Energy-Efficient Federated Learning-enabled Digital Twin in UAV-aided Vehicular Networks

2023 - Research Progress Seminar

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Contents

Introduction

Digital Twin (DT) in Vehicular Networks

- Virtual model of a physical object (PO), interacts and evolves synchronously with PO during its life cycles
- Enable self-sustaining (*minimum intervention*) and proactive intelligent analytic (*prior-to-request*) operations

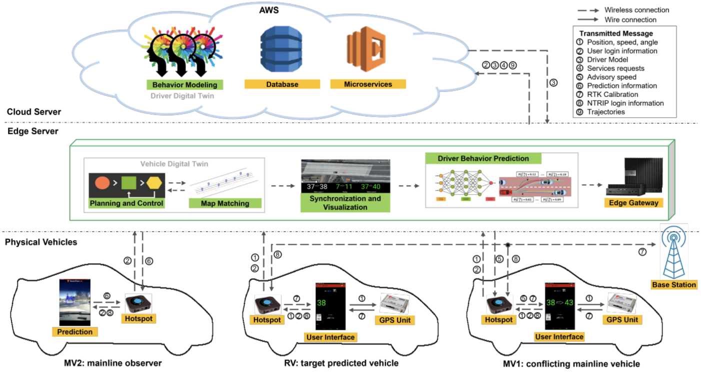
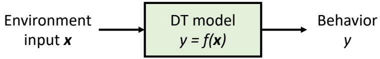


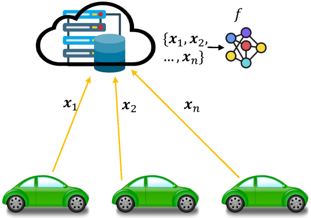
Figure 1: DT for Intelligent Transportation Systems [1]

Federated Learning (FL)-enabled Digital Twin

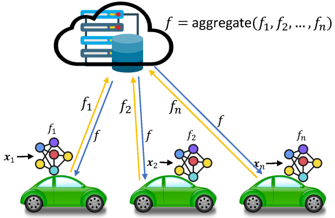
Construct a twin model as finding the f function



- Physical-based modeling: observe, formulate, solve math equations (*based on assumptions, not always possible* !!!)
- Data-driven approach: machine learning techniques
  - Centralized learning: transmit raw data to a central server, centralized train the model
  - Federated learning: locally train the models, transmit the models for aggregation at the central server



Centralized Learning



Federated Learning

Advantages:

- Preserve data privacy
- Reduce communication burden of transmitting raw data

Challenge: a large #global (comm.) rounds (*for exchanging the models*) required until convergence

- Vehicle mobility - more challenging in vehicular networks!!!

FL-enabled DT in Vehicular Networks (2)

Potential solutions:

- *Comm.*: UAV-aided vehicular networks: on-demand, flexible deployment, enhance network converage
- *Comp.*: increase local model training
  - Reduce #comm. rounds but also increase local computation energy
  - Pose trade-off between *energy consumption & latency and accuracy requirements*

Related work: consider this trade-off during the FL process

- [2–6]: energy minimization problem assuming the propagation channel remains stable
- [7]: the optimization problem for only one comm. round

Our Work

Problem:

Investigate the energy efficiency problem of FL-enabled DT for UAV-aided vehicular networks under the latency and accuracy constraints while considering vehicle mobility's impact on communication channels during FL process

Method:

- Dynamically update the latency and accuracy constraints at the beginning of each round
- Then solve a joint optimization of local training accuracy, local CPU frequency, relay UAV decision, and transmission power by convex optimization techniques

System Model

System Model

Network:

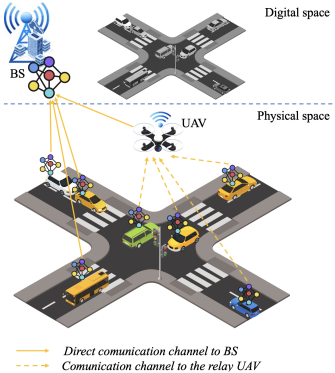
A set $\mathcal{K}$ of K moving connected vehicles (CVs), an edge-server integrated BS, a relay node UAV

FL-enabled DT modeling:

- Local dataset $\mathcal{D}_k = \{(\mathbf{x}_j, y_j)\}_{j=1}^{D_k}$, $\forall k$, D_k: # local samples
- Minimize the global loss function as

