3GPP TSG-RAN WG4 Meeting
Chicago, November 13- November 17, 2023

R4-2318589

Agenda item: 13
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R19 Study on AI/ML based RRM Enhancement

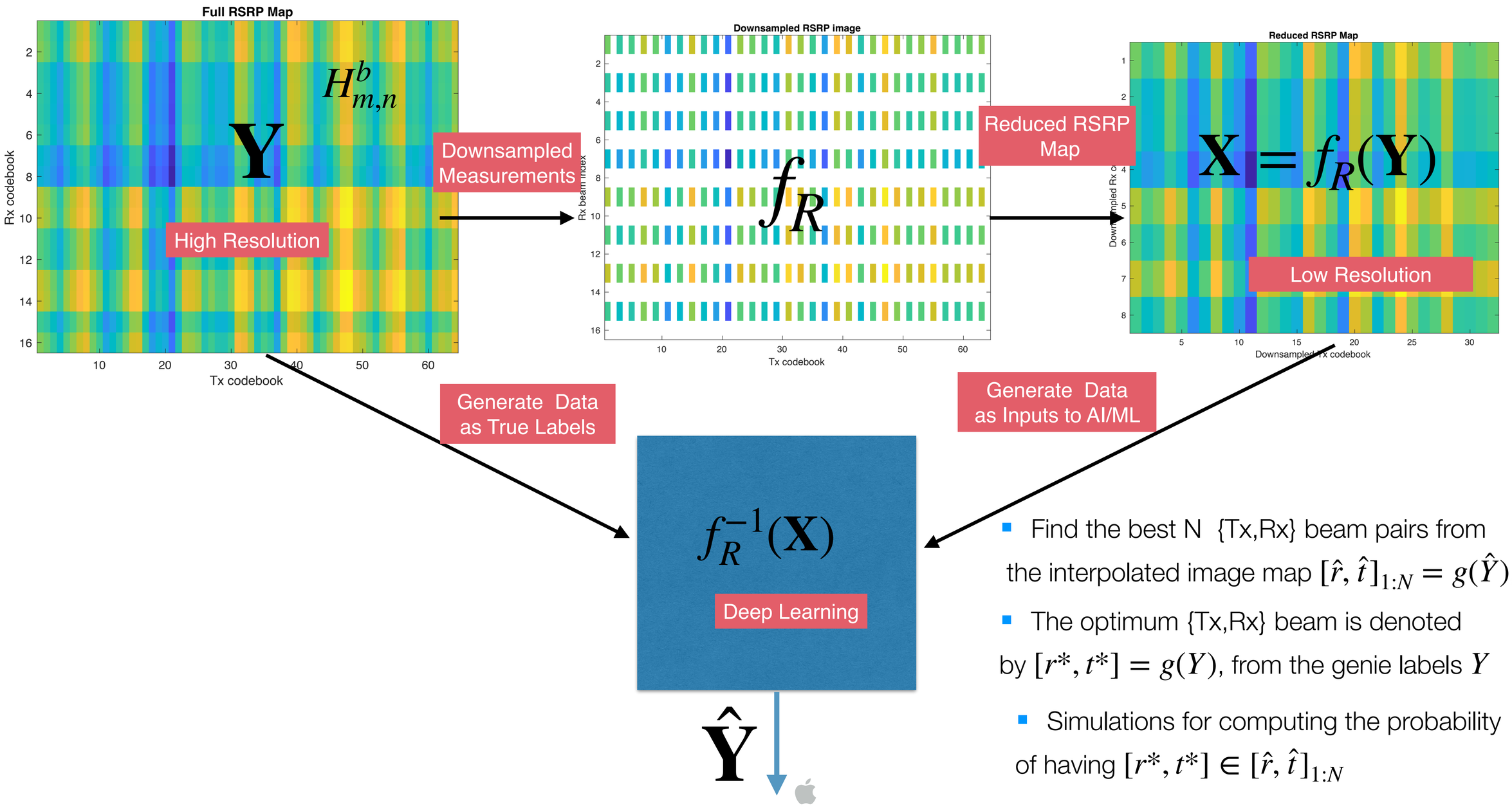
Rel-19 AI/ML based RRM enhancement | Current Status

