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

Research Progress Seminar

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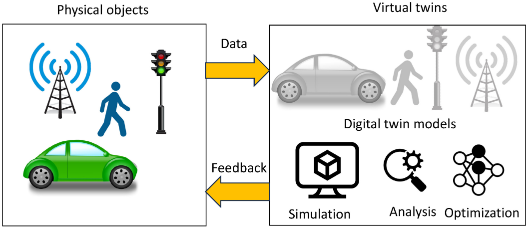
Contents

Introduction

Digital Twin (DT) in Vehicular Networks

- DT is a virtual model of a physical object (PO) that interacts, evolves synchronously with PO during its life cycle

  $\Longrightarrow$ **simulate, analyze, optimize PO via twin model**



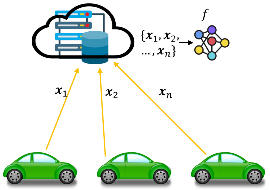
- DT is a **promising solution in vehicular networks** [1]
  - Build *DT models to enable applications* in vehicular networks
  - E.g., vehicle DT $\rightarrow$ autonomous driving, driver DT $\rightarrow$ service recommendations, parking space DT $\rightarrow$ smart parking, ...

Digital Twin Modeling

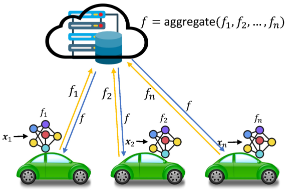
There are 2 ways to build DT model using **data-driven approach**:

- *Centralized learning-enabled DT*
  - A central server collects raw data & train DT model globally
    Disadvantages: centralized data collecting → high privacy risk
    large size raw data → communication burden
- *Federated learning (FL)-enabled DT*
  - Users locally train model by local data → privacy preservation
  - Only model parameters (*smaller size cf. raw data*) are transmitted to server for aggregation → reduce comm. burden

⟹ Our focus is the FL-enabled DT modeling approach



Centralized Learning



Federated Learning

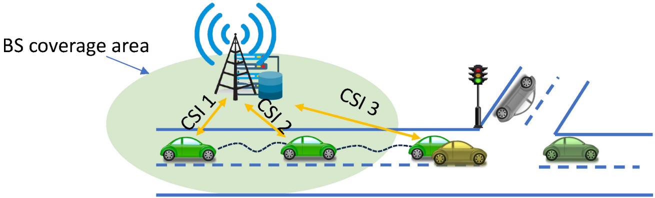
FL-enabled DT in Vehicular Networks (1)

There are two challenging issues of FL-enabled DT in Vehicular Networks:

1. **Seamless communication**
   - FL consists of *multiple global rounds of exchanging models* bw. server and vehicles → *require for seamless comm.*
   - *Comm. channel is dynamic* in vehicular networks (mobility):
     - Channel state information (CSI) changes during the FL process
     - Vehicles move out of base station (BS) coverage area
     - Higher traffic density at *junctions, traffic jam,...*

→ More BSs is required to increase coverage, reduce mobility impact

⟹ **UAVs**: deployed as flying BSs to aid vehicular networks (*flexible, on-demand deployment, provide line-of-sight channels*)



FL-enabled DT in Vehicular Networks (2)

2. Optimal resource allocation (RA)

- RA is necessary to **guarantee QoS requirements** (*accuracy, latency*) of DT model while **efficient use of energy**
- Most existing work proposed **static optimization** approach for RA to enable FL [2–7]
  - Consider static network scenarios: given short required latency ($\sim$ few 10s), *CSI is stable*
  - RA can be solved by static optimization approach: *solve once at the beginning but for the whole FL process*
- **But,** static optimization can't be applied in vehicular networks
  - Due to the *CSI changes*, the optimal RA for the first round is no longer appropriate (optimal) in the next rounds
    $\rightarrow$ The resource should be *dynamically allocated accordingly*

