

QOCO: A QoE-Oriented Computation Offloading Algorithm based on Deep Reinforcement Learning for Mobile Edge Computing

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Overview

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System Model

- Communication Model

- Computation Model

Problem Formulation

- Markov Decision Process

- QoE Optimization Problem

DRL-Based QOCO Algorithm

Performance Evaluation

- Simulation Settings

- Performance Comparison

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Edge Computing as a Solution

Edge Computing

- Computation at the edge of the network.

Computation Offloading

- Enhances the capacity of mobile devices.

Benefits

- Reduced task performance delay.
- Extended mobile device (MD) battery life.
- Enhanced Quality of Experience (QoE).

Challenges

- Dynamic network conditions.
- Heterogeneous device capabilities.

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Contribution

Research Focus: Computation Task Offloading Problem in MEC

- Task Processing Deadlines
- Energy Constraints

Key Contributions:

- Formulated the computation task offloading problem as a finite and discrete Markov Decision Process (MDP) to maximize the expected long term QoE for each MDs.
- Proposed a QoE-oriented computation offloading (QOCO) algorithm based on Deep Reinforcement Learning (DRL) to empower each MD to make offloading decisions independently.
- Conducting comprehensive experiments to evaluate the performance of QOCO compared with several benchmark methods.

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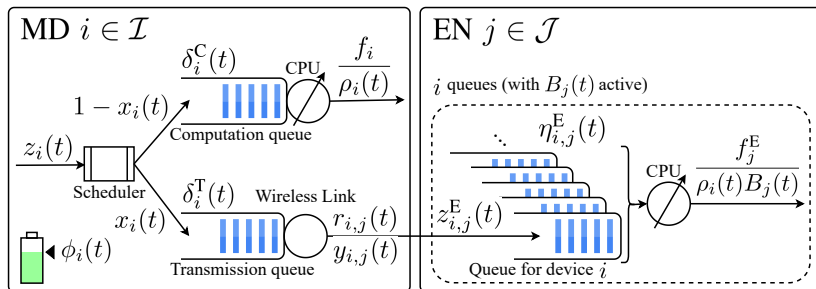
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System Model

We consider

- the set of MD $\mathcal{I} = \{1, 2, \dots, I\}$
- the set of EN $\mathcal{J} = \{1, 2, \dots, J\}$
- set of time slots $\mathcal{T} = \{1, 2, \dots, T\}$
- each MD $i \in \mathcal{I}$ are connected to each EN $j \in \mathcal{J}$ with it's wireless interface.
- each time slot consider as a diuration of time.

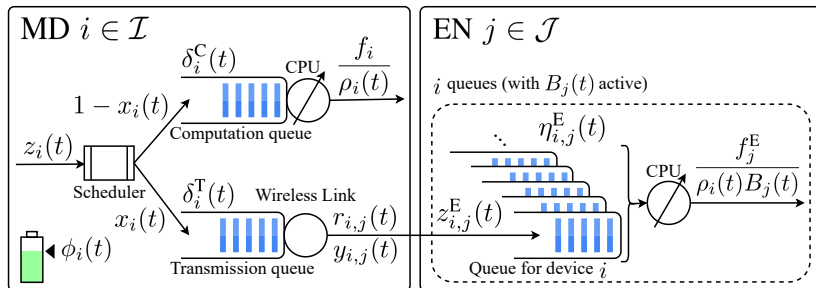
System Model



Task

- $z_i(t)$: arrived task in MD
- $\lambda_i(t)$: Required CPU cycles of task
- $\rho_i(t)$: Required CPU cycles of task
- $\Delta_i(t)$: Required CPU cycles of task

