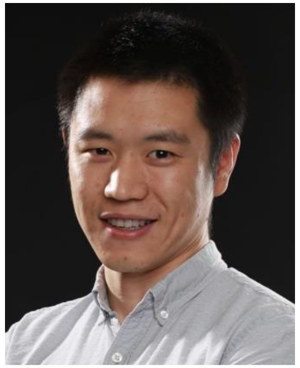
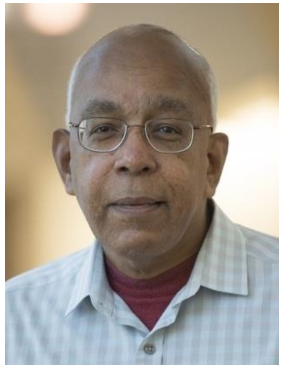
Joint Task Offloading and Routing in Wireless Multi-hop Networks Using Biased Backpressure Algorithm





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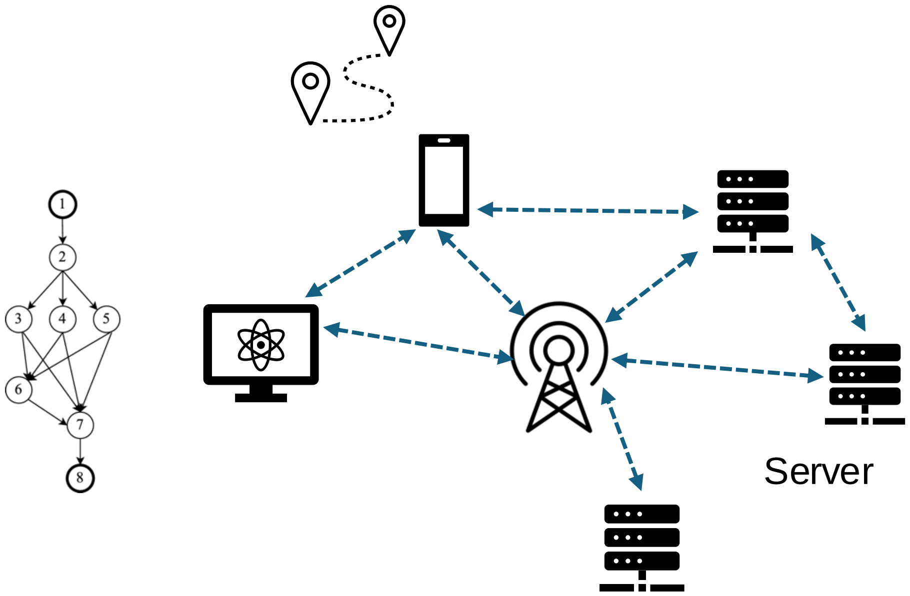
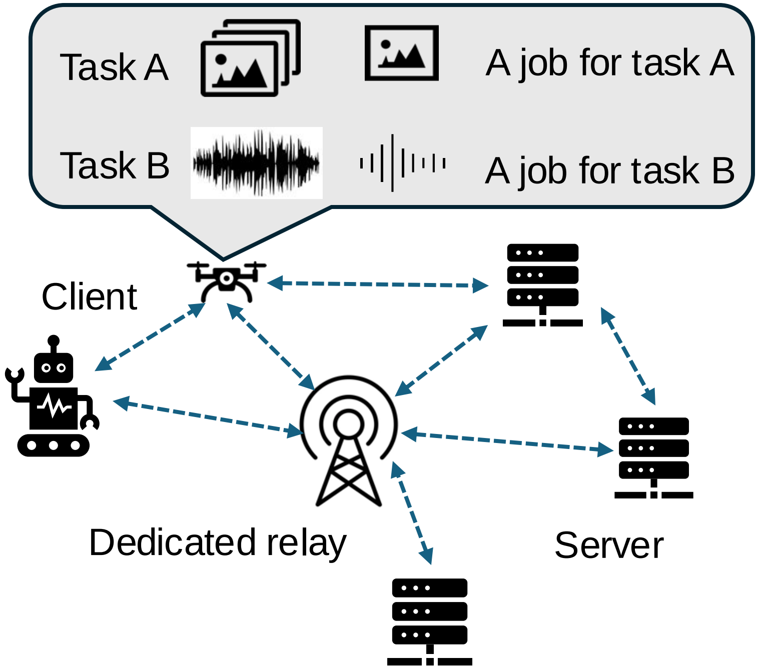
One-time vs recurrent task offloading

