simulations

In Fig. 1.2, we show the performance obtained in a setting with $n = 2$ TXs having each $M_1 = M_2 = 15$ antennas and $K = 30$ single antenna RXs with $\rho^{(1,2)} = \rho^{(2,1)}$ uniformly distributed between $[0, 1]$. At TX 1, $\mathbf{\Sigma}^{(1)} = 0\mathbf{I}_{N_{\mathrm{tot}}M_{\mathrm{tot}}}$, which indicates that the CSI is perfect at TX 1. At TX 2, $\mathbf{\Sigma}^{(2)} = \sigma\mathbf{I}_{N_{\mathrm{tot}}M_{\mathrm{tot}}}$ with σ varyings from 0 to 1, meaning that the CSI at TX 2 varies from perfect to fully inaccurate.

When TX 2 has quasi-perfect CSIT, the optimization of the regularization coefficient does not significantly enhance the system performance when compared to the naive choice of the parameters based on the locally available CSIT. In contrast, as the CSIT configuration becomes more asymmetric, the gap between the proposed TD robust parameter choice and the locally robust parameter choice becomes more

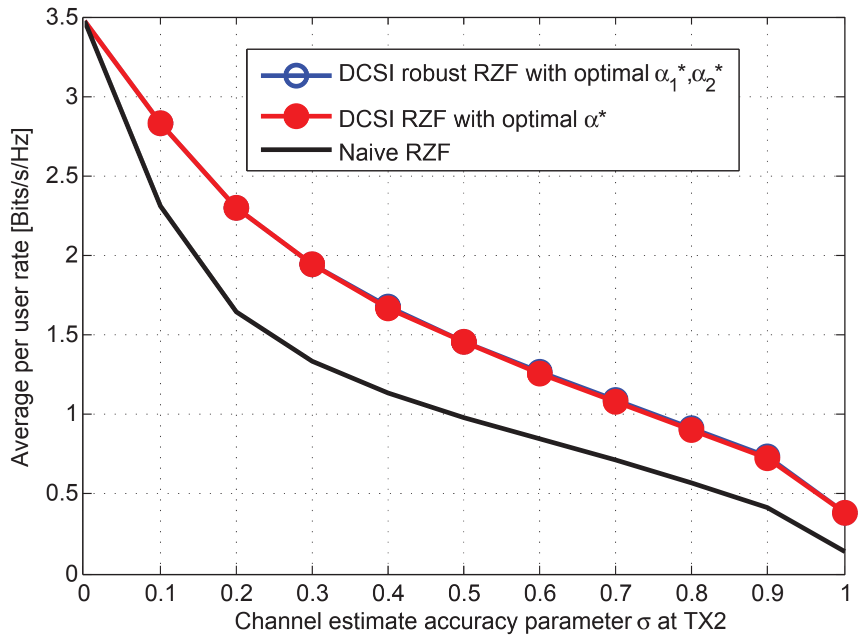

FIGURE 1.2 Average rate per user as a function of the CSIT accuracy σ

As the CSIT quality degrades at the second TX, the consistency between the estimates at the TXs degrades and it becomes more important to use an adapted robust precoding scheme.

important.

1.3.3 DISCRETIZATION-BASED APPROACH

Principle

The *Discretization-based* approach consists in quantizing the estimate (input) space, thus reducing the dimension of the decision space from an infinite dimensional space to a finite dimensional one. Clearly, good performance can only be obtained with sufficient quantization points, i.e., if the dimension of the approximating space is large. Following the well known *curse of dimensionality*, the number of quantization points should then grow exponentially with the dimension of the estimate space, such that this approach requires a lot of computing power and an efficient implementation if the dimension of the estimate is large. Yet, it has the advantage of being a generic method, independent of any heuristic and adapted to any distribution of the channel and the CSIT noise.

Specifically, let us denote the codebook used at each TX by $\mathcal{Q}^q$, and assume that it contains q instances of the multi-user channel state $\boldsymbol{h}$, i.e.,

$$\mathcal{Q}_q \triangleq \{\boldsymbol{h}_\ell | \boldsymbol{h}_\ell \in \mathbb{C}^{N^{\text{tot}}M^{\text{tot}}}, \ell = 1, \ldots, q\}. \tag{1.26}$$

