Robust Resource Provisioning in Time-Varying Edge Networks

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NC STATE UNIVERSITY

Outlines

Background and Motivation

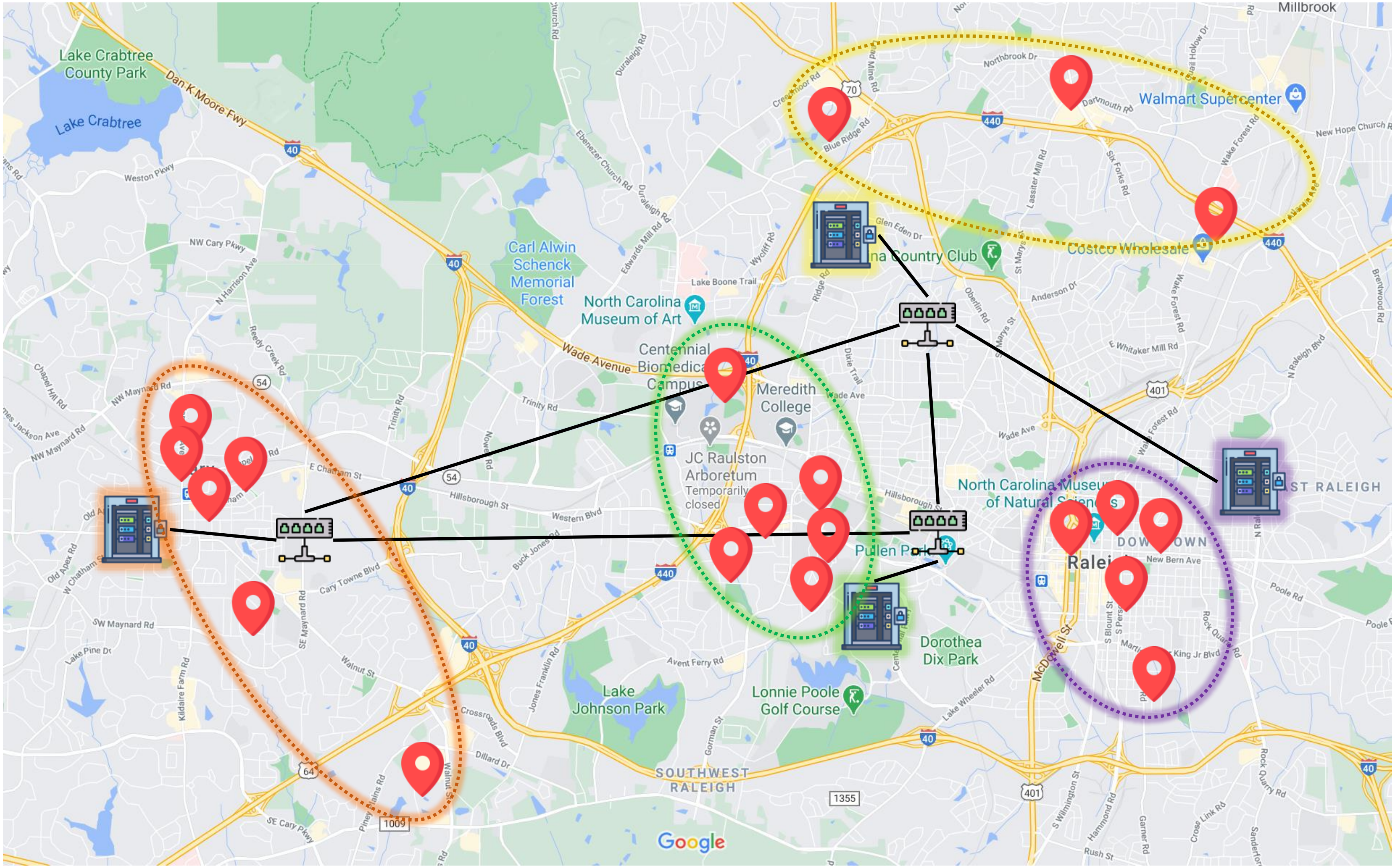
System Modeling

Algorithm Design and Analysis

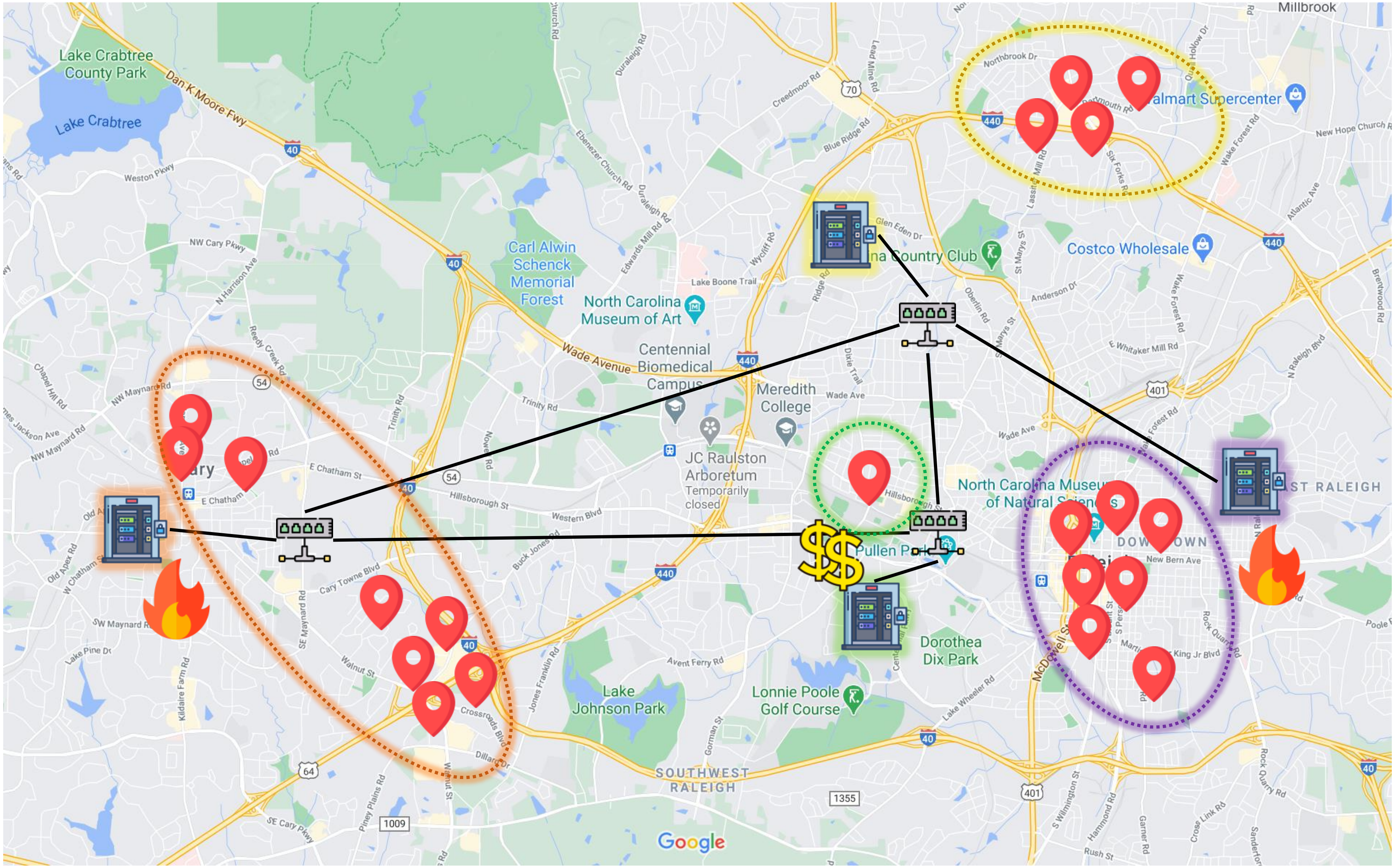
Performance Evaluation

