Resource Optimized Task Offloading in Delay Sensitive Edge Networks

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ICNC 2025

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2. Problem Statement
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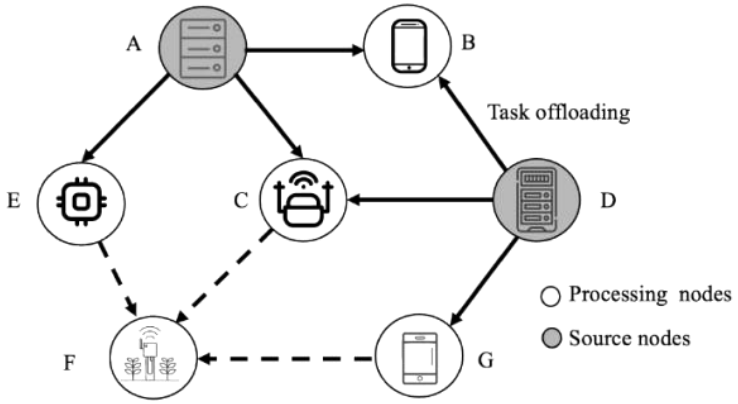
Introduction

- Edge computing brings computation closer to the source of data to reduce latency.
- Task offloading improves resource utilization and reduces execution time.

Challenges: Communication delays, energy constraints, and scalability issues.

Contribution of the Paper:

- A novel Effective Processing Rate (EPR) metric for task allocation.
- Evaluation of multi-hop task offloading performances.



Problem Statement

- Inefficiencies in task offloading due to communication delays, energy constraints, and processing limitations in edge networks.

- Need: A scalable, resource-optimized task offloading mechanism for delay-sensitive applications in edge networks.

- **Objective**

- Minimize task completion time while ensuring all nodes finish at the same time.

$$\text{minimize} \quad \max_{i \in N} \left(\frac{T_i}{P_i} + d_{S,i} \right)$$

Where, T_i is the number of tasks allocated to node i, P_i is the processing rate of node i, and $d_{S,i}$ is the shortest path delay from the source node to node i.

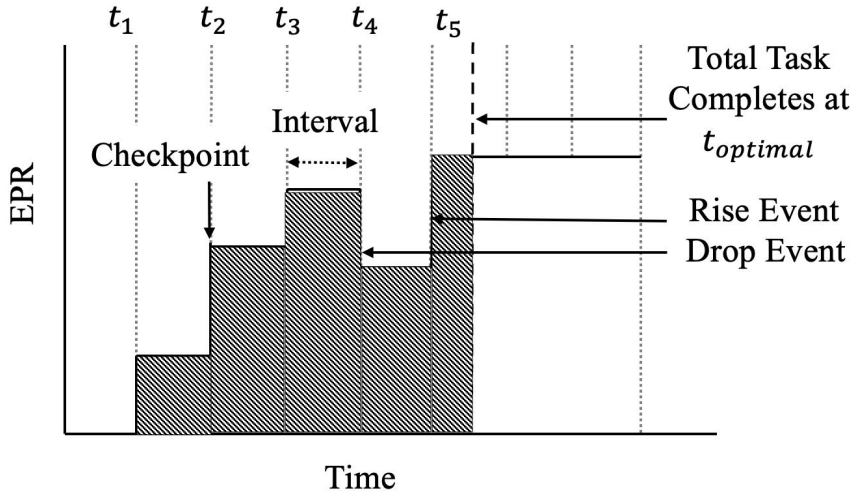
Background & Motivation

- Edge Computing
  - Edge computing minimizes latency by processing data closer to the data source rather than relying solely on centralized cloud servers.
  - Edge devices often have resource constraints like computation power and energy.
- Challenges in Existing Approaches
  - Traditional methods (e.g., brute force) are computationally expensive.
  - Adaptive methods require fine-tuning and often fail to achieve global optimization.
  - State-of-the-art approaches, such as heuristic methods like genetic algorithms and mixed-integer programming, face limitations due to high complexity, scalability issues, and the need for extensive fine-tuning.

Innovative Approach Checkpoint-Based Task Allocation

A **dynamic scheduling mechanism** that partitions execution time into **intervals**, ensuring efficient task distribution.

