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I. Note Technique: CSI estimation in massive MIMO systems and pilot contamination for different kinds of receiver architectures

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1- Context and System:

We consider L cells, where each cell contains one base station equipped with M antennas and K single-antenna users. Assume that the L base stations share the same frequency band. We consider uplink transmission, where the l th base station receives signals from all users in all cells (Fig.1). Then, the $M \times 1$ received vector at the l th base station is given by:

$$\mathbf{y}_l = \sqrt{p_u} \sum_{i=1}^L \Gamma_{i,l} \mathbf{x}_i + \mathbf{n}_l \quad (1)$$

Where $\Gamma_{i,l}$ represents the $M \times K$ channel matrix between the l th base station and the K users in the i th cell, i.e., $[\Gamma_{i,l}]_{m,k}$ is the channel coefficient between the m th antenna of the l th base station and the k th user in the i th cell. $\sqrt{p_u} \mathbf{x}_i$ is the $K \times 1$ transmitted vector of K users in the i th cell (the average power used by each user is p_u) and \mathbf{n}_l contains $M \times 1$ additive white Gaussian noise (AWGN) samples. We assume that the elements of \mathbf{n}_l are Gaussian distributed with zero mean and variance: $\mathcal{E}[\mathbf{n}_l \mathbf{n}_l^H] = \sigma_{\mathbf{n}_l}^2 \mathbf{I}_M$ and $\mathcal{E}[\mathbf{n}_l^H \mathbf{n}_l] = M \sigma_{\mathbf{n}_l}^2$.

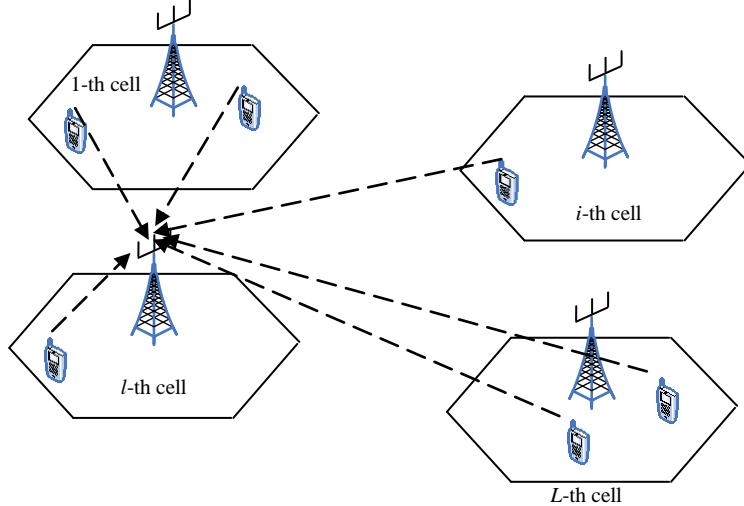


Fig. 1: Uplink transmission in multicell MU-MIMO system

2- Physical Channel Model:

Here, we introduce the finite-dimensional channel model that will be used throughout this technical note. The angular domain is divided into a large but finite number of directions P .

P is fixed regardless of the number of base station antennas ($P < M$). Each direction, corresponding to the angle: $\phi_k, \phi_k \in [-\pi/2, \pi/2], k = 1, \dots, P$, is associated with an $M \times 1$ array steering vector $\mathbf{a}(\phi_k)$ which is given by:

$$\mathbf{a}(\phi_k) = \frac{1}{\sqrt{P}} [e^{-j f_1(\phi_k)}, e^{-j f_2(\phi_k)}, \dots, e^{-j f_M(\phi_k)}]^T \quad (2)$$

Where $f_i(\phi)$ is some function of ϕ . Typically, for a regular phased array, we have:

$$f_i(\phi) = 2\pi \frac{d}{\lambda} (i-1) \sin(\phi)$$

The channel vector from k th user in the i th cell to the l th base station is then a linear combination of the steering vectors as follows: $\sum_{m=1}^P g_{ilk} \mathbf{a}(\phi_m)$, where g_{ilk} is the propagation coefficient from the k th user of the i th cell to the l th base station, associated with the physical direction m (direction of arrival ϕ_m). Let $\mathbf{G}_{i,l} \equiv [\mathbf{g}_{il1}, \dots, \mathbf{g}_{ilK}]$ be a $P \times K$ matrix with $\mathbf{g}_{ilk} \equiv [g_{ilk1}, \dots, g_{ilkP}]^T$ that contains the path gains from the k th user in the i th cell to the l th base station. The elements of $\mathbf{G}_{i,l}$ are assumed to be independent. Then, the $M \times K$ channel matrix between the l th base station and the K users in the i th cell is:

$$\boldsymbol{\Gamma}_{i,l} = \mathbf{A} \mathbf{G}_{i,l} \quad (3)$$

Where $\mathbf{A} \equiv [\mathbf{a}(\phi_1), \dots, \mathbf{a}(\phi_P)]$ is a full rank $M \times P$ matrix. The propagation channel $\mathbf{G}_{i,l}$ models independent fast fading, geometric attenuation, and log-normal shadow fading. Its elements g_{ilk} are given by:

$$g_{ilk} = h_{ilk} \sqrt{\beta_{ilk}} \quad m = 1, 2, \dots, P \quad (4)$$

Where h_{ilk} is a fast fading coefficient assumed to be zero mean and have unit variance. $\sqrt{\beta_{ilk}}$ models the path loss and shadowing which are assumed to be independent of the direction m and to be constant and known a priori. This assumption is reasonable since the value β_{ilk} changes very slowly with time. Then, we have:

$$\mathbf{G}_{i,l} = \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \quad (5)$$

Where $\mathbf{H}_{i,l}$ is the $P \times K$ matrix of fast fading coefficients between the K users in the i th cell and the l th base station, the columns $\mathbf{H}_{i,l}(:,k)$ are independent and we have:

$$\mathcal{E}\left[\mathbf{H}_{i,l}^H(:,k)\mathbf{H}_{i,l}(:,k)\right] = \mathcal{E}\left[\mathbf{h}_{ilk}^H\mathbf{h}_{ilk}\right] = \mathcal{E}\left[\sum_{m=1}^P|h_{il}(m,k)|^2\right] = \mathcal{E}\left[\sum_{m=1}^P|h_{ilkm}|^2\right] = 1$$

Furthermore within one given column we consider the elements: $h_{il}(m,k)$ independent, i.e.:

$\mathcal{E}[h_{ilkm} h_{ilkn}^*] = 0$ if $m \neq n$. $\mathbf{D}_{i,l}$ is a $K \times K$ diagonal matrix whose diagonal elements are given by $[\mathbf{D}_{i,l}]_{k,k} = \beta_{ilk}$. Therefore, (1) can be written as:

$$\mathbf{y}_l = \sqrt{p_u} \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{x}_i + \mathbf{n}_l = \sqrt{p_u} \mathbf{A} \sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \mathbf{x}_i + \mathbf{n}_l \quad (6)$$

In the following sections we will use the following intermediate parameters: $\beta_{jl} = \sum_{k=1}^K \beta_{jlk}$,

$$\bar{\beta}_{ln} = \sum_{i=1}^L \beta_{iln}, \text{ and } \hat{\beta}_l = \sum_{i=1}^L \beta_{il}.$$

3- Channel Estimation:

Channel estimation is performed by using training sequences received on the uplink. A part of the coherence interval is used for the uplink training. All users in all cells simultaneously transmit pilot sequences of length τ symbols. The assumption on synchronized transmission represents the worst case from the pilot contamination point of view, but it makes no fundamental difference to assume unsynchronized transmission. We assume that the same set of pilot sequences is used in all L cells. Therefore, the pilot sequences used in the l th cell can be represented by a $K \times \tau$ matrix $\sqrt{p_p} \boldsymbol{\phi}_l = \sqrt{p_p} \boldsymbol{\phi}$ ($\tau \geq K$), which satisfies $\boldsymbol{\phi} \boldsymbol{\phi}^H = \mathbf{I}_K$ where:

$p_p = \tau p_u$. From (6), the received pilot matrix at the l th base can be written as:

$$\mathbf{Y}_{p,l} = \sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \boldsymbol{\phi} + \mathbf{N}_l \quad (7)$$

\mathbf{N}_l is the resulting noise matrix of size $M \times \tau$ and of course we have: $\mathcal{E}[\mathbf{N}_l] = \mathbf{0}_{M \times \tau}$, $\mathcal{E}[\mathbf{N}_l \mathbf{N}_l^H] = \tau \sigma_n^2 \mathbf{I}_M$ and $\mathcal{E}[\mathbf{N}_l^H \mathbf{N}_l] = M \sigma_n^2 \mathbf{I}_\tau$.

3.1. Minimum Mean-Square Error (MMSE) Estimation:

We assume that the base station uses here MMSE estimation. The received pilot matrix $\mathbf{Y}_{p,l}$ is multiplied by $\boldsymbol{\phi}^H$ at the right side to obtain: $\tilde{\mathbf{Y}}_{p,l} = \mathbf{Y}_{p,l} \boldsymbol{\phi}^H$:

$$\begin{aligned}
\tilde{\mathbf{Y}}_{p,l} &= \mathbf{Y}_{p,l} \boldsymbol{\phi}^H \\
&= \sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} + \mathbf{N}_l \boldsymbol{\phi}^H \quad (8) \\
&= \sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} + \mathbf{W}_l
\end{aligned}$$

With: $\mathbf{W}_l = \mathbf{N}_l \boldsymbol{\phi}^H$. Since we consider here M -PSK modulation format for the transmit pilot matrix we can denote $\boldsymbol{\phi}$ as:

$$\boldsymbol{\phi} = \frac{1}{\sqrt{\tau}} \begin{bmatrix} e^{j\theta_{11}} & e^{j\theta_{12}} & \dots & e^{j\theta_{1p}} & \dots & e^{j\theta_{1r}} \\ e^{j\theta_{21}} & e^{j\theta_{22}} & \dots & e^{j\theta_{2p}} & \dots & e^{j\theta_{2r}} \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ e^{j\theta_{m1}} & e^{j\theta_{m2}} & \dots & e^{j\theta_{mp}} & \dots & e^{j\theta_{mr}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ e^{j\theta_{K1}} & e^{j\theta_{K2}} & \dots & e^{j\theta_{Kp}} & \dots & e^{j\theta_{Kr}} \end{bmatrix}$$

Hence, we have: $\boldsymbol{\phi}(k, m) = a_{k,m} = \frac{1}{\sqrt{\tau}} e^{j\theta_{k,m}}$ and $\boldsymbol{\phi}^H(n, k) = b_{n,k} = \frac{1}{\sqrt{\tau}} e^{-j\theta_{k,n}}$. The matrix product $\mathbf{N}_l \boldsymbol{\phi}^H$ yields:

$$\mathbf{N}_l \boldsymbol{\phi}^H(n, m) = \sum_{k=1}^{\tau} n_l(n, k) \boldsymbol{\phi}^H(k, m) = \frac{1}{\sqrt{\tau}} \sum_{k=1}^{\tau} n_l(n, k) e^{-j\theta_{m,k}}$$

In the same way we obtain:

$$\boldsymbol{\phi} \mathbf{N}_l^H(n, m) = \sum_{k=1}^{\tau} \boldsymbol{\phi}(n, k) n_l^*(m, k) = \frac{1}{\sqrt{\tau}} \sum_{k=1}^{\tau} n_l^*(m, k) e^{j\theta_{n,k}}$$

The matrix product: $\mathbf{W}_l \mathbf{W}_l^H = \mathbf{N}_l \boldsymbol{\phi}^H \mathbf{N}_l \boldsymbol{\phi} \mathbf{N}_l^H$ is thus equal to:

$$\begin{aligned}
\mathbf{N}_l \boldsymbol{\phi}^H \boldsymbol{\phi} \mathbf{N}_l^H(n, m) &= \sum_{k=1}^K \mathbf{N}_l \boldsymbol{\phi}^H(n, k) \boldsymbol{\phi} \mathbf{N}_l^H(k, m) \\
&= \sum_{k=1}^K \frac{1}{\sqrt{\tau}} \sum_{s=1}^{\tau} n_l(n, s) e^{-j\theta_{k,s}} \frac{1}{\sqrt{\tau}} \sum_{r=1}^{\tau} n_l^*(m, r) e^{j\theta_{k,r}} \\
&= \frac{1}{\tau} \sum_{k=1}^K \sum_{s=1}^{\tau} \sum_{r=1}^{\tau} n_l(n, s) n_l^*(m, r) e^{j(\theta_{k,r} - \theta_{k,s})}
\end{aligned}$$

Taking the expectation, we obtain:

$$\mathcal{E}\left[N_l \boldsymbol{\phi}^H \boldsymbol{\phi} N_l^H(n, m)\right] = \frac{1}{\tau} \sum_{k=1}^K \sum_{s=1}^\tau \sum_{r=1}^\tau \mathcal{E}\left[n_l(n, s) n_l^*(m, r)\right] e^{j(\theta_{k,r} - \theta_{k,s})}$$

Clearly, $\mathcal{E}\left[n_l(n, s) n_l^*(m, r)\right] = \sigma_{n_l}^2$ if and only if: $m=n$ and $r=s$. In these conditions we obtain:

$$\mathcal{E}\left[N_l \boldsymbol{\phi}^H \boldsymbol{\phi} N_l^H(n, n)\right] = \frac{1}{\tau} \sum_{k=1}^K \tau \sigma_{n_l}^2 = K \sigma_{n_l}^2$$

We eventually obtain : $\mathcal{E}\left[\mathbf{W}_l \mathbf{W}_l^H\right] = \mathcal{E}\left[N_l \boldsymbol{\phi}^H \boldsymbol{\phi} N_l^H\right] = K \sigma_{n_l}^2 \mathbf{I}_M$

Concerning the other quantity $\mathcal{E}\left[\mathbf{W}_l^H \mathbf{W}_l\right]$, we can obtain directly:

$$\mathcal{E}\left[\mathbf{W}_l^H \mathbf{W}_l\right] = \mathcal{E}\left[\boldsymbol{\phi} N_l^H N_l \boldsymbol{\phi}^H\right] = \boldsymbol{\phi} \mathcal{E}\left[N_l^H N_l\right] \boldsymbol{\phi}^H = M \sigma_{n_l}^2 \mathbf{I}_K$$

Remark : If we only consider one column (typically the n th column) of \mathbf{W}_l denoted as \mathbf{w}_{ln} , we have :

$$\mathcal{E}\left\{\mathbf{w}_{ln} \mathbf{w}_{ln}^H\right\} = \sigma_{n_l}^2 \mathbf{I}_M \text{ and } \mathcal{E}\left\{\mathbf{w}_{ln}^H \mathbf{w}_{ln}\right\} = M \sigma_{n_l}^2$$

We are now coming back to the channel estimation problem. Since $\mathbf{H}_{l,l}$ has independent columns, we can estimate each column of $\mathbf{H}_{l,l}$ independently. Let $\tilde{\mathbf{y}}_{pln}$ be the n th column of $\tilde{\mathbf{Y}}_{p,l}$. Then:

$$\tilde{\mathbf{y}}_{pln} = \sqrt{p_p} \mathbf{A} \mathbf{h}_{lln} \beta_{lln}^{1/2} + \sqrt{p_p} \mathbf{A} \sum_{i \neq l}^L \mathbf{h}_{iln} \beta_{iln}^{1/2} + \mathbf{w}_{ln} \quad (9)$$

Where \mathbf{h}_{iln} and \mathbf{w}_{ln} are the n th column of $\mathbf{H}_{i,l}$ and \mathbf{W}_l respectively. Denote by:

$\mathbf{z}_{ln} \equiv \sqrt{p_p} \mathbf{A} \sum_{i \neq l}^L \mathbf{h}_{iln} \beta_{iln}^{1/2} + \mathbf{w}_{ln}$, then the MMSE estimate of \mathbf{h}_{iln} is given by :

$$\hat{\mathbf{h}}_{lln} = \beta_{lln}^{1/2} \sqrt{p_p} \mathbf{A}^H (p_p \beta_{lln} \mathbf{A} \mathbf{A}^H + \mathbf{R}_{\mathbf{z}_{ln}})^{-1} \tilde{\mathbf{y}}_{pln} \quad (10)$$

$$\text{With: } \mathbf{R}_{\mathbf{z}_{ln}} = \mathcal{E}\left\{\mathbf{z}_{ln} \mathbf{z}_{ln}^H\right\} = p_p \mathbf{A} \mathbf{A}^H \sum_{i=1, i \neq l}^L \beta_{iln} + \sigma_{n_l}^2 \mathbf{I}_M \quad (11)$$

Reporting (11) into (10), we obtain:

$$\begin{aligned}\hat{\mathbf{h}}_{lln} &= \beta_{lln}^{1/2} \sqrt{p_p} \mathbf{A}^H \left(p_p \beta_{lln} \mathbf{A} \mathbf{A}^H + p_p \mathbf{A} \mathbf{A}^H \sum_{i=1, i \neq l}^L \beta_{iln} + \sigma_{n_l}^2 \mathbf{I}_M \right)^{-1} \tilde{\mathbf{y}}_{pln} \\ &= \beta_{lln}^{1/2} \sqrt{p_p} \mathbf{A}^H \left(p_p \mathbf{A} \mathbf{A}^H \sum_{i=1}^L \beta_{iln} + \sigma_{n_l}^2 \mathbf{I}_M \right)^{-1} \tilde{\mathbf{y}}_{pln}\end{aligned}$$

We can rewrite $\hat{\mathbf{h}}_{lln}$ in the following form :

$$\begin{aligned}\hat{\mathbf{h}}_{lln} &= \frac{\beta_{lln}^{1/2} \sqrt{p_p} \mathbf{A}^H}{\sigma_{n_l}^2} \left(\frac{p_p}{\sigma_{n_l}^2} \sum_{i=1}^L \beta_{iln} \mathbf{A} \mathbf{A}^H + \mathbf{I}_M \right)^{-1} \tilde{\mathbf{y}}_{pln} \\ &= \frac{\beta_{lln}^{1/2} \sqrt{p_p}}{\sigma_{n_l}^2} \mathbf{A}^H \left(\sqrt{\frac{p_p}{\sigma_{n_l}^2} \sum_{i=1}^L \beta_{iln}} \mathbf{A} \sqrt{\frac{p_p}{\sigma_{n_l}^2} \sum_{i=1}^L \beta_{iln} \mathbf{A}^H + \mathbf{I}_M} \right)^{-1} \tilde{\mathbf{y}}_{pln} \\ &= \left(\frac{\beta_{lln}^{1/2} \sqrt{p_p}}{\sigma_{n_l}^2} \sqrt{\frac{\sigma_{n_l}^2}{p_p \sum_{i=1}^L \beta_{iln}}} \right) \sqrt{\frac{p_p}{\sigma_{n_l}^2} \sum_{i=1}^L \beta_{iln}} \mathbf{A}^H \left(\sqrt{\frac{p_p}{\sigma_{n_l}^2} \sum_{i=1}^L \beta_{iln}} \mathbf{A} \sqrt{\frac{p_p}{\sigma_{n_l}^2} \sum_{i=1}^L \beta_{iln} \mathbf{A}^H + \mathbf{I}_M} \right)^{-1} \tilde{\mathbf{y}}_{pln} \\ &= \left(\frac{\beta_{lln}^{1/2}}{\sqrt{\sigma_{n_l}^2 \sum_{i=1}^L \beta_{iln}}} \right) \sqrt{\frac{p_p}{\sigma_{n_l}^2} \sum_{i=1}^L \beta_{iln}} \mathbf{A}^H \left(\sqrt{\frac{p_p}{\sigma_{n_l}^2} \sum_{i=1}^L \beta_{iln}} \mathbf{A} \sqrt{\frac{p_p}{\sigma_{n_l}^2} \sum_{i=1}^L \beta_{iln} \mathbf{A}^H + \mathbf{I}_M} \right)^{-1} \tilde{\mathbf{y}}_{pln}\end{aligned}$$

The former equation can be written: $\hat{\mathbf{h}}_{lln} = \lambda \mathbf{B}^H (\mathbf{B} \mathbf{B}^H + \mathbf{I}_M)^{-1} \tilde{\mathbf{y}}_{pln}$, with: $\mathbf{B} = \sqrt{\frac{p_p}{\sigma_{n_l}^2}} \sqrt{\sum_{i=1}^L \beta_{iln}} \mathbf{A}$,

and $\lambda = \frac{\beta_{lln}^{1/2}}{\sqrt{\sigma_{n_l}^2 \sum_{i=1}^L \beta_{iln}}}$. Using the matrix inversion lemma, we have:

$$\mathbf{P} (\mathbf{I}_m + \mathbf{Q} \mathbf{P})^{-1} = (\mathbf{I}_n + \mathbf{P} \mathbf{Q})^{-1} \mathbf{P}$$

With the following sizes for \mathbf{P} and \mathbf{Q} : $[\mathbf{Q}]_{m \times n}, [\mathbf{P}]_{n \times m}$. We use this lemma with: $\mathbf{P} = \mathbf{B}^H$, $\mathbf{Q} = \mathbf{B}$, we obtain: $\mathbf{B}^H (\mathbf{B} \mathbf{B}^H + \mathbf{I}_M)^{-1} = (\mathbf{I}_p + \mathbf{B}^H \mathbf{B})^{-1} \mathbf{B}^H$, so we eventually obtain:

$$\begin{aligned}
\hat{\mathbf{h}}_{lln} &= \frac{\beta_{lln}^{1/2}}{\sqrt{\sigma_{n_l}^2 \sum_{i=1}^L \beta_{iln}}} \left(\frac{p_p}{\sigma_{n_l}^2} \mathbf{A} \mathbf{A}^H \sum_{i=1}^L \beta_{iln} + \mathbf{I}_P \right)^{-1} \sqrt{\frac{p_p}{\sigma_{n_l}^2}} \sqrt{\sum_{i=1}^L \beta_{iln}} \mathbf{A}^H \tilde{\mathbf{y}}_{pln} \\
\hat{\mathbf{h}}_{lln} &= \frac{\sqrt{p_p} \beta_{lln}^{1/2}}{\sigma_{n_l}^2} \left(\frac{p_p}{\sigma_{n_l}^2} \mathbf{A} \mathbf{A}^H \sum_{i=1}^L \beta_{iln} + \mathbf{I}_P \right)^{-1} \mathbf{A}^H \tilde{\mathbf{y}}_{pln} \\
\hat{\mathbf{h}}_{lln} &= \sqrt{p_p} \beta_{lln}^{1/2} \left(p_p \mathbf{A} \mathbf{A}^H \sum_{i=1}^L \beta_{iln} + \sigma_{n_l}^2 \mathbf{I}_P \right)^{-1} \mathbf{A}^H \tilde{\mathbf{y}}_{pln}
\end{aligned} \tag{12}$$

The k th diagonal element of $p_p \mathbf{A} \mathbf{A}^H \sum_{i=1}^L \beta_{iln}$ in (12) equals: $\frac{Mp_p}{P} \sum_{i=1}^L \beta_{iln}$. Since the uplink is typically interference-limited we have: $\frac{Mp_p}{P} \sum_{i=1}^L \beta_{iln} \gg \sigma_{n_l}^2$, therefore, $\hat{\mathbf{h}}_{lln}$ can be approximated as:

$$\hat{\mathbf{h}}_{lln} = \beta_{lln}^{1/2} \sqrt{p_p} \left(p_p \mathbf{A} \mathbf{A}^H \sum_{i=1}^L \beta_{iln} \right)^{-1} \mathbf{A}^H \tilde{\mathbf{y}}_{pln} \tag{13}$$

Thus, the MMSE estimate of $\mathbf{H}_{l,l}$ is:

$$\hat{\mathbf{H}}_{l,l} = p_p^{-1/2} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll}^{1/2} \tag{14}$$

Where: $\mathbf{D}_l \equiv \sum_{i=1}^L \mathbf{D}_{il}$. Then, the estimate of the physical channel matrix between the l th base station and the K users in the l th cell is given by:

$$\hat{\Gamma}_{l,l} = \mathbf{A} \hat{\mathbf{H}}_{l,l} \mathbf{D}_{ll}^{1/2} = p_p^{-1/2} \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} \tag{15}$$

Where $\Pi_A \equiv \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H$ is the orthogonal projection onto \mathbf{A} . We can see that since post-multiplication of $\mathbf{Y}_{p,l}$ with ϕ^H means just multiplication with the pseudo-inverse ($\phi \phi^H = \mathbf{I}_K$), $\tilde{\mathbf{Y}}_{p,l}$ is the conventional least-squares channel estimate. The MMSE channel estimator that we derived thus performs conventional channel estimation and then projects the estimate onto the physical (beamspace) model for the array.

3.2. Bayesian estimator with MAP rule:

We start from equation (7):

$$\tilde{\mathbf{Y}}_{p,l} = \mathbf{Y}_{p,l} \phi^H = \sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} + \mathbf{W}_l$$

Let $\tilde{\mathbf{y}}_{pln}$ be the n th column of $\tilde{\mathbf{Y}}_{p,l}$. Then:

$$\tilde{\mathbf{y}}_{pln} = \sqrt{p_p} \mathbf{A} \mathbf{h}_{lln} \beta_{lln}^{1/2} + \sqrt{p_p} \mathbf{A} \sum_{i=1, i \neq l}^L \mathbf{h}_{iln} \beta_{iln}^{1/2} + \mathbf{w}_{ln} \quad (16)$$

Where \mathbf{h}_{iln} and \mathbf{w}_{ln} are the n th column of $\mathbf{H}_{i,l}$ and \mathbf{W}_l respectively. Denote by:

$z_{ln} \equiv \sqrt{p_p} \mathbf{A} \sum_{i \neq l}^L \mathbf{h}_{iln} \beta_{iln}^{1/2} + \mathbf{w}_{ln}$, we can write:

$$\tilde{\mathbf{y}}_{pln} = \sqrt{p_p} \mathbf{A} \mathbf{h}_{lln} \beta_{lln}^{1/2} + z_{ln} \quad (17)$$

Applying Bayes' rule, the conditional distribution of the channel \mathbf{h}_{lln} , given the observed received training signal $\tilde{\mathbf{y}}_{pln}$, is:

$$p(\mathbf{h}_{lln} | \tilde{\mathbf{y}}_{pln}) = \frac{p(\mathbf{h}_{lln}) p(\tilde{\mathbf{y}}_{pln} | \mathbf{h}_{lln})}{p(\tilde{\mathbf{y}}_{pln})} = p(\mathbf{h}_{lln}) p(\tilde{\mathbf{y}}_{pln} | \mathbf{h}_{lln}) \quad (18)$$

We use the Gaussian probability density function (PDF) of the random vector \mathbf{h}_{lln} and assume its elements: $h_{lln}(1), \dots, h_{lln}(i), \dots, h_{lln}(P)$, are mutually independent, giving the joint pdf :

$$p(\mathbf{h}_{lln}) = \frac{\exp[-\mathbf{h}_{lln}^H \mathbf{R}_{\mathbf{h}_{lln}}^{-1} \mathbf{h}_{lln}]}{(\sqrt{2\pi})^P \det \mathbf{R}_{\mathbf{h}_{lln}}} \quad (19)$$

Since the elements: $h_{lln}(1), \dots, h_{lln}(i), \dots, h_{lln}(P)$ are mutually independent this reduces to:

$$p(\mathbf{h}_{lln}) = \frac{\exp[-\mathbf{h}_{lln}^H \mathbf{h}_{lln}]}{(\sqrt{2\pi})^P} \quad (20)$$

We also have:

$$p(\tilde{\mathbf{y}}_{pln} | \mathbf{h}_{lln}) = \frac{\exp[-(\tilde{\mathbf{y}}_{pln} - \sqrt{p_p} \mathbf{A} \mathbf{h}_{lln} \beta_{lln}^{1/2})^H \mathbf{R}_{z_{ln}}^{-1} (\tilde{\mathbf{y}}_{pln} - \sqrt{p_p} \mathbf{A} \mathbf{h}_{lln} \beta_{lln}^{1/2})]}{\pi^P \det \mathbf{R}_{z_{ln}}} \quad (21)$$

Combining (20) and (21) and reporting into (18) we obtain:

$$p(\mathbf{h}_{lln} | \tilde{\mathbf{y}}_{pln}) = \frac{\exp(-f(\mathbf{h}_{lln}))}{(\sqrt{2\pi})^P \pi^P \det \mathbf{R}_{z_{ln}}} \quad (22)$$

With: $\mathbf{R}_{z_{ln}} = \mathbb{E} \left[(\sqrt{p_p} \mathbf{A} \sum_{i \neq l}^L \mathbf{h}_{iln} \beta_{iln}^{1/2} + \mathbf{w}_{ln}) (\sqrt{p_p} \mathbf{A} \sum_{i \neq l}^L \mathbf{h}_{iln} \beta_{iln}^{1/2} + \mathbf{w}_{ln})^H \right]$ and:
 $f(\mathbf{h}_{lln}) = \mathbf{h}_{lln}^H \mathbf{h}_{lln} + (\tilde{\mathbf{y}}_{pln} - \sqrt{p_p} \mathbf{A} \mathbf{h}_{lln} \beta_{lln}^{1/2})^H \mathbf{R}_{z_{ln}}^{-1} (\tilde{\mathbf{y}}_{pln} - \sqrt{p_p} \mathbf{A} \mathbf{h}_{lln} \beta_{lln}^{1/2})$

The ML estimation $\hat{\mathbf{h}}_{lln}$ of \mathbf{h}_{lln} is given by:

$$\begin{aligned}\hat{\mathbf{h}}_{lln} &= \arg \max_{\mathbf{h}_{lln} \in C^{P \times 1}} \exp(-f(\mathbf{h}_{lln})) \\ \hat{\mathbf{h}}_{lln} &= \arg \min_{\mathbf{h}_{lln} \in C^{P \times 1}} f(\mathbf{h}_{lln}) \\ \hat{\mathbf{h}}_{lln} &= \beta_{lln}^{1/2} \sqrt{p_p} \mathbf{A}^H \left(p_p \beta_{lln} \mathbf{A} \mathbf{A}^H + \mathbf{R}_{z_{ln}} \right)^{-1} \tilde{\mathbf{y}}_{pln}\end{aligned}\quad (23)$$

We have clearly:

$$\begin{aligned}\mathbf{R}_{z_{ln}} &= \mathbb{E} \left[(\sqrt{p_p} \mathbf{A} \sum_{i \neq l}^L \mathbf{h}_{iln} \beta_{iln}^{1/2} + \mathbf{w}_{ln}) (\sqrt{p_p} \mathbf{A} \sum_{i \neq l}^L \mathbf{h}_{iln} \beta_{iln}^{1/2} + \mathbf{w}_{ln})^H \right] \\ \mathbf{R}_{z_{ln}} &= \sigma_{n_l}^2 \mathbf{I}_M + p_p \sum_{i \neq l}^L \beta_{iln} \mathbf{A} \mathbf{A}^H\end{aligned}\quad (24)$$

And we find again:

$$\hat{\mathbf{h}}_{lln} = \beta_{lln}^{1/2} \sqrt{p_p} \mathbf{A}^H \left(p_p \mathbf{A} \mathbf{A}^H \sum_{i=1}^L \beta_{iln} + \sigma_{n_l}^2 \mathbf{I}_M \right)^{-1} \tilde{\mathbf{y}}_{pln} \quad (25)$$

To obtain (23) and (25) we have applied (39) and (40) (see Appendix) with: $\mathbf{R}_h = \mathbf{I}$, $\mathbf{R}_n = \mathbf{R}_{z_{ln}}$,
 $S = \sqrt{p_p} \beta_{lln}^{1/2} \mathbf{A}$.

