Chapter 2
Background on Channel Estimation

Abstract In this chapter, we introduce popular channel estimation approaches in the conventional point-to-point MIMO system, including the maximum likelihood (ML) estimation and minimum mean square error (MMSE) estimation, as well as their counterparts least square (LS) estimation and linear minimum mean square error (LMMSE) estimation. Moreover, the channel estimation for the amplify-and-forward (AF) unidirectional relaying system (URS) is also discussed, which is seen to be quite different from that of the point-to-point system. One should identify the "needed" channel parameters in URS and then carry out the corresponding estimation. Finally, we discuss the differences of the channel estimation in PLNC system and present the new challenges compared to the other systems.

2.1 Channel Estimation in Point-to-Point System

Most communication systems consist of two periods: training period and data transmission period. During the former period, channel is estimated from known symbols, namely the training sequence or pilots; During the latter period, the estimated channel is used to detect the unknown data symbols.

In the point-to-point system, the channel estimation model is usually formulated as

$$\mathbf{y} = \mathbf{S}\mathbf{h} + \mathbf{n}, \tag{2.1}$$

where $\mathbf{y}$ is the received signal during the training period, $\mathbf{S}$ is the matrix that is built from the training sequence, $\mathbf{h}$ is the unknown channel to be estimated, and $\mathbf{n}$ is the unknown noise. Note that the structure of $\mathbf{S}$ could be vary under different configurations.

2.1.1 Estimation of Deterministic Channel

The probability density function (PDF) of $\mathbf{y}$ conditioned on $\mathbf{h}$, i.e., $p(\mathbf{y}|\mathbf{h})$, is also named as the *likelihood function* because it tells us how likely a certain $\mathbf{y}$ is observed with a given $\mathbf{h}$. The ML estimation for $\mathbf{h}$ is then defined as

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$$\hat{\mathbf{h}}_{ML} = \arg\max_{\mathbf{h}} p(\mathbf{y}|\mathbf{h}). \tag{2.2}$$

When noise is Gaussian distributed with covariance matrix $\mathbf{C_n}$, $p(\mathbf{y}|\mathbf{h})$ can be explicitly written as

$$p(\mathbf{y}|\mathbf{h}) = \frac{1}{|\pi \mathbf{C_n}|} \exp\left[-(\mathbf{y}-\mathbf{Sh})^H \mathbf{C_n}^{-1}(\mathbf{y}-\mathbf{Sh})\right]. \tag{2.3}$$

From (2.2), we know the ML estimation of $\mathbf{h}$ can be derived as

$$\hat{\mathbf{h}}_{ML} = \arg\min_{\mathbf{h}} \underbrace{(\mathbf{y}-\mathbf{Sh})^H \mathbf{C_n}^{-1}(\mathbf{y}-\mathbf{Sh})}_{J_{ML}}, \tag{2.4}$$

where J_{ML} is the corresponding cost function. Setting the gradient of J_{ML} with respect to $\mathbf{h}$ as zero, we obtain

$$\hat{\mathbf{h}}_{ML} = (\mathbf{S}^H \mathbf{C_n}^{-1}\mathbf{S})^{-1}\mathbf{S}^H \mathbf{C_n}^{-1}\mathbf{y}. \tag{2.5}$$

The expectation of $\hat{\mathbf{h}}_{ML}$ is

$$E_{\mathbf{y}|\mathbf{h}}\{\hat{\mathbf{h}}_{ML}\} = \mathbf{h}, \tag{2.6}$$

which means that $\hat{\mathbf{h}}_{ML}$ is unbiased, and the covariance matrix of the estimation error vector $\Delta\mathbf{h}_{ML} \triangleq \mathbf{h} - \hat{\mathbf{h}}_{ML}$ can be computed as

$$\mathbf{C}_{\Delta\mathbf{h}_{ML}} = E_{\mathbf{y}|\mathbf{h}}\left\{\Delta\mathbf{h}_{ML}\Delta\mathbf{h}_{ML}^H\right\} = (\mathbf{S}^H \mathbf{C_n}^{-1}\mathbf{S})^{-1}. \tag{2.7}$$

However for a general case, we do not have statistic knowledge of the noise vector $\mathbf{n}$, and hence we could resort to the LS estimation. The principle of LS estimator is to minimize the square norm between the observation $\mathbf{y}$ and the noise-free data, i.e.,

$$\hat{\mathbf{h}}_{LS} = \min_{\mathbf{h}} \underbrace{\|\mathbf{y}-\mathbf{Sh}\|^2}_{J_{LS}}, \tag{2.8}$$

where J_{LS} is the corresponding cost function. Making the derivative of J_{LS} with respect to $\mathbf{h}$ be zero yields LS estimation

$$\hat{\mathbf{h}}_{LS} = (\mathbf{S}^H\mathbf{S})^{-1}\mathbf{S}^H\mathbf{y}. \tag{2.9}$$

Note that when noise $\mathbf{n}$ is Gaussian with $\mathbf{C_n} = \mathbf{I}$, LS estimation coincides with ML estimation.

