**3GPP TSG RAN WG1 Meeting #110e-bis R1-220xxxx**

**eMeeting, October 10 – 19, 2022**

**Source:** Moderator (Samsung)

**Title:** Feature lead summary #0 evaluation of AI/ML for beam management

**Agenda Item:**  9.2.3.1

**Document for:** Discussion and Decision

# Introduction

In RAN#94-e, Rel-18 new study item on “Study on Artificial Intelligence (AI)/Machine Learning (ML) for NR Air Interface” was approved. The following use cases were identified as the initial set:

* Initial set of use cases includes:
  + CSI feedback enhancement, e.g., overhead reduction, improved accuracy, prediction [RAN1]
  + Beam management, e.g., beam prediction in time, and/or spatial domain for overhead and latency reduction, beam selection accuracy improvement [RAN1]
  + Positioning accuracy enhancements for different scenarios including, e.g., those with heavy NLOS conditions [RAN1]

The performance of AI/ML based algorithms for the use cases includes the following aspects:

1. Evaluate performance benefits of AI/ML based algorithms for the agreed use cases in the final representative set:
   * Methodology based on statistical models (from TR 38.901 and TR 38.857 [positioning]), for link and system level simulations.
     + Extensions of 3GPP evaluation methodology for better suitability to AI/ML based techniques should be considered as needed.
     + Whether field data are optionally needed to further assess the performance and robustness in real-world environments should be discussed as part of the study.
     + Need for common assumptions in dataset construction for training, validation and test for the selected use cases.
     + Consider adequate model training strategy, collaboration levels and associated implications
     + Consider agreed-upon base AI model(s) for calibration
     + AI model description and training methodology used for evaluation should be reported for information and cross-checking purposes
   * KPIs: Determine the common KPIs and corresponding requirements for the AI/ML operations. Determine the use-case specific KPIs and benchmarks of the selected use-cases.
     + Performance, inference latency and computational complexity of AI/ML based algorithms should be compared to that of a state-of-the-art baseline
     + Overhead, power consumption (including computational), memory storage, and hardware requirements (including for given processing delays) associated with enabling respective AI/ML scheme, as well as generalization capability should be considered.

In this contribution summarized the discussions and proposal on evaluation methodology (EVM) and KPIs from contributions submitted to AI 9.2.3.1 for beam management (BM). The issues that are in the focus of this round of the discussion are furthermore tagged FL1.

Follow the naming convention in this example:

* Document-v000-Mod.docx
* Document-v001-Mod-CompanyA.docx
* Document-v002-CompanyA-CompanyB.docx

If needed, you may “lock” a spreadsheet file for 30 minutes by creating a checkout file, as in this example:

* CompanyC uploads an empty file named Document-v003-CompanyB-CompanyC.checkout
* CompanyC checks that no one else has created a checkout file simultaneously, and if there is a collision, CompanyC tries to coordinate with the company who made the other checkout
* CompanyC then has 30 minutes to upload Document*-v003-CompanyB-CompanyC.docx*
* If no update is uploaded in 30 minutes, other companies can ignore the checkout file.

To avoid excessive email load on the RAN1 email reflector, please note that there is NO need to send an info email to the reflector just to inform that you have uploaded a new version of this document. Companies are invited to enter the contact info in the table below.

#### FL1: Question 0-1

* **Please consider entering contact info below for the points of contact for this email discussion.**

|  |  |  |
| --- | --- | --- |
| Company | Point of contact | Email address |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |
|  |  |  |

# General evaluation assumptions

## 1.1 Open issues on evaluation assumption of SLS

The following proposals were discussed in contributions:

**gNB antenna configuration and transmission power**

Proposals in contributions:

* ZTE [3]
  + Proposal 1: Unified descriptions of the antenna configuration for BS and UE should be adopted to avoid confusion.
    - BS antenna configuration: antenna setup and port layouts at gNB: [4, 8, 2, 1, 1, 1, 1], (dV, dH) = (0.5, 0.5) λ
    - UE antenna configuration: antenna setup and port layouts at UE: [1, 4, 2, 1, 2, 1, 1], 2 panels (left, right)
* Google [9]
  + Proposal 1: For EVM, the BS antenna configuration should be (M, N, P, Mg, Ng) = (4, 8, 2, 1, 1), (dV, dH) = (0.5, 0.5) λ.
  + Proposal 2: Add BS height = 10m as a second option as evaluation assumption to be aligned with evaluation assumption in other agenda items and to create more beams for indoor UEs in vertical domain.
* Samsung [24]
  + Proposal # 1: Adopt the following parameter for BM SLS evaluation:
    - BS Antenna Configuration and BS Tx Power
      * Antenna setup and port layouts at gNB: [4, 8, 2, 1, 1,1,1], (dV, dH) = (0.5, 0.5) λ as baseline with 40dBm Tx power
* Qualcomm [26]
  + Proposal 1: Consider the following simulation assumptions for BM-Case1 and BM-Case2:
    - BS antenna configuration: [8, 16, 2, 1, 1,1,1], (dV, dH) = (0.5, 0.5) λ
    - BS Tx power: 34 dBm

#### FL1: Antenna configuration and DL Tx power

**Proposal 1-1-1a:**

* **BS antenna configuration:** 
  + **antenna setup and port layouts at gNB: [4, 8, 2, 1, 1, 1, 1], (dV, dH) = (0.5, 0.5) λ**
  + **Other assumptions are not precluded**
* **BS Tx power:** 
  + **40dB or 34 dBm reported by companies**
  + **Other values are not precluded**
* **UE antenna configuration (Clarification of agreement in RAN 1 #110):** 
  + **antenna setup and port layouts at UE: [1, 4, 2, 1, 2, 1, 1], 2 panels (left, right)**
  + **Other assumptions are not precluded**

|  |  |
| --- | --- |
| Supporting companies |  |
| Objecting companies |  |

**Please provide your view Proposal 1-1-1a, if any.**

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |

**Traffic model**

**Agreement in RAN 1 #109e**

|  |  |
| --- | --- |
| **Traffic Model** | FFS:   * Option 1: Full buffer * Option 2: FTP model   Other options are not precluded |

Proposals in contributions:

* Huawei/HiSi [2]
  + Proposal 8: For the selection of the traffic model for beam prediction, **full buffer** considered as the starting point.
* Interdigital [6]
  + Proposal 12: For traffic model, support the following evaluation assumptions:
    - For beam information related KPIs, no traffic model is needed to be defined as UE is only measuring reference signals not decoding actual PDSCHs.
    - For system performance related KPIs, FTP traffic should be used to reflect practical traffics for the evaluation.
    - For FTP traffic model, FTP model 3 is preferred as generating a new UE for each packet (FTP model 1) is not appropriate for evaluating benefits from AI/ML based beam prediction.
  + Proposal 13: For UE distribution, support the following evaluation assumptions:
    - For FTP traffic model, 10 UEs per cell/sector with 50% and 70% RUs is preferred.
    - 80% outdoor UEs and 20% indoor UEs for spatial domain beam prediction as defined in TR 38.901 (Option 1).
* LGE [10]
  + Proposal 1. FTP model 1 with packet size of 0.5 Mbytes can be considered as a baseline traffic model.
  + Proposal 2. If FTP model 1 is selected for the baseline traffic model, consider RU of 30%, 50%, 70%, and companies are required to report the assumption of load factor for each of RU values.
* Intel [14]
  + Proposal 4: For SLS UE distribution, large number of UEs per cell should be allowed for dataset generation but should be limited to 10 UEs/TRP for throughput evaluation using trained model for beam selection.
  + Proposal 5: For system performance KPIs, if supported, only full-buffer traffic models should be used.
* Samsung [24]
  + Proposal # 1: Adopt the following parameter for BM SLS evaluation:
    - Traffic Model
      * Option 1: Full buffer
      * Other options are not precluded

