

Appendix for the paper “Energy and Spectrum Efficient Federated Learning via High-Precision Over-the-Air Computation”

1 Proof of Theorem 1

Consider a non-convex FL model setting. Under the L-smoothness assumption of the global objective with the expectation taken, we have

$$\begin{aligned} & \mathbb{E} [\mathbb{E}_Q [\mathbb{E}_{\text{Air}} [f(\mathbf{w}^{r+1}) - f(\mathbf{w}^r)]]] \\ & \leq -\theta\eta\mathbb{E} [\mathbb{E}_Q [\mathbb{E}_{\text{Air}} [\langle \nabla f^r, \nabla F_Q^r \rangle]]] + \frac{\theta^2\eta^2L}{2}\mathbb{E} [\mathbb{E}_Q [\mathbb{E}_{\text{Air}} [\|\nabla F_Q^r\|^2]]], \end{aligned} \quad (1)$$

where we take the expectation over the sampling and operations. Next, the following lemmas are proposed to bound terms in the above inequality.

Lemma 1.1. *The inner product between the stochastic gradient ∇F_Q^r and full batch gradient ∇f^r can be bounded as*

$$\begin{aligned} & \mathbb{E}_{\xi^{(r)}}\mathbb{E}_Q\mathbb{E}_{\text{Air}} [\langle \nabla f^r, \nabla F_Q^r \rangle] \\ & = \mathbb{E}_{\xi^{(r)}} \left[\left\langle \nabla f^r, \frac{1}{K} \sum_{k=1}^K \sum_{h=0}^{H-1} \nabla F_k^{r,h} \right\rangle \right] \\ & \leq \frac{1}{2K} \sum_{k=1}^K \sum_{h=0}^H \left[-\|\nabla f^r\|_2^2 - \|\nabla f_k^{r,h}\|_2^2 + L^2\|\mathbf{w}^r - \mathbf{w}_k^{r,h}\|_2^2 \right]. \end{aligned} \quad (2)$$

Here, we set $\nabla F_k^r = \sum_{h=0}^{H-1} \nabla F_k^{r,h}$ and $\nabla F_{k,Q}^r = Q \left(\sum_{h=0}^{H-1} \nabla F_k^{(h,r)} \right)$. We further define $\nabla F_Q^r = \text{Air}_K \left(Q \left(\sum_{h=0}^{H-1} \nabla F_k^{r,h} \right) \right)$.

Lemma 1.2. *Similar to the Lemma D.3 in [11], we can bound the distance between the global model and the local model at r -th communication round under Assumption 2 as follows:*

$$\mathbb{E} [\|\mathbf{w}^r - \mathbf{w}_k^{r,h}\|_2^2] \leq \eta^2 H \sigma^2 + \eta^2 \sum_{h=0}^{H-1} H \|\nabla f_k^{r,h}\|_2^2 \quad (3)$$

Lemma 1.3. *The last term in (1) can be calculated as*

$$\begin{aligned} \mathbb{E}_{\xi(r)} \mathbb{E}_Q \mathbb{E}_{Air} \left[\left\| Air_{\mathcal{K}} \left(Q \left(\sum_{h=0}^{H-1} \nabla F_k^{r,h} \right) \right) \right\|^2 \right] &\leq \frac{\sigma_z^2}{p_b^2} \\ &+ \sum_{k=1}^K \frac{q + p_b}{K^2 p_b} \text{Var}(\nabla F_k^r) + \sum_{k=1}^K \frac{q(2 - p_b) + K p_b}{K^2 p_b} \|\nabla f_k^r\|^2 \end{aligned} \quad (4)$$

Proof.

