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Optimizing Data-Driven Federated Learning in UAV Networks

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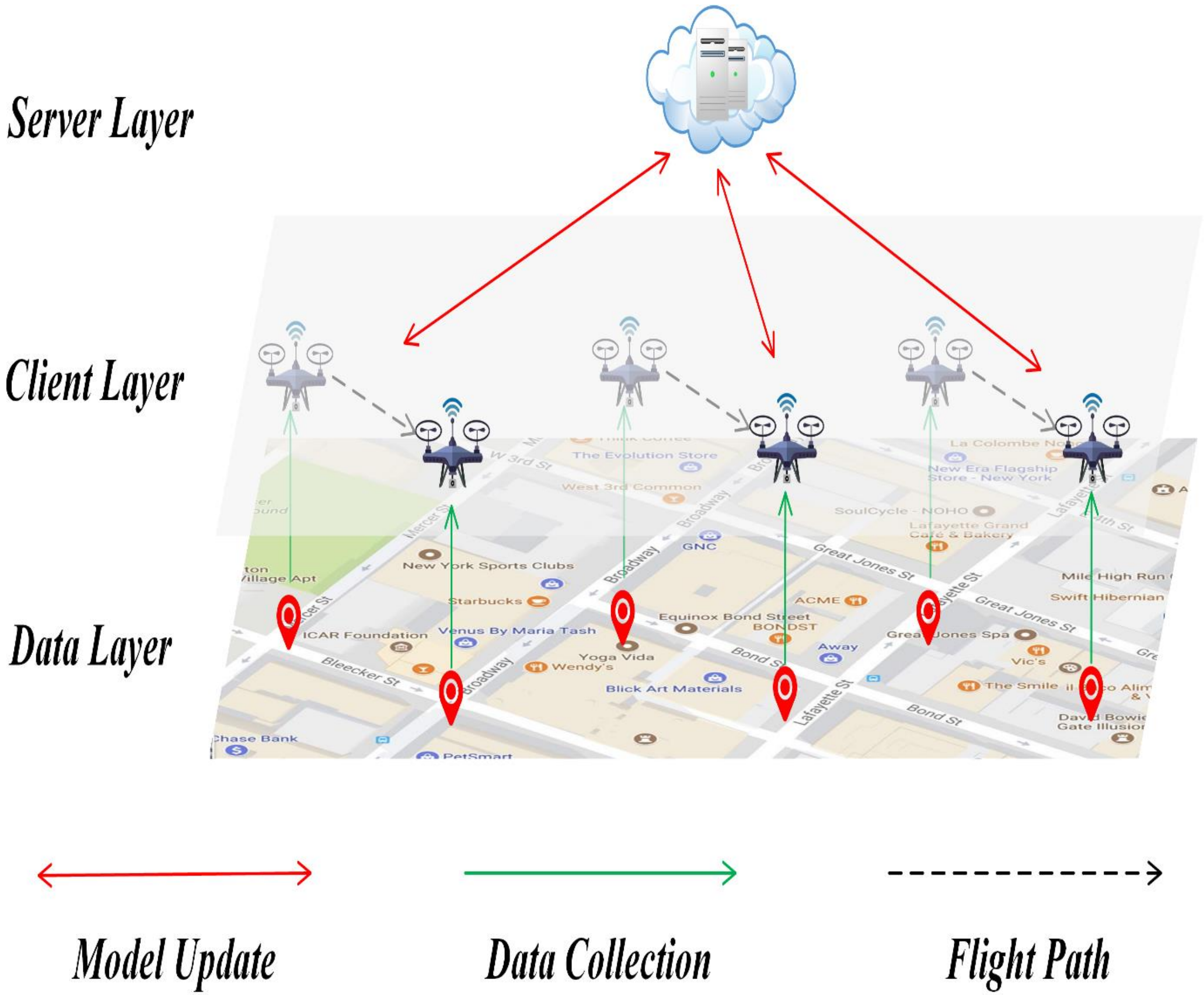
Outline

- Motivation & Challenges
- Preliminaries & Problem Formulation
- Basic Idea & Solution
- Evaluation & Conclusion

Motivation



Traditional FL

- ☐ **Pre-existing Local Datasets**: Clients' local datasets already exist before training, and the data is static;
- ☐ **No Time-Sensitivity**: The model does not need to account for the timeliness of the data.

Update Datasets ↓ *Train with Fresh Data*

Data-Driven FL in UAV networks

- ☐ **Active Data Collection**: Mobile clients (e.g., UAVs) actively collect data from PoIs;
- ☐ **Time-Sensitive Models**: The model needs to be trained as fast as possible;
- ☐ **Budget Limit**: Mobile clients spend some extra costs while the total budget from is limited.