#### FL1: Traffic model

**Proposal 1-1-2a:**

* **For system performance related KPI (if supported) [e.g, throughput] evaluation (model inference), companies report the traffic model:**
  + **Option 1: Full buffer**
  + **Option 2: FTP model with detail assumptions (e.g., FTP model 1, FTP model 3)**

|  |  |
| --- | --- |
| Supporting companies |  |
| Objecting companies |  |

**Please provide your view Proposal 1-1-2a, if any.**

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |

## 1.2 (Closed) Trajectory model for UE mobility

Companies provide views on the three options for UE trajectories:

* Huawei/HiSi [2]:
  + Proposal 11: For the evaluation of temporal domain beam prediction, Option 4, i.e., random direction straight-line trajectories for randomly dropped UEs, should be considered as the starting point.
* ZTE [3]:
  + Proposal 5: The random direction straight-line trajectories in Option #4 can be adopted for modelling UE trajectory, which is simpler than other UE trajectory options and beneficial for model generalization.
* Intel [14]:
  + UE trajectories with straight line movement without sharp turns should be considered as a first step for evaluation.
  + The UE trajectory should be sampled at least at the minimum decorrelation distance of the large-scale parameters corresponding to the scenario of evaluation.
* Nokia [19]:
  + Proposal 12: RAN1 further investigates the trajectory model for BM-Case#2, adopting Option #4 as a starting point for further studies.

FL0: There is no strong need to down select the baseline performance in this meeting other than current agreements.

## 1.3 Others

Other than the open issues for SLS, the following proposals were proposed by companies:

* Vivo [5]:
  + It is encouraged for companies to provide publicly accessible dataset and disclose the details for the dataset generation as much as possible for training and validation for cross-check purposes.
* FL0: We already have sufficient agreements for dataset. There is no need to have further agreements, especially under the discussion of sub-use case.
* Ericsson [11]:
  + Observation 6 For beam prediction evaluations consider providing the results with measurement accuracy noise modelled as additive gaussian noise with 95% of the density function within the measurement accuracy range, and/or uniformly distributed noise
  + Proposal 7 Study the impact of measurement imperfections on model performance for the considered beam prediction use cases.
  + Proposal 8 Consider the following to mitigate the L1-RSRP measurement inaccuracy impact in ML based beam prediction
    - Possibility to tighten requirements on L1-RSRP measurement accuracy
    - Define different UE capability based on their capability in fulfilling a measurement accuracy requirement.
* Mediatek [20]:
  + Observation 1: Both machine learning models perform better on ray-tracing dataset compared to SLS dataset.
  + Proposal 2: Study and evaluate the performance of AI/ML beam prediction using the dataset generated by the ray-tracing simulations.
* NVIDIA [23]
  + Proposal 1: Companies are encouraged to contribute real data to develop and evaluate AI/ML based algorithms for beam management.
* FL0: The above proposals can be covered by the agreements in framework. No need for further discussion.
* Samsung [24]:
  + **Data collection:**
    - 8 RBs as baseline, companies can report larger number of RBs
    - First 2 OFDM symbols for PDCCH, and following 12 OFDM symbols for data channel
  + **Channel model:**
    - LOS channel: CDL-D/E extension,
    - NLOS channel: CDL-A/B/C extension,
    - CDL-D extension, DS = 100ns as baseline.
    - Companies explains details of extension methodology considering spatial consistency.
    - Other channel models and DSs are not precluded.
* Qualcomm [26]:
  + Proposal 2: For both sub use cases BM-Case1 and BM-Case2, clarify interpretation of “set B” by selection of one of the following alternatives
    - Alt.1: Set B is a set of beams, whose measurements are performed (for prediction of set A)
    - Alt.2: Set B is a set of beam whose measurements are available as inputs of the AI/ML model (for prediction of set A)
* FL0: This is a good catch. This will be discussed in 9.2.3.2
  + Proposal 3: For BM-Case2, consider the scenario in which the UE orientation changes as a function of UE trajectory.
    - FFS: details of this function
* FL0: lack of discussion on “FFS part” for further discussion in this meeting on UE orientation.

|  |
| --- |
| **Agreement**   * For UE trajectory model, UE orientation can be independent from UE moving trajectory model. FFS on the details.   + Other UE orientation model is not precluded. |

#### FL1: Other assumptions

**Please indicate any other assumptions needs to be discussed and agreed in this meeting**

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |
|  |  |

# KPIs on AI/ML in beam management

## 2.1 Beam prediction accuracy related KPIs

Some observations/proposals were made in the contributions on beam prediction accuracy related KPIs:

**General discussion**

* Huawei [2]
  + Proposal 14: Since the prediction accuracy obtained from the AI/ML increases significantly with a larger K and then clearly outperforms the legacy baseline, adopt Top-K, K>1 (e.g., K=3, 5) for evaluation of spatial beam prediction accuracy.
  + Proposal 18: For temporal beam prediction evaluation, results for Top-K, K>1 should be presented in addition to Top-1 results.
    - The Top-1 predicted beam can be derived as the eventual result after the second round sweeping based on the AI/ML inferred Top-K beams.
  + FL0: the values of K can be reported by companies. Currently, K =3 and 5 are widely used.
* Interdigital [6]
  + Proposal 3: Support beam information related KPIs as optional for temporal measures.
    - Support average L1-RSRP difference of Top-1 predicted beam.
    - Support beam prediction accuracy (%) with multiple candidate margins (including 1 dB and other possible values) for Top-1 beam.
  + FL0: other margin can be reported by companies. There is no need to further agree on other KPIs.
* China Telecom [7]
  + Proposal 1: To evaluate the performance of AI/ML in beam management, at least following KPI should be considered as baseline, other options are not precluded:
    - Beam prediction accuracy (%) for Top-1 and/or Top-K beams.
    - The beam prediction accuracy (%) is the percentage of “the Top-1 predicted beam is one of the Top-K genie-aided beams”
    - Average L1-RSRP difference of Top-1 predicted beam
    - CDF of L1-RSRP difference for Top-1 predicted beam
  + FL0: no urgent need for down selection
* OPPO [8]
  + Proposal 6: Study another definition of L1-RSRP difference of Top-1 predicted beam
    - The difference between the predicted L1-RSRP of Top-1 predicted beam and the ideal L1-RSRP of the Top-1 genie-aided beam
  + FL0: There is no new/sufficient discussion compared with previous meeting for this proposal. Suggest to hold the discussion in later meetings
* Apple [21]
  + Proposal 1: The KPI for AI based beam prediction could be the beam prediction accuracy and the L1-RSRP distribution for the AI predicted beam. The KPI with RSRP can be used for making decision/drawing conclusion in the whole Rel-18 study item.

FL0: There is no intention to have down selection on the agreed KPIs in this meeting.