- **Precomputed Checkpoints**: Defined points where system state updates, based on task arrivals and completions.
- **Rise Events**: When a node becomes active and starts processing tasks at $t_{rise,}$.
- **Drop Events**: When a node stops processing tasks at t_{drop}.
- **Interval-Based Execution**: Tasks are allocated dynamically within each interval $[t_j + t_{j+1}]$, adapting to active nodes.



Innovative Approach (Cont.)

- **Goal**: Identify key time points (**checkpoints**) when nodes **start** and **stop** processing.

- **Steps:**
  - Compute shortest path delays.
  - Determine **rise time** and **drop time** for each node.
  - Sort these times to create a **global event timeline**.

- **Outcome**: A structured **sequence of events** for dynamic task allocation.

Algorithm 1 Precomputing Checkpoints

Require: Directed graph representing the network $G = (N, E)$, delays d_{ij}, lifetimes L_i

Ensure: Sorted list of checkpoints $\{t_1, t_2, \ldots, t_{2|N|}\}$

1: Run Dijkstra's algorithm to compute shortest path delays $d_{S,i}$ for all active nodes
2: **Compute:**
3: **for** each node $i \in N$ **do**
4: $\quad t_{\text{rise},i} \leftarrow d_{S,i}$
5: $\quad t_{\text{drop},i} \leftarrow t_{\text{rise},i} + L_i$
6: Sort the list of events $\{t_{\text{rise},i}, t_{\text{drop},i}\}$ in ascending order to form $\{t_1, t_2, \ldots, t_{2|N|}\}$
7: **return** Sorted list of checkpoints $\{t_1, t_2, \ldots, t_{2|N|}\}$

Innovative Approach (Cont.)

- **Goal**: Dynamically allocate tasks so that all nodes finish at the same time.
- **Steps:**
  - Start with **precomputed checkpoints** and initialize parameters.
  - Iterate through each **time interval** between checkpoints.
  - Update **processing rate** based on active nodes.
  - Compute **task completion** in the interval.
  - Update the **remaining tasks** and move to the next interval.

- **Outcome**: Tasks are distributed **efficiently** while ensuring **synchronized completion**.

Algorithm 2 Task Distribution with Checkpoints

Require: Precomputed checkpoints $\{t_1, t_2, \ldots, t_k\}$, total tasks T_{total}

Ensure: Tasks distributed so all nodes finish at the same time

1: Initialize $j \leftarrow 1$, $T_{\text{remaining}} \leftarrow T_{\text{total}}$, $\mathcal{R}_{\text{eff}} \leftarrow 0$

2: **while** $T_{\text{remaining}} > 0$ **do**

3: Update $\mathcal{R}_{\text{eff}}$ for all available nodes

4: Compute required processing time for that interval:

$$\Delta t = \min\left(t_{j+1} - t_j, \frac{T_{\text{remaining}}}{\mathcal{R}_{\text{eff}}}\right)$$

5: Compute tasks completed:

$$T[t_j, t_j + \Delta t] = \mathcal{R}_{\text{eff}} \times \Delta t$$

6: Update remaining tasks:

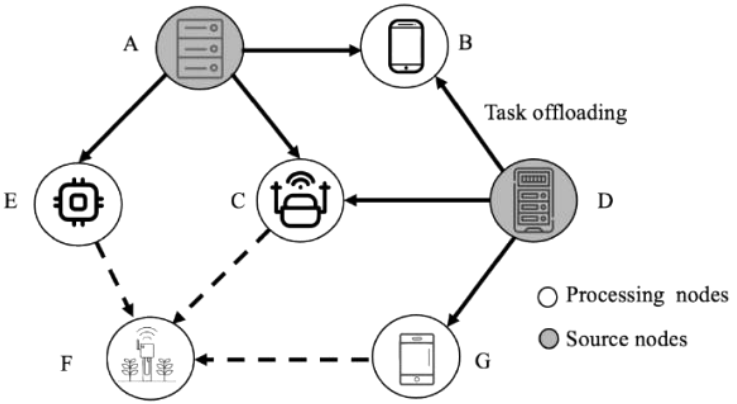
$$T_{\text{remaining}} \leftarrow T_{\text{remaining}} - T[t_j, t_j + \Delta t]$$