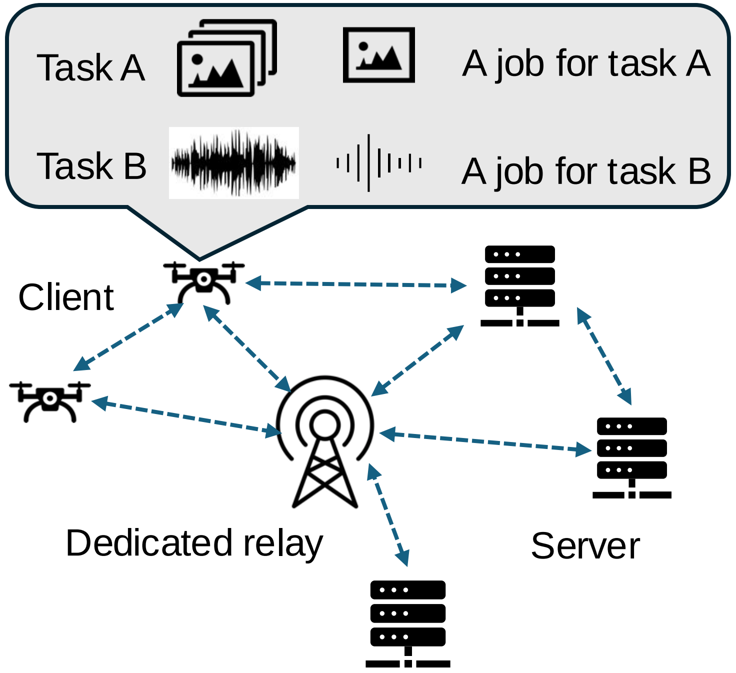


One-time computation offloading
- Path finding
- Scientific computing
- Data analysis



Recurrent computation offloading
- Video surveillance & analytics
- Autonomous robots
- Environmental, health monitoring