3.3. Bayesian estimation with vectorized model:

We start from equation (8):

$$\begin{aligned}\tilde{\mathbf{Y}}_{p,l} &= \mathbf{Y}_{p,l} \boldsymbol{\phi}^* = \sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} + \mathbf{N}_l \boldsymbol{\phi}^* = \sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} + \mathbf{W}_l \\ \tilde{\mathbf{Y}}_{p,l} &= \sqrt{p_p} \mathbf{A} \mathbf{H}_{l,l} \mathbf{D}_{l,l}^{1/2} + \sqrt{p_p} \mathbf{A} \sum_{i \neq l}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} + \mathbf{W}_l\end{aligned}$$

Starting from this equation we begin by vectorizing the received matrix $\tilde{\mathbf{Y}}_{p,l}$ of size $M \times K$, we obtain the vector:

$$\tilde{\mathbf{y}}_{p,l} = \begin{pmatrix} \tilde{\mathbf{Y}}_{p,l}(:,1) \\ \vdots \\ \tilde{\mathbf{Y}}_{p,l}(:,k) \\ \vdots \\ \tilde{\mathbf{Y}}_{p,l}(:,K) \end{pmatrix}_{MK \times 1} \quad (26)$$

With:

$$\begin{aligned} \tilde{\mathbf{Y}}_{p,l}(:,k) &= \sqrt{p_p} \left[\mathbf{A} \mathbf{H}_{l,l} \mathbf{D}_{l,l}^{1/2} \right](:,k) + \sqrt{p_p} \left[\mathbf{A} \sum_{i \neq l}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \right](:,k) + \mathbf{W}_l(:,k) \\ \tilde{\mathbf{Y}}_{p,l}(:,k) &= \sqrt{p_p} \left[\mathbf{A} \mathbf{H}_{l,l} \mathbf{D}_{l,l}^{1/2} \right](:,k) + \mathbf{Z}_l(:,k) \end{aligned} \quad (27)$$

$$\text{With: } \mathbf{Z}_l(:,k) \equiv \sqrt{p_p} \left[\mathbf{A} \sum_{i \neq l}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \right](:,k) + \mathbf{W}_l(:,k)$$

Clearly, we have the property:

$$\left[\mathbf{A} \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \right](:,k) = \mathbf{A} \mathbf{H}_{i,l}(:,k) \beta_{ilk}^{1/2} \quad (28)$$

Applying Bayes' rule, the conditional distribution of the channel $\mathbf{H}_{l,l}(:,k)$ given the observed received training signal $\tilde{\mathbf{y}}_{p,l}$ is:

$$\begin{aligned} p(\mathbf{H}_{l,l}(:,k) | \tilde{\mathbf{Y}}_{p,l}(:,k)) \\ = \frac{p(\mathbf{H}_{l,l}(:,k)) p(\tilde{\mathbf{Y}}_{p,l}(:,k) | \mathbf{H}_{l,l}(:,k))}{p(\tilde{\mathbf{Y}}_{p,l}(:,k))} = p(\mathbf{H}_{l,l}(:,k)) p(\tilde{\mathbf{Y}}_{p,l}(:,k) | \mathbf{H}_{l,l}(:,k)) \end{aligned} \quad (29)$$

We use the Gaussian probability density function (pdf) of the random vector $\mathbf{H}_{l,l}(:,k)$ and assume its elements: $H_{l,l}(1,k), \dots, H_{l,l}(l,k), \dots, H_{l,l}(P,k)$ are mutually independent, giving the joint pdf:

$$p(\mathbf{H}_{l,l}(:,k)) = \frac{\exp[-\mathbf{H}_{l,l}^H(:,k) \mathbf{R}_{\mathbf{H}_{l,l}(:,k)}^{-1} \mathbf{H}_{l,l}^H(:,k)]}{(\sqrt{2\pi})^P \det \mathbf{R}_{\mathbf{H}_{l,l}(:,k)}} \quad (30)$$

Since the elements: $H_{l,l}(1,k), \dots, H_{l,l}(m,k), \dots, H_{l,l}(P,k)$ are mutually independent, this reduces to:

$$p(\mathbf{H}_{l,l}(:,k)) = \frac{\exp[-\mathbf{H}_{l,l}^H(:,k) \mathbf{H}_{l,l}^H(:,k)]}{(\sqrt{2\pi})^P} \quad (31)$$

We also have:

$$\begin{aligned} & p(\tilde{\mathbf{Y}}_{p,l}(:,k) | \mathbf{H}_{l,l}(:,k)) \\ &= \frac{\exp[-(\tilde{\mathbf{Y}}_{p,l}(:,k) - A\mathbf{H}_{l,l}(:,k)\beta_{llk}^{1/2})^H \mathbf{R}_{\mathbf{Z}_l(:,k)}^{-1} (\tilde{\mathbf{Y}}_{p,l}(:,k) - A\mathbf{H}_{l,l}(:,k)\beta_{llk}^{1/2})]}{(\pi)^P \det \mathbf{R}_{\mathbf{Z}_l(:,k)}} \end{aligned} \quad (32)$$

Combining (31) and (32) and reporting into (29) we obtain:

$$p(\mathbf{H}_{l,l}(:,k) | \tilde{\mathbf{Y}}_{p,l}(:,k)) = \frac{\exp(-f(\mathbf{H}_{l,l}(:,k)))}{AB} \quad (33)$$

Where: $A \equiv (\sqrt{2\pi})^P$, $B \equiv (\pi)^P \det \mathbf{R}_{\mathbf{Z}_l(:,k)}$, this yields :

$$\begin{aligned} & f(\mathbf{H}_{l,l}(:,k)) \\ & \equiv \mathbf{H}_{l,l}^H(:,k) \mathbf{H}_{l,l}^H(:,k) + (\tilde{\mathbf{Y}}_{p,l}(:,k) - A\mathbf{H}_{l,l}(:,k)\beta_{llk}^{1/2})^H \mathbf{R}_{\mathbf{Z}_l(:,k)}^{-1} (\tilde{\mathbf{Y}}_{p,l}(:,k) - A\mathbf{H}_{l,l}(:,k)\beta_{llk}^{1/2}) \end{aligned} \quad (34)$$

Using the maximum a posteriori (MAP) decision rule, the Bayesian estimator yields the most probable value of channel estimation given the observation: $\tilde{\mathbf{Y}}_{p,l}(:,k)$.

$$\begin{aligned} \hat{\mathbf{H}}_{l,l}^H(:,k) &= \arg \max_{\mathbf{H}_{l,l}^H(:,k)} p(\mathbf{H}_{l,l}(:,k) | \tilde{\mathbf{Y}}_{p,l}(:,k)) \\ \hat{\mathbf{H}}_{l,l}^H(:,k) &= \arg \min_{\mathbf{H}_{l,l}^H(:,k)} f(\mathbf{H}_{l,l}(:,k)) \\ \hat{\mathbf{H}}_{l,l}^H(:,k) &= \sqrt{p_p} \beta_{llk}^{1/2} \mathbf{A}^H (p_p \beta_{llk} \mathbf{A} \mathbf{A}^H + \mathbf{R}_{\mathbf{Z}_l(:,k)})^{-1} \tilde{\mathbf{Y}}_{p,l}(:,k) \end{aligned} \quad (35)$$

It is straightforward to show that (see equation (24)):

$$\mathbf{R}_{\mathbf{Z}_l(:,k)} = \sigma_{n_l}^2 \mathbf{I}_M + p_p \sum_{i \neq l}^L \beta_{ilk} \mathbf{A} \mathbf{A}^H \quad (36)$$

And we find again:

$$\hat{\mathbf{H}}_{l,l}(:,k) = \sqrt{p_p} \beta_{llk}^{1/2} \mathbf{A}^H (\sigma_{n_l}^2 \mathbf{I}_M + p_p \sum_{i=1}^L \beta_{ilk} \mathbf{A} \mathbf{A}^H)^{-1} \tilde{\mathbf{Y}}_{p,l}(:,k) \quad (37)$$

Reminder Appendix 1:

If we have the following equivalent model:

$$\mathbf{y} = \mathbf{Sh} + \mathbf{n} \quad (38)$$

With the following pdf :

$$p(\mathbf{h}|\mathbf{y}) = \frac{\exp(-l(\mathbf{h}))}{K}$$

$$l(\mathbf{h}) = \mathbf{h}^H \mathbf{R}_h^{-1} \mathbf{h} + (\mathbf{y} - \mathbf{Sh})^H \mathbf{R}_n^{-1} (\mathbf{y} - \mathbf{Sh}) \quad (39)$$

The Bayesian estimator yields the most probable value given the observation \mathbf{y} and this yields:

$$\hat{\mathbf{h}} = \mathbf{R}_h S^H (\mathbf{R}_n + \mathbf{R}_h S S^H)^{-1} \mathbf{y} \quad (40)$$

4- Uplink Data Transmission:

We consider the context of an uplink transmission where the base station uses the channel estimates to perform signal processing techniques such as MRC (Maximum Ratio Combining), ZF (Zero Forcing) or MMSE (Minimum Mean Square Error).

4.1. Maximum Ratio Combining:

In this case the l th base station processes the received signal by multiplying it by the conjugate transpose (Hermitian) of the channel estimate. From (6) and (14), we obtain:

$$\begin{aligned} \mathbf{r}_l &= \hat{\boldsymbol{\Gamma}}_{ll}^H \mathbf{y}_l \\ &= p_p^{-1/2} \mathbf{D}_{ll} \mathbf{D}_l^{-1} \left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} + \mathbf{W}_l \right)^H \boldsymbol{\Pi}_A \left(\sqrt{p_u} \mathbf{A} \sum_{j=1}^L \mathbf{H}_{j,l} \mathbf{D}_{j,l}^{1/2} \mathbf{x}_j + \mathbf{n}_l \right) \end{aligned} \quad (41)$$

With: $\boldsymbol{\Pi}_A \equiv \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H$

Remark : $\boldsymbol{\Pi}_A^H \equiv \left[\mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \right]^H = \mathbf{A} \left[(\mathbf{A}^H \mathbf{A})^{-1} \right]^H \mathbf{A}^H = \mathbf{A} \left[(\mathbf{A}^H \mathbf{A})^{-1} \right] \mathbf{A}^H = \boldsymbol{\Pi}_A$

To further proceed with (41) we directly suppose that we operate with a huge number of antennas, i.e. we suppose that M grows towards infinity. We simplify first the quantity: $\boldsymbol{\Pi}_A$; to do this we consider the case of a uniform array. The response vector is thus given by:

$$\mathbf{a}(\phi_k) = \frac{1}{\sqrt{P}} \left[1, e^{-j2\pi d \sin(\phi_k)/\lambda}, \dots, e^{-j2\pi(M-1)d \sin(\phi_k)/\lambda} \right]^T \quad (42)$$

d is the antenna spacing between radiating elements and λ is the wavelength. Then, we have, for $k \neq l$:

$$\begin{aligned} \frac{1}{M} \mathbf{a}(\phi_k)^H \mathbf{a}(\phi_l) &= \frac{1}{MP} \sum_{m=0}^{M-1} e^{j2\pi d m (\sin(\phi_k) - \sin(\phi_l)) / \lambda} \\ &= \frac{1}{MP} \frac{1 - e^{j2\pi d M (\sin(\phi_k) - \sin(\phi_l)) / \lambda}}{1 - e^{j2\pi d (\sin(\phi_k) - \sin(\phi_l)) / \lambda}} \\ &= \frac{1}{P} e^{j2\pi d (M-1) (\sin(\phi_k) - \sin(\phi_l)) / \lambda} \left[\frac{\sin(\pi d M (\sin(\phi_k) - \sin(\phi_l)) / \lambda)}{M \sin(\pi d (\sin(\phi_k) - \sin(\phi_l)) / \lambda)} \right] \end{aligned} \quad (43)$$

From (43) it is clear that, for $k \neq l$: $\lim_{M \rightarrow \infty} \frac{1}{M} \mathbf{a}(\phi_k)^H \mathbf{a}(\phi_l) = 0$

For $k = l$, we have immediately, $\lim_{M \rightarrow \infty} \frac{1}{M} \mathbf{a}(\phi_l)^H \mathbf{a}(\phi_l) = 1/P$. Therefore, we deduce:

$$\lim_{M \rightarrow \infty} \frac{1}{M} \mathbf{A}^H \mathbf{A} = \frac{1}{P} \mathbf{I}_P. \text{ Furthermore, we have: } \lim_{M \rightarrow \infty} \text{Trace} [\mathbf{A}^H \mathbf{A}] = \frac{M}{P} P = M.$$

Using this property, we can write:

$$\mathbf{\Pi}_A \equiv \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \approx_{M \rightarrow \infty} \mathbf{A} \left(\frac{M}{P} \mathbf{I}_P \right)^{-1} \mathbf{A}^H = \frac{P}{M} \mathbf{A} \mathbf{A}^H \quad (44)$$

Remark: In the general case, we have:

$$\begin{aligned} \mathbf{A}^H \mathbf{A} &= \frac{1}{\sqrt{P}} \begin{bmatrix} e^{-jf_1(\phi_1)} & e^{-jf_1(\phi_2)} & \dots & e^{-jf_1(\phi_P)} \\ e^{-jf_2(\phi_1)} & e^{-jf_2(\phi_2)} & \dots & e^{-jf_2(\phi_P)} \\ \vdots & \vdots & \ddots & \vdots \\ e^{-jf_M(\phi_1)} & e^{-jf_M(\phi_2)} & \dots & e^{-jf_M(\phi_P)} \end{bmatrix} \\ &= \frac{1}{\sqrt{P}} \begin{bmatrix} e^{jf_1(\phi_1)} & e^{jf_2(\phi_1)} & \dots & e^{jf_M(\phi_1)} \\ e^{jf_1(\phi_2)} & e^{jf_2(\phi_2)} & \dots & e^{jf_M(\phi_2)} \\ \vdots & \vdots & \ddots & \vdots \\ e^{jf_1(\phi_P)} & e^{jf_2(\phi_P)} & \dots & e^{jf_M(\phi_P)} \end{bmatrix} = \frac{1}{P} \begin{bmatrix} M & \sum_{i=1}^M e^{j(f_i(\phi_1) - f_i(\phi_2))} & \dots & \sum_{i=1}^M e^{j(f_i(\phi_1) - f_i(\phi_P))} \\ \sum_{i=1}^M e^{j(f_i(\phi_2) - f_i(\phi_1))} & M & \dots & \sum_{i=1}^M e^{j(f_i(\phi_2) - f_i(\phi_P))} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^M e^{j(f_i(\phi_P) - f_i(\phi_1))} & \sum_{i=1}^M e^{j(f_i(\phi_P) - f_i(\phi_2))} & \dots & M \end{bmatrix} \end{aligned}$$

Concerning the product: $\mathbf{A} \mathbf{A}^H$, we obtain:

$$\mathbf{A} \mathbf{A}^H = \frac{1}{\sqrt{P}} \begin{bmatrix} e^{-jf_1(\phi_1)} & e^{-jf_1(\phi_2)} & \dots & e^{-jf_1(\phi_p)} \\ e^{-jf_2(\phi_1)} & e^{-jf_2(\phi_2)} & \dots & e^{-jf_2(\phi_p)} \\ \vdots & \vdots & \ddots & \vdots \\ e^{-jf_M(\phi_1)} & e^{-jf_M(\phi_2)} & \dots & e^{-jf_M(\phi_p)} \end{bmatrix} = \frac{1}{P} \begin{bmatrix} P & \sum_{i=1}^P e^{j(f_2(\phi_i) - f_1(\phi_i))} & \dots & \sum_{i=1}^P e^{j(f_M(\phi_i) - f_1(\phi_i))} \\ \sum_{i=1}^P e^{j(f_1(\phi_i) - f_2(\phi_i))} & P & \dots & \sum_{i=1}^P e^{j(f_M(\phi_i) - f_2(\phi_i))} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^P e^{j(f_1(\phi_i) - f_M(\phi_i))} & \sum_{i=1}^P e^{j(f_1(\phi_i) - f_2(\phi_i))} & \dots & P \end{bmatrix}$$

So, the term $\mathbf{A} \mathbf{A}^H(m, n)$ is equal to (in the case of a linear phased array):

$$\mathbf{A} \mathbf{A}^H(m, n) = \frac{1}{P} \sum_{i=1}^P e^{j(f_n(\phi_i) - f_m(\phi_i))} = \frac{1}{P} \sum_{i=1}^P e^{j2\pi((n-1)\sin(\phi_i) - (m-1)\sin(\phi_i))/\lambda}$$

$$\mathbf{A} \mathbf{A}^H(m, n) = \frac{1}{P} \sum_{i=1}^P e^{j2\pi((n-m)\sin(\phi_i))/\lambda}$$

A coarse approximation of matrix $\mathbf{A} \mathbf{A}^H$ in the case where $P \rightarrow \infty$ could be: $\mathbf{A} \mathbf{A}^H \approx \mathbf{I}_M$.

Using (43) and (44) into (41) and the fact that as $M \rightarrow \infty$ the products of uncorrelated quantities can be ignored [5], we have:

$$\frac{\mathbf{r}_l}{\sqrt{p_u} M} \xrightarrow{M \rightarrow \infty} \mathbf{D}_{ll} \mathbf{D}_l^{-1} \left(\sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \right)^H \frac{\mathbf{A}^H \mathbf{A}}{M} \left(\sum_{j=1}^L \mathbf{H}_{j,l} \mathbf{D}_{j,l}^{1/2} \mathbf{x}_j \right) \quad (45)$$

Then, using: $\lim_{M \rightarrow \infty} \frac{1}{M} \mathbf{A}^H \mathbf{A} = \frac{1}{P} \mathbf{I}_P$, it is straightforward to obtain :

$$\frac{\mathbf{r}_l}{\sqrt{p_u} M} \xrightarrow{M \rightarrow \infty} \frac{1}{P} \mathbf{D}_{ll} \mathbf{D}_l^{-1} \left(\sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \right)^H \left(\sum_{j=1}^L \mathbf{H}_{j,l} \mathbf{D}_{j,l}^{1/2} \mathbf{x}_j \right) \quad (46)$$

The interpretation of (46) is quite simple: since the elements of $\mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2}$ are independent, the above result reveals that the performance of the system under the finite-dimensional channel model with P angular bins and with an unlimited number of base station antennas is the same as the performance under an uncorrelated channel model with P antennas.

4.2. Analysis of the Pilot Contamination effect:

To gain further insight into the pilot contamination effect, we derive lower bounds on the achievable rate for a finite and an infinite number of base station antennas (the analysis requires that $M>P$). To obtain these lower bounds we use the techniques of [3,4,6]. We assume an uniform array at the base station, and the elements of $\mathbf{H}_{i,l}$ are i.i.d Gaussian random variables. Let r_{ln} be the n th element of the received $K \times 1$ vector \mathbf{r}_l and denote

$\tilde{r}_{ln} \equiv r_{ln} \sqrt{p_p} \sum_{i=1}^L \beta_{iln} / \beta_{lln}$, we deduce from (41) that:

$$\tilde{r}_{ln} = \left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{g}_{iln} + \mathbf{w}_{ln} \right)^H \boldsymbol{\Pi}_A \left(\sqrt{p_u} \mathbf{A} \sum_{j=1}^L \mathbf{G}_{j,l} \mathbf{x}_j + \mathbf{n}_l \right) \quad (47)$$

Remember that we have: $\mathbf{G}_{j,l} \equiv [\mathbf{g}_{j,l1}, \dots, \mathbf{g}_{j,lK}]$ which is a $P \times K$ matrix with: $\mathbf{g}_{j,lk} \equiv [g_{j,lk1}, \dots, g_{j,lkP}]^T$ which is a vector that contains the path gains from the k th user in the i th cell to the l th base station. Equation (47) can be rewritten as:

$$\begin{aligned} \tilde{r}_{ln} &= \left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{g}_{iln} + \mathbf{w}_{ln} \right)^H \boldsymbol{\Pi}_A \left(\sqrt{p_u} \mathbf{A} \sum_{j=1}^L \mathbf{G}_{j,l} \mathbf{x}_j + \mathbf{n}_l \right) \\ &= \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H + \mathbf{w}_{ln}^H \right) \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \left(\sqrt{p_u} \mathbf{A} \sum_{j=1}^L \mathbf{G}_{j,l} \mathbf{x}_j + \mathbf{n}_l \right) \\ &= \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H + \mathbf{w}_{ln}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \right) \left(\sqrt{p_u} \mathbf{A} \sum_{j=1}^L \mathbf{G}_{j,l} \mathbf{x}_j + \mathbf{n}_l \right) \quad (48) \\ &= \sqrt{p_p p_u} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \sum_{j=1}^L \mathbf{G}_{j,l} \mathbf{x}_j + \sqrt{p_u} \mathbf{w}_{ln}^H \mathbf{A} \sum_{j=1}^L \mathbf{G}_{j,l} \mathbf{x}_j + \sqrt{p_p} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{n}_l + \mathbf{w}_{ln}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{n}_l \end{aligned}$$

Equation (48) is eventually equivalent to:

$$\tilde{r}_{ln} = \boldsymbol{\alpha}_{ln}^T \mathbf{x}_l + \sum_{j \neq l}^L \boldsymbol{\alpha}_{jn}^T \mathbf{x}_j + z_{ln} \quad (49)$$

With: $\boldsymbol{\alpha}_{jn}^T \equiv \sqrt{p_p p_u} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} + \sqrt{p_u} \mathbf{w}_{ln}^H \mathbf{A} \mathbf{G}_{j,l}$ and $z_{ln} = (\sqrt{p_p} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H + \mathbf{w}_{ln}^H) \boldsymbol{\Pi}_A \mathbf{n}_l$

We have:

$$\mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\} \equiv \sqrt{p_p p_u} \mathcal{E}\{\mathbf{g}_{lln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{lln}\} \mathbf{e}_n^T \quad (50)$$

Where \mathbf{e}_n is the n th column of the $K \times K$ identity matrix. By adding and subtracting $\mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\}$ into (49) and using (50) we obtain:

$$\begin{aligned}
\tilde{r}_{ln} &= \mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\} \mathbf{x}_l + (\boldsymbol{\alpha}_{ln}^T - \mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\}) \mathbf{x}_l + \sum_{j \neq l}^L \boldsymbol{\alpha}_{jn}^T \mathbf{x}_j + z_{ln} \\
&= \sqrt{p_p p_u} \mathcal{E}\{\mathbf{g}_{lln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{lln}\} x_{ln} + (\boldsymbol{\alpha}_{ln}^T - \mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\}) \mathbf{x}_l + \sum_{j \neq l}^L \boldsymbol{\alpha}_{jn}^T \mathbf{x}_j + z_{ln}
\end{aligned} \tag{51}$$

Let define the function $C(x)$ as: $C(x) = \log_2(1 + x)$, the n th user in the l th cell can achieve an uplink rate of at least:

$$R_{ln} = C \left(\frac{p_p p_u |\mathcal{E}\{\mathbf{g}_{lln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{lln}\}|^2}{\sum_{j=1}^L \mathcal{E}\{\|\boldsymbol{\alpha}_{jn}^T\|^2\} - \|\mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\}\|^2 + \mathcal{E}\{|z_{ln}|^2\}} \right) \tag{52}$$

In this case, the achievable uplink rate of the n th user in the l th cell in (52) can be lower bounded by (60) since we have:

$$\begin{aligned}
\|\mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\}\|^2 &= \|\sqrt{p_p p_u} \mathcal{E}\{\mathbf{g}_{lln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{lln}\} \mathbf{e}_n^T\|^2 \\
&= p_p p_u \text{Trace}[\mathcal{E}\{\mathbf{g}_{lln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{lln}\} \mathbf{e}_n^T \mathbf{e}_n \mathcal{E}\{\mathbf{g}_{lln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{lln}\}] \\
&= p_p p_u [\mathcal{E}\{\mathbf{g}_{lln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{lln}\}]^2 \text{Trace}[\mathbf{e}_n^T \mathbf{e}_n] \\
&= p_p p_u [\mathcal{E}\{\mathbf{g}_{lln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{lln}\}]^2
\end{aligned}$$

We study the product $\mathbf{g}_{lln}^H \mathbf{A}^H$ by considering only one column of matrix: \mathbf{A}^H , we have :

$$\mathbf{A} \equiv [\mathbf{a}(\phi_1), \dots, \mathbf{a}(\phi_P)] = \frac{1}{\sqrt{P}} \begin{bmatrix} e^{-jf_1(\phi_1)} & e^{-jf_1(\phi_2)} & \dots & e^{-jf_1(\phi_P)} \\ e^{-jf_2(\phi_1)} & e^{-jf_2(\phi_2)} & \dots & e^{-jf_2(\phi_P)} \\ \vdots & \vdots & \ddots & \vdots \\ e^{-jf_M(\phi_1)} & e^{-jf_M(\phi_2)} & \dots & e^{-jf_M(\phi_P)} \end{bmatrix}$$

Hence, we obtain:

$$\mathbf{g}_{lln}^H \mathbf{A}^H(:,k) = \frac{1}{\sqrt{P}} [g_{lln1}^*, \dots, g_{llnP}^*] \begin{bmatrix} e^{jf_k(\phi_1)} \\ e^{jf_k(\phi_2)} \\ \vdots \\ e^{jf_k(\phi_P)} \end{bmatrix} = \frac{1}{\sqrt{P}} \sum_{j=1}^P g_{llnj}^* e^{jf_k(\phi_j)}$$

In this case, we obtain:

$$\mathbf{g}_{lln}^H \mathbf{A}^H = \frac{1}{\sqrt{P}} \left[\sum_{j=1}^P g_{lln,j}^* e^{j f_1(\phi_j)}, \dots, \sum_{j=1}^P g_{lln,j}^* e^{j f_k(\phi_j)}, \dots, \sum_{j=1}^P g_{lln,j}^* e^{j f_M(\phi_j)} \right]_{1 \times M}$$

And it is straightforward to calculate:

$$\begin{aligned} & \mathcal{E}\{\mathbf{g}_{lln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{lln}\} \\ &= \frac{1}{P} \mathcal{E}\left\{ \left(\sum_{j=1}^P g_{lln,j}^* e^{j f_1(\phi_j)} \right) \left(\sum_{j=1}^P g_{lln,j} e^{-j f_1(\phi_j)} \right) + \dots + \left(\sum_{j=1}^P g_{lln,j}^* e^{j f_M(\phi_j)} \right) \left(\sum_{j=1}^P g_{lln,j} e^{-j f_M(\phi_j)} \right) \right\} \quad (53) \\ &= \frac{M}{P} \sum_{j=1}^P \mathcal{E}\left[|g_{lln,j}|^2 \right] = \frac{M}{P} \sum_{j=1}^P \mathcal{E}\left[\beta_{lln} |h_{lln,j}|^2 \right] = \frac{M}{P} \beta_{lln} \sum_{j=1}^P \mathcal{E}\left[|h_{lln,j}|^2 \right] = \frac{M}{P} \beta_{lln} \end{aligned}$$

