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Signal Overhead Reduction for AI-Assisted Conditional Handover (CHO) Preparation

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1. Problem Statement and System Model
2. The Proposed Solution
3. Simulation Parameters and Results
4. Conclusion and Outlook

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Problem Statement

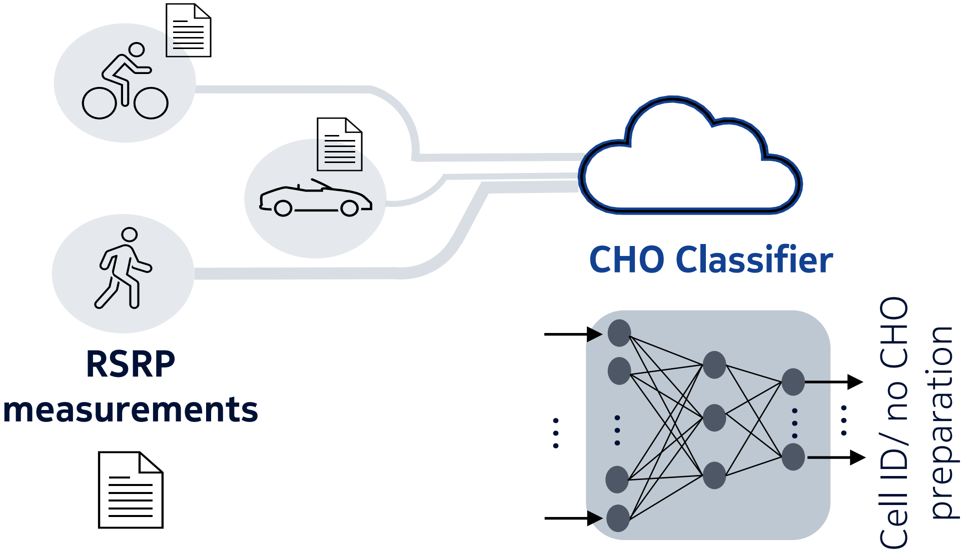
AI-assisted CHO Preparation and Signal Overhead Reduction (SOR)

AI deployment in network (not UE)

CHO preparation:
→ **"CHO Classifier"**

Signaling:

- CHO preparation
- CHO execution
- **RSRP reports for the CHO classifier → reduction?**



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System Model

CHO Classifier (Inference Mode)

CHO Classifier:

CNN

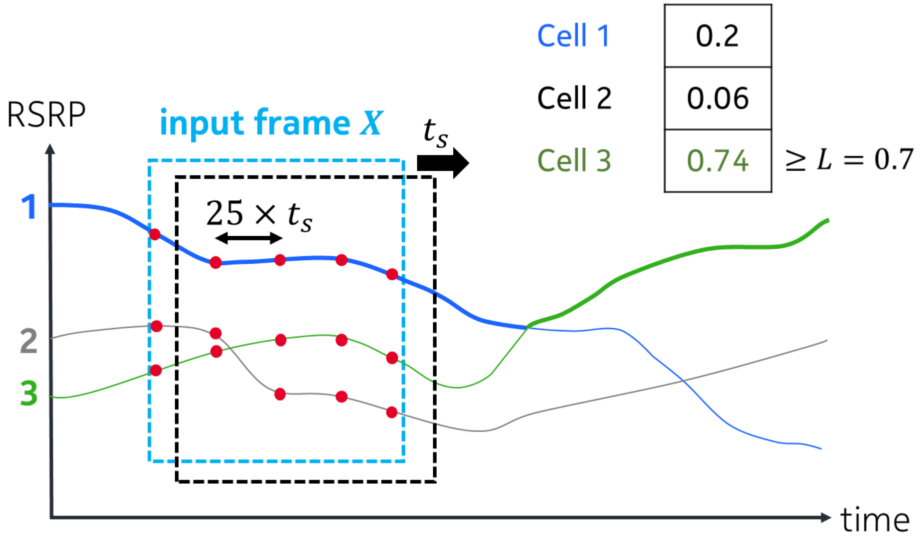
(Incl. convolutional, ReLU, FC, softmax layers)

Input: K RSRPs from N_c surrounding cells

Output: N_c softmax probabilities

Decision: with the threshold L

SOR: Transmission of RSRP matrices every t_s sec.



UE connected to **Cell 1**

CHO preparation to **Cell 3** → CHO classifier decision

System Model

Mobility Key Performance Indicators (KPIs) for Evaluations

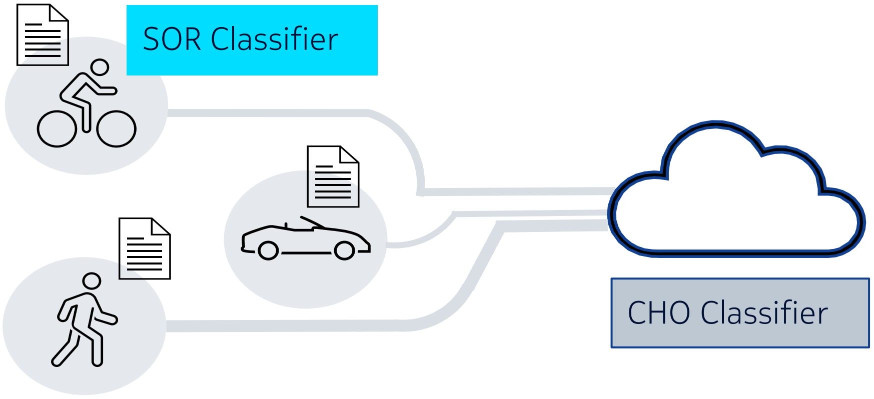
How to reduce the signal overhead without affecting performance of the CHO classifier?

Number of CHO preparations*	Requires SINR $\geq Q_{out}$
Number of Successful CHOs (SCHO)*	Successful execution, SINR $\geq Q_{out}$ within T304 sec.
Number of Ping-pong Events (PP)*	Successful executions from cell A to B and back in T_{pp} sec.
Radio Link Failure (RLF)*	Link quality $\leq Q_{out}$ for T310 sec.
Outage**	The time period of service interruption

*: Events per UE per minute, **Sec. per UE per minute

Proposed Method

Step 1: SOR Classifier



- **Motivation:** Many no-CHOs
- **SOR** avoids transmission of unnecessary RSRP reports!
- **Requirement:** Simple for operation at UE.

- Training and evaluation:
  - **FNR** ↔ KPIs
  - **FPR** ↔ SOR
- Same input as CHO classifier
- Linear Model (Logistic Regression)*

$$^{*}p(\mathrm{CHO}|\boldsymbol{X}) = \frac{1}{1+e^{-\sum_{i,k} x_{ik} w_{ik}}}$$

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Proposed Method

Step 2: Data Quantization

A. Number of quantization bits for each input component?

→ Minimizing MSE

$$\boldsymbol{\eta}^* = \underset{\boldsymbol{\eta}}{\operatorname{argmin}} \sum_{x \in \mathcal{T}_{\text{train}}} \mathbb{E}_{x_{ik}} \{(x_{ik} - \hat{x}_{ik})^2\}$$

$\hat{x}_{ik}$: quantized version of x_{ik}

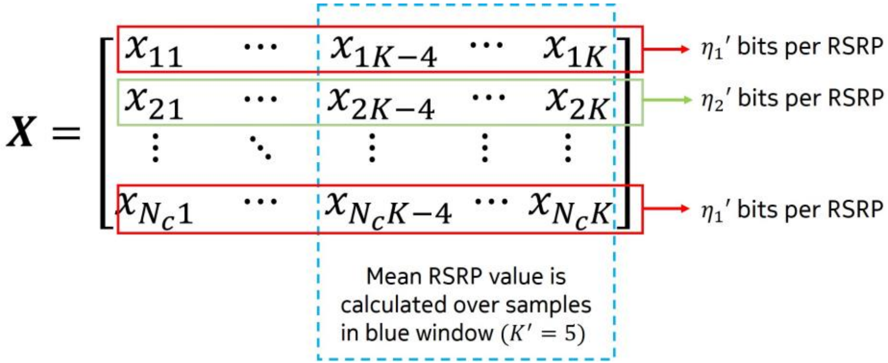
x_{ik} : elements of input matrix. $\boldsymbol{X}$

$\mathcal{T}_{\text{train}}$: training set

$\boldsymbol{\eta}$: a feasible bit allocation (size: $N_c \times K$), $\eta_{ik} \leq 7$

B. To limit the search space:

→ Categorizing cells into two groups



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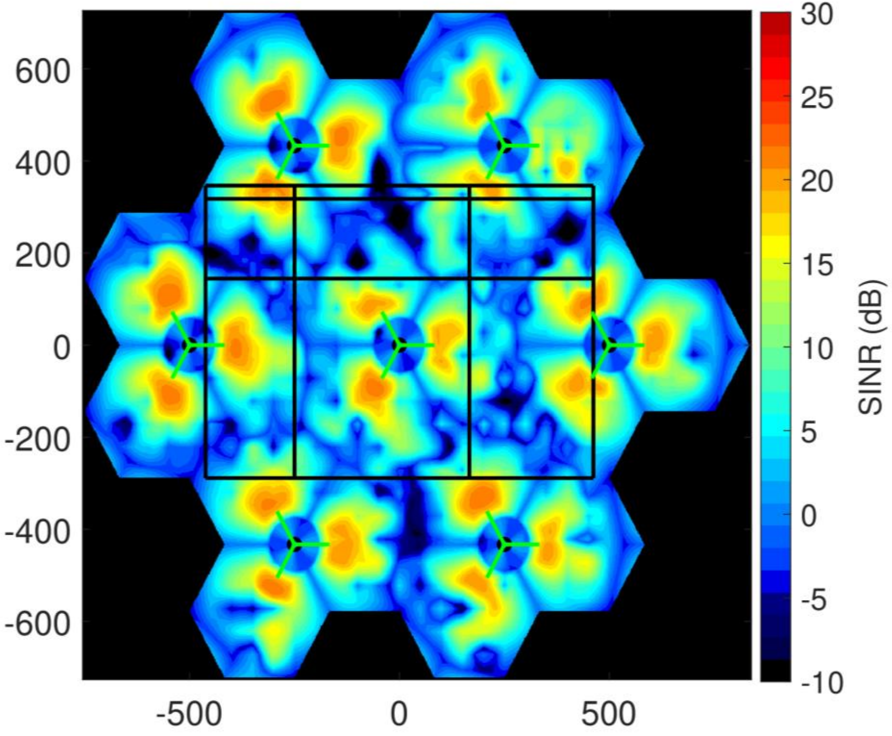
Simulation Results

Simulation Parameters

- 500 Street users and 105 pedestrians
- Path loss, fast and slow fading
- Imbalanced dataset generated using the network simulator → undersampling
- Two SOR classifiers:

	Accuracy	FNR	FPR
✓ SOR classifier 1	≈ 87%	≈ 2%	≈ 67%
✗ SOR classifier 2	≈ 87%	≈ 6%	≈ 49%



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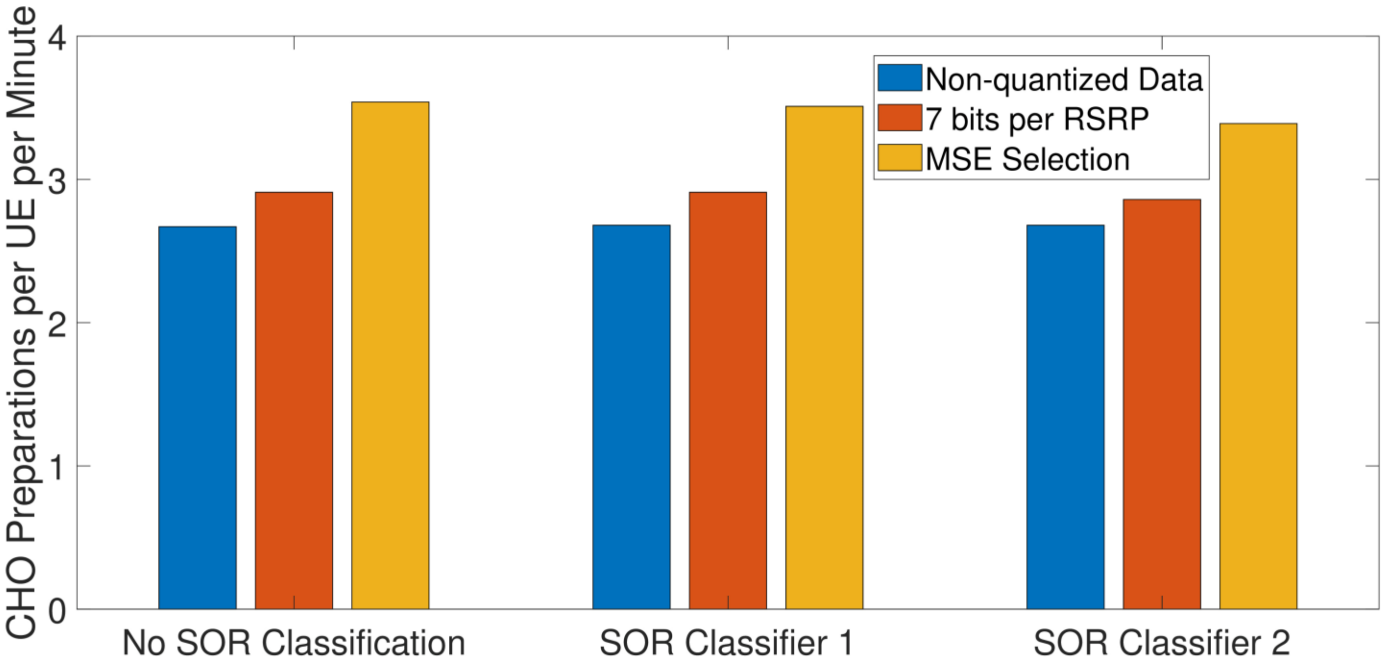
Simulation Results

- SOR classifier 1 (lower FNR):
  → **28.5-53% reduction**
  → Slight KPI degradation

- The MSE-based compression:
  → Improved PP
  → More CHO preparations

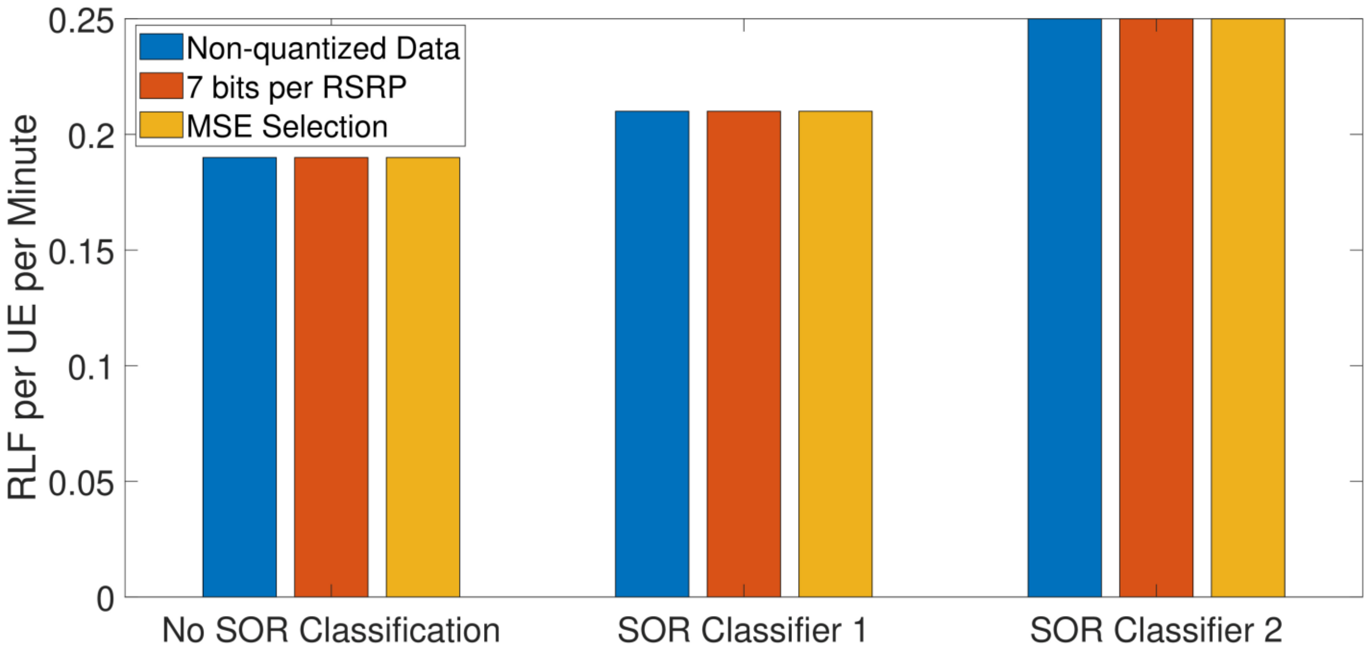
	CHO Preparations	SCHO	PP	RLF	Outage	SOR (%)
Non-quantized (Benchmark 1)	2.67	1.99	0.040	0.19	1.30	-
7 bits per RSRP (Benchmark 2)	2.91	1.99	0.040	0.19	1.29	-
MSE Selection	3.54	1.97	0.035	0.19	1.29	35
SOR Classifier 1 Non-quantized	2.68	1.97	0.039	0.21	1.32	28.5
SOR Classifier 1 7 bits per RSRP	2.91	1.97	0.039	0.21	1.33	28.5
SOR Classifier 1 MSE Selection	3.51	1.95	0.035	0.21	1.32	53
SOR Classifier 2 Non-quantized	2.68	1.92	0.030	0.25	1.40	44
SOR Classifier 2 7 bits per RSRP	2.86	1.92	0.030	0.25	1.40	44
SOR Classifier 2 MSE Selection	3.39	1.89	0.029	0.25	1.40	63

Simulation Results



Number of CHO Preparations increases with coarse quantization.

Simulation Results



SOR classifier and its FNR directly affects RLF performance.

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Conclusion

- The proposed method delivers 53% overhead reduction, a huge gain at cost of inconsiderable mobility KPI loss.
- The SOR classifiers:

  insignificant impact on RLF, outage and SCHO.
- The compression:

  affects the number of CHO preparations.

Outlook

- Modifying input attributes of SOR classifier, e.g., adding location information.
- Partitioning input space for better bit allocation.

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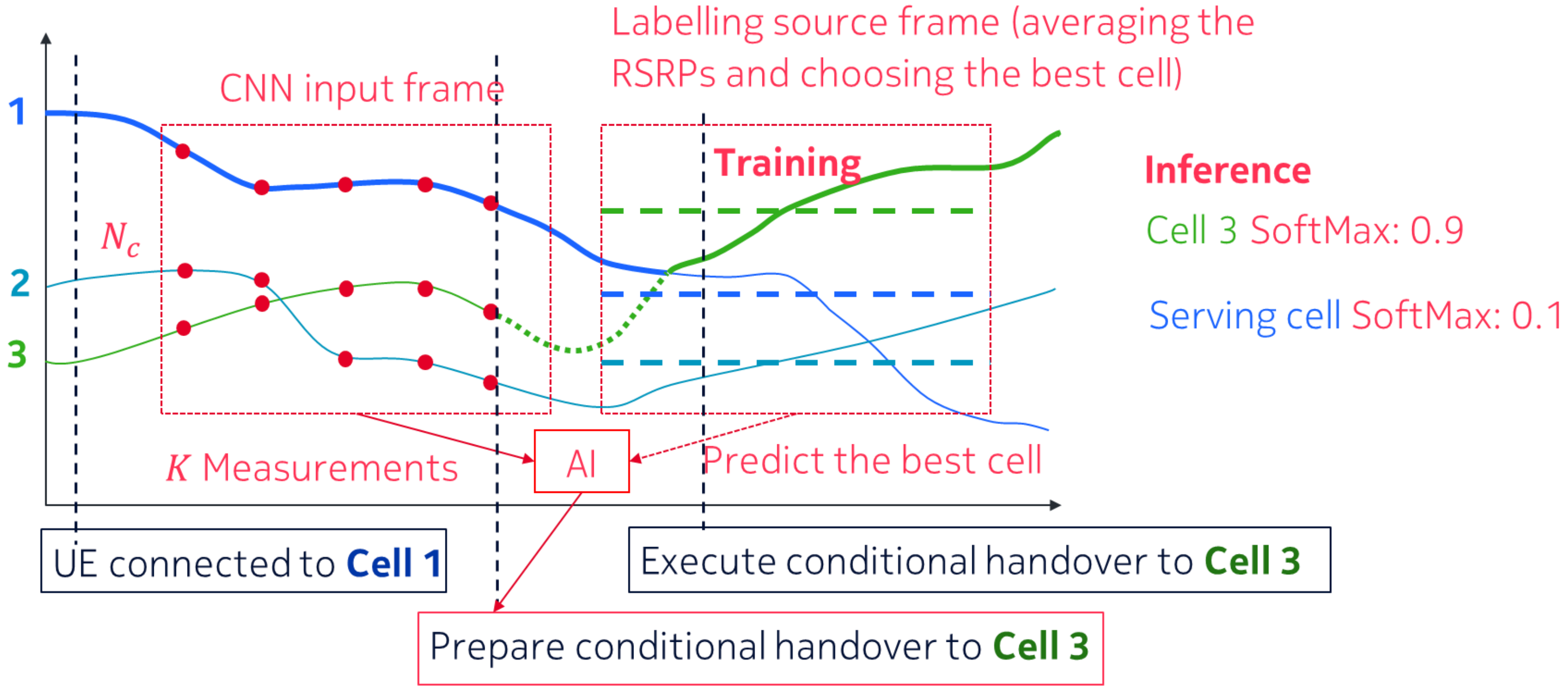
Appendix: Training of CHO-classifier



Appendix: Simulation Parameters

Carrier frequency	2 GHz
Cell layout	7-site hexagon
Inter-site distance	500 m
TX antenna height	30.5 m
UE height	1.5 m
TX antenna element gain	14 dBi
TX azimuth beamwidth	70
TX elevation beamwidth	10
TX max backwards attenuation	25 dB
Downlink transmit power	29 dBm/PRB
Noise power	-97 dB
Frequency dependent path loss component	128.1 dB
Distance dependent path loss exponent	3.76

Penetration loss	20 dB
Shadow fading	Log-normal $\sigma = 8$ dB
Shadow fading correlation distance	50 m
Fast fading	According to [1]
Total number of pedestrians	105
Total number of street UEs	500
Pedestrians' speed	3 km/h
Street UE speed	30 km/h
TX system bandwidth	100 MHz
PRB bandwidth	10 MHz
Outage threshold Q_{out}	-8 dB
T310 timer	1 sec
T304 timer	0.2 sec
L3 filter time constant	0.1 sec
CHO preparation offset	3 dB
CHO time to trigger T_{TTT}	0.12 sec
Ping-pong timer T_{PP}	5 sec

[1]: U. Karabulut, et. Al. "Low complexity channel model for mobility investigations in 5G networks," in IEEE Wireless Comm. and Networking Conference, 2020.