Challenges

- Selected PoIs: **explore** PoIs & **collect** high-quality data

  → **Quantify** the impact of PoI data on the model training of FL?

  → Reveal **relationship** between the **loss** of global model and the **decrease** of the time consumed by UAVs?

- **Dependence**: PoI selection and the corresponding UAV speed and path

  → Design decision-making strategies to obtain the **UAV path and speed** within the constraints of energy consumption and the global loss function?

Related Work

- **FL Data Selection:** make selection of sample data within clients

  e.g., A. Li, L. Zhang, J. Tan, Y. Qin, J. Wang, and X.-Y. Li, “Sample-level data selection for federated learning,” in IEEE INFOCOM, 2021, pp. 1–10.

- **UAV Data Collection:** UAV-based data collection in communication networks

  e.g., Z. Dai, H. Wang, C. H. Liu, R. Han, J. Tang, and G. Wang, “Mobile crowdsensing for data freshness: A deep reinforcement learning approach,” in IEEE INFOCOM, 2021, pp. 1–10.

- **CMAB:** arms are selected as combinations from a set

  e.g., G. Gao, J. Wu, M. Xiao, and G. Chen, “Combinatorial multi-armed bandit based unknown worker recruitment in heterogeneous crowdsensing,” in IEEE INFOCOM, 2020, pp. 179–188.

Ignore the importance of data collection

Ignore the relationship between data quality & energy consumption, time delays

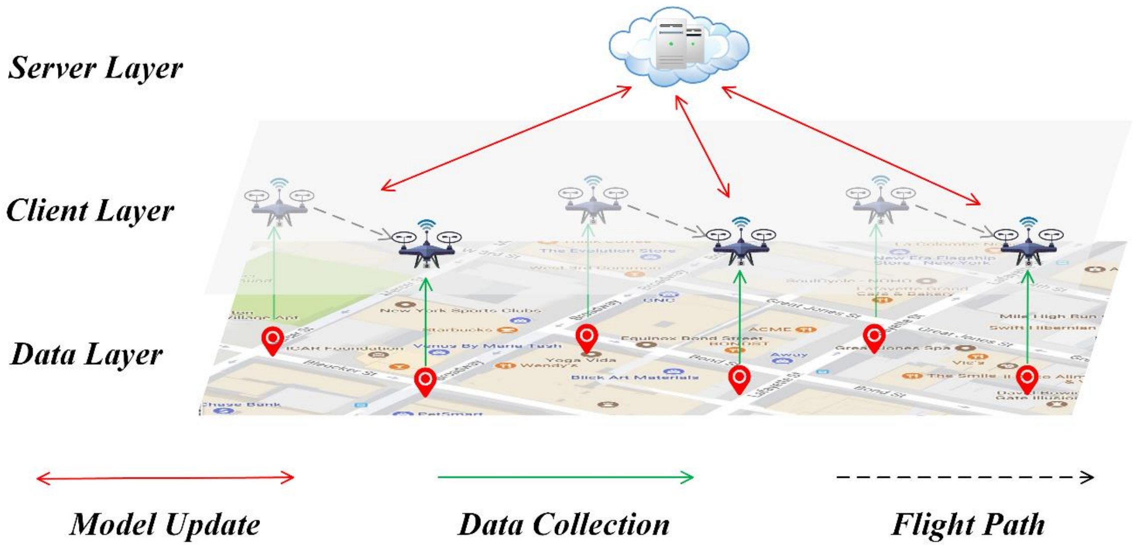
We aim to design a PoI selection mechanism for FL while considering **data quality and limited budget simultaneously**

Contributions

- ✓ **System:** Introduce a **novel DDFL** system with UAVs collecting data from PoIs under energy constraints.
- ✓ **Analysis:** Derive a **convergence upper bound**, which relates the global model performance and the data from PoIs.
- ✓ **Algorithm:** Propose the Adaptive Two-stage CMAB-based FL**(FedATC)** algorithm and prove its **approximate optimality**.
- ✓ **Experiments:** Conduct extensive **simulations** based on multiple datasets to verify the performance of the FedATC.

System Model

System Model



- **BS:** updates the global model and coordinates the flight paths and velocities of the UAVs
- **UAV {1,2,...,U}:** collect data and train the local model along a fight path and upload local model
- **PoI selection**: each PoI can be selected by at most one UAV at a time.