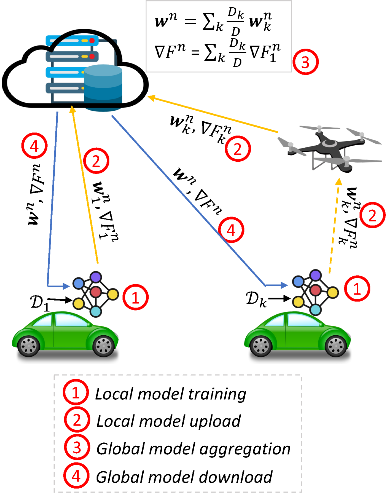
$$\min_{\mathbf{w}} F(\mathbf{w}) := \sum_{k \in \mathcal{K}} \frac{D_k}{D} F_k(\mathbf{w}),$$

where $D = \sum_k D_k$ - total samples



At the n-th global round

- $\mathbf{w}_k^n$, $\mathbf{w}^n$:
  local, global model parameters
- ∇F_k^n, ∇F^n:
  local, global model gradient
- $\mathbf{w}^n, \nabla F^n$:
  broadcasted to CVs (4) for the next round $(n+1)$-th



Time & Energy Consumption

	Energy	Time
Comp.	$e_{k,n}^{\text{cp}} = I_n \kappa C_k D_k f_{k,n}^2$	$t_k^{\text{cp}} = I_n \frac{C_k D_k}{f_{k,n}}$
Comm.	$e_{k,n}^{\text{co}} = p_{k,n} t_{k,n}^{co}$	$t_{k,n}^{\text{co}} = \frac{s_k}{B \log_2(1+\frac{p_{k,n} h_{k,n}}{BN_0})} + x_{k,n}\delta^{\text{uav}}$
Total	$e_{k,n} = e_{k,n}^{\text{co}} + e_{k,n}^{\text{cp}}$	$t_{k,n} = t_{k,n}^{\text{co}} + t_{k,n}^{\text{cp}}$

- $\eta_n, f_{k,n}, p_{k,n}, x_{k,n}$: optimization variables
    - η_n: local accuracy (- *suboptimal local models*)
    - $f_{k,n}$: local CPU frequency
    - $x_{k,n}$: relay decision, $x_k = 1$ *if* choosing UAV *else* 0
      $h_{k,n} = (1 - x_{k,n}) h_{k,n}^{uav} + x_{k,n} h_{k,n}^{bs}$
    - $p_{k,n}$: transmit power
- $I_n = v \log_2(\frac{1}{\eta_n})$ [2]: #local rounds to reach η_n, v: constant
- δ^{uav}: transmission time from UAV to BS

Problem Formulation

Problem Formulation (1)

Our objective: *Joint learning & communication resource allocation to minimize the energy while satisfying the latency, accuracy requirements*

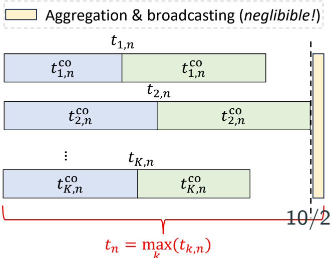
Our method: To eliminate vehicle mobility impact, we propose to instantaneously update latency & accuracy constraints, then solve the optimization at the beginning of each global round

- Instantaneously update latency & accuracy constraints

  τ_g, ϵ_g: global latency & accuracy requirements

$$\tau_0^{\text{req}} = \tau_g; \tau_{n\geq 1}^{\text{req}} = \tau_g - \sum_{n'=0}^{n-1} \max_k(t_{k,n'})$$

$$\epsilon_0^{\text{req}} = \epsilon_g; \epsilon_{n\geq 1}^{\text{req}} = \frac{\epsilon_g}{\prod_{n'=0}^{n-1} \epsilon_{n'}}$$



- Solve the optimization at the beginning of each global round[1]

$$\min_{\eta_n, \mathbf{f}_n, \mathbf{x}_n, \mathbf{p}_n} \quad \sum_{k\in\mathcal{K}} N_n \left(e^{\text{co}}_{k,n} + e^{\text{cp}}_{k,n}\right) \tag{1a}$$

$$\text{s.t.} \quad N_n \left(t^{\text{co}}_{k,n} + t^{\text{cp}}_{k,n}\right) \leq \tau_n^{\text{req}}, \forall k, \tag{1b}$$

$$0 \leq \eta_n \leq 1, \tag{1c}$$

$$x_{k,n} = \{0,1\}, \forall k, \tag{1d}$$

$$\sum_k x_{k,n} \leq N_0^{\text{uav}}, \tag{1e}$$

$$0 \leq f_{k,n} \leq f_k^{\max}, \forall k, \tag{1f}$$

$$0 \leq p_{k,n} \leq p_k^{\max}, \forall k, \tag{1g}$$

$N_n = \frac{a}{1-\eta_n}, a = \frac{2L^2}{\gamma^2\xi}\ln(\frac{1}{\epsilon_n^{\text{req}}})$: instant. #global rounds [2]