2.1.2 Estimation of Random Channel

If $\mathbf{h}$ is assumed to be a random vector whose prior knowledge, e.g., PDF or statistics, is known, then one can rely on this prior knowledge to improve the estimation accuracy.

Generally, the optimal estimation is obtained from the MMSE criterion, i.e.,

$$\hat{\mathbf{h}}_{MMSE} = \arg\min_{\mathbf{h}} \underbrace{E_{\mathbf{y},\mathbf{h}}\{\|\hat{\mathbf{h}} - \mathbf{h}\|^2\}}_{J_{MMSE}}, \tag{2.10}$$

where J_{MMSE} is the corresponding cost function. With the equality $p(\mathbf{y}, \mathbf{h}) = p(\mathbf{h}|\mathbf{y})p(\mathbf{y})$, the cost function J_{MMSE} can be reexpressed as

$$\begin{aligned} J_{MMSE} =& \mathbb{E}_{\mathbf{y}}\left\{\mathbb{E}_{\mathbf{h}|\mathbf{y}}\left\{\|\hat{\mathbf{h}} - \mathbf{h}\|^2\right\}\right\} \\ =& \int \left[\int \|\hat{\mathbf{h}} - \mathbf{h}\|^2 p(\mathbf{h}|\mathbf{y}) d\mathbf{h}\right] p(\mathbf{y}) d\mathbf{y}. \end{aligned} \tag{2.11}$$

Since $p(\mathbf{y}) \geq 0$ for all $\mathbf{y}$, we may simplify the MMSE estimator as

$$\hat{\mathbf{h}}_{MMSE} = E_{\mathbf{h}|\mathbf{y}}\{\mathbf{h}\}. \tag{2.12}$$

If $\mathbf{n}$ and $\mathbf{h}$ are assumed to be joint circularly complex symmetric Gaussian distributed, then the MMSE estimator of $\mathbf{h}$ can be simplified as

$$\begin{aligned} \hat{\mathbf{h}}_{MMSE} =& \boldsymbol{\mu}_{\mathbf{h}} + \mathbf{C}_{\mathbf{h}}\mathbf{S}^H(\mathbf{S}\mathbf{C}_{\mathbf{h}}\mathbf{S}^H + \mathbf{C}_{\mathbf{n}})^{-1}(\mathbf{y} - \mathbf{S}\boldsymbol{\mu}_{\mathbf{h}}) \\ =& \boldsymbol{\mu}_{\mathbf{h}} + (\mathbf{C}_{\mathbf{h}}^{-1} + \mathbf{S}^H\mathbf{C}_{\mathbf{n}}^{-1}\mathbf{S})^{-1}\mathbf{C}_{\mathbf{n}}^{-1}(\mathbf{y} - \mathbf{S}\boldsymbol{\mu}_{\mathbf{h}}), \end{aligned} \tag{2.13}$$

where $\boldsymbol{\mu}_{\mathbf{h}}$ and $\mathbf{C}_{\mathbf{h}}$ are the mean and covariance of $\mathbf{h}$. The estimation error $\Delta\mathbf{h}_{MMSE} = \mathbf{h} - \hat{\mathbf{h}}_{MMSE}$ is then also circularly complex symmetric Gaussian distributed with the covariance matrix

$$\mathbf{C}_{\Delta\mathbf{h}_{MMSE}} = \mathbb{E}_{\mathbf{y},\mathbf{h}}\{\Delta\mathbf{h}_{MMSE}(\Delta\mathbf{h}_{MMSE})^H\} = (\mathbf{C}_{\mathbf{h}}^{-1} + \mathbf{S}^H\mathbf{C}_{\mathbf{n}}^{-1}\mathbf{S})^{-1}. \tag{2.14}$$