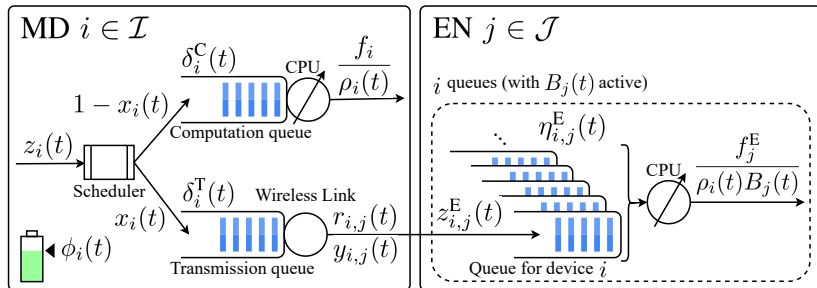
System Model



Offloading

- $x_i(t)$: Offloading Decision
- $y_{i,j}(t)$: Offloading Target

System Model



Queues' Information

- $\delta_i^C(t)$ Computation Queue in MD
- $\delta_i^T(t)$ Transsmition Queue in MD
- $\eta_{i,j}^E(t)$ MD Computation Queue in EN

Communication Model

- $\delta_i^T(t)$: MD i Transmission Queue Waiting Time

$$\delta_i^T(t) = \left[\max_{t' \in \{0,1,\dots,t-1\}} l_i^T(t') - t + 1 \right]^+ \quad (1)$$

- $l_i^T(t)$: Task Transmitted/Dropped Time Slot

$$l_i^T(t) = \min \left\{ t + \delta_i^T(t) + \lceil D_i^T(t) \rceil - 1, t + \Delta_i(t) - 1 \right\} \quad (2)$$

- $D_i^T(t)$: Task Transmission Time

$$D_i^T(t) = \sum_{\mathcal{J}} y_{i,j}(t) \frac{\lambda_i(t)}{r_{i,j}(t)\tau} \quad (3)$$

- $E_i^T(t)$: Task Transmission Energy Consumption

$$E_i^T(t) = D_i^T(t) p_i^T(t) \tau \quad (4)$$

Computation Model

Local Execution:

- $\delta_i^C(t)$: MD i Computation Queue Waiting Time

$$\delta_i^C(t) = \left[\max_{t' \in \{0,1,\dots,t-1\}} l_i^C(t') - t + 1 \right]^+ \quad (5)$$

- $l_i^C(t)$: Task Executed/Dropped Time Slot

$$l_i^C(t) = \min \left\{ t + \delta_i^C(t) + \lceil D_i^C(t) \rceil - 1, t + \Delta_i(t) - 1 \right\} \quad (6)$$

- $D_i^C(t)$: Task Execution Time

$$D_i^C(t) = \frac{\lambda_i(t)}{f_i \tau / \rho_i(t)} \quad (7)$$

- $E_i^L(t)$: Task Execution Energy Consumption

$$E_i^L(t) = D_i^C(t) p_i^C \tau \quad (8)$$

Computation Model

Edge Execution:

- $\eta_{i,j}^E(t)$: MD i Queue Backlog at EN j

$$\eta_{i,j}^E(t) = \left[\eta_{i,j}^E(t-1) + \lambda_{i,j}^E(t) - \frac{f_j^E}{\rho_i(t)B_j(t)} - \omega_{i,j}(t) \right]^+ \quad (9)$$

- $\hat{l}_{i,j}^E(t)$: Task Execution Start Time Slot at EN j

$$\hat{l}_{i,j}^E(t) = \max\{t, \max_{t' \in \{0,1,\dots,t-1\}} l_{i,j}^E(t') + 1\} \quad (10)$$

$$\sum_{t'=\hat{l}_{i,j}^E(t)}^{l_{i,j}^E(t)} \frac{f_j^E}{\rho_i(t)B_j(t')} \geq \lambda_{i,j}^E(t) > \sum_{t'=\hat{l}_{i,j}^E(t)}^{l_{i,j}^E(t)-1} \frac{f_j^E}{\rho_i(t)B_j(t')} \quad (11)$$

Computation Model

Edge Execution:

- $D_{i,j}^E(t)$: Task Execution Time at EN j

$$D_{i,j}^E(t) = \frac{\lambda_{i,j}^E(t) \rho_i(t)}{f_j^E \tau / B_j(t)} \quad (12)$$