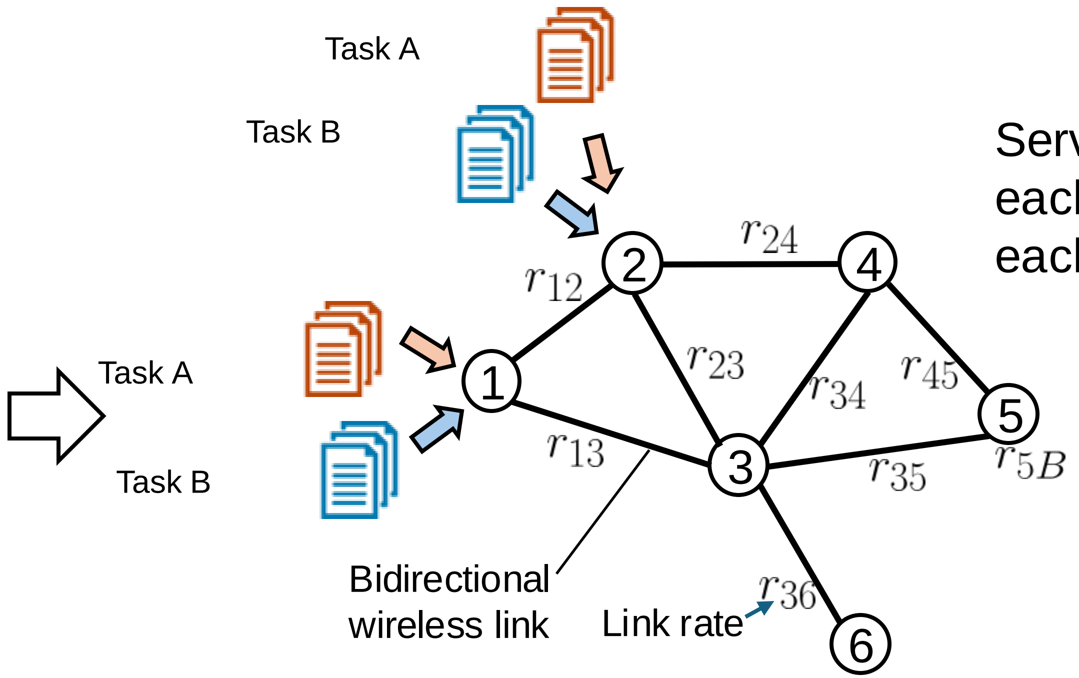
Recurrent task offloading



Task offloading in a wireless multihop network

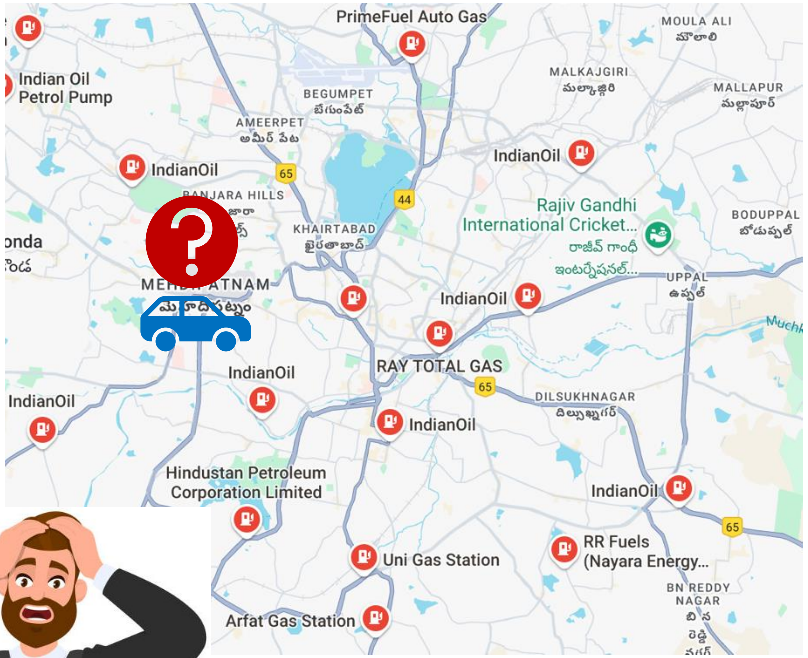
Job arrival rate of each task initialized by each client

Service rate of each server for each type of task



Connectivity Graph

Offloading and routing decisions



- **Where**: pick a destination,
  - server, gas/charging station
- **How**: find a route to destination
- Easy?
  - ★☆☆☆☆ [Greedy] let's go to the **nearest** one, on the **shortest** route
  - ★★☆☆☆ [Strategy 1] Check status of road and destinations, then decide
  - ★★★☆☆ [Strategy 2] Guess the future network status, then decide
  - ★★★☆☆ [Strategy 3] Centralized scheduler

Goal: reduce travel time, avoid congestion (on the road or at the destination)

Strategy 1: centralized joint offloading & routing

- Mixed-integer programming (MIP)
  - Collect full network state
  - Offline, batch operations
  - Joint decisions for all tasks
  - Ignore queueing and interference
  - Integer rate assignment → NP-hard
  - Poor scalability (comm. & compute)

  [Kiamari, 2022], [Li, 2022], [Dai, 2022]

- Linear relaxation for recurrent tasks
  - Model task as divisible liquid flow
  - Fractional probabilistic rate assignment
  - Can be solved quickly

  [Feng, 2021], [Funai, 2019], [Liu, 2020]

flow rate assignment for task type c of client m, on link e

Minimize total costs (latency)

$$\{f_m^c(e)\}^* = \underset{\{f_m^c(e)\}\in\{\mathbb{R}^+\}}{\operatorname{argmin}} \sum_{m\in\mathcal{M}}\sum_{c\in\mathcal{C}} \delta_m^c \quad \text{(1a)}$$

Linear cost (latency)

$$\text{s.t. } \delta_m^c = \sum_{e\in\mathcal{E}} f_m^c(e)u(e) + \sum_{v\in\mathcal{V}} g_m^c(v)u^c(v)\ , \quad \text{(1b)}$$

Flow conservation

$$\lambda_m^c \mathbb{1}(m{=}v) + \sum_{i\in\mathcal{N}(v)} f_m^c((i,v)) = g_m^c(v) + \sum_{i\in\mathcal{N}(v)} f_m^c((v,i)), \quad \text{(1c)}$$

In-flow = out-flow

$$\lambda_m^c = \sum_{v\in\mathcal{V}} g_m^c(v)\ ,\ \forall\ m\in\mathcal{M}, c\in\mathcal{C}\ , \quad \text{(1d)}$$

Server capacity

$$\psi(v) \geq \sum_{c\in\mathcal{C},m\in\mathcal{M}} g_m^c(v)h^c(v),\ \forall\ v\in\mathcal{V}\ , \quad \text{(1e)}$$

Link capacity

$$\psi(e) \geq \sum_{c\in\mathcal{C},m\in\mathcal{M}} f_m^c(e),\ \forall\ e\in\mathcal{E}\ , \quad \text{(1f)}$$

$$h^c(v), u(e), g_m^c(v), u^c(v) \in \mathbb{R}^+, \forall\ e\in\mathcal{E}, m, v\in\mathcal{V}, c\in\mathcal{C}, \quad \text{(1g)}$$

Non-negative costs

Ignore interference

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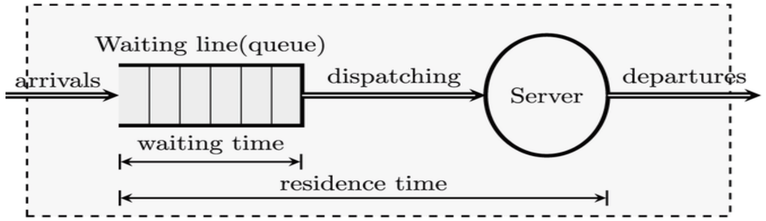
Strategy 2: separated offloading and routing

- Distributed solutions
  - Clients collect real-time state of servers
  - Online, asynchronized decisions
  - First decide destination, then find path
  - Consider queueing and interference
  - Various decision granularity
  - Limited scalability (comm. overhead)