Discussions, Future Work and Conclusions

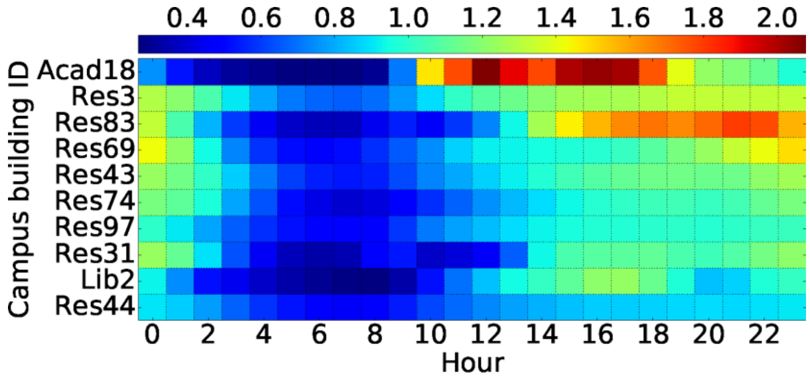
Geo-Distributed Services & Edge Computing



Time-Varying Demands in Geo-Distributed Apps

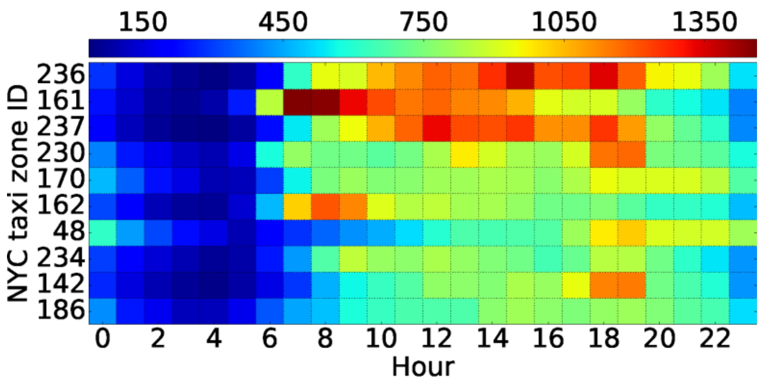


Patterns in Real-world Datasets



Dartmouth College Wireless APs

- Top 10 APs with highest loads