- Background:
  - SI of RP-213599 lists the use cases to focus on for AI/ML interface
  - Use cases to focus on:
    - CSI feedback enhancement, e.g., overhead reduction, improved accuracy, prediction
    - Beam management, e.g., beam prediction in time, and/or spatial domain for overhead and latency reduction, beam selection accuracy improvement
    - Positioning accuracy enhancements for different scenarios including, e.g., those with heavy NLOS conditions
  - SI of RP-213599 explored the benefits of augmenting the air-interface with features enabling improved support of AI/ML based algorithms for enhanced performance and/or reduced complexity/overhead.
    - However, RRM and L3 measurement enhancement from UE perspective has not been the focus of the existing RAN1 led SI

Rel-19 AI/ML based RRM enhancement | L3 Measurement Enhancement

- Motivation:
  - The overhead of RS used for RRM (i.e., SSB and CSI-RS) is quite high in the current NR design, e.g., when SMTC periodicity is 20ms, the related SMTC overhead in FR2 is 25%, especially for FR2 (with 5ms SSB burst)
  - It should be quite beneficial to reduce the number of beams at both Tx and/or Rx in L3 related measurements
  - Potential enhancement on RRM functionality with AI/ML:
    - L3 measurements delay reduction by minimizing the Tx/Rx beam sweeping set (spatial beam prediction). SMTC window duration can be reduced by reducing the beam sweeping factor. This way the measurement delay is reduced
    - L3 measurement reductions by periodically skipping the Tx/Rx beam sweeping. SMTC periodicity can be increased
    - As a result of minimizing the L3 measurements we achieve reductions in scheduling restrictions (which increases throughput)
- Justification
  - AI/ML algorithm can be utilized to enhance RRM performance
  - Key difference from beam management study in RAN1 includes
    - Model generalization.
      - All intra- and inter-frequency neighbor cells for L3 measurement vs. serving cell only for L1 measurement
    - Operating SNR difference
      - -6dB SNR for L3 measurement vs. >0dB SNR for L1 measurement

RSRP Map, Deep Learning and Image SuperResolution



- Find the best N {Tx,Rx} beam pairs from the interpolated image map $[\hat{r}, \hat{t}]_{1:N} = g(\hat{Y})$,
- The optimum {Tx,Rx} beam is denoted by $[r^*, t^*] = g(Y)$, from the genie labels Y
- Simulations for computing the probability of having $[r^*, t^*] \in [\hat{r}, \hat{t}]_{1:N}$

Simulation Results: AI/ML Spatial Prediction for High SNR

- The labels $aTx/bRx/c\,\%\,TR/N = d/CH$

in the figure denote:

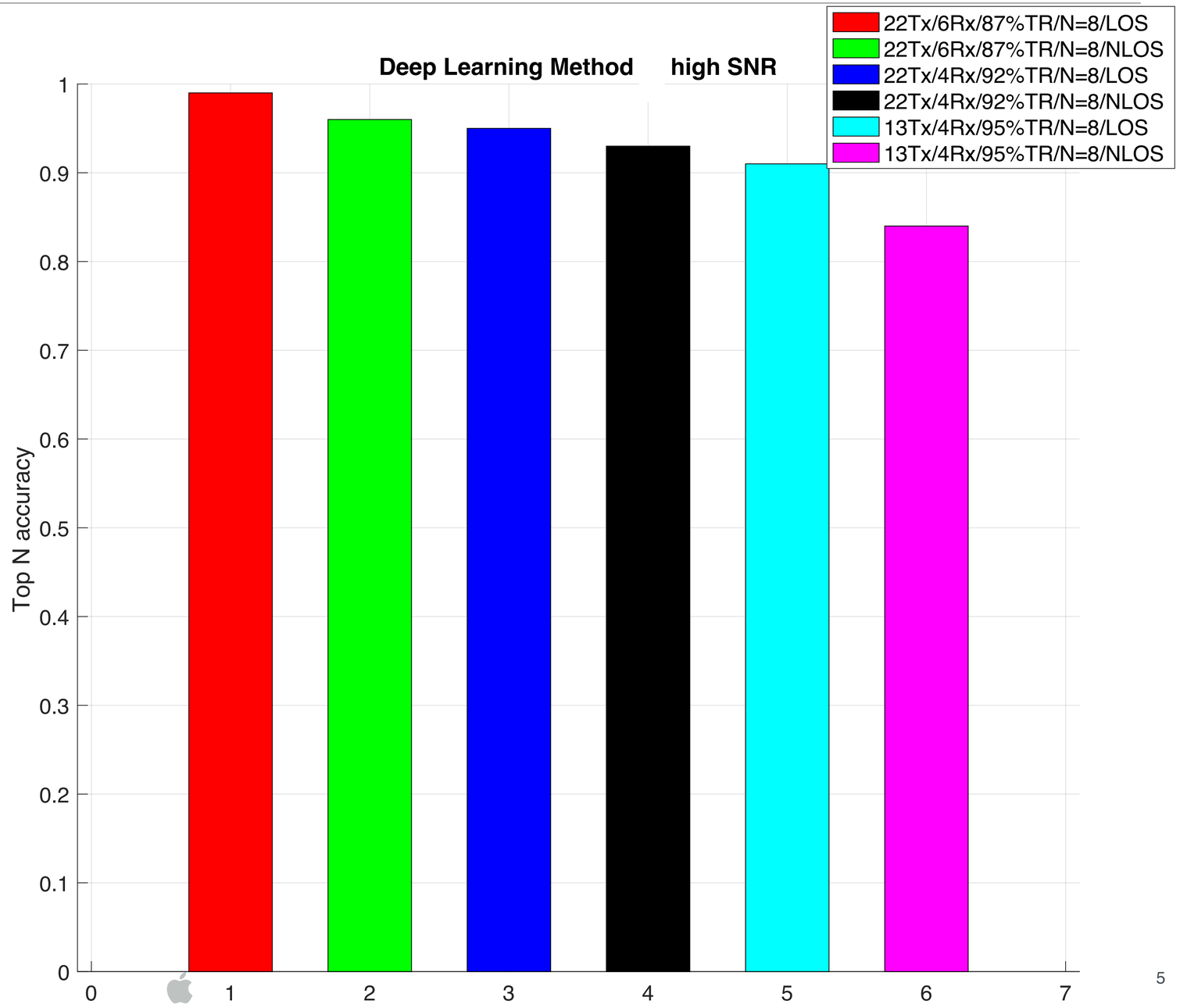
- a is the number of subsampled Tx beams
- b is the number of subsampled Rx beams
- $c = (1 - \frac{ab}{N_a M_a})100\,\%$ is the TR
- N=d is the number of top-N beams
- $CH = \{LOS, NLOS\}$ is the channel type