If only the second order statistics of $\mathbf{n}$ and $\mathbf{h}$ are known, then we may chose to retain the MMSE criterion but constrain the estimator to be linear. The so derived estimator is named as LMMSE estimator, which is formulated as $\hat{\mathbf{h}}_{LMMSE} = \mathbf{b}^H\mathbf{y}$, where the vector $\mathbf{b}$ is achieved through minimizing the following cost function

$$J_{LMMSE} = E_{\mathbf{y},\mathbf{h}}\{\|\mathbf{b}^H\mathbf{y} - \mathbf{h}\|^2\}. \tag{2.15}$$

After some mathematical operations, the LMMSE estimation of $\mathbf{h}$ can be written as

$$\hat{\mathbf{h}}_{LMMSE} = \boldsymbol{\mu}_{\mathbf{h}} + (\mathbf{C}_{\mathbf{h}}^{-1} + \mathbf{S}^H \mathbf{C}_{\mathbf{n}}^{-1} \mathbf{S})^{-1} \mathbf{C}_{\mathbf{n}}^{-1} (\mathbf{y} - \mathbf{S}\boldsymbol{\mu}_{\mathbf{h}}), \tag{2.16}$$

and the covariance matrix for the estimation error vector is

$$\mathbf{C}_{\Delta \mathbf{h}_{LMMSE}} = (\mathbf{C}_{\mathbf{h}}^{-1} + \mathbf{S}^H \mathbf{C}_{\mathbf{n}}^{-1} \mathbf{S})^{-1}. \tag{2.17}$$

Hence, the expression of LMMSE estimator coincides with MMSE estimator (2.13) when $\mathbf{n}$ and $\mathbf{h}$ are jointly Gaussian distributed.

2.2 Channel Estimation in AF Based URS

A typical AF based URS with M randomly placed relay nodes $\mathbb{R}_i$, $i = 1, \ldots, M$, one source node $\mathbb{S}$, and one destination node $\mathbb{D}$ is shown in Fig. 2.1. Compared to the conventional point-to-point system, there are three different types of channel parameters to be estimated: the individual channel $\mathbb{S} \to \mathbb{R}$ denoted as g_i's, the individual channel $\mathbb{R} \to \mathbb{D}$ denoted as h_i's, as well as the composite channels $\mathbb{S} \to \mathbb{R} \to \mathbb{D}$. Though the ideal channel estimation could target at the two individual channels g_i's and h_i's, [1] has mentioned that in order to achieve the maximum likelihood detection only the composite channels are needed. Interestingly, this idea reminds us that the ultimate purpose of the channel estimation is to realize the data detection, while one would only need those necessary channel information for data detection. In the conventional point-to-point system, such "needed" channel is just the channel between the transceivers, while in URS, one has to figure out what kind of channel is the "needed" one. In order to better illustrate this concept, we present a channel estimation example for URS with multiple relay nodes, where the space time coding (STC) is applied for data transmission.

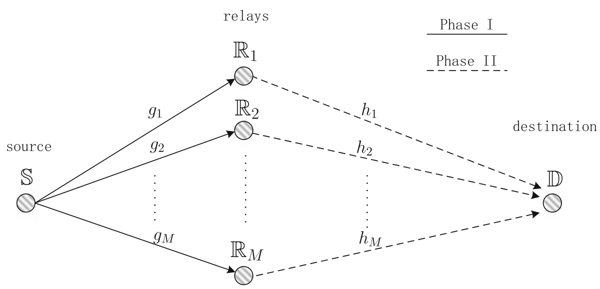

Fig. 2.1 Wireless relay networks with one source, one destination and M relays

2.2.1 Space Time Coding in AF Based URS

Consider the URS shown in Fig. 2.1, where each node has only a single antenna that cannot transmit and receive simultaneously. The channel between each node pair is assumed quasi-stationary with variances σ_{gi}^2 and σ_{hi}^2, respectively. The source node $\mathbb{S}$ sends a signal block $\mathbf{s} = [s_1, \ldots, s_T]^T$ to $\mathbb{D}$ via the aid of relay. The transmission is accomplished by two phases, each containing T consecutive time slots. During Phase I, $\mathbb{S}$ broadcasts the signal $\mathbf{s}$ to all $\mathbb{R}_i$, and the received signal at $\mathbb{R}_i$ is

$$\mathbf{r}_i = g_i \mathbf{s} + \mathbf{n}_{ri}, \tag{2.18}$$

where $\mathbf{n}_{ri}$ is the white complex Gaussian noise at the ith relays. For convenience, all noise variances are assumed as σ_n^2, namely, $\mathbf{n}_{ri} \in \mathcal{CN}(0, \sigma_n^2 \mathbf{I})$. The power constraint of the transmission is $\mathrm{E}\{\mathbf{s}^H \mathbf{s}\} = T P_s$, where P_s is the average transmitting power of the source.