- Load: avg. # devices / hour
- Averaged over a year (9/2002-9/2003)



NYC Yellow Taxi 2018

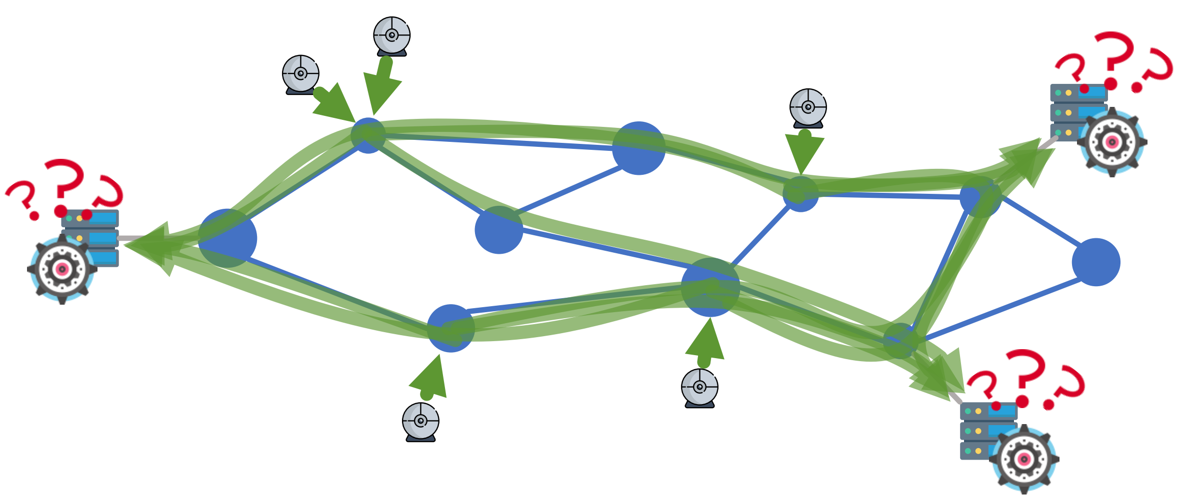
- Top 10 zones w/ most drop-offs
- Load: avg. # passenger drop-offs
- Averaged over a year

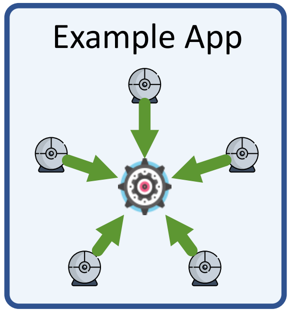
Observation 1: Non-i.i.d. demand distributions across time & locations.