$$\begin{aligned} &\mathbb{E}_{\xi(r)} \mathbb{E}_Q \mathbb{E}_{Air} \left[\left\| Air_{\mathcal{K}} \left(Q \left(\sum_{h=0}^{H-1} \nabla F_k^{r,h} \right) \right) \right\|^2 \right] \\ &= \mathbb{E}_{\xi(r), Q} \left[\frac{1}{K^2} \left(\left\| \sum_{k=1}^K \nabla F_{k,Q}^r \right\|^2 + \left(\frac{1}{p_b} - 1 \right) \sum_{k=1}^K \|\nabla F_{k,Q}^r\|^2 \right) + \frac{\sigma_z^2}{p_b^2} \right] \\ &= \mathbb{E}_{\xi(r)} \left[\mathbb{E}_Q \left[\left\| \frac{1}{K} \sum_{k=1}^K \nabla F_{k,Q}^r \right\|^2 + \frac{1}{K^2} \left(\frac{1}{p_b} - 1 \right) \sum_{k=1}^K \|\nabla F_{k,Q}^r\|^2 \right] \right] + \frac{\sigma_z^2}{p_b^2} \\ &= \mathbb{E}_{\xi(r)} \left[\mathbb{E}_Q \left[\frac{1}{K^2} \sum_{k=1}^K [\|\nabla F_{k,Q}^r - \nabla F_k^r\|^2] \right] + \left\| \frac{1}{K} \sum_{k=1}^K \nabla F_k^r \right\|^2 \right] + \\ &\quad \mathbb{E}_{\xi(r)} \left[\frac{1}{K^2} \left(\frac{1}{p_b} - 1 \right) \sum_{k=1}^K (\mathbb{E}_Q [\|\nabla F_{k,Q}^r - \nabla F_k^r\|^2] + \|\nabla F_k^r\|^2) \right] + \frac{\sigma_z^2}{p_b^2} \\ &= \mathbb{E}_{\xi(r)} \left[\mathbb{E}_Q \left[\frac{1}{K^2 p_b} \sum_{k=1}^K [\|\nabla F_{k,Q}^r - \nabla F_k^r\|^2] \right] + \left\| \frac{1}{K} \sum_{k=1}^K \nabla F_k^r \right\|^2 + \frac{1}{K} \left(\frac{1}{p_b} - 1 \right) \sum_{k=1}^K \|\nabla F_k^r\|^2 \right] + \frac{\sigma_z^2}{p_b^2} \\ &\leq \mathbb{E}_{\xi(r)} \left[\sum_{k=1}^K \frac{q}{K^2 p} \|\nabla F_k^r\|^2 + \left\| \frac{1}{K} \sum_{k=1}^K \nabla F_k^r \right\|^2 + \frac{1}{K} \left(\frac{1}{p_b} - 1 \right) \sum_{k=1}^K \|\nabla F_k^r\|^2 \right] + \frac{\sigma_z^2}{p_b^2} \\ &= \sum_{k=1}^K \frac{q}{K^2 p_b} [\text{Var}(\nabla F_k^r) + \|\nabla f_k^r\|^2] + \left[\frac{1}{K^2} \sum_{k=1}^K \text{Var}(\nabla F_k^r) + \left\| \frac{1}{K} \sum_{k=1}^K \nabla f_k^r \right\|^2 \right] + \\ &\quad \frac{1}{K} \left(\frac{1}{p_b} - 1 \right) \sum_{k=1}^K \|\nabla f_k^r\|^2 + \frac{\sigma_z^2}{p_b^2} \\ &\leq \sum_{k=1}^K \frac{q + p_b}{K^2 p_b} \text{Var}(\nabla F_k^r) + \sum_{k=1}^K \frac{q(2 - p_b) + K p_b}{K^2 p_b} \|\nabla f_k^r\|^2 + \frac{\sigma_z^2}{p_b^2} \end{aligned} \quad (5)$$

□

According to Assumption 2, we have $\text{Var}(\nabla F_k^r) \leq H\sigma^2$. We further have