The linear dispersion based STC has been proposed in [2], where $\mathbf{r}_i$ is firstly precoded by a unitary matrix $\mathbf{P}_i$ and is then scaled by a real factor α_i to keep the average power of $\mathbb{R}_i$ as P_{ri}, resulting in

$$\mathbf{t}_i = \alpha_i \mathbf{P}_i \mathbf{r}_i^{(*)}, \tag{2.19}$$

where $(\cdot)^{(*)}$ represents the item itself if the ith relay operates on $\mathbf{r}_i$ whereas represents the conjugate of the item if the ith relay operates on $\mathbf{r}_i^*$. Note that this type of STC, where one relay operates on either $\mathbf{r}_i$ or $\mathbf{r}_i^*$, exclusively, has been adopted in [2, 3]. Moreover, the scaling factor α_i could be chosen as

$$\alpha_i = \sqrt{\frac{P_{ri}}{\sigma_{gi}^2 P_s + \sigma_n^2}} \tag{2.20}$$

to keep the power constraint from the long term point of view. The destination $\mathbb{D}$ in Phase II then receives

$$\mathbf{d}_2 = \sum_{i=1}^{M} h_i \mathbf{t}_i + \mathbf{n}_{d2} = \mathbf{B} \boldsymbol{\Lambda} \mathbf{w} + \mathbf{n}_d, \tag{2.21}$$

where $\mathbf{n}_{d2} \in \mathcal{CN}(0, \sigma_n^2 \mathbf{I})$ represents the complex white Gaussian noise vector at $\mathbb{D}$ in the second phase, and

$$\mathbf{w} = [w_1, \ldots, w_M]^T, \quad w_i = h_i g_i^{(*)}, \quad \boldsymbol{\Lambda} = \mathrm{diag}\{\alpha_1, \ldots., \alpha_M\},$$

$$\mathbf{B} = [\mathbf{P}_1 \mathbf{s}_1^{(*)}, \mathbf{P}_2 \mathbf{s}_2^{(*)}, \ldots, \mathbf{P}_M \mathbf{s}_M^{(*)}], \quad \mathbf{n}_d = \sum_{i=1}^{M} h_i \alpha_i \mathbf{P}_i \mathbf{n}_{ri}^{(*)} + \mathbf{n}_{d2}.$$

Note that, by a slight abuse of notation we introduce the notation $\mathbf{s}_i \triangleq \mathbf{s}$ to discriminate the signal forwarded from the ith relay. Furthermore, the covariance of $\mathbf{n}_d$ is computed as

$$\mathrm{Cov}(\mathbf{n}_d|h_i, i = 1, \ldots, M) = \left(\sum_{i=1}^{M} |h_i|^2\alpha_i^2 + 1\right)\sigma_n^2\mathbf{I}, \tag{2.22}$$

where the property $\mathbf{P}_i\mathbf{P}_i^H = \mathbf{I}$ is utilized.

2.2.2 Channel Estimation

For coherent detection in the AF based URS [2–5], the destination $\mathbb{D}$ performs the maximum likelihood (ML) detection based only on a specific channel realization w_i while treating $\mathbf{n}_d$ as the overall white Gaussian noise. Therefore, the task of the channel estimation focuses only on estimating w_i at $\mathbb{D}$.

Two different channel estimation schemes could be considered. One is to separately estimate g_i, h_i and then construct w_i from $g_i^{(*)}h_i$. However, this approach is not as trivial as it seems to be:

1. Each relay should spend at least M additional time slots to send the estimated g_i to the destination. Moreover, additional energy will be consumed when transmitting over additional time slots.
2. Transmitting the estimated g_i will suffer from further distortion because of both the noise at the destination and the error in the estimated channel h_i. Most time, g_i has to be quantized before the transmission [6], and the quantization error must also be counted.