Observation 2: Repeating / seasonal patterns in temporal domain.

Resource Provisioning for Edge Services

- Inputs: edge network (edge nodes), app/service, demands
- Outputs: 1) app/service hosting, 2) traffic routing / engineering
- Studied in the literature, e.g. [1][2], …
- … but with **static inputs**!





[1] **Yu, R.**, Xue, G., & Zhang, X. (2018). Application Provisioning in Fog Computing-enabled Internet-of-Things: A Network Perspective. *Proc. IEEE INFOCOM*, 1–9.
[2] **Yu, R.**, Xue, G., & Zhang, X. (2019). Provisioning QoS-Aware and Robust Applications in Internet of Things: A Network Perspective. *IEEE/ACM Transactions on Networking*, *27*(5), 1931–1944

Methodology Overview

Inputs:

App Demands
Time-varying, geo-distributed

Edge Network
Topology, time-varying delays

System-wide Optimization:

Abstract System Model

- Time-varying model
- System risk model (CVaR)
- Three-stage stochastic optimiz.

Optimization Framework

- Nested Bender decomposition
- Efficient subproblem solving

Outputs:

Service Deployment
Global fixed decisions

Net Provisioning
Per-time slot decisions

Net Estimation
Per-realization decisions

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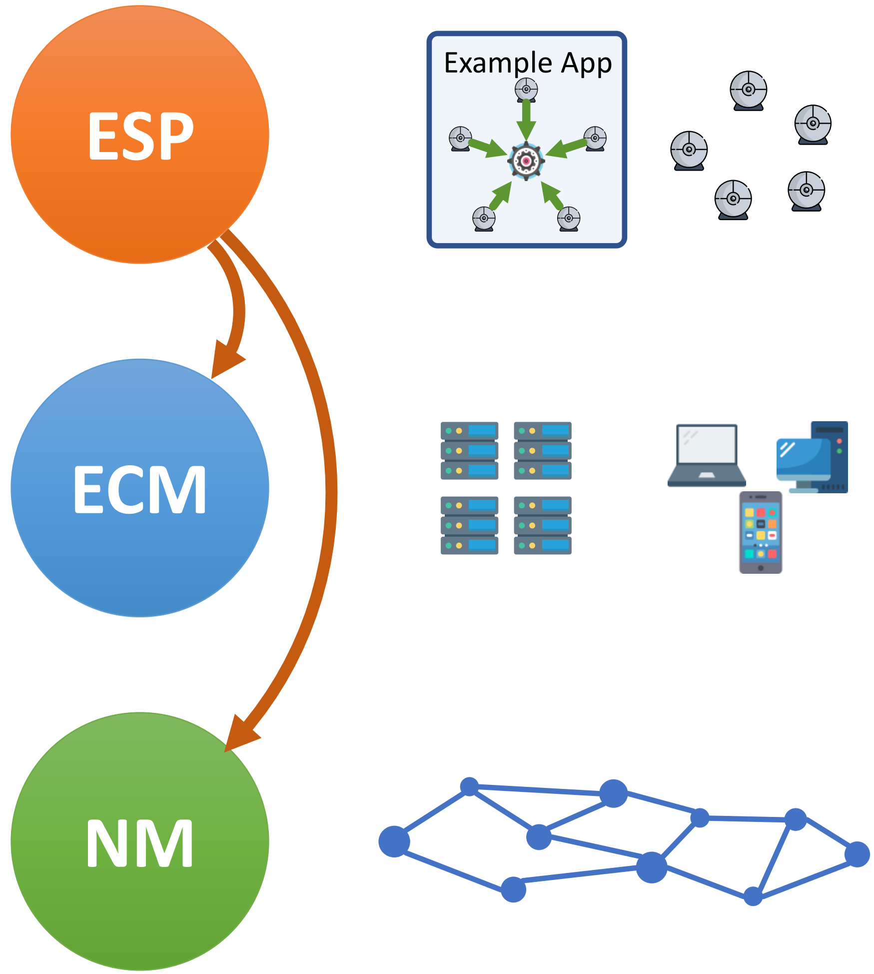
System Model: Involved Parties