$\|\nabla f_k^r\|^2 = \|\sum_{h=0}^{H-1} \nabla f_k^{r,h}\|^2 \leq H \sum_{h=0}^{H-1} \|\nabla f_k^{r,h}\|^2$. Therefore, we have

$$\begin{aligned} & \mathbb{E}_{\xi(r)} \mathbb{E}_Q \mathbb{E}_{\text{Air}} \left[\left\| \text{Air}_{\mathcal{K}} \left(Q \left(\sum_{h=0}^{H-1} \nabla F_k^{r,h} \right) \right) \right\|^2 \right] \\ & \leq \frac{q+p_b}{Kp_b} H \sigma^2 + H \frac{q(2-p_b) + Kp_b}{K^2 p_b} \sum_{k=1}^K \sum_{h=0}^H \|\nabla f_k^{r,h}\|^2 + \frac{\sigma_z^2}{p_b^2} \end{aligned} \quad (6)$$

Therefore, by integrating Lemma 1.1, 1.2, and 1.3 into (1), we will have:

$$\begin{aligned} & \mathbb{E} \left[\mathbb{E}_Q \left[\mathbb{E}_{\text{Air}} \left[f(\mathbf{w}^{r+1}) - f(\mathbf{w}^r) \right] \right] \right] \\ & \leq \frac{\eta\theta}{2K} \sum_{k=1}^K \sum_{h=0}^H \left[-\|\nabla f^r\|_2^2 - \|\nabla f_k^{r,h}\|_2^2 + L^2 \eta^2 H \left[\sigma^2 + H \|\nabla f_k^{r,h}\|_2^2 \right] \right] + \\ & \quad \frac{(q+p_b)\theta^2 \eta^2 L}{2Kp_b} H \sigma^2 + HL\theta^2 \eta^2 \frac{q(2-p_b) + Kp_b}{2K^2 p_b} \sum_{k=1}^K \sum_{h=0}^H \|\nabla f_k^{r,h}\|^2 + \frac{\theta^2 \eta^2 \sigma_z^2 L}{2p_b^2} \\ & = -\frac{\eta\theta H}{2} \|\nabla f^r\|_2^2 - \frac{\eta\theta}{2K} (1 - L^2 \eta^2 H^2 - HL\theta\eta \frac{q(2-p_b) + Kp_b}{Kp_b}) \sum_{k=1}^K \sum_{h=0}^H \|\nabla f_k^{r,h}\|_2^2 \\ & \quad + \frac{\theta\eta^2 LH}{2K} (\eta LHK + \frac{(p_b+q)\theta}{p_b}) \sigma^2 + \frac{\theta^2 \eta^2 \sigma_z^2 L}{2p_b^2} \end{aligned} \quad (7)$$

If we set $1 - L^2 \eta^2 H^2 - HL\theta\eta \frac{q(2-p_b) + Kp_b}{Kp_b} \geq 0$, we can get

$$\begin{aligned} & \mathbb{E} \left[\mathbb{E}_Q \left[\mathbb{E}_{\text{Air}} \left[f(\mathbf{w}^{r+1}) - f(\mathbf{w}^r) \right] \right] \right] \leq -\frac{\eta\theta H}{2} \|\nabla f^r\|_2^2 \\ & \quad + \frac{\theta\eta^2 LH}{2K} (\eta LHK + \frac{(p_b+q)\theta}{p_b}) \sigma^2 + \frac{\theta^2 \eta^2 \sigma_z^2 L}{2p_b^2} \end{aligned} \quad (8)$$

Next, we sum up the above equation over all R communication rounds and get

$$\begin{aligned} & \frac{1}{R} \sum_{r=0}^{R-1} \|\nabla f^r\|_2^2 \leq \frac{2(f(\mathbf{w}^0) - f(\mathbf{w}^*))}{\eta\theta HR} \\ & \quad + \frac{\eta L}{K} (\eta LHK + \frac{(p_b+q)\theta}{p_b}) \sigma^2 + \frac{\theta\eta L}{Hp_b^2} \sigma_z^2 \\ & = \frac{2(f(\mathbf{w}^0) - f(\mathbf{w}^*))}{\eta\theta HR} + \frac{\eta\theta L}{K} \frac{(p_b+q)}{p_b} \sigma^2 + \eta^2 L^2 H \sigma^2 + \frac{\theta\eta L \sigma_z^2}{Hp_b^2} \end{aligned} \quad (9)$$