7: Move to the next interval: $j \leftarrow j + 1$

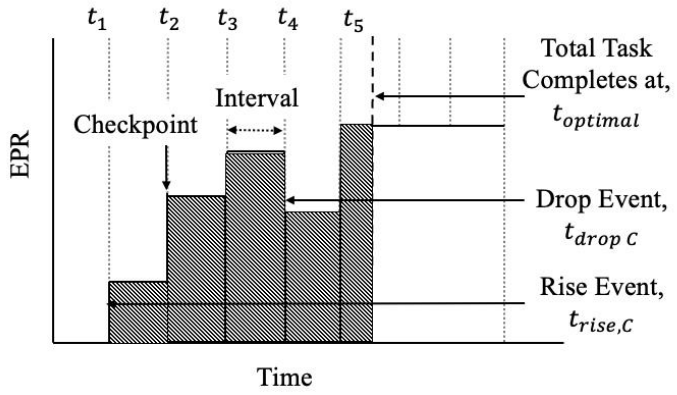
8: **return** Total completion time

Example (Single-source)

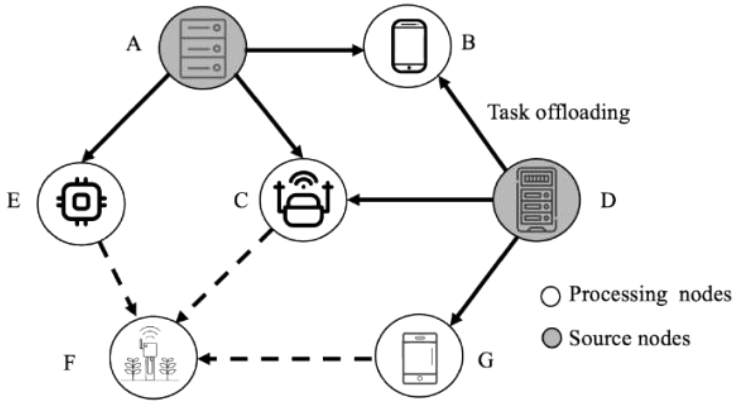
- Node **A** identifies **B, C, and E** as one-hop and **F** as a two-hop neighbor.
- **Checkpoints** are precomputed based on shortest path delays and node lifetimes.



- *C* starts processing at $t_{rise,C}$ and stops at $t_{drop,C}$ completing e.g. 30 task units.
- Tasks are processed dynamically in intervals $[t_j + t_{j+1}]$, with EPR updated as nodes join or leave.
- If *C* dies while processing the task, it is removed, and its remaining tasks are completed locally.



Example (Multi-source)



- Source A offloads tasks to nodes B, C, E, F, while source D offloads to B, C, F, G.
- Shared nodes prioritize tasks based on arrival time with busy time dynamically managed.
- Unique node G absorbs additional tasks to reduce delays and balance the load.
- Task transmission (shaded bars) and processing (unshaded bars) are sequentially managed across nodes.

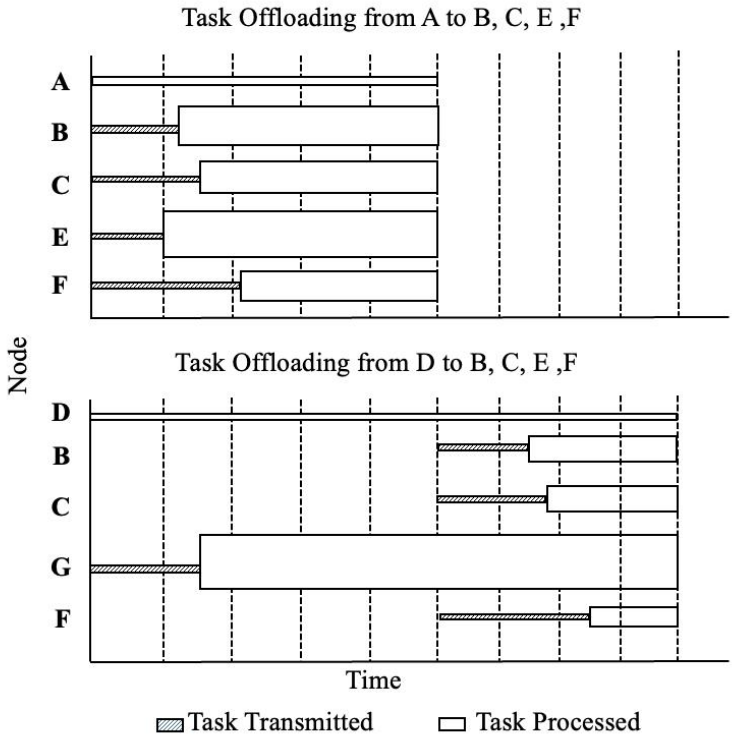


Fig: Multi-source task offloading with shared processing nodes.

