NFV Orchestration in Edge and Fog Scenarios

26th October, 2021

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Outline

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1. Generation of 5G infrastructure graphs
2. NFV Orchestration in federated environments
3. NFV orchestration for 5G networks: OKpi
4. Scaling of V2N services: a study case
5. Conclusions & future work

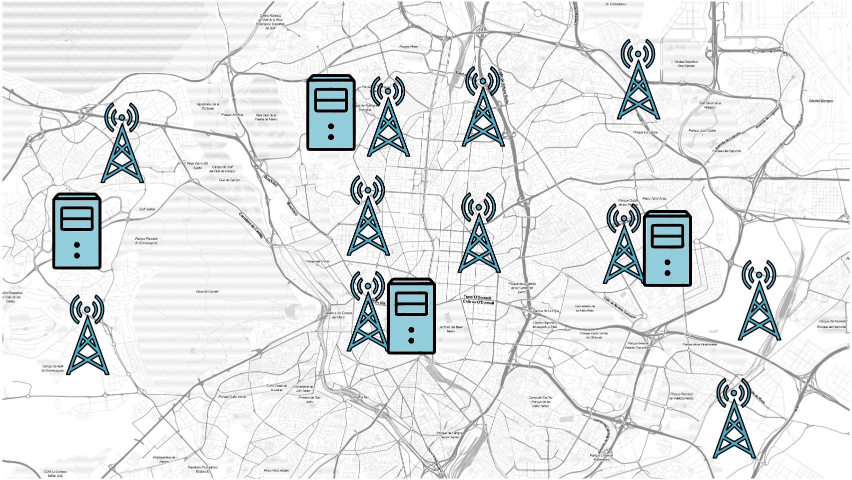

Figure 1: Illustration of BS and PoPs in Madrid

Location of BSs:

- Neyman-Scott Poisson Cluster Process [27]
- Poisson Point Processes (PPPs) [4]
  - homogeneous [28, 1]
  - hard-core [9]

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Location of MEC PoPs:

- along highways [29]
- within stadiums [8]

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Location of MEC PoPs:

- along highways [29]
- within stadiums [8]
- **population census**
- **access & aggregation rings**

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Derive:

- BS location
- MEC PoP location

Meet:

- Tactile RTT of **1 ms**

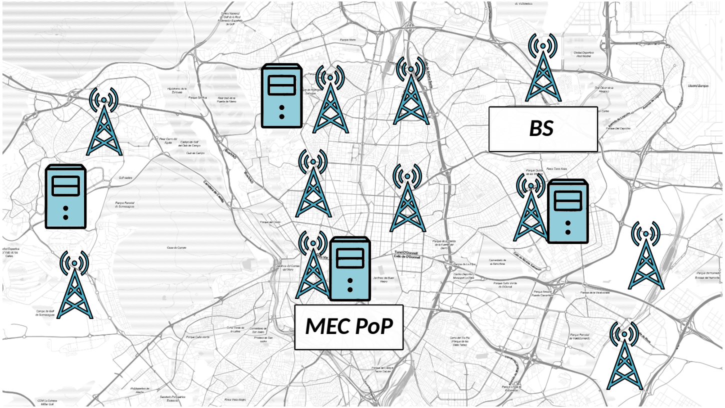

Figure 2: BS and MEC PoP locations

Higher gentrification $\implies$ more BSs

- R – region of interest
- C_i – area

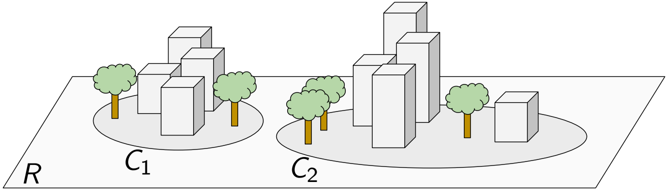

Figure 3: *Revolution functions* of a region with two building areas.

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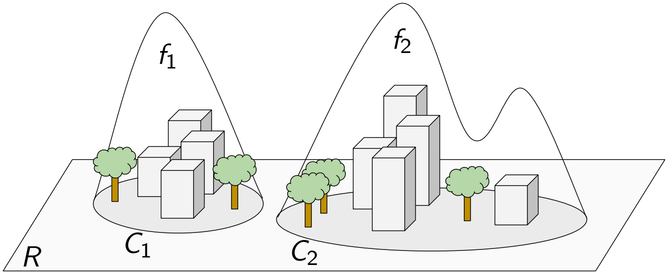

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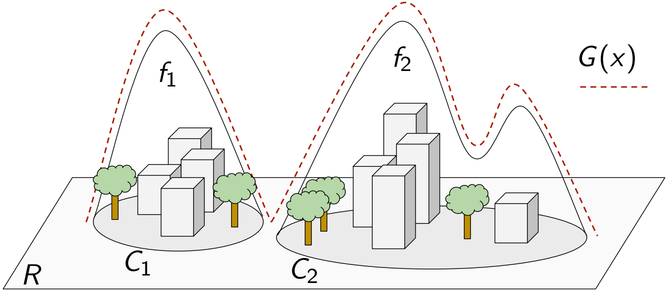
- R – region of interest
- C_i – area
- $f_i(x)$ – revolution func.
- $G(x)$ – gentrification
  - $G(x) = \sum_i f_i(x)$



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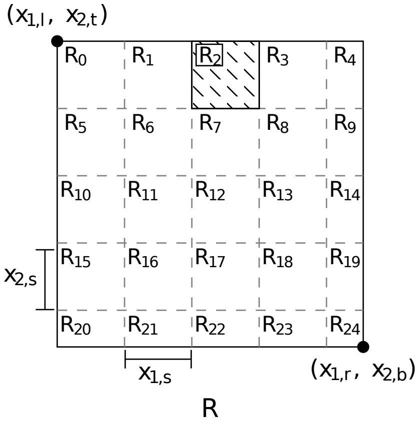


Figure 4: Gridded region

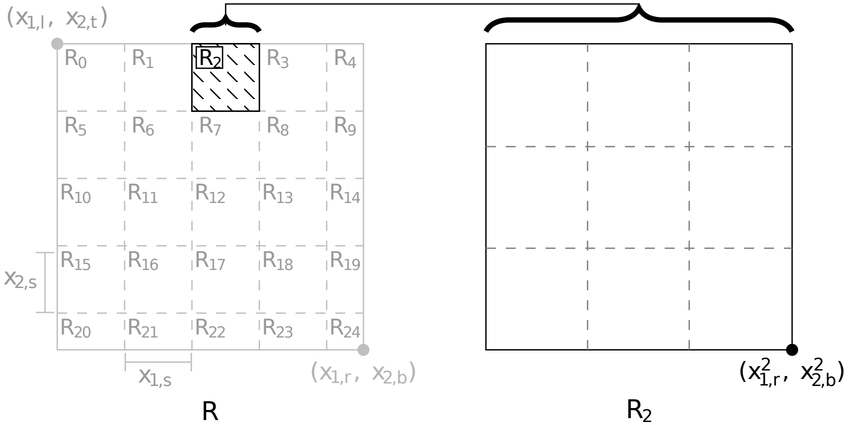
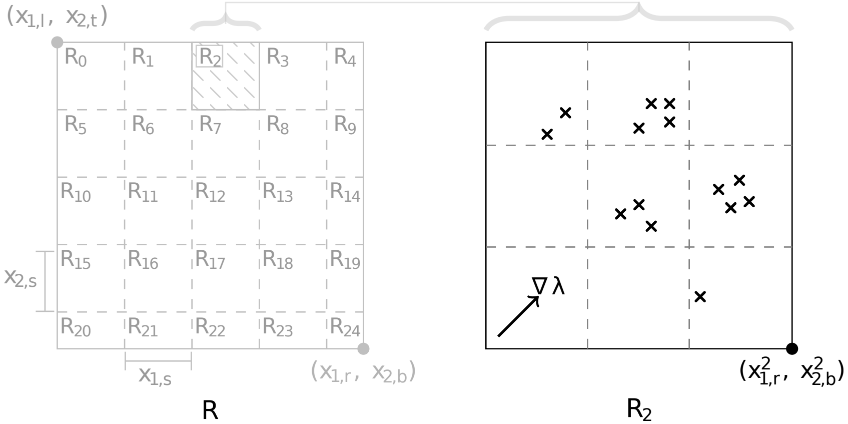


Figure 4: Gridded region (left), and inhomogeneous Mattérn II process of BSs (right).

BS intensity function $\lambda(x) \sim G(x)$ proportional to gentrification.



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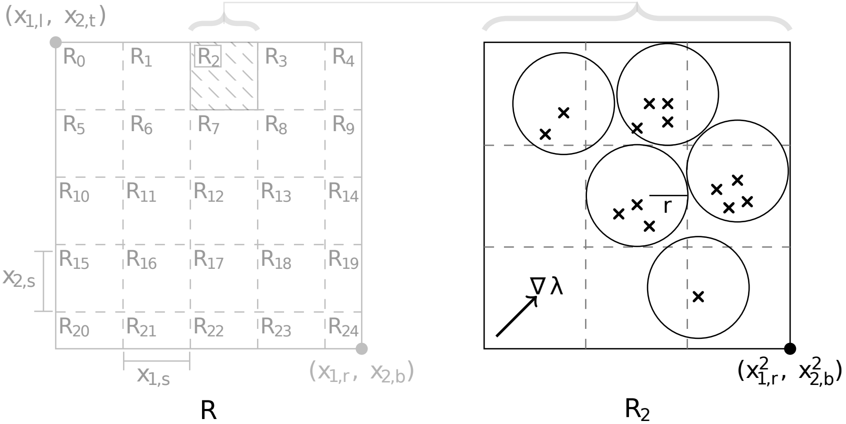

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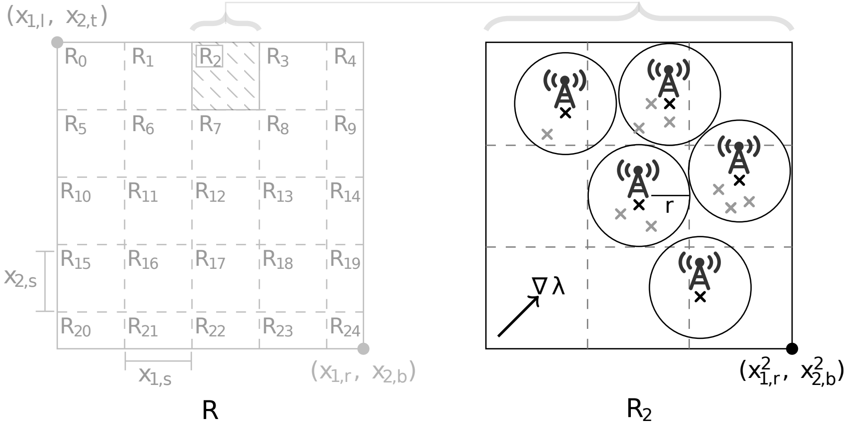

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Inhomogeneous Mattérn II PPs applied on:

- R: Madrid city
- $G(x)$: Madrid census

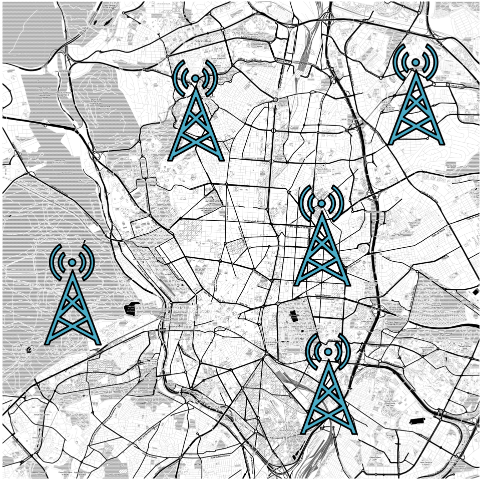

Figure 5: Location of BSs

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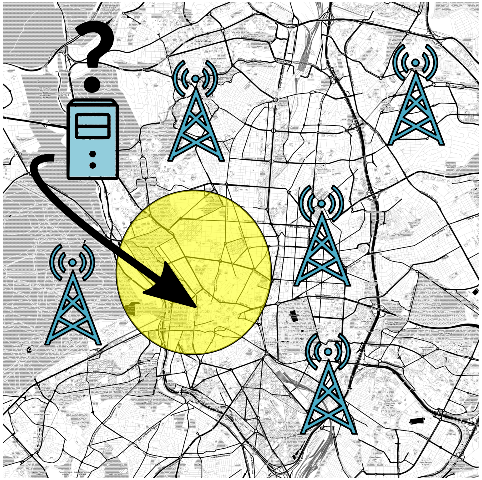


Figure 5: Location of BSs

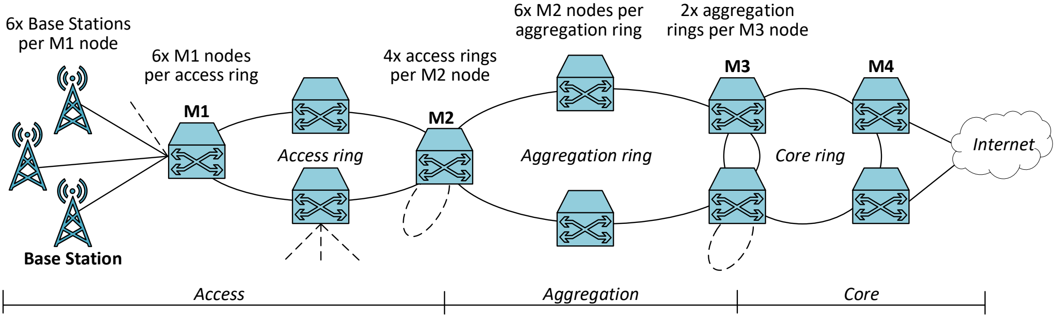
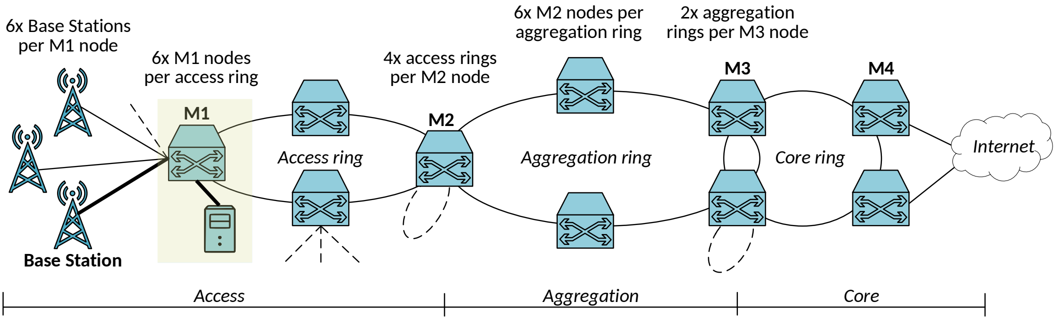


Figure 6: Reference network infrastructure as illustrated[1] in [6] and based on [10].

[1]Author: Dr. Luca Cominardi.



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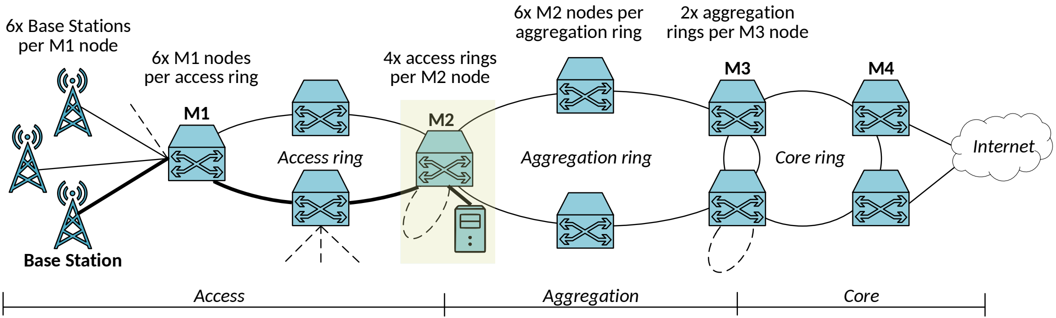

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Derive MEC PoP location considering:

$$RTT = \underbrace{2d \cdot 5\frac{\mu s}{km}}_{\text{fiber propagation}} + 2M \cdot 50\mu s + UL + DL \tag{1}$$

- d: distance between BS and MEC PoP
- M: network ring (M1,M2,M3,M4)
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- UL: Uplink propagation latency
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m_M: maximum distance between MEC PoP at ring M and BS

Figure 7: How to select MEC PoP location

m_2: maximum distance between MEC PoP at ring 2 and BS

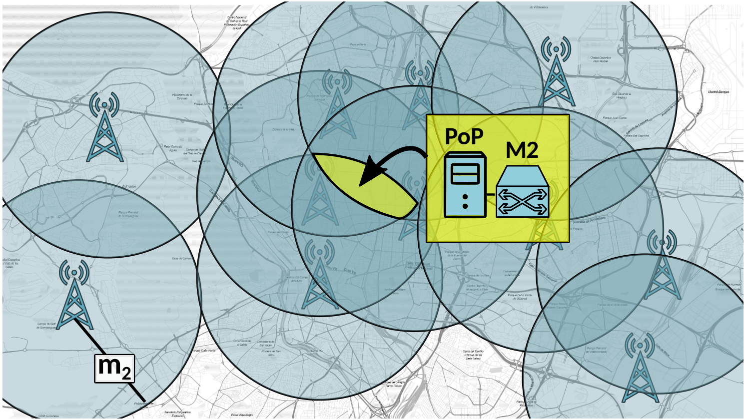
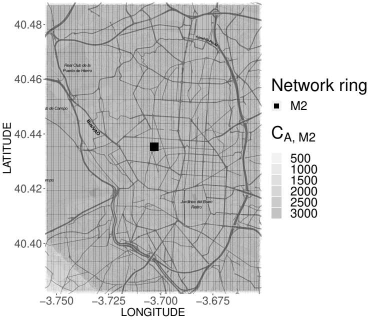
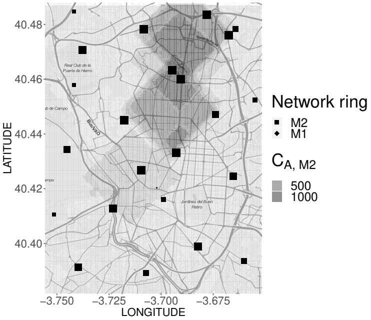


Figure 7: How to select MEC PoP location

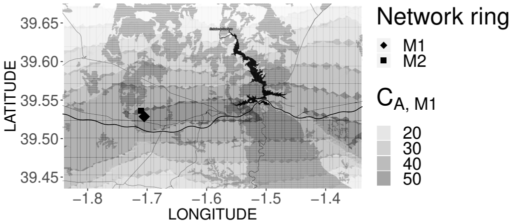


(a) FDD 120 kHz 7s



(b) TDD 120 kHz 7s

Figure 8: **Urban scenario** (Madrid city center) – $C_{A,M2}$ =covered BSs



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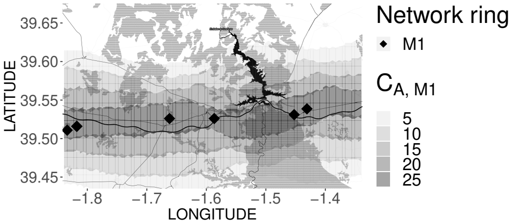

(b) TDD 120 kHz 7s

Figure 9: **Highway scenario** (Hoces del Cabriel A3) – $C_{A,M1}$ =covered BSs by M1 MEC PoP

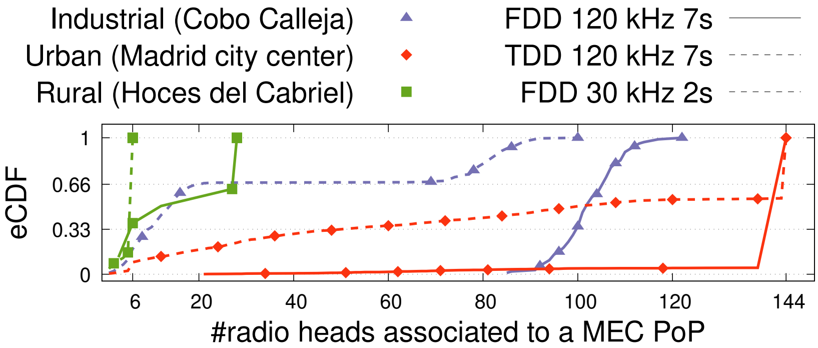

Figure 10: eCDF of the number of BSs assigned to a MEC PoP in the studied scenarios.

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Publications:

- **Martín-Pérez, Jorge**, L. Cominardi, C. J. Bernardos, A. de la Oliva, and A. Azcorra. "Modeling Mobile Edge Computing Deployments for Low Latency Multimedia Services". In: *IEEE Transactions on Broadcasting* 65.2 (2019), pp. 464–474. DOI: 10.1109/TBC.2019.2901406
- **Martín-Pérez, Jorge**, L. Cominardi, C. J. Bernardos, and A. Mourad. "5GEN: A tool to generate 5G infrastructure graphs". In: *2019 IEEE Conference on Standards for Communications and Networking (CSCN)*. 2019, pp. 1–4. DOI: 10.1109/CSCN.2019.8931334

Open-source:

- **BS & MEC PoP generation**: github.com/MartinPJorge/mec-generator
- **5GEN**: 5GEN R package

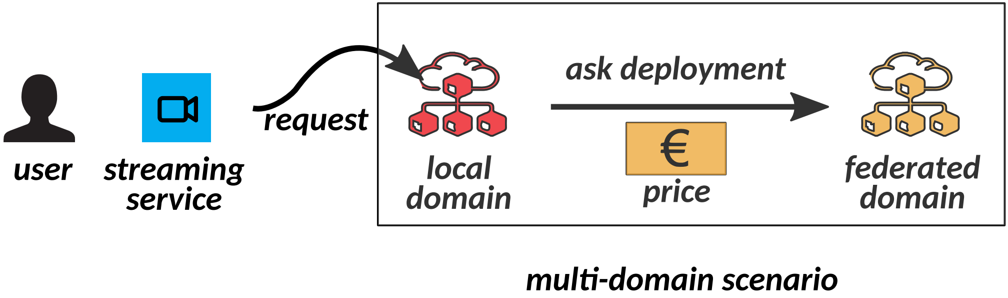

Figure 11: Service federation

Orchestration and **fixed pricing** in multi-domain:

- Alternating Direction Method of Multipliers (ADMM) [23]
- branching heuristic [11]
- graph-based message passing [33]
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- TID scenario

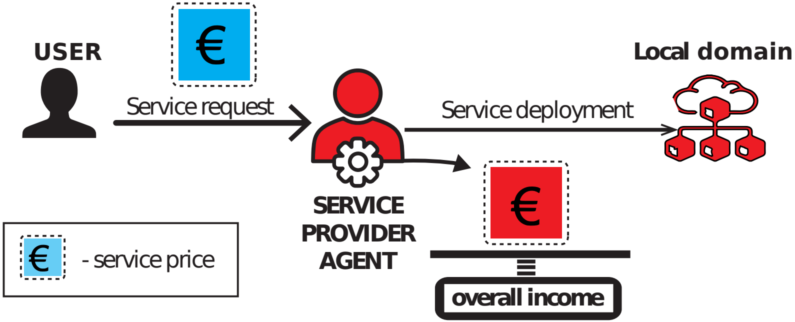

Figure 12: Business model - local deployment[2].

[2] Based on Kiril Antevski illustration

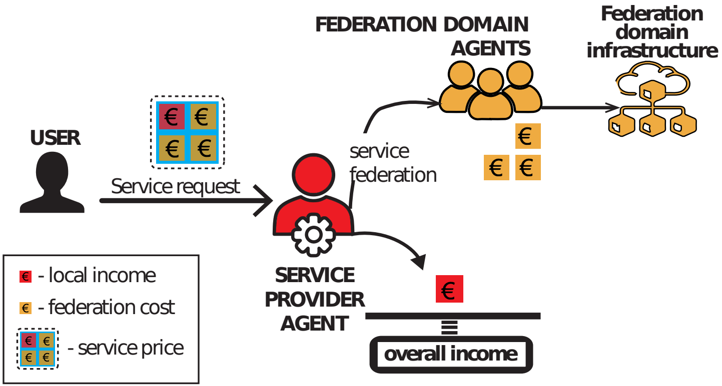

Figure 13: Business model - federate deployment[3].

[3] Based on Kiril Antevski illustration

t3a.small:

- 2 CPUs
- memory 2 GB
- storage 100 GB

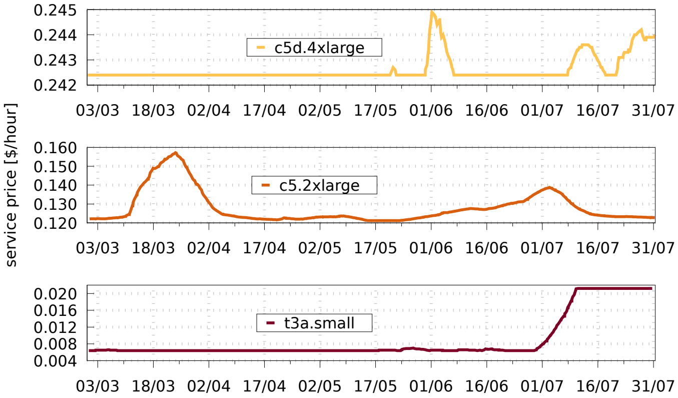

Figure 14: AWS service prices during 2020 in west Europe.

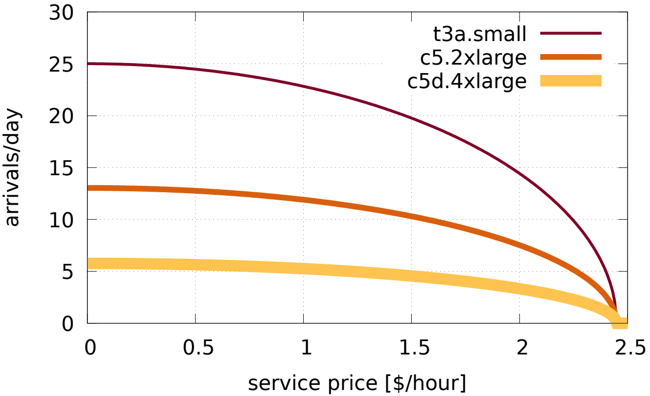

Figure 15: Impact of prices on arriving users – based on tid study [26] and [31].

Considering:

- Price changes
- Available resources (CPU, memory, disk)
- Service lifetime (e.g., 2 days)

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For each service σ, decide / take an **action**:

- $x(\sigma) = 0$: **reject**
- $x(\sigma) = 1$: **local**
- $x(\sigma) = 2$: **federate**

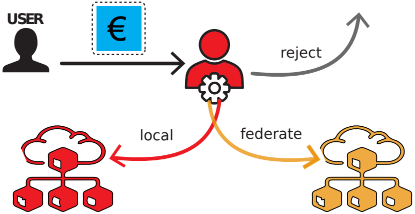


Figure 16: Possible actions.

Obtained **reward**:

$$r^{(t)}(X_t) := \sum_{\substack{\sigma:\ x(\sigma)=0\\ a(\sigma)\leq t\leq d(\sigma)}} p^{a(\sigma)}(\sigma) + \sum_{\substack{\sigma:\ x(\sigma)=1\\ a(\sigma)\leq t\leq d(\sigma)}} \left[p^{a(\sigma)}(\sigma) - f^{(t)}(\sigma)\right] \quad (2)$$

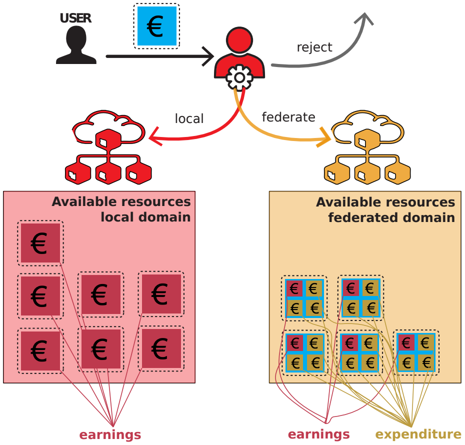
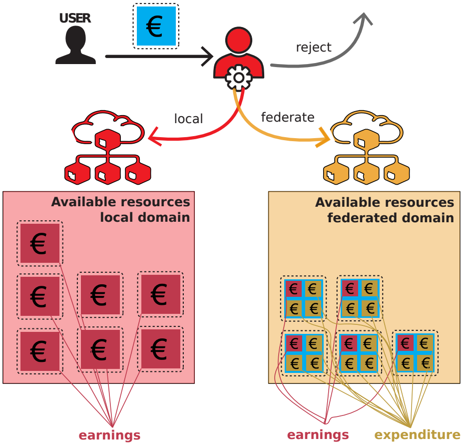


Figure 17: Environment snapshot at time t.

Obtained **reward**:

$$r^{(t)}(X_t) := \underbrace{\sum_{\substack{\sigma:\ x(\sigma)=0\\ a(\sigma)\leq t\leq d(\sigma)}} p^{a(\sigma)}(\sigma)}_{\text{local}} + \sum_{\substack{\sigma:\ x(\sigma)=1\\ a(\sigma)\leq t\leq d(\sigma)}} \left[p^{a(\sigma)}(\sigma) - f^{(t)}(\sigma)\right] \quad (2)$$



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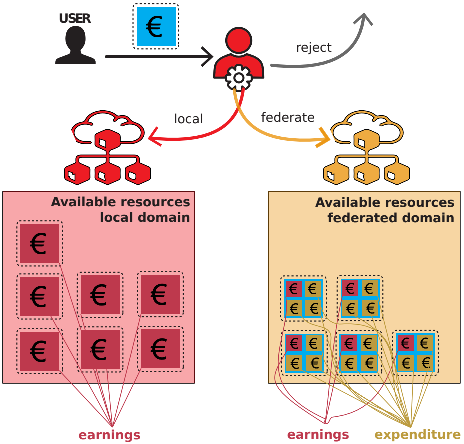

Figure 17: Environment snapshot at time t.

Online optimization problem:

- objective: $\max_{X_t} \frac{1}{T} \sum_t r^{(t)}(X_t)$
- constraints:
  - CPU
  - memory
  - disk

NP-hard: knapsack problem equivalence

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- constraints:
  - CPU
  - memory
  - disk

NP-hard: knapsack problem equivalence

Markov Decision Problem (MDP):

- find policy π to:
  $\max_\pi \mathbb{E}_{x(\sigma)\sim\pi} \left[\sum_t \gamma^t \; r^{(t)}(\pi)\right]$
- action space $\mathcal{A} = \{0, 1, 2\}$
- state space $\mathcal{S}$:
  - available & requested resources
  - current prices
  - service lifetime
- instant reward $r^{(t)}(\pi)$

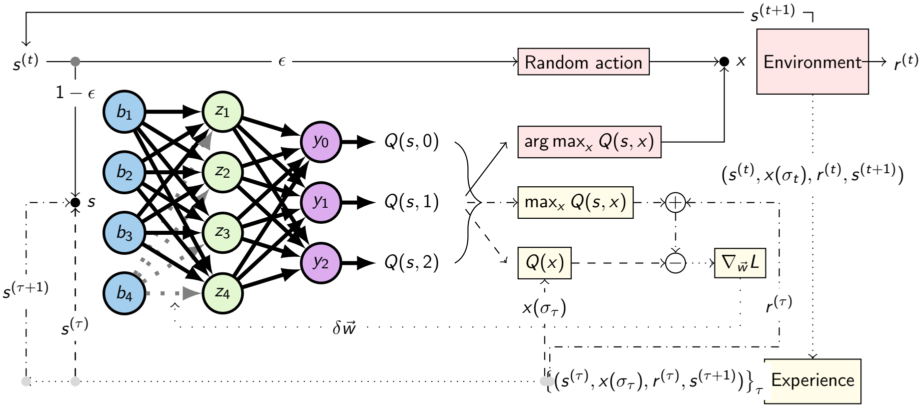

Figure 18: DQN architecture to decide rejection/local/federate.

Experimentation:

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  - training 29/02/2020 – 02/05/2020
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- TID infrastructure & resources [26]
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- Poissonian arrival of users

Comparison of:

- Optimal
- DQN
- Q-table
- Q-table explore
- greedy

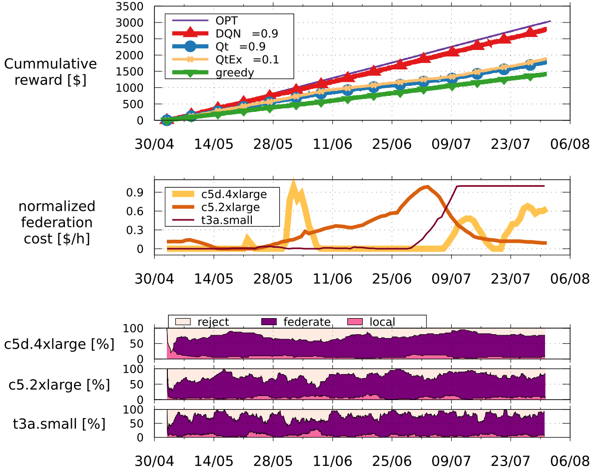

Figure 19: federation agents' performance.

Comparison of:

- Optimal
- DQN
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- Q-table explore
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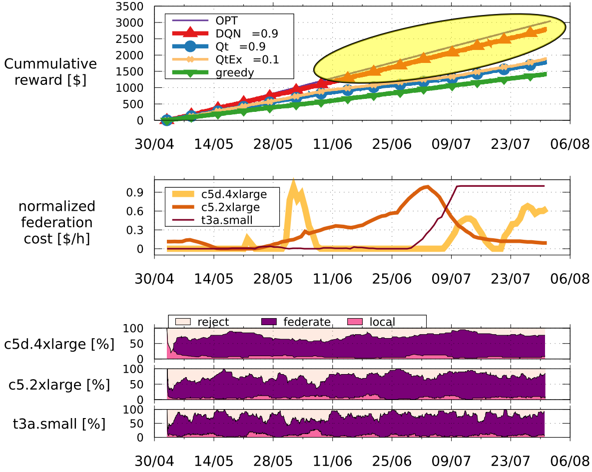
Results:

- near-optimal



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NFV Orchestration in federated environments
Thesis contribution

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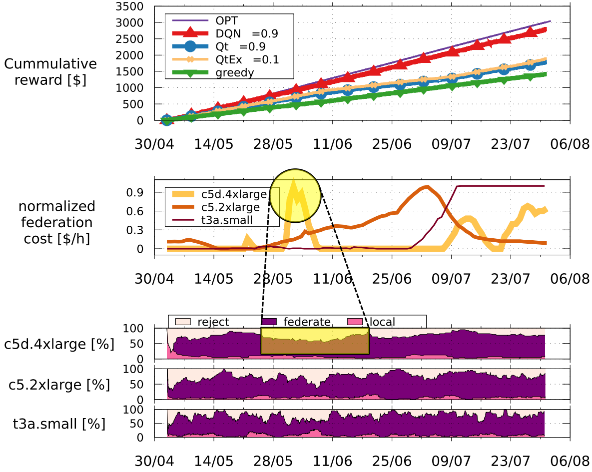
Comparison of:

- Optimal
- DQN
- Q-table
- Q-table explore
- greedy

Results:

- near-optimal
- react upon peaks



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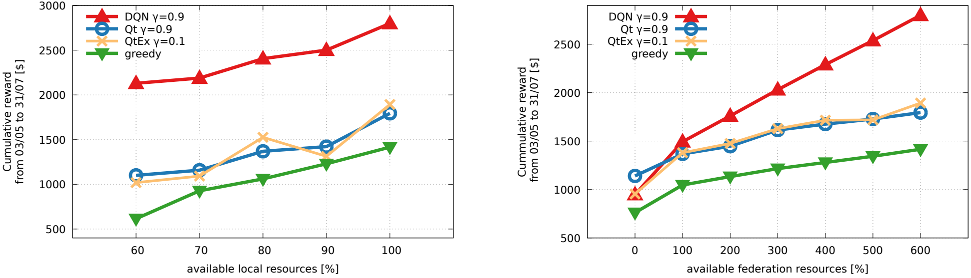


(a) Increasing local resources. (b) Increasing resources in federation.

Figure 20: Cumulative reward vs. available resources

Publications:

- **Martín-Pérez, Jorge** and C. J. Bernardos. "Multi-Domain VNF Mapping Algorithms". In: *2018 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*. 2018, pp. 1–6. DOI: 10.1109/BMSB.2018.8436765
- K. Antevski, **J. Martín-Pérez**, A. Garcia-Saavedra, C. J. Bernardos, X. Li, J. Baranda, J. Mangues-Bafalluy, R. Martnez, and L. Vettori. "A Q-learning strategy for federation of 5G services". In: *ICC 2020 - 2020 IEEE International Conference on Communications (ICC)*. 2020, pp. 1–6. DOI: 10.1109/ICC40277.2020.9149082
- **Martín-Pérez, Jorge**, K. Antevski, A. Garcia-Saavedra, X. Li, and C. J. Bernardos. "DQN Dynamic Pricing and Revenue driven Service Federation Strategy". In: *IEEE Transactions on Network and Service Management* (2021), pp. 1–1. DOI: 10.1109/TNSM.2021.3117589

Open-source:

- **DFS, BFS w/ cutoffs**: `https://github.com/MartinPJorge/placement`
- **Q-table**: `https://github.com/MartinPJorge/5gt-federation`
- **DQN & environment**: `https://github.com/MartinPJorge/5gt-federation/tree/extensionICC/utils/aws`

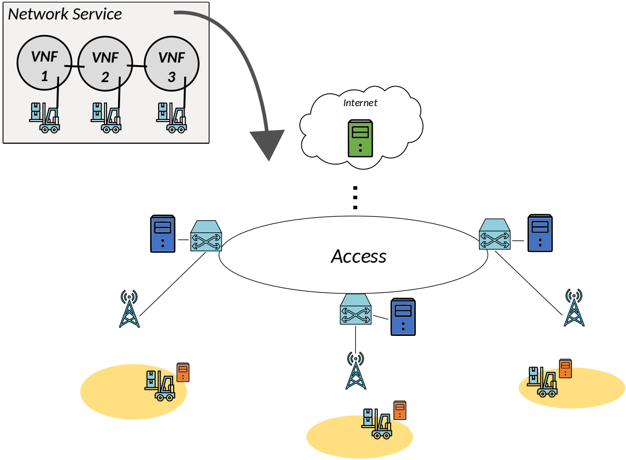
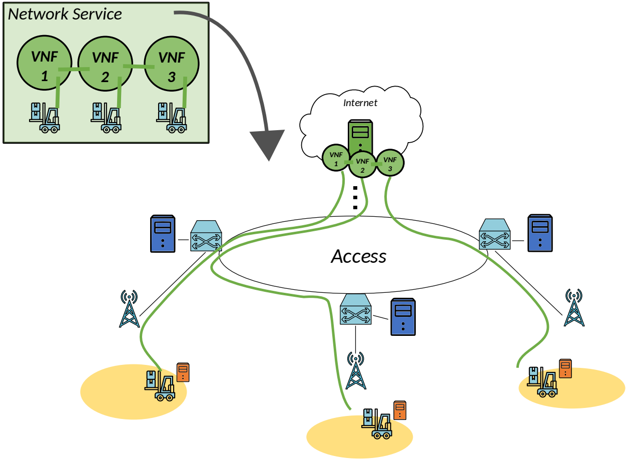


Figure 21: Virtual Network Function Embedding (VNE).



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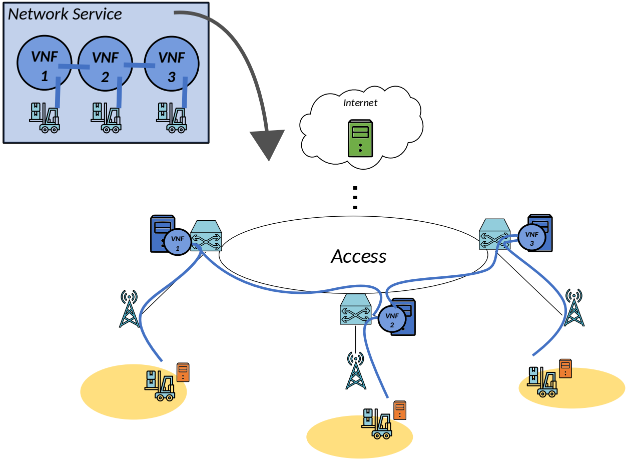


Figure 21: Virtual Network Function Embedding (VNE).

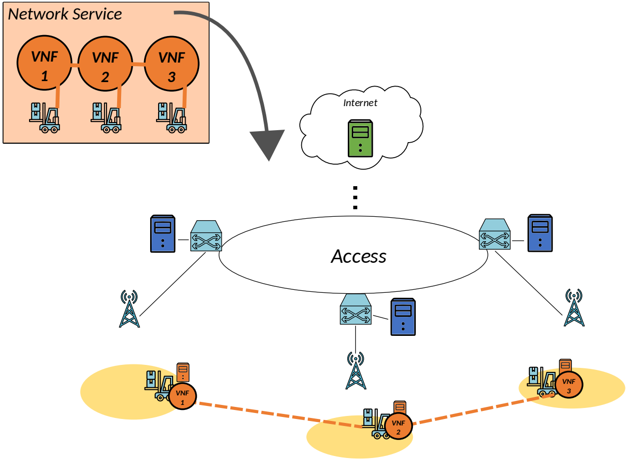


Figure 21: Virtual Network Function Embedding (VNE).

Existing Virtual Network Embedding (VNE) solutions:

- latency-aware, bipartite graph & Hungarian [12]
- maxZ: latency-aware, relaxed ILP [2]
- z-TORCH: KPI monitoring, k-means VNF assign [25]
- AIA: meet latency and throughput [32]

Existing Virtual Network Embedding (VNE) solutions:

- latency-aware, bipartite graph & Hungarian [12]
- maxZ: latency-aware, relaxed ILP [2]
- z-TORCH: KPI monitoring, k-means VNF assign [25]
- AIA: meet latency and throughput [32]

OKpi accounts for:

- latency constraints
- **radio coverage**
- **geographical availability**
- **reliability**

Latency constraint $D(s)$:

$$d_{\text{net}}(\psi) + d_{\text{proc}} \leq D(s) \qquad (3)$$

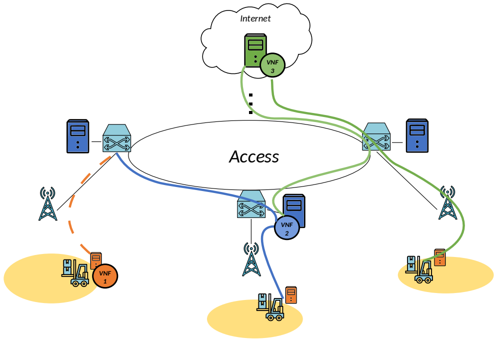


Figure 22: Service s delay.

Latency constraint $D(s)$:

$$\underbrace{d_{\text{net}}(\psi)}_{\text{propagation delay}} + d_{\text{proc}} \leq D(s) \quad (3)$$

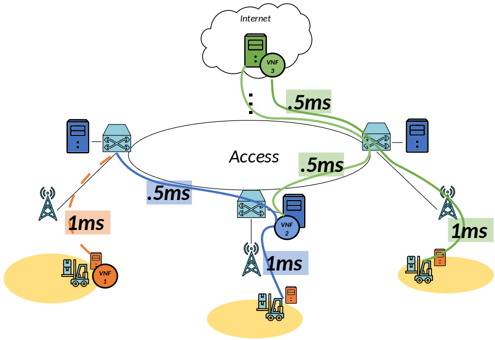


Figure 22: Service s delay.

Latency constraint $D(s)$:

$$d_{\text{net}}(\psi) + \boxed{d_{\text{proc}}(\psi)} \leq D(s) \quad (3)$$

processing delay

d_{proc}: VNF as M/M/1-PS queue

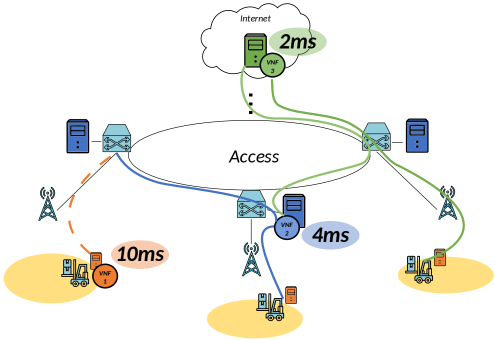


Figure 22: Service *s* delay.

Radio technology i constraint:

$$\rho(v,c)r_i(v) \leq R_i(c) \tag{4}$$

- $\rho(v,c)$: VNF v is deployed in c
- $R_i(c)$: radio point of access c has radio technology i
- $r_i(v)$: VNF v needs radio technology i

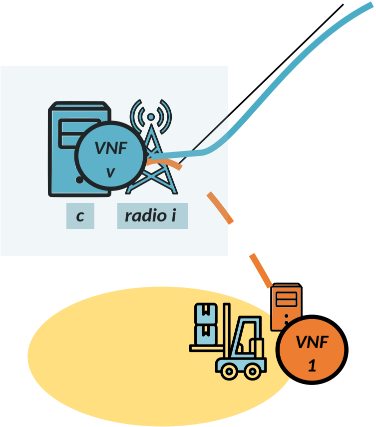


Figure 23: Radio VNF.

Geographical availability:

$$\forall\psi = (\alpha, s), \exists c, v_1, v_2 : \tau_{\psi,c}(e, v_1, v_2) > 0 \quad (5)$$

- location α
- $\tau_{e,c}(e, v_1, v_2)$: flow (ψ, v_1, v_2) traverses link (ψ, c)

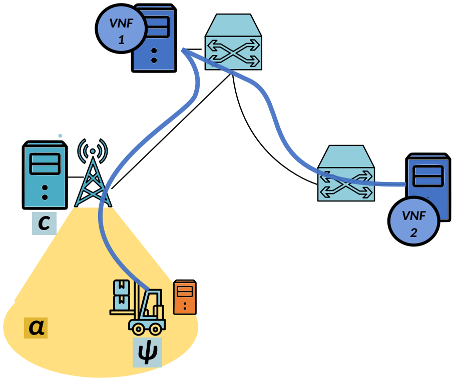


Figure 24: coverage of region α.

Service **reliability** $H(s)$:

$$\prod_{\substack{v_1, v_2 \in \mathcal{V} \\ (i,j) \in w}} \eta(j,t)\eta(i,j,t) \geq H(s) \quad (6)$$

- $\eta(j,t)$: node reliability at t
- $\eta(i,j,t)$: node reliability at t

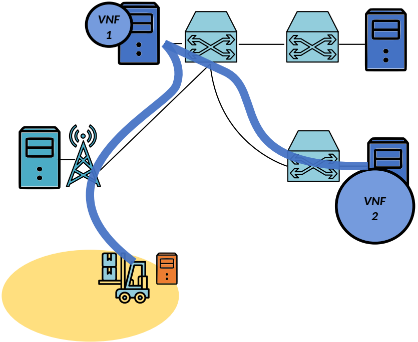


Figure 25: Traffic path.

Service **reliability** $H(s)$:

$$\prod_{v_1,v_2\in\mathcal{V}} \sum_{w\in\mathcal{W}} \underbrace{f(\psi, v_1, v_2, w)}_{\text{traffic fraction}}$$

$$\prod_{(i,j)\in w} \eta(j,t)\eta(i,j,t) \geq H(s) \quad (6)$$

- $\eta(j,t)$: node reliability at t
- $\eta(i,j,t)$: node reliability at t
- w: traffic path

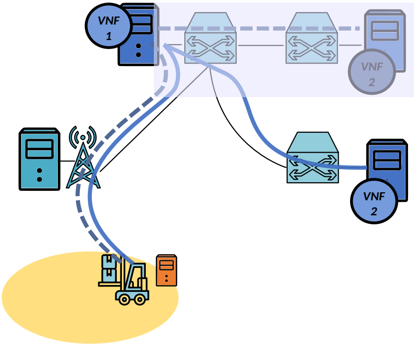


Figure 25: Fractioned traffic path.

Formulate an optimization problem:

$$\min \sum_c \sum_v \left[c_c(v) + \sum_e \sum_\kappa c_c(\kappa) a_c(\psi, v, \kappa) \right] + \sum_{(i,j)} \sum_e \sum_{v_1, v_2} c_{i,j} \tau_{i,j}(\psi, v_1, v_2) \tag{7}$$

$$s.t. (3) - (6) \tag{8}$$

Formulate an optimization problem:

$$\min \sum_{c} \sum_{v} \left[\underbrace{c_c(v)}_{\text{VNF cost}} + \sum_{e} \sum_{\kappa} c_c(\kappa) a_c(\psi, v, \kappa) \right] + \sum_{(i,j)} \sum_{e} \sum_{v_1, v_2} c_{i,j} \tau_{i,j}(\psi, v_1, v_2) \quad (7)$$

$$s.t. (3) - (6) \quad (8)$$

Formulate an optimization problem:

$$\min \sum_{c} \sum_{v} \left[c_c(v) + \sum_{e} \sum_{\kappa} \underbrace{c_c(\kappa) a_c(\psi, v, \kappa)}_{\text{assigned resource } \kappa \text{ cost}} \right] + \sum_{(i,j)} \sum_{e} \sum_{v_1, v_2} c_{i,j} \tau_{i,j}(\psi, v_1, v_2) \quad (7)$$

$$s.t. (3) - (6) \quad (8)$$

Formulate an optimization problem:

$$\min \sum_{c} \sum_{v} \left[c_c(v) + \sum_{e} \sum_{\kappa} c_c(\kappa) a_c(\psi, v, \kappa) \right] + \sum_{(i,j)} \sum_{e} \sum_{v_1, v_2} \underbrace{c_{i,j} \tau_{i,j}(\psi, v_1, v_2)}_{\text{traffic steering cost}} \tag{7}$$

$$s.t. (3) - (6) \tag{8}$$

Formulate an optimization problem:

$$\min \sum_{c} \sum_{v} \left[c_c(v) + \sum_{e} \sum_{\kappa} c_c(\kappa) a_c(\psi, v, \kappa) \right] + \sum_{(i,j)} \sum_{e} \sum_{v_1, v_2} c_{i,j} \tau_{i,j}(\psi, v_1, v_2) \tag{7}$$

$$s.t.(3) - (6) \tag{8}$$

NP-hard: bin-packing problem equivalence.

The **OKpi** (all KPI) solution:

- infrastructure as a graph
- edges with:
  - delay
  - reliability

The **OKpi** (all KPI) solution:

- infrastructure as a graph
- edges with:
    - delay
    - reliability

Solve in two steps:

1. Create a decision graph
2. Create an expanded graph

Decision graph $\tilde{G} = (\tilde{N}, \tilde{E})$.

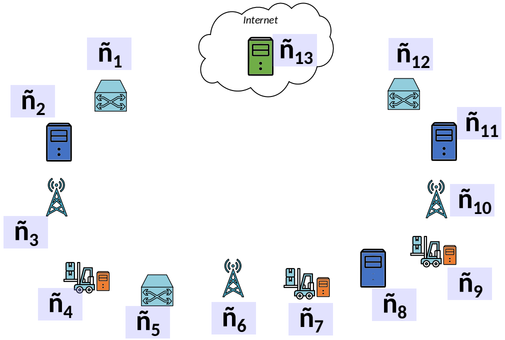


Figure 26: OKpi decision graph.

Decision graph $\tilde{G} = (\tilde{N}, \tilde{E})$.

Nodes $\tilde{N} = \{\tilde{n}_1, \tilde{n}_2, \ldots\}$:

- $|\mathcal{V}| - 1$ replicas

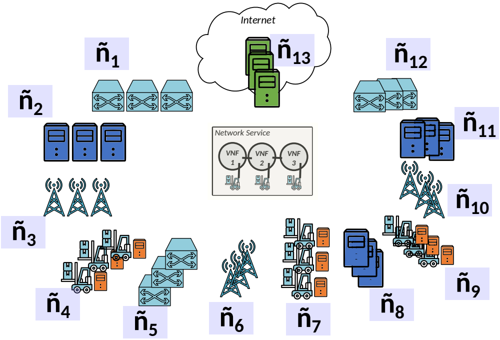


Figure 26: OKpi decision graph.

Decision graph $\tilde{G} = (\tilde{N}, \tilde{E})$.

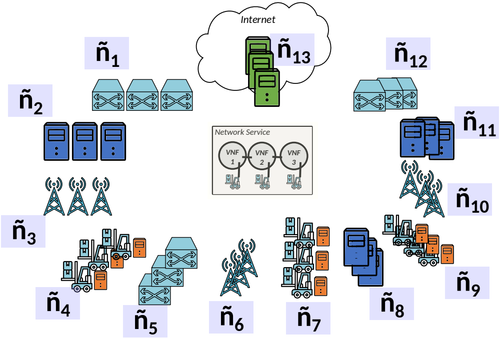
Nodes $\tilde{N} = \{\tilde{n}_1, \tilde{n}_2, \dots\}$:

- $|\mathcal{V}| - 1$ replicas

Edges $\tilde{E} = \{(\tilde{n}_1, \tilde{n}_2), \dots\}$:

- two weights:

$$\left(\frac{\tilde{D}_{\tilde{n}_1,\tilde{n}_2}}{D(s)}, \frac{\log \tilde{\eta}_{\tilde{n}_1,\tilde{n}_2}}{\log H(s)} \right) \quad (9)$$



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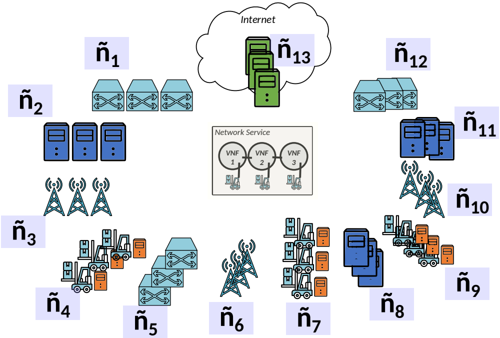
Nodes $\tilde{N} = \{\tilde{n}_1, \tilde{n}_2, \dots\}$:

- $|\mathcal{V}| - 1$ replicas

Edges $\tilde{E} = \{(\tilde{n}_1, \tilde{n}_2), \dots\}$:

- two weights:

$$\left(\underbrace{\frac{\tilde{D}_{\tilde{n}_1,\tilde{n}_2}}{D(s)}}_{\text{delay fraction}}, \frac{\log \tilde{\eta}_{\tilde{n}_1,\tilde{n}_2}}{\log H(s)} \right) \tag{9}$$



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Decision graph $\tilde{G} = (\tilde{N}, \tilde{E})$.

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Edges $\tilde{E} = \{(\tilde{n}_1, \tilde{n}_2), \ldots\}$:

- two weights:

$$\left(\frac{\tilde{D}_{\tilde{n}_1,\tilde{n}_2}}{D(s)}, \underbrace{\frac{\log \tilde{\eta}_{\tilde{n}_1,\tilde{n}_2}}{\log H(s)}}_{\text{reliability fraction}} \right) \tag{9}$$

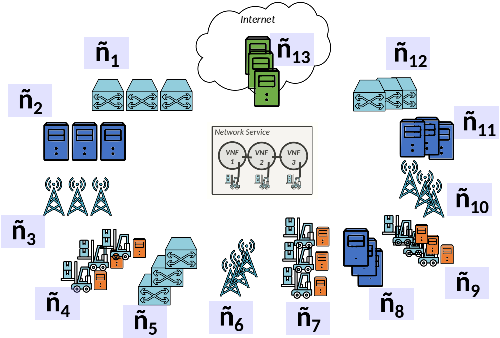


Figure 26: OKpi decision graph.

Decision graph $\tilde{G} = (\tilde{N}, \tilde{E})$.

Nodes $\tilde{N} = \{\tilde{n}_1, \tilde{n}_2, \dots\}$:

- $|\mathcal{V}| - 1$ replicas

Edges $\tilde{E} = \{(\tilde{n}_1, \tilde{n}_2), \dots\}$:

- two weights:

$$\left(\frac{\tilde{D}_{\tilde{n}_1,\tilde{n}_2}}{D(s)}, \frac{\log \tilde{\eta}_{\tilde{n}_1,\tilde{n}_2}}{\log H(s)} \right) \qquad (9)$$

- create links $(\tilde{n}_1, \tilde{n}_2)$

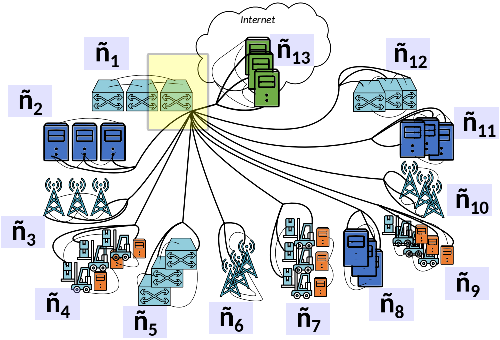


Figure 26: OKpi decision graph.

Expanded graph:

1. add superscripts $\tilde{n}^{d,r}$
   - d: delay to reach it
   - r: reliab. to reach it

Figure 27: OKpi expanded graph.

Expanded graph:

1. add superscripts $\tilde{n}^{d,r}$
   - d: delay to reach it
   - r: reliab. to reach it
2. add $(\gamma + 1)^2$ replicas

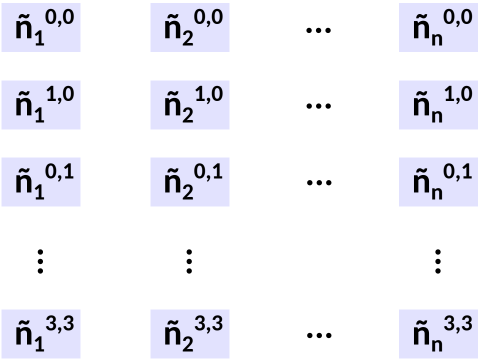
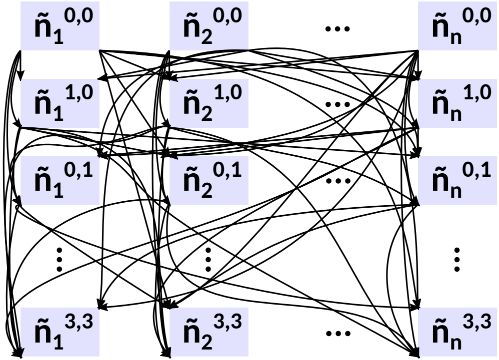


Figure 27: OKpi expanded graph.

Expanded graph:

1. add superscripts $\tilde{n}^{d,r}$
   - d: delay to reach it
   - r: reliab. to reach it
2. add $(\gamma+1)^2$ replicas
3. connect $\tilde{n}_1{}^{d_1,r_2}$ with $\tilde{n}_2{}^{d_2,r_2}$



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Expanded graph:

1. add superscripts $\tilde{n}^{d,r}$
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   - r: reliab. to reach it
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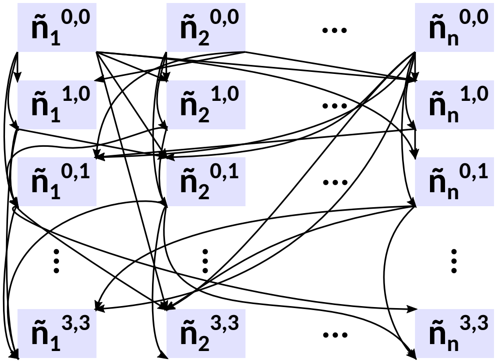
3. connect ${\tilde{n}_1}^{d_1,r_2}$ with ${\tilde{n}_2}^{d_2,r_2}$
   - link $(\tilde{n}_1, \tilde{n}_2) \in \tilde{E}$
   - $d_1 + \gamma \cdot d(\tilde{n}_1, \tilde{n}_2) \leq d_2$
   - $r_1 + \gamma \cdot r(\tilde{n}_1, \tilde{n}_2) \leq r_2$



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   - $d_1 + \gamma \cdot d(\tilde{n}_1, \tilde{n}_2) \leq d_2$
   - $r_1 + \gamma \cdot r(\tilde{n}_1, \tilde{n}_2) \leq r_2$
4. one jump per VNF

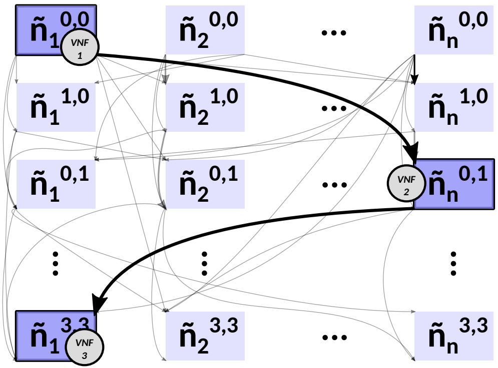

Figure 27: OKpi expanded graph.

Expanded graph:

1. add superscripts $\tilde{n}^{d,r}$
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2. add $(\gamma+1)^2$ replicas
3. connect $\tilde{n}_1{}^{d_1,r_2}$ with $\tilde{n}_2{}^{d_2,r_2}$
   - link $(\tilde{n}_1, \tilde{n}_2) \in \tilde{E}$
   - $d_1 + \gamma \cdot d(\tilde{n}_1, \tilde{n}_2) \leq d_2$
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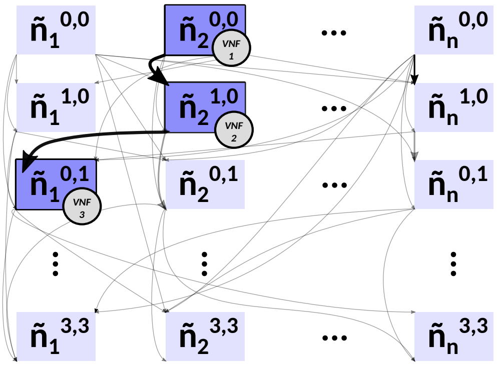
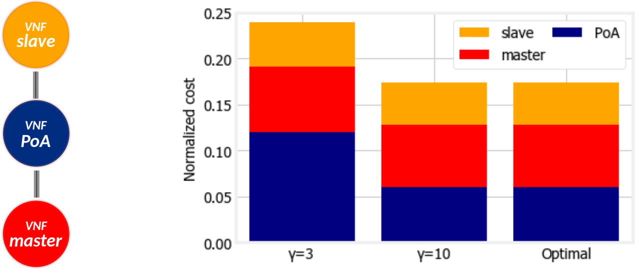


Figure 27: OKpi expanded graph.

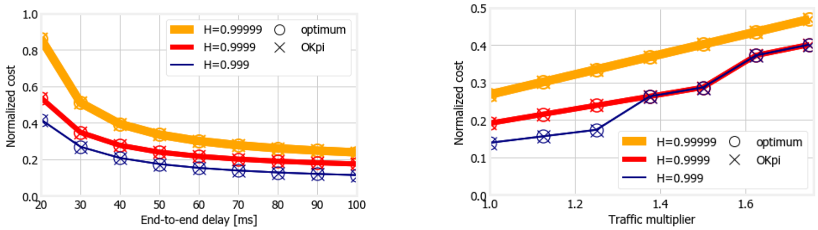
Simulations using realistic ITU+3GPP 5G scenarios [16]:



(a) (b)

Figure 28: (a) master-slave robotic VS illustration, and (b) optimality comparison of the VNFs' deployment costs using OKpi with $\gamma = 3, 10$.

Simulations using realistic ITU+3GPP 5G scenarios [16]:



(a) (b)

Figure 29: (a) end-to-end delay, and (b) traffic impact on deployment cost of master-slave robotic VS

uc3m

Publications:

- **Martín-Peréz, Jorge**, F. Malandrino, C. F. Chiasserini, and C. J. Bernardos. "OKpi: All-KPI Network Slicing Through Efficient Resource Allocation". In: *IEEE INFOCOM 2020 - IEEE Conference on Computer Communications*. 2020, pp. 804–813. DOI: `10.1109/INFOCOM41043.2020.9155263`
- **Martín-Peréz, Jorge**, F. Malandrino, C. F. Chiasserini, M. Groshev, and C. J. Bernardos. "KPI Guarantees in Network Slicing". In: *IEEE/ACM Transactions on Networking* (2021). Accepted
- B. Nemeth, N. Molner, **Martín-Pérez, J.**, C. J. Bernardos, A. de la Oliva, and B. Sonkoly. "Delay and reliability-constrained VNF placement on mobile and volatile 5G infrastructure". In: *IEEE Transactions on Mobile Computing* (2021), pp. 1–1. DOI: `10.1109/TMC.2021.3055426`

Open-source:

- **AMPLPY**: `https://github.com/ampl/amplpy`
- **networkx**: `https://github.com/networkx/networkx`
- **OKpi**: `https://github.com/MartinPJorge/placement`
- **FMC**: `https://github.com/MartinPJorge/placement`

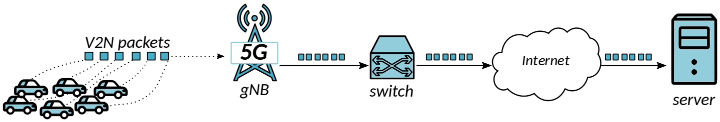


Figure 30: V2N service scaling.

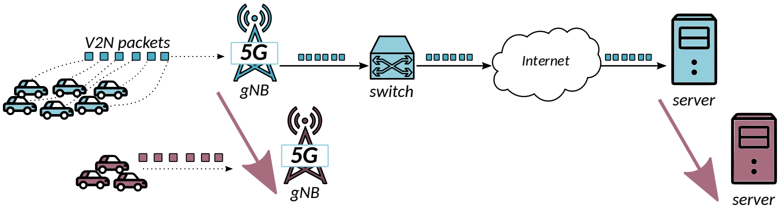


Figure 30: V2N service scaling.

V2N scaling solutions:

- asign radio resource blocks [22]
- computing resources scaling:
    - threshold-based [5, 24]
    - LSTM-based [7]

V2N scaling solutions:

- asign radio resource blocks [22]
- computing resources scaling:
  - threshold-based [5, 24]
  - LSTM-based [7]
  - **compare**:
    - DES, TES
    - HTM
    - GRU
    - LSTM
    - TCN
    - TCNLSTM

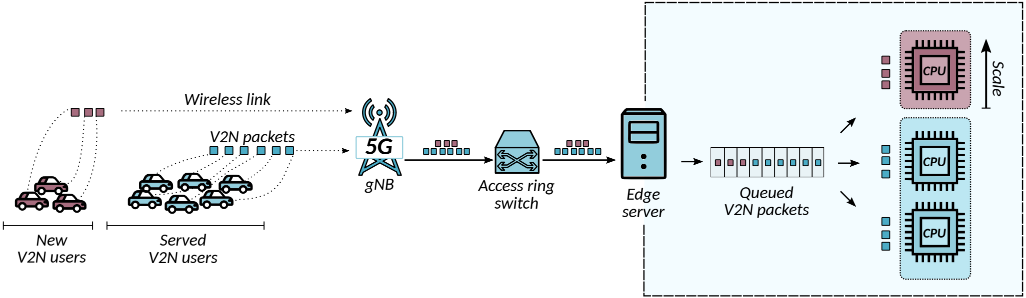


Figure 31: V2N service vertical scaling.

Edge server – $M/M/c$ queue:

- $\lambda(t)$: cars' arrival rate
- μ: CPU service rate
- $c(t)$: number of CPUs

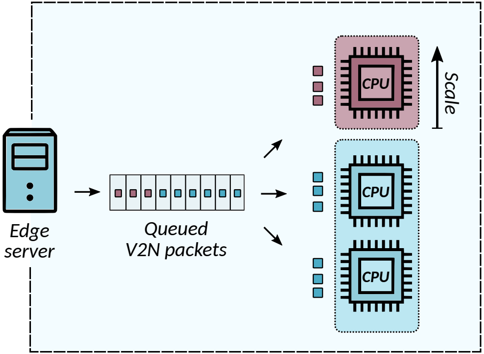


Figure 32: Server as $M/M/c$ queue.

Edge server – $M/M/c$ queue:

- $\lambda(t)$: cars' arrival rate
- μ: CPU service rate
- $c(t)$: number of CPUs

Scale to meet avg. latency:

$$\frac{1}{\mu} + \frac{P_Q}{c(t)\mu - \lambda(t)} \tag{10}$$

with P_Q the prob. of all servers bussy (Earlang C).

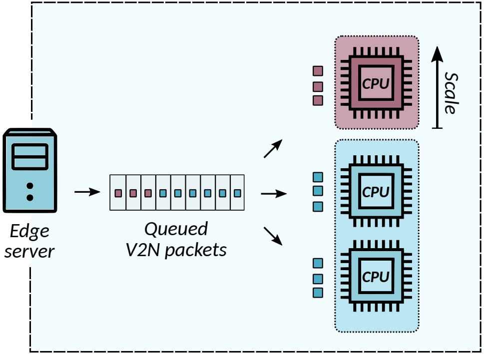


Figure 32: Server as $M/M/c$ queue.

Dataset to derive $\lambda(t)$:

- 116 roads in Torino
- (lat,lng) of roads
- traffic [vehicles/hour] each 5 min.
- avg. speed [vehicles/hour] each 5 min.
- from 28/01/2020 – now

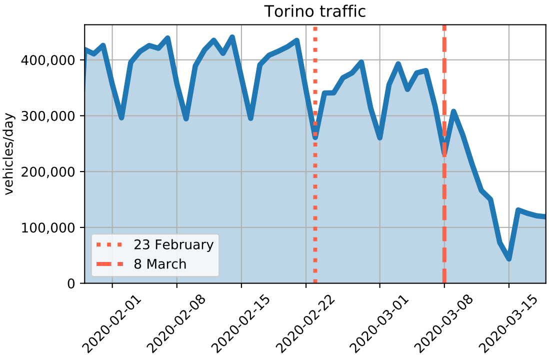


Figure 33: Traffic after COVID-19 lockdowns – 8 March.

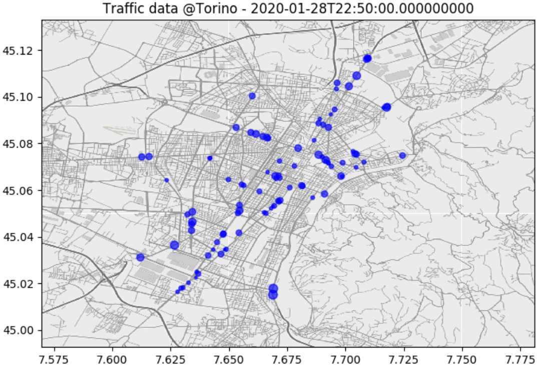


Figure 34: Vehicular traffic – wee hours @Torino.

Predict future traffic $\lambda(t+n)$

- **time-series techniques**: DES, TES
- **proprietary**: HTM
- **neural networks**: GRU, LSTM, TCN, TCNLSTM

Patterns:

- strong **seasonality**.

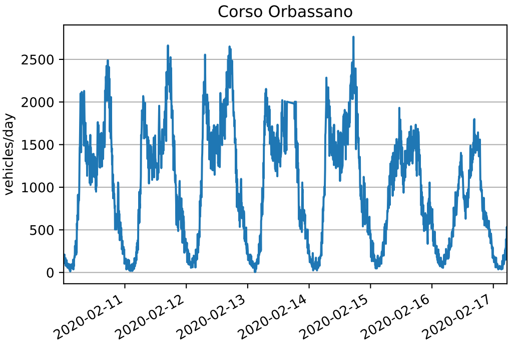


Figure 35: Weekly traffic at Corso Orbassano road.

Predict future traffic $\lambda(t+n)$

- **time-series techniques**: DES, TES
- **proprietary**: HTM
- **neural networks**: GRU, LSTM, TCN, TCNLSTM

Patterns:

- strong **seasonality**.
- week & weekend flows

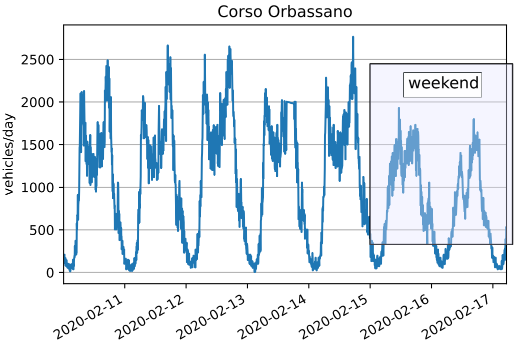


Figure 35: Weekly traffic at Corso Orbassano road.

Predict future traffic $\lambda(t+n)$

- **time-series techniques**: DES, TES
- **proprietary**: HTM
- **neural networks**: GRU, LSTM, TCN, TCNLSTM

Patterns:

- strong **seasonality**.
- week & weekend flows
- night hours,

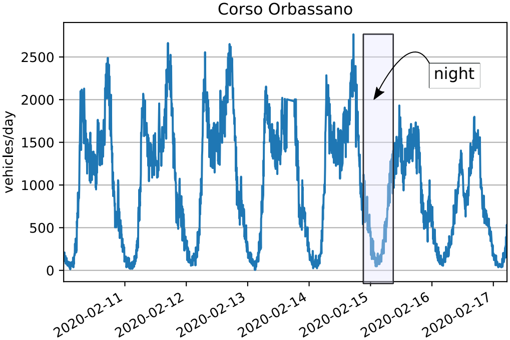


Figure 35: Weekly traffic at Corso Orbassano road.

Predict future traffic $\lambda(t+n)$

- **time-series techniques**: DES, TES
- **proprietary**: HTM
- **neural networks**: GRU, LSTM, TCN, TCNLSTM

Patterns:

- strong **seasonality**.
- week & weekend flows
- night hours, rush hours,

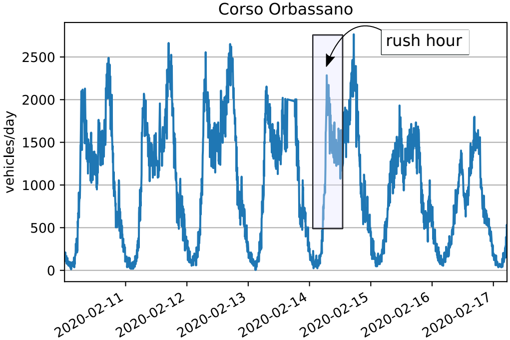


Figure 35: Weekly traffic at Corso Orbassano road.

Predict future traffic $\lambda(t+n)$

- **time-series techniques**: DES, TES
- **proprietary**: HTM
- **neural networks**: GRU, LSTM, TCN, TCNLSTM

Patterns:

- strong **seasonality**.
- week & weekend flows
- night hours, rush hours, schools' out

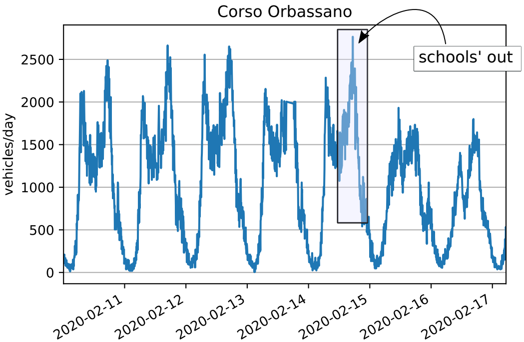


Figure 35: Weekly traffic at Corso Orbassano road.

non-COVID-19 (2020)

- training: 28thFeb - 28thMar
- testing: 29thFeb - 07thMar

COVID-19 (2020)

- training: 06thFeb - 07thMar
- testing: 08thMar - 15thMar

non-COVID-19 (2020)

- training: 28thFeb - 28thMar
- testing: 29thFeb - 07thMar

COVID-19 (2020)

- training: 06thFeb - 07thMar
- testing: 08thMar - 15thMar

Train:

- offline training
- online training

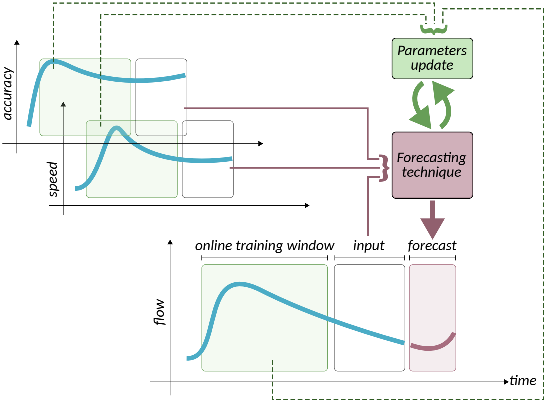


Figure 36: Online training.

Vertical scaling:

1. $\lambda(t+n)$: traffic prediction

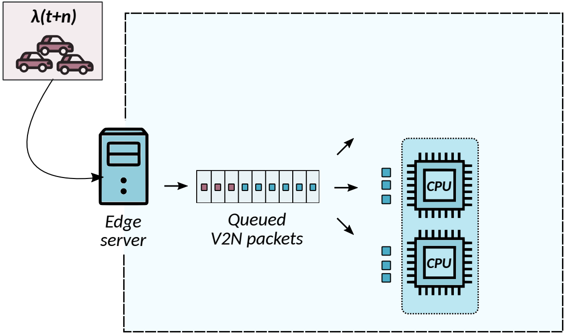


Figure 37: $M/M/c$-based scaling.

Vertical scaling:

1. $\lambda(t+n)$: traffic prediction
2. derive $c(t+n)$ s.t.:

$$\frac{1}{\mu}+\frac{P_Q}{c(t+n)\mu+\lambda(t+n)} \leq D(s) \tag{11}$$

with $D(s)$ the target delay

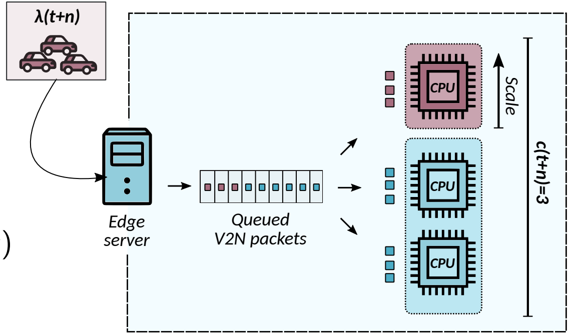
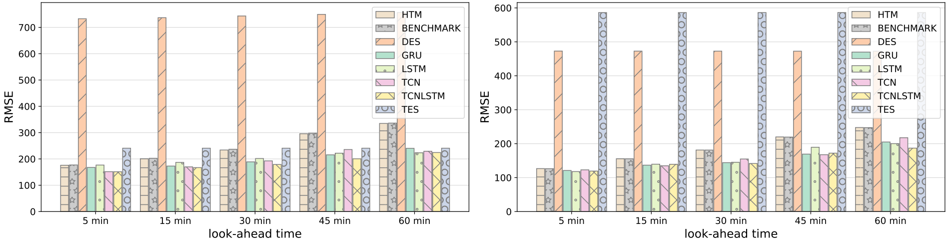


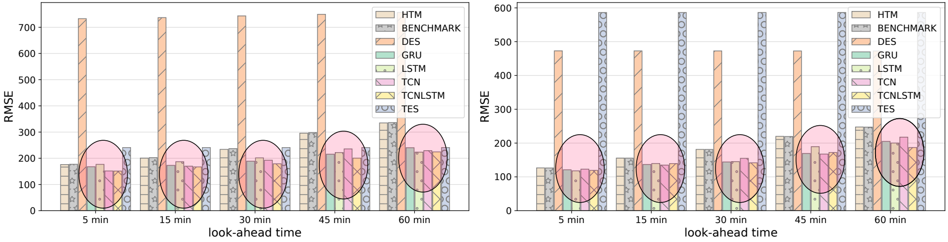
Figure 37: $M/M/c$-based scaling.



(a) non-COVID-19 (b) COVID-19

Figure 38: Prediction accuracy (offline training).

Most accurate: **Neural Networks**



(a) non-COVID-19 (b) COVID-19

Figure 38: Prediction accuracy (offline training).

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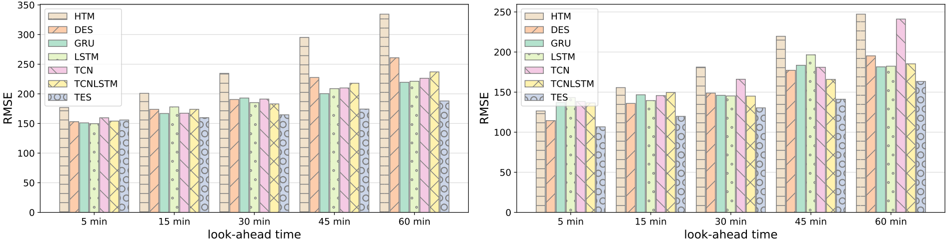
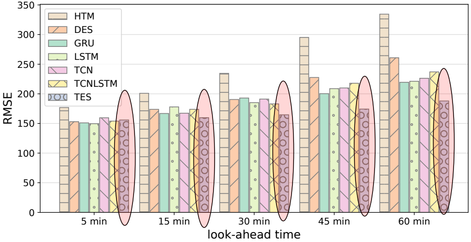


(a) non-COVID-19

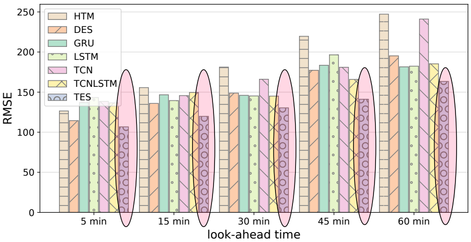
(b) COVID-19

Figure 39: Prediction accuracy (online training).

Most accurate: **TES**



(a) non-COVID-19



(b) COVID-19

Figure 39: Prediction accuracy (online training).

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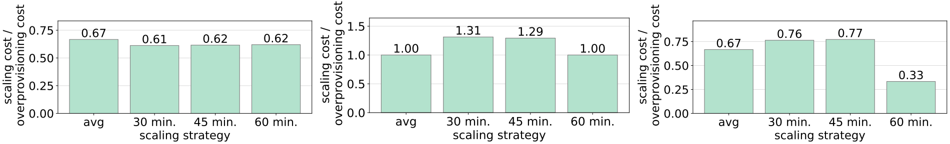
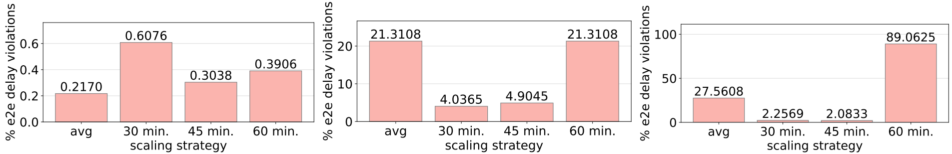
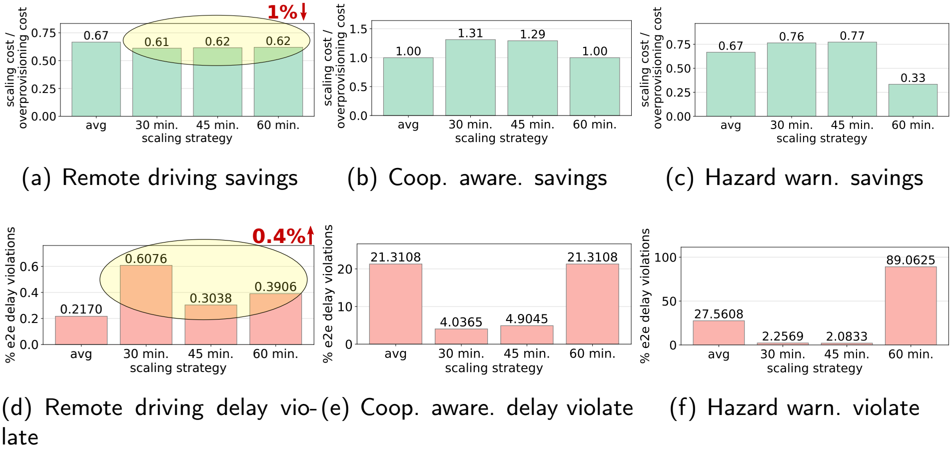


(a) Remote driving savings (b) Coop. aware. savings (c) Hazard warn. savings



(d) Remote driving delay violate (e) Coop. aware. delay violate (f) Hazard warn. violate

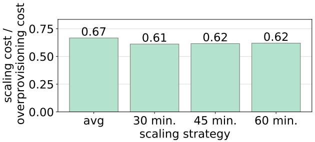
Figure 40: Cost savings and delay violations due to scaling – TES with online training was used.



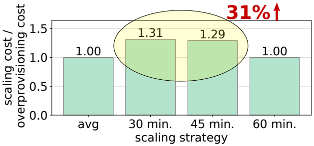
(a) Remote driving savings (b) Coop. aware. savings (c) Hazard warn. savings

(d) Remote driving delay violate (e) Coop. aware. delay violate (f) Hazard warn. violate

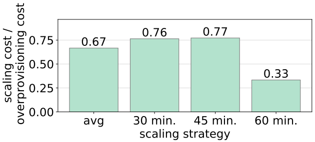
Figure 40: Cost savings and delay violations due to scaling – TES with online training was used.



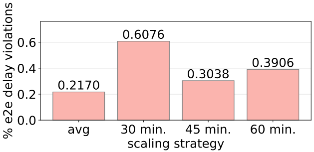
(a) Remote driving savings



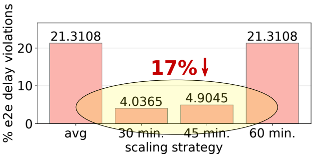
(b) Coop. aware. savings



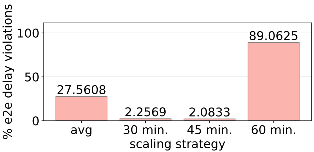
(c) Hazard warn. savings



(d) Remote driving delay violate

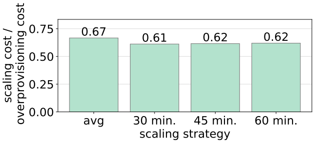


(e) Coop. aware. delay violate

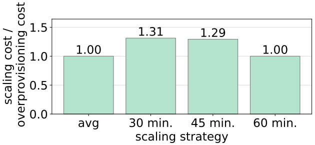


(f) Hazard warn. violate

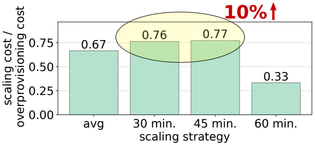
Figure 40: Cost savings and delay violations due to scaling – TES with online training was used.



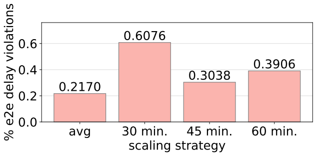
(a) Remote driving savings



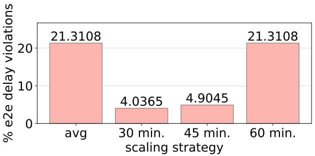
(b) Coop. aware. savings



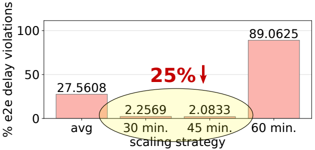
(c) Hazard warn. savings



(d) Remote driving delay violate



(e) Coop. aware. delay violate



(f) Hazard warn. violate

Figure 40: Cost savings and delay violations due to scaling – TES with online training was used.

Publications:

- D. de Vleeschauwer, J. Baranda, J. Mangues-Bafalluy, C. F. Chiasserini, M. Malinverno, C. Puligheddu, L. Magoula, **Martín-Pérez, J.**, S. Barmpounakis, K. Kondepu, L. Valcarenzhi, X. Li, C. Papagianni, and A. Garcia-Saavedra. "5Growth Data-Driven AI-Based Scaling". In: *2021 EuCNC/6G Summit*. 2021, pp. 383–388. DOI: 10.1109/EuCNC/6GSummit51104.2021.9482476
- **Martín-Pérez, Jorge**, K. Kondepu, D. de Vleeschauwer, V. Reddy, C. Guimarães, A. Sgambelluri, L. Valcarenghi, C. Papagianni, and C. J. Bernardos. "Dimensioning of V2N Services in 5G Networks through Forecast-based Scaling". In: *IEEE Access* (2021). Under review

Open-source (to be released):

- https://github.com/MartinPJorge/5growth-scaling/
- https://github.com/MartinPJorge/5growth-forecasting

:

1. methodology to **generate BS & MEC PoP locations**

:

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2. **DQN** agent to **federate** services

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1. methodology to **generate BS & MEC PoP** locations
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3. **OKpi** solves VNE problem: delay, reliability, availability

:

1. methodology to **generate BS & MEC PoP** locations
2. **DQN** agent to **federate** services
3. **OKpi** solves VNE problem: delay, reliability, availability
4. reduce delay violations with **V2N scaling** using real traffic **dataset**

:

1. **generate multi-domain** infrastructure graphs

:

1. **generate multi-domain** infrastructure graphs
2. **DQN** agent +**LSTM** layer to **predict**

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1. **generate multi-domain** infrastructure graphs
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:

1. **generate multi-domain** infrastructure graphs
2. **DQN** agent +**LSTM** layer to **predict**
3. **OKpi** study on γ/runtime/optimality
4. **V2N scaling** to meet **99.9999%** latency quantile & ST-GCN

Thanks for your attention!

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Lemma

Given an inhomogeneous marked PPP X with intensity function λ, the thinning function I_2, and marks $m \sim \frac{1}{\lambda(x)}$, the resulting thinned point process, called inhomogeneous Matérn II PP, has the following average number of points at C:

$$\mathbb{E}\left[N(C)\right] := \int_C e^{-\int_{B(x,r)} \mathbb{1}(\lambda(u)>\lambda(x))\lambda(u)du} \lambda(x)\; dx \tag{12}$$

where r is the thinning radius of I_2.

with

$$I_2(x, m, X, M_X) := \begin{cases} 1 & \text{if } m = \min_{m' \in M_X} \left\{(x', m') : x' \in B(x, r)\right\} \\ 0 & \text{otherwise} \end{cases} \tag{13}$$

The RTT considered is computed as

$$RTT := 2l\left(\|x-m\|_1\right) + 2p(M) + UL + DL \tag{14}$$

We find m_M, the maximum distance from MEC PoP m to the BS at position x, as:

$$\|x-m\|_1 \leq l^{-1}\left(\frac{RTT - 2p(M) - t_r}{2}\right) = m_M \tag{15}$$

with $\|\cdot\|_1$ denoting the Manhattan distance.

User pays $p^{(t)}$ for the service σ

$$p^{(t)}(\sigma) = (1 + P)l^{(t)}(\sigma) \tag{16}$$

with P the profit margin, and $l^{(t)}$ the local deployment cost (based on uncertain phenomena).

User pays $p^{(t)}$ for the service σ

$$p^{(t)}(\sigma) = (1 + P)I^{(t)}(\sigma) \tag{16}$$

with P the profit margin, and $I^{(t)}$ the local deployment cost (based on uncertain phenomena).

Given the federation fee $f(\sigma)$ the **reward** is:

$$r^{(t)}(X_t) := \sum_{\substack{\sigma:\ x(\sigma)=0 \\ a(\sigma)\le t\le d(\sigma)}} p^{a(\sigma)}(\sigma) + \sum_{\substack{\sigma:\ x(\sigma)=1 \\ a(\sigma)\le t\le d(\sigma)}} \left[p^{a(\sigma)}(\sigma) - f^{(t)}(\sigma)\right] \tag{17}$$

where $X_t := \{x(\sigma)\}_{\sigma:a(\sigma)\le t}$.

$$f(p^{(t)}(\sigma)) := \begin{cases} k\left(1 - \left(\frac{p^{(t)}(\sigma)}{K\cdot M}\right)^a\right)^b, & p^{(t)}(\sigma) \leq K\cdot M \\ 0, & p^{(t)}(\sigma) > K\cdot M \end{cases} \tag{18}$$

where $M = \max_{\sigma,t}\{l^{(t)}(\sigma)\}$ is the maximum local deployment cost over time across all services σ (e.g., *t3a.small*), and K is a normalization constant to control the decay of the arrival rate.

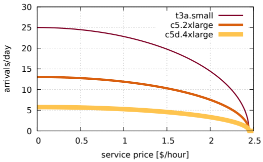

Figure 41: Impact of prices on arriving users.

Increase of P leads to:

- less user arrivals
- larger reward

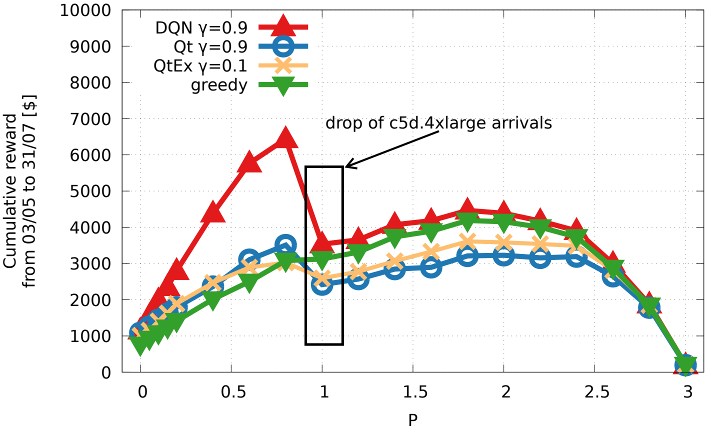

Figure 42: Impact of the marginal benefit P in the commutative reward achieved by each solution.