[Kamran, 2022], [Lin, 2020], [Jiang, 2023], [Liu 2019], [Bi 2021], [Zhao 2024]

- An ideal benchmark
  - Clients know real-time servers' state at no cost
  - SOTA routing in wireless multihop networks
    - Backpressure offloading
    - SP-BP routing
  - Maximum queue stability



SP-BP: shortest-path biased Backpressure routing and scheduling*

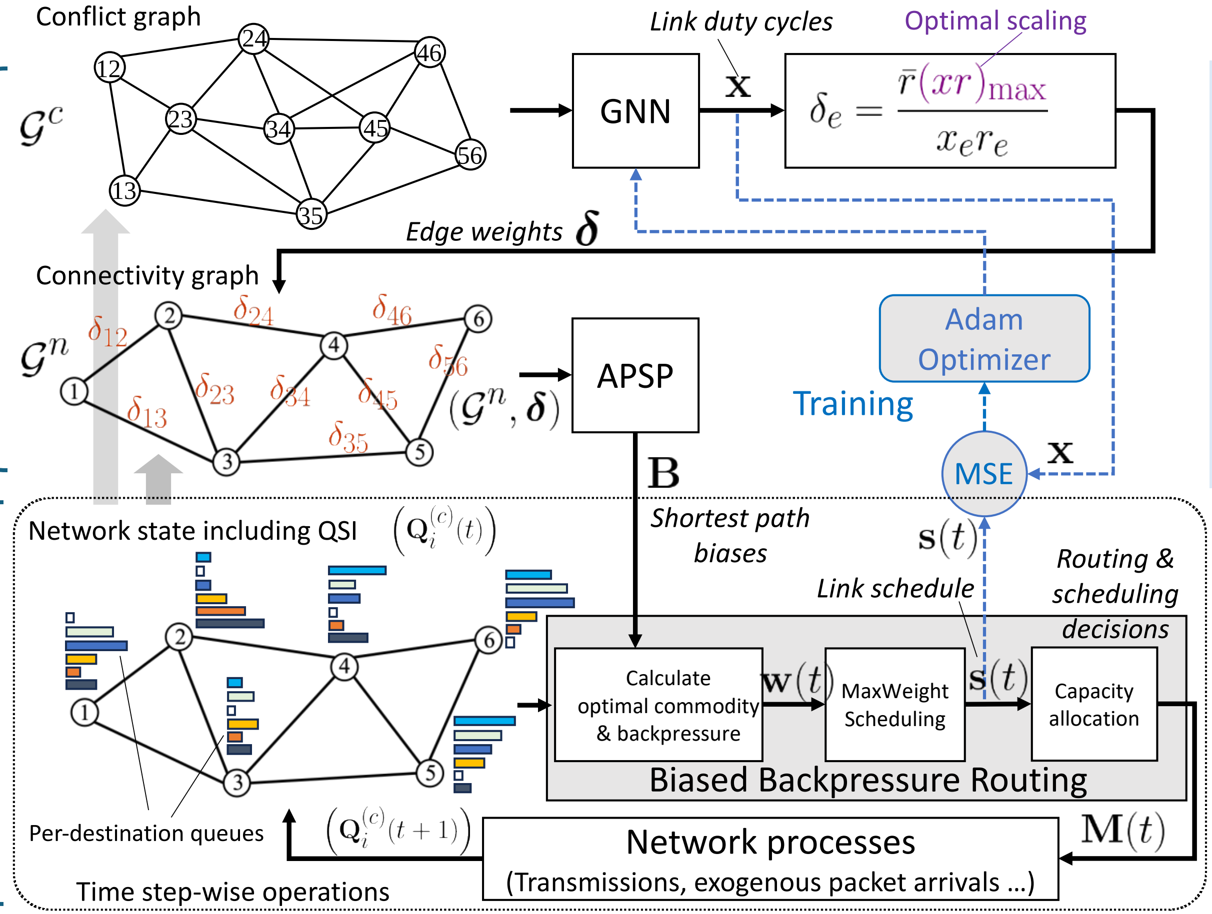
SP_SP-BP:
offload a job to the server with the shortest queue, then SP-BP routing takes the job to the server

SPBP_SP-BP:
offload a job to the server with the shortest queue + processing bandwidth,
then SP-BP routing takes the job to the server

SP-BP: shortest-path biased backpressure

One-time shortest path bias computing

Fully distributed routing and scheduling



Per-destination queueing system

SP-BP routing and scheduling*, considers both the shortest path and congestion state,

- minimize latency
- maximum queue stability (throughput optimality)
- Mitigate last packet problem
- Minimize startup time, random walking