Procedure

① BS sends the initial model and flight route to the UAVs

② UAV *u*: collect dataset from PoIs, local train and upload model

③ BS updates the global model asynchronously

④ BS sends global model and new flight route to UAV u

Problem Formulation

Original Optimization problem:

$$
\begin{aligned}
\textbf{P1:} \quad & \min_{\mathcal{R}_u^t, v_u} \quad T_{\text{total}}(L, n, v_u), \\
\text{s. t.} \quad & F(w^t) - F^*(w^t) \leq \gamma_{\text{L}}, \\
& E_{\text{total}}(L, n, v_u) \leq \gamma_{\text{E}_u}, \\
& 0 \leq v_u \leq v_{\max},
\end{aligned}
$$

Goal

Optimization Objective:
Find the UAV velocity v_u and data collection path R_u^t that minimizes the total time delay T_{total}.

Constraints

- ☐ **Constraint 1:** gap between global loss and the optimal loss without considering delay is limited.
- ☐ **Constraint 2:** the energy consumption of UAV u does not exceed its specified limits.
- ☐ **Constraint 3:** the UAV's speed remains within operational bounds.

Conergence Analysis

Assumption 1

For each UAV $u \in U$, the loss function $F_u^t(w)$ is K_u-Lipschitz gradient, i.e., $||\nabla F_t^u(w_1) - \nabla F_t^u(w_2)||_2 \leq K_u||w_1 - w_2||_2$, which implies that the global loss function $F(w)$ is K-Lipschitz gradient with $K = \frac{1}{|U|}\sum_{\{u \in U\}} K_u$.

Theorem 1 (Global Loss Reduction). Given Assumption 1, when a UAV collects data along path R_u^t for training local models, the reduction of the aggregated global loss $F(w^t)$ is bounded as follows:

$$\begin{aligned} & F\left(w^t\right) - F\left(w^{t-1}\right) \\ & \leq \sum_{p \in \mathcal{P}_u^t} \sum_{i=0}^{m-1} \sum_{(x,y) \in D_p} \left(\alpha_p \left\|\nabla f\left(w_u^{t,i}, x, y\right)\right\|^2 \right. \\ & \left. \quad -\beta_p \left\langle \nabla F\left(w^{t-1}\right), \nabla f\left(w_u^{t,i}, x, y\right)\right\rangle\right), \end{aligned}$$

where $\alpha_p = \frac{k}{2U^2}\left(\frac{\eta}{|D_p|}\right)^2$ and $\beta_p = \frac{1}{U}\left(\frac{\eta}{|D_p|}\right)$.

Step 1: Convert Problem

Theorem 2. Given Assumption 1, we can derive an upper bound for the discrepancy between the flight path R_t^u utilized by UAV u in the t−th major round and the optimal path R_1^*, under the constraints of UAV speed and energy consumption. The bound is formulated as:

$$\mathrm{F}(\mathrm{w}^{\mathrm{t}}) - \mathrm{F}^*(\mathrm{w}^{\mathrm{t}}) \leq \Sigma_{p\in P_1^*}\Sigma_{i=0}^{m-1}V_p - \Sigma_{p\in P_u^t}\Sigma_{i=0}^{m-1}V_p$$

where $V_p = \frac{\eta}{U} <$

$$\sum_{x,y\in D_p}\frac{1}{|D_p|}\nabla f(w^{t-1},x,y),\nabla F\left((w^t)^*\right) > +\frac{K\eta^2}{2U^2}||\sum_{(x,y)\in D_p}\frac{1}{|D_p|}\nabla f(w^{t-1},x,y)||^2.$$

NOTE: controlling $\Sigma_{p\in P_1^*}\Sigma_{i=0}^{m-1}V_p - \Sigma_{p\in P_u^t}\Sigma_{i=0}^{m-1}V_p$ can control the the satisfaction of the constraint

Step 1: Convert Problem

➢ Converted Optimization problem:

$$
\textbf{P2:} \quad \min_{\mathcal{R}_u^t, v_u} \quad T_{\text{total}}(L, n, v_u),
$$

$$
\text{s. t.} \quad \sum_{p \in \mathcal{P}_1^*} \sum_{i=0}^{m-1} \boldsymbol{V}_p - \sum_{p \in \mathcal{P}_u^t} \sum_{i=0}^{m-1} \boldsymbol{V}_p \leq \gamma_{\text{L}},
$$

$$
E_{\text{total}}(L, n, v_u) \leq \gamma_{\text{E}_u}, \quad \forall u \in \mathcal{U},
$$

$$
0 \leq v_u \leq v_{\max}.
$$

Goal

Optimization Objective:
Find the UAV velocity v_u and data collection path R_u^t that minimizes the total time delay T_{total}.