**Definition of beam prediction accuracy (%) if Top-1/K beams**

* Huawei [2]
  + Proposal 2: As KPI for the evaluation of the prediction accuracy, Option 2 should be selected, i.e., the beam prediction accuracy (%) is the percentage of “the Top-1 genie-aided beam is one of the Top-K predicted beams”.
* Spreadtrum [4]
  + Proposal 2: To evaluate the performance of AI/ML in beam management, Option 2 should be considered.
* Vivo [5]
  + Proposal 6: Support Option 2, i.e. the beam prediction accuracy (%) is the percentage of “the Top-1 genie-aided beam is one of the Top-K predicted beams”, to be the definition of beam prediction accuracy (%) for Top-1 and/or Top-K beams.
* China Telecom [7]
  + Proposal 1: To evaluate the performance of AI/ML in beam management, at least following KPI should be considered as baseline, other options are not precluded:
    - The beam prediction accuracy (%) is the percentage of “the Top-1 predicted beam is one of the Top-K genie-aided beams” (Note by FL0: option 2)
* OPPO [8]
  + Proposal 5: For beam prediction accuracy, adopt Option 2 (beam prediction accuracy (%) is the percentage of “the Top-1 genie-aided beam is one of the Top-K predicted beams”) for AI/ML beam prediction.
  + Proposal 6: Study another definition of L1-RSRP difference of Top-1 predicted beam
    - The difference between the predicted L1-RSRP of Top-1 predicted beam and the ideal L1-RSRP of the Top-1 genie-aided beam
* CATT [12]
  + Proposal 1: To evaluate the performance of AI/ML in beam management, the definition of beam prediction accuracy for Top-1 and/or Top-K beams is Option 2, i.e., the Top-1 genie-aided beam is one of the Top-K predicted beams.
* Xiaomi [17]
  + Proposal 1: For the definition of beam prediction accuracy (%) for Top-1 and/or Top-K beams, Option 2 is preferred.
* CMCC [18]
  + Proposal 1: The definition of beam prediction accuracy (%) for Top-1 and/or Top-K beams is:
    - Option 2: The beam prediction accuracy (%) is the percentage of “the Top-1 genie-aided beam is one of the Top-K predicted beams”
  + Proposal 2: The definition of beam prediction accuracy (%) with 1 dB margin for Top-K beams is:
    - The percentage of “the ideal highest L1-RSRP of the predicted Top-K beams is within 1 dB of the L1-RSRP of the Top-1 genie-aided beam”

Based on the above proposals, the following proposals are proposed:

#### FL1: Definition on beam prediction accuracy (%) if Top-1/K beams

**Proposal 2-1-1a:**

* **The definition of beam prediction accuracy (%) for Top-1 and/or Top-K beams:**
  + **Option 1 (optional): The beam prediction accuracy (%) is the percentage of “the Top-1 predicted beam is one of the Top-K genie-aided beams”**
  + **Option 2 (baseline): The beam prediction accuracy (%) is the percentage of “the Top-1 genie-aided beam is one of the Top-K predicted beams”**

|  |  |
| --- | --- |
| Supporting companies |  |
| Objecting companies |  |

**Please provide your view Proposal 2-1-1a, if any.**

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |
|  |  |

**Clarification on “Top1 genie-aided Tx beam”**

* Huawei [2]
  + Proposal 3: For DL Tx beam prediction, the Top-1 genie-aided Tx beam is defined as the Tx beam that results in the largest RSRP at the UE side
    - For Case A (L1-RSRP of Tx beams in Set B, measured by a “best” Rx beam), the Top-1 genie-aided Tx beam should be the Tx beam ID that results in the largest RSRP over all Tx and Rx beams
    - For Case B (L1-RSRP of Tx beams in Set B, measured by the same Rx beam), the Top-1 genie-aided TX beam should be the Tx beam ID that results in the largest RSRP over all Tx beams with that specific Rx beam

#### FL1: Clarification on Top1 genie-aided Tx beam

**Proposal 2-1-2a:**

* **For DL Tx beam prediction, the Top-1 genie-aided Tx beam is defined as the Tx beam that results in the largest L1-RSRP, FFS:** 
  + **Option A, the Top-1 genie-aided Tx beam is the Tx beam ID that results in the largest L1-RSRP over all Tx and Rx beams**
  + **Option B, the Top-1 genie-aided TX beam is the Tx beam ID that results in the largest L1-RSRP over all Tx beams with specific Rx beam(s)**

**Please provide your view Proposal 2-1-2a, if any.**

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |
|  |  |

**Other aspects**

* Futurewei [1]
  + Observation 4: When evaluating AI/ML model performance, using “Average L1-RSRP difference of Top-1 (or Top-K) predicted beam” alone may not directly indicate the performance unless the average L1-RSRP difference between the ideal L1-RSRP of the Top-1 genie-aided beam and the ideal L1-RSRP of the Top-K genie-aided beams in the (testing) dataset is known.
  + Proposal 2: For AI/ML based spatial beam prediction, to help performance evaluation discussion, companies are encouraged to share simulation details for the dataset generation and provide the average L1-RSRP difference between the ideal L1-RSRP of the Top-1 genie-aided beam and the ideal L1-RSRP of the Top-K genie-aided beams in the training/testing dataset.
* Ericsson [11]
  + Observation 1: The agreed simulation scenarios might have heavily skewed beam statistics. AI/ML models can be trained to work well for common beams and ignore uncommon beams. The poor performance of AI/ML models on uncommon beams might not be reflected in average beam prediction statistics. Visualizing the edge percentiles of the L1-RSRP CDF could be one method to illustrate the ability to predict uncommon beams
* Qualcomm [26]
  + Proposal 4: For BM-Case1 and BM-Case2, study the impact of incorporating beam prediction quality information (e.g., a measure for prediction confidence such as std of predicted RSRPs) on evaluating the performance of AI/ML model, using the agreed KPIs
    - Note: The results from this study could help in defining criteria or metrics for AI/ML model performance monitoring which could lead to model activation/deactivation or updating of AI/ML models.

Other than the points raised by companies, by reading companies simulation results, FL feels that directly using average L1-RSRP different of Top-1/K beam may have some issues (e.g. may not be applicable), especially for generalization performance when basic configuration changed.

#### FL1: Other aspects for L1-RSRP related KPIs

**Please indicate whether any other aspects including additional KPIs/definitions are needed for L1-RSRP difference? And please explain the reason, at least including:**

* **A1:** For AI/ML based spatial beam prediction, to help performance evaluation discussion, companies are encouraged to share simulation details for the dataset generation and provide the average L1-RSRP difference between the ideal L1-RSRP of the Top-1 genie-aided beam and the ideal L1-RSRP of the Top-K genie-aided beams in the training/testing dataset.
* **A2:** Visualizing the edge percentiles of the L1-RSRP CDF could be one method to illustrate the ability to predict uncommon beams
* **A3:** For BM-Case1 and BM-Case2, study the impact of incorporating beam prediction quality information (e.g., a measure for prediction confidence such as std of predicted RSRPs) on evaluating the performance of AI/ML model, using the agreed KPIs
* **A4:** Other comments

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |
|  |  |

## 2.2 System performance related KPIs

### 2.2.1 (Closed) User throughput

Other than beam measurement related KPIs, several companies mentioned that the system performance shall be also evaluated:

* Interdigital [6]:
  + Proposal 2: Support system performance related KPIs as mandatory KPIs.
    - Support Avg. and 5% UE tput for system performance KPIs.
  + Proposal 5: Prioritize system performance related KPIs and beam information related KPIs than other KPIs.
* Samsung [24]:
  + Proposal 7: Shannon capacity-based simplified model for UPT can be further considered as additional system performance related KPI.
* Qualcomm [26]
  + Proposal 7: At least for spatial domain beam prediction, consider spectral efficiency CDF for SLS evaluations as a KPI.

FL0: there is no need for further discussion on user throughput in this meeting.