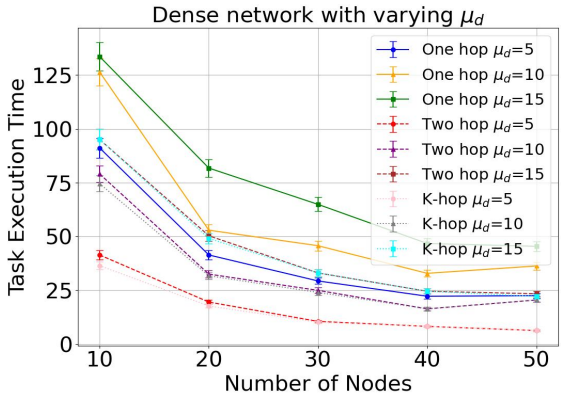
Proof Of Optimality

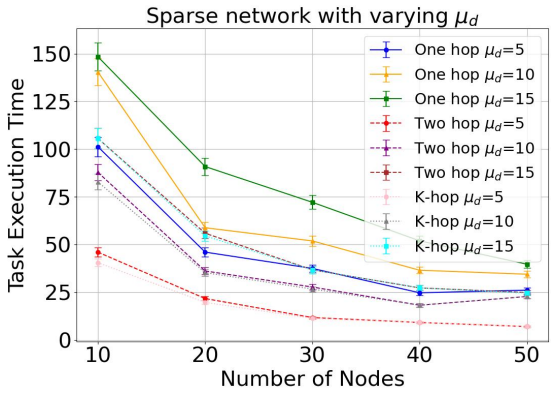
- Suppose an alternative allocation A' achieves a lower completion time or better efficiency than our algorithm's allocation A^* .
- Our algorithm ensures that all **terminally-active nodes** (nodes that remain active until the last processing interval) **finish at the same time**, while making maximum use of available nodes.
- If an alternative allocation A' assigns more tasks to a terminally-active node n_{higher}, its completion time is at least:

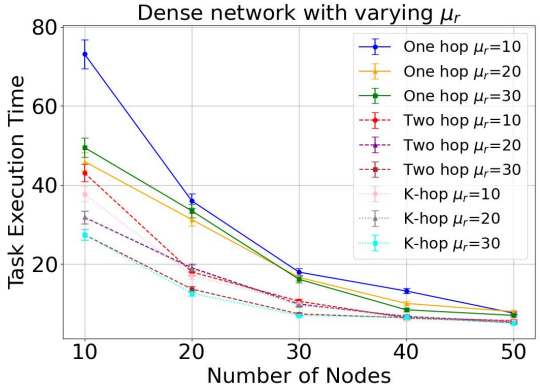
$$t_{\text{higher}} = d_{S,n_{\text{higher}}} + \frac{A'}{P_{n_{\text{higher}}}}$$

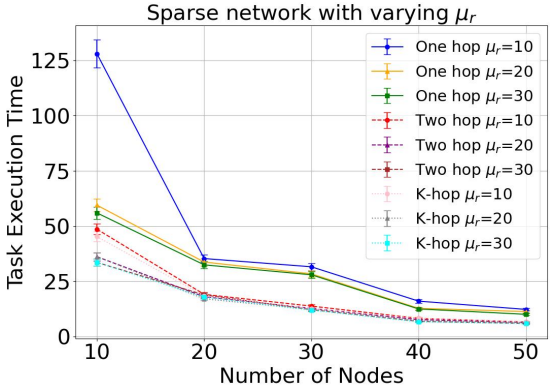
- Since our algorithm ensures all terminally-active nodes complete at t^*_{final} with $A^* < A'$, n_{higher} would take **longer** under A'.

