Appendix A
Proof of Policy Invariance

The following proposition shows the one-step potential-based difference reward guarantees policy invariance and establishes the convergence of our method to a locally optimal policy theoretically.

Proposition 1. *By introducing the potential-based difference reward shaping in our framework, the policy invariant still holds and does not influence the convergence.*

Proof. For Agent 1, let $Q_1(s_1, a_1, a_2, a_3) = Q_1(s_1, \boldsymbol{a})$ be the original Q-function, and $\tilde{Q}_1(s_1, a_1, a_2, a_3) = \tilde{Q}_1(s_1, \boldsymbol{a})$ be the modified Q-function with the reward shaping method. We have:

$$Q_1(s_1, \boldsymbol{a}) = \mathbb{E}_{\boldsymbol{\pi}}\Big[\sum_{t=0}^{T} \gamma^t R_1^t\Big], \tag{26}$$

$$\tilde{Q}_1(s_1, \boldsymbol{a}) = \mathbb{E}_{\boldsymbol{\pi}}\Big[\sum_{t=0}^{T} \gamma^t \Big(R_1^t + \gamma \mathbb{E}_{\tilde{a}_1^{t+1}}\big[R_1(s_1^{t+1}, a_2^{t+1}, a_3^{t+1}, \tilde{a}_1^{t+1})\big] - \mathbb{E}_{\tilde{a}_1^t}\big[R_1(s_1^t, a_2^t, a_3^t, \tilde{a}_1^t)\big]\Big)\Big]. \tag{27}$$

where the expectation $\mathbb{E}_{\boldsymbol{\pi}}$ is with respect to the state-action distribution induced by the joint policy $\{\pi_1, \pi_2, \pi_3\}$ Then, $\tilde{Q}_1(s_1, \boldsymbol{a})$ can be further:

$$\begin{aligned}\tilde{Q}_1 =& \mathbb{E}_{\boldsymbol{\pi}}\Big[\sum_{t=0}^{T} \gamma^t R_1^t\Big] + \mathbb{E}_{\boldsymbol{\pi}}\Big[\sum_{t=1}^{T} \gamma^t \mathbb{E}_{\tilde{a}_1^t \sim \pi_1}\big[R_1(s_1^t, a_2^t, a_3^t, \tilde{a}_1^t)\big]\Big] \\ &- \mathbb{E}_{\boldsymbol{\pi}}\Big[\sum_{t=0}^{T} \gamma^t \mathbb{E}_{\tilde{a}_1^t \sim \pi_1}\big[R_1(s_1^t, a_2^t, a_3^t, \tilde{a}_1^t)\big]\Big], \end{aligned}\tag{28}$$

$$= \mathbb{E}_{\boldsymbol{\pi}}\Big[\sum_{t=0}^{T} \gamma^t R_1^t\Big] - \mathbb{E}_{\boldsymbol{\pi}}\Big[\gamma^0 \mathbb{E}_{\tilde{a}_1^0}\big[R_1(s_1^0, a_2^0, a_3^0, \tilde{a}_1^0)\big]\Big], \tag{29}$$

$$= Q_1 - \mathbb{E}_{\tilde{a}_1^0}\Big[R_1(s_1^0, a_2^0, a_3^0, \tilde{a}_1^0)\Big]. \tag{30}$$

Note that the expectation $\mathbb{E}_{\boldsymbol{\pi}}$ is $\mathbb{E}_{(s_1^t, s_2^t, a_1^t, a_2^t) \sim \boldsymbol{\pi}}$, considering the specific initial state s^0, this expectation becomes deterministic, eliminating variability in trajectories induced by $\boldsymbol{\pi}$. Therefore, the outer expectation can be omitted. Similar arguments apply for $Q_2, \tilde{Q}_2$ and $Q_3, \tilde{Q}_3$. For brevity in the ensuing discussion, let's denote $\mathcal{E}_1(s_1^0, a_2^0, a_3^0) = \mathbb{E}_{\tilde{a}_1^0}[R_1(s_1^0, a_2^0, a_3^0, \tilde{a}_1^0)]$, and similar to $\mathcal{E}_2(s_2^0, a_1^0, a_3^0)$, and $\mathcal{E}_3(s_3^0, a_1^0, a_2^0)$.