### 2.2.1 RS overhead

There were several proposals/discussions related to RS overhead:

* Huawei/HiSi [2]:
  + Proposal 10: For the evaluation of the overhead for spatial domain AI/ML-based BM, two metrics should be reported:
    - The RS overhead, consisting of the beams being swept in Set B and the Top-K beams for P2 beam sweeping after inference (if applicable)
      * RS OH = N + K for K > 1 and RS OH = N for K = 1, where N is the number of beams in Set B and K is the number of Top-K selected beams.
    - The RS overhead reduction compared to an exhaustive beam sweep over set A
      * RS OH RD [%] = 1-(N+K)/M for K > 1 and RS OH [%] = 1-N/M for K =1, where N is the number of beams in Set B, K is the number of Top-K selected beams and M is the number of beams in Set A.
  + Proposal 13: For the evaluation of the overhead for temporal domain AM//ML-based BM, the observation and prediction window are jointly considered, and two metrics should be reported
    - The RS overhead, consisting of the beams being swept in Set B during observation and the Top-K beams for P2 beam sweeping during prediction (if applicable)
      * for K>1 and for K = 1
    - The RS overhead reduction compared to an exhaustive beam sweep over Set A during observation and the Top-K beams for P2 beam sweeping during prediction (if applicable)
      * for K > 1 and for K = 1
    - Where: M is beams in Set A, N is beams in Set B and K is the number of beams as inference output
* ZTE [3]
  + Proposal 2: RS overhead reduction should be considered as a basic KPI for evaluation and should be further studied with considering following factors: the number of UE, the beam pattern, and the refined beam sweeping procedure.
* Spreadtrum [4]:
  + Proposal 3: For RS overhead or RS overhead reduction, option 1 should be considered as KPI for spatial domain beam prediction.
* Vivo [5]
  + Proposal 7: The metric of beam sweeping overhead reduction is calculated as 1-N/M where N is the number of beams required for measurement in both non-AI algorithm and AI algorithm, and M can be the total number of all possible beams to be predicted.
* OPPO [8]
  + Proposal 7: For BM-Case1, study how to accurately capture the overhead, considering beam measurement on Set B and potential follow-up measurement after beam prediction.
  + Proposal 8: For BM-Case2, study how to capture the overhead reduction, considering the T1 duration (measurement on Set B) and T2 duration (prediction among Set A).
* Ericsson [11]
  + Proposal 3: Define a RS measurement overhead KPI, e.g. N/M where N is the number of beams measured by a UE, and M is the total number of beams.
* Fujitsu [13]
  + Proposal 3: For the KPI of RS overhead reduction, it is suggested to consider three alternatives of predicted beams.
    - Alt.1: DL Tx beam prediction
    - Alt.2: DL Rx beam prediction
    - Alt.3: Beam pair prediction
  + Proposal 4: Regarding the three alternatives of predicted beam, the KPI of RS overhead reduction is suggested to be calculated as：

|  |  |  |  |
| --- | --- | --- | --- |
|  | Tx beam prediction | Rx beam prediction | Beam pair prediction |
| RS overhead reduction |  |  |  |

* FL0: please check current wording. I think it can be covered by the case in your mind.
* Lenovo [15]
  + The RS overhead reduction, for at least top-1 spatial-domain beam prediction, is given by

,

* + where *N* is the number of beams (with reference signal, i.e., (SSB and/or CSI-RS)) required for measurement and *M* is the total number of beams.
  + *Note* that this metric is meaningful for reference signals and there would not be any RS overhead reduction when only SSBs are considered, because *M* SSBs would be transmitted on *M* beams.
  + To accommodate the AI/ML models that perform varying number of beam measurements in each time slot, the above metric may be modified as follows [4], [6]:

,

* + Where is the number of beam measurements in time slot and the is the total number of time slots.
  + Thus, the above metric is a general version of the first metric for RS overhead reduction.
* CAICT [16]:
  + Proposal 3: RS overhead calculation for DL tx beam prediction and temporal domain beam prediction (BM-Case2) could be reported by different companies.
* Xiaomi [17]
  + Proposal 3: Study the following options on RS overhead reduction for temporal beam prediction:
    - Option 1: "RS " OH[%]=1-N/(N+M)
      * For the case of the same periodicity of history measurement instance and future time instance, where N is the number of history measurement instance and M is the number of predicted future time instance.
    - Option 2: "RS " OH[%]=1-1/L
      * For the case of the periodicity of history measurement instance is L times of that of future time instance.
* Nokia [19]:
  + RS overhead reduction at least for spatial-domain beam prediction at least for Top-1 beam

|  |
| --- |
| where N is the number of beams (with reference signal (SSB and/or CSI-RS)) required for measurement, M is the total number of beams. Non-AI/ML approach based on the measurement of these M beams may be used as a baseline.  When N is variable, the overhead reduction is computed using an average measurement set size, such that  Where is the number of beams required for measurement during time slot |

* Samsung [24]
  + Proposal # 6: For RS overhead reduction, further study the following options:
    - Option 1: at least for BM-Case 1
      * where N is the number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement (in Set B and in Top-K beams (pairs) for P2 beam sweep after inference (if applicable))
      * where M is the total number of beams (pairs) to be predicted (in Set A)
    - Option 2: at least for BM-Case 2
      * Where N\_n is the number of beams (pair) (in Set B and in Top-K beams (pairs) for P2 beam sweep after inference (if applicable)) required for measurement during time slot n
      * where M is the total number of beams (pair) to be predicted (in Set A)
    - FFS on other options
* DoCoMo [25]:
  + For example, the following equation can be considered as KPI for RS overhead reduction.
  + Observation 1: Additional beam measurements might be necessary for PDSCH/PDCCH reception with top1/K predicted beam(s), when the top-1/K predicted beam(s) are not included in beams measured for the beam prediction.
  + Proposal 1: Discuss the requirement of actual QCL relation, and consider the additional RS measurement overhead to obtain the actual QCL relation if necessary.



Figure 1. Additional beam measurements with the top-1 predicted beam for reception with the beam, when the top-1 predicted beam is not included in beam measurements for the beam prediction.

#### FL1: RS overhead

**Proposal 2-2-1a:**

* For the evaluation of the overhead for **BM-Case1**, further study the following two metrics:
  + RS overhead reduction, FFS for potential down selection:
    - Option 1:
      * where N is the number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement (in Set B)
      * where M is the total number of beams (pairs) to be predicted (in Set A)
    - Option 2:
      * where N is the number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement (in Set B)
      * where M is the total number of beams (pairs) to be predicted (in Set A)
      * FFS:
        + K is the number of Top-K selected beams (pairs) for P2 beam sweeping (if applicable)
        + K is the number of Top-K selected beams (pairs) not in Set B for P2 beam sweeping (if applicable)
    - Other options can be reported by companies
  + RS overhead, FFS for potential down selection:
    - Option 1: RS OH = N,
      * where N is the number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement (in Set B)
    - Option 2: RS OH = N + K
      * where N is the number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement (in Set B)
      * FFS:
        + K is the number of Top-K selected beams (pairs) for P2 beam sweeping (if applicable)
        + K is the number of Top-K selected beams (pairs) not in Set B for P2 beam sweeping (if applicable)
    - Other options can be reported by companies

|  |  |
| --- | --- |
| Supporting companies |  |
| Objecting companies |  |

**Proposal 2-2-2a:**

* For the evaluation of the overhead for **BM-Case2**, further study the following two metrics:
  + RS overhead reduction, FFS for potential down selection:
    - Option 1:
      * where N is the number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement (in Set B) in each slot of T1
      * where M is the total number of beams (pairs) to be predicted (in Set A) in each slot of both T1 and T2
    - Option 2:
      * where N is the number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement (in Set B) in each slot of T1
      * where M is the total number of beams (pairs) to be predicted (in Set A) in each slot of both T1 and T2
      * FFS:
        + K is the number of Top-K selected beams (pairs) for P2 beam sweeping (if applicable) in each slot of T2
        + K is the number of Top-K selected beams (pairs) not in Set B for P2 beam sweeping (if applicable) in each slot of T2
    - Other options can be reported by companies
  + RS overhead, FFS for potential down selection:
    - Option 1: RS OH = ,
      * where N is the number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement (in Set B) in each slot of T1
    - Option 2: RS OH =
      * where N is the number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement (in Set B) in each slot of T1
      * FFS:
        + K is the number of Top-K selected beams (pairs) for P2 beam sweeping (if applicable) in each slot of T2
        + K is the number of Top-K selected beams (pairs) not in Set B for P2 beam sweeping (if applicable) in each slot of T2
    - Other options can be reported by companies

|  |  |
| --- | --- |
| Supporting companies |  |
| Objecting companies |  |

**Please provide your view Proposal 2-2-1a and Proposal 2-2-2a,**

|  |  |
| --- | --- |
| Company | Comments |
| FL0: | FL encourages to discuss/think on the following questions:   * For RS overhead reduction in option 2, whether M includes beam sweeping, e.g., P1 +P2, especially when Set B does not belong to Set A, e.g., Set B is wide beam? * Whether the above equations can apply to both case when Set B is subset of Set A and when Set B is different from Set A? * Whether there is a need to separate the equations for DL Tx beam prediction and Tx-Rx pair prediction? |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |

#### FL1: QCL relation

* DoCoMo [25]:
  + Observation 1: Additional beam measurements might be necessary for PDSCH/PDCCH reception with top1/K predicted beam(s), when the top-1/K predicted beam(s) are not included in beams measured for the beam prediction.
  + Proposal 1: Discuss the requirement of actual QCL relation, and consider the additional RS measurement overhead to obtain the actual QCL relation if necessary.