- * Z. Zhao, B. Radojičić, G. Verma, A. Swami and S. Segarra, "Biased Backpressure Routing Using Link Features and Graph Neural Networks," in IEEE TMLCN, vol. 2, pp. 1424-1439, 2024
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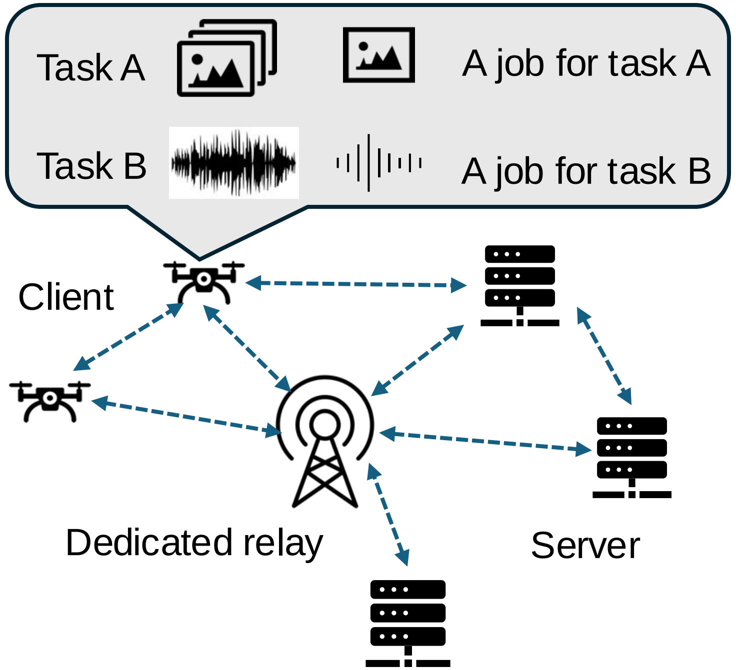
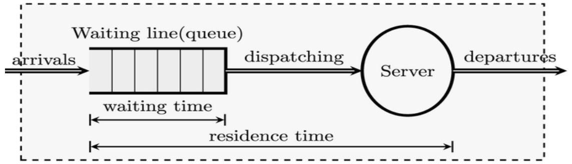
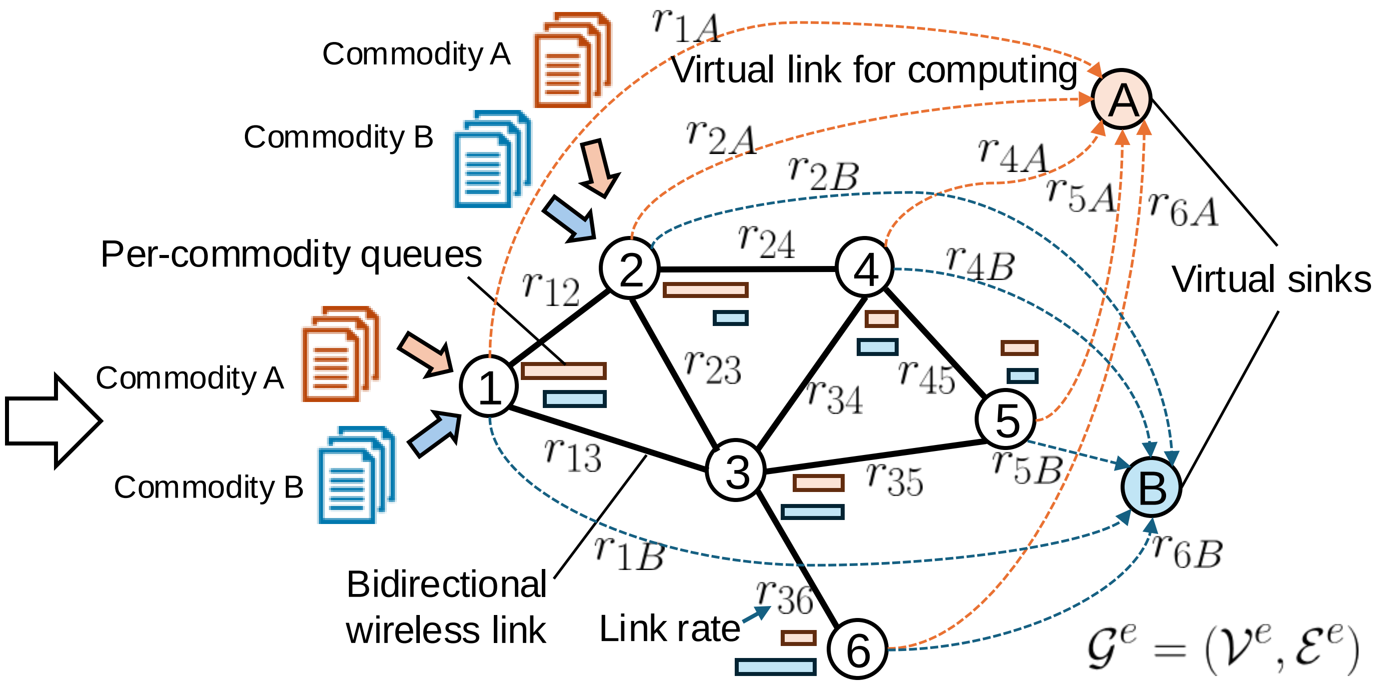
Our approach