Edge Service Provider
- Submits service requests
- Measures and predicts demands
- Dynamically balances load

Edge Computing Manager(s)
- Manages edge nodes & resources
- Decides computing costs

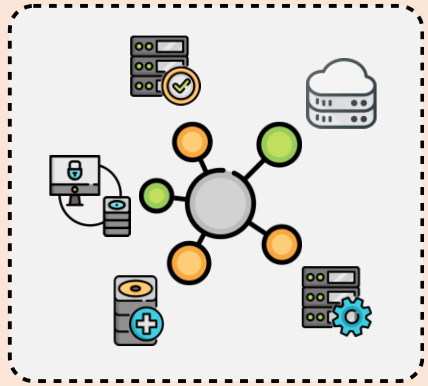
Network Manager
- Manages edge network
- Decides network policies
- Provisions network resources (bw)



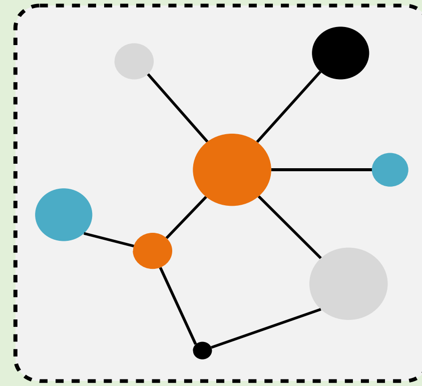
Edge Network: A General Model

- **Challenge:** heterogeneous network environments

Wireless RANs:
- Geo-distributed
- Limited capacity
- Interference



Edge Network:
- Complex topo
- Distributed
- Dynamic load



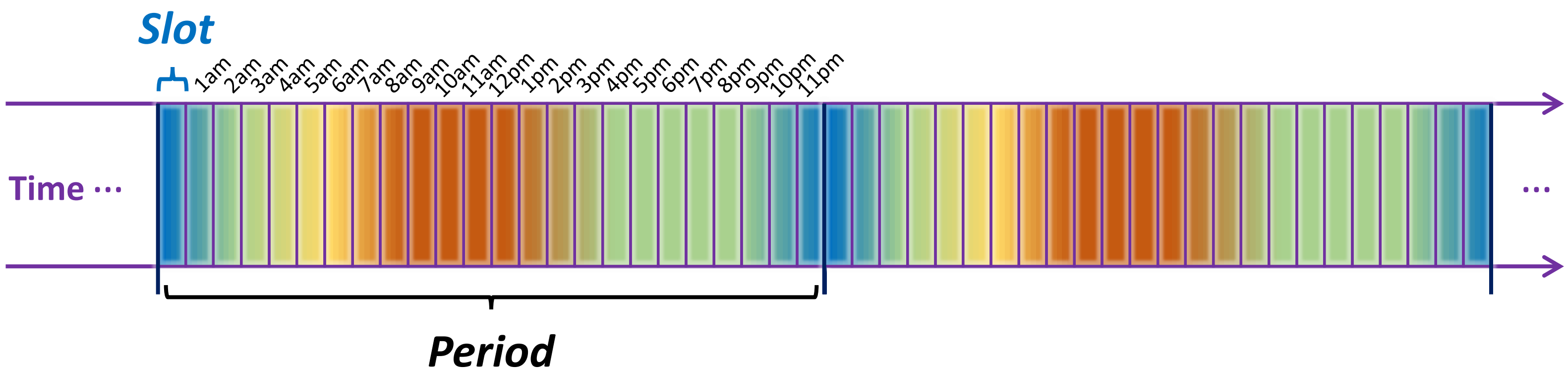
Backbones:
- Large-scale
- High latency
- ISP policies

- **Model:** general directed graph G=(N, L), with edge nodes H and APs A
  - Weights: link bandwidth, <link delay>, edge node cost, <AP demand>

Edge Demand Model

- **Challenge:** non-static, time-varying
- **Observation:** seasonal/repeating patterns
  - *Example:* the load in the same hour of workdays at an AP is similar

- **Repeating time-slotted demand model**



  - **Demand across slots in one period:** non-i.i.d.
  - **Demand per slot across periods:** i.i.d.