Figure 1. Additional beam measurements with the top-1 predicted beam for reception with the beam, when the top-1 predicted beam is not included in beam measurements for the beam prediction.

**Please provide your view on additional RS measurement overhead to obtain the actual QCL relation?**

|  |  |
| --- | --- |
| Company | Comments |
| FL0 | This might be a valid issue. However, in FL’s views, there is no urgency to discuss addition RS for P3 beam sweeping for this meeting. However, companies are encouraged to describe the assumption of P1/P2/P3 in their simulation assumption, and provide analysis on RS overhead reduction accordingly. For example, whether all of the procedure or only part of the procedure is considered, QCL assumption, reuse some of legacy procedures, etc. |
|  |  |
|  |  |
|  |  |

### 2.2.3 UCI report

In RAN 1 #110, the following agreement on UCI report was agreed.

|  |
| --- |
| **Agreement**   * **To evaluate the performance of AI/ML in beam management at least for NW side beam prediction, UCI report overhead can be further studied as one of KPI options.**    + **FFS: number of UCI reports and UCI payload size** |

The following was discussed in contributions:

* Vivo [5]:
  + Proposal 8: UCI reporting overhead reduction, including the number of UCI report and UCI payload size, should be considered as basic KPI.
* Lenovo [15]:
  + To account for the other kind of overhead, it is required to account for the number of UCI reports and the size of each UCI report (in bits). These quantities (i.e., the no. of UCI reports and the size of such reports) need to be compared with the case of exhaustive search for arriving at a meaningful measure of the amount of reporting overhead reduction offered by the AI/ML model under consideration.
  + Any other signals that need to be exchanged between UE and gNB to support the AI/ML model, such as signaling in another carrier (e.g., FR1), UE location information, spatial features of the environment etc., should also be considered accounted for.
* DoCoMo [25]:
  + Proposal 2: Consider the number of transmissions for UCI as performance KPI:
    - It is beneficial to reduce the number of uplink transmissions for commercial aspects
    - Temporal beam prediction with NW side model can enable beam management with low frequent beam measurement reports

#### FL1: UCI report

**Proposal 2-2-3a: (updated from Agreement in RAN 1 #110)**

* **To evaluate the performance of AI/ML in beam management at least for NW side beam prediction, UCI report overhead can be further studied as one of KPI options.** 
  + **~~FFS:~~ number of UCI reports and/or UCI payload size for each prediction**

|  |  |
| --- | --- |
| Supporting companies |  |
| Objecting companies |  |

**Please provide your view Proposal 2-2-3a:**

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |

### 2.2.3 Other KPIs

The following other KPIs were proposed in the contributions:

RRC signaling overhead:

* Vivo [5]:
  + Proposal 9: RRC singling overhead can be considered as optional KPI if huge amount of data, such as training data, assistant information, and AI model data, is exchanged via RAN air interference.

Latency reduction

* Interdigital [6]
  + Proposal 4: Reporting overhead and latency aspects should be considered in evaluation of system performance not as independent KPIs.
* Lenovo [15]
  + Proposal 4 Consider Beam Prediction Accuracy, Overhead Reduction and Latency Reduction as the key KPIs in evaluating an AI/ML model for beam management and consider adopting the definitions proposed above.

FL0: no urgency to discuss other KPIs in this meeting.

## 2.3 (Closed) Model size and computational complexity

Several companies proposed to consider model size and computation complexity for AI/ML model.

* Ericsson [11]
  + Proposal 2: When presenting results for AI/ML models, the proponent should report a model size (e.g., number of parameters) and an estimate of the number of floating-point operations (FLOPs) for inference.
* MTK [20]
  + Proposal 1: For AI/ML-based beam prediction evaluation, adopt the FLOPs and/or MACs as the time complexity, and the number of parameters as the space complexity, other options are not precluded.
* NVIDA [23]
  + Proposal 3: For evaluation of AI/ML based beam management, the computational complexity can be reported via the metric of floating point operations (FLOPs) for inference.
  + Proposal 4: For evaluation of AI/ML based beam management, the model complexity may be measured by memory storage in terms of number of AI/ML model parameters.
  + Observation 1: Increasing hardware performance can support successively more complex AI/ML models. For example, GPU inference performance has improved by 317x in 8 years (2012-2020), more than doubling each year.
  + Proposal 5: AI/ML model complexity and computational complexity should not be regarded as a roadblock to the adoption of AI/ML based algorithms for beam management enhancements.

FL0: In FL’s understanding, the agreements in 9.2.1 also apply to beam management. Therefore, no need to reopen the discussion here.

|  |
| --- |
| **Agreement**  *The following is an initial list of common KPIs (if applicable) for evaluating performance benefits of AI/ML*   * *Performance*   + *Intermediate KPIs*   + *Link and system level performance*   + *Generalization performance* * *Over-the-air Overhead*   + *Overhead of assistance information*   + *Overhead of data collection*   + *Overhead of model delivery/transfer*   + *Overhead of other AI/ML-related signaling* * *Inference complexity*   + *Computational complexity of model inference: FLOPs*   + *Computational complexity for pre- and post-processing*   + *Model complexity: e.g., the number of parameters and/or size (e.g. Mbyte)* * *Training complexity* * *LCM related complexity and storage overhead*   + *FFS: specific aspects* * *FFS: Latency, e.g., Inference latency*   *Note: Other aspects may be added in the future, e.g. training related KPIs*  *Note: Use-case specific KPIs may be additionally considered for the given use-case.* |

## 2.4 (Closed) Baseline performance

Some companies provided some analysis on baseline performance for benchmark.

* Huawei/HiSi [2]
  + Proposal 15: For spatial domain beam prediction, both of the two baselines for performance evaluation shall be considered:
    - An upper performance bound obtained by exhaustive sweep over Set A
    - A lower performance bound obtained by non-AI/ML-based legacy sparse beam sweeping with the same overhead as the AI/ML-based approach
* Vivo [3]
  + Proposal 3: Support both option 1 and option 2 as baseline performance in spatial domain beam prediction and temporal domain beam prediction, and set B selection method in option 2 should be reported.
* InterDigital [6]
  + Observation 1: Legacy beam management with Rel-17 without AI/ML algorithms is not an appropriate baseline as implementation-based AI/ML operation is available for UE and gNB implementations.
  + Proposal 1: ‘No collaboration framework: AI/ML algorithms purely implementation based and not requiring air-interface changes’ could be an appropriate baseline to accurately evaluate the benefits of AI/ML with specification enhancements.
  + FL0: based on current agreements, company can report the conventional scheme as baseline.
* OPPO [8]
  + Proposal 9: For spatial domain beam prediction, select the best beam within Set A via exhaustive beam sweeping (Option 1) as baseline.
  + Proposal 10: For temporal domain beam prediction, select the best beam for T2 within Set A via exhaustive beam sweeping (Option 1a) as baseline.
* Google [9]
  + Proposal 3: For spatial-domain beam prediction, the baseline performance should be the performance from the beam selected from set B beams.
  + Proposal 4: For time-domain beam prediction, the baseline performance should be the performance without beam change for T2, i.e. the beam used prior to T2 is applied for T2.
* Intel [14]
  + For baseline performance evaluation, Option 2 should correspond to hierarchical beam search where, based on sub-use case being evaluated, set B may be a subset of set A or set B can contain both wide and correlated narrow beams.