Hence, we obtain:

$$[\mathcal{E}\{\mathbf{g}_{lln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{lln}\}]^2 = \frac{M^2}{P^2} \beta_{lln}^2 \quad (54)$$

- Concerning: $\mathcal{E}\{|z_{ln}|^2\}$, we have :

$$\begin{aligned} \mathcal{E}\{|z_{ln}|^2\} &= \mathcal{E}\left\{ \left| \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H + \mathbf{w}_{ln}^H \right) \boldsymbol{\Pi}_A \mathbf{n}_l \right|^2 \right\} \\ &= \mathcal{E}\left\{ \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H + \mathbf{w}_{ln}^H \right) \boldsymbol{\Pi}_A \mathbf{n}_l \mathbf{n}_l^H \boldsymbol{\Pi}_A^H \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{A} \mathbf{g}_{iln} + \mathbf{w}_{ln}^H \right) \right\} \\ &= \mathcal{E}\left\{ \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H + \mathbf{w}_{ln}^H \right) \boldsymbol{\Pi}_A \mathcal{E}\left[\mathbf{n}_l \mathbf{n}_l^H \right] \boldsymbol{\Pi}_A^H \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{A} \mathbf{g}_{iln} + \mathbf{w}_{ln}^H \right) \right\} \\ &= \mathcal{E}\left\{ \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H + \mathbf{w}_{ln}^H \right) \boldsymbol{\Pi}_A \sigma_{\mathbf{n}_l}^2 \mathbf{I}_M \boldsymbol{\Pi}_A^H \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{A} \mathbf{g}_{iln} + \mathbf{w}_{ln}^H \right) \right\} \\ &= \sigma_{\mathbf{n}_l}^2 \mathcal{E}\left\{ \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H + \mathbf{w}_{ln}^H \right) \boldsymbol{\Pi}_A \boldsymbol{\Pi}_A^H \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{A} \mathbf{g}_{iln} + \mathbf{w}_{ln}^H \right) \right\} \\ &= \sigma_{\mathbf{n}_l}^2 \mathcal{E}\left\{ \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H + \mathbf{w}_{ln}^H \right) \boldsymbol{\Pi}_A \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{A} \mathbf{g}_{iln} + \mathbf{w}_{ln}^H \right) \right\} \end{aligned}$$

Remark :

$$\begin{aligned} \boldsymbol{\Pi}_A \boldsymbol{\Pi}_A^H &= \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \left[\mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \right]^H \\ &= \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \\ &= \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H = \boldsymbol{\Pi}_A \end{aligned}$$

We use the independency of columns \mathbf{g}_{iln} and \mathbf{g}_{jln} , i.e.: $\mathcal{E}[\mathbf{g}_{iln}^H \mathbf{g}_{jln}] = 0$, for $i \neq j$.

$$\begin{aligned}\mathcal{E}\left\{|z_{ln}|^2\right\} &= \sigma_{n_l}^2 \left\{ \mathcal{E}\left[p_p \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{g}_{iln} \right] + \mathcal{E}\left[\mathbf{w}_{ln}^H \boldsymbol{\Pi}_A \boldsymbol{\Pi}_A^H \mathbf{w}_{ln} \right] \right\} \\ &= \sigma_{n_l}^2 \left\{ \mathcal{E}\left[p_p \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{A} \mathbf{g}_{iln} \right] + \mathcal{E}\left[\mathbf{w}_{ln}^H \boldsymbol{\Pi}_A \mathbf{w}_{ln} \right] \right\} \\ &= \sigma_{n_l}^2 \left\{ \mathcal{E}\left[p_p \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{iln} \right] + \mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{w}_{ln} \right] \right\}\end{aligned}$$

Due to (53), we have :

$$\mathcal{E}\left\{\mathbf{g}_{ln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{ln}\right\} = \frac{M}{P} \beta_{ln}$$

The singular value decomposition of matrix $(\mathbf{A}^H \mathbf{A})^{-1}$ yields :

$$(\mathbf{A}^H \mathbf{A})^{-1} = \mathbf{U} \mathbf{D} \mathbf{U}^H$$

\mathbf{D} is a diagonal matrix which can be written as: $\mathbf{D} = \text{diag}[\lambda_1, \lambda_2, \dots, \lambda_k, \dots, \lambda_p]$ with $\lambda_i = 1/\beta_i$, $i = 1, \dots, P$ designing the eigenvalues of matrix $\mathbf{A}^H \mathbf{A}$. Thus, we have:

$$\mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{w}_{ln} \right] = \mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{A} \mathbf{U} \mathbf{D} \mathbf{U}^H \mathbf{A}^H \mathbf{w}_{ln} \right] = \mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{A} \mathbf{U} \mathbf{D} [\mathbf{w}_{ln}^H \mathbf{A} \mathbf{U}]^H \right]$$

We have:

$$\begin{aligned}\mathbf{w}_{ln}^H \mathbf{A} &= \frac{1}{\sqrt{P}} [w_{ln}^*(1), w_{ln}^*(2), \dots, w_{ln}^*(M)] \begin{bmatrix} e^{-jf_1(\phi_1)} & e^{-jf_1(\phi_2)} & \dots & e^{-jf_1(\phi_P)} \\ e^{-jf_2(\phi_1)} & e^{-jf_2(\phi_2)} & \dots & e^{-jf_2(\phi_P)} \\ \vdots & \vdots & \ddots & \vdots \\ e^{-jf_M(\phi_1)} & e^{-jf_M(\phi_2)} & \dots & e^{-jf_M(\phi_P)} \end{bmatrix} \\ &= \frac{1}{\sqrt{P}} [w_{ln}^*(1)e^{-jf_1(\phi_1)} + \dots + w_{ln}^*(M)e^{-jf_M(\phi_1)}, \dots, w_{ln}^*(1)e^{-jf_1(\phi_P)} + \dots + w_{ln}^*(M)e^{-jf_M(\phi_P)}]\end{aligned}$$

Hence, the k th column of matrix $\mathbf{w}_{ln}^H \mathbf{A} \mathbf{U}$ is thus written as:

$$\begin{aligned}&(\mathbf{w}_{ln}^H \mathbf{A} \mathbf{U})(:,k) \\ &= \frac{1}{\sqrt{P}} \left[\sum_{m=1}^P U(m, k) \sum_{i=1}^M w_{ln}^*(i) e^{-jf_i(\phi_m)} \right]\end{aligned}$$

In these conditions we have:

$$\begin{aligned}
& \mathcal{E} \left[(\mathbf{w}_{ln}^H \mathbf{A} \mathbf{U})(:,k) \mathbf{D} (\mathbf{w}_{ln}^H \mathbf{A} \mathbf{U})^H (:,k) \right] \\
&= \frac{1}{P} \mathcal{E} \left[\sum_{m=1}^P U(m,k) \sum_{i=1}^M w_{ln}^*(i) e^{-j f_i(\phi_m)} \lambda_k \sum_{p=1}^P U^*(p,k) \sum_{j=1}^M w_{ln}(j) e^{j f_j(\phi_p)} \right] \\
&= \frac{1}{P} \left[\lambda_k \sum_{m=1}^P U(m,k) \sum_{p=1}^P U^*(p,k) \mathcal{E} \left[\sum_{i=1}^M w_{ln}^*(i) e^{-j f_i(\phi_m)} \sum_{j=1}^M w_{ln}(j) e^{j f_j(\phi_p)} \right] \right] \\
&= \frac{1}{P} \left[\lambda_k \sum_{m=1}^P U(m,k) \sum_{p=1}^P U^*(p,k) \sum_{j=1}^M \sum_{i=1}^M \mathcal{E} [w_{ln}^*(i) w_{ln}(j)] e^{j f_j(\phi_p)} e^{-j f_i(\phi_m)} \right] \\
&= \frac{1}{P} \left[\lambda_k \sum_{m=1}^P U(m,k) \sum_{p=1}^P U^*(p,k) \sum_{i=1}^M \sigma_{n_l}^2 e^{j[f_i(\phi_p) - f_i(\phi_m)]} \right] \\
&= \frac{\lambda_k \sigma_{n_l}^2}{P} \sum_{m=1}^P U(m,k) \sum_{p=1}^P U^*(p,k) \sum_{i=1}^M e^{j[f_i(\phi_p) - f_i(\phi_m)]}
\end{aligned}$$

And we eventually obtain:

$$\mathcal{E} \left[\mathbf{w}_{ln}^H \mathbf{A} \mathbf{U} \mathbf{D} [\mathbf{w}_{ln}^H \mathbf{A} \mathbf{U}]^H \right] = \frac{\sigma_{n_l}^2}{P} \sum_{k=1}^P \sum_{p=1}^P \sum_{m=1}^M \sum_{i=1}^M \lambda_k U(m,k) U^*(p,k) e^{j[f_i(\phi_p) - f_i(\phi_m)]} \quad (55)$$

Concerning: $\mathcal{E} \{ |z_{ln}|^2 \}$, this yields :

$$\begin{aligned}
\mathcal{E} \{ |z_{ln}|^2 \} &= \frac{\sigma_{n_l}^2 M}{P} p_p \sum_{i=1}^L \beta_{iln} + \frac{\sigma_{n_l}^2}{P} \sum_{k=1}^P \sum_{p=1}^P \sum_{m=1}^M \sum_{i=1}^M \lambda_k U(m,k) U^*(p,k) e^{j[f_i(\phi_p) - f_i(\phi_m)]} \\
\mathcal{E} \{ |z_{ln}|^2 \} &= \frac{M \sigma_{n_l}^2}{P} \left(p_p \sum_{i=1}^L \beta_{iln} + \frac{\sigma_{n_l}^2}{M} \sum_{k=1}^P \sum_{p=1}^P \sum_{m=1}^M \sum_{i=1}^M \lambda_k U(m,k) U^*(p,k) e^{j[f_i(\phi_p) - f_i(\phi_m)]} \right) \quad (56) \\
\mathcal{E} \{ |z_{ln}|^2 \} &= \frac{M \sigma_{n_l}^2}{P} \left(p_p \bar{\beta}_{ln} + \frac{\sigma_{n_l}^2}{M} \sum_{k=1}^P \sum_{p=1}^P \sum_{m=1}^M \sum_{i=1}^M \lambda_k U(m,k) U^*(p,k) e^{j[f_i(\phi_p) - f_i(\phi_m)]} \right)
\end{aligned}$$

Using the notation: $S_{U^2(:,k)}^{f_i} \equiv \sum_{p=1}^P \sum_{m=1}^M U(m,k) U^*(p,k) e^{j[f_i(\phi_p) - f_i(\phi_m)]}$, we obtain :

$$\mathcal{E} \{ |z_{ln}|^2 \} = \frac{M \sigma_{n_l}^2}{P} \left(p_p \bar{\beta}_{ln} + \frac{\sigma_{n_l}^2}{M} \sum_{k=1}^P S_{U^2(:,k)}^{f_i} \right) \quad (57)$$

Remark: in the case of a uniform array, we have:

$$f_i(\phi_p) = \frac{2\pi(i-1)d}{\lambda} \sin(\phi_p)$$

And we obtain:

$$\mathcal{E}\left\{|z_{ln}|^2\right\} = \frac{M\sigma_{n_l}^2}{P} \left(p_p \bar{\beta}_{ln} + \frac{\sigma_{n_l}^2}{M} \sum_{k=1}^P \sum_{p=1}^P \sum_{m=1}^M \sum_{i=1}^M \lambda_k U(m, k) U^*(p, k) e^{\frac{j2\pi(i-1)d}{\lambda} [\sin(\phi_p) - \sin(\phi_m)]} \right) \quad (58)$$

Remark: Using Lemma 1(Eq. (59)), it is possible to obtain a simpler expression. We have:

$$\begin{aligned} & \mathcal{E}\left[\mathbf{w}_{ln}^H \Pi_A \Pi_A^H \mathbf{w}_{ln}\right] \\ &= \frac{1}{M} \text{Trace}\left[\Pi_A \Pi_A^H\right] \mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{w}_{ln}\right] \\ &= \frac{1}{M} \text{Trace}\left[\Pi_A \Pi_A^H\right] M\sigma_{n_l}^2 \quad (\text{see (59)}) \\ &= \sigma_{n_l}^2 \text{Trace}\left[\Pi_A\right] \end{aligned}$$

To proceed further on with this expression, we need to calculate:

$$\begin{aligned} \text{Trace}\left[\Pi_A\right] &= \text{Trace}\left[A(A^H A)^{-1} A^H\right] \\ &\approx_{M \rightarrow \infty} \frac{P}{M} \text{Trace}\left[A A^H\right] = \frac{P}{M} M = P \end{aligned}$$

And, hence we obtain:

$$\mathcal{E}\left\{|z_{ln}|^2\right\}_{M \rightarrow \infty} = \sigma_{n_l}^2 \left(p_p \frac{M}{P} \bar{\beta}_{ln} + \sigma_{n_l}^2 P \right) \quad (58)$$

- Concerning: $\mathcal{E}\left(\|\boldsymbol{\alpha}_{jn}^T\|^2\right)$, we have:

$$\begin{aligned} & \mathcal{E}\left(\|\boldsymbol{\alpha}_{jn}^T\|^2\right) = \mathcal{E}\left(\boldsymbol{\alpha}_{jn}^T \boldsymbol{\alpha}_{jn}^*\right) \\ &= \mathcal{E}\left(\left(\sqrt{p_p p_u} \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} + \sqrt{p_u} \mathbf{w}_{ln}^H \mathbf{A} \mathbf{G}_{j,l}\right) \left(\sqrt{p_p p_u} \sum_{m=1}^L \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{mln}^H + \sqrt{p_u} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{w}_{ln}\right)\right) \\ &= p_p p_u \mathcal{E}\left(\sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \sum_{m=1}^L \mathbf{A}^H \mathbf{A} \mathbf{g}_{mln}^H\right) + p_u \mathcal{E}\left(\mathbf{w}_{ln}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{w}_{ln}\right) \\ &= p_p p_u \mathcal{E}\left(\sum_{i=1, i \neq j}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \mathcal{E}\left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H\right] \sum_{m=1}^L \mathbf{A}^H \mathbf{A} \mathbf{g}_{mln}^H\right) + p_p p_u \mathcal{E}\left(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln}\right) \\ &\quad + p_u \mathcal{E}\left(\mathbf{w}_{ln}^H \mathbf{A} \mathcal{E}\left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H\right] \mathbf{A}^H \mathbf{w}_{ln}\right) \end{aligned}$$

Concerning the product: $\mathbf{G}_{j,l}\mathbf{G}_{j,l}^H$, we have:

$$\mathbf{G}_{j,l}\mathbf{G}_{j,l}^H = \begin{bmatrix} g_{jl11}^* & g_{jl12}^* & \cdots & g_{jl1k}^* & \cdots & g_{jl1P}^* \\ g_{jl21}^* & g_{jl22}^* & \cdots & g_{jl2k}^* & \cdots & g_{jl2P}^* \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ g_{jlm1}^* & g_{jlm2}^* & \cdots & g_{jlmk}^* & \cdots & g_{jlmP}^* \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ g_{jIK1}^* & g_{jIK2}^* & \cdots & g_{jIKk}^* & \cdots & g_{jIKP}^* \end{bmatrix} \begin{bmatrix} \sum_{k=1}^K |g_{jlk1}|^2 & \sum_{k=1}^K g_{jlk1} g_{jlk2}^* & \cdots & \sum_{k=1}^K g_{jlk1} g_{jlkM}^* & \cdots & \sum_{k=1}^K g_{jlk1} g_{jlkP}^* \\ \sum_{k=1}^K g_{jlk2} g_{jlk1}^* & \sum_{k=1}^K |g_{jlk2}|^2 & \cdots & \sum_{k=1}^K g_{jlk2} g_{jlkM}^* & \cdots & \sum_{k=1}^K g_{jlk2} g_{jlkP}^* \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \sum_{k=1}^K g_{jlkM} g_{jlk1}^* & \sum_{k=1}^K g_{jlkM} g_{jlk2}^* & \cdots & \sum_{k=1}^K |g_{jlkM}|^2 & \cdots & \sum_{k=1}^K g_{jlkM} g_{jlkP}^* \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \sum_{k=1}^K g_{jlkP} g_{jlk1}^* & \sum_{k=1}^K g_{jlkP} g_{jlk2}^* & \cdots & \sum_{k=1}^K g_{jlkP} g_{jlkM}^* & \cdots & \sum_{k=1}^K |g_{jlkP}|^2 \end{bmatrix}$$

So, we obtain:

$$\mathcal{E}[\mathbf{G}_{j,l}\mathbf{G}_{j,l}^H] = \text{diag} \left[\mathcal{E} \left[\sum_{k=1}^K |g_{jlk1}|^2 \right], \mathcal{E} \left[\sum_{k=1}^K |g_{jlk2}|^2 \right], \dots, \mathcal{E} \left[\sum_{k=1}^K |g_{jlkM}|^2 \right], \dots, \mathcal{E} \left[\sum_{k=1}^K |g_{jlkP}|^2 \right] \right]$$

With:

$$\mathcal{E} \left[\sum_{k=1}^K |g_{jlkM}|^2 \right] = \sum_{k=1}^K \beta_{jlk} \mathcal{E} \left[|h_{jlkM}|^2 \right]$$

Thus :

$$\mathcal{E}[\mathbf{G}_{j,l}\mathbf{G}_{j,l}^H] = \text{diag} \left[\sum_{k=1}^K \beta_{jlk} \mathcal{E} \left[|h_{jlk1}|^2 \right], \sum_{k=1}^K \beta_{jlk} \mathcal{E} \left[|h_{jlk2}|^2 \right], \dots, \sum_{k=1}^K \beta_{jlk} \mathcal{E} \left[|h_{jlkM}|^2 \right], \dots, \sum_{k=1}^K \beta_{jlk} \mathcal{E} \left[|h_{jlkP}|^2 \right] \right]$$

Then, we use the following lemma:

Lemma 1: If we consider a given complex random vector \mathbf{V} of size $K \times 1$ with i.i.d random variables of variance σ^2 and a complex deterministic matrix \mathbf{W} of size $K \times M$, then we have:

$$\begin{aligned} & \mathcal{E}[\mathbf{V}^H \mathbf{W} \mathbf{W}^H \mathbf{V}] \\ &= \frac{1}{K} \mathcal{E}[\mathbf{V}^H \mathbf{V}] \text{Trace}(\mathbf{W} \mathbf{W}^H) \quad (59) \end{aligned}$$

Proof:

We take \mathbf{V} as: $\mathbf{V} = \begin{pmatrix} d_1 \\ d_2 \\ \vdots \\ d_K \end{pmatrix}$ and \mathbf{W} as: $\mathbf{W} = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} & \cdots & w_{1M} \\ w_{21} & w_{22} & \vdots & w_{2n} & \cdots & w_{2M} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ w_{p1} & w_{p2} & \cdots & w_{pn} & \cdots & w_{pM} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{K1} & w_{K2} & \cdots & w_{Kn} & \cdots & w_{KM} \end{pmatrix}$, in these

conditions, we have :

$$\mathbf{V}^H \mathbf{W}$$

$$= \begin{pmatrix} d_1^* & d_2^* & \cdots & d_m^* & \cdots & d_K^* \end{pmatrix} = \begin{pmatrix} \sum_{k=1}^K w_{k1} d_k^* & \sum_{k=1}^K w_{k2} d_k^* & \cdots & \sum_{k=1}^K w_{km} d_k^* & \cdots & \sum_{k=1}^K w_{kM} d_k^* \end{pmatrix}$$

And, we have:

$$\begin{aligned} & \mathcal{E}[\mathbf{V}^H \mathbf{W} \mathbf{W}^H \mathbf{V}] \\ &= \mathcal{E}\left(\left|\sum_{k=1}^K w_{k1} d_k^*\right|^2 + \left|\sum_{k=1}^K w_{k2} d_k^*\right|^2 + \cdots + \left|\sum_{k=1}^K w_{km} d_k^*\right|^2 + \cdots + \left|\sum_{k=1}^K w_{kM} d_k^*\right|^2\right) \\ &= \sum_{k=1}^K |w_{k1}|^2 \mathcal{E}[|d_k^*|^2] + \sum_{k=1}^K |w_{k2}|^2 \mathcal{E}[|d_k^*|^2] + \cdots + \sum_{k=1}^K |w_{km}|^2 \mathcal{E}[|d_k^*|^2] + \cdots + \sum_{k=1}^K |w_{kM}|^2 \mathcal{E}[|d_k^*|^2] \\ &= \sigma^2 \left[\sum_{k=1}^K |w_{k1}|^2 + |w_{k2}|^2 + \cdots + |w_{km}|^2 + \cdots + |w_{kM}|^2 \right] \\ &= \frac{1}{K} \mathcal{E}[\mathbf{V}^H \mathbf{V}] \text{Trace}(\mathbf{W} \mathbf{W}^H) \end{aligned}$$

Remark: It is possible to generalize this lemma to the case of a random matrix \mathbf{V} of size $K \times M$, and with a matrix \mathbf{W} of size $K \times P$. We still have:

$$\begin{aligned} & \mathbb{E}[V^H W W^H V] \\ &= \frac{1}{K} \mathbb{E}[V^H V] \text{Trace}(W W^H) \end{aligned}$$

We take V as:

$$V = \begin{pmatrix} d_{11} & d_{12} & \cdots & d_{1m} & \cdots & d_{1M} \\ d_{21} & d_{22} & \cdots & d_{2m} & \cdots & d_{2M} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ d_{k1} & d_{k2} & \cdots & d_{km} & \cdots & d_{kM} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ d_{K1} & d_{K2} & \cdots & d_{Km} & \cdots & d_{KM} \end{pmatrix} \quad \text{and} \quad W \quad \text{as:}$$

$W = \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} & \cdots & w_{1P} \\ w_{21} & w_{22} & \vdots & w_{2n} & \cdots & w_{2P} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} & \cdots & w_{nP} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{K1} & w_{K2} & \cdots & w_{Kn} & \cdots & w_{KP} \end{pmatrix}$, in these conditions we have:

$$\begin{aligned} & V^H W \\ &= \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} & \cdots & w_{1P} \\ w_{21} & w_{22} & \vdots & w_{2n} & \cdots & w_{2P} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} & \cdots & w_{nP} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{K1} & w_{K2} & \cdots & w_{Kn} & \cdots & w_{KP} \end{pmatrix} \\ &= \begin{pmatrix} d_{11}^* & d_{21}^* & \cdots & d_{k1}^* & \cdots & d_{K1}^* \\ d_{12}^* & d_{22}^* & \cdots & d_{k2}^* & \cdots & d_{K2}^* \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ d_{1m}^* & d_{2m}^* & \cdots & d_{km}^* & \cdots & d_{Km}^* \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ d_{1M}^* & d_{2M}^* & \cdots & d_{kM}^* & \cdots & d_{KM}^* \end{pmatrix} \Rightarrow V^H W(m, n) = \sum_{k=1}^K d_{km}^* w_{kn} = a_{m,n} \end{aligned}$$

The general term of matrix $V^H W W^H V$ is thus written as:

$$V^H W W^H V(m, n) = \sum a_{m,k} b_{k,n} = \sum_{k=1}^M a_{m,k} a_{n,k}^* = \sum_{k=1}^M \left(\sum_{j=1}^K d_{jm}^* w_{jk} \right) \left(\sum_{i=1}^K d_{in} w_{ik}^* \right)$$

Hence, we obtain :

$$\mathbb{E}[\mathbf{V}^H \mathbf{W} \mathbf{W}^H \mathbf{V}(m, n)] = \sum_{k=1}^M \mathbb{E}\left[\left(\sum_{j=1}^K d_{jm}^* w_{jk}\right) \left(\sum_{i=1}^K d_{in} w_{ik}^*\right)\right] = \sum_{k=1}^M \sum_i \sum_j \mathbb{E}[d_{jm}^* d_{in}] w_{jk} w_{ik}^*$$

Clearly, we have: $\mathbb{E}[d_{jm}^* d_{in}] = \sigma^2$ if $i = j$ and $m = n$, otherwise $\mathbb{E}[d_{jm}^* d_{in}] = 0$. Hence we obtain:

$$\mathbb{E}[\mathbf{V}^H \mathbf{W} \mathbf{W}^H \mathbf{V}] = \text{Diag}[\sigma^2 \text{Trace}(\mathbf{W} \mathbf{W}^H), \dots, \sigma^2 \text{Trace}(\mathbf{W} \mathbf{W}^H)] = \frac{1}{K} \mathbb{E}[\mathbf{V}^H \mathbf{V}] \text{Trace}(\mathbf{W} \mathbf{W}^H)$$

$$\mathbf{V}^H \mathbf{V}$$

$$= \begin{pmatrix} d_{11} & d_{12} & \cdots & d_{1n} & \cdots & d_{1M} \\ d_{21} & d_{22} & \ddots & d_{2n} & \cdots & d_{2M} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nn} & \cdots & d_{nM} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ d_{K1} & d_{K2} & \cdots & d_{Kn} & \cdots & d_{KM} \end{pmatrix} \\ = \begin{pmatrix} d_{11}^* & d_{21}^* & \cdots & d_{k1}^* & \cdots & d_{K1}^* \\ d_{12}^* & d_{22}^* & \cdots & d_{k2}^* & \cdots & d_{K2}^* \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ d_{1m}^* & d_{2m}^* & \cdots & d_{km}^* & \cdots & d_{Km}^* \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ d_{1M}^* & d_{2M}^* & \cdots & d_{kM}^* & \cdots & d_{KM}^* \end{pmatrix} \Rightarrow \mathbf{V}^H \mathbf{V}(n, n) = \sum_{k=1}^K d_{kn}^* d_{kn}$$

Hence:

$$\mathbb{E}[\mathbf{V}^H \mathbf{V}(n, n)] = K\sigma^2$$

And: $\mathbb{E}[\mathbf{V}^H \mathbf{V}] = K\sigma^2 \mathbf{I}_K$ End of proof.