Constraints

- ☐ **Constraint 1:** gap between the sum of the current path's V_p and the optimal path's V_p is limited.
- ☐ **Constraint 2:** the energy consumption of UAV u does not exceed its specified limits.
- ☐ **Constraint 3:** the UAV's speed remains within operational bounds.

Step 2: Decoupling and Modeling

- **Decouple** UAV Velocity and Path Planning

- **Divide** the path planning problem into two steps:
  - PoI Selection
  - Route Planning

- **Model** PoI Selection as a **Combinatorial Multi-Armed Bandit** (CMAB) Problem

CAMB	Our problem
Arm	Each available PoI
Reward	The reduction of the global model loss function

Step 3: Two-stage CMAB

We introduce N_p^t and $\overline{\nabla \mathbf{f}_\mathbf{p}^\mathbf{t}}$ to record:

•N_p^t : the number of times that PoI p has been selected up to round t.

•$\overline{\nabla \mathbf{f}_\mathbf{p}^\mathbf{t}}$: the average gradient of PoI p

$$N_p^t = \begin{cases} N_p^{t-1} + 1; & p \in \mathcal{P}_u^t, \\ N_p^{t-1}; & p \notin \mathcal{P}_u^t, \end{cases}$$

$$\nabla\bar{f}_p^t = \begin{cases} \frac{\nabla\bar{f}_p^{t-1} N_p^{t-1} + \nabla f_p^t}{N_p^{t-1}+1}; & p \in \mathcal{P}_u^t, \\ \nabla\bar{f}_p^t; & p \notin \mathcal{P}_u^t. \end{cases}$$

$$\widehat{q}_i^t(p) = \bar{q}_i^t(p) + Q_{t,p}; \quad Q_{t,p} = \sqrt{\frac{2\ln\left(\sum_{p' \in \mathcal{P}} N_{p'}^t\right)}{N_p^t}}.$$

$$p^* = \underset{p \in \mathcal{P} \setminus \mathcal{P}_u^t}{\operatorname{argmax}} \frac{\widehat{q}_i^t(p)}{c_i(l_p)}.$$

- Stage 1:
  - Quality Function

$$q_1^t(p) = \sum_{i=0}^{m-1} \sum_{x,y \in D_p} \left(\alpha_p \left\|\nabla\bar{f}_p^t\right\|^2 - \beta_p \left\langle \nabla F\left(w^{t-1}\right), \nabla\bar{f}_p^t \right\rangle\right).$$

  - Cost Function

$$C_1 = \mathrm{E}_{total}$$

  - Cost Bound

$$\mathrm{B}_1 = \gamma_{E_u}$$

Basic idea: Select the PoI that can maximally boost the UCB-based quality function per unit cost under budget constraint B.

Step 3: Two-stage CMAB

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$$p^* = \underset{p \in \mathcal{P} \setminus \mathcal{P}_u^t}{\operatorname{argmax}} \frac{\widehat{q}_i^t(p)}{c_i(l_p)}.$$