- $E_{i,j}^E(t)$: Task Execution Energy Consumption at EN j

$$E_{i,j}^E(t) = \frac{D_{i,j}^E(t) p_j^E \tau}{B_j(t)} \quad (13)$$

- $E_i^I(t)$: MD i Standby Energy Consumption

$$E_i^I(t) = D_{i,j}^E(t) p_i^I \tau \quad (14)$$

- $E_i^O(t)$: Overall Offloading Energy Consumption

$$E_i^O(t) = E_i^T(t) + \sum_{\mathcal{J}} E_{i,j}^E(t) + E_i^I(t). \quad (15)$$

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Markov Decision Process

State Space:

$$\mathbf{s}_i(t) = \left(\lambda_i(t), \delta_i^C(t), \delta_i^T(t), \boldsymbol{\eta}_i^E(t-1)^\circ, \phi_i(t)^\times, \mathcal{H}(t)^\diamond \right) \quad (16)$$

$^\diamond \mathcal{H}(t)$: Edge Load History Matrix

$^\times \phi_i(t)$: MD Battery Level

$$\left[\mathcal{S} = \Lambda \times T^2 \times \mathcal{U} \times 3 \times I^{T^s \times J} \right]$$

Action Space:

$$\mathbf{a}_i(t) = (x_i(t), \mathbf{y}_i(t)^*) \quad (17)$$

$$^* \mathbf{y}_i(t) = (y_{i,j}(t), j \in \mathcal{J})$$

Markov Decision Process

QoE Function:

[Delay]

$$\begin{aligned} \mathcal{D}_i(\mathbf{s}_i(t), \mathbf{a}_i(t)) = & (1 - x_i(t)) \left(l_i^{\mathbf{C}}(t) - t + 1 \right) + \\ & x_i(t) \left(\sum_{\mathcal{J}} \sum_{t'=t}^T \mathbb{1}(z_{i,j}^{\mathbf{E}}(t') = z_i(t)) l_{i,j}^{\mathbf{E}}(t') - t + 1 \right) \end{aligned} \quad (18)$$

[Energy]

$$\begin{aligned} \mathcal{E}_i(\mathbf{s}_i(t), \mathbf{a}_i(t)) = & (1 - x_i(t)) E_i^{\mathbf{L}}(t) + \\ & x_i(t) \left(\sum_{\mathcal{J}} \sum_{t'=t}^T \mathbb{1}(z_{i,j}^{\mathbf{E}}(t') = z_i(t)) E_i^{\mathbf{O}}(t) \right) \end{aligned} \quad (19)$$

Markov Decision Process

[Cost]

$$\begin{aligned} \mathcal{C}_i(\mathbf{s}_i(t), \mathbf{a}_i(t)) = \\ \phi_i(t) \mathcal{D}_i(\mathbf{s}_i(t), \mathbf{a}_i(t)) + (1 - \phi_i(t)) \mathcal{E}_i(\mathbf{s}_i(t), \mathbf{a}_i(t)) \end{aligned} \quad (20)$$

[QoE]

$$\begin{aligned} \mathbf{q}_i(\mathbf{s}_i(t), \mathbf{a}_i(t)) = \\ \begin{cases} \mathcal{R}^* - \mathcal{C}_i(\mathbf{s}_i(t), \mathbf{a}_i(t)) & \text{if task } z_i(t) \text{ processed,} \\ -\mathcal{E}_i(\mathbf{s}_i(t), \mathbf{a}_i(t)) & \text{if task } z_i(t) \text{ dropped,} \end{cases} \end{aligned} \quad (21)$$

* \mathcal{R} : A Constant Reward for Completed Task

QoE Optimization Problem

$$^{\circ}\pi_i^* = \arg \max_{\pi_i} \mathbb{E} \left[\sum_{t \in \mathcal{T}} {}^*\gamma^{t-1} \mathbf{q}_i(\mathbf{s}_i(t), \mathbf{a}_i(t)) \middle| \pi_i \right] \quad (22)$$