Using this lemma here, we obtain:

$$\begin{aligned}
& \mathcal{E} \left(\sum_{i=1, i \neq j}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \mathcal{E} [\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H] \sum_{m=1}^L \mathbf{A}^H \mathbf{A} \mathbf{g}_{mln} \right) \\
& = \frac{1}{P} \text{Trace} \left[\mathcal{E} [\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H] \right] \sum_{i=1, i \neq j}^L \mathcal{E} [\mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \mathbf{A}^H \mathbf{A} \mathbf{g}_{iln}] \\
& = \frac{1}{P^2} \left(\sum_{i=1, i \neq j}^L \mathcal{E} [\mathbf{g}_{iln}^H \mathbf{g}_{iln}] \right) \text{Trace} \left[(\mathbf{A}^H \mathbf{A}) (\mathbf{A}^H \mathbf{A}) \right] \text{Trace} \left[\mathcal{E} [\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H] \right] \\
& = \frac{1}{P^2} \left(\sum_{i=1, i \neq j}^L \mathcal{E} [\mathbf{g}_{iln}^H \mathbf{g}_{iln}] \right) \text{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] \text{Trace} \left[\mathcal{E} [\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H] \right] \\
& \text{Trace} \left[\mathcal{E} [\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H] \right] \\
& = \text{Trace} \left[\text{diag} \left[\sum_{k=1}^K \beta_{jlk} \mathcal{E} [|h_{jlk1}|^2], \sum_{k=1}^K \beta_{jlk} \mathcal{E} [|h_{jlk2}|^2], \dots, \sum_{k=1}^K \beta_{jlk} \mathcal{E} [|h_{jlk m}|^2], \dots, \sum_{k=1}^K \beta_{jlk} \mathcal{E} [|h_{jlk P}|^2] \right] \right] \\
& = \sum_{k=1}^K \beta_{jlk} \mathcal{E} \left[\sum_{m=1}^P |h_{jlk m}|^2 \right] \\
& = \sum_{k=1}^K \beta_{jlk} = \beta_{jl}
\end{aligned}$$

Hence:

$$\begin{aligned}
& \mathcal{E} \left(\sum_{i=1, i \neq j}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \mathcal{E} [\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H] \sum_{m=1}^L \mathbf{A}^H \mathbf{A} \mathbf{g}_{mln} \right) \\
& = \frac{1}{P^2} \left(\sum_{i=1, i \neq j}^L \mathcal{E} [\mathbf{g}_{iln}^H \mathbf{g}_{iln}] \right) \text{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] \beta_{jl}
\end{aligned}$$

And, using:

$$\sum_{i=1, i \neq j}^L \mathcal{E} [\mathbf{g}_{iln}^H \mathbf{g}_{iln}] = \sum_{i=1, i \neq j}^L \sum_{m=1}^P \mathcal{E} [|g_{ilm m}|^2] = \sum_{i=1, i \neq j}^L \beta_{iln} \sum_{m=1}^P \mathcal{E} [|h_{ilm m}|^2] = \sum_{i=1, i \neq j}^L \beta_{iln}$$

We eventually obtain:

$$\begin{aligned}
& \mathcal{E} \left(\sum_{i=1, i \neq j}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \mathcal{E} [\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H] \sum_{m=1}^L \mathbf{A}^H \mathbf{A} \mathbf{g}_{mln} \right) \quad (60) \\
& = \frac{1}{P^2} \text{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] \beta_{jl} \sum_{i=1, i \neq j}^L \beta_{iln}
\end{aligned}$$

Using the approximation: $\lim_{M \rightarrow \infty} \frac{1}{M} \mathbf{A}^H \mathbf{A} = \frac{1}{P} \mathbf{I}_P$, we obtain:

$$\begin{aligned}
& \lim_{M \rightarrow \infty} \mathcal{E} \left(\sum_{i=1, i \neq j}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \mathcal{E} [\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H] \sum_{m=1}^L \mathbf{A}^H \mathbf{A} \mathbf{g}_{mln} \right) \\
& = \frac{M^2}{P^3} \beta_{jl} \sum_{i=1, i \neq j}^L \beta_{iln} = \frac{M^2 \beta_{jl} \sum_{i=1, i \neq j}^L \beta_{iln}}{P^3}
\end{aligned} \tag{61}$$

Concerning the term: $\mathcal{E}(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln})$, we have:

$$\begin{aligned}
& \mathcal{E}(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln}) \\
& = \mathcal{E} \left(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \sum_{p=1}^K \mathbf{G}_{j,l}(:,p) \mathbf{G}_{j,l}^H(:,p) \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln} \right) \\
& = \mathcal{E} \left(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \sum_{p=1}^K \mathbf{g}_{jlp} \mathbf{g}_{jlp}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln} \right) \\
& = \mathcal{E} \left(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \sum_{p=1, p \neq n}^K \mathbf{g}_{jlp} \mathbf{g}_{jlp}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln} \right) + \mathcal{E} \left(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln} \mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln} \right)
\end{aligned} \tag{62}$$

For $p \neq n$ we have:

$$\begin{aligned}
& \mathcal{E}(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jlp} \mathbf{g}_{jlp}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln}) \\
& = \mathcal{E}(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathcal{E}[\mathbf{g}_{jlp} \mathbf{g}_{jlp}^H] \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln}) \\
& = \frac{1}{P} \text{Trace}[\mathcal{E}[\mathbf{g}_{jlp} \mathbf{g}_{jlp}^H]] \mathcal{E}[\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln}] \\
& = \frac{1}{P^2} \mathcal{E}[\mathbf{g}_{jln}^H \mathbf{g}_{jln}] \text{Trace}[(\mathbf{A}^H \mathbf{A})(\mathbf{A}^H \mathbf{A})] \text{Trace}[\mathcal{E}[\mathbf{g}_{jlp} \mathbf{g}_{jlp}^H]] \\
& = \frac{1}{P^2} \mathcal{E}[\mathbf{g}_{jln}^H \mathbf{g}_{jln}] \text{Trace}[(\mathbf{A}^H \mathbf{A})^2] \text{Trace}[\mathcal{E}[\mathbf{g}_{jlp} \mathbf{g}_{jlp}^H]]
\end{aligned}$$

With:

$$\text{Trace}[\mathcal{E}[\mathbf{g}_{jlp} \mathbf{g}_{jlp}^H]] = \mathcal{E}\left[\left|\mathbf{g}_{jlp1}\right|^2 + \left|\mathbf{g}_{jlp2}\right|^2 + \cdots + \left|\mathbf{g}_{jlpP}\right|^2\right] = \beta_{jlp}$$

So:

$$\begin{aligned}
& \mathcal{E}(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jlp} \mathbf{g}_{jlp}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln}) \\
& = \frac{1}{P^2} \mathcal{E}[\mathbf{g}_{jln}^H \mathbf{g}_{jln}] \text{Trace}[(\mathbf{A}^H \mathbf{A})^2] \beta_{jlp} \tag{63} \\
& = \frac{1}{P^2} \text{Trace}[(\mathbf{A}^H \mathbf{A})^2] \beta_{jlp} \beta_{jln}
\end{aligned}$$

And:

$$\begin{aligned}
& \mathcal{E} \left(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \sum_{p=1, p \neq n}^K \mathbf{g}_{jlp} \mathbf{g}_{jlp}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln} \right) \\
&= \frac{1}{P^2} \operatorname{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] \beta_{jln} \sum_{p=1, p \neq n}^K \beta_{jlp} \\
&= \frac{1}{P^2} \operatorname{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] \beta_{jln} \sum_{p=1}^K \beta_{jlp} - \frac{1}{P^2} \operatorname{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] \beta_{jln}^2 \quad (64) \\
&= \frac{1}{P^2} \operatorname{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] \beta_{jln} \beta_{jl} - \frac{1}{P^2} \operatorname{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] \beta_{jln}^2 \\
&= \frac{1}{P^2} \operatorname{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] (\beta_{jln} \beta_{jl} - \beta_{jln}^2)
\end{aligned}$$

The only term we have to evaluate now is:

$$\begin{aligned}
& \mathcal{E} \left(\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln} \mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln} \right) \\
&= \mathcal{E} \left([\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln}]^2 \right)
\end{aligned}$$

We have:

$$\begin{aligned}
& \mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln} \\
&= \frac{1}{P} \left\{ \left(\sum_{m=1}^P g_{jlnm}^* e^{j f_1(\phi_m)} \right) \left(\sum_{m=1}^P g_{jlnk} e^{-j f_1(\phi_k)} \right) + \dots + \left(\sum_{m=1}^P g_{jlnm}^* e^{j f_M(\phi_m)} \right) \left(\sum_{m=1}^P g_{jlnk} e^{-j f_M(\phi_k)} \right) \right\} \\
&= \frac{1}{P} \left\{ \sum_k \sum_m g_{jlnm}^* g_{jlnk} e^{j[f_1(\phi_m) - f_1(\phi_k)]} + \dots + \sum_k \sum_m g_{jlnm}^* g_{jlnk} e^{j[f_M(\phi_m) - f_M(\phi_k)]} \right\} \\
&= \frac{1}{P} \left\{ A_{m,k}^1 + A_{m,k}^2 + \dots + A_{m,k}^M \right\}
\end{aligned}$$

$$\text{With : } A_{m,k}^r = \sum_k \sum_m g_{jlnm}^* g_{jlnk} e^{j[f_r(\phi_m) - f_r(\phi_k)]}$$

And:

$$\begin{aligned}
& [\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln}]^2 \\
&= \frac{1}{P^2} \left[(A_{m,k}^1)^2 + (A_{m,k}^2)^2 + \dots + (A_{m,k}^M)^2 + \sum_r \sum_t A_{m,k}^r A_{m,k}^t \right]
\end{aligned}$$

We have:

$$\begin{aligned}
\mathcal{E}\left[\left(A_{m,k}^n\right)^2\right] &= \mathcal{E}\left[\left(\sum_k \sum_m g_{jlnm}^* g_{jlnk} e^{j[f_n(\phi_m) - f_n(\phi_k)]}\right)\left(\sum_s \sum_t g_{jlns}^* g_{jlns} e^{j[f_n(\phi_s) - f_n(\phi_t)]}\right)\right] \\
&= \mathcal{E}\left[\left(\sum_k \sum_m \sum_s \sum_t g_{jlnm}^* g_{jlnk} g_{jlns}^* g_{jlns} e^{j[f_n(\phi_m) - f_n(\phi_k) + f_n(\phi_s) - f_n(\phi_t)]}\right)\right] \\
&= \sum_k \sum_m \sum_s \sum_t \mathcal{E}\left[g_{jlnm}^* g_{jlnk} g_{jlns}^* g_{jlns} e^{j[f_n(\phi_m) - f_n(\phi_k) + f_n(\phi_s) - f_n(\phi_t)]}\right] \\
&= \sum_k \sum_s \mathcal{E}\left[|g_{jlnk}|^2\right] \mathcal{E}\left[|g_{jlns}|^2\right] \\
&= \beta_{jln}^2
\end{aligned}$$

Then, we have to calculate:

$$\begin{aligned}
\mathcal{E}\left[A_{m,k}^r A_{m,k}^t\right] &= \mathcal{E}\left[\left(\sum_k \sum_m g_{jlnm}^* g_{jlnk} e^{j[f_r(\phi_m) - f_r(\phi_k)]}\right)\left(\sum_s \sum_p g_{jlns}^* g_{jlnp} e^{j[f_t(\phi_s) - f_t(\phi_p)]}\right)\right] \\
&= \sum_k \sum_m \sum_s \sum_p \mathcal{E}\left[g_{jlnm}^* g_{jlnk} g_{jlns}^* g_{jlnp} e^{j[f_r(\phi_m) - f_r(\phi_k) + f_t(\phi_s) - f_t(\phi_p)]}\right] \\
&= \sum_k \sum_m \mathcal{E}\left[g_{jlnm}^* g_{jlnk}\right] \mathcal{E}\left[g_{jlns}^* g_{jlns}\right] \\
&= \beta_{jln}^2
\end{aligned}$$

With these approximations, we obtain:

$$\begin{aligned}
&\mathcal{E}\left[\mathbf{g}_{jln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{jln}\right]^2 \\
&\approx \frac{1}{P^2} \left[M \beta_{jln}^2 + M^2 \beta_{jln}^2 \right] \quad (65) \\
&= \frac{M(M+1)\beta_{jln}^2}{P^2}
\end{aligned}$$

In the same manner we obtain:

$$\begin{aligned}
&\mathcal{E}\left(\mathbf{w}_{ln}^H \mathbf{A} \mathcal{E}\left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H\right] \mathbf{A}^H \mathbf{w}_{ln}\right) \\
&= \frac{1}{P} \text{Trace}\left[\mathcal{E}\left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H\right] \mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{A} \mathbf{A}^H \mathbf{w}_{ln}\right]\right] \\
&= \frac{\beta_{jl}}{P} \frac{1}{P} \sum P \mathcal{E}\left[\left|w_{ln}(1)\right|^2 + \left|w_{ln}(1)\right|^2 + \left|w_{ln}(M)\right|^2\right] \quad (66) \text{ (see (68))} \\
&= \frac{M\sigma_{nl}^2 \beta_{jl}}{P}
\end{aligned}$$

We deduce:

$$\mathcal{E}\left(\|\boldsymbol{\alpha}_{jn}^T\|^2\right) = \frac{p_p p_u}{P^2} \text{Trace}\left[\left(\mathbf{A}^H \mathbf{A}\right)^2\right] (\bar{\beta}_{ln} \beta_{jl} - \beta_{jl}^2) + \frac{p_p p_u M(M+1)}{P^2} \beta_{jln}^2 + \frac{p_u M \sigma_{n_l}^2 \beta_{jl}}{P} \quad (67)$$

The calculation of $\mathbf{w}_{ln}^H \mathbf{A}$ yields:

$$\begin{aligned} \mathbf{w}_{ln}^H \mathbf{A} &= \frac{1}{\sqrt{P}} [w_{ln}^*(1), w_{ln}^*(2), \dots, w_{ln}^*(M)] \begin{bmatrix} e^{-jf_1(\phi_1)} & e^{-jf_1(\phi_2)} & \dots & e^{-jf_1(\phi_P)} \\ e^{-jf_2(\phi_1)} & e^{-jf_2(\phi_2)} & \dots & e^{-jf_2(\phi_P)} \\ \vdots & \vdots & \ddots & \vdots \\ e^{-jf_M(\phi_1)} & e^{-jf_M(\phi_2)} & \dots & e^{-jf_M(\phi_P)} \end{bmatrix} \\ &= \frac{1}{\sqrt{P}} [w_{ln}^*(1)e^{-jf_1(\phi_1)} + \dots + w_{ln}^*(M)e^{-jf_M(\phi_1)}, \dots, w_{ln}^*(1)e^{-jf_1(\phi_P)} + \dots + w_{ln}^*(M)e^{-jf_M(\phi_P)}] \end{aligned}$$

And, in these conditions, we have:

$$\begin{aligned} \mathcal{E}[\mathbf{w}_{ln}^H \mathbf{A} \mathbf{A}^H \mathbf{w}_{ln}] &= \frac{1}{P} \sum P \mathcal{E}[|w_{ln}(1)|^2 + |w_{ln}(2)|^2 + \dots + |w_{ln}(M)|^2] \quad (68) \\ &= M \sigma_{n_l}^2 \end{aligned}$$

Remark : Using the lemma of appendix 2, we can directly obtain:

$$\mathcal{E}[\mathbf{w}_{ln}^H \mathbf{A} \mathbf{A}^H \mathbf{w}_{ln}] = \frac{1}{M} \mathcal{E}[\mathbf{w}_{ln}^H \mathbf{w}_{ln}] \text{Trace}[\mathbf{A} \mathbf{A}^H] = \frac{1}{M} M \sigma_{n_l}^2 M = M \sigma_{n_l}^2$$

We obtain the uplink rate of the n th user in the l th cell as:

$$R_{ln} = C \left(\frac{p_p p_u M^2 / P^2 \beta_{jln}^2}{\sum_{j=1}^L \left(p_p p_u / P^2 \text{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] (\bar{\beta}_{ln} \beta_{jl} - \beta_{jl}^2) + p_p p_u M(M+1) \beta_{jln}^2 / P^2 + p_u M \sigma_{n_l}^2 \beta_{jl} / P \right) - p_p p_u M^2 / P^2 \beta_{jln}^2 + M \sigma_{n_l}^2 / P \left(p_p \bar{\beta}_{ln} + \frac{\sigma_{n_l}^2}{M} \sum_{k=1}^P S_{U^2(:,k)}^{f_i} \right)} \right)$$

This can be simplified as:

$$R_{ln} = C \left(\frac{\beta_{jln}^2}{\sum_{j=1}^L \left(\text{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] (\bar{\beta}_{ln} \beta_{jl} - \beta_{jl}^2) / M^2 + M(M+1) \beta_{jln}^2 / M^2 + \sigma_{n_l}^2 \beta_{jl} P / M p_p \right) - \beta_{jln}^2 + \sigma_{n_l}^2 P / M \left(\bar{\beta}_{ln} / p_u + \frac{\sigma_{n_l}^2}{p_p p_u M} \sum_{k=1}^P S_{U^2(:,k)}^{f_i} \right)} \right)$$

With: $C(x) = \log_2(1+x)$ and $S_{U^2(:,k)}^{f_i}$ which has been defined in equation (57).

If we examine the behaviour of the former expression for an unlimited number of base station antennas, we have clearly:

$$\lim_{M \rightarrow \infty} \frac{1}{M^2} \text{Trace} [\mathbf{A}^H \mathbf{A}]^2 = \frac{1}{P^2} \text{Trace} [\mathbf{I}_P] = \frac{1}{P}$$

Concerning the term at the extreme side of the denominator we have to resort to the original definition:

$$\begin{aligned} \mathcal{E}\{|z_{ln}|^2\} &= \sigma_{n_l}^2 \left\{ \mathcal{E}\left[p_p \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{\Pi}_A \mathbf{A} \mathbf{g}_{iln} \right] + \mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{\Pi}_A \mathbf{\Pi}_A^H \mathbf{w}_{ln} \right] \right\} \\ &= \sigma_{n_l}^2 \left\{ \mathcal{E}\left[p_p \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{A} \mathbf{g}_{iln} \right] + \mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{\Pi}_A \mathbf{w}_{ln} \right] \right\} \\ &= \sigma_{n_l}^2 \left\{ \mathcal{E}\left[p_p \sum_{i=1}^L \mathbf{g}_{iln}^H \mathbf{A}^H \mathbf{A} \mathbf{g}_{iln} \right] + \mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{w}_{ln} \right] \right\} \end{aligned}$$

We have:

$$\mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{w}_{ln} \right] \approx_{M \rightarrow \infty} \mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{A} \frac{P}{M} \mathbf{I}_P \mathbf{A}^H \mathbf{w}_{ln} \right] = \frac{P}{M} \mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{A} \mathbf{A}^H \mathbf{w}_{ln} \right]$$

We have (see (68)): $\mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{A} \mathbf{A}^H \mathbf{w}_{ln} \right] = M \sigma_{n_l}^2$, so we obtain :

$$\mathcal{E}\left[\mathbf{w}_{ln}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{w}_{ln} \right] \approx_{M \rightarrow \infty} P \sigma_{n_l}^2$$

Reporting all these obtained equivalent values into the former expression, we obtain:

$$R_{ln} \approx_{M \rightarrow \infty} C \left(\frac{\beta_{lln}^2}{\sum_{j=1}^L \left((\bar{\beta}_{ln} \beta_{jl} - \beta_{jln}^2) / P + \beta_{jln}^2 \right) - \beta_{lln}^2} \right) \quad (69)$$

Which can be rewritten as:

$$R_{ln} \approx_{M \rightarrow \infty} C \left(\frac{\beta_{lln}^2}{\bar{\beta}_{ln} \sum_{j=1}^L \beta_{jl} / P + \sum_{j=1}^L \beta_{jln}^2 (1 - 1/P) - \beta_{lln}^2} \right) \quad (70)$$

If P also goes to infinity, the lower bound on the achievable rate becomes:

$$R_{ln} \approx_{M \rightarrow \infty} C \left(\frac{\beta_{lln}^2}{\sum_{j=1, j \neq l}^L \beta_{jln}^2} \right) \quad (71)$$

4.3. Zero forcing Receiver:

In this case the l th base station processes the received signal by multiplying it by the pseudo-invert of the channel estimate. From (6) and (14), we obtain:

$$\mathbf{r}_l = (\hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll})^{-1} \hat{\Gamma}_{ll}^H \mathbf{y}_l \quad (72)$$

With: $\hat{\Gamma}_{ll} = \mathbf{A}_{M \times P} [\hat{\mathbf{H}}_{ll} \mathbf{D}_{ll}^{1/2}]_{P \times K} = p_p^{-1/2} \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll}$. Π_A is of size $M \times M$, $\tilde{\mathbf{Y}}_{p,l}$ is of size $M \times K$. The product $\hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll}$ can be written as:

$$\begin{aligned} \hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll} &= p_p^{-1/2} [\Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll}]^H p_p^{-1/2} \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} \\ &= p_p^{-1} \mathbf{D}_{ll}^H (\mathbf{D}_l^{-1})^H \tilde{\mathbf{Y}}_{p,l}^H \Pi_A^H \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} \end{aligned} \quad (73)$$

Of course, we have: $\Pi_A^H \Pi_A = \Pi_A$, so (73) reduces to :

$$\begin{aligned} \hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll} &= p_p^{-1} \mathbf{D}_{ll}^H (\mathbf{D}_l^{-1})^H \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} \\ &= \frac{1}{p_p} \mathbf{D}_{ll} \mathbf{D}_l^{-1} \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} \end{aligned} \quad (74)$$

In these conditions, we have:

$$\begin{aligned} [\hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll}]^{-1} &= p_p \left[\mathbf{D}_{ll} (\mathbf{D}_l^{-1})^H \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} \right]^{-1} \\ &= p_p \mathbf{D}_{ll}^{-1} \mathbf{D}_l [\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l}]^{-1} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \end{aligned} \quad (75)$$

Then, we obtain:

$$\begin{aligned} &[\hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll}]^{-1} \hat{\Gamma}_{ll}^H \\ &= p_p \mathbf{D}_{ll}^{-1} \mathbf{D}_l [\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l}]^{-1} \mathbf{D}_l \mathbf{D}_{ll}^{-1} p_p^{-1/2} [\Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll}]^H \\ &= p_p^{1/2} \mathbf{D}_{ll}^{-1} \mathbf{D}_l [\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l}]^{-1} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll} \mathbf{D}_l^{-1} \tilde{\mathbf{Y}}_{p,l}^H \Pi_A^H \\ &= p_p^{1/2} \mathbf{D}_{ll}^{-1} \mathbf{D}_l [\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l}]^{-1} \tilde{\mathbf{Y}}_{p,l}^H \Pi_A^H \end{aligned} \quad (76)$$

And:

$$\begin{aligned}\mathbf{r}_l &= \left(\hat{\boldsymbol{\Gamma}}_{ll}^H \hat{\boldsymbol{\Gamma}}_{ll} \right)^{-1} \hat{\boldsymbol{\Gamma}}_{ll}^H \mathbf{y}_l \\ &= p_p^{1/2} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \left[\tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \right]^{-1} \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{y}_l\end{aligned}\quad (77)$$

Let $\tilde{\mathbf{r}}_l$ the received $K \times 1$ vector: $\tilde{\mathbf{r}}_l \equiv \frac{1}{\sqrt{p_p}} \mathbf{D}_l^{-1} \mathbf{D}_{ll} \mathbf{r}_l$, we deduce from (77) that :

$$\tilde{\mathbf{r}}_l = \left[\tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \right]^{-1} \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{y}_l \quad (78)$$

4.4. Analysis of the Pilot Contamination effect:

We denote as $\mathbf{M}_{p,l}^A$ the matrix: $\left[\tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \right]_{K \times K}^{-1}$. In this case, if we look at the n th component of vector $\tilde{\mathbf{r}}_l$, we have :

$$\begin{aligned}\tilde{r}_l(n) &= \tilde{r}_{ln} \\ &= \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{y}_l \\ &= \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \left[\sqrt{p_u} A \sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \mathbf{x}_i + \mathbf{n}_l \right] \\ &= \sqrt{p_u} \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{H}_{l,l} \mathbf{D}_{l,l}^{1/2} \mathbf{x}_l + \sqrt{p_u} \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \sum_{i \neq l}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \mathbf{x}_i + \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{n}_l \\ &= \boldsymbol{\alpha}_{ln}^T \mathbf{x}_l + \sum_{j \neq l}^L \boldsymbol{\alpha}_{jn}^T \mathbf{x}_j + z_{ln} \quad (79)\end{aligned}$$

With: $\boldsymbol{\alpha}_{jn}^T \equiv \sqrt{p_u} \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{H}_{j,l} \mathbf{D}_{j,l}^{1/2}$ and $z_{ln} \equiv \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{n}_l$. We have :

$$\mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\} = \mathcal{E}\left[\sqrt{p_u} \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{H}_{l,l} \mathbf{D}_{l,l}^{1/2}\right] \mathbf{e}_n \quad (80)$$

Where \mathbf{e}_n is the n th column of the $K \times K$ identity matrix. By adding and subtracting $\mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\}$ from $\boldsymbol{\alpha}_{ln}^T$ in (79), we obtain:

$$\tilde{r}_{ln} = \mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\} \mathbf{x}_l + (\boldsymbol{\alpha}_{ln}^T - \mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\}) \mathbf{x}_l + \sum_{j \neq l}^L \boldsymbol{\alpha}_{jn}^T \mathbf{x}_j + z_{ln} \quad (81)$$

We obtain again the capacity of the n th user in the l th cell:

$$R_{ln} = C \left(\frac{\mathbb{E}\{\alpha_{ln}^T\|^2}{\sum_{j=1}^L \mathbb{E}\{\|\alpha_{jn}^T\|^2\} - \mathbb{E}\{\alpha_{ln}^T\|^2 + \mathbb{E}\{|z_{ln}|^2\}} \right) \quad (82)$$

To develop (82) we detail first the calculation of the matrix: $(\mathbf{M}_{p,l}^A)^{-1} = \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}$, we have :

$$\begin{aligned} (\mathbf{M}_{p,l}^A)^{-1} &= \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \\ &= \left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l \right)^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l \right) \\ &= \left(\sqrt{p_p} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H + \mathbf{W}_l^H \right) \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l \right) \\ &= p_p \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l + \dots \\ &\quad + \sqrt{p_p} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l + \sqrt{p_p} \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \\ &= p_p \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l + \sqrt{p_p} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l + \sqrt{p_p} \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \end{aligned}$$

Clearly, this reduces to:

$$\begin{aligned} \mathbb{E}[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}] &= p_p \mathbb{E}\left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{j=1}^L \mathbf{G}_{j,l} \right] + \mathbb{E}[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l] \\ &= p_p \sum_{i,j}^L \mathbb{E}[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}] + \mathbb{E}[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l] \end{aligned}$$

To further proceed this quantity, we have to calculate:

$$G_{j,l}^H A^H = \frac{1}{\sqrt{P}} \begin{bmatrix} g_{jl11}^* & g_{jl12}^* & \cdots & g_{jl1k}^* & \cdots & g_{jl1P}^* \\ g_{jl21}^* & g_{jl22}^* & \cdots & g_{jl2k}^* & \cdots & g_{jl2P}^* \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ g_{jlm1}^* & g_{jlm2}^* & \cdots & g_{jlmk}^* & \cdots & g_{jlmP}^* \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ g_{jlK1}^* & g_{jlK2}^* & \cdots & g_{jlKk}^* & \cdots & g_{jlKP}^* \end{bmatrix} = \frac{1}{\sqrt{P}} \begin{bmatrix} e^{jf_1(\phi_1)} & e^{jf_2(\phi_1)} & \cdots & e^{jf_M(\phi_1)} \\ e^{jf_1(\phi_2)} & e^{jf_2(\phi_2)} & \cdots & e^{jf_M(\phi_2)} \\ \vdots & \vdots & \ddots & \vdots \\ e^{jf_1(\phi_P)} & e^{jf_2(\phi_P)} & \cdots & e^{jf_M(\phi_P)} \end{bmatrix} \begin{bmatrix} \sum_{k=1}^P g_{jl1k}^* e^{jf_1(\phi_k)} & \sum_{k=1}^P g_{jl1k}^* e^{jf_2(\phi_k)} & \cdots & \sum_{k=1}^P g_{jl1k}^* e^{jf_M(\phi_k)} \\ \sum_{k=1}^P g_{jl2k}^* e^{jf_1(\phi_k)} & \sum_{k=1}^P g_{jl2k}^* e^{jf_2(\phi_k)} & \cdots & \sum_{k=1}^P g_{jl2k}^* e^{jf_M(\phi_k)} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{k=1}^P g_{jlKk}^* e^{jf_1(\phi_k)} & \sum_{k=1}^P g_{jlKk}^* e^{jf_2(\phi_k)} & \cdots & \sum_{k=1}^P g_{jlKk}^* e^{jf_M(\phi_k)} \end{bmatrix}$$

The (m,n) th element of $\mathbf{G}_{i,l}^H \mathbf{A}^H$ is thus written as :

$$[\mathbf{G}_{i,l}^H \mathbf{A}^H(m,n)]_{K \times M} = a_{m,n} = \frac{1}{\sqrt{P}} \sum_{k=1}^P g_{ilmk}^* e^{jf_n(\phi_k)} \quad (83)$$

Concerning the matrix: $\mathbf{A}\mathbf{G}_{j,l}$, we obtain :

$$\mathbf{A}\mathbf{G}_{j,l} = \frac{1}{\sqrt{P}} \begin{bmatrix} \sum_{n=1}^P e^{-jf_1(\phi_n)} g_{jl1n} & \sum_{n=1}^P e^{-jf_1(\phi_n)} g_{jl2n} & \cdots & \sum_{n=1}^P e^{-jf_1(\phi_n)} g_{jln} & \cdots & \sum_{n=1}^P e^{-jf_1(\phi_n)} g_{jlKn} \\ \sum_{n=1}^P e^{-jf_2(\phi_n)} g_{jl1n} & \sum_{n=1}^P e^{-jf_2(\phi_n)} g_{jl2n} & \cdots & \sum_{n=1}^P e^{-jf_2(\phi_n)} g_{jln} & \cdots & \sum_{n=1}^P e^{-jf_2(\phi_n)} g_{jlKn} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ \sum_{n=1}^P e^{-jf_m(\phi_n)} g_{jl1n} & \sum_{n=1}^P e^{-jf_m(\phi_n)} g_{jl2n} & \cdots & \sum_{n=1}^P e^{-jf_m(\phi_n)} g_{jln} & \cdots & \sum_{n=1}^P e^{-jf_m(\phi_n)} g_{jlKn} \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots \\ \sum_{n=1}^P e^{-jf_M(\phi_n)} g_{jl1n} & \sum_{n=1}^P e^{-jf_M(\phi_n)} g_{jl2n} & \cdots & \sum_{n=1}^P e^{-jf_M(\phi_n)} g_{jln} & \cdots & \sum_{n=1}^P e^{-jf_M(\phi_n)} g_{jlKn} \end{bmatrix}$$

Thus, the (m,k) th element of $\mathbf{A}\mathbf{G}_{j,l}$ is thus written as :

$$[\mathbf{A}\mathbf{G}_{j,l}(m,k)]_{M \times K} = \frac{1}{\sqrt{P}} \sum_{n=1}^P g_{jlk_n} e^{-jf_m(\phi_n)} \quad (84)$$