We then denote by $\mathcal{Q}(\bullet)$ a quantizer from $\mathbb{C}^{N^{\text{tot}}M^{\text{tot}}}$ to the codebook $\mathcal{Q}_q$. The optimization of both the quantizer and the codebook is key to improved performance. Yet, this is a challenging research problem outside the scope of this work. In the following, we use a random codebook distributed according to $p_{\boldsymbol{h}}$ and use a Grassmannian quantizer [23]:

$$\mathcal{Q}(\boldsymbol{h}) \triangleq \operatorname*{argmax}_{\hat{\boldsymbol{h}} \in \mathcal{Q}_q} \left| \frac{\hat{\boldsymbol{h}}^{\text{H}}}{\|\hat{\boldsymbol{h}}\|} \cdot \frac{\boldsymbol{h}}{\|\boldsymbol{h}\|} \right|. \tag{1.27}$$

Following this quantization step at each TX, the TD optimization problem (1.18) is approximated as

$$(\boldsymbol{w}_1^\star, \ldots, \boldsymbol{w}_n^\star) = \operatorname*{argmax}_{(\boldsymbol{w}_1, \ldots, \boldsymbol{w}_n) \in \mathcal{W}_q} \mathbb{E}[\text{R}(\boldsymbol{w}_1(\mathcal{Q}(\hat{\boldsymbol{h}}^{(1)})), \ldots, \boldsymbol{w}_n(\mathcal{Q}(\hat{\boldsymbol{h}}^{(n)})))] \tag{1.28}$$

where we have defined $\mathcal{W}_q$ as the set of policies operating on the codebook $\mathcal{Q}_q$:

$$\mathcal{W}^q \triangleq \{(\boldsymbol{w}_1^q, \ldots, \boldsymbol{w}_n^q) | \boldsymbol{w}_j^q : \mathcal{Q}^q \to \mathbb{C}^{M_j \times d^{\text{tot}}}, \|\boldsymbol{w}_j^q(\hat{\boldsymbol{h}})\|^2 \leq P_j, \forall \hat{\boldsymbol{h}} \in \mathcal{Q}^q, \forall j\}. \tag{1.29}$$

This approach requires to consider the best-response formulation (1.20) as the optimization remains otherwise intractable. For each codebook element $\boldsymbol{h}_\ell \in \mathcal{Q}^q$ and each TX j, we then solve

$$\boldsymbol{w}_j^{\text{BR}}(\boldsymbol{h}_\ell) = \operatorname*{argmax}_{\boldsymbol{w}_j} \mathbb{E}[\text{R}\left(h, \boldsymbol{w}_1^{\text{BR}} \circ \mathcal{Q}, \ldots, \boldsymbol{w}_{j-1}^{\text{BR}} \circ \mathcal{Q}, \boldsymbol{w}_j, \boldsymbol{w}_{j+1}^{\text{BR}} \circ \mathcal{Q}, \ldots, \boldsymbol{w}_n^{\text{BR}} \circ \mathcal{Q}\right) | \hat{\boldsymbol{h}}^{(j)} = \boldsymbol{h}_\ell]. \tag{1.30}$$

Optimization (1.30) is a conventional stochastic optimization problem, for which many efficient methods can be used. In what follows, Sample Average Approximation (SAA) using Monte-Carlo runs is used [22]. The details of the algorithms are skipped and can be found in [24].

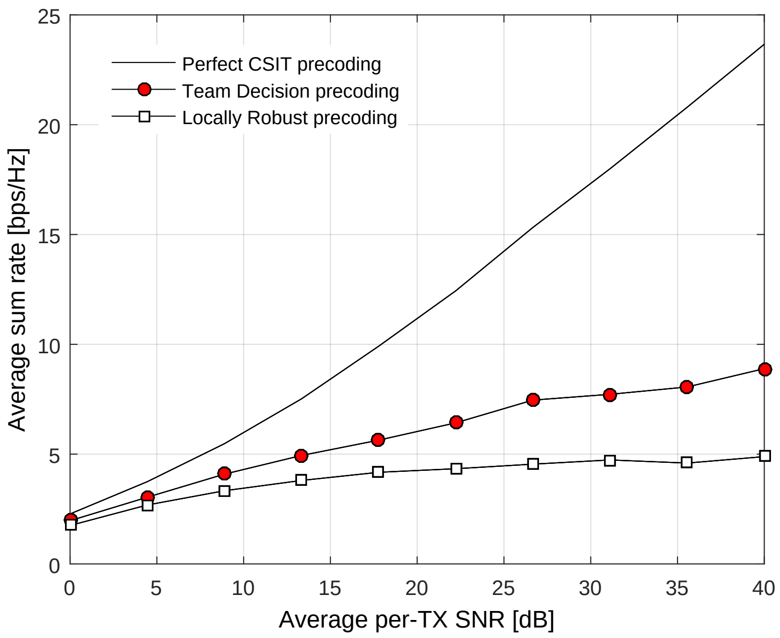

FIGURE 1.3 Average sum rate as a function of the per-TX power constraint.

