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Paris, May 2, 2019

Mobile Edge Computing

Enabler of 5G that provides

- computing resources close to the end users
- support for autonomous IoT devices
- bandwidth and computing resource orchestration on demand



Enabler of 5G that provides

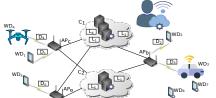
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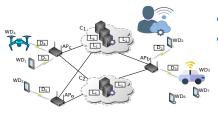
 How do device autonomy and infrastructure resource management interact?

Mobile Edge Computing System

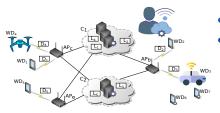
Problem Definition •0000



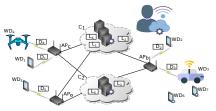
Wireless devices (WDs) \mathcal{N}



- Wireless devices (WDs) \mathcal{N}
- Operator manages
 - Edge clouds (ECs) C
 - APs A



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 - APs \mathcal{A}
 - WD i can connect to APs $A_i \subseteq A$

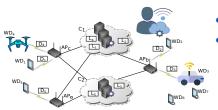


- Wireless devices (WDs) \mathcal{N}
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Computation offloading

- Task of WD $i, < D_i, L_i >$
 - size of the input data D_i
 - computational complexity L_i

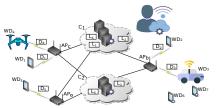
Mobile Edge Computing System



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Computation offloading

- Task of WD $i, < D_i, L_i >$
 - size of the input data D_i
 - computational complexity L_i
- Decision d_i of WD $i \in \mathcal{N}$
- Set of decisions for all WDs is a strategy profile **d**

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- $R_{i,a}$: PHY rate of WD i on AP a
- $u_{i,a}$: uplink access provisioning coefficient

Communication Model

Problem Definition 00000



- $R_{i,a}$: PHY rate of WD i on AP a
- $u_{i,a}$: uplink access provisioning coefficient

Transmission time

 $O_a(\mathbf{d})$: set of offloaders via AP a in strategy profile **d**

• Uplink rate of WD i via AP a

$$\omega_{i,a}(\mathbf{d}, \mathbf{u}_a) = R_{i,a} \frac{u_{i,a}}{\sum_{j \in O_a(\mathbf{d})} u_{j,a}}$$

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Communication Model

Problem Definition 00000



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e.g., $u_{i,a} = 1 \implies$ time-fair policy

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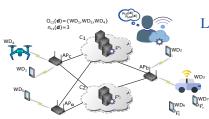
$$\omega_{i,a}(\mathbf{d}, \mathbf{u}_a) = R_{i,a} \frac{u_{i,a}}{\sum_{j \in O_a(\mathbf{d})} u_{j,a}}$$

• Transmission time of WD i for offloading via AP a

$$T_{i,a}^{off}(\mathbf{d}, \mathbf{u}_a) = \frac{D_i}{\omega_{i,a}(\mathbf{d}, \mathbf{u}_a)}$$

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Computation Model

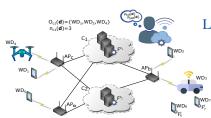


Local computing

- F_i^l computing capability of WD i
- Local execution time of WD *i*'s task

$$T_{i,l}^{exe} = \frac{L_i}{F_i^l}$$

Computation Model



Local computing

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- Local execution time of WD i's task

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Computation offloading

- F^c : computing capability of EC c
- p_{i,c}: computing power provisioning coefficient

$O_c(\mathbf{d})$: set offloaders to EC c in strategy profile \mathbf{d}

 Computing capability allocated to WD i by EC c

$$F_i^c(\mathbf{d}, \mathbf{p}_c) = F^c \frac{p_{i,c}}{\sum_{j \in O_c(\mathbf{d})} p_{j,c}}$$

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Computation Model



Local computing

- F_i^l computing capability of WD i
- Local execution time of WD i's task

$$T_{i,l}^{exe} = \frac{L_i}{F_i^l}$$

Computation offloading

- F^c : computing capability of EC c
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Computing capability allocated to WD

 i by EC c

$$F_i^c(\mathbf{d}, \mathbf{p}_c) = F^c \frac{p_{i,c}}{\sum_{j \in O_c(\mathbf{d})} p_{j,c}}$$

• Execution time of WD i's task in EC c

$$T_{i,c}^{exe}(\mathbf{d},\mathbf{p}_c) = \frac{L_i}{F_i^c(\mathbf{d},\mathbf{p}_c)}$$

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Cost - Task Completion Time

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Computation offloading cost

$$C_{i,a}^{c}(\mathbf{d}, \mathbf{u}_{a}, \mathbf{p}_{c}) = T_{i,a}^{off}(\mathbf{d}, \mathbf{u}_{a}) + T_{i,c}^{exe}(\mathbf{d}, \mathbf{p}_{c})$$