Hence, a better way is to directly estimate the overall channel w_i at $\mathbb{D}$. We assume that the length of the training sequence sent from $\mathbb{S}$ is N, which may be different from the data block size T. The training sequence, denoted as $\mathbf{z}$, can be embedded into a data frame and will also be sent from $\mathbb{S}$ to $\mathbb{D}$ via the aid of $\mathbb{R}_i$'s. A linear transformation will be performed at each relay node before it forwards the training to the destination during Phase II. Denote the $N \times N$ unitary precoding matrix at the ith relay as $\mathbf{A}_i$ and define

$$\mathbf{C} = [\mathbf{A}_1\mathbf{z}_1^{(*)}, \mathbf{A}_2\mathbf{z}_2^{(*)}, \ldots, \mathbf{A}_M\mathbf{z}_M^{(*)}]. \tag{2.23}$$

The transmitting model with other equations from (2.18) to (2.22) could be applied straightforwardly. With slight abuse of notations, we will keep all other notations unchanged from the previous section. During the training period, the power constraint is replaced by $\mathbf{z}^H\mathbf{z} \leq NP_s = E_s$.

1. *LS Estimation*: From (2.21), the LS estimate of $\mathbf{w}$ is derived as

$$\hat{\mathbf{w}}_{LS} = \boldsymbol{\Lambda}^{-1}\mathbf{C}^{\dagger}\mathbf{d}_2 = \mathbf{w} + \Delta\mathbf{w} \tag{2.24}$$

with error

$$\Delta\mathbf{w} = \boldsymbol{\Lambda}^{-1}\mathbf{C}^{\dagger}\mathbf{n}_d. \tag{2.25}$$

The covariance of $\Delta\mathbf{w}$ is then

$$\mathrm{Cov}(\Delta\mathbf{w}|\mathbf{g}^{(*)}, \mathbf{h}) = \sigma_n^2 \left(\sum_i |h_i|^2|\alpha_i|^2 + 1\right) \boldsymbol{\Lambda}^{-1}(\mathbf{C}^H\mathbf{C})^{-1}\boldsymbol{\Lambda}^{-1}, \tag{2.26}$$

where $\mathbf{g}^{(*)} = [g_1^{(*)}, g_2^{(*)}, \ldots, g_M^{(*)}]^T$ and $\mathbf{h} = [h_1, h_2, \ldots, h_M]^T$ are defined for convenience. Since $\boldsymbol{\Lambda}$ is a constant matrix, the optimization is conducted by varying the value of $\mathbf{C}$. Since the diagonal elements of $\mathbf{C}$ must all be no greater than E_s, the optimal $\mathbf{C}$ can be found by solving the following constrained optimization problem:

$$\begin{aligned} \min_{\mathbf{A}_i, \mathbf{z}} \quad & \mathrm{tr}\left(\boldsymbol{\Lambda}^{-1}(\mathbf{C}^H\mathbf{C})^{-1}\boldsymbol{\Lambda}^{-1}\right) \\ \text{s.t.} \quad & [\mathbf{C}^H\mathbf{C}]_{ii} \le E_s, \quad i = 1, \ldots M. \end{aligned} \tag{2.27}$$

Note that, the above optimization problem is different from that of traditional multiple input single output (MISO) system, where there is a total power constraint over all transmit antennas [7]. In URS, since different relays could not share a common power pool, each relay will have its own power constraint P_{ri}, which is reflected by M individual constraints in (2.27).

2. *LMMSE Estimation*: Denote the covariance of $\mathbf{h}$ and $\mathbf{g}^{(*)}$ as $\mathbf{R}_h$ and $\mathbf{R}_{g^{(*)}}$ respectively. Then, the covariance matrix of $\mathbf{w}$, assuming channels of Phase I are independent from channels of Phase II, is

$$\mathbf{R}_w = \mathrm{E}\{\mathbf{w}\mathbf{w}^H\} = \mathbf{R}_{g^{(*)}} \odot \mathbf{R}_h, \tag{2.28}$$

where $\odot$ denotes the Hadamard product. The LMMSE estimator of $\mathbf{w}$ is expressed as

$$\begin{aligned} \hat{\mathbf{w}}_{MMSE} &= \mathrm{E}\{\mathbf{w}\mathbf{d}_2^H\}(\mathrm{E}\{\mathbf{d}_2\mathbf{d}_2^H\})^{-1}\mathbf{d}_2 \\ &= \mathbf{R}_w\boldsymbol{\Lambda}\mathbf{C}^H\left(\mathbf{C}\boldsymbol{\Lambda}\mathbf{R}_w\boldsymbol{\Lambda}\mathbf{C}^H + \sigma_n^2\sum_i(\sigma_{hi}^2|\alpha_i|^2 + 1)\mathbf{I}\right)^{-1}\mathbf{d}_2, \end{aligned} \tag{2.29}$$

and the error covariance could also be obtained as

$$\mathrm{Cov}(\Delta\mathbf{w}) = \left(\mathbf{R}_w^{-1} + \frac{1}{\sigma_n^2\sum_i(\sigma_{hi}^2|\alpha_i|^2 + 1)}\boldsymbol{\Lambda}\mathbf{C}^H\mathbf{C}\boldsymbol{\Lambda}\right)^{-1}. \tag{2.30}$$

