

OPEX-Limited 5G RAN Slicing: an Over-Dataset Constrained Deep Learning Approach

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Use of AI/ML in Networks Workshop

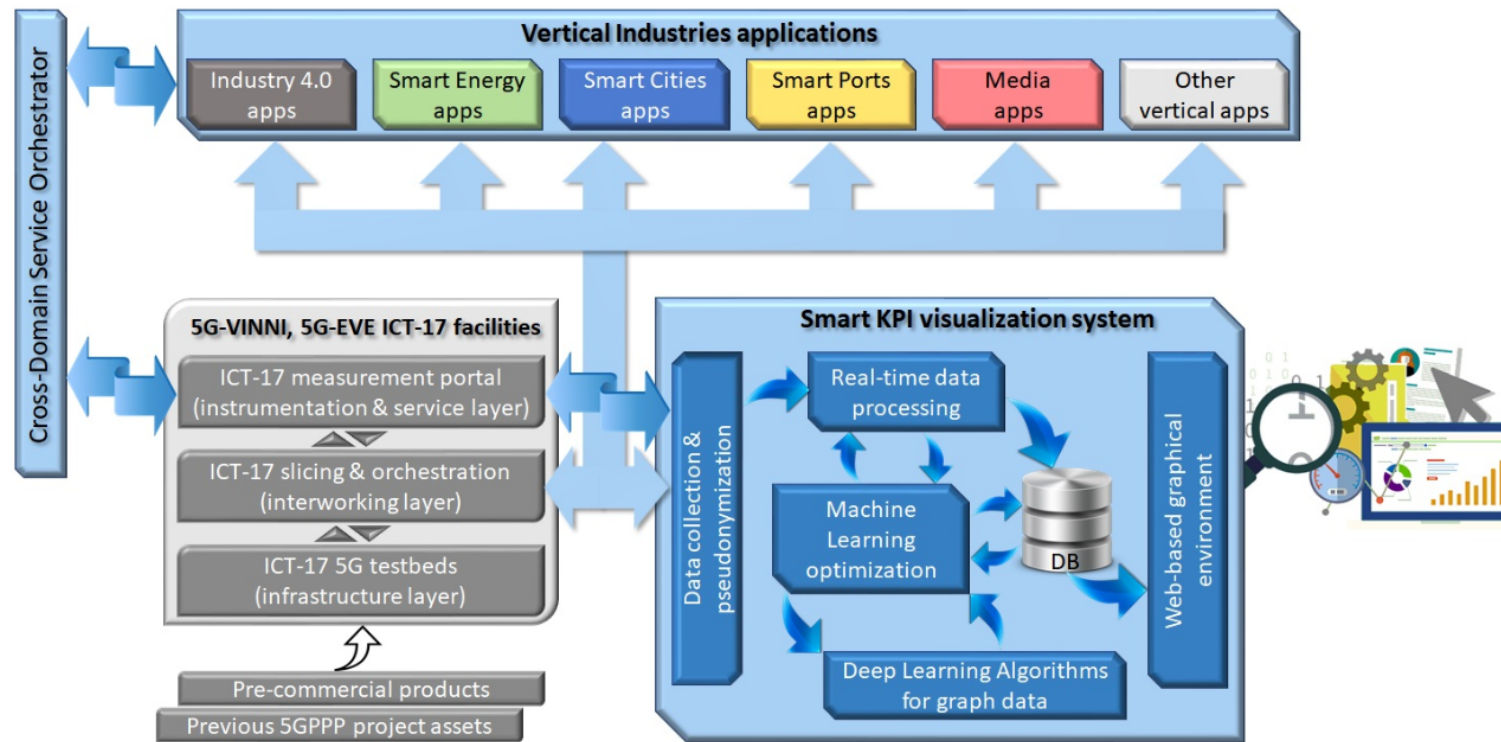
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5GSolutions Concept

- Vertical domains of Factories of the Future, Smart Energy, Smart Cities, Smart Ports, and Media & Entertainment
- Mapped with the eMBB, URLLC and mMTC service classes



