Proof for – User Cooperation-Enhanced Dynamic Resource Allocation for Throughput Maximization in NOMA-Enabled Wireless Powered MEC

Huaiwen He, Feng Huang, Chenghao Zhou, Hong Shen, Hui Tian

APPENDIX A PROOF OF LEMMA 1

We define YP1 as the optimal policy for P1, which maximizes utility $\psi\left(\overline{r^{\text{opt}}}\right)$ by making the optimal decisions $r^{\text{opt}}(t)$ over time slot t. For **P2**, Y^{P2} is its optimal policy that maximizes utility through the optimal decisions of $\lambda^*(t)$ and $r^*(t)$ in each time slot, while satisfying all the constraints of **P2.** Since $\log(x)$ is a concave and non-decreasing function, constraint (27b) ensures that $\psi(\lambda^*) \leq \psi(r^*)$, and by Jensen's inequality, $\overline{\psi(\lambda^*)} \leq \psi(\overline{\lambda^*}) \leq \psi(\overline{r^*})$. Furthermore, we consider a strategy $Y^{P2'}$ that always selects $\lambda(t)$ equal to $\overline{r^{\text{opt}}}$, satisfying all constraints of **P2**. Under $Y^{\text{P2}'}$, we have $\overline{\psi(\lambda)} = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \psi(\overline{r^{\text{opt}}}) = \psi(\overline{r^{\text{opt}}})$. Since Y^{P2} is the optimal policy for **P2**, we have $\overline{\psi(\lambda^*)} \geq \overline{\psi(\lambda)} = \overline{\psi(\lambda^*)}$ $\psi\left(\overline{r^{\text{opt}}}\right)$. So, we can deduce that $\psi\left(\overline{r^*}\right) \geq \overline{\psi\left(\lambda^*\right)} \geq \psi\left(\overline{r^{\text{opt}}}\right)$. The transformed P2 meets all the constraints of the original **P1** and $\psi(\overline{r^{\text{opt}}})$ is the maximum utility of **P1**, we confirm $\psi\left(\overline{r^*}\right) = \psi\left(\overline{r^{\text{opt}}}\right)$, proving **P2** is equivalent to **P1**.

APPENDIX B

PROOF OF OPTIMAL AUXILIARY VARIABLE.

The first-order derivation of $\Phi_1(\lambda_i(t))$ for $\lambda_i(t)$ is derived as

$$\frac{\partial \left(\Phi_1\left(\lambda_i(t)\right)\right)}{\partial \left(\lambda_i(t)\right)} = \frac{V/\ln 2}{1/\omega_i + \lambda_i(t)} - Z_i(t) \tag{1}$$

From (1), $\frac{\partial (\Phi_1(\lambda_i(t)))}{\partial (\lambda_i(t))}$ decreases as $\lambda_i(t) \in (0, A_i^{\max})$ rises. If $\frac{\partial (\Phi_1(\lambda_i(t)))}{\partial (\lambda_i(t))} \bigg|_{\lambda_i(t)=0} = \frac{V\omega_i}{\ln 2} - Z_i(t) \le 0$, we have $\frac{\partial (\Phi_1(\lambda_i(t)))}{\partial \lambda_i(t)} < 0$ over $\lambda_i(t) \in (0, A_i^{\max})$. Therefore, $\Phi_1(\lambda_i(t))$ decreases as $\lambda_i(t)$ increases. In this case, the optimal auxiliary variable yields $\lambda_i^*(t) = 0$.

Otherwise, according to

$$\frac{\partial \left(\Phi_{1}\left(\lambda_{i}(t)\right)\right)}{\partial \left(\lambda_{i}(t)\right)}\bigg|_{\lambda_{i}(t)=\frac{V}{Z_{i}(t)\ln 2}-\frac{1}{\omega_{i}}}=0\tag{2}$$

If $\frac{V}{Z_i(t) \ln 2} - \frac{1}{\omega_i} \geq A_i^{\max}$, we have $\frac{\partial (\Phi_1(\lambda_i(t)))}{\partial (\lambda_i(t))} > 0$ over $\lambda_i(t) \in (0, A_i^{\max})$. Therefore, $\Phi_1(\lambda_i(t))$ increases as $\lambda_i(t)$ increases. In this case, $\lambda_i^*(t) = A_i^{\max}$. If $\frac{V}{Z_i(t) \ln 2} - \frac{1}{\omega_i} \leq A_i^{\max}$ we have either $\frac{\partial (\Phi_1(\lambda_i(t)))}{\partial (\lambda_i(t))} > 0$ if $\lambda_i(t) \in \left(0, \frac{V}{Z_i(t) \ln 2} - \frac{1}{\omega_i}\right)$ or $\frac{\partial (\Phi_1(\lambda_i(t)))}{\partial (\lambda_i(t))} < 0$ if $\lambda_i(t) \in$

If
$$\frac{V}{Z_i(t)\ln 2} - \frac{1}{\omega_i} \le A_i^{\max}$$
 we have either $\frac{\partial (\Phi_1(\lambda_i(t)))}{\partial (\lambda_i(t))} > 0$ if $\lambda_i(t) \in \left(0, \frac{V}{Z_i(t)\ln 2} - \frac{1}{\omega_i}\right)$ or $\frac{\partial (\Phi_1(\lambda_i(t)))}{\partial (\lambda_i(t))} < 0$ if $\lambda_i(t) \in$

 $\left(\frac{V}{Z_i(t)\ln 2}-\frac{1}{\omega_i},A_i^{\max}\right)$. In this case, the optimal auxiliary variable is $\lambda_i^*(t)=\frac{V}{Z_i(t)\ln 2}-\frac{1}{\omega_i}$.