And the (m,n) th element of matrix $\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A}\mathbf{G}_{j,l}$ is equal to:

$$\begin{aligned}
\left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \right] (m,n) &= \sum_{k=1}^M a_{m,k} b_{k,n} \\
&= \frac{1}{P} \sum_{k=1}^M \left(\sum_{r=1}^P g_{ilmr}^* e^{j f_k(\phi_r)} \right) \left(\sum_{q=1}^P g_{jlnq} e^{-j f_k(\phi_q)} \right) \\
&= \frac{1}{P} \sum_{k=1}^M \left(\sum_{r=1}^P \sum_{q=1}^P g_{ilmr}^* g_{jlnq} e^{j [f_k(\phi_r) - f_k(\phi_q)]} \right) \quad (85) \\
&= \frac{1}{P} \sum_{k=1}^M \left(\sum_{r=1}^P \sum_{q=1}^P h_{ilmr}^* h_{jlnq} \sqrt{\beta_{ilm} \beta_{jln}} e^{j [f_k(\phi_r) - f_k(\phi_q)]} \right)
\end{aligned}$$

Hence, we have:

$$\mathcal{E} \left[\left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \right] (m,n) \right] = \frac{1}{P} \sum_{k=1}^M \left(\sum_{r=1}^P \sum_{q=1}^P \mathcal{E} \left[h_{ilmr}^* h_{jlnq} \right] \sqrt{\beta_{ilm} \beta_{jln}} e^{j [f_k(\phi_r) - f_k(\phi_q)]} \right) \quad (86)$$

For $i=j$, we obtain:

$$\mathcal{E} \left[\left[\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \right] (m,n) \right] = \frac{1}{P} \sum_{k=1}^M \left(\sum_{r=1}^P \sum_{q=1}^P \mathcal{E} \left[h_{jlmr}^* h_{jlnq} \right] \sqrt{\beta_{jlm} \beta_{jln}} e^{j [f_k(\phi_r) - f_k(\phi_q)]} \right)$$

The quantity: $\mathcal{E} \left[h_{ilmr}^* h_{jlnq} \right]$ is equal to zero for $i \neq j$ and for $i=j$, due to the independency between columns, we have $\mathcal{E} \left[h_{ilmr}^* h_{jlnq} \right] = 0$ if $m \neq n$. For $i=j$ and $m=n$ we have:

$$\begin{aligned}
\mathcal{E} \left[\left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l} \right] (n,n) \right] &= \frac{1}{P} \sum_{k=1}^M \left(\sum_{r=1}^P \sum_{q=1}^P \mathcal{E} \left[h_{ilnr}^* h_{ilnq} \right] \beta_{iln} e^{j [f_k(\phi_r) - f_k(\phi_q)]} \right) \quad (87) \\
\mathcal{E} \left[\left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l} \right] (n,n) \right] &= \frac{1}{P} \sum_{k=1}^M \left(\sum_{r=1}^P \mathcal{E} \left[|h_{ilnr}|^2 \beta_{iln} \right] \right) = \frac{M \beta_{iln}}{P}
\end{aligned}$$

Concerning the quantity: $\mathcal{E} \left[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \right]$, we have already developed the calculations in the former section,

$$\begin{aligned}
&\mathcal{E} \left[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \right] \\
&= \frac{1}{M} \mathcal{E} \left[\mathbf{W}_l^H \mathbf{W}_l \right] \text{Trace} \left(\mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \right) \quad (88) \\
&= \frac{1}{M} M \sigma_{n_l}^2 \mathbf{I}_K \text{Trace} \left[\mathbf{\Pi}_A \right] \approx_{M \rightarrow \infty} \sigma_{n_l}^2 P \mathbf{I}_K
\end{aligned}$$

We eventually obtain:

$$\mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right] = \text{diag}\left(\rho_{1,l}, \rho_{2,l}, \dots, \rho_{K,l}\right) \quad (89)$$

With:

$$\begin{aligned}\rho_{n,l} &= p_p \frac{M}{P} \sum_{i=1}^L \beta_{iln} + \sigma_{n_l}^2 P \\ \rho_{n,l} &= p_p \frac{M}{P} \bar{\beta}_{ln} + \sigma_{n_l}^2 P\end{aligned}$$

We come back to the calculation of $\mathcal{E}\{\alpha_{ln}^T\}$, remember we have :

$$\begin{aligned}\mathcal{E}\{\alpha_{ln}^T\} &= \mathcal{E}\left[\sqrt{p_u} \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{H}_{l,l} \mathbf{D}_{l,l}^{1/2}\right] \mathbf{e}_n \\ \mathcal{E}\{\alpha_{ln}^T\} &\approx \sqrt{p_u} \mathcal{E}\left[\mathbf{M}_{p,l}^A(n,:)\right] \mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{G}_{l,l}\right] \mathbf{e}_n \\ &= \sqrt{p_u} \mathcal{E}\left[\mathbf{M}_{p,l}^A(n,:)\right] \mathcal{E}\left[\left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l\right)^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{A} \mathbf{G}_{l,l}\right] \mathbf{e}_n \\ &= \sqrt{p_u} \mathcal{E}\left[\mathbf{M}_{p,l}^A(n,:)\right] \mathcal{E}\left[\sqrt{p_p} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{A} \mathbf{G}_{l,l}\right] \mathbf{e}_n \\ &= \sqrt{p_p p_u} \mathcal{E}\left[\mathbf{M}_{p,l}^A(n,:)\right] \mathcal{E}\left[\mathbf{G}_{l,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{l,l}\right] \mathbf{e}_n\end{aligned}$$

We have already found that (see equation (87)):

$$\mathcal{E}\left[\left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l}\right](n,n)\right] = \frac{M \beta_{iln}}{P}$$

Using: $\mathcal{E}\left[\mathbf{M}_{p,l}^A(n,:)\right] \approx 1 / \rho_{n,l}$, we eventually obtain:

$$\begin{aligned}\mathcal{E}\{\alpha_{ln}^T\} &\approx \sqrt{p_p p_u} \frac{M \beta_{ln}}{P \rho_{n,l}} \mathbf{e}_n \\ &= \sqrt{p_p p_u} \frac{M \beta_{ln}}{P \left[p_p \frac{M}{P} \bar{\beta}_{ln} + \sigma_{n_l}^2 P \right]} \mathbf{e}_n \\ &= \sqrt{p_p p_u} \frac{M \beta_{ln}}{p_p M \bar{\beta}_{ln} + P^2 \sigma_{n_l}^2} \mathbf{e}_n \\ &= \sqrt{p_p p_u} \frac{\beta_{ln}}{p_p \bar{\beta}_{ln} + P^2 \sigma_{n_l}^2 / M} \mathbf{e}_n\end{aligned} \quad (90)$$

Concerning the quantity: $\mathcal{E}\left\{\|\alpha_{jn}^T\|^2\right\}$, we have:

$$\begin{aligned}
& \mathcal{E} \left\{ \left\| \boldsymbol{\alpha}_{jn}^T \right\|^2 \right\} = \mathcal{E} \left(\boldsymbol{\alpha}_{jn}^T \boldsymbol{\alpha}_{jn}^* \right) \\
& = p_u \mathcal{E} \left[\mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \boldsymbol{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \mathbf{M}_{p,l}^A(n,:)^H \right] \\
& = p_u \mathcal{E} \left[\mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \boldsymbol{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \mathbf{M}_{p,l}^A(n,:)^H \right]
\end{aligned}$$

We have:

$$\begin{aligned}
& \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \boldsymbol{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \\
& = \left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l \right)^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \left(\sqrt{p_p} \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l} + \mathbf{W}_l \right) \\
& = \left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l \right)^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \left(\sqrt{p_p} \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l} + \mathbf{W}_l \right)
\end{aligned}$$

And this yields:

$$\begin{aligned}
& \mathcal{E} \left[\mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \boldsymbol{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \mathbf{M}_{p,l}^A(n,:)^H \right] \\
& = \mathcal{E} \left[\mathbf{M}_{p,l}^A(n,:) \left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l \right)^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \left(\sqrt{p_p} \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l} + \mathbf{W}_l \right) \mathbf{M}_{p,l}^A(n,:)^H \right] \\
& = \mathcal{E} \left[p_p \mathbf{M}_{p,l}^A(n,:) \sum_{i=1, i \neq j}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \sum_{m=1, m \neq j}^L \mathbf{G}_{m,l} \mathbf{M}_{p,l}^A(n,:)^H \right] + \dots \\
& \dots + \mathcal{E} \left[p_p \mathbf{M}_{p,l}^A(n,:) \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{M}_{p,l}^A(n,:)^H \right] + \dots \\
& \dots + \mathcal{E} \left[\mathbf{M}_{p,l}^A(n,:) \mathbf{W}_l^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{M}_{p,l}^A(n,:)^H \right]
\end{aligned}$$

And, we have:

$$\begin{aligned}
& \mathcal{E} \left[p_p \mathbf{M}_{p,l}^A(n,:) \sum_{i=1, i \neq j}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \sum_{m=1, m \neq j}^L \mathbf{G}_{m,l} \mathbf{M}_{p,l}^A(n,:)^H \right] \\
& = \frac{p_p}{P} \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \right] \right] \sum_{i=1, i \neq j}^L \mathcal{E} \left[\mathbf{M}_{p,l}^A(n,:) \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l} \mathbf{M}_{p,l}^A(n,:)^H \right] \\
& = \frac{p_p}{P^2} \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \right] \right] \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \sum_{i=1, i \neq j}^L \mathcal{E} \left[\mathbf{M}_{p,l}^A(n,:) \mathbf{G}_{i,l}^H \mathbf{G}_{i,l} \mathbf{M}_{p,l}^A(n,:)^H \right] \\
& = \frac{p_p}{P^2 K} \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \right] \right] \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \text{Trace} \left[\mathcal{E} \left[\sum_{i=1, i \neq j}^L \mathbf{G}_{i,l}^H \mathbf{G}_{i,l} \right] \right] \mathcal{E} \left[\mathbf{M}_{p,l}^A(n,:) \mathbf{M}_{p,l}^A(n,:)^H \right]
\end{aligned}$$

$$\begin{aligned}
&= \frac{p_p}{P^2 K} \text{Trace} \left[\mathbb{E} \left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \right] \right] \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \left[\sum_{i=1, i \neq j}^L \text{Trace} \left[\mathbb{E} \left[\mathbf{G}_{i,l}^H \mathbf{G}_{i,l} \right] \right] \right] \mathbb{E} \left[\mathbf{M}_{p,l}^A(n,:) \mathbf{M}_{p,l}^A(n,:)^H \right] \\
&= \frac{p_p \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right) \mathbb{E} \left[\mathbf{M}_{p,l}^A(n,:) \mathbf{M}_{p,l}^A(n,:)^H \right]}{P^2 K} \\
&= \frac{p_p \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right) \gamma_{n,l}}{P^2 K}
\end{aligned}$$

With : $\mathbb{E} \left[\mathbf{M}_{p,l}^A(n,:) \mathbf{M}_{p,l}^A(n,:)^H \right] \approx \gamma_{n,l}$

We have (already demonstrated in the former paragraph):

$$\mathbb{E} \left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \right] = \text{diag} \left[\sum_{k=1}^K \beta_{jlk} \mathbb{E} \left[|h_{jlk1}|^2 \right], \sum_{k=1}^K \beta_{jlk} \mathbb{E} \left[|h_{jlk2}|^2 \right], \dots, \sum_{k=1}^K \beta_{jlk} \mathbb{E} \left[|h_{jlkP}|^2 \right] \right]$$

And : $\text{Trace} \left[\mathbb{E} \left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \right] \right] = \sum_{k=1}^K \beta_{jlk} = \beta_{jl}$. Concerning the quantity $\mathbb{E} \left[\mathbf{G}_{i,l}^H \mathbf{G}_{i,l} \right]$, we have :

$$\mathbf{G}_{j,l}^H \mathbf{G}_{j,l} = \begin{bmatrix} g_{jl11}^* & g_{jl12}^* & \cdots & g_{jl1k}^* & \cdots & g_{jl1P}^* \\ g_{jl21}^* & g_{jl22}^* & \cdots & g_{jl2k}^* & \cdots & g_{jl2P}^* \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ g_{jl1m}^* & g_{jl2m}^* & \cdots & g_{jlmk}^* & \cdots & g_{jl1P}^* \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ g_{jl1P}^* & g_{jl2P}^* & \cdots & g_{jlkP}^* & \cdots & g_{jlKP}^* \end{bmatrix} = \begin{bmatrix} \sum_{k=1}^P |g_{jl1k}|^2 & \sum_{k=1}^P g_{jl1k}^* g_{jl2k} & \cdots & \sum_{k=1}^P g_{jl1k}^* g_{jlmk} & \cdots & \sum_{k=1}^P g_{jl1k}^* g_{jlKk} \\ \sum_{k=1}^P g_{jl2k}^* g_{jl1k} & \sum_{k=1}^P |g_{jl2k}|^2 & \cdots & \sum_{k=1}^P g_{jl2k}^* g_{jlmk} & \cdots & \sum_{k=1}^P g_{jl2k}^* g_{jlKk} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \sum_{k=1}^P g_{jlmk}^* g_{jl1k} & \sum_{k=1}^P g_{jlmk}^* g_{jl2k} & \cdots & \sum_{k=1}^P |g_{jlmk}|^2 & \cdots & \sum_{k=1}^P g_{jlmk}^* g_{jlKk} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \sum_{k=1}^P g_{jlKk}^* g_{jl1k} & \sum_{k=1}^P g_{jlKk}^* g_{jl2k} & \cdots & \sum_{k=1}^P g_{jlKk}^* g_{jlmk} & \cdots & \sum_{k=1}^P |g_{jlKk}|^2 \end{bmatrix}$$

$$\begin{aligned}
\mathcal{E}\left[\mathbf{G}_{j,l}^H \mathbf{G}_{j,l}\right] &= \text{diag}\left[\mathcal{E}\left[\sum_{k=1}^P |g_{jl1k}|^2\right], \mathcal{E}\left[\sum_{k=1}^P |g_{jl2k}|^2\right], \dots, \mathcal{E}\left[\sum_{k=1}^P |g_{jlmk}|^2\right], \dots, \mathcal{E}\left[\sum_{k=1}^P |g_{jlKk}|^2\right]\right] \\
&= \text{diag}\left[\beta_{jl1} \mathcal{E}\left[\sum_{k=1}^P |h_{jl1k}|^2\right], \beta_{jl2} \mathcal{E}\left[\sum_{k=1}^P |h_{jl2k}|^2\right], \dots, \beta_{jlm} \mathcal{E}\left[\sum_{k=1}^P |h_{jlmk}|^2\right], \dots, \beta_{jlK} \mathcal{E}\left[\sum_{k=1}^P |h_{jlKk}|^2\right]\right] \\
&= \text{diag}\left[\beta_{jl1}, \beta_{jl2}, \dots, \beta_{jlm}, \dots, \beta_{jlK}\right]
\end{aligned}$$

$$\text{And: } \text{Trace}\left[\mathcal{E}\left[\mathbf{G}_{j,l}^H \mathbf{G}_{j,l}\right]\right] = \sum_{k=1}^K \beta_{jlk} = \beta_{jl}.$$

Concerning the term: $\mathcal{E}\left[p_p \mathbf{M}_{p,l}^A(n,:) \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{M}_{p,l}^A(n,:)^H\right]$, we have:

$$\begin{aligned}
&\mathcal{E}\left[p_p \mathbf{M}_{p,l}^A(n,:) \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{M}_{p,l}^A(n,:)^H\right] \\
&= \frac{p_p}{K} \mathcal{E}\left[\mathbf{M}_{p,l}^A(n,:) \mathbf{M}_{p,l}^A(n,:)^H\right] \text{Trace}\left[\mathcal{E}\left[\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}\right]\right] \\
&= \frac{p_p \gamma_{n,l}}{K} \text{Trace}\left[\mathcal{E}\left[\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}\right]^2\right]
\end{aligned}$$

We use the following approximation (the demonstration is given later):

$$\begin{aligned}
&\mathcal{E}\left[\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}\right] \\
&= \frac{M^2 \beta_{jl}}{P^2} \text{diag}(\beta_{jl1}, \beta_{jl2}, \dots, \beta_{jlK})
\end{aligned}$$

Hence this yields:

$$\begin{aligned}
&\mathcal{E}\left[p_p \mathbf{M}_{p,l}^A(n,:) \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{M}_{p,l}^A(n,:)^H\right] \\
&= \frac{p_p}{K} \text{Trace}\left[\mathcal{E}\left[\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}\right]^2\right] \gamma_{n,l} \\
&= \frac{p_p}{K} \frac{M^2 \beta_{jl}^2}{P^2} \gamma_{n,l}
\end{aligned}$$

Concerning the last quantity, we have :

$$\begin{aligned}
&\mathcal{E}\left[\mathbf{M}_{p,l}^A(n,:) \mathbf{W}_l^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{M}_{p,l}^A(n,:)^H\right] \\
&= \frac{\gamma_{n,l}}{K} \text{Trace}\left[\mathcal{E}\left[\mathbf{W}_l^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{W}_l\right]\right] \\
&= \frac{\gamma_{n,l}}{K} \frac{M^2 \sigma_{n_l}^2}{P} \beta_{jl} \\
&= \frac{M^2 \sigma_{n_l}^2}{KP} \beta_{jl} \gamma_{n,l}
\end{aligned}$$

We have:

$$\begin{aligned}
& \mathbb{E}[\mathbf{W}_l^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{W}_l] \\
&= \frac{1}{K} \mathbb{E}[\mathbf{W}_l^H \mathbf{W}_l] \text{Trace}(\mathbb{E}[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H]) \\
&= \frac{M \sigma_{n_l}^2}{K} \frac{M}{P} \beta_{jl} \mathbf{I}_K = \frac{M^2 \sigma_{n_l}^2}{KP} \beta_{jl} \mathbf{I}_K
\end{aligned}$$

Concerning the quantity: $\mathbb{E}([\mathbf{M}_{p,l}^A(n,:) \mathbf{M}_{p,l}^{A^H}(n,:)^H])$, we have:

$$\begin{aligned}
\mathbb{E}([\mathbf{M}_{p,l}^A \mathbf{M}_{p,l}^{A^H}]) &= \mathbb{E}\left(\left[\left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right)^{-1} \left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right)^{-1 H}\right]\right) \\
&= \mathbb{E}\left(\left[\left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right)^H \left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right)\right]^{-1}\right) \\
&= \mathbb{E}\left(\left[\left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right) \left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right)\right]^{-1}\right) \\
&= \mathbb{E}\left(\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right]^{-1}\right) = \mathbb{E}\left(\left[\left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right)^2\right]^{-1}\right)
\end{aligned}$$

We have:

$$\begin{aligned}
& \left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right)^2 \\
&= \left[p_p \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l + \sqrt{p_p} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l + \sqrt{p_p} \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \right]^2 \\
&= p_p^2 \left(\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{k=1}^L \mathbf{G}_{k,l} \right) \left(\sum_{j=1}^L \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l} \right) + \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l + \dots \\
&\dots + p_p \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \sum_{m=1}^L \mathbf{G}_{m,l}^H \mathbf{A}^H \mathbf{W}_l + p_p \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{W}_l^H \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l} + p_p \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l + \dots \\
&\dots + p_p^{3/2} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l + p_p^{3/2} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \dots \\
&\dots + p_p \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \sqrt{p_p} \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l + \dots \\
&\dots + \sqrt{p_p} \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + p_p^{3/2} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \dots \\
&\dots + \sqrt{p_p} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l + p_p \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \dots \\
&\dots + p_p^{3/2} \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \sqrt{p_p} \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l + \dots \\
&\dots + p_p \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l
\end{aligned}$$

When we take the expectation of the different terms in the former expression we make the

following assumptions, due to the independency between channel parameters and additive noise we neglect the corresponding expectation term each time the stochastic variable appears an odd number of times in the calculation. Using this rule, it is not difficult to demonstrate that the following expectation terms are equal to zero:

$$\begin{aligned} \mathcal{E}\left(\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l\right) &\approx \mathbf{0}, \quad \mathcal{E}\left(\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l}\right) \approx \mathbf{0} \\ \mathcal{E}\left(\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l\right) &\approx \mathbf{0}, \quad \mathcal{E}\left(\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l}\right) \approx \mathbf{0} \\ \mathcal{E}\left(\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l}\right) &\approx \mathbf{0}, \quad \mathcal{E}\left(\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l\right) \approx \mathbf{0} \\ \mathcal{E}\left(\mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l}\right) &\approx \mathbf{0}, \quad \mathcal{E}\left(\mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l\right) \approx \mathbf{0} \end{aligned}$$

This yields:

$$\begin{aligned} \mathcal{E}\left(\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right]^2\right) \\ \approx p_p^2 \mathcal{E}\left[\left(\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{k=1}^L \mathbf{G}_{k,l}\right)\left(\sum_{j=1}^L \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l}\right)\right] \\ \dots + \mathcal{E}\left[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l\right] + p_p \mathcal{E}\left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \sum_{m=1}^L \mathbf{G}_{m,l}^H \mathbf{A}^H \mathbf{W}_l\right] + \dots \\ \dots + p_p \mathcal{E}\left[\mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{W}_l^H \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l}\right] + p_p \mathcal{E}\left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l\right] + \dots \\ \dots + p_p \mathcal{E}\left[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l}\right] + p_p \mathcal{E}\left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l}\right] + \dots \\ \dots + p_p \mathcal{E}\left[\mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l\right] \end{aligned}$$

Due to the independency between channel parameters and additive noise, we can further simplify using:

$$\mathcal{E}\left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \sum_{m=1}^L \mathbf{G}_{m,l}^H \mathbf{A}^H \mathbf{W}_l\right] \approx \mathcal{E}\left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \sum_{m=1}^L \mathcal{E}\left[\mathbf{W}_l \mathbf{G}_{m,l}^H\right] \mathbf{A}^H \mathbf{W}_l\right] \approx \mathbf{0}$$

And, for the same reason:

$$\mathcal{E}\left[\mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{W}_l^H \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l}\right] \approx \mathbf{0}$$

This reduces the calculation of $\mathcal{E}\left(\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right]^2\right)$ and this gives:

$$\begin{aligned}
& \mathcal{E}\left(\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right]^2\right) \\
& \approx p_p^2 \mathcal{E}\left[\left(\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{k=1}^L \mathbf{G}_{k,l}\right)\left(\sum_{j=1}^L \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l}\right)\right] + \dots \\
& \dots + \mathcal{E}\left[\mathbf{W}_l^H \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l\right] + \dots \\
& \dots + p_p \mathcal{E}\left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{W}_l^H \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l\right] + \dots \\
& \dots + p_p \mathcal{E}\left[\mathbf{W}_l^H \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l}\right] + \dots \\
& \dots + p_p \mathcal{E}\left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l}\right] + p_p \mathcal{E}\left[\mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l\right]
\end{aligned}$$

$$\begin{aligned}
& \mathcal{E}\left(\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right]^2\right) \\
& \approx p_p^2 \mathcal{E}\left[\left(\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{k=1}^L \mathbf{G}_{k,l}\right)\left(\sum_{j=1}^L \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l}\right)\right] + \dots \\
& \dots + \mathcal{E}\left[\mathbf{W}_l^H \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l\right] + 2p_p \sum_{i=1}^L \mathcal{E}\left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l}\right] \mathcal{E}\left[\mathbf{W}_l^H \mathbf{A}(\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l\right] + \dots \\
& \dots + p_p \mathcal{E}\left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathcal{E}\left[\mathbf{W}_l \mathbf{W}_l^H\right] \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l}\right] + p_p \mathcal{E}\left[\mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathcal{E}\left[\mathbf{G}_{i,l} \mathbf{G}_{i,l}^H\right] \mathbf{A}^H \mathbf{W}_l\right]
\end{aligned}$$

Concerning the first term in the expectation, we take a particular case with $L = 3$ before a complete generalization. We use the notation: $\mathbf{a}_i = \mathbf{A} \mathbf{G}_{i,l}$, then, we obtain :

$$\begin{aligned}
& \mathcal{E}\left[\left(\sum_{i=1}^3 \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{k=1}^L \mathbf{G}_{k,l}\right)\left(\sum_{j=1}^3 \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l}\right)\right] \\
& = \mathcal{E}\left[\left(\sum_{j=1}^3 \mathbf{a}_j^H \sum_{i=1}^3 \mathbf{a}_i\right)\left(\sum_{m=1}^3 \mathbf{a}_m^H \sum_{k=1}^3 \mathbf{a}_k\right)\right] \\
& = \mathcal{E}\left[\left(\mathbf{a}_1^H \mathbf{a}_1 + \mathbf{a}_2^H \mathbf{a}_2 + \mathbf{a}_3^H \mathbf{a}_3 + \mathbf{a}_1^H \mathbf{a}_2 + \mathbf{a}_1^H \mathbf{a}_3 + \mathbf{a}_2^H \mathbf{a}_1 + \mathbf{a}_2^H \mathbf{a}_3 + \mathbf{a}_3^H \mathbf{a}_1 + \mathbf{a}_3^H \mathbf{a}_2\right)^2\right]
\end{aligned}$$

In fact, due to the independency between different channels, we have the following results:

$$\mathcal{E}[a_i^H a_i a_i^H a_j] = 0, \mathcal{E}[a_i^H a_j a_j^H a_j] = 0, \mathcal{E}[a_i^H a_j a_j^H a_k] = 0, \mathcal{E}[a_i^H a_j a_k^H a_j] = 0$$

We have to calculate three kinds of terms:

-1) The first one is:

$$\mathcal{E}[\mathbf{a}_i^H \mathbf{a}_i \mathbf{a}_i^H \mathbf{a}_i] = \mathcal{E}[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l} \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l}]$$

Concerning first matrix: $G_{i,l}^H A^H A G_{i,l}$, the general term of matrix is:

$$\begin{aligned} & \left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l} \right] (m,n) = a_{m,n} \\ &= \frac{1}{P} \sum_{k=1}^M \left(\sum_{r=1}^P \sum_{q=1}^P h_{ilmr}^* h_{ilnq} \sqrt{\beta_{ilm} \beta_{iln}} e^{j[f_k(\phi_r) - f_k(\phi_q)]} \right) \\ &= \frac{1}{P} \sum_{k=1}^M A_{r,q}^{i,k} (m,n) \end{aligned}$$

With:

$$A_{r,q}^{i,k}(m,n) = \sum_{r=1}^P \sum_{q=1}^P h_{ilmr}^* h_{ilnq} \sqrt{\beta_{ilm} \beta_{iln}} e^{j[\phi_r(m) - \phi_q(n)]}$$

We have, in this case:

$$\mathcal{E}\left(\left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l}\right](m,n)\right) = \frac{1}{P} \sum_{k=1}^M \left(\sum_{r=1}^P \sum_{q=1}^P \mathcal{E}\left[h_{ilmr}^* h_{ilnq}\right] \sqrt{\beta_{ilm} \beta_{iln}} e^{j\left[f_k(\phi_r) - f_k(\phi_q)\right]} \right)$$

Of course, this quantity is not equal to zero only and only if $n = m$ and $r = q$, this yields :

$$\begin{aligned}\mathcal{E}\left(\left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l}\right](n,n)\right) &= \frac{1}{P} \sum_{k=1}^M \left(\sum_{r=1}^P \mathcal{E}\left[|h_{ilnr}|^2\right] \beta_{iln} \right) \\ &= \frac{1}{P} \sum_{k=1}^M \beta_{iln} \\ &= \frac{M}{P} \beta_{iln}\end{aligned}$$

Then, we obtain:

$$\mathcal{E}\left(\left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l}\right]\right) = \frac{M}{P} \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK})$$

In these conditions, the general term of matrix $\left(\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}\right)^2$ is:

$$\begin{aligned}\left(\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}\right)^2(m,n) &= \sum_{p=1}^K a_{m,p} a_{p,n} \\ &= \sum_{p=1}^K \left(\frac{1}{P} \sum_{k=1}^M A_{r,q}^{j,k}(m,p) \right) \left(\frac{1}{P} \sum_{u=1}^M A_{s,t}^{j,u}(p,n) \right) \\ &= \frac{1}{P^2} \sum_{p=1}^K \sum_{k=1}^M \sum_{u=1}^M A_{r,q}^{j,k}(m,p) A_{s,t}^{j,u}(p,n)\end{aligned}$$

We have:

$$\begin{aligned}&\mathcal{E}\left[A_{r,q}^{j,k}(m,p) A_{s,t}^{j,u}(p,n)\right] \\ &= \mathcal{E}\left[\left(\sum_{r=1}^P \sum_{q=1}^P h_{jlmr}^* h_{jlpq} \sqrt{\beta_{jlm} \beta_{jlp}} e^{j[f_k(\phi_r) - f_k(\phi_q)]}\right) \left(\sum_{s=1}^P \sum_{t=1}^P h_{jlpq}^* h_{jlnt} \sqrt{\beta_{jlp} \beta_{jln}} e^{j[f_u(\phi_s) - f_u(\phi_t)]}\right)\right] \\ &= \sum_{r=1}^P \sum_{q=1}^P \sum_{s=1}^P \sum_{t=1}^P \mathcal{E}\left[h_{jlmr}^* h_{jlpq} h_{jlpq}^* h_{jlnt} \right] \beta_{jlp} \sqrt{\beta_{jlm} \beta_{jln}} e^{j[f_k(\phi_r) - f_k(\phi_q) + f_u(\phi_s) - f_u(\phi_t)]}\end{aligned}$$