FL0: There is no strong need to down select the baseline performance in this meeting other than current agreements as below:

|  |
| --- |
| **Agreement**   * For spatial-domain beam prediction, further study the following options as baseline performance   + Option 1: Select the best beam within Set A of beams based on the measurement of all RS resources or all possible beams of beam Set A (exhaustive beam sweeping)      - FFS CSI-RS/SSB as the RS resources   + Option 2: Select the best beam within Set A of beams based on the measurement of RS resources from Set B of beams     - FFS: Set B is a subset of Set A and/or Set A consists of narrow beams and Set B consists of wide beams     - FFS: how conventional scheme to obtain performance KPIs     - FFS: how to determine the subset of RS resources is reported by companies   + Other options are not precluded.   **Agreement**   * For temporal beam prediction, further study the following options as baseline performance   + Option 1a: Select the best beam for T2 within Set A of beams based on the measurements of all the RS resources or all possible beams from Set A of beams at the time instants within T2   + Option 2: Select the best beam for T2 within Set A of beams based on the measurements of all the RS resources from Set B of beams at the time instants within T1     - Companies explain the detail on how to select the best beam for T2 from Set A based on the measurements in T1   + Where T2 is the time duration for the best beam selection, and T1 is a time duration to obtain the measurements of all the RS resource from Set B of beams.     - T1 and T2 are aligned with those for AI/ML based methods   + Whether Set A and Set B are the same or different depend on the sub-use case   + Other options are not precluded. |

# AI/ML model Generalization

Generalization is one of the important aspects to verify the performance of AI/ML model.

## 3.1 Evaluation assumption for generalization performance

The follow discussions/proposals were summarized:

**General principle**

* Futurewei [1]
  + Table 4.1-1: Model generalization evaluation report example

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Sub use case** | **Training scenario / config.** | **Testing scenario/ config.** | **Set A/B configurations** | **Dataset size** | | **Perf. KPIs** | **Other KPIs** | **Mechanism applied** |
| Train | Test |
|  |  |  |  |  |  |  |  |  |

* + Proposal 3: When reporting AI/ML model generalization evaluation results for beam management enhancements, companies are encouraged to align the reporting attributes and format as depicted in Table 4.1-1.
  + Proposal 4: In AI/ML model generalization across different scenarios/configurations for spatial-domain beam prediction sub use case, further study the applicable generalization mechanism(s) that can be applied to different scenario/configuration combinations.
* Huawei/HiSi [2]:
  + Proposal 4: To verify the generalization of AI/ML models on AI/ML-based beam management in both spatial and temporal domain, the following cases to construct the training dataset and testing dataset should be considered:
    - Case 1: The AI/ML model is trained based on training dataset from one Scenario#A/Configuration#A, and then the AI/ML model is tested on dataset from the same Scenario#A/Configuration#A
    - Case 2: The AI/ML model is trained based on training dataset from one Scenario#A/Configuration#A, and then the AI/ML model is tested on dataset from a different Scenario#B/Configuration#B
    - Case 2A: The AI/ML model is trained based on training dataset from one Scenario#A/Configuration#A, and then the AI/ML model is fine-tuned based on the fine-tuning dataset from a different Scenario#B/Configuration#B. After that, the AI/ML model is tested on dataset subject to the same Scenario#B/Configuration#B as the fine-tuning dataset
    - Case 3: The AI/ML model is trained based on training dataset constructed by mixing datasets from multiple scenarios including Scenario#A/Configuration#A and Scenario#B/Configuration#B, and then the AI/ML model is tested on dataset from a single Scenario#A/Configuration#A or Scenario#B/Configuration#B from the multiple scenarios
* Vivo [5]
  + Proposal 10: Support to define generalization performance KPI.
* China Telecom[7]
  + Proposal 3: The following cases are considered for verifying the generalization performance of an AI/ML model over various scenarios/configurations as a starting point:
    - Case 1: The AI/ML model is trained based on training dataset from one Scenario#A/Configuration#A, and then the AI/ML model performs inference/test on a dataset from the same Scenario#A/Configuration#A
    - Case 2: The AI/ML model is trained based on training dataset from one Scenario#A/Configuration#A, and then the AI/ML model performs inference/test on a different dataset than Scenario#A/Configuration#A, e.g., Scenario#B/Configuration#B, Scenario#A/Configuration#B
    - Case 3: The AI/ML model is trained based on training dataset constructed by mixing datasets from multiple scenarios/configurations including Scenario#A/Configuration#A and a different dataset than Scenario#A/Configuration#A, e.g., Scenario#B/Configuration#B, Scenario#A/Configuration#B, and then the AI/ML model performs inference/test on a dataset from a single Scenario/Configuration from the multiple scenarios/configurations, e.g., Scenario#A/Configuration#A, Scenario#B/Configuration#B, Scenario#A/Configuration#B.
* OPPO [8]
  + Proposal 11: Study the techniques of pre-processing at model input and post-processing at model output to enable the generalization capability of AI/ML model.
* Lenovo [15]
  + For evaluating the generalizability of an AI/ML model for beam management, the full list of network conditions/scenarios/parameter values need to be discussed and decided. Further, based on the effort and time required for testing an AI/ML model under such different network conditions/scenarios/parameter values, consider a limited set of parameters to for testing whether an AI/ML model is generalizable.
  + Generalizability of a proposed AI/ML model for beam management is evaluated by computing all the KPIs, inclusive of all the gains achieved and all the costs incurred, by the model for each of the different network conditions/scenarios/parameter values.
  + Discuss how to decide on the generalization ability of an AI/ML model based on the KPIs, inclusive of all the gains achieved and the costs incurred, that are evaluated for each of the different network conditions/scenarios/parameter values. Further, consider the threshold-based methods discussed above for further study.
* CAICT [16]
  + Proposal 1: The framework agreement in 9.2.2.1 for verifying the generalization performance of an AI/ML model could also be considered as a starting point for BM.

#### FL1: Principle for generalization performance evaluation

**Proposal 3-1-1a: (Same agreements as in 9.2.2.1)**

**The following cases are considered for verifying the generalization performance of an AI/ML model over various scenarios/configurations as a starting point:**

* **Case 1: The AI/ML model is trained based on training dataset from one Scenario#A/Configuration#A, and then the AI/ML model performs inference/test on a dataset from the same Scenario#A/Configuration#A**
* **Case 2: The AI/ML model is trained based on training dataset from one Scenario#A/Configuration#A, and then the AI/ML model performs inference/test on a different dataset than Scenario#A/Configuration#A, e.g., Scenario#B/Configuration#B, Scenario#A/Configuration#B**
* **Case 3: The AI/ML model is trained based on training dataset constructed by mixing datasets from multiple scenarios/configurations including Scenario#A/Configuration#A and a different dataset than Scenario#A/Configuration#A, e.g., Scenario#B/Configuration#B, Scenario#A/Configuration#B, and then the AI/ML model performs inference/test on a dataset from a single Scenario/Configuration from the multiple scenarios/configurations, e.g., Scenario#A/Configuration#A, Scenario#B/Configuration#B, Scenario#A/Configuration#B.**
  + - * **Note: Companies to report the ratio for dataset mixing**
      * **Note: number of the multiple scenarios/configurations can be larger than two**
* **FFS the detailed set of scenarios/configurations**
* **FFS other cases for generalization verification, e.g.,**
  + - * **Case 2A: The AI/ML model is trained based on training dataset from one Scenario#A/Configuration#A, and then the AI/ML model is updated based on a fine-tuning dataset different than Scenario#A/Configuration#A, e.g., Scenario#B/Configuration#B, Scenario#A/Configuration#B. After that, the AI/ML model is tested on a different dataset than Scenario#A/Configuration#A, e.g., subject to Scenario#B/Configuration#B, Scenario#A/Configuration#B.**