The robust precoding solution significantly improve the sum rate, in particular at high SNR. Higher gains are expected to be possible through the optimization of the codebook at each TX.

Performance Evaluation

In these simulations, we choose $n = 2$ TXs and $K = 2$ RXs with all the nodes having a single-antenna. We also choose

$$\mathbf{\Sigma}_1 = \sqrt{0.5}\mathbf{I}_{N_{\text{tot}}M_{\text{tot}}}, \quad \mathbf{\Sigma}_2 = \sqrt{0.1}\mathbf{I}_{N_{\text{tot}}M_{\text{tot}}}, \quad \rho_{1,2} = 0. \tag{1.31}$$

To evaluate the efficiency of the proposed precoding scheme, we compare its performance with the upper bound obtained in the case where both TXs have access to the perfect instantaneous CSI and use the sum-rate maximization algorithm from [25]. We also compare the robust precoding scheme to the conventional decentralized precoding approach where each TX designs its precoder using the robust sum-rate maximization algorithm from [26] which is hence the *Locally Robust (LR) precoding scheme*. The quantization codebook is designed with $q = 10000$ elements.

In Fig. 1.3, the average sum rate is plotted as a function of the SNR. It can be seen that the discretization approach outperforms the locally robust precoding at any SNR value. The robust precoding performs well at low to medium SNR and, in contrast to the LR precoding, is able to achieve a positive slope by serving only one user at high SNR. The proposed precoding suffers at high SNR from a degradation of the performance due to the quantization noise. This loss is expected to be reduced with more computational power and the optimization of the codebooks and the quantizer.

1.3.4 HIERARCHICAL APPROACH

Principles

We now consider the Deterministic Hierarchical Information Structure (DHIS) described in Section 1.2.5.2. Consequently, the TXs can be ordered such that TX j has also access to the CSIT at TX j' for $j' < j$. In this case, the best-response optimization problem (1.20) for a given channel realization $\hat{\boldsymbol{h}}^{(j)}$ simplifies to

$$\boldsymbol{w}_j^{\mathrm{BR}}(\hat{\boldsymbol{h}}^{(j)}) = \operatorname*{argmax}_{\boldsymbol{w}_j} \mathbb{E}_{\boldsymbol{h},\hat{\boldsymbol{h}}^{(j+1)},\ldots,\hat{\boldsymbol{h}}^{(n)}\middle|\hat{\boldsymbol{h}}^{(1)},\ldots,\hat{\boldsymbol{h}}^{(j)}} \left[\mathrm{R}\left(\boldsymbol{w}_1^{\mathrm{BR}},\ldots,\boldsymbol{w}_{j-1}^{\mathrm{BR}},\boldsymbol{w}_j,\boldsymbol{w}_{j+1}^{\mathrm{BR}},\ldots,\boldsymbol{w}_n^{\mathrm{BR}}\right)\right]. \tag{1.32}$$

The key element in (1.32) is the conditioning on $\hat{\boldsymbol{h}}^{(1)},\ldots,\hat{\boldsymbol{h}}^{(j)}$ which implies that the uncertainty concerns only the estimates at the TXs having a more accurate estimate, i.e., TX j' with $j' > j$. This deterministic hierarchical assumption strongly simplifies the problem as it allows to start from the most informed TX which knows all the estimates before turning to the decision at the less informed TXs. Yet, the remaining difficulty resides in the fact that for $j < n$, TX j must still cope with its lack of knowledge associated with the better informed devices. Fortunately this problem can be circumvented by resorting to a simple heuristic strategy consisting in considering that TX j –when computing its precoding coefficients– assumes that TX j' for $j' > j$, has also received the same channel estimate $\hat{\boldsymbol{h}}^{(j)}$. Following this approximation, the policy $\boldsymbol{w}_j^{\mathrm{HC}}$ at TX j is obtained from

$$(\boldsymbol{w}_j^{\mathrm{HC}},\boldsymbol{v}_{j+1}\ldots,\boldsymbol{v}_n) = \operatorname*{argmax}_{\boldsymbol{w}_j,\ldots,\boldsymbol{w}_n} \mathbb{E}[\mathrm{R}(\boldsymbol{w}_1^{\mathrm{HC}},\ldots\boldsymbol{w}_{j-1}^{\mathrm{HC}},\boldsymbol{w}_j(\hat{\boldsymbol{h}}^{(j)}),\ldots,\boldsymbol{w}_n(\hat{\boldsymbol{h}}^{(j)}))]. \tag{1.33}$$

The auxiliary variables $\boldsymbol{v}_{j+1},\ldots,\boldsymbol{v}_n$ are not used for the actual transmission due to that fact that TX j' with $j' > j$ will use whatever more accurate information is available locally to improve the precoding decision, i.e., it will solve (1.33) with its own local CSIT $\hat{\boldsymbol{h}}^{(j')}$.