$\Longrightarrow$ Require **dynamic optimization** approach in veh. networks

Goals of the Study

Our Goal:
We want to minimize energy consumption under latency & accuracy requirements for FL-enabled DT in UAV-aided vehicular networks

Our Approach:

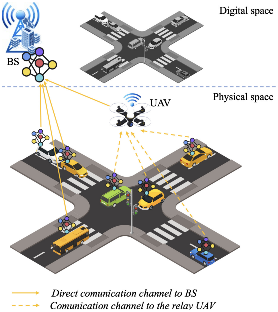
- We first propose a dynamic optimization, where the optim. problem is solved at the beginning of each global round during FL process
- We derive the formulas to instantaneously update the latency, accuracy requirements, then solve the optim. problem accordingly

System Model & Problem Formulation

System Model

We consider the FL-enabled DT in a UAV-aided vehicular network, which is constructing a global DT model by FL:

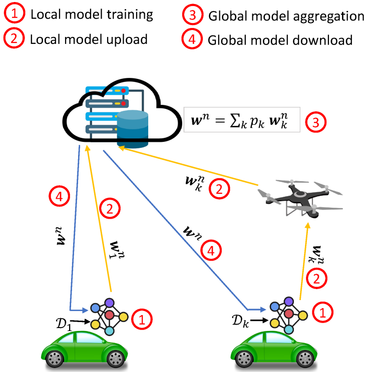
- K moving connected vehicles (CVs).
  Each CV has a local dataset $\mathcal{D}_k$ for training the local model
- An server integrated BS for aggregating the local models to the global model
- A relay node UAV deployed near the intersection for relaying local models from CVs to BS



FL-enabled DT Dataflow

Let $\mathbf{w}_k^n$, $\mathbf{w}^n$ be the local model and global model at a global round n.
There are 4 phases at one round:

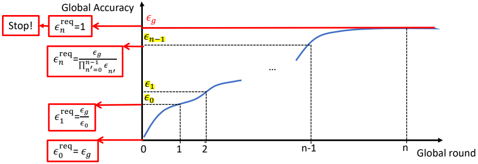
1. Local model training:
   CVs trains the local models on $\mathcal{D}_k$ to update $\mathbf{w}_k^n$ with initialization $\mathbf{w}^{n-1}$
2. Local model upload:
   CVs upload $\mathbf{w}_k^n$ to BS, directly or via relay node UAV
3. Global model aggregation:
   BS aggregates $\mathbf{w}_k^n$ to update $\mathbf{w}^n$
4. Global model download:
   BS broadcasts $\mathbf{w}^n$ to CVs



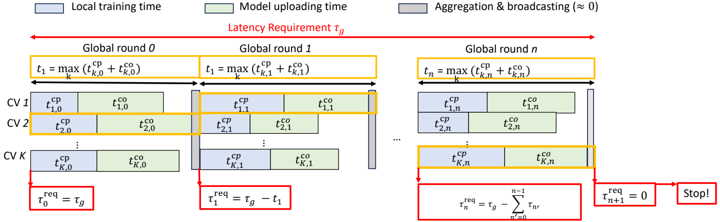
Instantaneous Accuracy and Latency

Let $\mathbf{w}^*$, $\mathbf{w}^n$ be the optimal & suboptimal model (satisfying a certain accuracy).
We conside two requirements to guarantee DT construction's QoS:

- Global accuracy (*accuracy of* $\mathbf{w}^n$ *cf.* $\mathbf{w}^*$): $\epsilon_g = \prod_{n'=0}^{n-1} \epsilon_{n'}$
  $\rightarrow$ derive the instantaneous accuracy requirement of each round $\epsilon_{n'}^{\text{req}}$



- Global latency (*total time to obtain* $\mathbf{w}^n$): $\tau_g = \sum_{n'=0}^{n-1} \max_k(t_{k,n'})$
  $\rightarrow$ derive the instantaneous latency requirement of each round $\tau_{n'}^{\text{req}}$



