SUPPLEMENTARY MATERIALS

Federated Learning-Enabled Jamming Detection for Stochastic Terrestrial and Non-Terrestrial Networks

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TABLE I
MEANINGS OF MAIN NOTATIONS

Notations	**Meanings**
$\mathcal{V}$	Coverage volumetric network, where $\mathcal{V} = a \times a \times a[m^3]$
M	Number of cells, UAV cluster heads (CHs)
$\mathcal{M}$	Set of all UAVs
L	Number of antennas, $L \gg 1$
N, N_m	Number of all UEs in the network, number of legitimate UEs in the m-th cell, $\sum_m N_m = N$
$\mathcal{S}_m$	Serving area of $\mathcal{A}$ in the m-th cell
$\mathcal{C}_m$	Set of N_m UEs in the m-th cell, $\lvert\mathcal{C}_m\rvert = N_m$
$\mathcal{N}$	Set of all UEs, where $\mathcal{N} = \bigcup_{m=1}^{M} \mathcal{C}_m$, $\lvert\mathcal{N}\rvert = N$
$\mathrm{U}_n^{[m]}$	n-th user in the m-th cell, where $\mathrm{U}_n^{[m]} \in \mathcal{S}_m, \forall n = [N_m]$
θ_{A}, v_{A}, t_{pause}	direction, speed of node A and the pause time between two WPs
λ_{A}, ϕ_{A}	the density point, the HPPP of node A
$\mathcal{D}_{\mathrm{U}_n - \mathrm{CH}_m}$	Euclidean distance between the m-th UAV and the n-th UE
$\mathcal{J}$, $\mathcal{J}_m$	Set of all active jammers in the network, where $\lvert\mathcal{J}_m\rvert = K_m$
K_m	Number of jammers in the m-th cell
$\mathrm{J}_j^{[m]}$	j-th jammer in the m-th
$\mathbf{n}^{[m]}$	Complex additive white Gaussian noise (AWGN)
G_A	Antenna gain of legitimate node A
$\mathbf{h}_{\mathrm{AB}}^{[m]}(t)$	The complex small-scale fading channel vector
$\mathrm{PL}_{\mathrm{AB}}$	Path-loss
N_0, NF, BW	Power density, noise figure, bandwidth
$\boldsymbol{\theta}_{cvae,m}$	Set weights of the CVAE model
$\boldsymbol{\theta}_{dec,m}$	Set weights of the decoder model
$\boldsymbol{\theta}_{enc,m}$	Set weights of the encoder model
$\boldsymbol{\theta}_{latent,m}$	Set weights of the latent neural network
$\mathcal{D}_{cvae,m}^{loc}$	Local dataset on the m-th UAV CH
$\mathcal{B}_{cvae,m}^{t}$, B_s	Local mini-batch of the $\mathcal{D}_{cvae,m}^{loc}$ in the t-th round, the size of batch $\mathcal{B}_{cvae,m}^{t}$.
E	Number of epoch/iteration
n_m	Number of samples available from the m-th UAV, with $n_m = \lvert\mathcal{D}_{cvae,m}^{loc}\rvert$
n	Size of all UAV data, where $n = \sum_{m=1}^{M} n_m$
η_l	Local learning rate
η_g	Global learning rate

Appendix A
Parameter Optimization Problem

Generally, in federated learning, a total of K UAV CHs aim to jointly solve the following optimization problem (1). They are often designed to minimize the weighted average of the local objective function across all the UAV CHs and find the $\boldsymbol{\theta}^{\star}_{cae,ps}$ model parameters that best minimize the overall loss function as follows

$$\boldsymbol{\theta}^{\star}_{cae,ps} = \arg\min_{\boldsymbol{\theta}_{cae,ps}} \left[F_{cae,ps}(\boldsymbol{\theta}_{cae,ps}) := \sum_{k=1}^{K} \frac{n_k}{n} f_{cae,k}(\boldsymbol{\theta}_{cae,k}) \right] \tag{1}$$

where $F_{cae,ps}(\boldsymbol{\theta}_{cae,ps})$ presents the global objective function, which is the sum of local objectives function, $f_{cae,k}(\boldsymbol{\theta}_{cae,k})$, weighted by the dataset size n_k at the k-th UAV CH. Then, the objective function of k-th UAV CH is $f_{cae,k}(\boldsymbol{\theta}_{cae,k}) = \mathbb{E}_{\mathbf{X}^{(i)}_k \sim \mathcal{D}_k}[f_{cae,k}(\boldsymbol{\theta}_{cae,k}; \mathbf{X}^{(i)}_{\mathrm{C}_k})]$.

More specifically, the local objective function of the k-th UAV CH at the e-th iteration, $e = \{1, \ldots, E\}$, in round t, $f_{cae,k}(\boldsymbol{\theta}^{[t],[e]}_{cae,k})$, is given by

$$\begin{aligned} f_{cae,k}(\boldsymbol{\theta}^{[t],[e]}_{cae,k}) &= \frac{1}{n_k} \sum_{i=1}^{n_k} \mathcal{L}^{[t],[e]}_{cae,k}(\mathbf{z}^i_k; \boldsymbol{\theta}^{[t],[e]}_{cae,k}) = \frac{1}{n_k} \sum_{i=1}^{n_k} \mathcal{L}^{[t],[e]}_{cae,k}(\mathbf{y}_i, f(\mathbf{x}_i; \boldsymbol{\theta}^{[t],[e]}_{cae,k}))) \\ &= \frac{1}{n_k} \sum_{i=1}^{n_k} - \log p(\mathbf{y}_i \mid f(\mathbf{x}_i; \boldsymbol{\theta}^{[t],[e]}_{cae,k}))) \end{aligned} \tag{2}$$

where $\mathcal{L}^{[t],[e]}_{cae,k}(.)$ denotes the loss function defined by the parameters to be learned, $\boldsymbol{\theta}^{[t],[e]}_{cae,k}$ at the e-th iteration in the t-th round and $\mathbf{z}_k$ that represents a data sample input-output pair from the local dataset $D^{loc}_{cae,k}$. Consequently, the objective function of the k-th UAV CH is to optimize the $\boldsymbol{\theta}_{cae,k}$ parameters that minimize the loss function, i.e.,

$$\boldsymbol{\theta}^{\star}_{cae,k} = \arg\min_{\boldsymbol{\theta}_{cae,k}} f_{cae,k}(\boldsymbol{\theta}^{[t]}_{cae,k}), \tag{3}$$