The term $\mathcal{E}\left[h_{jlmr}^* h_{jlpq} h_{jlpq}^* h_{jlnt}\right]$ is not equal to zero when $n = m$ and $s = q$ and $r = t$. In these conditions we have:

$$\begin{aligned}
& \mathcal{E} \left[A_{r,q}^{j,k}(n,p) A_{s,t}^{j,u}(p,n) \right] \\
&= \sum_{r=1}^P \sum_{q=1}^P \mathcal{E} \left[h_{jlnr}^* h_{jlpq} h_{jlpq}^* h_{jlnr} \right] \beta_{jlp} \beta_{jln} e^{j[f_k(\phi_r) - f_k(\phi_q) + f_u(\phi_q) - f_u(\phi_r)]} \\
&= \sum_{r=1}^P \sum_{q=1}^P \mathcal{E} \left[|h_{jlnr}|^2 \right] \mathcal{E} \left[|h_{jlpq}|^2 \right] \beta_{jlp} \beta_{jln} e^{j[f_k(\phi_r) - f_k(\phi_q) + f_u(\phi_q) - f_u(\phi_r)]} \\
&= \beta_{jlp} \beta_{jln} \sum_{q=1}^P \mathcal{E} \left[|h_{jlpq}|^2 \right] e^{j[f_u(\phi_q) - f_k(\phi_q)]} \sum_{r=1}^P \mathcal{E} \left[|h_{jlnr}|^2 \right] e^{j[f_k(\phi_r) - f_u(\phi_r)]}
\end{aligned}$$

We have:

$$\begin{aligned}
e^{j[f_u(\phi_q) - f_k(\phi_q)]} &= e^{j[2\pi \frac{d}{\lambda} (u-1)\sin(\phi_q) - 2\pi \frac{d}{\lambda} (k-1)\sin(\phi_q)]} = e^{j[2\pi \frac{d}{\lambda} (u-k)\sin(\phi_q)]} \\
e^{j[f_k(\phi_r) - f_u(\phi_r)]} &= e^{j[2\pi \frac{d}{\lambda} (k-1)\sin(\phi_r) - 2\pi \frac{d}{\lambda} (u-1)\sin(\phi_r)]} = e^{j[2\pi \frac{d}{\lambda} (k-u)\sin(\phi_r)]}
\end{aligned}$$

This yields:

$$\begin{aligned}
S &= \sum_{k=1}^M \sum_{u=1, u \neq k}^M e^{j[2\pi \frac{d}{\lambda} (u-k)(\sin(\phi_q) - \sin(\phi_r))]} = \left[\sum_{k=1}^M e^{-j2\pi \frac{d}{\lambda} k(\sin(\phi_q) - \sin(\phi_r))} \right] \left[\sum_{u=1, u \neq k}^M e^{j2\pi \frac{d}{\lambda} u(\sin(\phi_q) - \sin(\phi_r))} \right] \\
&= \left[\sum_{k=1}^M e^{-j2\pi \frac{d}{\lambda} k(\sin(\phi_q) - \sin(\phi_r))} \right] \left[\sum_{u=1}^M e^{j2\pi \frac{d}{\lambda} u(\sin(\phi_q) - \sin(\phi_r))} - e^{j2\pi \frac{d}{\lambda} k(\sin(\phi_q) - \sin(\phi_r))} \right] \\
&= \left(\sum_{k=1}^M e^{-j2\pi \frac{d}{\lambda} k(\sin(\phi_q) - \sin(\phi_r))} \right) \left(\sum_{u=1}^M e^{j2\pi \frac{d}{\lambda} u(\sin(\phi_q) - \sin(\phi_r))} \right) - M \\
&= \left(e^{-j2\pi \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))} \frac{1 - e^{-j2\pi M \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))}}{1 - e^{-j2\pi \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))}} \right) \left(e^{j2\pi \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))} \frac{1 - e^{j2\pi M \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))}}{1 - e^{j2\pi \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))}} \right) - M \\
&= \left(\frac{\sin \left[\pi M \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r)) \right]}{\sin \left[\pi \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r)) \right]} \right)^2 - M \\
&= M^2 \left(\frac{\sin \left[\pi M \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r)) \right]}{M \sin \left[\pi \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r)) \right]} \right)^2 - M
\end{aligned}$$

Using this result, and supposing $\mathcal{E}\left[\left|h_{jlpq}\right|^2\right] = \mathcal{E}\left[\left|h_{jlnr}\right|^2\right] = 1/P \quad \forall r, \forall q$, (this means that the contributions of each multipath component is the same) we obtain:

$$\begin{aligned}
& \mathcal{E}\left[\left(\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}\right)^2(n,n)\right] \\
&= \frac{1}{P^2} \sum_{p=1}^K \sum_{k=1}^M \sum_{u=1}^M \mathcal{E}\left[A_{r,q}^{j,k}(n,p) A_{s,t}^{j,u}(p,n)\right] \\
&= \frac{1}{P^2} \sum_{p=1}^K \sum_{k=1}^M \sum_{u=1}^M \beta_{jlp} \beta_{jln} \sum_{r=1}^P \mathcal{E}\left[\left|h_{jlnr}\right|^2\right] \sum_{q=1}^P \mathcal{E}\left[\left|h_{jlpq}\right|^2\right] e^{j[f_k(\phi_r) - f_k(\phi_q) + f_u(\phi_q) - f_u(\phi_r)]} \\
&= \frac{1}{P^2} \beta_{jln} \sum_{p=1}^K \beta_{jlp} \sum_{k=1}^M \left[\sum_{r=1}^P \mathcal{E}\left[\left|h_{jlnr}\right|^2\right] \sum_{q=1}^P \mathcal{E}\left[\left|h_{jlpq}\right|^2\right] \right] + \dots \\
&\dots + \frac{1}{P^2} \beta_{jln} \sum_{p=1}^K \beta_{jlp} \sum_{k=1}^M \sum_{u=1, u \neq k}^M \left[\sum_{r=1}^P \mathcal{E}\left[\left|h_{jlnr}\right|^2\right] \sum_{q=1}^P \mathcal{E}\left[\left|h_{jlpq}\right|^2\right] e^{j[f_k(\phi_r) - f_k(\phi_q) + f_u(\phi_q) - f_u(\phi_r)]} \right] \\
&= \frac{M}{P^2} \beta_{jln} \beta_{jl} + \frac{1}{P^4} \beta_{jln} \beta_{jl} \sum_{k=1}^M \sum_{u=1, u \neq k}^M \left[\sum_{r=1}^P \sum_{q=1}^P e^{j[f_k(\phi_r) - f_k(\phi_q) + f_u(\phi_q) - f_u(\phi_r)]} \right] \\
&= \frac{M}{P^2} \beta_{jln} \beta_{jl} + \frac{1}{P^4} \beta_{jln} \beta_{jl} \sum_{r=1}^P \sum_{q=1}^P \left[\sum_{k=1}^M \sum_{u=1, u \neq k}^M e^{j[f_k(\phi_r) - f_k(\phi_q) + f_u(\phi_q) - f_u(\phi_r)]} \right] \\
&= \frac{M}{P^2} \beta_{jln} \beta_{jl} + \frac{1}{P^4} \beta_{jln} \beta_{jl} \sum_{r=1}^P \sum_{q=1}^P \left[M^2 \left(\frac{\sin\left[\pi M \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))\right]}{M \sin\left[\pi \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))\right]} \right)^2 - M \right] \\
&= \frac{M}{P^2} \beta_{jln} \beta_{jl} + \frac{M^2}{P^4} \beta_{jln} \beta_{jl} \sum_{r=1}^P \sum_{q=1}^P \left[\left(\frac{\sin\left[\pi M \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))\right]}{M \sin\left[\pi \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))\right]} \right)^2 - \frac{1}{M} \right] \\
&= \frac{M^2}{P^4} \beta_{jln} \beta_{jl} \sum_{r=1}^P \sum_{q=1}^P \left(\frac{\sin\left[\pi M \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))\right]}{M \sin\left[\pi \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))\right]} \right)^2
\end{aligned}$$

Using the notation: $S_{r,q} = \sum_{r=1}^P \sum_{q=1}^P \left(\frac{\sin\left[\pi M \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))\right]}{M \sin\left[\pi \frac{d}{\lambda} (\sin(\phi_q) - \sin(\phi_r))\right]} \right)^2$, we obtain eventually :

$$\begin{aligned} & \mathbb{E}\left[\left(\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}\right)^2(n,n)\right] \\ & \approx \frac{M^2}{P^4} \beta_{jln} \beta_{jl} S_{r,q} \end{aligned}$$

This yields:

$$\begin{aligned} & \mathbb{E}\left[\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}\right] \\ & = \frac{M^2 \beta_{jl} S_{r,q}}{P^4} \text{diag}(\beta_{jl1}, \beta_{jl2}, \dots, \beta_{jlK}) \end{aligned}$$

And:

$$\begin{aligned} & \mathbb{E}\left[\sum_{j=1}^L \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}\right] \\ & = \frac{M^2 S_{r,q}}{P^4} \sum_{j=1}^L \beta_{jl} \text{diag}(\beta_{jl1}, \beta_{jl2}, \dots, \beta_{jlK}) \end{aligned}$$

-2) The second one is:

$$\mathbb{E}[\mathbf{a}_i^H \mathbf{a}_i \mathbf{a}_j^H \mathbf{a}_j] = \mathbb{E}[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}]$$

If we suppose that the channels are independent, we can write:

$$\begin{aligned} \mathbb{E}[\mathbf{a}_i^H \mathbf{a}_i \mathbf{a}_j^H \mathbf{a}_j] & = \mathbb{E}[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}] = \mathbb{E}[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l}] \mathbb{E}[\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l}] \\ & = \frac{M^2}{P^2} \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \text{diag}(\beta_{jl1}, \beta_{jl2}, \dots, \beta_{jlK}) \\ & = \frac{M^2}{P^2} \text{diag}(\beta_{il1} \beta_{jl1}, \beta_{il2} \beta_{jl2}, \dots, \beta_{ilK} \beta_{jlK}) \end{aligned}$$

-3) The third one is:

$$\mathbb{E}[\mathbf{a}_i^H \mathbf{a}_j \mathbf{a}_j^H \mathbf{a}_i] = \mathbb{E}[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l}] = \mathbb{E}[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbb{E}[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H] \mathbf{A} \mathbf{G}_{i,l}]$$

The general term of matrix $\mathbf{A} \mathbf{G}_{j,l}$ is written as :

$$\left[\mathbf{A} \mathbf{G}_{j,l}(m,k) \right]_{M \times K} = \frac{1}{\sqrt{P}} \sum_{s=1}^P g_{jls} e^{-j f_m(\phi_s)} = a_{m,k}$$

And we have :

$$\left[\mathbf{G}_{j,l}^H \mathbf{A}^H(n, p) \right]_{K \times M} = \frac{1}{\sqrt{P}} \sum_{r=1}^P g_{jlnr}^* e^{j f_p(\phi_r)} = b_{n,p}$$

The general term of matrix $\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H$ is thus :

$$\begin{aligned} & \left[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \right](m, p) = \sum a_{m,k} b_{k,p} \\ &= \sum_{k=1}^K \left(\frac{1}{\sqrt{P}} \sum_{s=1}^P g_{jlns} e^{-j f_m(\phi_s)} \right) \left(\frac{1}{\sqrt{P}} \sum_{r=1}^P g_{jlnr}^* e^{j f_p(\phi_r)} \right) \\ &= \frac{1}{P} \sum_{k=1}^K \sum_{r=1}^P \sum_{s=1}^P g_{jlnr}^* g_{jlns} e^{j f_p(\phi_r) - j f_m(\phi_s)} \\ &= \frac{1}{P} \sum_{k=1}^K \sum_{r=1}^P \sum_{s=1}^P h_{jlnr}^* h_{jlns} \sqrt{\beta_{jln} \beta_{jln}} e^{j f_p(\phi_r) - j f_m(\phi_s)} \end{aligned}$$

Hence, we have :

$$\mathcal{E} \left[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \right](m, p) = \frac{1}{P} \sum_{k=1}^K \sum_{r=1}^P \sum_{s=1}^P \mathcal{E} \left[h_{jlnr}^* h_{jlns} \right] \beta_{jln} e^{j f_p(\phi_r) - j f_m(\phi_s)}$$

For $m=p$, we obtain:

$$\mathcal{E} \left[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \right](m, m) = \frac{1}{P} \sum_{k=1}^K \sum_{r=1}^P \mathcal{E} \left[|h_{jlnr}|^2 \right] \beta_{jln} = \frac{1}{P} \sum_{k=1}^K \beta_{jln} = \frac{1}{P} \beta_{jl}$$

However, if $m \neq p$, we have:

$$\begin{aligned} & \mathcal{E} \left[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \right](m, p) = \frac{1}{P} \sum_{k=1}^K \sum_{r=1}^P \mathcal{E} \left[|h_{jlnr}|^2 \right] \beta_{jln} e^{j f_p(\phi_r) - j f_m(\phi_r)} \\ &= \frac{1}{P} \sum_{k=1}^K \sum_{r=1}^P \mathcal{E} \left[|h_{jlnr}|^2 \right] \beta_{jln} e^{j 2\pi \frac{d}{\lambda} (p-m) \sin(\phi_r)} \\ &= \frac{1}{P^2} \sum_{k=1}^K \beta_{jln} \sum_{r=1}^P e^{j 2\pi \frac{d}{\lambda} (p-m) \sin(\phi_r)} \\ &= \frac{\beta_{jl}}{P^2} \sum_{r=1}^P e^{j 2\pi \frac{d}{\lambda} (p-m) \sin(\phi_r)} \end{aligned}$$

And this quantity is not necessarily equal to zero. We can approximate $\mathcal{E} \left[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \right]$ as :

$$\mathcal{E} \left[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \right] = \frac{1}{P} \beta_{jl} \mathbf{I}_M$$

The (m,n) th element of $\mathbf{G}_{i,l}^H \mathbf{A}^H$ is written as :

$$\left[\mathbf{G}_{i,l}^H \mathbf{A}^H(m,n) \right]_{K \times M} = a_{m,n} = \frac{1}{\sqrt{P}} \sum_{k=1}^P g_{ilmk}^* e^{j f_n(\phi_k)}$$

And we obtain:

$$\begin{aligned}
& \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{E} \left[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \right] (m, p) = \sum_{r=1}^M a_{m,r} b_{r,p} \\
&= \sum_{r=1}^M \frac{1}{\sqrt{P}} \left[\sum_{k=1}^P g_{ilmk}^* e^{j f_r(\phi_k)} \right] \frac{\beta_{jl}}{P^2} \sum_{q=1}^P e^{j 2\pi \frac{d}{\lambda} (p-r) \sin(\phi_q)} \\
&= \sum_{r=1}^M \frac{1}{\sqrt{P}} \left[\sum_{k=1}^P g_{ilmk}^* e^{j 2\pi \frac{d}{\lambda} (r-1) \sin(\phi_k)} \right] \frac{\beta_{jl}}{P^2} \sum_{q=1}^P e^{j 2\pi \frac{d}{\lambda} (p-r) \sin(\phi_q)} \\
&= \frac{\beta_{jl}}{P^{5/2}} \sum_{r=1}^M \sum_{k=1}^P \sum_{q=1}^P g_{ilmk}^* e^{j 2\pi \frac{d}{\lambda} (r-1) \sin(\phi_k)} e^{j 2\pi \frac{d}{\lambda} (p-r) \sin(\phi_q)} \\
&= \frac{\beta_{jl}}{P^{5/2}} \sum_{r=1}^M \sum_{k=1}^P \sum_{q=1}^P g_{ilmk}^* e^{j 2\pi \frac{d}{\lambda} r (\sin(\phi_k) - \sin(\phi_q))} e^{j 2\pi \frac{d}{\lambda} (p \sin(\phi_q) - \sin(\phi_k))} \\
&= \frac{\beta_{jl}}{P^{5/2}} \sum_{k=1}^P \sum_{q=1}^P g_{ilmk}^* e^{j 2\pi \frac{d}{\lambda} (p \sin(\phi_q) - \sin(\phi_k))} \sum_{r=1}^M e^{j 2\pi \frac{d}{\lambda} r (\sin(\phi_k) - \sin(\phi_q))} \\
&= \frac{\beta_{jl}}{P^{5/2}} \sum_{k=1}^P \sum_{q=1}^P g_{ilmk}^* e^{j 2\pi \frac{d}{\lambda} (p \sin(\phi_q) - \sin(\phi_k))} e^{j 2\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q))} \frac{1 - e^{j 2\pi \frac{d}{\lambda} M (\sin(\phi_k) - \sin(\phi_q))}}{1 - e^{j 2\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q))}} \\
&= \frac{M \beta_{jl}}{P^{5/2}} \sum_{k=1}^P \sum_{q=1}^P g_{ilmk}^* e^{j 2\pi \frac{d}{\lambda} (p-1) \sin(\phi_q)} e^{j \pi \frac{d}{\lambda} (M-1) (\sin(\phi_k) - \sin(\phi_q))} \frac{\sin \left[\pi \frac{d}{\lambda} M (\sin(\phi_k) - \sin(\phi_q)) \right]}{M \sin \left[\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q)) \right]} \\
&= \frac{M \beta_{jl}}{P^{5/2}} \sum_{k=1}^P g_{ilmk}^* e^{j \pi \frac{d}{\lambda} (M-1) \sin(\phi_k)} \sum_{q=1}^P e^{j \pi \frac{d}{\lambda} \sin(\phi_q) [2p-M-1]} \frac{\sin \left[\pi \frac{d}{\lambda} M (\sin(\phi_k) - \sin(\phi_q)) \right]}{M \sin \left[\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q)) \right]} \\
&= \frac{M \beta_{jl}}{P^{5/2}} \sum_{k=1}^P \sum_{q=1}^P g_{ilmk}^* e^{j \pi \frac{d}{\lambda} [(M-1) \sin(\phi_k) + (2p-M-1) \sin(\phi_q)]} \frac{\sin \left[\pi \frac{d}{\lambda} M (\sin(\phi_k) - \sin(\phi_q)) \right]}{M \sin \left[\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q)) \right]}
\end{aligned}$$

The general term of matrix $\mathbf{A} \mathbf{G}_{i,l}$ is written as :

$$\left[\mathbf{A} \mathbf{G}_{i,l}(p,n) \right]_{M \times K} = \frac{1}{\sqrt{P}} \sum_{s=1}^P g_{ils} e^{-j f_p(\phi_s)} = a_{p,n}$$

We have :

$$\begin{aligned}
& \left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathcal{E} \left[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \right] \mathbf{A} \mathbf{G}_{i,l} \right] (m,n) \\
&= \sum_{p=1}^M \frac{M \beta_{jl}}{P^{5/2}} \sum_{k=1}^P g_{ilmk}^* e^{j\pi \frac{d}{\lambda} (M-1) \sin(\phi_k)} \sum_{q=1}^P e^{j\pi \frac{d}{\lambda} \sin(\phi_q) [2p-M-1]} \frac{\sin \left[\pi \frac{d}{\lambda} M (\sin(\phi_k) - \sin(\phi_q)) \right]}{M \sin \left[\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q)) \right]} \frac{1}{\sqrt{P}} \sum_{s=1}^P g_{ilns} e^{-jf_p(\phi_s)} \\
&= \frac{M \beta_{jl}}{P^3} \sum_{p=1}^M \sum_{k=1}^P \sum_{s=1}^P g_{ilmk}^* g_{ilns} e^{j\pi \frac{d}{\lambda} (M-1) \sin(\phi_k)} e^{-j2\pi \frac{d}{\lambda} (p-1) \sin(\phi_s)} \sum_{q=1}^P e^{j\pi \frac{d}{\lambda} \sin(\phi_q) [2p-M-1]} \frac{\sin \left[\pi \frac{d}{\lambda} M (\sin(\phi_k) - \sin(\phi_q)) \right]}{M \sin \left[\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q)) \right]}
\end{aligned}$$

We obtain eventually :

$$\begin{aligned}
& \mathcal{E} [\mathbf{G}_{i,l}^H \mathbf{A}^H \mathcal{E} \left[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \right] \mathbf{A} \mathbf{G}_{i,l}] (m,n) \\
&= \frac{M \beta_{jl}}{P^3} \sum_{p=1}^M \sum_{k=1}^P \sum_{s=1}^P \mathcal{E} \left[g_{ilmk}^* g_{ilns} \right] e^{j\pi \frac{d}{\lambda} (M-1) \sin(\phi_k)} e^{-j2\pi \frac{d}{\lambda} (p-1) \sin(\phi_s)} \sum_{q=1}^P e^{j\pi \frac{d}{\lambda} \sin(\phi_q) [2p-M-1]} \frac{\sin \left[\pi \frac{d}{\lambda} M (\sin(\phi_k) - \sin(\phi_q)) \right]}{M \sin \left[\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q)) \right]}
\end{aligned}$$

The quantity is not equal to zero when $m = n$ and $k = s$, this entails:

$$\begin{aligned}
& \mathcal{E} [\mathbf{G}_{i,l}^H \mathbf{A}^H \mathcal{E} \left[\mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \right] \mathbf{A} \mathbf{G}_{i,l}] (n,n) \\
&= \frac{M \beta_{jl}}{P^3} \sum_{p=1}^M \sum_{k=1}^P \frac{\beta_{iln}}{P} e^{j\pi \frac{d}{\lambda} (M-1) \sin(\phi_k)} e^{-j2\pi \frac{d}{\lambda} (p-1) \sin(\phi_k)} \sum_{q=1}^P e^{j\pi \frac{d}{\lambda} \sin(\phi_q) [2p-M-1]} \frac{\sin \left[\pi \frac{d}{\lambda} M (\sin(\phi_k) - \sin(\phi_q)) \right]}{M \sin \left[\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q)) \right]} \\
&= \frac{M \beta_{jl} \beta_{iln}}{P^4} \sum_{p=1}^M \sum_{k=1}^P e^{j\pi \frac{d}{\lambda} \sin(\phi_k) [M-2p+1]} \sum_{q=1}^P e^{j\pi \frac{d}{\lambda} \sin(\phi_q) [2p-M-1]} \frac{\sin \left[\pi \frac{d}{\lambda} M (\sin(\phi_k) - \sin(\phi_q)) \right]}{M \sin \left[\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q)) \right]} \\
&= \frac{M \beta_{jl} \beta_{iln}}{P^4} \sum_{p=1}^M \sum_{k=1}^P \sum_{q=1}^P e^{j\pi \frac{d}{\lambda} [M-2p+1] (\sin(\phi_k) - \sin(\phi_q))} \frac{\sin \left[\pi \frac{d}{\lambda} M (\sin(\phi_k) - \sin(\phi_q)) \right]}{M \sin \left[\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q)) \right]}
\end{aligned}$$

$$\text{Using the notation: } T_{p,k,q} = \sum_{p=1}^M \sum_{k=1}^P \sum_{q=1}^P e^{j\pi \frac{d}{\lambda} [M-2p+1] (\sin(\phi_k) - \sin(\phi_q))} \frac{\sin \left[\pi \frac{d}{\lambda} M (\sin(\phi_k) - \sin(\phi_q)) \right]}{M \sin \left[\pi \frac{d}{\lambda} (\sin(\phi_k) - \sin(\phi_q)) \right]},$$

we obtain :

$$\begin{aligned} & \mathcal{E}[G_{i,l}^H A^H \mathcal{E}[A G_{j,l} G_{j,l}^H A^H] A G_{i,l}] \\ &= \frac{M}{P^4} \beta_{jl} T_{p,k,q} \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \end{aligned}$$

In fact, for the sake of simplicity we will use a lower bound for the different expectation forms due to the difficulty of obtaining asymptotic expressions. We will have in this case:

$$\begin{aligned} & \mathcal{E}\left[\left(G_{j,l}^H A^H A G_{j,l}\right)^2 (n,n)\right] \\ &> \frac{M}{P^2} \beta_{jln} \beta_{jl} \end{aligned}$$

And:

$$\begin{aligned} & \mathcal{E}\left[\sum_{j=1}^L G_{j,l}^H A^H A G_{j,l} G_{j,l}^H A^H A G_{j,l}\right] \\ &> \frac{M}{P^2} \sum_{j=1}^L \beta_{jl} \text{diag}(\beta_{jl1}, \beta_{jl2}, \dots, \beta_{jlK}) \end{aligned}$$

And, in the same way :

$$\begin{aligned} & \mathcal{E}[G_{i,l}^H A^H \mathcal{E}[A G_{j,l} G_{j,l}^H A^H] A G_{i,l}] \\ &> \frac{M}{P^2} \beta_{jl} \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \end{aligned}$$

Using these lower bounds we obtain in the general case:

$$\begin{aligned} & \mathcal{E}\left[\left(\sum_{i=1}^L G_{i,l}^H A^H A \sum_{k=1}^L G_{k,l}\right) \left(\sum_{j=1}^L G_{j,l}^H A^H A \sum_{m=1}^L G_{m,l}\right)\right] \\ &= \sum_{i=1}^L \mathcal{E}(G_{i,l}^H A^H A G_{i,l} G_{i,l}^H A^H A G_{i,l}) + \sum_{i=1}^L \sum_{j=1, j \neq i}^L \mathcal{E}(G_{i,l}^H A^H A G_{i,l} G_{j,l}^H A^H A G_{j,l}) + \dots \\ & \dots + \sum_{i=1}^L \sum_{j=1, j \neq i}^L \mathcal{E}[G_{i,l}^H A^H A G_{j,l} G_{j,l}^H A^H A G_{i,l}] \\ &> \sum_{i=1}^L \frac{M \beta_{il}}{P^2} \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) + \sum_{i=1}^L \sum_{j=1, j \neq i}^L \frac{M^2}{P^2} \text{diag}(\beta_{il1} \beta_{jl1}, \beta_{il2} \beta_{jl2}, \dots, \beta_{ilK} \beta_{jlK}) + \\ & \dots + \sum_{i=1}^L \sum_{j=1, j \neq i}^L \frac{M}{P^2} \beta_{jl} \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \\ &> \frac{M}{P^2} \sum_{i=1}^L \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \left[\beta_{il} \mathbf{I}_K + M \sum_{j=1, j \neq i}^L \text{diag}(\beta_{jl1}, \beta_{jl2}, \dots, \beta_{jlK}) + \sum_{j=1, j \neq i}^L \beta_{jl} \mathbf{I}_K \right] \end{aligned}$$

$$\begin{aligned}
& > \frac{M}{P^2} \sum_{i=1}^L \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \left[\sum_{j=1}^L \beta_{jl} \mathbf{I}_K + M \sum_{j=1, j \neq i}^L \text{diag}(\beta_{jl1}, \beta_{jl2}, \dots, \beta_{jlK}) \right] \\
& > \frac{M}{P^2} \sum_{i=1}^L \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \left[\hat{\beta}_l \mathbf{I}_K + M \sum_{j=1, j \neq i}^L \text{diag}(\beta_{jl1}, \beta_{jl2}, \dots, \beta_{jlK}) \right] \\
& > \frac{M^2}{P^2} \sum_{i=1}^L \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \left[\frac{\hat{\beta}_l}{M} \mathbf{I}_K + \sum_{j=1, j \neq i}^L \text{diag}(\beta_{jl1}, \beta_{jl2}, \dots, \beta_{jlK}) \right] \\
& > \frac{M^2}{P^2} \sum_{i=1}^L \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \left[\text{diag} \left(\sum_{j=1, j \neq i}^L \beta_{jl1} + \frac{\hat{\beta}_l}{M}, \sum_{j=1, j \neq i}^L \beta_{jl2} + \frac{\hat{\beta}_l}{M}, \dots, \sum_{j=1, j \neq i}^L \beta_{jlK} + \frac{\hat{\beta}_l}{M} \right) \right]
\end{aligned}$$

We obtain a lower bound which is quite accurate.