- ➢ Stage 2:
  - ➢ Quality Value

$$q_2^t(p) = \sum_{i=0}^{m-1} \boldsymbol{V}_p.$$

  - ➢ Cost Function

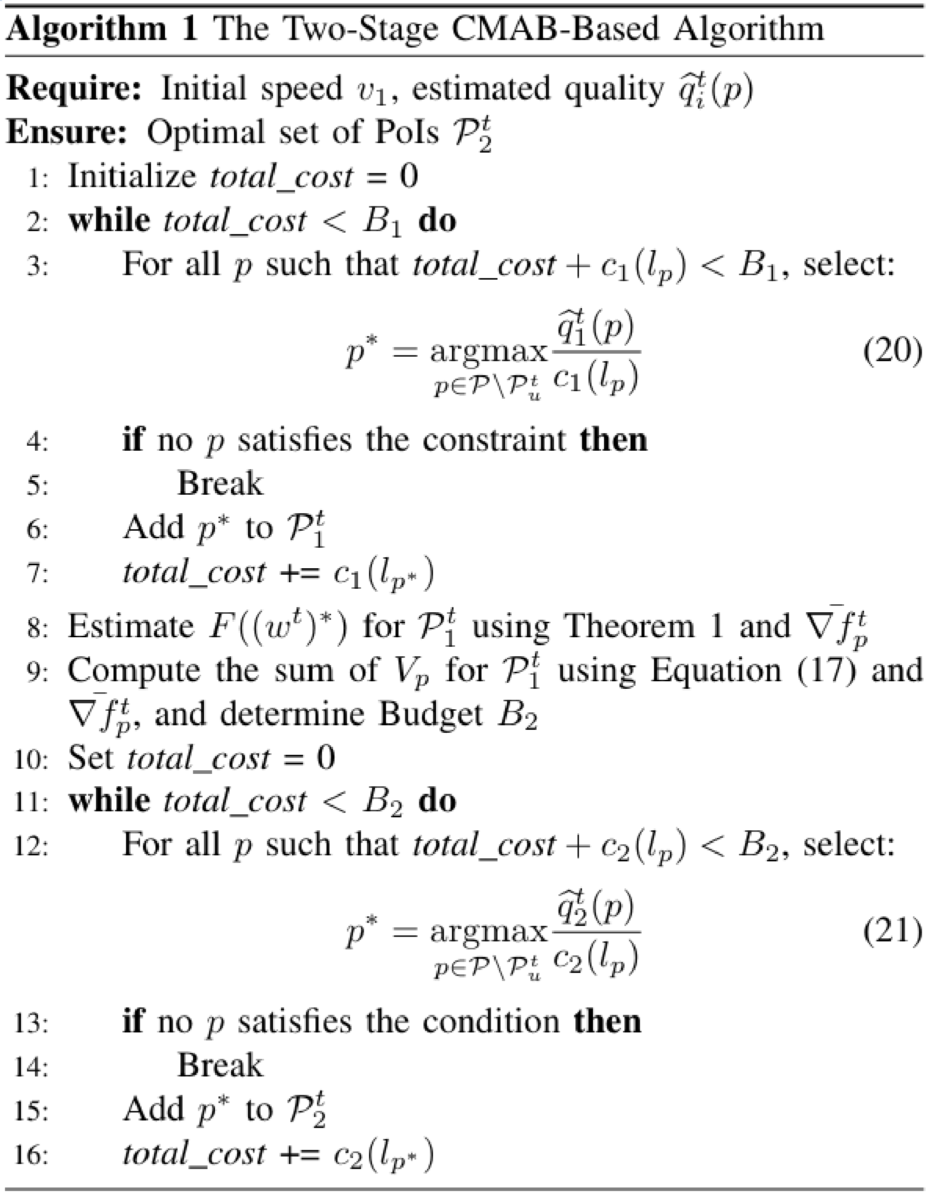
$$c_2(l_p) = \frac{1}{\lambda_1} T_{\text{total}}(l_p, 1, v_1) + \frac{\lambda_2}{\lambda_1} E_{\text{total}}(l_p, 1, v_1),$$

  - ➢ Cost Bound

$$B_2 = \gamma_L - \sum_{p \in \boldsymbol{\mathcal{P}}_1^*} \sum_{i=0}^{m-1} \boldsymbol{V}_p + \frac{\lambda_2}{\lambda_1} \gamma_{E_u}.$$

Basic idea: Select the PoI that can maximally boost the UCB-based quality function per unit cost under budget constraint B.