1. Model computing as sending jobs to virtual sinks over virtual links
2. Joint offloading and routing → SP-BP routing



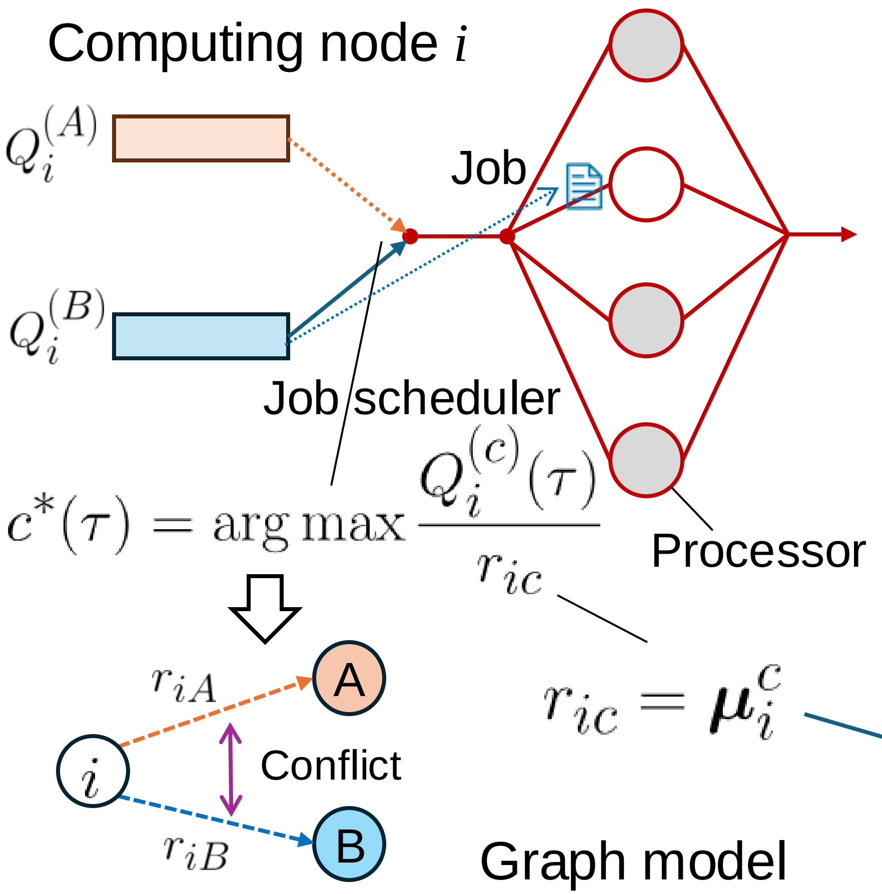




A job can take flexible route to virtual sink (its server is not pre-determined)

