Low-latency communications in MEC-enabled UAV systems: A deep reinforcement learning approach

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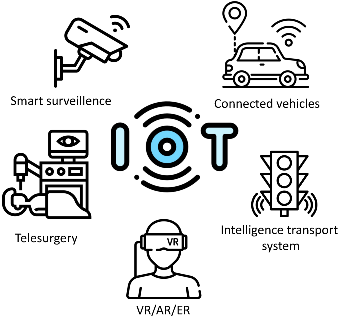
We are in the era of Internet of Things (IoT)[1]:

- Enormous IoT devices (IoTDs) with emerging applications
- Problem: We exploit Computation-intensive & Delay-sensitive applications on resource-limited (computational, on-board power) IoTDs



[1] Mehdi Mohammadi et al. "Deep Learning for IoT Big Data and Streaming Analytics: A Survey". In: *IEEE Communications Surveys & Tutorials* 20.4 (2018), pp. 2923–2960. DOI: 10.1109/COMST.2018.2844341.

Introduction - Emerging technologies support IoT systems

- Mobile Edge Computing (MEC)[2]
  - Extend cloud computing capabilities (computational, caching resources) to the edge network
  - Real-time, high-bandwidth, low-latency access
- Unmanned Arial Vehicle (UAV)[3]
  - High-mobility, flexible deployment
  - Low-latency line-of-sight (LoS) propagation link, context-awareness networks

→MEC-enabled UAV systems provide computional resources while reducing the transmission latency to IoTDs

[2] Pawani Porambage et al. "Survey on Multi-Access Edge Computing for Internet of Things Realization". In: *IEEE Communications Surveys & Tutorials* 20.4 (2018), pp. 2961–2991. DOI: 10.1109/COMST.2018.2849509.

[3] Lav Gupta, Raj Jain, and Gabor Vaszkun. "Survey of Important Issues in UAV Communication Networks". In: *IEEE Communications Surveys & Tutorials* 18.2 (2016), pp. 1123–1152. DOI: 10.1109/COMST.2015.2495297.

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Introduction - Current work on MEC-enabled UAV systems

[4,5,6] **Energy efficiency** in multiple timeslots (**time-evolving**) while considering **the stability of system queues** (not delay)

[7,8,9] **Latency** minimization **without queueing** consideration (not queuing delay, time-evolving in stochastic environments)

[4] Jiao Zhang et al. "Stochastic Computation Offloading and Trajectory Scheduling for UAV-Assisted Mobile Edge Computing". In: *IEEE Internet of Things Journal* 6.2 (2019), pp. 3688–3699. DOI: 10.1109/JIOT.2018.2890133.

[5] Zheyuan Yang, Suzhi Bi, and Ying-Jun Angela Zhang. "Dynamic Trajectory and Offloading Control of UAV-enabled MEC under User Mobility". In: *2021 IEEE International Conference on Communications Workshops (ICC Workshops)*. 2021, pp. 1–6. DOI: 10.1109/ICCWorkshops50388.2021.9473504.

[6] Linh T. Hoang et al. "Joint Uplink and Downlink Resource Allocation for UAV-enabled MEC Networks under User Mobility". In: *2022 IEEE International Conference on Communications Workshops (ICC Workshops)*. 2022, pp. 1059–1064. DOI: 10.1109/ICCWorkshops53468.2022.9814687.

[7] Zhe Yu et al. "Joint Task Offloading and Resource Allocation in UAV-Enabled Mobile Edge Computing". In: *IEEE Internet of Things Journal* 7.4 (2020), pp. 3147–3159. DOI: 10.1109/JIOT.2020.2965898.

[8] Ali A. Nasir. "Latency Optimization of UAV-Enabled MEC System for Virtual Reality Applications Under Rician Fading Channels". In: *IEEE Wireless Communications Letters* 10.8 (2021), pp. 1633–1637. DOI: 10.1109/LWC.2021.3075762.

[9] Ying Liu, Junjie Yan, and Xiaohui Zhao. "Deep Reinforcement Learning Based Latency Minimization for Mobile Edge Computing With Virtualization in Maritime UAV Communication Network". In: *IEEE Transactions on Vehicular Technology* 71.4 (2022), pp. 4225–4236. DOI: 10.1109/TVT.2022.3141799.

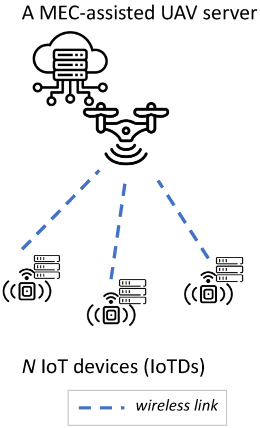
Introduction - Our proposal

Problem: Optimizing the **offloading decision** and **resource allocation** for

- The **energy efficiency** while considering the **low latency requirements** problem in MEC enabled UAV systems
- Holistic latency: **queuing delay** + transmission delay

Solution:

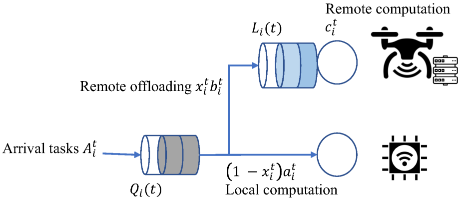
- **Deep Reinforcement Learning** (DRL)-based approach for sub-optimal solutions



Contents

System Model

System model



A MEC-enabled UAV server, N IoTDs, T sequential timeslots TSs:
$i = \{1, 2, \dots N\}, t = \{0, 1, \dots, T-1\}$

Params	Optimization vars
Arrival packets A_i^t	Offloading decision x_i^t
Local queue $Q_i(t)$	Local computation frequency f_i^t
Remote buffer at UAV for i $L_i(t)$	Offloading tasks b_i^t
Local computation tasks a_i^t	Remote CPU frequency for i $f_{u,i}^t$

Problem Formulation

Problem formulation

	IoTD	UAV	Offloading
Power	$p_{i,L}^{t} = \kappa (f_i^t)^3$	$p_{u,i}^{t} = \kappa (f_{u,i}^t)^3$	$p_{i,O}^{t}$
	$P_s^t = {}^1\!/_T \sum_t \left(\psi_1 \sum_{i \in \mathcal{M}_0^t} p_{i,L}^t + \psi_1 \sum_{i \in \mathcal{M}_1^t} p_{i,O}^t + \psi_2 \sum_{i=1}^{N} p_{u,i}^t \right)$		
Latency	${}^1\!/_T \sum_t {}^{(Q_i(t)+L_i(t))}\!/_{\overline{A_i}}$ [10]		fixed Δ_T
	$D_s^t = {}^1\!/_T \cdot \sum_t \left(Q_i(t) + L_i(t) + x_i^t \Delta \right), \Delta = \overline{A_i} \Delta_T$		

- ψ_1, ψ_2 : adjustable, balanced weight factors
- $\mathcal{M}_0^t, \mathcal{M}_1^t$: local or offloading-IoTDs set

[10] John DC Little and Stephen C Graves. "Little's law". In: *Building intuition*. Springer, 2008, pp. 81–100.

System power minimization s.t the latency constraint problem

$$
\begin{aligned}
\min_{\mathbf{X}} \quad & P_s^t = {}^1/_T \sum_t \left(\psi_1 \textstyle\sum_{i \in \mathcal{M}_0^t} p_{i,L}^t + \psi_1 \sum_{i \in \mathcal{M}_1^t} p_{i,O}^t + \psi_2 \sum_{i=1}^N p_{u,i}^t \right) \\
\text{s.t.} \quad & D_s^t = {}^1/_T \cdot \textstyle\sum_t \left(Q_i(t) + L_i(t) + x_i^t \Delta \right) \leq Y^{\text{th}}, \forall i, t, \\
& x_i^t \in \{0, 1\}, \quad \forall i, t, \\
& 0 \leq f_i^t \leq f_i^{max},\ a_i^t \leq Q_i(t), \forall x_i^t = 0, t, \\
& 0 \leq p_{i,O}^t \leq p_i^{max}, \quad b_i^t \leq Q_i(t), \forall x_i^t = 1, t, \\
& 0 \leq \textstyle\sum_{i=1}^N f_{u,i}^t \leq f_u^{max},\ c_i^t \leq L_i(t), \forall i, t \\
& \text{with } \mathbf{X} \triangleq \{\mathbf{x}^t, \mathbf{b}^t, \mathbf{f}_i^t, \mathbf{f}_u^t\}
\end{aligned}
\tag{1}
$$

→Exponential complexity

- Long-term avarage, evolving multiple timeslots
- Mixed-integer non-linear-programming (MINLP)

System power minimization s.t the latency constraint problem

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\min_{\mathbf{X}} \quad & P_s^t = 1/T \sum_t \left(\psi_1 \textstyle\sum_{i \in \mathcal{M}_0^t} p_{i,L}^t + \psi_1 \sum_{i \in \mathcal{M}_1^t} p_{i,O}^t + \psi_2 \sum_{i=1}^N p_{u,i}^t \right) \\
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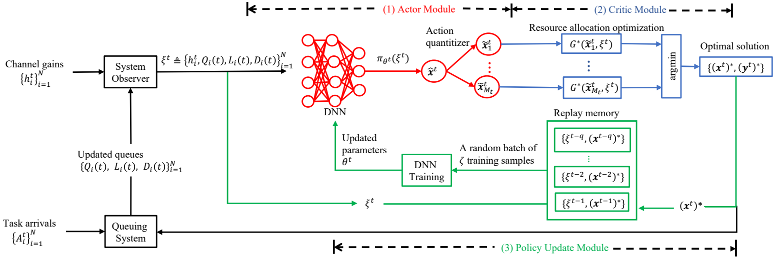
Lyapunov-guided DRL-based Online Optimization

Lyapunov-guided DRL-based online optimization

- Lyapunov framework: decouple the problem into per-slot deterministic problems[11]
- DRL optimization: deal with MINLP
  - Iterative: a deep neural network (DNN) to predict offloading decisions, then convex optimization to allocate resources
  - Actor-critic loop: obtain the best state-action pairs, gradually improve the model accuracy



[11] Michael J Neely. "Stochastic network optimization with application to communication and queueing systems". In: *Synthesis Lectures on Communication Networks* 3.1 (2010), pp. 1–211.

Numerical Results

Simulation Settings

Parameter settings:

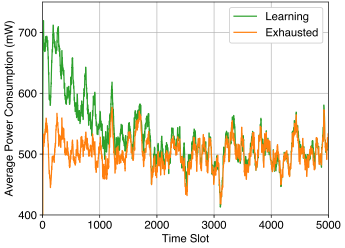
- $H_{\text{UAV}} = 150$m with horizontal distance between UAV and IoTDs $r = [10, 100]$m
- Model the air-to-gound propagation channel with LoS probability as in[12]

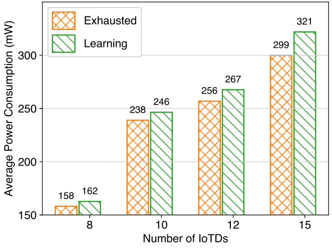
Comparative methods:

- Lyapunov-guided DRL online optimization: *Learning*
- Exhausted approach, which searches through all possible oploading decisions: *Exhausted*

[12] Akram Al-Hourani, Sithamparanathan Kandeepan, and Simon Lardner. "Optimal LAP Altitude for Maximum Coverage". In: *IEEE Wireless Communications Letters* 3.6 (2014), pp. 569–572. DOI: 10.1109/LWC.2014.2342736.

Simulation Results





- Suboptimal solution: *Learning* gradually approachs *Exhausted*'s performance
- Short execution time: Execution time with number of IoTDs:
  - *Learning*: $\{0.017, 0.018, 0.019, 0.019\}$
  - *Exhausted*: $\{0.037, 0.067, 0.436, 3.53\}$
- Scalability characteristic for high-density networks
  - Execution time: $\{0.017, 0.018, 0.019, 0.019\}$ with $N = \{5, 10, 12, 15\}$

Conclusions

Conclusions

- Considered the latency constraint requirement with power efficiency in MEC-enabled UAV systems
- Proposed the Lyapunov-guided DRL online optimization, which provides the suboptimal solution in short execution time

Thank you.

Any Questions are welcomed.