[1] We drop the supscript n in next parts for ease of presentation

Joint Optimization Algorithm

Problem Decomposition

We have a joint learning and communication resource allocation:

- Fixed (f_k^*, x_k^*, p_k^*), optimize η - Learning optimization (LO) ($A_k = vC_kD_k$):

$$\min_{\eta} \quad \frac{a}{1-\eta}\left(\sum_k e_k^{co} + \sum_k \frac{\kappa A_k f_k^2}{\ln 2} \ln(1/\eta)\right) \tag{2a}$$

$$\text{s.t.} \quad T_k = \frac{a}{1-\eta}\left(t_k^{co} + \frac{A_k}{f_k \ln 2}\ln(1/\eta)\right) \le \tau, \forall k, \tag{2b}$$

$$0 \le \eta \le 1 \tag{2c}$$

- Fixed η^*, optimize (f_k, x_k, p_k) - Resource allocation (RA):

$$\min_{\{f_k, x_k, p_k\}_{k=1}^K} \quad \sum_k \left(p_k\left[\frac{(\ln 2)s_n/B}{\ln\left(1+\frac{p_k h_k}{N_0}\right)} + x_k\delta_t\right] + \kappa A_k \log_2(1/\eta) f_k^2\right) \tag{3a}$$

$$\text{s.t.} \quad \left(\frac{(\ln 2)s_n/B}{\ln\left(1+\frac{p_k h_k}{N_0}\right)} + x_k\delta_t\right) + A_k \log_2(1/\eta)\frac{1}{f_k} \le \frac{\tau}{n}, \forall k, \tag{3b}$$

$$0 \le f_k \le f_k^{\max}, 0 \le p_k \le p_k^{\max}, \tag{3c}$$

$$x_k = \{0,1\}, \sum_k x_k \le N_0 \tag{3d}$$

We iteratively solve these 2 subproblems until convergence.

Algorithm 1 Joint Optimization Algorithm

Initialize a feasible solution $(\mathbf{f}^{(0)}, \mathbf{x}^{(0)}, \mathbf{p}^{(0)})$ of problem (1) and set $t = 0$

repeat

  Given $(\mathbf{f}^{(t)}, \mathbf{x}^{(t)}, \mathbf{p}^{(t)})$, obtain the optimal $\eta^{(t)}$ of (2)

  Given $\eta^{(t)}$,

    Case 1: $\mathbf{x}^{(t)} = \{1\}_{k\in\mathcal{K}}$ ▷ *All CVs relay via UAV*

      For $\forall k$ **in** $\mathcal{K}$:

        Obtain the optimal $f_k^{\text{uav},(t)}, p_k^{\text{uav},(t)}$ of (3)

    Case 2: $\mathbf{x}^{(t)} = \{0\}_{k\in\mathcal{K}}$ ▷ *Directly upload to BS*

      For $\forall k$ **in** $\mathcal{K}$:

        Obtain the optimal $f_k^{\text{bs},(t)}, p_k^{\text{bs},(t)}$ of (3)

    Select the optimal $\mathbf{x}^{(t)}$ that satisfies (4f)

    Update the optimal $(\mathbf{f}^{(t)}, \mathbf{p}^{(t)})$ with respect to $\mathbf{x}^{(t)}$

  Set $t = t + 1$

until objective value (4a) converges

Simulation Results

Simulation Settings

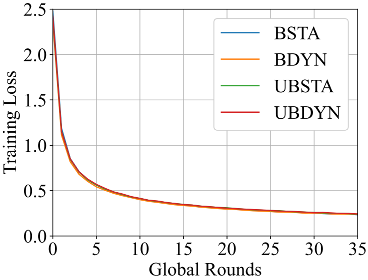
MNIST Dataset [8]: Each CV has

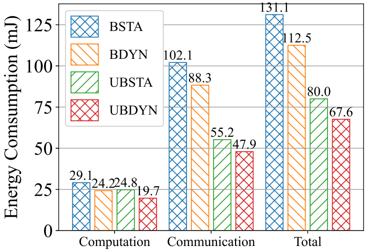
- Only 3 of the total 10 labels
- #samples: $\in [138, 799]$, heterogeneously distributed following the power law
- 80-20%: ratio between train & test set