Motivations

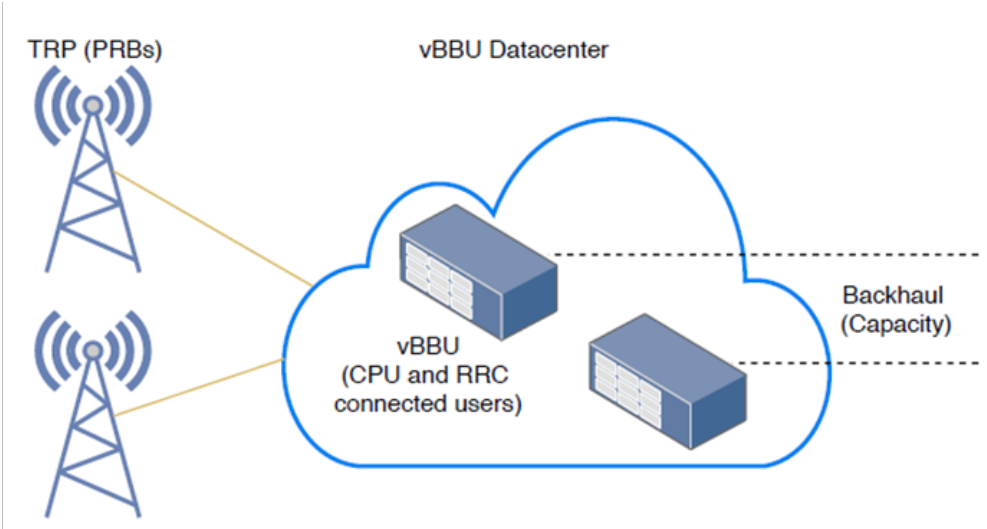
- Reduce OPEX: Softwarization and virtualization technologies employed in network slicing,
- Joint network slicing OPEX control and resource allocation
- Novel constrained DNN models performing offline learning from datasets.



- Joint multi-slice DNN model for resource provisioning based on the traffic per slice,
- Live network key performance indicators(KPIs) datasets,
- Constraints on OPEX violation rate:
 - Dataset-dependent custom non-convex constraints to the DNN output,
 - Use of a two-player non-zero sum game strategy.

CRAN Setup and Dataset (1/2)

- LTE-advanced (LTE-A) dense urban area, covered by 440 LTE-A eNodeBs (eNBs) and 3200 cells.



Entity	Quantity
TRP	3200
eNB	440
BBU datacenters	10 uniformly distributed, with x100 CPU resources compared to a single 4G eNodeB

CRAN Setup and Dataset (2/2)

- Two datasets sources:
 - Dedicated probes—collecting and analyzing the traffic per OTT
 - Key performance indicators collected by the operational support system (OSS) platform at TRP, eNB and vBBU levels.

	Feature	Description
TRP	OTT Traffics per TRP	Includes the hourly traffic for the top OTTs: Apple, Facebook, Facebook Messages, Facebook Video, Instagram, NetFlix, HTTPS, QUIC, Whatsapp, and Youtube
	CQI	Channel quality indicator reflecting the average quality of the radio link of the TRP
	MIMO Full-Rank	Usage of MIMO full-rank spatial multiplexing in %
	DLPRB	Number of occupied downlink physical resource blocks
vBBU	OTT Traffics per eNB	Aggregated OTT traffics per eNB
	CPU Load	CPU resource consumption in %
	RRC Connected Users	Number of RRC users licenses consumed per eNB
Backhaul	OTT Traffics per BBU datacenter	Aggregated OTT traffics per BBU datacenter
	Backhaul capacity	Effective aggregated throughput per BBU datacenter

Constrained DNN Concept

- Minimize DNN loss function subject to data-dependent constraints, expressed in terms of expectations over a data distribution \mathcal{D} :

$$\begin{aligned} \min_{\mathbf{W}} \mathbb{E}_{\mathbf{x} \sim \mathcal{D}} \ell_0(\mathbf{x}, \mathbf{W}), \\ \text{s.t. } \mathbb{E}_{\mathbf{x} \sim \mathcal{D}} \ell_i(\mathbf{x}, \mathbf{W}) \leq 0, i = 1, \dots, m, \end{aligned}$$

- Where \mathbf{W} are the weights of the DNN, \mathbf{x} are the features, while ℓ_0 and ℓ_i stand for the DNN loss function and the m constraints, respectively.

Offline Violation Rate-Based OPEX Enforcement (1/3)

- Pay-per-use strategy RAN resource pricing π :

$$\pi \left(r_{m,n,k}^{(i)} \right) = \gamma_{m,n,k} r_{m,n,k}^{(i)},$$

Unitary price
Consumed resource

- Example: Amazon Web Services/Elastic Compute Cloud (EC2)
- Offline approach to train dataset-based DNN models.
 - Directly enforcing an upper bound on the OPEX violation rate:

$$\begin{aligned} & \min \frac{1}{N_B} \sum_{i=1}^{N_B} \ell \left(r_{m,n,k}^{(i)}, \hat{r}_{m,n,k}^{(i)} (\mathbf{W}_n, \mathbf{b}_n, \mathbf{s}_n) \right), & \text{Loss function} \\ & \text{s.t. } \mathbf{W}_{l,n} \in \mathbb{R}^{N_{l-1} \times N_l}, l = 1, \dots, L+1, \\ & \quad \mathbf{b}_{l,n} \in \mathbb{R}^{N_l \times 1}, l = 1, \dots, L+1, & \text{Weights and Biases} \\ & \frac{1}{N_B} \sum_{i=1}^{N_B} \mathbb{1} \left(\pi \left(\hat{r}_{m,n,k}^{(i)} \right) < \alpha_{m,n,k} \right) \leq \rho_{m,n,k}, \\ & \frac{1}{N_B} \sum_{i=1}^{N_B} \mathbb{1} \left(\pi \left(\hat{r}_{m,n,k}^{(i)} \right) > \beta_{m,n,k} \right) \leq \rho_{m,n,k}, & \text{Violation rate constraints,} \\ & & \alpha \text{ and } \beta \text{ are the bounds} \\ & & \rho \text{ is the target threshold} \end{aligned}$$

Offline Violation Rate-Based OPEX Enforcement (2/3)

- **Problems:**

- Nonconvex objective and constraint functions.
- The violation rate constraint is a linear combination of indicators,

$$\begin{aligned}\Phi_1(\mathbf{W}_n) &= \frac{1}{N_B} \sum_{i=1}^{N_B} \underbrace{\mathbb{1} \left(\pi \left(\hat{r}_{m,n,k}^{(i)} \right) < \alpha_{m,n,k} \right)}_{\text{Indicator function}} - \rho_{m,n,k}, \\ \Phi_2(\mathbf{W}_n) &= \frac{1}{N_B} \sum_{i=1}^{N_B} \mathbb{1} \left(\pi \left(\hat{r}_{m,n,k}^{(i)} \right) > \beta_{m,n,k} \right) - \rho_{m,n,k},\end{aligned}$$

- **Solution:**

- Sufficiently-smooth approximations of the constraints

$$\begin{aligned}\Psi_1(\mathbf{W}_n) &= \frac{1}{N_B} \sum_{i=1}^{N_B} \sigma \left(\alpha_{m,n,k}^{(i)} - \pi \left(\hat{r}_{m,n,k} \right) \right) - \rho_{m,n,k} \leq 0, \\ \Psi_2(\mathbf{W}_n) &= \frac{1}{N_B} \sum_{i=1}^{N_B} \underbrace{\sigma \left(\pi \left(\hat{r}_{m,n,k} \right) - \beta_{m,n,k} \right)}_{\text{Sigmoid function}} - \rho_{m,n,k} \leq 0,\end{aligned}$$

Offline Violation Rate-Based OPEX Enforcement (3/3)

- Proxy Lagrangian framework [R1]:

$$\mathcal{L}_{\mathbf{W}_n} = \frac{1}{N_B} \sum_{i=1}^{N_B} \ell \left(\mathbf{r}_{m,n,k}^{(i)}, \hat{\mathbf{r}}_{m,n,k}^{(i)} (\mathbf{W}_n, \mathbf{b}_n, \mathbf{s}_n) \right) + \lambda_1 \Psi_1(\mathbf{W}_n) + \lambda_2 \Psi_2(\mathbf{W}_n),$$

Lagrangian w.r.t. weights

$$\mathcal{L}_\lambda = \lambda_1 \Phi_1(\mathbf{W}_n) + \lambda_2 \Phi_2(\mathbf{W}_n),$$

Lagrangian w.r.t. λ

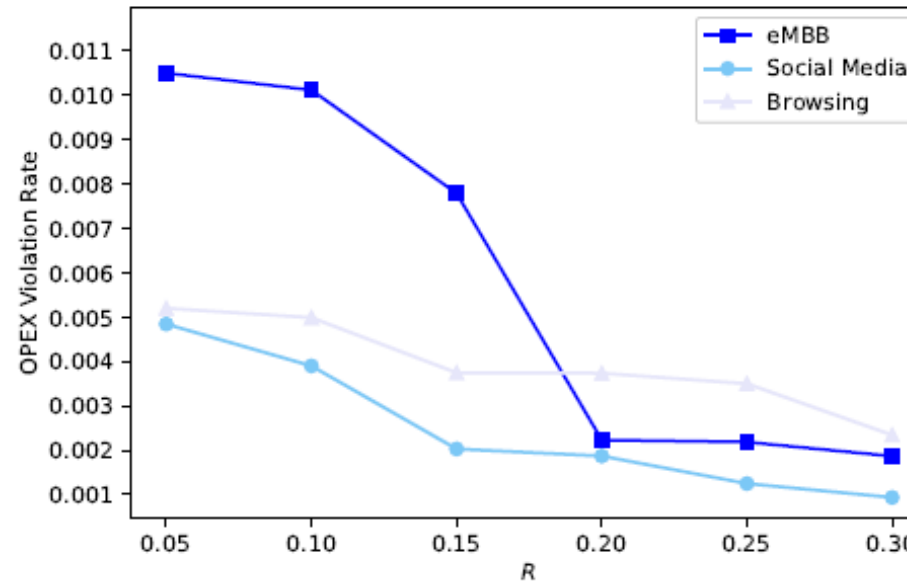
- Equivalent to a non-zero-sum two-player game in which the \mathbf{W}_n -player wishes to minimize $\mathcal{L}_{\mathbf{W}_n}$, while the λ -player wishes to maximize \mathcal{L}_λ .
- R measures the dependency to the constraints.

[R1] A. Cotter et al., "Training well-generalizing classifiers for fairness metrics and other data-dependent constraints" [Online]. Available: arxiv.org/abs/1807.00028.

- **eMBB:** NetFlix, Youtube and Facebook Video,
- **Social Media:** Facebook, Facebook Messages, Whatsapp and Instagram,
- **Browsing:** Apple, HTTP and QUIC.
- **Training dataset sizes:**
 - 21417 samples at TRPs
 - 9681 samples at vBBUs levels
 - Batch size $N_B = 100$.

Results (2/4)

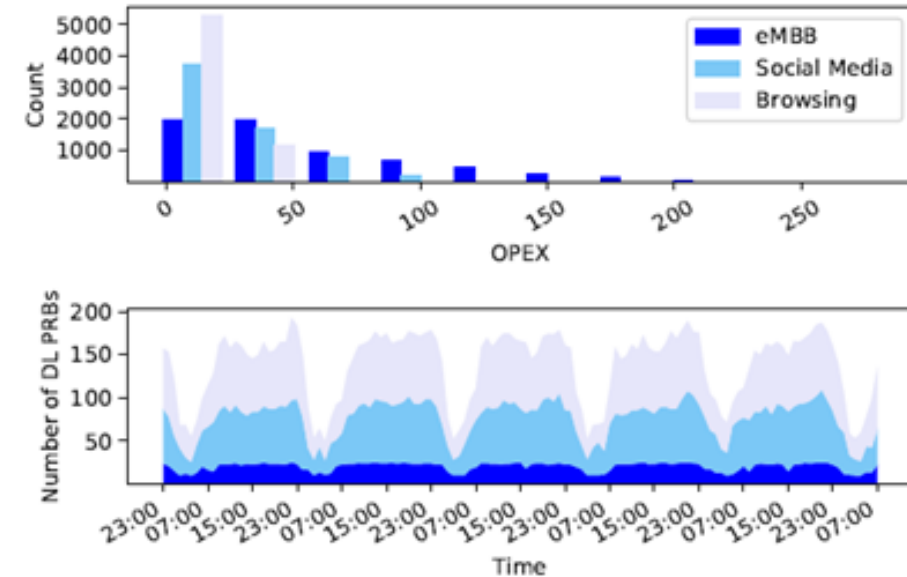
- The achieved violation rate is a decreasing function of R
- To achieve the target violation rate $= 0.005$ for the three considered slices, one should set $R = 0.2$.



DL PRB OPEX violation rate vs. R with $\alpha = [0, 0, 0]$
and $\beta = [200, 250, 250]$ \$, $\gamma = [4, 2, 1]$, for target $\rho = 0.005$.

Results (3/4)

- With $R = 0.2$, the DLPRB OPEX bounds are respected,
- The slices differ in the incurred hourly OPEX due to the difference in the unitary price,
- DL PRBs variation over time is induced by the trend of hourly traffics per slice
- Massive access for Social Media and Browsing

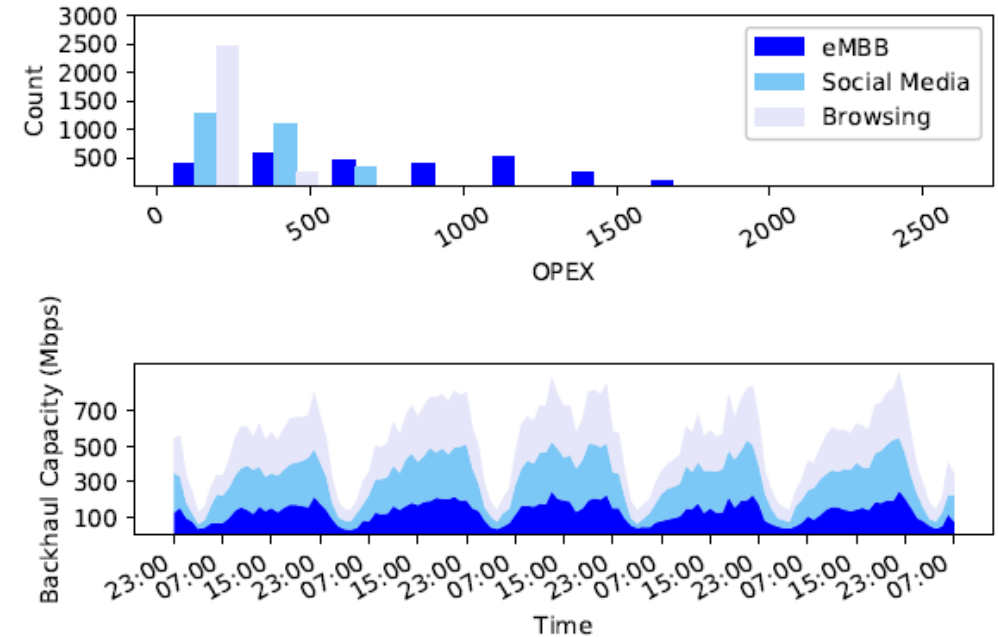


$R = 0.2$

DL PRBs evolution and OPEX distribution per slice,
with $\alpha = [0, 0, 0]$ and $\beta = [200, 250, 250]$ \$, $\gamma = [4, 2, 1]$,
 $\rho = 0.005$.

Results (4/4)

- With $R = 0.2$, the enforced OPEX upper bounds = [2000; 1000; 500] \$ are respected.
- eMBB service is presenting the lowest number of users but requires a backhaul capacity comparable to the other slices.



Backhaul capacity and OPEX distribution per slice,
with $\alpha = [0, 0, 0]$ and $\beta = [2000, 1000, 500]$ \$, $\gamma = [5, 2, 1]$,
 $\rho = 0.005$ and $R = 0.2$.

5G Solutions for European Citizens

[EXPLORE](#)

Questions