Local computing cost

$$C_i^l = T_{i,l}^{exe}$$

Cost - Task Completion Time

Computation offloading cost

$$C_{i,a}^{c}(\mathbf{d}, \mathbf{u}_{a}, \mathbf{p}_{c}) = T_{i,a}^{off}(\mathbf{d}, \mathbf{u}_{a}) + T_{i,c}^{exe}(\mathbf{d}, \mathbf{p}_{c})$$

Local computing cost

$$C_i^l = T_{i,l}^{exe}$$

System cost

$$C(\mathbf{d}, \mathbf{u}, \mathbf{p}) = \underbrace{\sum_{i \in \mathcal{N}} \sum_{(a,c) \in \mathcal{A}_i \times \mathcal{C}} I_{d_i,(a,c)} C^c_{i,a}(\mathbf{d}, \mathbf{u}_a, \mathbf{p}_c)}_{|\mathbf{d}_i = \mathbf{d}_i = \mathbf{d}_i + \mathbf{d}_i + \mathbf{d}_i + \mathbf{d}_i = \mathbf{d}_i + \mathbf{d}_i + \mathbf{d}_i + \mathbf{d}_i = \mathbf{d}_i + \mathbf{d}_i + \mathbf{d}_i + \mathbf{d}_i + \mathbf{d}_i + \mathbf{d}_i = \mathbf{d}_i + \mathbf{d}_i$$

offloading

local execution

$$I_{d_i,r} = \begin{cases} 1, & \text{if } d_i = r \\ 0, & \text{otherwise} \end{cases}$$

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 Multi-leader common-follower Stackelberg game



Multi-leader common-follower Stackelberg game

Objective of the operator

Minimization of total cost $\min_{\mathbf{u},\mathbf{p}\succeq 0} C(\mathbf{d},\mathbf{u},\mathbf{p})$

Objective of WDs

Minimization of own cost $\min_{d_i \in \mathfrak{D}_i} C_i(d_i, d_{-i}, \mathbf{u}_a^*, \mathbf{p}_c^*)$

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 Multi-leader common-follower Stackelberg game

Objective of the operator

• Minimization of total cost $\min_{\mathbf{u}, \mathbf{p} \succ 0} C(\mathbf{d}, \mathbf{u}, \mathbf{p})$

Objective of WDs

• Minimization of own cost $\min_{d_i \in \mathfrak{D}_i} C_i(d_i, d_{-i}, \mathbf{u}_a^*, \mathbf{p}_c^*)$

Strategic game played by WDs

• For any allocation policy of the operator, game $\Gamma = <\mathcal{N}, (\mathfrak{D}_i)_i, (C_i)_i >$ played by WDs is a player-specific weighted congestion game

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Questions Addressed

- 1 Does the MEC-OG have a subgame perfect equilibrium (SPE)?
 - How should an operator allocate resources to selfish WDs?
 - Is there an offloading strategy profile in which all WDs are satisfied?

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- 1 Does the MEC-OG have a subgame perfect equilibrium (SPE)?
 - How should an operator allocate resources to selfish WDs?
 - Is there an offloading strategy profile in which all WDs are satisfied?
- 2 Can it be computed using a decentralized algorithm?
- 3 How good is the system performance?

Optimal resource allocation policy of the operator

• Best response of the operator to strategy profile **d** chosen by WDs

$$\begin{aligned} u_{i,a}^*(\mathbf{d}) &= \frac{\sqrt{D_i/R_{i,a}}}{\sum_{j \in O_a(\mathbf{d})} \sqrt{D_j/R_{j,a}}}, \forall i \in O_a(\mathbf{d}), \forall a \in \mathcal{A} \\ p_{i,c}^*(\mathbf{d}) &= \frac{\sqrt{L_i/F^c}}{\sum_{j \in O_c(\mathbf{d})} \sqrt{L_j/F^c}}, \forall i \in O_c(\mathbf{d}), \forall c \in \mathcal{C} \end{aligned}$$

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Game Γ under the optimal operator policy

• We transform Γ into a congestion game Γ^* with resource dependent weights

Offloading cost:
$$C_{i,a}^c(\mathbf{d}) = \omega_{i,a} \sum_{j \in O_a(\mathbf{d})} \omega_{j,a} + \omega_{i,c} \sum_{j \in O_c(\mathbf{d})} \omega_{j,c}$$

Weights: $\omega_{i,a} = \sqrt{\frac{D_i}{R_{i,a}}}, \omega_{i,c} = \sqrt{\frac{L_i}{F^c}}$

Results

Optimal resource allocation policy of the operator

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• Does strategic game Γ^* have a Nash equilibrium (NE)?