The following term is: $\mathcal{E}[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l]$, we have:

$$\begin{aligned}
& \mathcal{E}[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l] \\
& \approx \mathcal{E}[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathcal{E}[\mathbf{W}_l \mathbf{W}_l^H] \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l] \\
& = K \sigma_{n_l}^2 \mathcal{E}[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l]
\end{aligned}$$

$$\boldsymbol{\Pi}_A \equiv \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \approx_{M \rightarrow \infty} \mathbf{A} \left(\frac{M}{P} \mathbf{I}_P \right)^{-1} \mathbf{A}^H = \frac{P}{M} \mathbf{A} \mathbf{A}^H$$

$$\begin{aligned}
& \mathcal{E}[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l] \\
& = \frac{1}{M} \mathcal{E}[\mathbf{W}_l^H \mathbf{W}_l] \text{Trace}(\mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H) \\
& = \frac{1}{M} M \sigma_{n_l}^2 \mathbf{I}_K \text{Trace}[\boldsymbol{\Pi}_A] \approx_{M \rightarrow \infty} \sigma_{n_l}^2 \frac{P}{M} \text{Trace}(\mathbf{A} \mathbf{A}^H) \mathbf{I}_K
\end{aligned}$$

We eventually obtain:

$$\begin{aligned}
& \mathcal{E}[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l] \\
& = \frac{KP}{M} \sigma_{n_l}^4 \text{Trace}(\mathbf{A} \mathbf{A}^H) \mathbf{I}_K
\end{aligned}$$

Then, we find :

$$\begin{aligned}
& \mathcal{E} \left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \right] \\
&= \sum_{i=1}^L \mathcal{E} [\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l}] \mathcal{E} [\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l] \\
&= \sum_{i=1}^L \frac{M}{P} \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \sigma_{n_l}^2 \frac{P}{M} \text{Trace}(\mathbf{A} \mathbf{A}^H) \mathbf{I}_K \\
&= \sigma_{n_l}^2 \text{Trace}(\mathbf{A} \mathbf{A}^H) \text{diag} \left(\sum_{i=1}^L \beta_{il1}, \sum_{i=1}^L \beta_{il2}, \dots, \sum_{i=1}^L \beta_{ilK} \right) \\
&= \sigma_{n_l}^2 \text{Trace}(\mathbf{A} \mathbf{A}^H) \text{diag}(\bar{\beta}_{l1}, \bar{\beta}_{l2}, \dots, \bar{\beta}_{lK})
\end{aligned}$$

$$\begin{aligned}
& \mathcal{E} \left[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \right] \\
&= \mathcal{E} [\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l] \sum_{i=1}^L \mathcal{E} [\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l}] \\
&= \sigma_{n_l}^2 \text{Trace}(\mathbf{A} \mathbf{A}^H) \text{diag}(\bar{\beta}_{l1}, \bar{\beta}_{l2}, \dots, \bar{\beta}_{lK})
\end{aligned}$$

The remaining terms are : $\mathcal{E} \left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \right]$ and $\mathcal{E} \left[\mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \right]$,

we have :

$$\mathcal{E} \left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \right] = \mathcal{E} \left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathcal{E} [\mathbf{W}_l \mathbf{W}_l^H] \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \right]$$

And using : $\mathcal{E} [\mathbf{W}_l \mathbf{W}_l^H] = K \sigma_{n_l}^2 \mathbf{I}_M$, this yields :

$$\begin{aligned}
& \mathcal{E} \left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \right] = K \sigma_{n_l}^2 \mathcal{E} \left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \right] = K \sigma_{n_l}^2 \sum_{i=1}^L \mathcal{E} [\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l}] \\
&= K \sigma_{n_l}^2 \sum_{i=1}^L \frac{M}{P} \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) = \frac{K \sigma_{n_l}^2 M}{P} \text{diag}(\bar{\beta}_{l1}, \bar{\beta}_{l2}, \dots, \bar{\beta}_{lK})
\end{aligned}$$

And, for the last term :

$$\begin{aligned}
& \mathcal{E} \left[\mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathcal{E} \left[\mathbf{G}_{i,l} \mathbf{G}_{i,l}^H \right] \mathbf{A}^H \mathbf{W}_l \right] = \frac{1}{P} \mathcal{E} \left[\mathbf{W}_l^H \mathbf{A} \mathbf{A}^H \mathbf{W}_l \right] \text{Trace} \left[\sum_{i=1}^L \mathcal{E} \left[\mathbf{G}_{i,l} \mathbf{G}_{i,l}^H \right] \right] \\
& = \frac{1}{P} \mathcal{E} \left[\mathbf{W}_l^H \mathbf{A} \mathbf{A}^H \mathbf{W}_l \right] \sum_{i=1}^L \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{i,l} \mathbf{G}_{i,l}^H \right] \right] \\
& = \frac{\text{Trace}(\mathbf{A} \mathbf{A}^H)}{MP} \mathcal{E} \left[\mathbf{W}_l^H \mathbf{W}_l \right] \sum_{i=1}^L \beta_{il} \\
& = M \sigma_{n_l}^2 \mathbf{I}_K \frac{\text{Trace}(\mathbf{A} \mathbf{A}^H)}{MP} \sum_{i=1}^L \beta_{il} \\
& = \sigma_{n_l}^2 \frac{\text{Trace}(\mathbf{A} \mathbf{A}^H)}{P} \sum_{i=1}^L \beta_{il} \mathbf{I}_K \\
& = \frac{\sigma_{n_l}^2 \hat{\beta}_l \text{Trace}(\mathbf{A} \mathbf{A}^H)}{P} \mathbf{I}_K
\end{aligned}$$

We eventually obtain :

$$\begin{aligned}
& p_p^2 \mathcal{E} \left[\left(\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{k=1}^L \mathbf{G}_{k,l} \right) \left(\sum_{j=1}^L \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l} \right) \right] + \dots \\
& \dots + \mathcal{E} \left[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \right] + 2p_p \sum_{i=1}^L \mathcal{E} \left[\mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l} \right] \mathcal{E} \left[\mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W}_l \right] + \dots \\
& \dots + p_p \mathcal{E} \left[\sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathcal{E} \left[\mathbf{W}_l \mathbf{W}_l^H \right] \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} \right] + p_p \mathcal{E} \left[\mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathcal{E} \left[\mathbf{G}_{i,l} \mathbf{G}_{i,l}^H \right] \mathbf{A}^H \mathbf{W}_l \right] \\
& \mathcal{E} \left(\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \right]^2 \right) \\
& = p_p^2 \frac{M^2}{P^2} \sum_{i=1}^L \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \left[\text{diag} \left(\sum_{j=1, j \neq i}^L \beta_{jl1} + \frac{\hat{\beta}_l}{M}, \sum_{j=1, j \neq i}^L \beta_{jl2} + \frac{\hat{\beta}_l}{M}, \dots, \sum_{j=1, j \neq i}^L \beta_{jlk} + \frac{\hat{\beta}_l}{M} \right) \right] + \dots \\
& \dots + \frac{KP}{M} \sigma_{n_l}^4 \text{Trace}(\mathbf{A} \mathbf{A}^H) \mathbf{I}_K + 2p_p \sigma_{n_l}^2 \text{Trace}(\mathbf{A} \mathbf{A}^H) \text{diag}(\bar{\beta}_{l1}, \bar{\beta}_{l2}, \dots, \bar{\beta}_{lK}) + p_p \frac{K \sigma_{n_l}^2 M}{P} \text{diag}(\bar{\beta}_{l1}, \bar{\beta}_{l2}, \dots, \bar{\beta}_{lK}) + \dots \\
& \dots + p_p \frac{\sigma_{n_l}^2 \hat{\beta}_l \text{Trace}(\mathbf{A} \mathbf{A}^H)}{P} \mathbf{I}_K \\
& = p_p^2 \frac{M^2}{P^2} \sum_{i=1}^L \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \left[\text{diag} \left(\bar{\beta}_{l1} - \beta_{il1} + \frac{\hat{\beta}_l}{M}, \bar{\beta}_{l2} - \beta_{il2} + \frac{\hat{\beta}_l}{M}, \dots, \bar{\beta}_{lK} - \beta_{ilK} + \frac{\hat{\beta}_l}{M} \right) \right] + \dots \\
& \dots + \left(2p_p \sigma_{n_l}^2 \text{Trace}(\mathbf{A} \mathbf{A}^H) + p_p \frac{K \sigma_{n_l}^2 M}{P} \right) \text{diag}(\bar{\beta}_{l1}, \bar{\beta}_{l2}, \dots, \bar{\beta}_{lK}) + \text{Trace}(\mathbf{A} \mathbf{A}^H) \left(\frac{KP}{M} \sigma_{n_l}^4 + p_p \frac{\sigma_{n_l}^2 \hat{\beta}_l}{P} \right) \mathbf{I}_K
\end{aligned}$$

We obtain in these conditions:

$$\mathcal{E} \left[\mathbf{M}_{p,l}^A(n,:) \mathbf{M}_{p,l}^A(n,:)^H \right] \approx \gamma_{n,l}$$

Considering the case where M is sufficiently high, we have $\mathbf{A}\mathbf{A}^H \approx \mathbf{I}_M$ and this yields:

$$\gamma_{n,l} = \frac{1}{p_p^2 \frac{M^2}{P^2} \left(\sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} + \frac{\hat{\beta}_l}{M} \right] \right) + p_p M \sigma_{n_l}^2 \left(2 + \frac{K}{P} \right) \bar{\beta}_{ln} + \sigma_{n_l}^2 M \left(p_p \frac{\hat{\beta}_l}{P} + \frac{KP}{M} \sigma_{n_l}^2 \right)}$$

$$\gamma_{n,l} \approx \frac{P^2}{p_p^2 M^2 \left[\left(\sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} + \frac{\hat{\beta}_l}{M} \right] \right) + \frac{P^2 \sigma_{n_l}^2}{Mp_p} \left(2 + \frac{K}{P} \right) \bar{\beta}_{ln} + \sigma_{n_l}^2 \frac{P^2}{p_p^2 M} \left(p_p \frac{\hat{\beta}_l}{P} + \frac{KP}{M} \sigma_{n_l}^2 \right) \right]}$$

This can be simplified as:

$$\gamma_{n,l} = \frac{P^2}{p_p^2 M^2 \left[\left(\sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} + \frac{\hat{\beta}_l}{M} \right] \right) + \frac{P^2 \sigma_{n_l}^2}{Mp_p} \left[\left(2 + \frac{K}{P} \right) \bar{\beta}_{ln} + \frac{\hat{\beta}_l}{P} + \frac{KP}{M} \frac{\sigma_{n_l}^2}{p_p} \right] \right]}$$

$$\gamma_{n,l} \approx_{M \rightarrow \infty} \frac{P^2}{p_p^2 M^2 \left[\left(\sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} \right] \right) \right]}$$

And, we eventually obtain:

$$\begin{aligned} \mathcal{E} \left\{ \left\| \boldsymbol{\alpha}_{jn}^T \right\|^2 \right\} &= \mathcal{E} \left(\boldsymbol{\alpha}_{jn}^T \boldsymbol{\alpha}_{jn}^* \right) \\ &= \frac{\gamma_{n,l} p_u p_p \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right)}{P^2 K} + \frac{\gamma_{n,l} p_u p_p M^2 \beta_{jl}^2}{KP^2} + \frac{\sigma_{n_l}^2 p_u M^2 \beta_{jl} \gamma_{n,l}}{KP} \\ &= \frac{\gamma_{n,l} \left[p_u p_p \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right) + p_u p_p M^2 \beta_{jl}^2 + \sigma_{n_l}^2 p_u M^2 P \beta_{jl} \right]}{P^2 K} \quad (91) \\ &= \frac{\left[p_u p_p \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right) + p_u p_p M^2 \beta_{jl}^2 + \sigma_{n_l}^2 p_u M^2 P \beta_{jl} \right]}{p_p^2 M^2 K \left[\left(\sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} + \frac{\hat{\beta}_l}{M} \right] \right) + \frac{P^2 \sigma_{n_l}^2}{Mp_p} \left[\left(2 + \frac{K}{P} \right) \bar{\beta}_{ln} + \frac{\hat{\beta}_l}{P} + \frac{KP}{M} \frac{\sigma_{n_l}^2}{p_p} \right] \right]} \end{aligned}$$

Considering the case where M goes towards infinity, we have:

$$\lim_{M \rightarrow \infty} \frac{1}{M} \mathbf{A}^H \mathbf{A} = \frac{1}{P} \mathbf{I}_P$$

This yields: $\lim_{M \rightarrow \infty} \mathbf{A}^H \mathbf{A} = \frac{M}{P} \mathbf{I}_P$ and $\lim_{M \rightarrow \infty} \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] = \frac{M^2}{P^2} P = \frac{M^2}{P}$ and we obtain:

$$\begin{aligned}
& \mathcal{E} \left\{ \left\| \boldsymbol{\alpha}_{jn}^T \right\|^2 \right\} \\
&= \frac{\left[p_u p_p \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right) M^2 / P + p_u p_p M^2 \beta_{jl}^2 + \sigma_{n_l}^2 p_u M^2 P \beta_{jl} \right]}{p_p^2 M^2 K \left[\left(\sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} + \frac{\hat{\beta}_l}{M} \right] \right) + \frac{P^2 \sigma_{n_l}^2}{M p_p} \left[\left(2 + \frac{K}{P} \right) \bar{\beta}_{ln} + \frac{\hat{\beta}_l}{P} + \frac{KP}{M} \frac{\sigma_{n_l}^2}{p_p} \right] \right]} \\
&= \frac{\left[p_u p_p \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right) / P + p_u p_p \beta_{jl}^2 + \sigma_{n_l}^2 p_u P \beta_{jl} \right]}{p_p^2 K \left[\left(\sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} + \frac{\hat{\beta}_l}{M} \right] \right) + \frac{P^2 \sigma_{n_l}^2}{M p_p} \left[\left(2 + \frac{K}{P} \right) \bar{\beta}_{ln} + \frac{\hat{\beta}_l}{P} + \frac{KP}{M} \frac{\sigma_{n_l}^2}{p_p} \right] \right]} \\
&\approx_{M \rightarrow \infty} \frac{p_u p_p \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right) / P + p_u p_p \beta_{jl}^2 + \sigma_{n_l}^2 p_u P \beta_{jl}}{p_p^2 K \sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} \right]} \\
&= \frac{p_u}{p_p} \beta_{jl} \frac{\left(\hat{\beta}_l - \beta_{jl} \right) / P + \beta_{jl} + \frac{\sigma_{n_l}^2}{p_p} P}{K \sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} \right]} \tag{92}
\end{aligned}$$

Concerning the last term: $\mathcal{E} \left[|z_{ln}|^2 \right] = \mathcal{E} \left[\left| \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \mathbf{n}_l \right|^2 \right]$, we have :

$$\begin{aligned}
& \mathcal{E} \left\{ |z_{ln}|^2 \right\} = \mathcal{E} \left\{ \left| \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \mathbf{n}_l \right|^2 \right\} \\
&= \mathcal{E} \left\{ \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \mathbf{n}_l \mathbf{n}_l^H \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \mathbf{M}_{p,l}^A(n,:)^H \right\} \\
&= \mathcal{E} \left\{ \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \mathcal{E} \left[\mathbf{n}_l \mathbf{n}_l^H \right] \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \mathbf{M}_{p,l}^A(n,:)^H \right\} \\
&= \mathcal{E} \left\{ \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \sigma_{n_l}^2 \mathbf{I}_M \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \mathbf{M}_{p,l}^A(n,:)^H \right\} \\
&= \sigma_{n_l}^2 \mathcal{E} \left\{ \mathbf{M}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \mathbf{M}_{p,l}^A(n,:)^H \right\} \\
&= \sigma_{n_l}^2 \mathcal{E} \left\{ \mathbf{M}_{p,l}^A(n,:) \mathcal{E} \left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \right] \mathbf{M}_{p,l}^A(n,:)^H \right\} \\
&= \sigma_{n_l}^2 \mathcal{E} \left\{ \mathbf{M}_{p,l}^A(n,:) \text{diag}(\rho_{1,l}, \rho_{2,l}, \dots, \rho_{K,l}) \mathbf{M}_{p,l}^A(n,:)^H \right\} \\
&= \frac{\sigma_{n_l}^2}{K} \sum_{i=1}^K \rho_{i,l} \mathcal{E} \left\{ \mathbf{M}_{p,l}^A(n,:) \mathbf{M}_{p,l}^A(n,:)^H \right\} \\
&\approx \frac{\sigma_{n_l}^2 \gamma_{n,l} \sum_{i=1}^K \rho_{i,l}}{K} \tag{93}
\end{aligned}$$

We have: $\frac{\sum_{i=1}^K \rho_{i,l}}{K} = \frac{1}{K} \sum_{n=1}^K \left[p_p \frac{M}{P} \bar{\beta}_{ln} + \sigma_{n_l}^2 P \right] = \frac{p_p M}{KP} \sum_{n=1}^K \bar{\beta}_{ln} + \sigma_{n_l}^2 P$

$$\mathcal{E}\{|z_{ln}|^2\} = \frac{\left(p_p \frac{M}{KP} \sum_{n=1}^K \bar{\beta}_{ln} + \sigma_{n_l}^2 P \right) \sigma_{n_l}^2 P^2}{p_p^2 M^2 \left[\left(\sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} + \frac{\hat{\beta}_l}{M} \right] \right) + \frac{P^2 \sigma_{n_l}^2}{Mp_p} \left[\left(2 + \frac{K}{P} \right) \bar{\beta}_{ln} + \frac{\hat{\beta}_l}{P} + \frac{KP}{M} \frac{\sigma_{n_l}^2}{p_p} \right] \right]}$$

The final expression for the uplink capacity in the case of a ZF receiver is then equal to:

$$R_{ln} = C \left(\frac{\|\mathcal{E}(\alpha_{ln}^T)\|^2}{\sum_{j=1}^L \mathcal{E}\{\|\alpha_{jn}^T\|^2\} - \|\mathcal{E}(\alpha_{ln}^T)\|^2 + \mathcal{E}(|z_{ln}|^2)} \right)$$

$$R_{ln} = C \left(\frac{\frac{p_p p_u \beta_{lln}^2}{(p_p \bar{\beta}_{ln} + P^2 \sigma_{n_l}^2 / M)^2}}{\frac{p_u}{p_p} \sum_{j=1}^L \beta_{jl} \frac{(\hat{\beta}_l - \beta_{jl}) / P + \beta_{jl} + \frac{\sigma_{n_l}^2}{p_p} P}{K \sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}]} - \frac{p_p p_u \beta_{lln}^2}{(p_p \bar{\beta}_{ln} + P^2 \sigma_{n_l}^2 / M)^2} + \frac{\sigma_{n_l}^2 \gamma_{n,l} \sum_{i=1}^K \rho_{i,l}}{K}} \right) \quad (94)$$

When M goes towards infinity, we obtain:

$$R_{ln} = C \left(\frac{\|\mathcal{E}(\alpha_{ln}^T)\|^2}{\sum_{j=1}^L \mathcal{E}\{\|\alpha_{jn}^T\|^2\} - \|\mathcal{E}(\alpha_{ln}^T)\|^2 + \mathcal{E}(|z_{ln}|^2)} \right)$$

$$R_{ln} \approx_{M \rightarrow \infty} C \left(\frac{\frac{p_u \beta_{lln}^2}{p_p (\bar{\beta}_{ln})^2}}{\frac{p_u}{p_p} \sum_{j=1}^L \beta_{jl} \frac{(\hat{\beta}_l - \beta_{jl}) / P + \beta_{jl} + \frac{\sigma_{n_l}^2}{p_p} P}{K \sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}]} - \frac{p_u \beta_{lln}^2}{p_p (\bar{\beta}_{ln})^2}} \right) \quad (95)$$

At high SNR we can neglect the term $\frac{\sigma_{n_l}^2}{P_p} P \beta_{jl}$ and, doing this, when we consider also the case where P goes towards infinity, we obtain:

$$\begin{aligned}
R_{ln} &\approx_{M \rightarrow \infty} C \left(\frac{\frac{p_u}{p_p} \frac{\beta_{lln}^2}{(\bar{\beta}_{ln})^2}}{\frac{p_u}{p_p} \frac{\sum_{j=1}^L \beta_{jl}^2}{K \sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}]} - \frac{p_u}{p_p} \frac{\beta_{lln}^2}{(\bar{\beta}_{ln})^2}} \right) \\
R_{ln} &\approx_{M \rightarrow \infty} C \left(\frac{\frac{\beta_{lln}^2}{(\bar{\beta}_{ln})^2}}{\frac{\sum_{j=1}^L \beta_{jl}^2}{K \sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}]} - \frac{\beta_{lln}^2}{(\bar{\beta}_{ln})^2}} \right) = \left(\frac{\beta_{lln}^2 \left[K \sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}] \right]}{(\bar{\beta}_{ln})^2 \sum_{j=1}^L \beta_{jl}^2 - \beta_{lln}^2 K \sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}]} \right)
\end{aligned} \tag{96}$$

4.5. MMSE Receiver:

In this case the l th base station processes the received signal by multiplying it by matrix:

$$\left(\hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{I}_K \right)^{-1}. \text{From (6) and (14), we obtain:}$$

$$\mathbf{r}_l = \left(\hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{I}_K \right)^{-1} \hat{\Gamma}_{ll}^H \mathbf{y}_l \tag{97}$$

With:

$$\hat{\Gamma}_{ll} = \mathbf{A}_{M \times P} \left[\hat{\mathbf{H}}_{ll} \mathbf{D}_{ll}^{1/2} \right]_{P \times K} = p_p^{-1/2} \boldsymbol{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll}.$$

$\boldsymbol{\Pi}_A$ is of size $M \times M$, $\tilde{\mathbf{Y}}_{p,l}$ is of size $M \times K$. The product $\hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll}$ can be written as:

$$\hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll} = p_p^{-1} \mathbf{D}_{ll}^H \left(\mathbf{D}_l^{-1} \right)^H \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A^H \boldsymbol{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} \tag{98}$$

Of course, we have:

$$\begin{aligned}
\Pi_A^H \Pi_A &= \left[A(A^H A)^{-1} A^H \right]^H A(A^H A)^{-1} A^H \\
&= A \left[(A^H A)^{-1} \right]^H A^H A (A^H A)^{-1} A^H \\
&= A \left[(A^H A)^{-1} \right]^H A^H = A \left[(A^H A)^{-1} \right] A^H \\
&= \Pi_A
\end{aligned}$$

So (98) reduces to:

$$\begin{aligned}
\hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll} &= p_p^{-1} \mathbf{D}_{ll}^H \left(\mathbf{D}_l^{-1} \right)^H \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} \\
&= \frac{1}{p_p} \mathbf{D}_{ll} \mathbf{D}_l^{-1} \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} \\
\left[\hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{I}_K \right]^{-1} &= \left[\frac{1}{p_p} \mathbf{D}_{ll} \mathbf{D}_l^{-1} \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{I}_K \right]^{-1} \\
&= \left[\frac{1}{p_p} \mathbf{D}_{ll} \mathbf{D}_l^{-1} \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} + \mathbf{D}_{ll} \mathbf{D}_l^{-1} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \frac{\sigma_{n_l}^2}{p_u} \mathbf{I}_K \mathbf{D}_{ll}^{-1} \mathbf{D}_l \mathbf{D}_l^{-1} \mathbf{D}_{ll} \right]^{-1} \\
&= \left[\frac{1}{p_p} \mathbf{D}_{ll} \mathbf{D}_l^{-1} \left(\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} + \mathbf{D}_l \mathbf{D}_{ll}^{-1} \frac{\sigma_{n_l}^2}{p_u} \mathbf{I}_K \mathbf{D}_{ll}^{-1} \mathbf{D}_l \right) \mathbf{D}_l^{-1} \mathbf{D}_{ll} \right]^{-1} \\
&= p_p \left(\mathbf{D}_l^{-1} \mathbf{D}_{ll} \right)^{-1} \left(\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} + \mathbf{D}_l \mathbf{D}_{ll}^{-1} \frac{\sigma_{n_l}^2}{p_u} \mathbf{I}_K \mathbf{D}_{ll}^{-1} \mathbf{D}_l \right)^{-1} \left(\mathbf{D}_{ll} \mathbf{D}_l^{-1} \right)^{-1} \\
&= p_p \mathbf{D}_{ll}^{-1} \mathbf{D}_l \left(\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \right)^{-1} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \tag{99}
\end{aligned}$$

With: $[\mathbf{D}_{ll}]_{k,k} = \beta_{llk}$ and $\mathbf{D}_l \triangleq \sum_{i=1}^L \mathbf{D}_{il}$. We obtain:

$$\begin{aligned}
&\left(\hat{\Gamma}_{ll}^H \hat{\Gamma}_{ll} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{I}_K \right)^{-1} \hat{\Gamma}_{ll}^H \\
&= p_p \mathbf{D}_{ll}^{-1} \mathbf{D}_l \left(\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \right)^{-1} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \left(p_p^{-1/2} \Pi_A \tilde{\mathbf{Y}}_{p,l} \mathbf{D}_l^{-1} \mathbf{D}_{ll} \right)^H \\
&= p_p^{1/2} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \left(\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \right)^{-1} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll} \mathbf{D}_l^{-1} \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \\
&= p_p^{1/2} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \left(\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \right)^{-1} \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \tag{100}
\end{aligned}$$

We deduce from (100):

$$\begin{aligned}\hat{\mathbf{r}}_l &= \left[\hat{\boldsymbol{\Gamma}}_{ll}^H \hat{\boldsymbol{\Gamma}}_{ll} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{I}_K \right]^{-1} \hat{\boldsymbol{\Gamma}}_{ll}^H \mathbf{y}_l \\ &= p_p^{1/2} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \left(\tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \right)^{-1} \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{y}_l\end{aligned}\quad (101)$$

Let $\tilde{\mathbf{r}}$ the received $K \times 1$ vector: $\tilde{\mathbf{r}}_l \triangleq p_p^{-1/2} \sum_{i=1}^L \beta_{iln} / \beta_{lln} \hat{\mathbf{r}}_l$, we deduce from (101) that:

$$\tilde{\mathbf{r}}_l = \left[\tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \right]^{-1} \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{y}_l \quad (102)$$

4.6. Analysis of the Pilot Contamination effect:

We denote as $\mathbf{S}_{p,l}^A$ the matrix: $\left[\tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \right]_{K \times K}^{-1}$. In this case, if we look at

the n th component of vector $\tilde{\mathbf{r}}_l$, we have :

$$\begin{aligned}\tilde{r}_l(n) &= \tilde{r}_{ln} \\ &= \mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{y}_l \\ &= \mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \left[\sqrt{p_u} A \sum_{i=1}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \mathbf{x}_i + \mathbf{n}_l \right] \\ &= \sqrt{p_u} \mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{H}_{l,l} \mathbf{D}_{l,l}^{1/2} \mathbf{x}_l + \sqrt{p_u} \mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \sum_{i \neq l}^L \mathbf{H}_{i,l} \mathbf{D}_{i,l}^{1/2} \mathbf{x}_i + \mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{n}_l \\ &= \boldsymbol{\alpha}_{ln}^T \mathbf{x}_l + \sum_{j \neq l}^L \boldsymbol{\alpha}_{jn}^T \mathbf{x}_j + z_{ln} \quad (103)\end{aligned}$$

With: $\boldsymbol{\alpha}_{jn}^T \triangleq \sqrt{p_u} \mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{H}_{j,l} \mathbf{D}_{j,l}^{1/2}$ and $z_{ln} = \mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{n}_l$. We have:

$$\mathcal{E}[\boldsymbol{\alpha}_{ln}^T] = \mathcal{E}\left[\sqrt{p_u} \mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \boldsymbol{\Pi}_A \mathbf{A} \mathbf{H}_{l,l} \mathbf{D}_{l,l}^{1/2}\right] \mathbf{e}_n \quad (104)$$

Where \mathbf{e}_n is the n th column of the $K \times K$ identity matrix. By adding and subtracting $\mathcal{E}[\boldsymbol{\alpha}_{ln}^T]$ from $\boldsymbol{\alpha}_{ln}^T$ in (103), we obtain:

$$\tilde{r}_n = \mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\} \mathbf{x}_l + (\boldsymbol{\alpha}_{ln}^T - \mathcal{E}\{\boldsymbol{\alpha}_{ln}^T\}) \mathbf{x}_l + \sum_{j \neq l}^L \boldsymbol{\alpha}_{jn}^T \mathbf{x}_j + z_{ln} \quad (105)$$

We obtain again the capacity of the n th user in the l th cell :

$$R_{ln} = C \left(\frac{\mathbb{E}\{\alpha_{ln}^T\}^2}{\sum_{j=1}^L \mathbb{E}\{\|\alpha_{jn}^T\|^2\} - \mathbb{E}\{\alpha_{ln}^T\}^2 + \mathbb{E}\{|z_{ln}|^2\}} \right) \quad (106)$$

To develop (106) we detail first the calculation of the matrix:

$$\left(\mathbf{S}_{p,l}^A\right)^{-1} = \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l, \text{ we have:}$$

$$\begin{aligned} \left(\mathbf{S}_{p,l}^A\right)^{-1} &= \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \\ &= p_p \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{W} + \dots \\ &\dots + \sqrt{p_p} \mathbf{W}_l^H \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \sqrt{p_p} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{W}_l + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \end{aligned} \quad (107)$$

Re-using equations (83) up to (89) we deduce that the matrix $\mathbb{E}\left[\left(\mathbf{S}_{p,l}^A\right)^{-1}\right]$ is a diagonal matrix with the n th term equal to :

$$\begin{aligned} \mathbb{E}\left[\left(\mathbf{S}_{p,l}^A\right)^{-1}\right] &= \mathbb{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l\right] \\ &= \text{diag}(\xi_{1,l}, \xi_{2,l}, \dots, \xi_{K,l}) \end{aligned} \quad (108)$$

With:

$$\xi_{n,l} = p_p \frac{M}{P} \sum_{i=1}^L \beta_{iln} + \sigma_{n_l}^2 P + \frac{\sigma_{n_l}^2}{p_u} \frac{\beta_{lln}^2}{\left(\sum_{i=1}^L \beta_{iln}\right)^2} \quad (109)$$

$$\xi_{n,l} = p_p \frac{M}{P} \bar{\beta}_n + \sigma_{n_l}^2 P + \frac{\sigma_{n_l}^2}{p_u} \frac{\beta_{lln}^2}{\bar{\beta}_n^2}$$