Thus, the optimal auxiliary variable is

$$\lambda_i^*(t) = \begin{cases} 0, & \text{if } \frac{V\omega_i}{\ln 2} - Z_i(t) \le 0; \\ \min\left\{\frac{V}{Z_i(t)\ln 2} - \frac{1}{\omega_i}, A^{\max}\right\}, & \text{otherwise.} \end{cases}$$
(3)

APPENDIX C **PROOF OF THEREM 5**

Assuming that π represents a viable strategy for **P1**, the minimum upper bound of $\Delta_V(\Theta(t))$ can be expressed as

$$\Delta_{V}\left(\mathbf{\Theta}(t)\right) \\
\leq H - V\mathbb{E}\left\{\sum_{i \in \{1,2\}} \log\left(1 + \omega_{i}\lambda_{i}\right) \mid \mathbf{\Theta}(t), \pi\right\} \\
+ \sum_{i \in \{1,2\}} Q_{i}(t)\mathbb{E}\left\{R_{i}(t) - d_{i}^{l}(t) - d_{i}^{f}(t) \mid \mathbf{\Theta}(t), \pi\right\} \\
+ \sum_{i \in \{1,2\}} Z_{i}(t)\mathbb{E}\left\{\lambda_{i}(t) - R_{i}(t) \mid \mathbf{\Theta}(t), \pi\right\} \tag{4}$$

Referring to [1], it states that if **P1** is a feasible problem, then for any $\epsilon > 0$, it is guaranteed that there is at least one randomized stationary policy π^* which meets the following specified conditions

$$-\phi\left(\boldsymbol{\lambda(t)}\mid\boldsymbol{\pi}^*\right) \le -\psi^{\text{opt}} + \epsilon \tag{5a}$$

$$\mathbb{E}\left\{R_i(t) - d_i^l(t) - d_i^f(t) \mid \pi^*\right\} \le \epsilon \tag{5b}$$

$$\mathbb{E}\left\{\lambda_i(t) - R_i(t) \mid \pi^*\right\} \le \epsilon \tag{5c}$$

By integrating these results into (4) and taking $\epsilon \to 0$, we obtain

$$\Delta_V \left(\mathbf{\Theta}(t) \right) < H - V \psi^{\text{opt}} \tag{6}$$

Utilizing the iterated expectation and summing up all the telescoping series of (6) over time $t \in \{0, 1, \dots, T-1\}$, we

$$\mathbb{E}\left\{L\left(\mathbf{\Theta}(t)\right)\right\} - \mathbb{E}\left\{L\left(\mathbf{\Theta}\left(0\right)\right)\right\} - V \sum_{t=0}^{T-1} \mathbb{E}\left\{\psi\left(\boldsymbol{\lambda}(t)\right)\right\} \\ \leq HT - VT\psi^{\text{opt}} \quad (7)$$

By dividing both sides of (7) by VT, applying Jensen's inequality, and considering that the expected value $\mathbb{E}\left\{L\left(\mathbf{\Theta}\left(0\right)\right)\right\} \geq 0$ yields

$$\frac{1}{T} \lim_{T \to \infty} \sum_{t=0}^{T-1} \mathbb{E} \left\{ \psi \left(\boldsymbol{\lambda}(t) \right) \right\} \ge \psi^{\text{opt}} - \frac{H}{V}$$
 (8)

that is

$$\overline{\psi\left(\boldsymbol{\lambda(t)}\right)} \ge \psi^{\text{opt}} - \frac{H}{V} \tag{9}$$

According to $\overline{\psi(\pmb{\lambda}^*)} \leq \psi(\overline{\pmb{r}^*})$ proved in Lemma 1, we have $\psi(\overline{\pmb{r}^*}) \geq \overline{\psi(\pmb{\lambda}(t))}$. Thus, $\psi^{\text{opt}} - \psi(\overline{\pmb{r}^*}) \leq \frac{H}{V}$.

APPENDIX D PROOF OF THEREM 6

Utilizing the iterated expectations technique and recursively applying telescoping sums over each time slot $t \in \{0, 1, \dots, T-1\}$ as per equation (31) yields.

$$\mathbb{E}\left\{L\left(\mathbf{\Theta}(t)\right)\right\} - \mathbb{E}\left\{L\left(\mathbf{\Theta}(0)\right)\right\} - V\mathbb{E}\left\{\psi\left(\boldsymbol{\lambda}(t)\right) \mid \mathbf{\Theta}(t)\right\}$$

$$\leq TH - \varepsilon \sum_{t=0}^{T-1} \sum_{i \in \{1,2\}} \mathbb{E}\left\{Q_i(t) + Z_i(t)\right\}$$
(10)

By dividing both sides of equation (10) by $T\varepsilon$ and taking the limit as $T\to\infty$, we manipulate the terms to achieve the desired outcome

$$\frac{H}{\varepsilon} - \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} \sum_{i \in \{1,2\}} \mathbb{E} \left\{ Q_i(t) + Z_i(t) \right\} + V \frac{\overline{\psi(\lambda(t))}}{\varepsilon} \ge 0$$
(11)

Specifically

$$Q^{\sum} \leq \frac{H}{\varepsilon} + V \frac{\overline{\psi(\lambda(t))}}{\varepsilon}$$
 (12)

REFERENCES

[1] W. Zhan, C. Luo, G. Min, C. Wang, Q. Zhu, and H. Duan, "Mobility-aware multi-user offloading optimization for mobile edge computing," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 3, pp. 3341–3356, 2020.