Algorithm Analysis



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Algorithm 1 The Two-Stage CMAB-Based Algorithm
Require: Initial speed $v_1$, estimated quality $\widehat{q}_i^t(p)$
Ensure: Optimal set of PoIs $\mathcal{P}_2^t$
Initialize $total\_cost = 0$
while $total\_cost < B_1$ do
    For all $p$ such that $total\_cost + c_1(l_p) < B_1$, select:
        $$p^* = \mathop{\mathrm{argmax}}_{p \in \mathcal{P} \setminus \mathcal{P}_u^t} \frac{\widehat{q}_1^t(p)}{c_1(l_p)} \qquad (20)$$
    if no $p$ satisfies the constraint then
        Break
    Add $p^*$ to $\mathcal{P}_1^t$
    $total\_cost$ += $c_1(l_{p^*})$
Estimate $F((w^t)^*)$ for $\mathcal{P}_1^t$ using Theorem 1 and $\nabla \bar{f}_p^t$
Compute the sum of $V_p$ for $\mathcal{P}_1^t$ using Equation (17) and
$\nabla \bar{f}_p^t$, and determine Budget $B_2$
Set $total\_cost = 0$
while $total\_cost < B_2$ do
    For all $p$ such that $total\_cost + c_2(l_p) < B_2$, select:
        $$p^* = \mathop{\mathrm{argmax}}_{p \in \mathcal{P} \setminus \mathcal{P}_u^t} \frac{\widehat{q}_2^t(p)}{c_2(l_p)} \qquad (21)$$
    if no $p$ satisfies the condition then
        Break
    Add $p^*$ to $\mathcal{P}_2^t$
    $total\_cost$ += $c_2(l_{p^*})$
```

Theorem 3:

The worst α −approximate regret of Alg. 1, symbolized by $R_2(B_2)$, can be expressed as:

$$R_2(B_2) = O(P_f \ln(B_2 + P_f \ln B_1).$$

Computational Complexity:

$$O(P^2)$$

Step 4: The FedATC Algorithm

- Based on the selected PoIs, use the **2-Opt TSP heuristic** algorithm as an example to obtain the path.
- An **iterative** approach is used to handle speed and path separately:
  - Initialize UAV's speed as v_1.