|  |  |
| --- | --- |
| Supporting companies |  |
| Objecting companies |  |

**Please provide your view Proposal 3-1-1a:**

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |

**Proposed scenarios/configurations for generalization**

* Huawei/HiSi [2]:
  + Proposal 9: For verifying the AI/ML model generalization for spatial domain beam management, the scenarios/configurations for performing the inference for the AI/ML model should initially consider the following aspects:
    - Various channel types, e.g., UMa, UMi, InH
    - Various numbers of beams in Set A (including Tx beams and/or Rx beams)
    - Various Tx beam widths of Set B, e.g., wide beam, narrow beam
    - Various numbers of Set B (including Tx beams and/or Rx beams)
    - Various patterns of Set B, if Set B is a subset of Set A
  + Proposal 12: For verifying the AI/ML model generalization for temporal domain beam prediction, the scenarios/configurations for performing the inference for the AI/ML model should initially consider the following aspects:
    - Various channel types, e.g., UMa, UMi, InH
    - Various numbers of beams in Set A (including Tx beams and/or Rx beams)
    - Various Tx beam widths of Set B, e.g., wide beam, narrow beam
    - Various numbers of Set B (including Tx beams and/or Rx beams)
    - Various patterns of Set B, if Set B is a subset of Set A
    - Various UE speeds (e.g., 30km/h, 60km/h, 90km/h, 120km/h)
    - Various types of UE trajectories (e.g., Option 2/3/4)
* ZTE [3]
  + Proposal 4: Different inputs of AI/ML model (number/pattern of beams (pairs) in Set B, etc) can be considered for the evaluation of model generalization capability.
  + Proposal 6: Different UE speeds can be considered for the evaluation of model generalization capability for temporal beam prediction.
  + Proposal 6: Different UE speeds can be considered for the evaluation of model generalization capability for temporal beam prediction.
* Vivo [5]
  + Proposal 11: To study and evaluate generalization, at least the aspects including different scenarios, different UE speeds, different number of Tx beams and Rx beams, and different gNB/UE antenna configurations, should be prioritized.
  + Proposal 12: For evaluation of generalization performance, support to evaluate KPIs for a separately generated testing dataset generation method with at least 1 target parameter difference. Multiple target parameters can also be verified in further study.
  + ***Beam pair prediction with expected beam information***
  + Proposal 17: Study generalization performance of different number of Tx/Rx beams in BM-Case1.
  + Proposal 18: Study beam pair prediction with expected information as the AI input as one of the solutions for generalization to different number of Tx/Rx beams in BM-Case1.
  + Proposal 19: Further study expected information method in BM-Case2.
  + Proposal 20: Further study multiple expected beam information simultaneously used in AI input.
  + ***Generalization study for different beam shape patterns***
  + Proposal 22: Further study generalization performance for different antenna configurations and different beam shapes in BM-Case1.
  + Proposal 23: Further study assistance information, such as beam shape pattern, 3dB beam width, etc., as model input to address performance deterioration for generalization of different beam shapes in BM-Case1.
  + ***BM-Case 2***
  + Proposal 24: Further study beam pair prediction scheme with expected information as AI input for improving generalization performance in BM-Case2.
  + ***BM-Case 2: with different beam shape patterns***
  + Proposal 26: Further study generalization performance for different antenna configurations and different beam shapes in BM-Case2.
  + Proposal 27: Further study assistance information, such as beam shape pattern, 3dB beam width, etc., as model input to address performance deterioration for generalization of different beam shapes in BM-Case2.
  + Proposal 28: Suggest to use beam pointing angle or global beam ID as assistance information for AI model input.
* China Telecom [7]
  + Proposal 4: For beam management enhancement evaluations, to verify the generalization performance of an AI/ML model over various scenarios, the set of scenarios are considered focusing on one or more of the following aspects as a starting point:
    - Various deployment scenarios (e.g., UMa, UMi, InH)
    - Various outdoor/indoor UE distributions for UMa/UMi
    - Various carrier frequencies
    - Other aspects of scenarios are not precluded, e.g., various antenna spacing, various antenna virtualization (TxRU mapping), various ISDs, various UE speeds, etc.
* Ericsson [11]
  + Proposal 5: Discuss generalization in terms of different UE parameters, NW settings, deployment scenarios and propagation environment scenarios as a starting point
* CATT [12]
  + Proposal 3: For AI/ML based beam management, the AI/ML model trained with mixed numbers of beams (pairs) in Set B has significant generalization performance for different numbers of beams (pairs) in Set B.
* CAICT [16]
  + Proposal 2: For verifying the generalization performance of an AI/ML model, different NW settings and UE parameters could be classified as configurations.
* Xiaomi [17]
  + Proposal 5: To investigate the model generalization capability, the following aspect(s) can be considered with high priority for the evaluation for AI/ML in beam management:
    - Different UE parameters: UE speed, number of Rx beam
    - Different Scenarios, UMa, UMi including UE distribution, etc
* Nokia [19]
  + Proposal 9: RAN1 further investigates the ML model generalization capabilities of BM Case-1 with configurations that can be either included or not included in the training dataset. The following list of configurations can be prioritized:
    - gNB antenna array dimensions, e.g., 4x8 and 8x16.
    - UE antenna array dimensions/Number of Panels.
    - Set A dimension, e.g., 64 beams and 128 beams.
    - Set B dimension, e.g., 16 beams and 32 beams.
  + Proposal 10: RAN1 further investigates the ML model generalization capabilities of BM Case-1 with scenarios that can be either included or not included in the training dataset. The following list of scenarios can be prioritized:
    - Channel propagation models, e.g. UMa/UMi.
    - Outdoor/Indoor UE distribution (e.g. 100% Oudoor, 80% Outdoor/20% Indoor).
* Apple [21]
  + Proposal 2: For AI model generalization, discuss aspects related to analog beam design, antenna configurations including M/N, and antenna spacing and deployment scenario.
  + Observation: The AI/ML model trained with Dataset 1 does not generalize well to Dataset 2:
    - where
      * Dataset 1 is with d\_V=0.5,d\_H=0.5.
      * Dataset 2 is with d\_V=0.8,d\_H=0.4.
    - With mismatched AI model, the AI performance with set B beam at 16 beams is worse than the AI performance with set B at 8 beams without mismatched AI model.
* NVIDIA [23]
  + Proposal 2: To investigate the model generalization capability, the following aspects can be considered for the evaluation for AI/ML in beam management:
    - Different UE parameters: UE speed, UE antenna configuration, UE trajectory, number of Rx beams, UE antenna height, etc.
    - Different NW settings: BS antenna configuration (e.g., number of Tx beams, Tx beam width, TX beam boresight directions, etc.), Tx beam pattern, BS antenna height, etc.
    - Different Scenarios: UMa, UMi, including UE distribution, etc.
* Samsung [24]
  + Proposal # 8: Generalization is defined for UE side AI/ML model and gNB side AI/ML model separately.
  + Proposal # 9: For UE side AI/ML model, the following can be considered to verify the generalization performance.
    - Different UE parameters: UE speed, UE trajectories
    - Different gNB setting: number of Tx beam, Tx beam widths, Tx beam pattern, number or pattern in Set B (when applicable),
    - Different Scenario, like UMa, UMi including UE distribution
  + Proposal # 10: For gNB side AI/ML model, the following can be considered as a starting point to verify the generalization performance.
    - Different UE parameters: e.g., UE trajectories, UE speed, UE antenna config, number of Rx beam (when applicable),
    - FFS Different gNB setting: number of Tx beam, different beam widths, Tx beam pattern, number or pattern in Set B(when applicable)
    - FFS Scenario, like UMa, UMi including UE distribution e.g., outdoor: in door
* Qualcomm [26]
  + Proposal 3: Consider the following categorizations for definition of scenarios/configurations for evaluating the generalization capability of AI/ML models for temporal beam prediction:
    - Inter-site (heterogeneous): train AI/ML model on a first set of deployment type(s) and test it on a second (unseen) deployment type.
    - Inter-site (homogeneous): train on a first set of site(s) of a given deployment type and test it on a second (unseen) site of that same deployment type.
    - Intra-site: train AI/ML model for a given site and test it on unseen variations within that same site.
    - Across configurations: train AI/ML model on a first set of configuration(s) and test on a second configuration