Extended connectivity graph

Job Scheduling for computing nodes

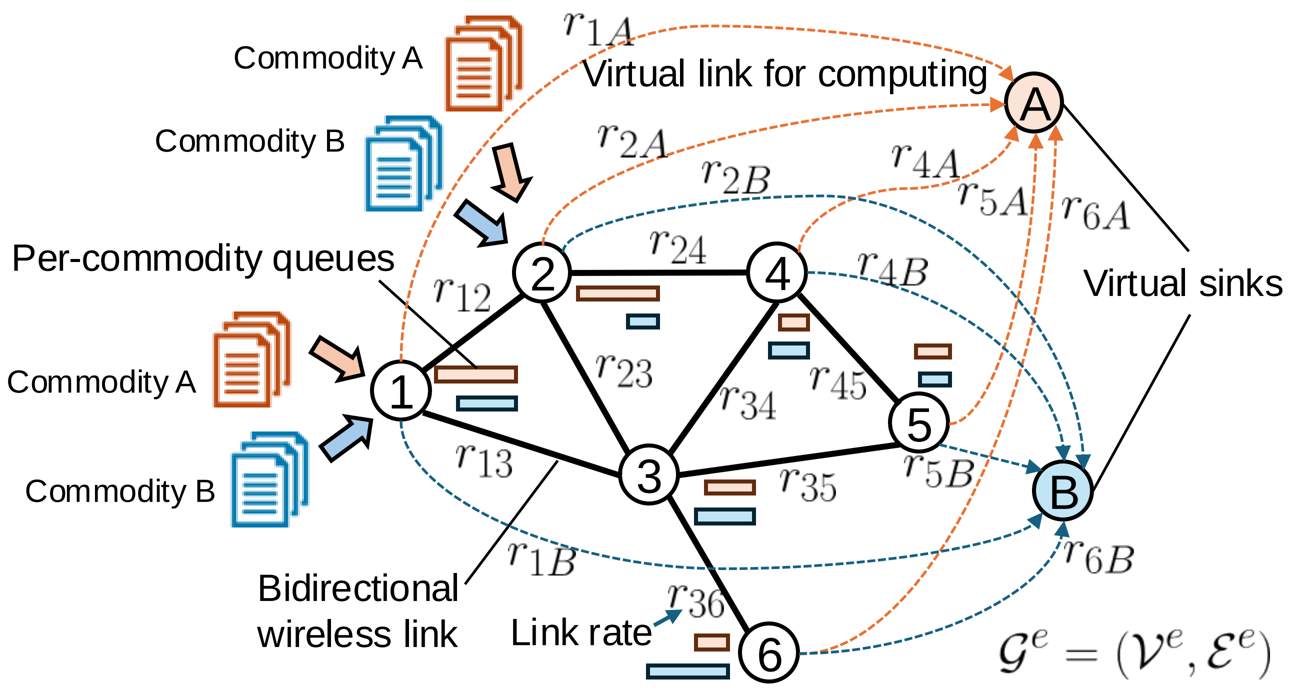


Job scheduling operation
Whenever there is free processor on a server, send it a job from the queue requires the longest time to clear

Virtual link model
Conflict: virtual links on the same server conflicting with each other

Virtual link rate: how many jobs can be processed by the server in a time slot, assuming no other types of jobs

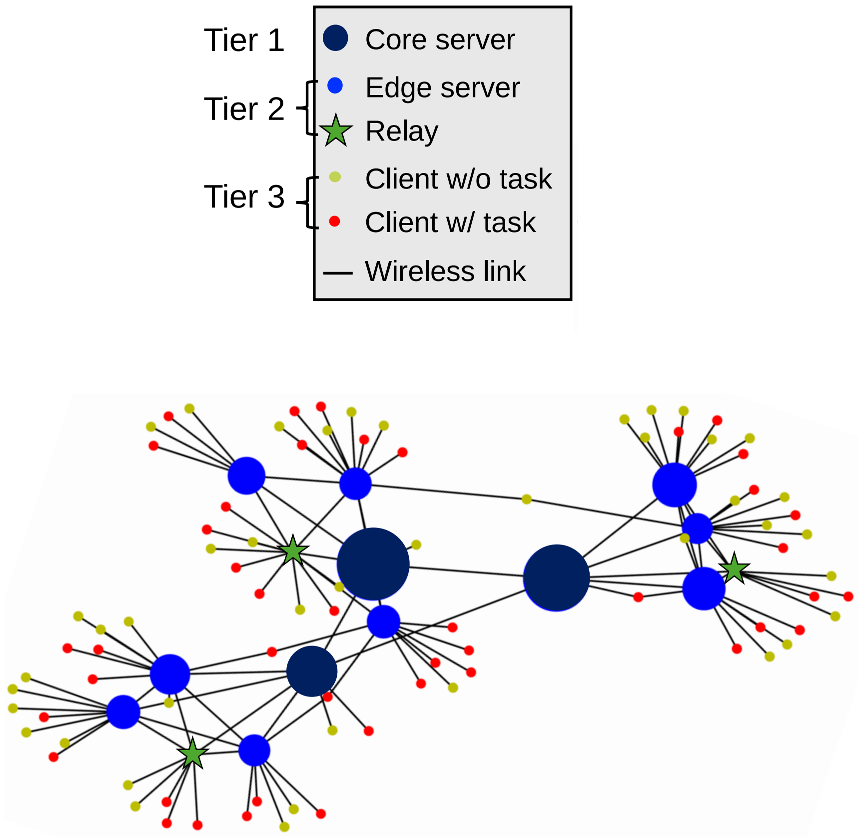
SP-BP on extended connectivity graph



- Computing (virtual links) operate in continuous time
- Physical link scheduling not impacted