Let $\boldsymbol{\theta}$ be the parameters of joint actor policies $\theta_1, \theta_2, \theta_3$, the multi-agent policy gradient with the reward shaping is [17]:

$$\begin{aligned} g = \mathbb{E}_{\boldsymbol{\pi}}[&\nabla_{\boldsymbol{\theta}} \log \pi_1(a_1^t|s_1^t)\tilde{Q}_1(s_1, \boldsymbol{a}) \\ &+ \nabla_{\boldsymbol{\theta}} \log \pi_2(a_2^t|s_2^t)\tilde{Q}_2(s_2, \boldsymbol{a}) \\ &+ \nabla_{\boldsymbol{\theta}} \log \pi_3(a_3^t|s_3^t)\tilde{Q}_3(s_3, \boldsymbol{a})], \end{aligned}\tag{31}$$

$$\begin{aligned} = \mathbb{E}_{\boldsymbol{\pi}}[&\nabla_{\boldsymbol{\theta}} \log \pi_1(a_1^t|s_1^t)(Q_1(s_1, \boldsymbol{a}) - \mathcal{E}_1(s_1^0, a_2^0, a_3^0)) \\ &+ \nabla_{\boldsymbol{\theta}} \log \pi_2(a_2^t|s_2^t)(Q_2(s_2, \boldsymbol{a}) - \mathcal{E}_2(s_2^0, a_1^0, a_3^0)) \\ &+ \nabla_{\boldsymbol{\theta}} \log \pi_3(a_3^t|s_3^t)(Q_3(s_3, \boldsymbol{a}) - \mathcal{E}_3(s_3^0, a_1^0, a_2^0))]. \end{aligned}\tag{32}$$

Let's focus on the second term, and let $d^{\boldsymbol{\pi}}(s_i)$ be the stationary state distribution [13], and $-i$ be the other agent indicator:

$$\begin{aligned} g_p = -\mathbb{E}_{\boldsymbol{\pi}}[&\nabla_{\boldsymbol{\theta}} \log \pi_1(a_1^t|s_1^t)\mathcal{E}_1(s_1^0, a_2^0, a_3^0) \\ &+ \nabla_{\boldsymbol{\theta}} \log \pi_2(a_2^t|s_2^t)\mathcal{E}_2(s_2^0, a_1^0, a_3^0) \\ &+ \nabla_{\boldsymbol{\theta}} \log \pi_3(a_3^t|s_3^t)\mathcal{E}_3(s_3^0, a_1^0, a_2^0)] \end{aligned}\tag{33}$$

$$= -\mathbb{E}_{\boldsymbol{\pi}}[\sum_{i=1}^{3} \nabla_{\boldsymbol{\theta}} \log \pi_i(a_i^t|s_i^t)\mathcal{E}_i(s_i^0, a_{-i}^0)], \tag{34}$$

$$\begin{aligned} = -\sum_{i=1}^{3}\sum_{t=0}^{T}\sum_{s_i} d^{\boldsymbol{\pi}}(s_i^t) \sum_{a_{-i}} \pi_{-i}(a_{-i}^t|s_{-i}^t)\cdot \\ \sum_{a_i} \nabla_{\boldsymbol{\theta}} \pi_i(a_i^t|s_i^t)\mathcal{E}_i(s_i^0, a_{-i}^0), \end{aligned}\tag{35}$$

$$\begin{aligned} &= -\sum_{i=1}^{3}\sum_{t=0}^{T}\sum_{s_i} d^{\boldsymbol{\pi}}(s_i^t) \sum_{a_{-i}} \pi_{-i}(a_{-i}^t|s_{-i}^t)\mathcal{E}_i(s_i^0, a_{-i}^0)\nabla_{\boldsymbol{\theta}} 1 \\ &= 0. \end{aligned}\tag{36}$$