We come back to the calculation of $\mathbb{E}\left[\alpha_{ln}^T\right]$, remember we have :

$$\begin{aligned}
\mathcal{E}[\alpha_{ln}^T] &= \mathcal{E}\left[\sqrt{p_u} S_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \mathbf{A} \mathbf{H}_{l,l} \mathbf{D}_{l,l}^{1/2}\right] \mathbf{e}_n \\
\mathcal{E}[\alpha_{ln}^T] &\approx \sqrt{p_u} \mathcal{E}[S_{p,l}^A(n,:)] \mathcal{E}[\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \mathbf{A} \mathbf{G}_{l,l}] \mathbf{e}_n \\
&= \sqrt{p_u} \mathcal{E}[S_{p,l}^A(n,:)] \mathcal{E}\left[\left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l\right)^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{A} \mathbf{G}_{l,l}\right] \mathbf{e}_n \\
&= \sqrt{p_u} \mathcal{E}[S_{p,l}^A(n,:)] \mathcal{E}\left[\sqrt{p_p} \sum_{i=1}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H \mathbf{A} \mathbf{G}_{l,l}\right] \mathbf{e}_n \\
&= \sqrt{p_u p_p} \mathcal{E}[S_{p,l}^A(n,:)] \mathcal{E}[\mathbf{G}_{l,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{l,l}] \mathbf{e}_n
\end{aligned}$$

We have already found that (see equation (86)):

$$\mathcal{E}[\mathbf{G}_{l,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{l,l}](n,n) = \frac{M \beta_{ln}}{P}$$

We eventually obtain:

$$\begin{aligned}
\mathcal{E}\{\alpha_n^T\} &= \sqrt{p_u p_p} \frac{M \beta_{ln}}{P \xi_{n,l}} \mathbf{e}_n \\
&= \sqrt{p_u p_p} \frac{M \beta_{ln}}{P \left[p_p \frac{M}{P} \bar{\beta}_{ln} + \sigma_{n_l}^2 P + \frac{\sigma_{n_l}^2}{p_u} \frac{\beta_{ln}^2}{\bar{\beta}_{ln}^2} \right]} \mathbf{e}_n \quad (110) \\
&= \sqrt{\frac{p_u}{p_p}} \frac{\beta_{ln}}{\frac{P^2 \sigma_{n_l}^2}{M p_p} + \frac{P \sigma_{n_l}^2}{M p_p p_u} \frac{\beta_{ln}^2}{\bar{\beta}_{ln}^2}} \mathbf{e}_n
\end{aligned}$$

Then, we have to calculate $\mathcal{E}\{\|\alpha_{jn}^T\|^2\}$, we have:

$$\begin{aligned}
\mathcal{E}\{\|\alpha_{jn}^T\|^2\} &= \mathcal{E}(\alpha_{jn}^T \alpha_{jn}^{*}) \\
&= p_u \mathcal{E}[S_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \Pi_A^H \tilde{\mathbf{Y}}_{p,l} S_{p,l}^A(n,:)^H] \\
&= p_u \mathcal{E}[S_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \Pi_A \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \Pi_A^H \tilde{\mathbf{Y}}_{p,l} S_{p,l}^A(n,:)^H]
\end{aligned}$$

We have:

$$\begin{aligned}
&\tilde{\mathbf{Y}}_{p,l}^H \Pi_A \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \Pi_A^H \tilde{\mathbf{Y}}_{p,l} \\
&= \left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l \right)^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \left(\sqrt{p_p} \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l} + \mathbf{W}_l \right)
\end{aligned}$$

And this yields:

$$\begin{aligned}
& \mathcal{E} \left[\mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \mathbf{S}_{p,l}^A(n,:)^H \right] \\
&= \mathcal{E} \left[\mathbf{S}_{p,l}^A(n,:) \left(\sqrt{p_p} \mathbf{A} \sum_{i=1}^L \mathbf{G}_{i,l} + \mathbf{W}_l \right)^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \left(\sqrt{p_p} \mathbf{A} \sum_{m=1}^L \mathbf{G}_{m,l} + \mathbf{W}_l \right) \mathbf{S}_{p,l}^A(n,:)^H \right] \\
&= \mathcal{E} \left[p_p \mathbf{S}_{p,l}^A(n,:) \sum_{i=1, i \neq j}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \sum_{m=1, m \neq j}^L \mathbf{G}_{m,l} \mathbf{S}_{p,l}^A(n,:)^H \right] + \dots \\
&\dots + \mathcal{E} \left[p_p \mathbf{S}_{p,l}^A(n,:) \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{S}_{p,l}^A(n,:)^H \right] + \dots \\
&\dots + \mathcal{E} \left[\mathbf{S}_{p,l}^A(n,:) \mathbf{W}_l^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{S}_{p,l}^A(n,:)^H \right]
\end{aligned}$$

And, we have:

$$\begin{aligned}
& \mathcal{E} \left[p_p \mathbf{S}_{p,l}^A(n,:) \sum_{i=1, i \neq j}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \sum_{m=1, m \neq j}^L \mathbf{G}_{m,l} \mathbf{S}_{p,l}^A(n,:)^H \right] \\
&= \frac{p_p}{P} \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \right] \right] \sum_{i=1, i \neq j}^L \mathcal{E} \left[\mathbf{S}_{p,l}^A(n,:) \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{A}^H \mathbf{A} \mathbf{G}_{i,l} \mathbf{S}_{p,l}^A(n,:)^H \right] \\
&= \frac{p_p}{P^2} \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \right] \right] \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \sum_{i=1, i \neq j}^L \mathcal{E} \left[\mathbf{S}_{p,l}^A(n,:) \mathbf{G}_{i,l}^H \mathbf{G}_{i,l} \mathbf{S}_{p,l}^A(n,:)^H \right] \\
&= \frac{p_p}{P^2 K} \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \right] \right] \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \text{Trace} \left[\mathcal{E} \left[\sum_{i=1, i \neq j}^L \mathbf{G}_{i,l}^H \mathbf{G}_{i,l} \right] \right] \mathcal{E} \left[\mathbf{S}_{p,l}^A(n,:) \mathbf{S}_{p,l}^A(n,:)^H \right] \\
&= \frac{p_p}{P^2 K} \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \right] \right] \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \left[\sum_{i=1, i \neq j}^L \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{i,l}^H \mathbf{G}_{i,l} \right] \right] \right] \mathcal{E} \left[\mathbf{S}_{p,l}^A(n,:) \mathbf{S}_{p,l}^A(n,:)^H \right] \\
&= \frac{p_p \text{Trace} \left[\left(\mathbf{A}^H \mathbf{A} \right)^2 \right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right) \mathcal{E} \left[\mathbf{S}_{p,l}^A(n,:) \mathbf{S}_{p,l}^A(n,:)^H \right]}{P^2 K}
\end{aligned}$$

Concerning the quantity: $\mathcal{E} \left(\left[\mathbf{S}_{p,l}^A(n,:) \mathbf{S}_{p,l}^A(n,:)^H \right] \right)$, we have:

$$\begin{aligned}
& \mathcal{E} \left(\left[\mathbf{S}_{p,l}^A \mathbf{S}_{p,l}^{A^H} \right] \right) \\
&= \mathcal{E} \left(\left[\left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \right)^H \left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l \right) \right]^{-1} \right)
\end{aligned}$$

We use the following notation: $\mathbf{A}_l = \mathbf{D}_l \mathbf{D}_{ll}^{-1} \mathbf{D}_{ll}^{-1} \mathbf{D}_l$, \mathbf{A}_l is a diagonal matrix with deterministic elements, $\mathbf{A}_l = \text{diag}(\eta_{1,l}, \eta_{2,l}, \dots, \eta_{n,l}, \dots, \eta_{K,l})$ and n th element equal to: $\eta_{n,l} = \frac{\beta_{ln}^2}{\left(\sum_{i=1}^L \beta_{iln} \right)^2} = \frac{\beta_{ln}^2}{\bar{\beta}_{ln}^2}$. In these conditions we have:

$$\begin{aligned}
& \mathcal{E}\left(\left[\mathbf{S}_{p,l}^A \mathbf{S}_{p,l}^{A^H}\right]\right) \\
&= \mathcal{E}\left(\left[\left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{A}_l\right)^H \left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{A}_l\right)\right]^{-1}\right) \\
&= \mathcal{E}\left(\left[\left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{A}_l\right) \left(\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \mathbf{A}_l\right)\right]^{-1}\right) \\
&= \mathcal{E}\left(\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^2}{p_u} \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \mathbf{A}_l + \frac{\sigma_{n_l}^2}{p_u} \mathbf{A}_l \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} + \frac{\sigma_{n_l}^4}{p_u^2} \mathbf{A}_l^2\right]^{-1}\right) \\
&\approx \left(\mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right] + \frac{\sigma_{n_l}^2}{p_u} \mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l}\right] \mathbf{A}_l + \frac{\sigma_{n_l}^2}{p_u} \mathbf{A}_l \mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right] + \frac{\sigma_{n_l}^4}{p_u^2} \mathbf{A}_l^2\right)^{-1} \\
&= \left(\mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right] + \frac{\sigma_{n_l}^2}{p_u} \mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right] \mathbf{A}_l + \frac{\sigma_{n_l}^2}{p_u} \mathbf{A}_l \mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right] + \frac{\sigma_{n_l}^4}{p_u^2} \mathbf{A}_l^2\right)^{-1} \\
&= \left(\mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right]^2 + \frac{\sigma_{n_l}^2}{p_u} \mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right] \mathbf{A}_l + \frac{\sigma_{n_l}^2}{p_u} \mathbf{A}_l \mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right] + \frac{\sigma_{n_l}^4}{p_u^2} \mathbf{A}_l^2\right)^{-1}
\end{aligned}$$

We have already found that:

$$\begin{aligned}
& \mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right]^2 \\
&= p_p^2 \frac{M^2}{P^2} \sum_{i=1}^L \text{diag}(\beta_{il1}, \beta_{il2}, \dots, \beta_{ilK}) \left[\text{diag}\left(\bar{\beta}_{l1} - \beta_{il1} + \frac{\hat{\beta}_l}{M}, \bar{\beta}_{l2} - \beta_{il2} + \frac{\hat{\beta}_l}{M}, \dots, \bar{\beta}_{lK} - \beta_{ilK} + \frac{\hat{\beta}_l}{M}\right) \right] + \dots \\
& \dots + \left(2p_p \sigma_{n_l}^2 \text{Trace}(\mathbf{A} \mathbf{A}^H) + p_p \frac{K \sigma_{n_l}^2 M}{P}\right) \text{diag}(\bar{\beta}_{l1}, \bar{\beta}_{l2}, \dots, \bar{\beta}_{lK}) + \text{Trace}(\mathbf{A} \mathbf{A}^H) \left(\frac{KP}{M} \sigma_{n_l}^4 + p_p \frac{\sigma_{n_l}^2 \hat{\beta}_l}{P}\right) \mathbf{I}_K \\
&= \text{diag}(\mu_{l,1}, \mu_{l,2}, \dots, \mu_{l,n}, \dots, \mu_{l,K})
\end{aligned}$$

With:

$$\mu_{l,n} = p_p^2 \frac{M^2}{P^2} \sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} + \frac{\hat{\beta}_l}{M} \right] + \left(2p_p M \sigma_{n_l}^2 + p_p K \sigma_{n_l}^2 \frac{M}{P}\right) \bar{\beta}_{ln} + \sigma_{n_l}^2 \text{Trace}(\mathbf{A} \mathbf{A}^H) \left(p_p \frac{\hat{\beta}_l}{P} + \frac{KP}{M} \sigma_{n_l}^2\right)$$

We have:

$$\mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right] = \text{diag}(\rho_{1,l}, \rho_{2,l}, \dots, \rho_{K,l})$$

With:

$$\rho_{n,l} = p_p \frac{M}{P} \bar{\beta}_{ln} + \sigma_{n_l}^2 P$$

We obtain eventually :

$$\mathbb{E}\left(\left[\mathbf{S}_{p,l}^A \mathbf{S}_{p,l}^{A^H}\right]\right) = \text{diag}(\lambda_{1,l}, \lambda_{2,l}, \dots, \lambda_{n,l}, \dots, \lambda_{K,l})$$

With :

$$\lambda_{n,l} = \frac{1}{\mu_{n,l} + 2\frac{\sigma_{n_l}^2}{p_u} \rho_{n,l} \eta_{n,l} + \frac{\sigma_{n_l}^4}{p_u^2} \eta_{n,l}^2} \quad (111)$$

We have :

$$\begin{aligned} \frac{1}{\lambda_{n,l}} &= \mu_{n,l} + 2\frac{\sigma_{n_l}^2}{p_u} \rho_{n,l} \eta_{n,l} + \frac{\sigma_{n_l}^4}{p_u^2} \eta_{n,l}^2 \\ &= p_p^2 \frac{M^2}{P^2} \sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} + \frac{\hat{\beta}_l}{M} \right] + \left(2p_p M \sigma_{n_l}^2 + p_p K \sigma_{n_l}^2 \frac{M}{P} \right) \bar{\beta}_{ln} + \sigma_{n_l}^2 \text{Trace}(\mathbf{A} \mathbf{A}^H) \left(p_p \frac{\hat{\beta}_l}{P} + \frac{KP}{M} \sigma_{n_l}^2 \right) + \dots \\ &\quad + 2 \frac{\sigma_{n_l}^2}{p_u} \left(p_p \frac{M}{P} \bar{\beta}_{ln} + \sigma_{n_l}^2 P \right) \frac{\beta_{lln}^2}{\bar{\beta}_{ln}^2} + \frac{\sigma_{n_l}^4}{p_u^2} \frac{\beta_{lln}^4}{\bar{\beta}_{ln}^4} \\ &\approx_{M \rightarrow \infty} p_p^2 \frac{M^2}{P^2} \sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} + \frac{\hat{\beta}_l}{M} \right] + \left(2p_p M \sigma_{n_l}^2 + p_p K \sigma_{n_l}^2 \frac{M}{P} \right) \bar{\beta}_{ln} + \sigma_{n_l}^2 M \left(p_p \frac{\hat{\beta}_l}{P} + \frac{KP}{M} \sigma_{n_l}^2 \right) + \dots \\ &\quad + 2 \frac{\sigma_{n_l}^2}{p_u} \left(p_p \frac{M}{P} \bar{\beta}_{ln} + \sigma_{n_l}^2 P \right) \frac{\beta_{lln}^2}{\bar{\beta}_{ln}^2} + \frac{\sigma_{n_l}^4}{p_u^2} \frac{\beta_{lln}^4}{\bar{\beta}_{ln}^4} \\ &= p_p^2 \frac{M^2}{P^2} \sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} + \frac{\hat{\beta}_l}{M} \right] + \dots \\ &\quad + M \left(\left[2p_p \sigma_{n_l}^2 + p_p \frac{K}{P} \sigma_{n_l}^2 \right] \bar{\beta}_{ln} + \sigma_{n_l}^2 \left[p_p \frac{\hat{\beta}_l}{P} + \frac{KP}{M} \sigma_{n_l}^2 \right] \right) + 2 \frac{\sigma_{n_l}^2}{p_u} \left(p_p \frac{\bar{\beta}_{ln}}{P} + \sigma_{n_l}^2 \frac{P}{M} \right) \frac{\beta_{lln}^2}{\bar{\beta}_{ln}^2} + \frac{\sigma_{n_l}^4}{p_u^2} \frac{\beta_{lln}^4}{\bar{\beta}_{ln}^4} \\ &\approx_{M \rightarrow \infty} p_p^2 \frac{M^2}{P^2} \sum_{i=1}^L \beta_{iln} \left[\bar{\beta}_{ln} - \beta_{iln} \right] \end{aligned}$$

Then, with (111) it is possible to reuse the calculations of the ZF and we obtain:

$$\begin{aligned}
& \mathcal{E} \left[p_p S_{p,l}^A(n,:) \sum_{i=1, i \neq j}^L \mathbf{G}_{i,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \sum_{m=1, m \neq j}^L \mathbf{G}_{m,l} S_{p,l}^A(n,:)^H \right] \\
& = \frac{p_p \text{Trace} \left[(\mathbf{A}^H \mathbf{A})^2 \right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right) \lambda_{n,l}}{P^2 K} \\
& \approx_{M \rightarrow \infty} \frac{p_p M^2 \beta_{jl}}{P^3 K} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right) \lambda_{n,l} \\
& = p_p \frac{M^2 \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right)}{P^3 K} \frac{P^2}{p_p^2 M^2 \left(\sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}] \right)} \\
& \approx_{M \rightarrow \infty} \frac{1}{p_p P K} \frac{\beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right)}{\sum_{i=1}^L \beta_{iln} [\beta_{il} + \bar{\beta}_{ln} - \beta_{iln}]}
\end{aligned}$$

Concerning the term: $\mathcal{E} \left[p_p S_{p,l}^A(n,:) \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} S_{p,l}^A(n,:)^H \right]$, we have :

$$\begin{aligned}
& \mathcal{E} \left[p_p S_{p,l}^A(n,:) \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} S_{p,l}^A(n,:)^H \right] \\
& = \frac{p_p}{K} \mathcal{E} \left[S_{p,l}^A(n,:) S_{p,l}^A(n,:)^H \right] \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \right] \right] \\
& = \frac{p_p \lambda_{n,l}}{K} \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \right]^2 \right]
\end{aligned}$$

Hence this yields:

$$\begin{aligned}
& \mathcal{E} \left[p_p \mathbf{M}_{p,l}^A(n,:) \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{M}_{p,l}^A(n,:)^H \right] \\
& = \frac{p_p}{K} \text{Trace} \left[\mathcal{E} \left[\mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{A} \mathbf{G}_{j,l} \right]^2 \right] \lambda_{n,l} \\
& = \frac{p_p}{K} \frac{M^2 \beta_{jl}^2}{P^2} \lambda_{n,l} \\
& \approx_{M \rightarrow \infty} \frac{p_p}{K} \frac{M^2 \beta_{jl}^2}{P^2} \frac{P^2}{p_p^2 M^2 \left(\sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}] \right)} \\
& = \frac{\beta_{jl}^2}{K p_p \left(\sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}] \right)}
\end{aligned}$$

The remaining last term is: $\mathcal{E}\left[\mathbf{S}_{p,l}^A(n,:) \mathbf{W}_l^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{S}_{p,l}^A(n,:)^H\right]$, we have:

$$\begin{aligned} & \mathcal{E}\left[\mathbf{S}_{p,l}^A(n,:) \mathbf{W}_l^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{S}_{p,l}^A(n,:)^H\right] \\ &= \frac{\lambda_{n,l}}{K} \text{Trace}\left[\mathcal{E}\left[\mathbf{W}_l^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{W}_l\right]\right] \end{aligned}$$

With:

$$\begin{aligned} & \mathcal{E}\left[\mathbf{W}_l^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{W}_l\right] \\ &= \frac{M^2 \sigma_{n_l}^2}{KP} \beta_{jl} \mathbf{I}_K \end{aligned}$$

And :

$$\begin{aligned} & \mathcal{E}\left[\mathbf{S}_{p,l}^A(n,:) \mathbf{W}_l^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{W}_l \mathbf{S}_{p,l}^A(n,:)^H\right] \\ &= \frac{\lambda_{n,l}}{K} \text{Trace}\left[\mathcal{E}\left[\mathbf{W}_l^H \mathbf{A} \mathbf{G}_{j,l} \mathbf{G}_{j,l}^H \mathbf{A}^H \mathbf{W}_l\right]\right] \\ &= \frac{\lambda_{n,l}}{K} \frac{M^2 \sigma_{n_l}^2}{P} \beta_{jl} \\ &= \frac{M^2 \sigma_{n_l}^2}{KP} \beta_{jl} \lambda_{n,l} \\ &\approx_{M \rightarrow \infty} \frac{\sigma_{n_l}^2 P}{p_p^2 K} \frac{\beta_{jl}}{\left(\sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}]\right)} \end{aligned}$$

And, we eventually obtain:

$$\begin{aligned}
& \mathcal{E}\left\{\|\boldsymbol{\alpha}_{jn}^T\|^2\right\} = \mathcal{E}\left(\boldsymbol{\alpha}_{jn}^T \boldsymbol{\alpha}_{jn}^*\right) \\
&= \frac{\lambda_{n,l} p_u p_p \text{Trace}\left[\left(\mathbf{A}^H \mathbf{A}\right)^2\right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il}\right)}{P^2 K} + \frac{\lambda_{n,l} p_u p_p M^2 \beta_{jl}^2}{KP^2} + \frac{\sigma_{n_l}^2 p_u M^2 \beta_{jl} \lambda_{n,l}}{KP} \\
&= \frac{\lambda_{n,l} \left[p_u p_p \text{Trace}\left[\left(\mathbf{A}^H \mathbf{A}\right)^2\right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il}\right) + p_u p_p M^2 \beta_{jl}^2 + \sigma_{n_l}^2 p_u M^2 P \beta_{jl} \right]}{P^2 K} \\
&= \frac{\left[p_u p_p \text{Trace}\left[\left(\mathbf{A}^H \mathbf{A}\right)^2\right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il}\right) + p_u p_p M^2 \beta_{jl}^2 + \sigma_{n_l}^2 p_u M^2 P \beta_{jl} \right]}{\mu_{n,l} + 2 \frac{\sigma_{n_l}^2}{p_u} \rho_{n,l} \eta_{n,l} + \frac{\sigma_{n_l}^4}{p_u^2} \eta_{n,l}^2} \\
&\approx_{M \rightarrow \infty} \frac{P^2 \left(p_u p_p \text{Trace}\left[\left(\mathbf{A}^H \mathbf{A}\right)^2\right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il}\right) + p_u p_p M^2 \beta_{jl}^2 + \sigma_{n_l}^2 p_u M^2 P \beta_{jl} \right)}{p_p^2 P^2 K M^2 \left(\sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}] \right)} \quad (112)
\end{aligned}$$

Considering the case where M goes towards infinity, we have:

$$\lim_{M \rightarrow \infty} \frac{1}{M} \mathbf{A}^H \mathbf{A} = \frac{1}{P} \mathbf{I}_P$$

This yields: $\lim_{M \rightarrow \infty} \mathbf{A}^H \mathbf{A} = \frac{M}{P} \mathbf{I}_P$ and $\lim_{M \rightarrow \infty} \text{Trace}\left[\left(\mathbf{A}^H \mathbf{A}\right)^2\right] = \frac{M^2}{P^2} P = \frac{M^2}{P}$ and we obtain:

$$\begin{aligned}
& \mathcal{E}\left\{\|\boldsymbol{\alpha}_{jn}^T\|^2\right\} \\
& \approx_{M \rightarrow \infty} \frac{P^2 \left(p_u p_p M^2 \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il}\right) / P + p_u p_p M^2 \beta_{jl}^2 + \sigma_{n_l}^2 p_u M^2 P \beta_{jl} \right)}{p_p^2 P^2 K M^2 \left(\sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}] \right)} \\
&= \frac{p_u p_p \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il}\right) / P + p_u p_p \beta_{jl}^2 + \sigma_{n_l}^2 p_u P \beta_{jl}}{p_p^2 K \left(\sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}] \right)} \quad (113) \\
&\approx_{M \rightarrow \infty} \frac{p_u}{p_p} \frac{\beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il}\right) / P + \beta_{jl}^2 + \frac{\sigma_{n_l}^2}{p_p} P \beta_{jl}}{K \left(\sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}] \right)}
\end{aligned}$$

Concerning the last term: $\mathcal{E}\left[\left|z_{ln}\right|^2\right] = \mathcal{E}\left[\left|\mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \mathbf{n}_l\right|^2\right]$, we have :

$$\begin{aligned}
\mathcal{E}\left\{\left|z_{ln}\right|^2\right\} &= \mathcal{E}\left\{\left|\mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \mathbf{n}_l\right|^2\right\} \\
&= \mathcal{E}\left\{\mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \mathbf{n}_l \mathbf{n}_l^H \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \mathbf{S}_{p,l}^A(n,:)^H\right\} \\
&= \mathcal{E}\left\{\mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \mathcal{E}\left[\mathbf{n}_l \mathbf{n}_l^H\right] \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \mathbf{S}_{p,l}^A(n,:)^H\right\} \\
&= \mathcal{E}\left\{\mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \sigma_{n_l}^2 \mathbf{I}_M \mathbf{\Pi}_A^H \tilde{\mathbf{Y}}_{p,l} \mathbf{S}_{p,l}^A(n,:)^H\right\} \\
&= \sigma_{n_l}^2 \mathcal{E}\left\{\mathbf{S}_{p,l}^A(n,:) \tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l} \mathbf{S}_{p,l}^A(n,:)^H\right\} \\
&= \sigma_{n_l}^2 \mathcal{E}\left\{\mathbf{S}_{p,l}^A(n,:) \mathcal{E}\left[\tilde{\mathbf{Y}}_{p,l}^H \mathbf{\Pi}_A \tilde{\mathbf{Y}}_{p,l}\right] \mathbf{S}_{p,l}^A(n,:)^H\right\} \\
&= \sigma_{n_l}^2 \mathcal{E}\left\{\mathbf{S}_{p,l}^A(n,:) \text{diag}(\rho_{1,l}, \rho_{2,l}, \dots, \rho_{K,l}) \mathbf{S}_{p,l}^A(n,:)^H\right\} \\
&= \frac{\sigma_{n_l}^2}{K} \sum_{i=1}^K \rho_{i,l} \mathcal{E}\left\{\mathbf{S}_{p,l}^A(n,:) \mathbf{S}_{p,l}^A(n,:)^H\right\} \\
&= \frac{\sigma_{n_l}^2 \lambda_{n,l} \sum_{i=1}^K \rho_{i,l}}{K} \tag{114}
\end{aligned}$$

$$\mathcal{E}\left\{\left|z_{ln}\right|^2\right\} \approx_{M \rightarrow \infty} \frac{\left(p_p \frac{M}{KP} \sum_{n=1}^K \bar{\beta}_{ln} + \sigma_{n_l}^2 P\right) \sigma_{n_l}^2 P^2}{p_p^2 M^2 \left(\sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}]\right)} \approx_{M \rightarrow \infty} \frac{\sum_{n=1}^K \bar{\beta}_{ln} \sigma_{n_l}^2 P}{p_p M K \left(\sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}]\right)} \tag{115}$$

The final expression for the uplink capacity in the case of a MMSE receiver is then equal to:

$$\begin{aligned}
R_{ln} &= C \left(\frac{\left\| \mathcal{E}(\boldsymbol{\alpha}_{ln}^T) \right\|^2}{\sum_{j=1}^L \mathcal{E}\left\{ \left\| \boldsymbol{\alpha}_{jn}^T \right\|^2 \right\} - \left\| \mathcal{E}(\boldsymbol{\alpha}_{ln}^T) \right\|^2 + \mathcal{E}\left\{ \left| z_{ln} \right|^2 \right\}} \right) \\
R_{ln} &= C \left(\frac{\frac{p_u}{p_p} \left[\frac{\beta_{lln}}{\bar{\beta}_{ln} + \frac{P^2 \sigma_{n_l}^2}{M p_p} + \frac{P \sigma_{n_l}^2}{M p_p p_u} \frac{\beta_{lln}^2}{\bar{\beta}_{ln}^2}} \right]^2}{\sum_{j=1}^L \left[\frac{p_u p_p \text{Trace}\left[\left(\mathbf{A}^H \mathbf{A}\right)^2\right] \beta_{jl} \left(\sum_{i=1, i \neq j}^L \beta_{il} \right) + p_u p_p M^2 \beta_{jl}^2 + \sigma_{n_l}^2 p_u M^2 P \beta_{jl}}{\mu_{n,l} + 2 \frac{\sigma_{n_l}^2}{p_u} \rho_{n,l} \eta_{n,l} + \frac{\sigma_{n_l}^4}{p_u^2} \eta_{n,l}^2} \right] - \frac{p_u}{p_p} \left[\frac{\beta_{lln}}{\bar{\beta}_{ln} + \frac{P^2 \sigma_{n_l}^2}{M p_p} + \frac{P \sigma_{n_l}^2}{M p_p p_u} \frac{\beta_{lln}^2}{\bar{\beta}_{ln}^2}} \right]^2 + \frac{\sigma_{n_l}^2 \lambda_{n,l} \sum_{i=1}^K \rho_{i,l}}{K}} \right)
\end{aligned}$$

$$\begin{aligned}
R_{ln} &\approx_{M \rightarrow \infty} C \left(\frac{\frac{\beta_{lln}^2}{(\bar{\beta}_{ln})^2}}{\frac{\sum_{j=1}^L \beta_{jl}^2}{K \sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}]} - \frac{\beta_{lln}^2}{(\bar{\beta}_{ln})^2}} \right) \\
&= \left(\frac{\beta_{lln}^2 \left[K \sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}] \right]}{(\bar{\beta}_{ln})^2 \sum_{j=1}^L \beta_{jl}^2 - \beta_{lln}^2 K \sum_{i=1}^L \beta_{iln} [\bar{\beta}_{ln} - \beta_{iln}]} \right)
\end{aligned} \tag{116}$$

We obtain the same expression as for the ZF.