$^{\circ}\pi_i^*$: Optimal Policy

\Rightarrow maximizes the long-term QoE

${}^*\gamma$: Discount Factor

\Rightarrow balance between instant QoE and long-term QoE

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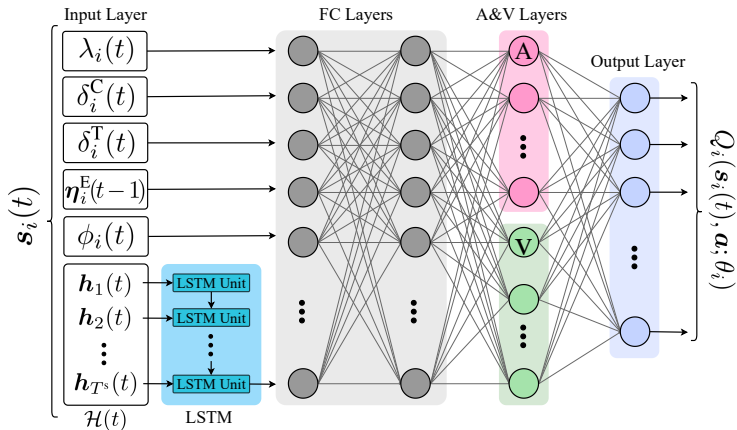
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DQN-based solution



- LSTM: ENs Load Level Prediction
- FC: State-Action Q-Value Mapping
- A&V: Dueling-DQN Approach for Q-Value Estimation

QOCO Algorithm

Offloading Decision Algorithm at MD:

- Receive network parameter vector θ_i^E from EN
- Select an Action for each Computation Task based on

$$\mathbf{a}_i(t) = \begin{cases} \arg \max_{\mathbf{a} \in \mathcal{A}} Q_i^E(\mathbf{s}_i(t), \mathbf{a}; \theta_i^E), & \text{with } p(1 - \epsilon) \\ \text{pick an random action from } \mathcal{A}, & \text{with } p(\epsilon) \end{cases} \quad (23)$$

- Observes a set of QoEs
- Send Experience $(\mathbf{s}_i(t), \mathbf{a}_i(t), \mathbf{q}_i(t), \mathbf{s}_i(t + 1))$ to EN

QOCO Algorithm

Training Process Algorithm at EN:

- Stores the Receives Experience $(\mathbf{s}_i(t), \mathbf{a}_i(t), \mathbf{q}_i(t), \mathbf{s}_i(t+1))$
- Calculates the Q-value given the MD experience

$$\hat{Q}_{i,n}^T = \mathbf{q}_i(n) + \gamma Q_i^T(\mathbf{s}_i(n+1)), \tilde{\mathbf{a}}_n; \theta_i^T \quad (24)$$

- optimal action for the state

$$\tilde{\mathbf{a}}_n = \arg \max_{\mathbf{a} \in \mathcal{A}} Q_i^E(\mathbf{s}_i(n+1), \mathbf{a}; \theta_i^E) \quad (25)$$

- Updating network based on loss function

$$L(\theta_i^E, \hat{\mathbf{Q}}_i^T) = \frac{1}{|\mathcal{N}|} \sum_{n \in \mathcal{N}} \left(Q_i^E(\mathbf{s}_i(n), \mathbf{a}_i(n); \theta_i^E) - \hat{Q}_{i,n}^T \right)^2 \quad (26)$$

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Simulation Settings

Parameter	Value
Computation capacity of MD f_i	2.6 GHz
Computation capacity of EN f_j^E	42.8 GHz
Transmission capacity of MD $r_{i,j}(t)$	14 Mbps
Task arrival rate	150 Task/Sec
Size of task $\lambda_i(t)$	{1.0, 1.1, ..., 7.0} Mbits
Required CPU cycles of task $\rho_i(t)$	{0.197, 0.297, 0.397} G/Mbits
Deadline of task Δ_i	10 time slots (1 Sec)
Battery level of MD $\phi_i(t)$	{25, 50, 75} Percent
Computation power of MD p_i^C	$10^{-27}(f_i)^3$
Computation power of EN p_j^E	5 w
Transmission power of MD p_i^T	2.3 w
Standby power of MD p_i^I	0.1 w

50 MD and 5 EN

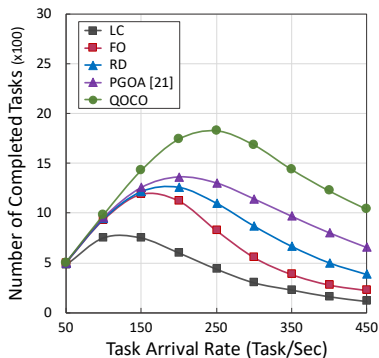
1000 Episode and 100 Time Slot

Performance Comparison

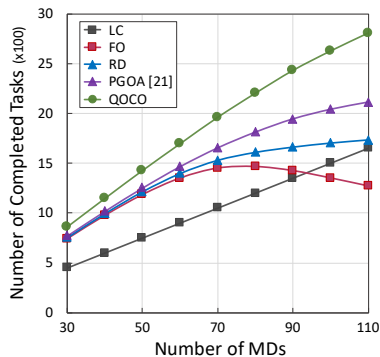
Benchmark Methods:

- **Local Computing (LC)**: MDs execute all of their computation tasks using their own computing capacity
- **Full Offloading (FO)**: MDs dispatches all of their computation tasks to ENs and selects their offloading target randomly
- **Random Decision (RD)**: MDs randomly makes offloading decisions and selects the offloading target
- **PGOA[21]**: A distributed optimization algorithm designed for delay-sensitive tasks in an environment where MDs interact strategically with multiple ENs.

Performance Comparison



(a)

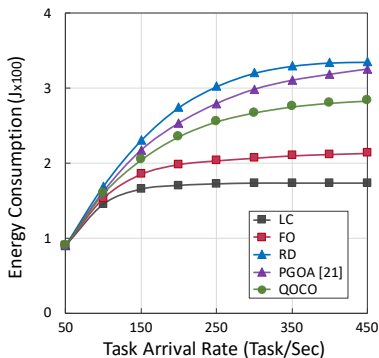


(b)

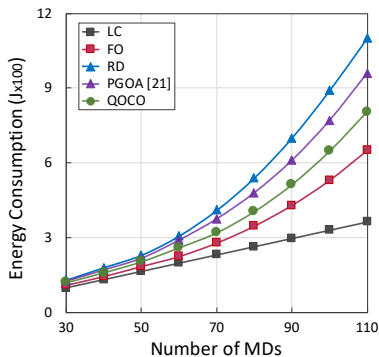
Number of completed tasks under different computation loads:

- (a) task arrival rate
- (b) the number of MDs

Performance Comparison



(a)

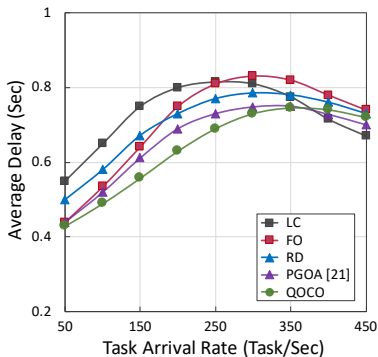


(b)

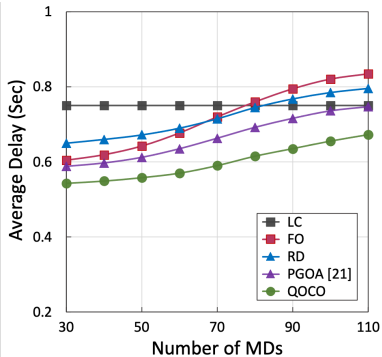
Overall energy consumption under different computation loads:

- (a) task arrival rate
- (b) the number of MDs

Performance Comparison



(a)

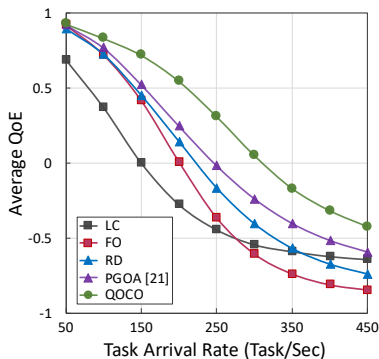


(b)

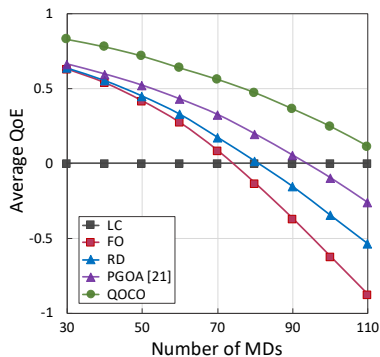
Average delay under different computation loads:

- (a) task arrival rate
- (b) the number of MDs

Performance Comparison



(a)



(b)

Average **QOE** under different computation loads:

- (a) task arrival rate
- (b) the number of MDs

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- (a) task arrival rate
- (b) the number of MDs