The optimization problem now reduces to a conventional robust precoder optimization. Indeed, the expression in (1.33) depends only on the channel estimate $\hat{\boldsymbol{h}}^{(j)}$ such that it is not anymore necessary for TX j to *estimate* the information available at the other TXs. Hence, it is possible to adapt the Locally Robust precoding scheme from the literature to that setting using standard linear algebra (see [27, 28] for more details on the computation of the precoder at each TX).

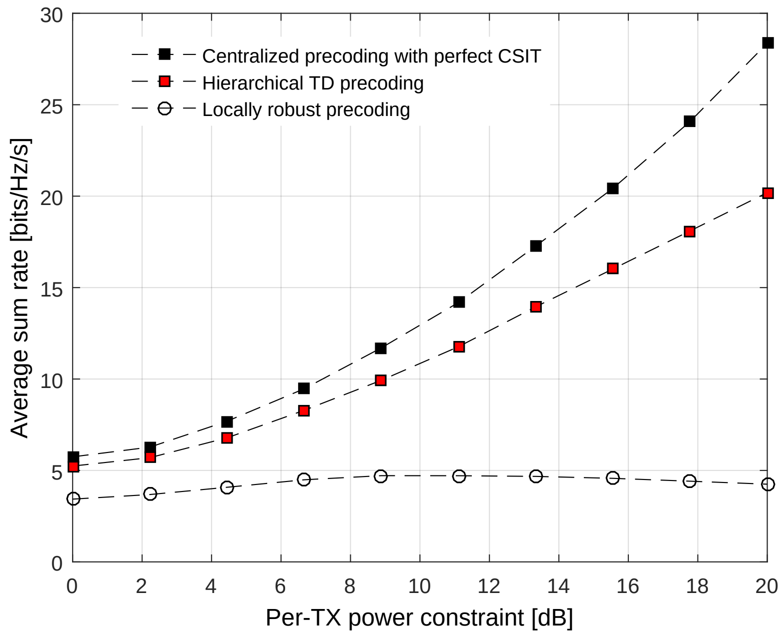

FIGURE 1.4 Average sum rate as a function of the available transmit power *P*.

The hierarchical precoding algorithm performs very well as the hierarchical structure allows the TXs with an accurate CSIT to reduce the interference generated by the other TXs, i.e., to compensate for their precoding decisions.

Performance Evaluation

To evaluate the performance of the proposed hierarchical precoding algorithm, the performance is averaged over 1000 channel realizations via Monte-Carlo simulations. We consider a simple configuration with $n = 4$ single antenna TXs and $K = 4$ single antenna RXs. We furthermore assume that each TX has the same power constraint P. The hierarchical precoding algorithm is compared with the maximum sum rate algorithm from [25] using perfect CSIT at every TX and with a *Locally Robust* algorithm from the literature [29, 26] which is hence applied in a distributed manner at each TX using the CSI locally available. We show in Fig. 1.4, the average sum rate as a function of the per-TX power constraint in the following simple CSI configuration

$$\begin{aligned} \mathbf{\Sigma}^{(1)} &= \mathbf{\Sigma}^{(2)} = \sqrt{0.25}\mathbf{I}_{N_{\text{tot}}M_{\text{tot}}} \\ \mathbf{\Sigma}^{(3)} &= \mathbf{\Sigma}^{(4)} = 0\mathbf{I}_{N_{\text{tot}}M_{\text{tot}}} \end{aligned} \tag{1.34}$$

It can be seen that the TD robust scheme outperforms significantly the locally robust scheme. In particular, a positive slope is achieved. This follows from the DHIS which allows the TXs having perfect CSIT to adapt to the transmit coefficients of the TXs having less accurate CSIT, thus effectively reducing interference. This simulation confirms hence the intuition that hierarchical CSIT can be beneficial to enforce consistency and allows to reach good performance even when some TXS have very inaccurate CSIT.

1.4 CONCLUSION

This chapter introduces the challenges related to device-centric coordination where devices only have their own local and noisy versions of the channel state information. We present a few avenues for further research and some initial results for solving the decentralized policy design arising from device-centric coordination. An illustration of the benefits of robust coordination design is given for the example of decentralized MIMO precoding in wireless networks.

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