Experimental Results (Multi-hop Offloading)



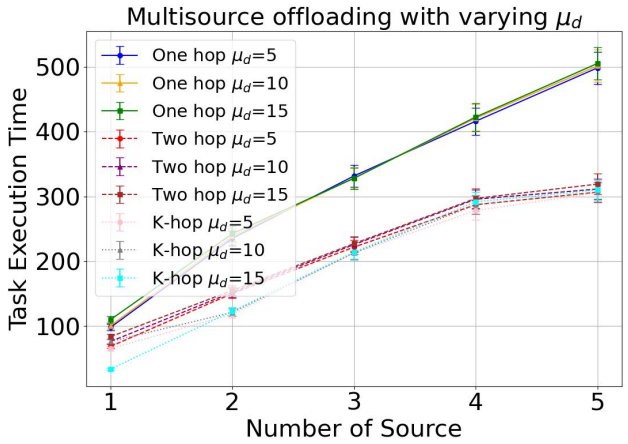


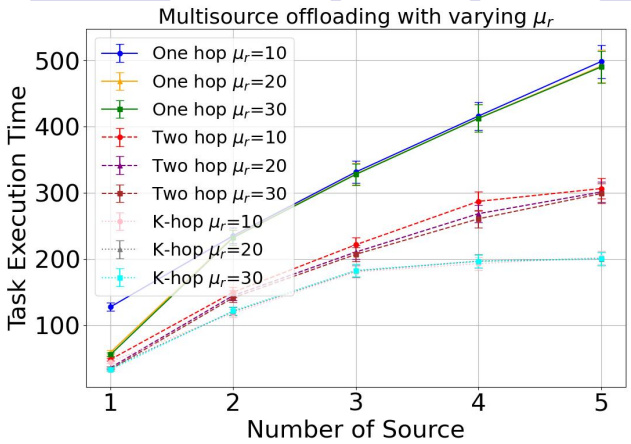




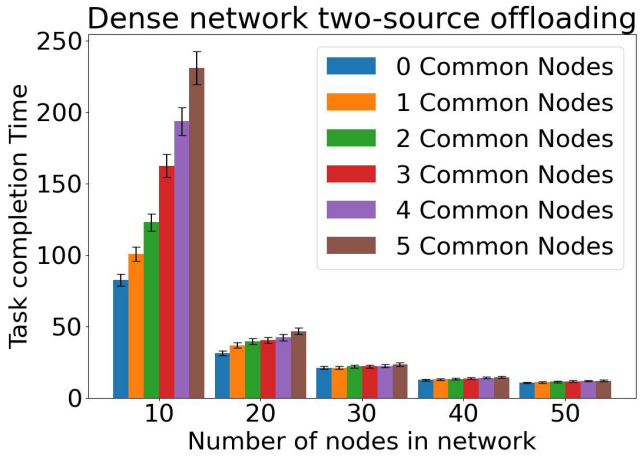
Task offloading performance with a fixed task size TA = 50, varying node count, mean delay μ_d, and mean computation power μ_r

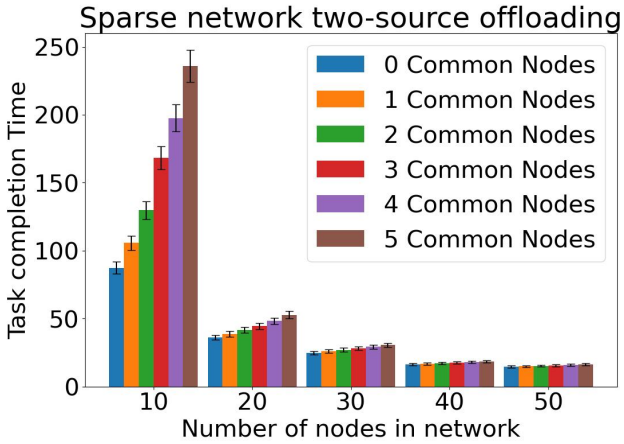
Experimental Results





Multi-source task offloading with Task size = 50, P = 0.5, and varying μr , μd.





Two-source offloading vs. common nodes and increasing network size.

Algorithm Extension for Willingness to Help

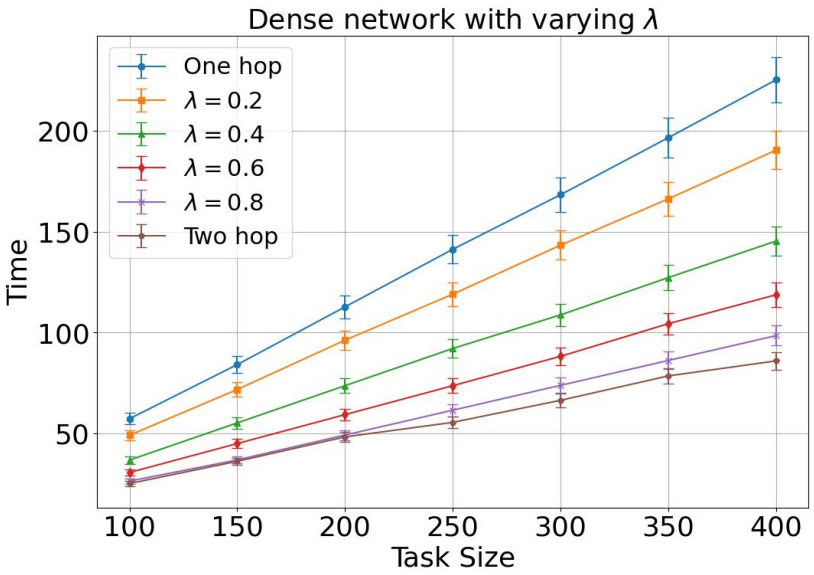
- In multi-hop networks, **willingness to help** reflects a node's likelihood to assist in task processing.
- The EPR metric is adjusted to incorporate a **scaling factor** (λ) representing willingness:

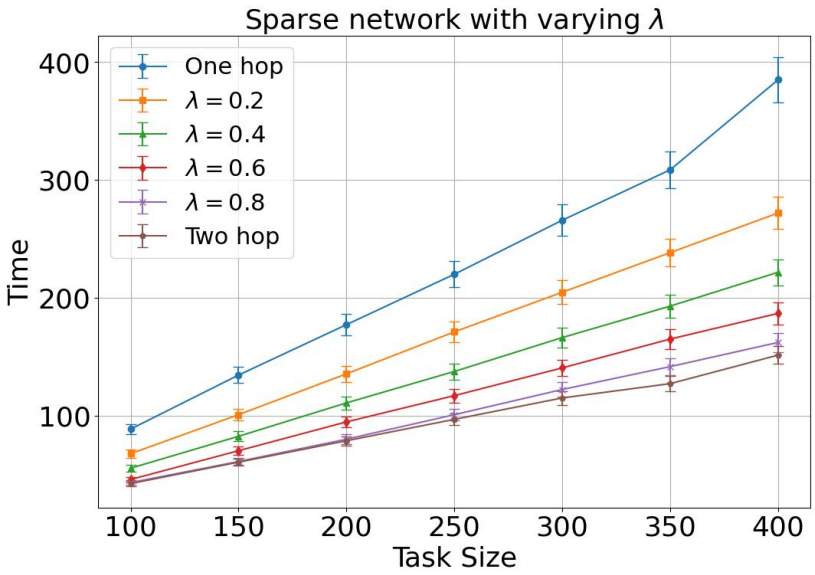
$$R_{\text{eff}} = \sum_{i \in \text{Active Nodes}} \lambda_i \cdot P_i$$

- **Impact of Willingness**:
  - Higher λ values improve task allocation efficiency and reduce overall execution time.
  - Lower λ values represent less effective nodes in processing due to higher delays or shared dependencies.

- **Significance**:
  - Incorporating willingness ensures realistic modeling of node behavior in dynamic edge networks.
  - It highlights the trade-offs between node utilization and task completion time.

Experimental Results





Task offloading for one hop, two hop and two hop with λ = 0.2, 0.4, 0.6, 0.8 .

Conclusion

- Proposed SSROTA is optimal for task offloading in multi-hop single source edge networks.
- Introduced the concept of willingness to help to improve task allocation by dynamically adapting to network conditions.
- Suitable for dynamic and heterogeneous networks, enhancing scalability and adaptability.
- Potential to support real-world applications like IoT and edge-cloud integration.

- **Future Directions**:
  - Extend algorithms to heterogeneous environments with dynamic node mobility and fluctuating resources.
  - Explore machine learning integration for predictive task allocation and network optimization.
  - Investigate further refinements for energy-aware multi-tier networks.

Thank you!
Q & A

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