The optimal training should then be obtained from

$$\begin{aligned} \min_{\mathbf{A}_i, \mathbf{z}} \quad & \mathrm{tr}(\mathrm{Cov}(\Delta \mathbf{w})) \\ \text{s.t.} \quad & [\mathbf{C}^H \mathbf{C}]_{ii} \leq E_s, \; i = 1, \ldots, M. \end{aligned} \tag{2.31}$$

Remark. It is not difficult to see that the channel estimation as well as the corresponding training design in URS is quite different from the conventional point-to-point system since the insertion of relay node changes the whole transmitting configurations. One should try to recognize the "needed" channel for different schemes such that the estimation can be simplified and the resources consumed could be saved.

2.3 Challenges of Channel Estimation for PLNC

We have discussed the channel estimation in conventional point-to-point system as well as in URS in previous sections. Though the main difference between PLNC and URS is its bi-directional transmission, the channel estimation may, still, demonstrates much difference.

A typical PLNC model is presented in Fig. 2.2. We see that the channels from $\mathbb{T}_1$ to $\mathbb{R}$, denoted as $\mathbf{h}_1$, and that from $\mathbb{T}_2$ to $\mathbb{R}$, denoted as $\mathbf{h}_2$ can be estimated at $\mathbb{R}$ during the first phase, thanks to the simultaneous transmission from the two terminals. Most PLNC works focus on the TDD system that could save half of the bandwidth. Due to the reciprocity, the reverse channels from $\mathbb{R}$ to $\mathbb{T}_1$ and that from $\mathbb{R}$ to $\mathbb{T}_2$ remain $\mathbf{h}_1$ and $\mathbf{h}_2$, respectively. Based on these channel information, the relay node $\mathbb{R}$ could take on certain signal processing approach to optimize the overall performance of PLNC. Typical operations at $\mathbb{R}$ include

1. Beamforming design and power allocation [8];
2. Carrier permutation in an OFDM modulation [9].

Not like in URS, the task of channel estimation in PLNC should be obtaining the individual channels $\mathbf{h}_1$ and $\mathbf{h}_2$ at both $\mathbb{T}_1$ and $\mathbb{T}_2$ because of the following reasons:

Typically, the optimal operation at $\mathbb{R}$ varies according to the instant $\mathbf{h}_1$ and $\mathbf{h}_2$, while $\mathbb{T}_1$ and $\mathbb{T}_2$ must know the current signal operation at $\mathbb{R}$ in order to construct the overall "needed" channels. Hence, knowing $\mathbf{h}_1$ and $\mathbf{h}_2$ at $\mathbb{T}_1$ and $\mathbb{T}_2$ can help them predict the relay's operation and thus eliminates the necessity of the feedback channel.

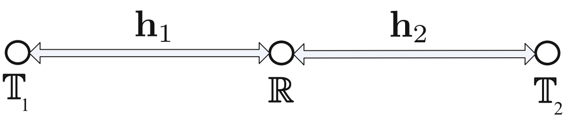

Fig. 2.2 An example of general PLNC system

The most trivial way to obtain $\mathbf{h}_1$ and $\mathbf{h}_2$ at $\mathbb{T}_1$ and $\mathbb{T}_2$ is to ask $\mathbb{R}$ to send separate training sequence. As the training sequence is usually embedded in the data frame, one may hesitate to apply this way since it is not compatible with the two-phase transmission structure. Hence, the key challenge of the channel estimation in PLNC is **how to achieve the individual channel knowledge of $\mathbf{h}_1$ and $\mathbf{h}_2$ within two-phase training**.

In the next three chapters, we will present novel channel estimation schemes as well as their corresponding training design for PLNC under three typical scenarios: frequency flat fading environment, frequency selective environment, and time selective environment. We will see how the channel estimation differs in PLNC from that in the conventional point-to-point system or even from the unidirectional relay system.

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