TR: Training Reduction

Network is trained at antenna spacing = $\lambda/2$

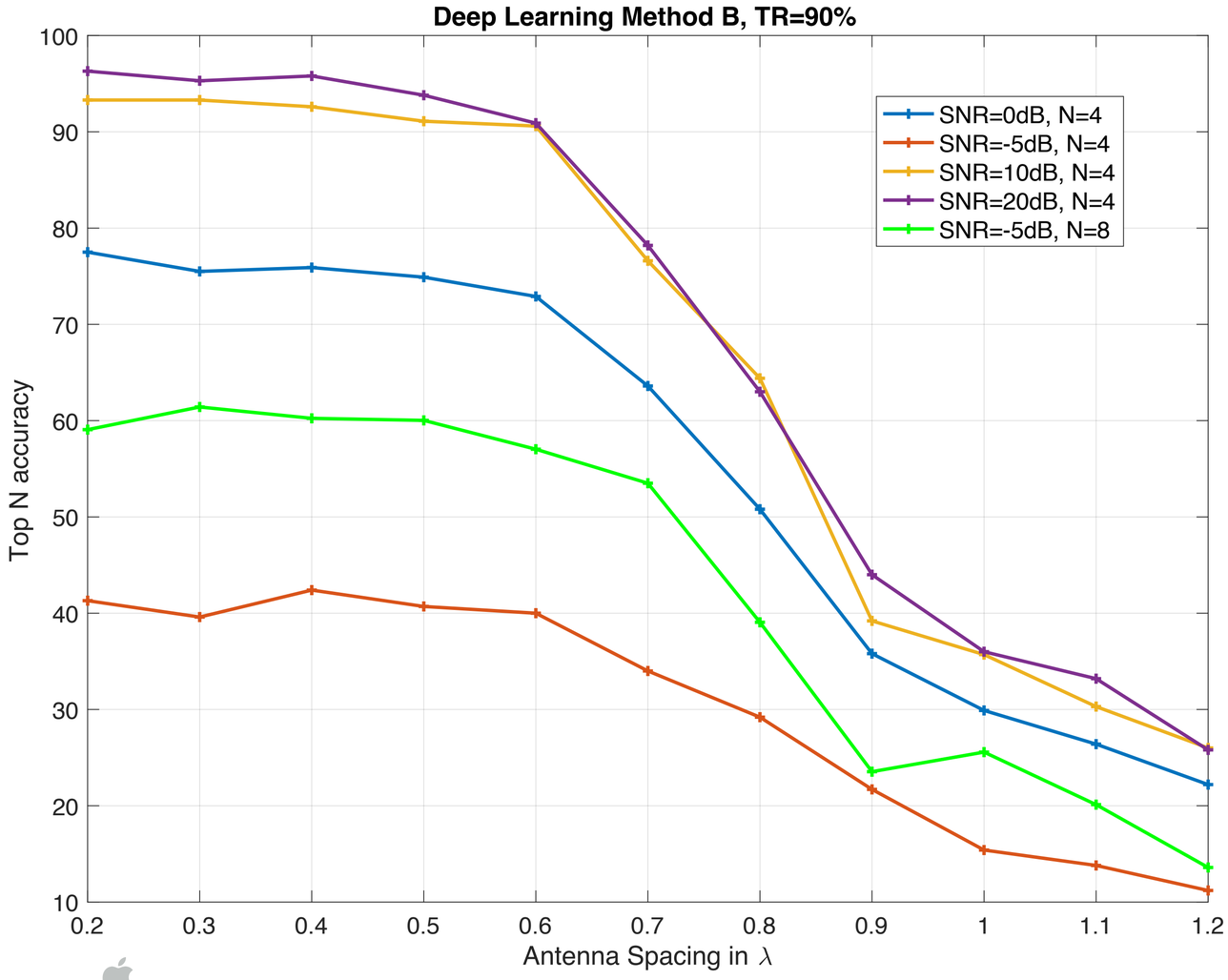
Full search= 64*16 =1024
1- 22(Tx)*6(Rx)/64*16= 87.5% TR

TR: Training Reduction



Challenges: Simulation Results for Different SNR Levels

- For L3 RSRP measurements, SNR becomes more important. Noise and Cell interference could be dominant during handover
- We trained and simulated the Deep learning Network for various levels of SNR
- The system was simulated with the parameters:
- $22Tx/5Rx/90\,\%\,TR/N = 4/NLOS$
- We also tested the generalization ability of the AI/ML model to different gNB implementations (different antenna spacing)

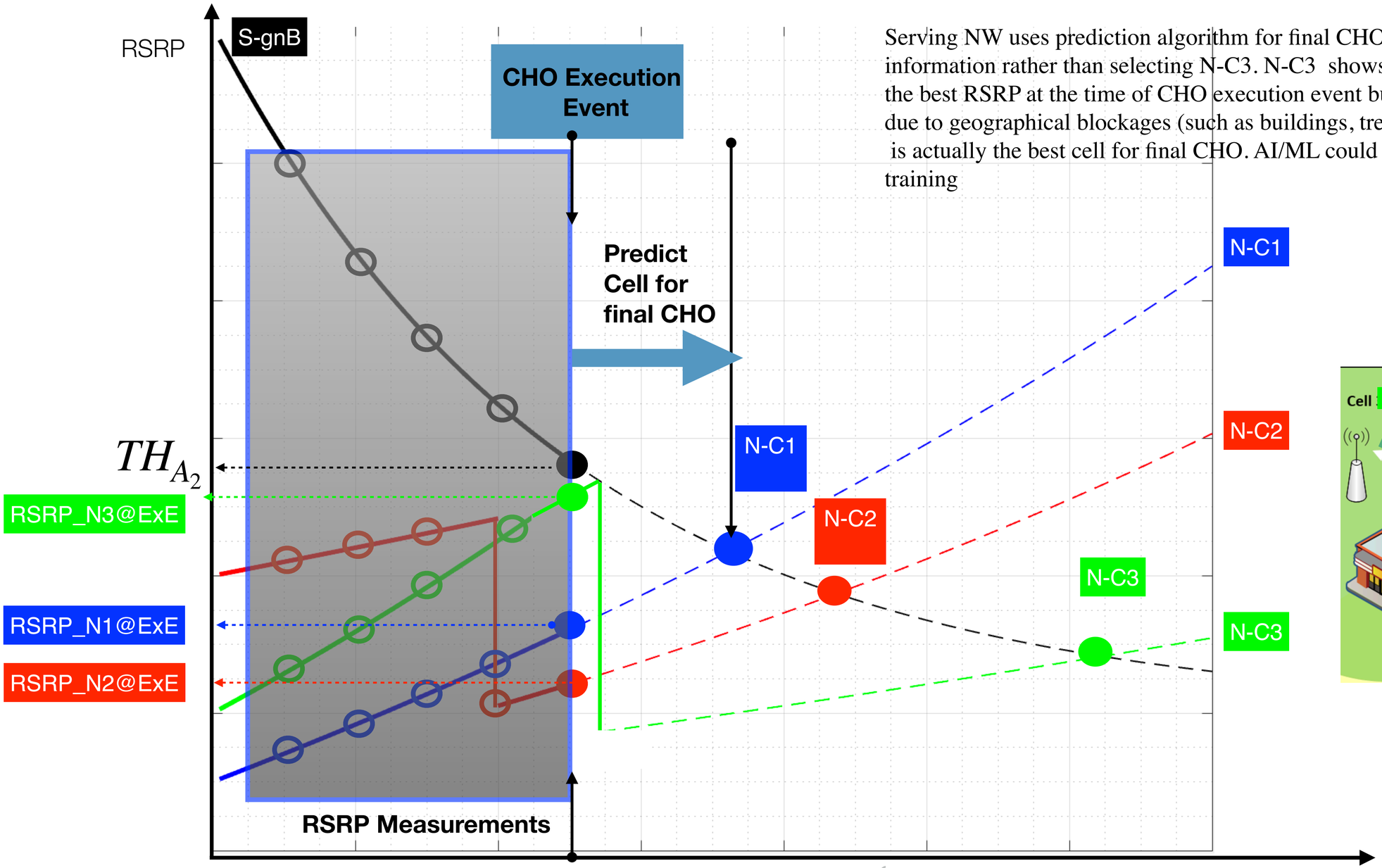


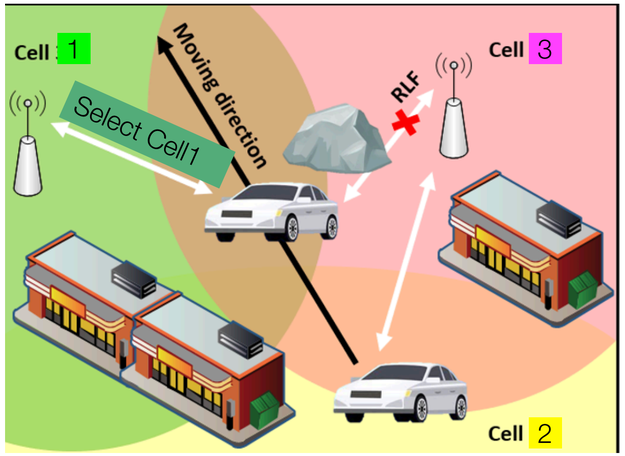
Rel-19 AI/ML based RRM enhancement | RSRP/RSRQ/SINR Accuracy Enhanc

- Motivation: AI/ML based RSRP/RSRQ/SINR temporal prediction
- Definition:
  - Current RSRP is the filtered value of the L3 RSRP measurements (including current and past measurement)
  - Predicted RSRP is the prediction of a future RSRP sample based on current and past RSRP measurements
- AI/ML based RSRP Accuracy enhancement could improve HOF (handover failure) rate based on the temporal RSRP prediction and reduce mobility interruption interval during HO.

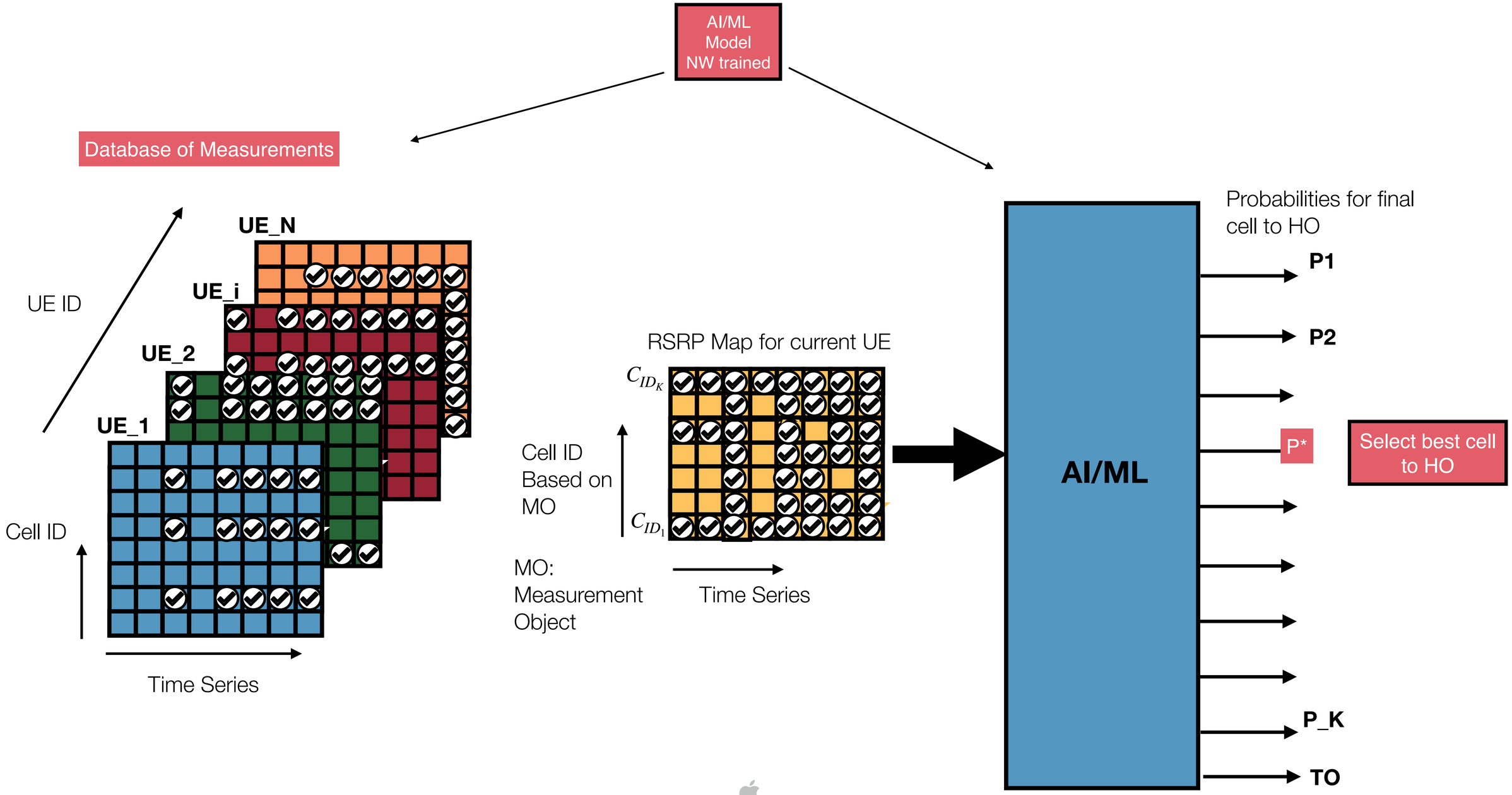
Example of AI/ML Aided (temporal prediction) Conditional Handover (CHO)

Serving NW uses prediction algorithm for final CHO based on the received RSRP information rather than selecting N-C3. N-C3 shows the best RSRP at the time of CHO execution event but it suffers sudden RSRP degradation due to geographical blockages (such as buildings, trees, mobile objects), and N-C1 is actually the best cell for final CHO. AI/ML could predict the best cell based on database training





Conventional HO Enhancement: NW Implementation



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