2 Proof of Lemma 1

The second-order partial derivative of functions Θ_1 and Θ_2 can be calculated as:

$$\begin{aligned}
\frac{\partial \Theta_1}{\partial p_b} &= -\frac{A_0 q}{p_b^2 H} - \frac{B_0 q}{2 p_b^{\frac{3}{2}} H^{\frac{1}{2}} (p_b + q)^{\frac{1}{2}}} \\
\frac{\partial^2 \Theta_1}{\partial p_b^2} &= \frac{2q \left(A_0 \sqrt{H} (q \sqrt{p_b} + p_b^{3/2}) \sqrt{p_b + q} + \frac{1}{2} H p_b B_0 (p_b + \frac{3}{4} q) \right)}{H^{3/2} p_b^{7/2} (p_b + q)^{3/2}} \\
\frac{\partial^2 \Theta_1}{\partial p_b \partial H} &= \frac{q \left(A_0 \sqrt{p_b} \sqrt{H} \sqrt{p_b + q} + \frac{1}{4} B_0 p_b H \right)}{H^{5/2} \sqrt{p_b + q} p_b^{5/2}} \\
\frac{\partial \Theta_1}{\partial H} &= -\frac{A_0 (p_b + q)}{p_b H^2} - \frac{1}{2} \frac{B_0 \sqrt{p_b + q} p_b}{(p_b H)^{3/2}} \\
\frac{\partial^2 \Theta_1}{\partial H^2} &= \frac{2 \left(A_0 (p_b + q) \sqrt{p_b H} + \frac{3}{8} B_0 \sqrt{p_b + q} p_b H \right)}{\sqrt{p_b H} p_b H^3} \\
\frac{\partial^2 \Theta_1}{\partial H \partial p_b} &= \frac{1}{4} \frac{q (4 A_0 \sqrt{p_b + q} \sqrt{p_b H} + B_0 p_b H)}{p_b^2 H^2 \sqrt{p_b + q} \sqrt{p_b H}} \\
\frac{\partial^2 \Theta_2}{\partial p_b^2} &= \lambda \frac{\ln^2 p_b - 3 \ln p_b + 1}{p_b \ln^2 p_b (\ln p_b - 1)^2} T^{comm} \\
\frac{\partial^2 \Theta_2}{\partial H^2} &= \frac{\partial^2 \Theta_2}{\partial H \partial p_b} = \frac{\partial^2 \Theta_2}{\partial p_b \partial H} = 0
\end{aligned} \tag{10}$$

We further have $\frac{\partial^2 \Theta_1}{\partial p_b^2} \geq 0$ and $\frac{\partial^2 \Theta_1}{\partial p_b^2} \times \frac{\partial^2 \Theta_1}{\partial H^2} - \frac{\partial^2 \Theta_1}{\partial p_b \partial H} \times \frac{\partial^2 \Theta_1}{\partial H \partial p_b} \geq 0$. Thus, both function $\Theta_1(\phi)$ and $\Theta_2(\phi)$ are positive and convex.

The Hessian matrix of the function Θ_1 can be described as $\begin{bmatrix} \frac{\partial^2 \Theta_1}{\partial p_b^2} & \frac{\partial^2 \Theta_1}{\partial p_b \partial H} \\ \frac{\partial^2 \Theta_1}{\partial H \partial p_b} & \frac{\partial^2 \Theta_1}{\partial H^2} \end{bmatrix}$,

where we can find that both $\frac{\partial^2 \Theta_1}{\partial p_b^2}$ and $\begin{vmatrix} \frac{\partial^2 \Theta_1}{\partial p_b^2} & \frac{\partial^2 \Theta_1}{\partial p_b \partial H} \\ \frac{\partial^2 \Theta_1}{\partial H \partial p_b} & \frac{\partial^2 \Theta_1}{\partial H^2} \end{vmatrix}$ are positive. In addition, the Hessian matrix of the function Θ_1 is positive-definite, and we can also easily obtain that the Hessian matrix of the function Θ_2 is positive semi-definite. Therefore, both function $\Theta_1(\phi)$ and $\Theta_2(\phi)$ are positive and convex.