#### FL1: Assumptions for generalization performance verification

**Proposal 3-1-2a:**

* **For BM Case-1 and BM Case 2, to verify the generalization performance of an AI/ML model over various scenarios, the set of scenarios are considered focusing on one or more of the following aspects as a starting point:**
  + **Various deployment scenarios (e.g., UMa, UMi, InH; e.g., ISD 200m, ISD 500m)**
  + **Various outdoor/indoor UE distributions (e.g., 0:1, 2:8, 5:5, 8:2, 1:0)**
  + **Various UE speeds (e.g., 3km/h, 30km/h, 60km/h, 90km/h, 120km/h)**
  + **Various UE parameters (e.g., number of Rx beam: 4, 8)**
  + **Various gNB settings (e.g., number of Tx beam: 32, 64)**
  + **Other aspects of scenarios are not precluded, e.g., various number of Set B of beam(pairs) (e.g., ¼, 1/8 of set A beams (pairs)), carrier frequencies, etc.**
  + **Companies to report the selected scenarios for generalization verification**

|  |  |
| --- | --- |
| Supporting companies |  |
| Objecting companies |  |

**Please provide your view Proposal 3-1-2a, and your views on the following questions:**

Whether the set of scenarios for generalization performance verification needs to consider:

* A: BM Case-1 and BM Case-2
* B: AI model inference node, e.g. @UE side vs @ gNB side
* C: Different cases for evaluation: e.g., DL Tx beam prediction, DL Rx beam prediction, Tx-Rx beam pair prediction
* D: Others

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |

## 3.2 (on hold) Evaluation Results

**Observations for generalization**:

* Futurewei [1]
  + Observation 5: In AI/ML model generalization across different scenarios for spatial-domain beam prediction when using fixed beam pattern sampling, our experiments show the following based on the datasets we used:
    - The AI/ML model trained using dataset generated for UMi\_UMa scenario/channel model CAN generalize to UMi\_UMi scenario/channel model without performance degradation.
    - The AI/ML model trained using dataset generated for UMi\_UMi scenario/channel model may be used for UMi\_UMa scenario/channel model with small performance degradation.
  + Observation 6: In AI/ML model generalization across different scenarios for spatial-domain beam prediction when using pre-configured beam patterns sampling, our experiments show the following based on the datasets we used:
    - The AI/ML model trained using dataset generated for UMi\_UMa scenario/channel model CAN generalize to UMi\_UMi scenario/channel model without performance degradation.
    - The AI/ML model trained using dataset generated for UMi\_UMi scenario/channel model may be used for UMi\_UMa scenario/channel model with small performance degradation
* ZTE [3]
  + Observation 4:The case of AI generalization with different model inputs can achieve a better performance than that of the case of <T8 R1>, but is outperformed by the case of <T32 R1>.
  + Observation 7: The AI/ML method suffers from a little performance loss for scenarios with mixed UE speeds.
* Vivo [5]
  + ***DL Tx beam prediction***
  + Observation 10: More flexible AI model deployment for different number of Rx beams can be obtained by expected Rx beam information method with only marginal performance loss as well as expected Tx beam information scheme.
  + ***Generalization study for different beam shape patterns***
  + Observation 14: As the difference of beam shape pattern increases, the performance loss of both average RSRP difference and beam prediction accuracy increases along with the difference of the antenna configurations between training subset and validation subset.
  + ***BM-Case 2: with different beam shape patterns***
  + Observation 17: Performance loss can be observed with difference datasets represented different beam shape patterns for training and validation in BM-Case2.
  + Observation 18: For the case using local beam ID as model input, beam loss and accuracy degenerate significantly compared to the performance of AI model training and inference with beam pointing angle.
* OPPO [8]
  + Observation 12: Thanks to generalization capability of well-trained AI/ML model, changing scenario from UMa to UMi may not necessarily deteriorate the beam prediction performance.
  + Observation 13: Changing beam pair configuration on Set B and Set A from training phase to inference phase would slightly lower the beam prediction performance.
  + Observation 14: When more predicted beam pairs are provided by AI/ML model, e.g. Top-K = 4, the beam selection accuracy can be up to 95% and avg. L1-RSRP difference can be lower than 1dB.
* Ericsson [11]
  + Observation 9: With identical antenna configuration, initial evaluations indicates that a model trained in one cell is found to be generalized well to another cell except for one or two fixed cells.
* CATT [12]
  + Observation 5: For AI/ML based beam management, there is significant performance degradation when the number of beams (pairs) of Set B for inference is smaller than that of Set B for training.
  + Observation 6: For AI/ML based beam management, the performance of AI/ML model, which is trained with mixed numbers of beams (pairs) in Set B, is similarity for different numbers of beams (pairs) in Set B.
* Fujitsu [13]
  + Observation 1: The module of pre-processing provides the flexibility to adapt to variable Set B for AI/ML model.
  + Observation 3: For variable Set B, the model trained by mixed dataset constructed by samples with different sampling rates from beams of Set A will improve the performance of AI/ML model.
  + Observation 4: For variable Set B, the performance of the model trained by mixed dataset is almost the same as the model trained by separated dataset for fixed Set B.
* Xiaomi [17]
  + BM Case 1:
  + Observation 2: AI model trained by hybrid data of Uma and Umi for beam prediction in spatial domain can provide good generalization capability for Uma or Umi. While AI model trained by data of only Uma or only Umi provide a little worse generalization capability
  + Observation 3: AI model trained by hybrid data of different UE distribution for beam prediction in spatial domain can provide good generalization capability. While AI model trained by data of only UE distribution Option A provides a little worse generalization capability for UE distribution Option B.
  + Observation 4: AI model for beam prediction in spatial domain can provide good generalization capability among different number of UE Rx beam, e.g., AI model with more Rx beam number can be applied for beam prediction of less Rx beam number.
  + BM Case 2:
  + Observation 8: AI model for beam prediction in time domain trained by data of 30km/h or only 60 km/h or hybrid can provide good generalization capability to UE speed with both 60km/h and 30km/h.
* Nokia [19]
  + Observation 11: model's generalization capabilities should be assessed considering different combination of configurations as ML model performances can be affected significantly.
  + Observation 12: Several configurations/scenarios can be considered for assessing the ML model generalization capabilities. In this study, we considered the gNB antenna array dimensions, but other configurations/scenarios are not precluded. Supporting multiple configurations may further affect ML performance.
  + Observation 13: For BM-Case1, the Set A/B model generalization issue can be addressed with a training model based on an oversampled Set C that satisfies Set B∈Set A∈Set C for any given Set A/B.
  + Observation 14: For BM Case1, the training model with a fixed Set B pattern will have poor beam prediction performance if the testing Set B does not match with the training Set B.
  + Observation 15: For BM-Case1, training the model with random Set B is possible to provide beam prediction performance close to the optimal case – training and testing on the same Set B.
* