3GPP TSG RAN#102
December 11 – 15, 2023
Edinburgh, UK

RP-233277
9.1.2.4

AI/ML for Air Interface-Mobility

Scope and Initial Evaluation

Mediatek Inc.

AI/ML over Air Interface-Mobility

Justification: Limitation of Rule-based Mobility Mechanism

- Rule-based mobility performs well in normal mobility scenarios
  - with acceptable complexity and overhead
  - has been repeatedly verified and systematically improved in deployments
- but cannot achieve optimum performance in extreme scenarios (FR2 and/or high mobility)
  - It is reactive by design
    - The overall mobility procedure (incl. measurement, report and HO/cell switch) is not fast enough to adapt to channel variations in extreme mobility scenarios.
  - It features high a) complexity b) measurement effort c) signaling overhead for suboptimum mobility performance in these scenarios
  - New capacity-hungry services like e.g. XR require a reliable mobility connection with high throughput and low latency
- Need for
  - Optimum mobility performance with minimum measurement and overhead in both FR1 and FR2
  - Shift from conventional reactive mobility mechanism to proactive data-driven mechanism (with autonomous optimization without human intervention)

AI/ML over Air Interface-Mobility

Objectives (vs. RP-232745 baseline) [1/2]

- Type of mobility
  - L3-based mobility (including. basic HO in Rel-15 and CHO in Rel-16) and L1/L2-triggered mobility (LTM) are both considered
- HO optimization in Network side ~~[/UE side]~~, including
  - Candidate/target cell prediction in L3-based mobility to improve candidate cell configuration and target cell determination; ~~, or,~~ candidate/target beam(s) and cell(s) prediction in LTM to improve candidate cell configuration and target cell determination with pre-sync and cell switch[RAN2/RAN3].
- RRM measurement and event prediction, including
  - Beam-level measurement prediction with reduced RSs and measurement, e.g., spatial and temporal beam prediction cross cells [RAN2];
  - Cell-level measurement prediction, e.g., using intra-frequency measurement results to forecast the RRM measurement of inter-frequency/inter-RAT cells[RAN2];
  - HO failure/RLF prediction [RAN2];
  - Measurement events prediction to simplify the filtering configuration and operation[RAN2];
  - Solutions impacting measurement performance and requirement are in the SI scope. RAN4 should be involved by triggered LS from RAN2 [RAN4].
- Note 1: no intention to change the existing framework for the mobility under connected mode.
- ~~Note 2: In the SID, target performance metrics and impacts should be clarified~~
- Note 3: Avoid overlap work with RAN3.

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AI/ML over Air Interface-Mobility

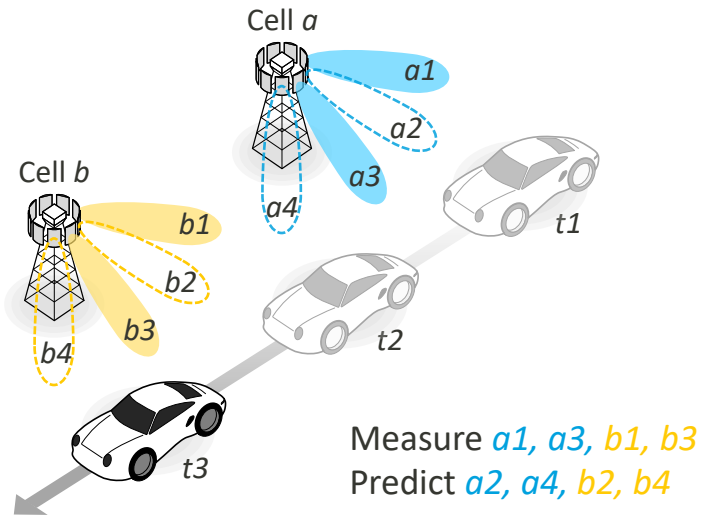
Objectives (vs. RP-232745 baseline) [2/2]

- Study the impacts on LCM framework if identified: ~~LCM framework and others~~
  - The conclusions in Rel-18 AI/ML study should be used as baseline.
  - ~~Other impacts are further studied~~
- Specify the methodology for evaluating the performance benefits of AI/ML based algorithms:
  - Methodology based on statistical models (from TR 38.901) for system level simulation as a starting point.
    - Need for common assumptions for the simulation setting, e.g., network deployment and configuration and UE trajectory.
  - System-level and intermediate KPIs:
    - Determine the KPIs and benchmarks for each use cases. The conventional system-level KPIs for mobility performance evaluation incl. HOF/RLF rate, ToS/PingPong rate, HO Interruption time and RSRP distribution are considered as baseline. Other system KPIs, e.g., overhead, power consumption should be discussed as part of the study;
    - Intermediate KPIs to evaluate the AI/ML algorithms performance e.g., prediction accuracy, RSRP difference as well as inference latency, computation complexity should be discussed as part of the study.
  - Generalization performance evaluation and methodology should be discussed as part of the study.
- Assess potential specification impact:
  - Protocol aspects: Consider aspects related to e.g., RRM measurement procedures, L3-based and LTM mobility procedures, AI trigger events, as well as configuration corresponding to the AI/ML approaches for each use case;
  - PHY aspects: Consider aspects related to e.g., the additional physical layer signaling/measurement and the corresponding processing. RAN1 only starts the work after sufficient progress is made on the use case study in RAN2.

AI-assisted RRM measurement

Spatial Domain Beam Prediction Cross Cells

[1/3]



- Basic HO and LTM as benchmark
- Setting: FR2, 30km/h, 120km/h, simulation time 200s,
  - AI-RRM uses half of the beam's RSRP as input and predict the other half of the beam's RSRP. (**50%** RS reduction)
  - The UE trajectory is considered as input

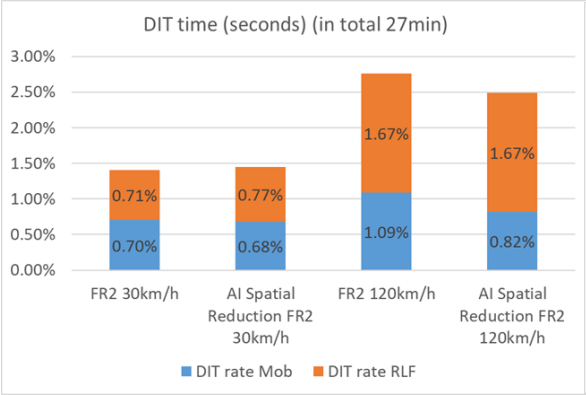
FR2

	RSRP-Diff (dB)	
	Train	**Test**
AI Spatial Reduction 30kph	2.11	2.95
AI Spatial Reduction 120kph	1.84	2.72

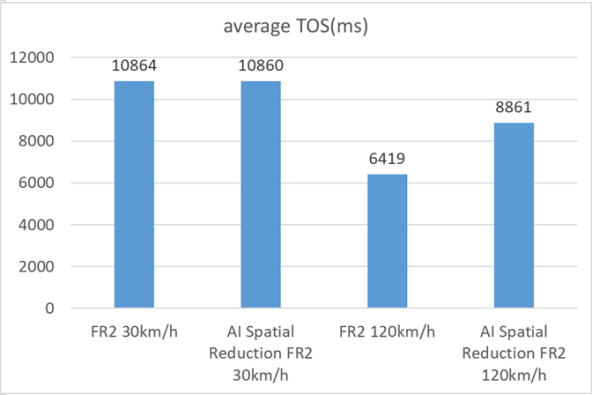
AI-assisted RRM measurement

Spatial Domain Beam Prediction Cross Cells vs. Basic HO: FR2 [50% RS Reduction]

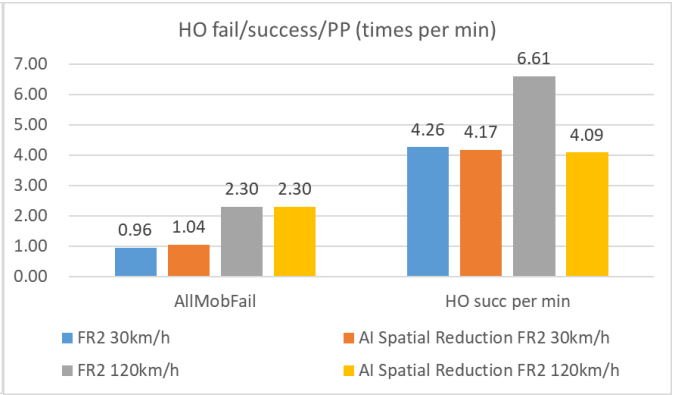
[2/3]



Data Interruption Time



Average Time of Stay



Mobility Failure and HO success times

30km/h	DIT	Average TOS (ms)	MobFail (per min)	Opt cell camping on rate
Non-AI	1.41%	10864	0.96	0.63
AI-RRM	1.45%	10860	1.04	0.62

120km/h	DIT	Average TOS (ms)	MobFail (per min)	Opt cell camping on rate
Non-AI	2.76%	6419	2.30	0.49
AI-RRM	2.49%	8861	2.30	0.30

Observation: While reducing the spatial domain measurement effort by 50%, AI can ensure that the HO performance (DIT and ToS) does not deteriorate much at the cost of camping on best cell rate decrease.

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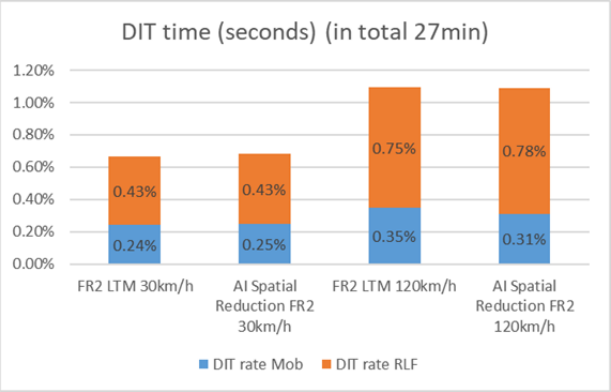
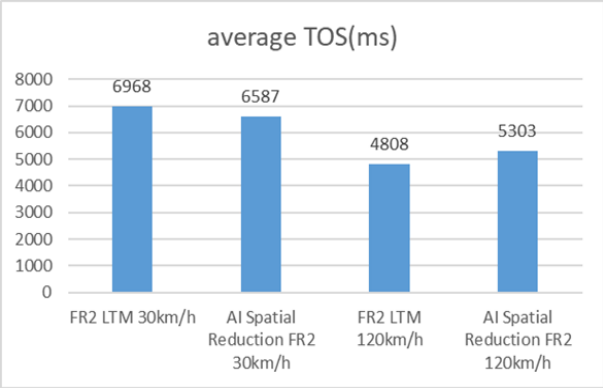
AI-assisted RRM measurement

Spatial Domain Beam Prediction Cross Cells vs. LTM: FR2 [50% RS Reduction]

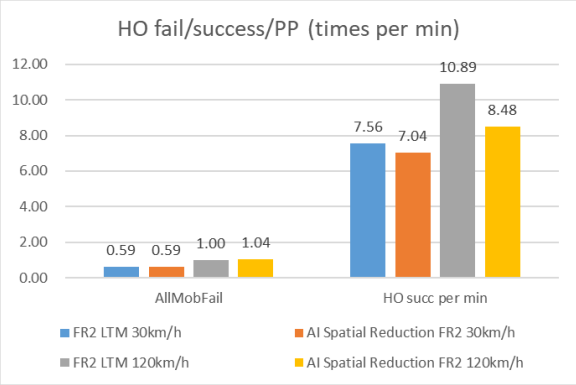
[3/3]



Data Interruption Time



Average Time of Stay



Mobility Failure and HO success times

30km/h	DIT	Average TOS (ms)	MobFail (per min)	Opt cell camping on rate
Non-AI	0.67%	6968	0.59	0.73
AI-RRM	0.68%	6587	0.59	0.68

120km/h	DIT	Average TOS (ms)	MobFail (per min)	Opt cell camping on rate
Non-AI	1.10%	4808	1.00	0.58
AI-RRM	1.09%	5303	1.04	0.50

Observation: While reducing the spatial domain measurement effort by 50%, AI can ensure that the HO performance (DIT and ToS) does not deteriorate much at the cost of camping on best cell rate decrease.

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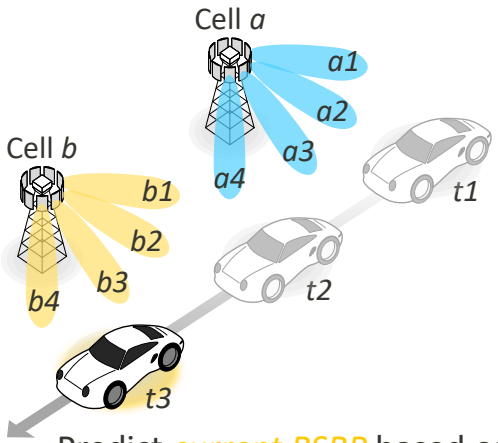
AI-assisted RRM measurement

Temporal Domain Beam Prediction Cross Cells

[1/3]



Measure *all beam pairs*

Predict *current RSRP* based on previous measurements

- Basic HO and LTM as benchmark
- Setting: FR2, 30km/h, 120km/h, simulation time 200s,
  - Basic HO:160ms observation window; 160ms prediction window,
  - LTM: 20ms observation window: 20 ms prediction window
  - **50%** measurement effort reduction
  - The UE trajectory is considered as input

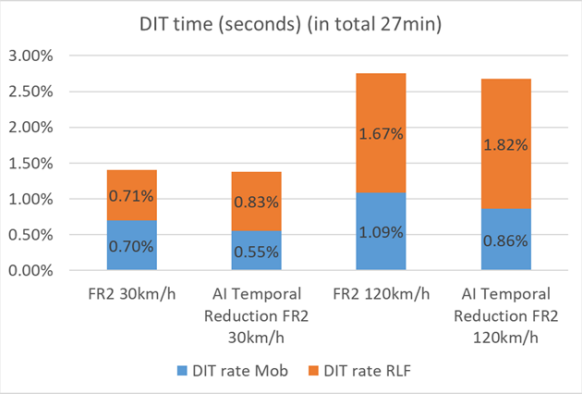
FR2

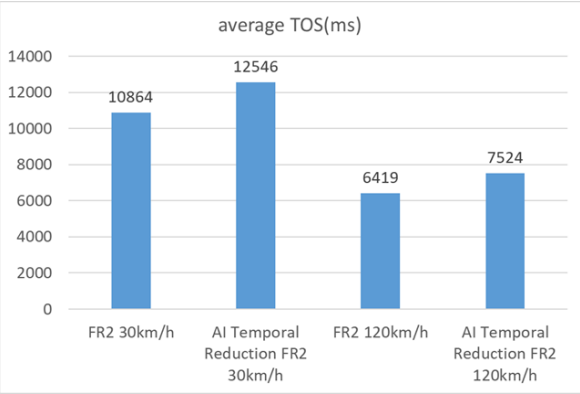
	RSRP-Diff (dB)	
	Train	**Test**
AI Temporal Reduction 30kph	2.27	2.85
AI Temporal Reduction 120kph	2.53	2.81

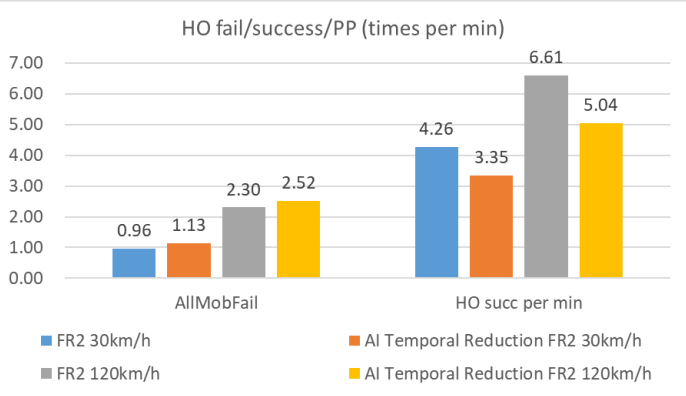
AI-assisted RRM measurement

Temporal Domain Beam Prediction Cross Cells vs. Basic HO: FR2 [50% Meas. Effort Reduction]

[2/3]







Data Interruption Time

30km/h	DIT	Average TOS (ms)	MobFail (per min)	Opt cell camping on rate
Non-AI	1.41%	10864	0.96	0.49
AI-RRM	1.38%	12546	1.13	0.34

Average Time of Stay

Mobility Failure and HO success times

120km/h	DIT	Average TOS (ms)	MobFail (per min)	Opt cell camping on rate
Non-AI	2.76%	6419	2.30	0.49
AI-RRM	2.68%	7524	2.52	0.34

Observation: While reducing the temporal domain measurement effort by 50%, AI can ensure that the HO performance (DIT and ToS) does not deteriorate at the cost of camping on best cell rate decrease.

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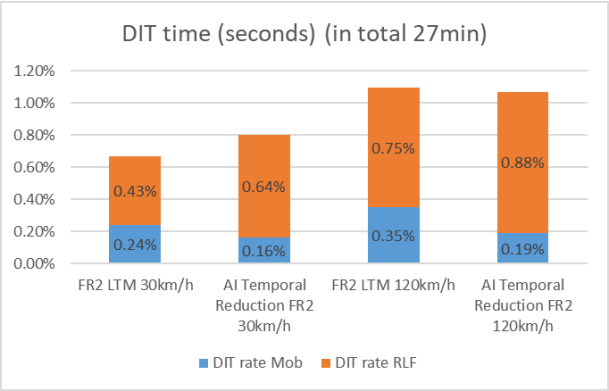
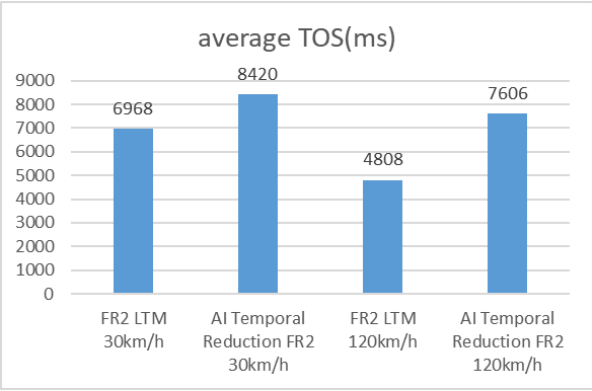
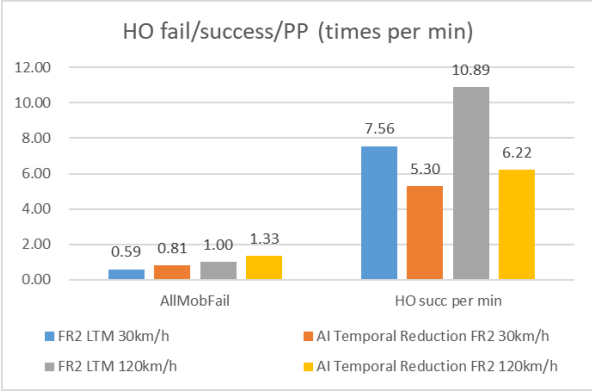
AI-assisted RRM measurement

Temporal Domain Beam Prediction Cross Cells vs. LTM: FR2 [50% Meas. Effort Reduction]

[3/3]







Data Interruption Time

Average Time of Stay

Mobility Failure and HO success times

30km/h	DIT	Average TOS (ms)	MobFail (per min)	Opt cell camping on rate
Non-AI	0.67%	6968	0.59	0.73
AI-RRM	0.80%	8420	0.81	0.53

120km/h	DIT	Average TOS (ms)	MobFail (per min)	Opt cell camping on rate
Non-AI	1.10%	4808	1.00	0.58
AI-RRM	1.07%	7606	1.33	0.47

Observation: While reducing the temporal domain measurement effort by 50%, AI can ensure that the HO performance (DIT and ToS) does not deteriorate at the cost of camping on best cell rate decrease.

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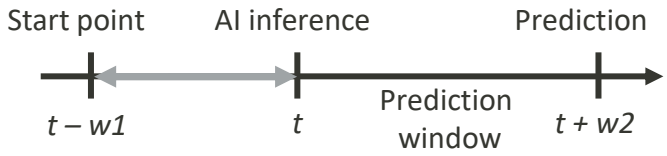
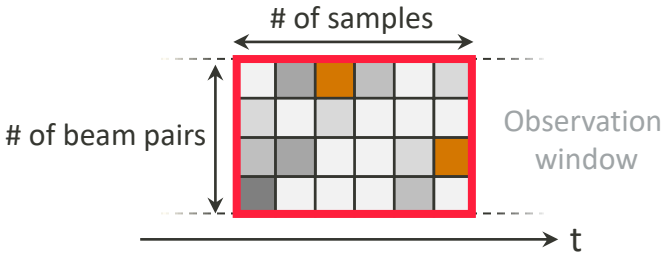
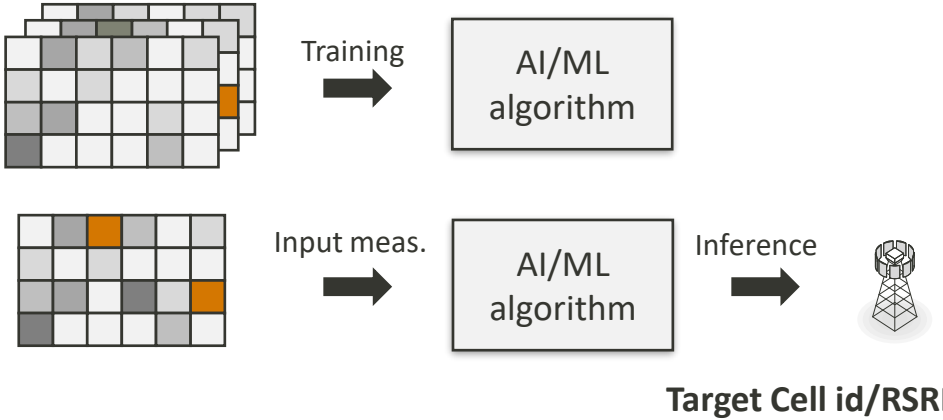
Measurement Event Prediction

Experiment (1/3)

- Basic Algorithm
  - To learn the pattern from the dataset and
  - To predict measurement event from previous measurement
  - Inputs: each beam pair's RSRP, CSI, etc.
  - Output: Target Cell id, Target cell RSRP
  - AI Model: CNN, LSTM, Transformer, etc.
- Simplify the filtering configuration (offset, TTT, hysteresis, coefficient and so on) and operation
- Predict multiple future steps
  - i.e., predict the best RSRP cell for the next 20ms, 40ms, …140ms
- Make HO decision based on prediction





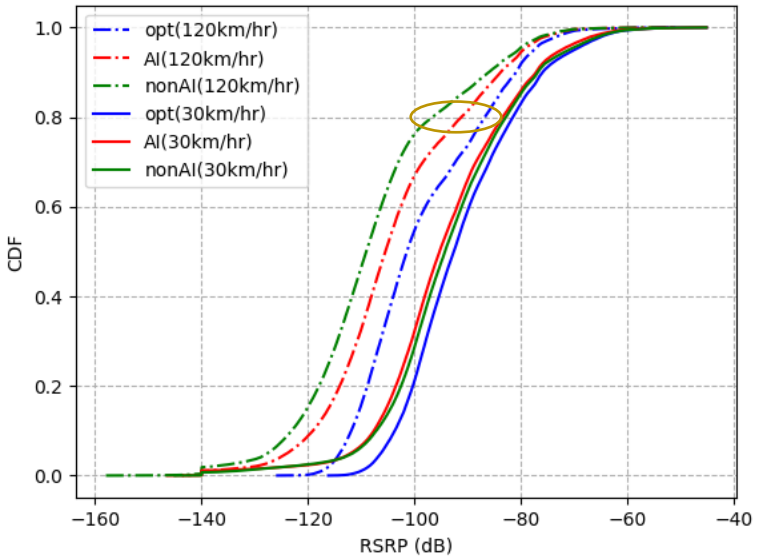


Measurement Event Prediction

Experimental Results (2/3)

- Due to the multiple-step prediction, AI approach does not need TTT mechanism
  - More sensitive
  - No TTT latency
- Better performance in quick variation scenarios, e.g., 120km/hr.
- Slightly worse than the basic HO in slow UE speed scenario, e.g., 30km/hr.

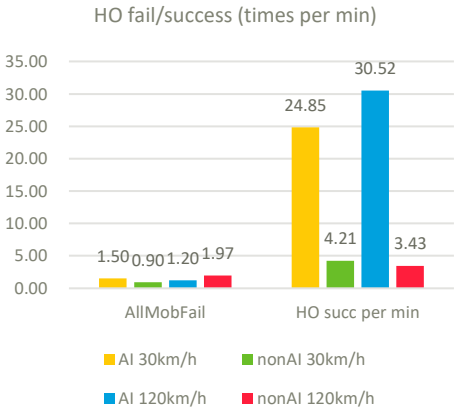
- Compare with basic HO with the typical setting, e.g., 160TTT and 2dB A3 event offset.

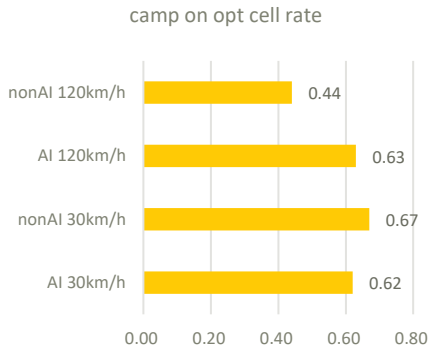


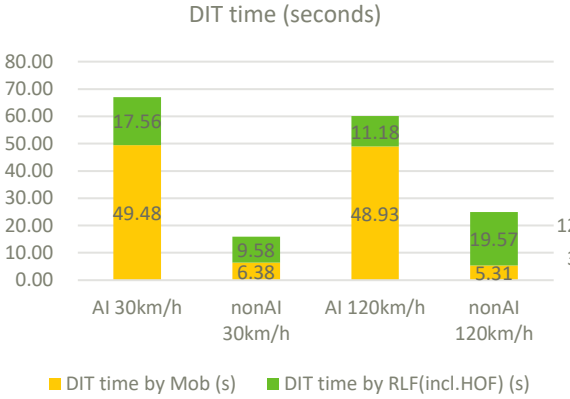
Measurement Event Prediction

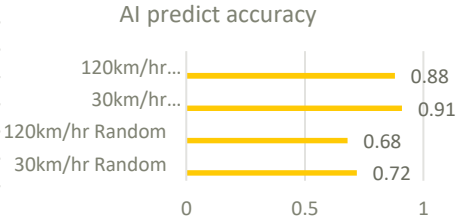
Experimental Results (3/3)

- AI filter can be trained for different optimization targets, e.g., target to have optimum link quality
  - Keep the same level of # of mobility fail
  - Higher camp on opt cell rate
  - Higher interruption time from the HO procedure.
- Challenge I: Metrics Tradeoff
  - Hard to compare with basic HO for those tradeoff metrics, e.g., interruption time, ping-pong, camp on rate, under all different configurations, e.g., TTT, offsets.
  - Consider the overall system performance metric, e.g., average throughput, and show the AI gain, which should be positively correlated to RSRP CDF result.
- Challenge II: AI accuracy in different scenarios.









Annex: Simulation Setting

Items	FR2
ISD(Inter-site distance)	200m
Number of sites/sectors	21cell, 7 sites, each site 3 sectors
Carrier Frequency	30GHz
Bandwidth	50MHz
Beam setting	Horizontal: 12; Vertical: 2 Total: 24 beams
Sub-carrier spacing	60KHz
BS Total TX power	46 dBm
BS height	25m
Minimum distance	Minimum distance between UE and regular node. >=35m
UE trajectory	The random moving model studied in R18 RAN1 BM case
UE speed	30/120 km/h
UE number	8
Sample interval	20ms
Simulation time	1600s(each UE 200s)

Thank you!

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