Numerical results

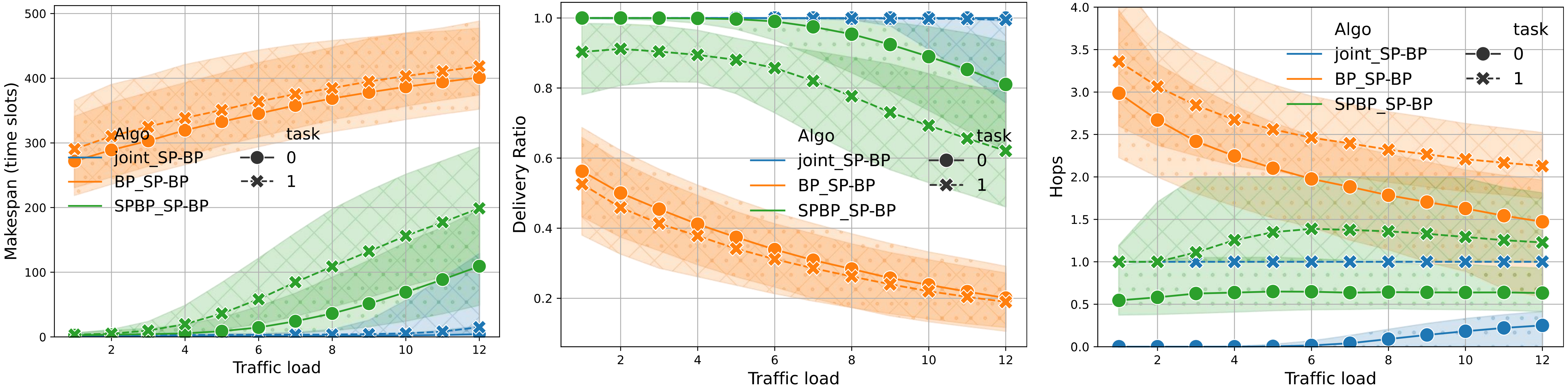
- Random hierarchical wireless multihop networks
  - Network size: 100 nodes,
  - 100 instances = 10 networks X 10 test cases
- Job arrivals: 50% streaming and 50% bursty
  - Arrival time of bursty clients are random
- Time horizon T=1000
- Computing capacity
  - Servers: Pareto distribution (shape=2, scale=8)
  - Clients: Uniform (8, 12)
- Long-term link rates: uniform
- Real-time link rates: truncated Gaussian



Node size indicates computing power

Two types of tasks

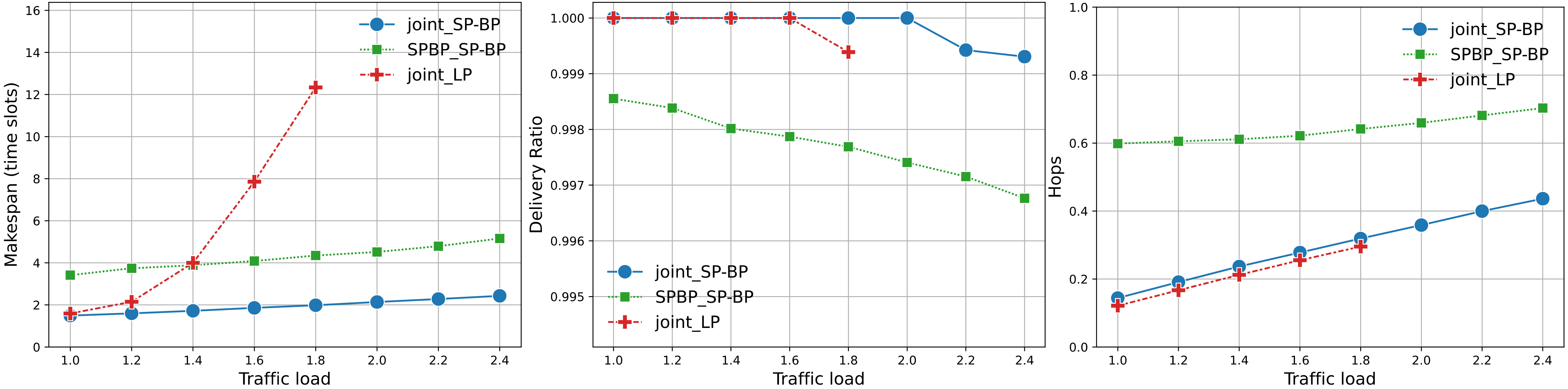
Task 0: can be computed locally and remotely
Task 1: can not be computed by clients



- BP_SP-BP: worst makespan, delivery ratio, hop-distance
  - Offloading only consider QSI, offload to remote servers
- SPBP_SP-BP:
  - Offloading considers QSI and server capacity, significant improvement
- Joint_SP-BP: far better than separated offloading and routing

Single task type

- Task 0: can be computed locally and remotely
- Scaled down job arrival rates and computing bandwidth by a factor of 8.0
- Communication bandwidth is relatively scaled up



- Easier setting to test joint_LP (linear programming relaxation)
- Joint_LP (unable to find solution for load > 1.8)
  - Matches joint_SP-BP in lowest traffic load
  - Quickly degrade with traffic intensity, due to inter-flow interference
- joint_SP-BP: best, scales well by traffic intensity

Conclusion + future direction

- Joint offloading, routing, scheduling
  - A fully distributed, asynchronized solution
    - Need no real-time server-side QSI
    - Tasks can be initialized at any time
  - Offloading without (prescribed) destinations, routing without route
    - The next step of a job is decided by its current hosting node
    - Long-term global potential + updated QSI in local neighborhood
  - High performance, good scalability, maximum queue stability
- Future directions
  - Context switching cost in job scheduling
  - Multi-stage task (forward/return trip), complex workflows
  - Task/traffic priorities
  - Compatibility with regular data traffics

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