Time & Energy Consumption

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

Let η_n, $f_{k,n}$, $p_{k,n}$, $x_{k,n}$ be optimization variables:

- η_n: local accuracy (*after running $I_n = v \log_2(\frac{1}{\eta_n})$ local rounds*)
- $f_{k,n}$: local CPU frequency (*for local model training*)
- $p_{k,n}$: transmit power (*for local model uploading*)
- $x_{k,n}$: relay decision (*for local model uploading*)
  $x_k = 1$ *if* choosing UAV *else* 0

Problem Formulation

- We first update **remaining instantaneous latency, accuracy requirements** in each round during the FL process
- The optimization problem is to **minimize energy consumption** under the **remaining instantaneous latency, accuracy requirements** in **each round** as

$$
\begin{aligned}
\min_{\eta_n, \mathbf{f}_n, \mathbf{x}_n, \mathbf{p}_n} \quad & \sum_{k \in \mathcal{K}} N_n \left(e_{k,n}^{\mathrm{co}} + e_{k,n}^{\mathrm{cp}} \right) \\
\text{s.t.} \quad & N_n \left(t_{k,n}^{\mathrm{co}} + t_{k,n}^{\mathrm{cp}} \right) \leq \tau_n^{\mathrm{req}}, \\
& 0 \leq \eta_n \leq 1, \\
& x_{k,n} = \{0, 1\}, \sum_k x_{k,n} \leq N_0^{\mathrm{uav}}, \\
& 0 \leq f_{k,n} \leq f_k^{\max}, 0 \leq p_{k,n} \leq p_k^{\max},
\end{aligned}
$$

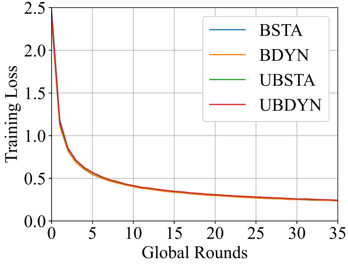
  - $N_n = \frac{a}{1-\eta_n}$: #global rounds expected to reach accuracy $\epsilon_n^{\mathrm{req}}$
  - $N_0^{\mathrm{uav}}, f_k^{\max}, p_k^{\max}$: #available channels at UAV, maximum CPU freq., transmit power

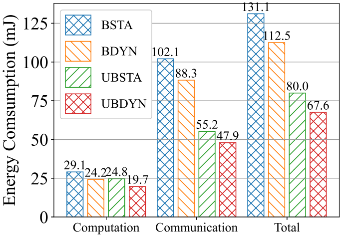
Simulation Results

Simulation Settings

- We validate the FL-enabled DT on the hand-written digits MNIST dataset. Each CV has only 3 of the total 10 labels, #samples: $\in [138, 799]$ following the power law to **mimic the heterogeneous characteristic of vehicular networks**:
- We consider 4 approaches to compare the performance *(with vs. without UAV, static vs. dynamic optimization*
  - BSTA: noUAV/static optimization
  - BDYN: noUAV/dynamic optimization
  - UBSTA: UAV/static optimization
  - UBDYN: UAV/dynamic optimization (our proposal!)

Simulation Results





- 4 approaches give similar learning performance (training loss)
- Energy of UAV/dynamic optimization (UBDYN) is smallest:
  - 15.5% less than UAV/static optimization (UBSTA)

  $\Rightarrow$ *Dynamic optimization improves both comp. and comm. energy*
  - 39.9% lower than noUAV/dynamic optimization (BDYN)

  $\Rightarrow$ *UAV significantly improves comm. energy*

Conclusion

Conclusion

1. We investigated the energy-efficient resource allocation problem for FL-enabled DT in UAV-aided vehicular networks
2. Observations from the results:
   - The deployment of UAV can improve the communication channel between BS and CVs during the FL process
   - The dynamic optimization can improve both computation and communication energy, thus lowering energy consumption

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Thank you for your attention.