Edge Resource Provisioning /I

- Challenges: which decisions should be dynamic, which static?
- Formulation: a three-stage decision problem

- **Stage 1: Service Deployment (SD)**
  - *Deploy edge service on host nodes by ECM*
  - **Globally fixed:** **static** across time slots & periods.

- **Stage 2: Network Provisioning (NPR)**
  - *Network routing and bandwidth allocation by NM*
  - **Per-slot:** **dynamic** across time slots, but **static** for same slot across periods!

- **Stage 3: Network Estimation (NE)**
  - *Instantaneous traffic allocation by ESP*
  - **Dynamic:** **dynamic** across both time slots and periods!

Objective and Overall Formulation

- **Objective:** minimize max traffic-averaged delay across time slots

$$\min_{\mathcal{X}\in\mathcal{F}} \max_t \{D_t\}, \quad (8)$$

$s.t.$

Stage 1: SD

$$\sum_{h\in H} c_h \underline{x(h)} \le C. \quad (1)$$

$$\sum_{h\in H} x(h) \ge 1. \quad (2)$$

Stage 2: NPR

$$\underline{y(t,p)} \le b_p^{\max} x(h_p), \quad \forall t, p \in P, \quad (3)$$

$$\sum_{p\in P: l\in p} y(t,p) \le b_l, \quad \forall t, l \in L. \quad (4)$$

Stage 3: NE

$$\underline{z(t,p)} \le y(t,p), \quad \forall t, p \in P. \quad (5)$$

$$\sum_{p\in P_a} z(t,p) \ge \delta_{t,a}, \quad \forall t, a \in A, \quad (6)$$

$$D_t \triangleq \frac{1}{\delta_t} \sum_{p\in P} d_{t,p} z(t,p). \quad (7)$$

- But $\{\delta_{t,a}\}$ and $\{d_{t,p}\}$ are both random…

SO and CVaR

- **Stochastic Optimization (SO)**: optimize a function in presence of randomness (random objective and/or constraints)
  - Traditional approach: expectation optimization

$$\min_{\chi \in \mathcal{F}} \max_t \ \mathbb{E}[\ D_t\ ]$$

  - **Issue**: unbounded risk in rare but unfortunate scenarios
    - E.g., abnormal demands due to public events, rare large-scale failures, …

  - How to model these *unfortunate scenarios*?
  - Value-at-Risk (VaR) and Conditional-Value-at-Risk (CVaR):
    - Widely used in economics and finance
    - $\text{VaR}_\alpha(\text{R}) = \min \{ \text{c} \in \mathbb{R} \mid \text{R does not exceed c with at least } \alpha \text{ prob.} \}$
    - $\text{CVaR}_\alpha(\text{R}) = \mathbb{E}[\ \text{R} \mid \text{R} \geq \text{VaR}_\alpha(\text{R})\ ]$
      - Expectation of R in the worst (1-α) scenarios
  - **Our approach**: optimize both expectation and CVaR

$$\min_{\mathcal{X} \in \mathcal{F}} \max_t \left\{ \rho_1 \cdot \mathbb{E}[D_t] + \rho_2 \cdot \text{CVaR}_\alpha(D_t) \right\}, \qquad (11)$$

Final SAA Formulation

- The **Robust Edge Provisioning (REP)** problem

$\max_t$ **Linearization**

SAA Terms

$$\min_{\substack{X,Y,Z,\\R,W,D}} \quad \boxed{D} \tag{14a}$$

$$\text{s.t.} \quad D \geq \rho_1 \boxed{\frac{1}{K}\sum_{k=1}^{K} D_t^k} + \rho_2 \left(r(t) + \frac{1}{1-\alpha} \boxed{\frac{1}{K}\sum_{k=1}^{K} w(t,k)} \right), \forall t; \tag{14b}$$

$$w(t,k) \geq D_t^k - r(t), \quad \forall t, k; \tag{14c}$$

(1)–(4), and $\forall t, k$, (5)–(6).

CVaR LP Transformation
(Rockafella & Uryasev)

MILP with $\Theta(TKP)$ variables.

NP-hard by reduction from *Knapsack*.

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Iterative Optimization Algorithm

- **Benders' decomposition**: (Row Generation) In each iteration, add new constraints (cuts) to the problem that push the main problem towards the optimal:
  - INIT: feasible main solution; then proceed in iterations:
    - Solve sub dual problem based on main solution (UB).
    - If sub dual unbounded, add feasibility cut to main;
if sub dual optimal, add optimality cut to main.
    - Solve updated main (LB).
  - Until UB – LB < ϵ.

- **Nested Benders' decomposition**
  - Apply two Benders' decompositions for Phase-I and Phase-II respectively.

Convergence to **optimality**: proof by Benders.

Additional Techniques Applied

Multiple Cuts (Birge & Louveaux)

- Dividing one optimality cut into one cut per sub-problem.
- Improves efficiency by pruning more sub-optimal region per-iteration.

Fast Forward Fast Backward (FFFB)

- Do not wait till Phase-II convergence to update Phase-I main problem
- Cuts based on non-optimal Phase-II solutions help prune more sub-optimal region per-iteration.

Analytical Stage-3 Dual Solving

- Linear time algorithm for solving the Stage-3 dual problems…
- … instead of cubic time for solving as an LP

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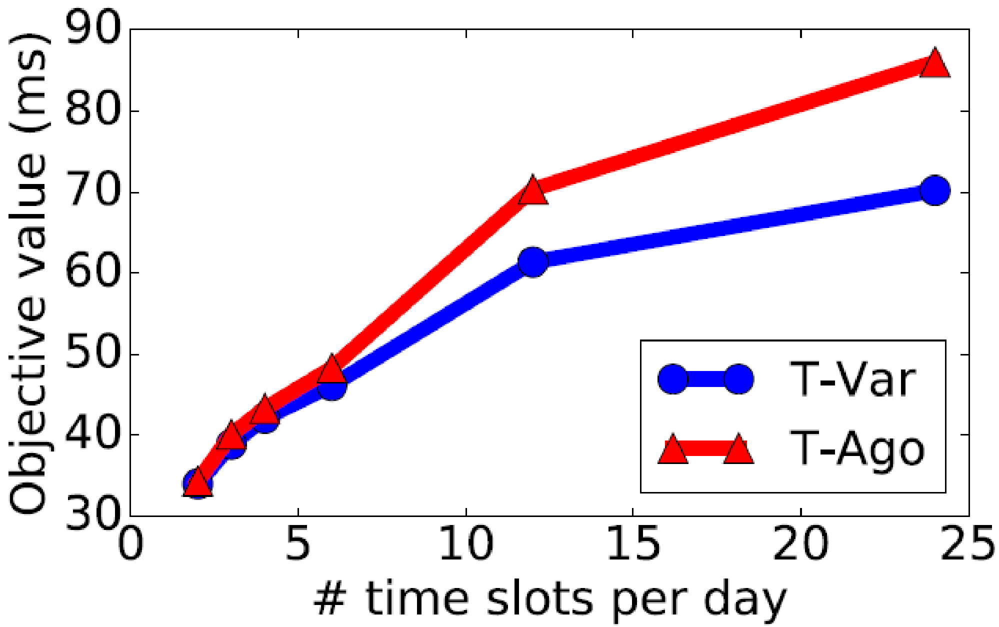
Simulation Settings

- Settings
  - Dataset: NYC Yellow Taxi 2018
    - 12 months of Taxi drop-off data (~112 million taxi trips)
    - Picked 5 or 20 most popular zones out of 262 (18% or 55% of all demands)
    - 100-days for training: solving SAA formulation for SD and NPR
    - 265-days for testing: evaluating solutions with NE
  - Synthetic Data
    - Random topologies: Watts-Strogatz with k = 4 and p = 0.3 (5 edge nodes)
    - Deployment costs: $\mathcal{N}(1000, 200^2)$; cost budget: 3300 (uniform)
    - Pathbook: 3 min-hop paths for each AP-Edge node pair
    - Network conditions:
      - Normal scenario: 5 Gbps links with $\mathcal{N}(10, 4^2)$ ms delays
      - Congested scenario: 2 Gbps links with half nodes experiencing 50× delays
  - $\rho_1 = \rho_2 = 0.5$ (expectation vs. CVaR), $\alpha = 0.95$ (CVaR confidence), $\epsilon = 10^{-3}$ (convergence)