NE existence

- Game Γ^* has a NE \mathbf{d}^*
 - Proof based on exact potential function

NE existence

- Game Γ* has a NE **d***
 - Proof based on exact potential function

Improve Local Computing (ILC) algorithm

- Starts from a strategy profile in which all WDs perform computation locally
- Allows WDs to start to offload in non-increasing order of their task complexities

NIE

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SPE existence

- The MEC-OG has a SPE (**d***, **u***, **p***)
 - Optimal provisioning coefficients \mathbf{u}^* and \mathbf{p}^* have closed form expressions
 - ILC algorithm computes an equilibrium \mathbf{d}^* of offloading decisions

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Results

NE existence

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Price of Anarchy (PoA) bound

• Upper bound on the PoA for the MEC-OG is $\frac{3+\sqrt{5}}{2}$

Evaluation scenario

- A = 5 APs, heterogeneous ECs $F^{c,tot} = 192$ Gcycles
- Tasks: $D_i \sim \mathcal{U}(0.2,4)~\textit{Mb}$, $L_i = D_i X~\textit{Gcycles}$, $X \sim \Gamma(0.5,1.6)~\textit{Gcycles/b}$

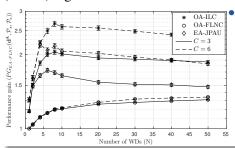
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Performance gain

Defined w.r.t. equal alocation (EA) policy and the fastest-link nearest-cloud (FLNC) algorithm



Performance gain increases with decreasing marginal gain in N

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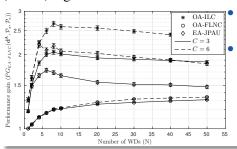
User Focused Performance Analysis

Evaluation scenario

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Performance gain

Defined w.r.t. equal alocation (EA) policy and the fastest-link nearest-cloud (FLNC) algorithm



- Performance gain increases with decreasing marginal gain in N
- Performance gain increases with the number of edge ECs

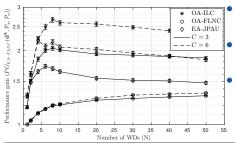
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Performance gain

Defined w.r.t. equal alocation (EA) policy and the fastest-link nearest-cloud (FLNC) algorithm



- Performance gain increases with decreasing marginal gain in N
- Performance gain increases with the number of edge ECs
- Largest performance gain
 - Operator implements OA policy
 - WDs compute offloading decisions using the ILC algorithm

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Evaluation scenario

- A = 5 APs, C = 3 heterogeneous ECs $F^{c,tot} = 192$ Gcycles
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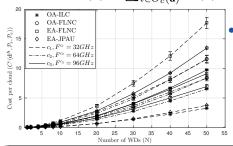
Cloud Focused Performance Analysis

Evaluation scenario

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Cost per cloud

Defined as $C^c(\mathbf{d}) = \sum_{i \in O_c(\mathbf{d})} C_i(\mathbf{d})$



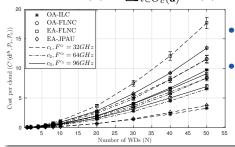
Cost per cloud increases with the number N of WDs

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Cost per cloud

Defined as $C^c(\mathbf{d}) = \sum_{i \in O_c(\mathbf{d})} C_i(\mathbf{d})$



- Cost per cloud increases with the number N of WDs
- Cost per cloud is proportional to the EC's computing capability in case of equilibria under OA and EA policies

Evaluation scenario

- A = 5 APs, homogeneous ECs $F^{c,tot} = 192$ Gcycles
- Tasks: $D_i \sim \mathcal{U}(0.2, 4) \; Mb$, $L_i = D_i X \; Gcycles$, $X \sim \Gamma(0.5, 1.6) \; Gcycles/b$

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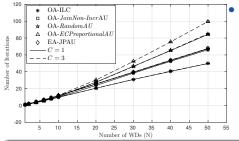
Computational Complexity

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Number of iterations

- Randomly chosen strategy profile
- All WDs offload-congestion per EC proportional to its computing capability
- Empty system-WDs added in non-increasing order of their task complexities



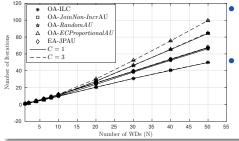
 Number of iterations scales approximately linearly with the number N of WDs

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- Randomly chosen strategy profile
- All WDs offload-congestion per EC proportional to its computing capability
- Empty system-WDs added in non-increasing order of their task complexities



- Number of iterations scales approximately linearly with the number N of WDs
 - Number of iterations is sensitive to the starting strategy profile
 - Smallest in the case of the ILC algorithm

Summary and Future Work

- Provided game theoretical analysis of the interaction between
 - an edge operator that jointly manages wireless and computing resources
 - autonomous WDs that aim at minimizing their own tasks completion times

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Summary and Future Work

- Provided game theoretical analysis of the interaction between
 - an edge operator that jointly manages wireless and computing resources
 - autonomous WDs that aim at minimizing their own tasks completion times
- Interesting extensions
 - energy consumption minimization problem
 - stochastic model of task arrivals
 - learning in congestion games

Wireless and Computing Resource Allocation for Selfish Computation Offloading in Edge Computing

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Paris, May 2, 2019

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