Table 1: Simulation Parameters

Parameter	Value	Parameter	Value
BS location	(0, -500, 0) m	UAV location	(200, 220, 100) m
N_0	-174 dBm/Hz	B	1 MHz
K, N_0^{uav}	10, 5	κ	10^{-28}
p_k^{max}	0.1 W	f_k^{max}	2 GHz
s	0.3 Mb	ϵ_g	10^{-3}
γ, L	3, 5	δ, ξ	0.01, 1

Simulation Results





- 4 scenarios:
  - BSTA, BDYN: BS w/ static, dynamic optim
  - UBSTA, UBDYN: BS, a relay UAV w/ static, dynamic optim
- Results:
  - Give similar learning performance
  - Energy consumption of UBDYN is 15.5% less than that of UBSTA and 39.9% lower than that of BDYN

Conclusions

- The energy-efficient impact of UAV in UAV-aided vehicular networks
- The energy-efficient impact of dynamic resource allocation during the FL-enabled DT modeling

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Thank you for your attention.

Extension Ideas

Extension Ideas

- Lyapunov framework is utilized for optimization in stochastic environments, where it is difficult to expect short-term guarantees/performances, but we can expect to guarantee a steady-state performances.
- Define the local accuracy as $\eta^n \in (0, 1]$, where distributed devices trains the local model to find the suboptimal solution as

$$J_k(\mathbf{w}_k^n) - J_k(\mathbf{w}_k^{n,*}) \le \eta^n (J_k(\mathbf{w}_k^{n,0}) - J_k(\mathbf{w}_k^{n,*})),$$

With local accuracy η, the global accuracy ϵ_n obtained as $\epsilon_n \le \exp\left(-\frac{(1-\eta^n)\gamma^2\xi}{2L^2}\right)$, where

$$F(\mathbf{w}^{n+1}) - F(\mathbf{w}^*) \le \epsilon_n (F(\mathbf{w}^n) - F(\mathbf{w}^*))$$

Extension Ideas (2)

- We define the instant. accuracy level by $G(n)$

$$\begin{aligned} G(n) &= -\ln\left[\frac{F(w^n)-F(w^*)}{F(w^0)-F(w^*)}\right] \\ &= -\ln\left[\frac{F(w^n)-F(w^*)}{F(w^{n-1})-F(w^*)} \times \frac{F(w^{n-1})-F(w^*)}{F(w^0)-F(w^*)}\right] \\ &= \frac{(1-\eta^n)\gamma^2\xi}{2L^2} + G(n-1), \end{aligned}$$

Behavior of $G(n)$ is similar to a queue!!!

- We can expect for a long-term accuracy level as

$$\lim_{N\to\infty} \frac{1}{N}\sum_{n=0}^{N-1} \mathbb{E}\{G(n)\} \geq \overline{G}$$

Extension Ideas (3)

- The steady-state latency required of a global round (or latency required before global aggregation) can be defined as

$$\lim_{N \to \infty} \frac{1}{N} \sum_{n=0}^{N-1} \mathbb{E}\{T_k(n)\} \leq \overline{T}$$

Extension Ideas (4)

Thus we formulate our optimization to minimize the energy while guaranteeing a steady-state performance

$$
\begin{aligned}
\min_{\eta_n, \mathbf{f}_n, \mathbf{x}_n, \mathbf{p}_n} \quad & \lim_{N\to\infty} \frac{1}{N} \sum_{n=0}^{N-1} \sum_{k\in\mathcal{K}} \left(e^{\mathrm{co}}_{k,n} + e^{\mathrm{cp}}_{k,n} \right) && \text{(4a)} \\
\text{s.t.} \quad & \lim_{N\to\infty} \frac{1}{N} \sum_{n=0}^{N-1} \mathbb{E}\{T_k(n)\} \le \overline{T}, \forall k, && \text{(4b)} \\
& \lim_{N\to\infty} \frac{1}{N} \sum_{n=0}^{N-1} \mathbb{E}\{G(n)\} \ge \overline{G}, && \text{(4c)} \\
& 0 \le \eta_n \le 1, && \text{(4d)} \\
& x_{k,n} = \{0, 1\}, \forall k, && \text{(4e)} \\
& \textstyle\sum_k x_{k,n} \le N_0^{\mathrm{uav}}, && \text{(4f)} \\
& 0 \le f_{k,n} \le f_k^{\max}, \forall k, && \text{(4g)} \\
& 0 \le p_{k,n} \le p_k^{\max}, \forall k, && \text{(4h)}
\end{aligned}
$$