  - Use the previously mentioned method to obtain the approximate optimal path.
  - Re-estimate the optimal speed using gradient descent or a decrement method until the energy consumption limit is met.
- The **computational complexity** of FedATC is $O(\frac{P^2 v_{max}(N_L+N_T)}{v_{step}})$.

Experimental Settings

Dataset and Model

- **Dataset**: MNIST, Fashion-MNIST(FMNIST), SVHN, CIFAR-10
- Model: LR (**convex**) and CNN (**non-convex)**

Parameter settings

- The number of UAVs is 4 or 8
- The energy bound ranges from $[10^5, 5 * 10^5]$
- The number of PoIs ranges from [10, 30]

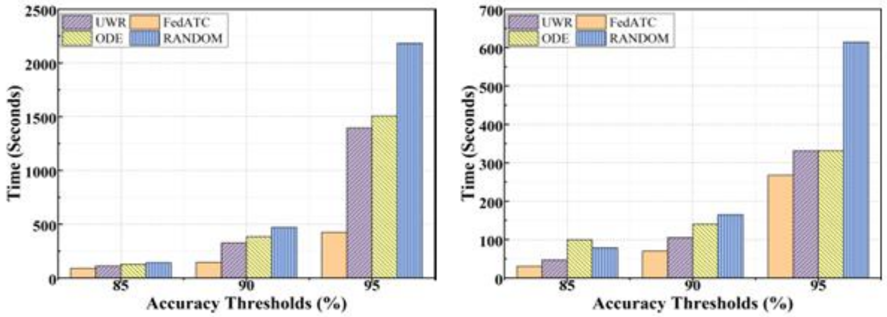
Compared Algorithms

- FedATC : our proposed algorithm
- Random
- ODE: based on data quality
- UWR: based on data quality and energy

Evaluation Metrics

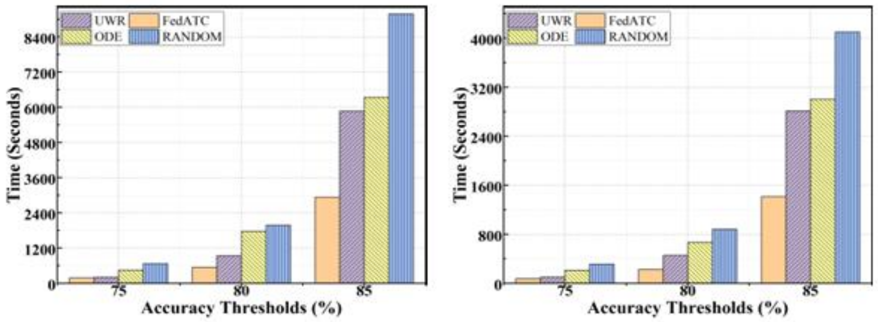
- **Accuracy**: the number of correct predictions
- **Time:** the cumulative time to achieve the required accuracy
- **Time Speedup:** based on Random algorithm

Performance of CNN on MNIST, FMNIST, SVHN and CIAFR10



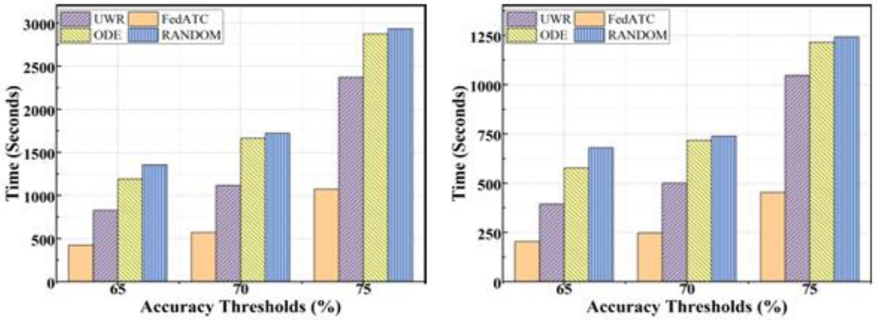
(a) 4 UAVs performance (b) 8 UAVs performance

Fig. 2: Performance across UAVs on MNIST



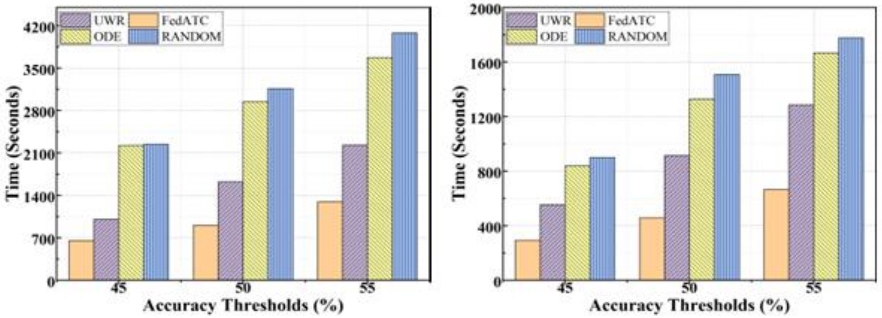
(a) 4 UAVs performance (b) 8 UAVs performance

Fig. 3: Performance across UAVs on FMNIST



(a) 4 UAVs performance (b) 8 UAVs performance

Fig. 4: Performance across UAVs on SVHN

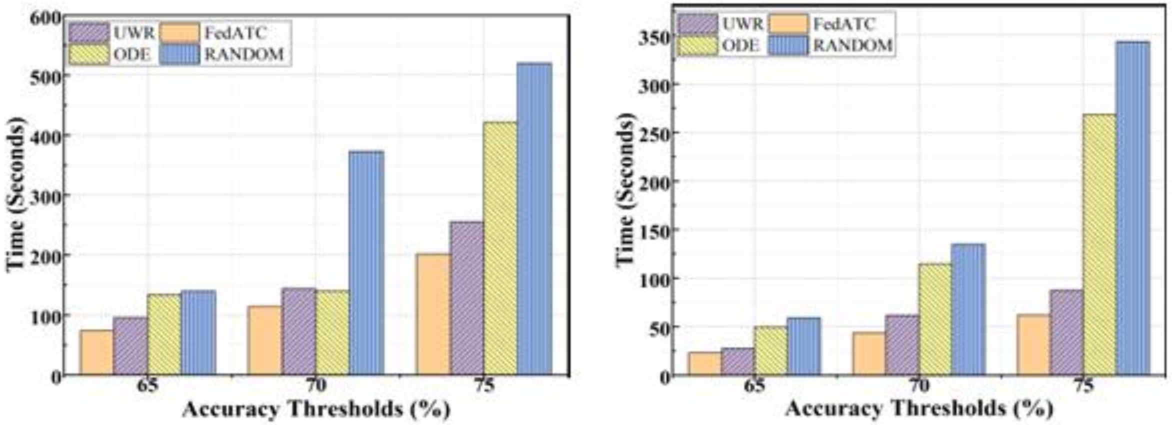


(a) 4 UAVs performance (b) 8 UAVs performance

Fig. 5: Performance across UAVs on CIFAR10

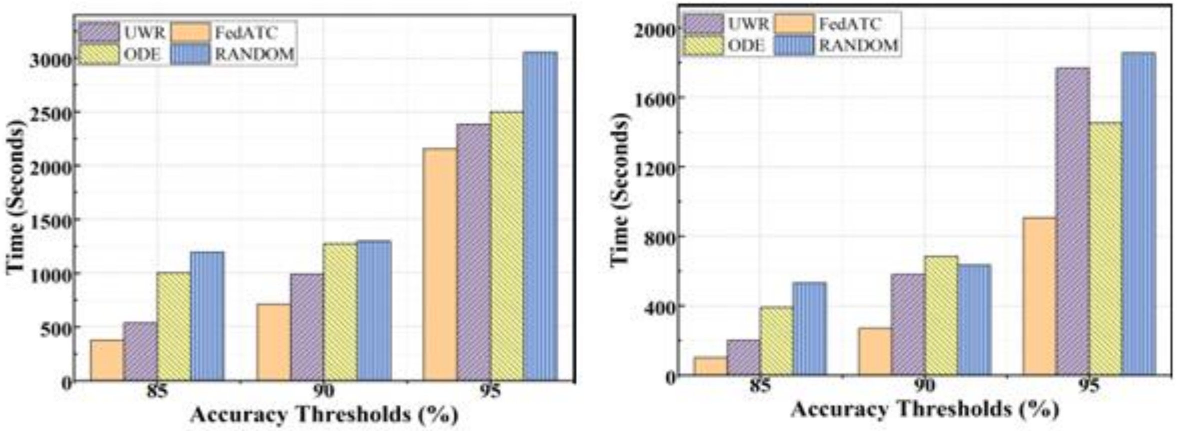
- The cumulative time taken by FedATC is significantly less than the other three algorithms
- This difference is more pronounced at higher accuracy thresholds