Therefore, we have:

$$\mathbb{E}_{\boldsymbol{\pi}}[\sum_{i=1}^{3} \nabla_{\boldsymbol{\theta}} \log \pi_i(a_i|s_i)\tilde{Q}_i(s_i, a_i, a_{-i})] \tag{37}$$

$$= \mathbb{E}_{\boldsymbol{\pi}}[\sum_{i=1}^{3} \nabla_{\boldsymbol{\theta}} \log \pi_i(a_i|s_i)Q_i(s_i, a_i, a_{-i})]. \tag{38}$$

This demonstrates this reward-shaping technique in our framework doesn't inherently change the expected gradient. Moreover, this proof remains valid for continuous actions. By employing Gaussian policies, we can treat the action as a Gaussian distribution, which only changes the calculation of $\nabla_\theta \log_\pi(a|s)$, and in the proof, we can replace $\sum_a$ with $\int_a$.

Then the expected policy gradient is:

$$\begin{aligned} g' &= \mathbb{E}_{\boldsymbol{\pi}}[\sum_{i=1}^{3} \nabla_{\boldsymbol{\theta}} \log \pi_i(a_i^t|s_i^t)Q_i(s_i, a_i, a_{-i})] \\ &= \mathbb{E}_{\boldsymbol{\pi}}[\nabla_{\boldsymbol{\theta}} \log \prod_{i=1}^{3} \pi_i(a_i^t|s_i^t)Q_i(s_i, a_i, a_{-i})] \\ &= \mathbb{E}_{\boldsymbol{\pi}}[\nabla_{\boldsymbol{\theta}} \log \boldsymbol{\pi}(\boldsymbol{a}^t|\boldsymbol{s}^t)Q_i(s_i, a_i, a_{-i})] \end{aligned}\tag{39}$$

where $\boldsymbol{\pi}(\boldsymbol{a}^t|\boldsymbol{s}^t) = \pi_1(a_1^t|s_1^t) \cdot \pi_2(a_2^t|s_2^t) \cdot \pi_3(a_3^t|s_3^t)$. Konda and Tsitsiklis [34] showed that a single-agent actor-critic with a given gradient converges to a local maximum of expected return under specific conditions, and the most important one is the policy is differentiable. Given that our policy gradient (i.e., the joint learner is broken down into separate, independent actors) in equation (39) is differentiable and the policy parameterization doesn't hinder convergence, our actor-critic model's convergence remains intact and assured. □

Appendix B
Numerical Setting

Under a single EVS, we support 5 to 9 users with varying settings. The total transmission power of the EVS is denoted as P Watts, and the EVS operates at a frequency of 10 GHz. We set the cycles per bit to a constant value of 150 [19]. Each pixel is represented using 16 bits [35], and the compression rate is randomly sampled from a uniform distribution ranging between 800 and 1000. We consider four different resolution settings: 720p (1280×720 pixels), 1080p (1920×1080 pixels), 2k (2560×1440 pixels), and 3k (3840×1920 pixels). The number of total frames per second T is fixed at 100, and the available bandwidth per channel is 10^6 Hz. We model the channel gain as $h_n^t = \sqrt{\beta_n^t} g_n^t$. For small-scale fading, we use Rician fading, where $g_n^t = \sqrt{\frac{K}{K+1}}\bar{g}_n^t + \sqrt{\frac{1}{K+1}}\tilde{g}_n^t$. Here, $\bar{g}_n^t$ represents the Line-Of-Sight (LOS) component, and $\tilde{g}_n^t$ characterizes the Non-LOS (NLOS) component, both following a standard complex normal distribution $\mathcal{CN}(0,1)$. Large-scale fading is modeled as $\beta_n^t = \beta_0(L_n)^{-\alpha}$, where L_n denotes the distance between the nth VU and the server. Here, β_0 represents the channel gain at the reference distance of $L_0 = 1$ m, and α is the path-loss exponent. For our simulations, we set α to 2 and the Rician factor K to 3. All experiments utilize the multiple same global random seeds, and we include error margins in our results.

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