Experiment Results



T-Var: time-varying

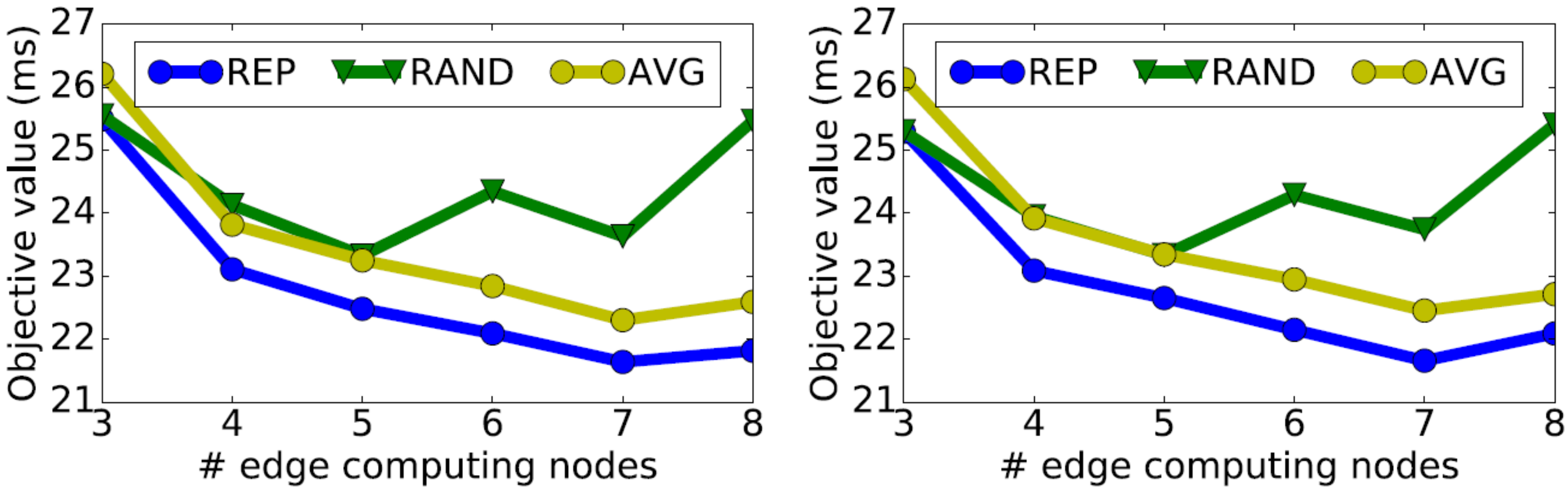
T-Ago: time-agnostic

Setting: Small/Congested

Time-varying vs. Time-agnostic

- Time-varying has increased advantage over time-agnostic with more slots.
  => **Fixed provisioning** without per-slot adjustment has **poor performance**.
  (For each slot, load is averaged over entire slot.)

Experiment Results



(a) Training objective value **(b) Testing objective value**

Optimal vs. Heuristics

- Consistent performance advantage over heuristics
  => User satisfaction / revenue in the long-term

RAND: random edge node

AVG: optimiz. avg. delay

Setting: Medium/Normal

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Other Perspectives, Conclusions

- So far, we've talked about
  - Model: time-varying demands & network
  - CVaR w/ multi-stage stochastic optimization
  - Provisioning with single service & pathbook

  First-attempt modeling & solving

- What could be improved
  - Multi-service provisioning / sharing
  - Dynamic routing w/o pathbook
  - Multi-dimensional network resources

  Modeling Perspective

  - Distribution-aware formulations

  Stochastic Perspective

  - Improved optimization methods
  - Learning-based optimization

  Algorithmic Perspective

- **Conclusions:** observed uncertainties => risk-aware networking

Thank you very much!

Q&A?