- Deploying more UAVs reduces cumulative time, but the performance gap between algorithms narrows due to a fewer number of available PoIs

Performance of LR on MNIST with non-IID data



(a) 4 UAVs performance (b) 8 UAVs performance

Fig. 6: Performance of LR on MNIST

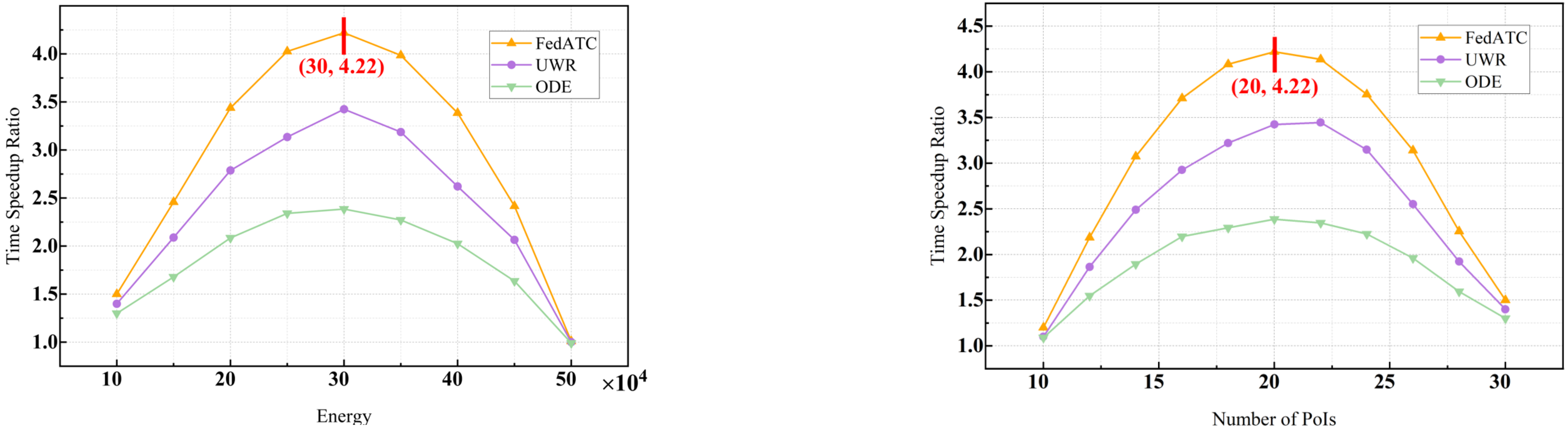


(a) 4 UAVs performance (b) 8 UAVs performance

Fig. 7: Performance on MNIST with non-IID Data

- Transitioning to a **LR** model, FedATC consistently outperforms other algorithms, with 8 UAVs significantly reducing cumulative time
- In **non-IID** data scenarios, FedATC shows better time efficiency, but performance gains are less pronounced due to data distribution effects

Time Speedup Ratio



NOTE:The speed-up ratio is defined as $\Delta = \frac{T_{random}}{T}$.

- The time speed-up ratio increases with **energy bound**, peaking at $30 * 10^4$ units, then begins to decline
- The time speed-up ratio rises with the **number of PoIs**, peaking at 20 or 22, after which it decreases due to increased convergence time

Conclusions

- Introduce a novel DDFL system in UAV networks that abstracts a **data layer** alongside conventional server and client layers.
- Model the **PoI selection** problem as a CMAB issue and propose a two-stage CMAB-based algorithm for approximate optimal selection.
- Propose the **FedATC** algorithm to jointly optimize data collection routes and UAV velocity and evaluate the algorithm performance via **simulations**.

Future work:

- Investigate improvements for PoI selection when data distribution is **non-IID**, as current performance is less than ideal.
- Explore data-driven problems in **decentralized** scenarios.

Q & A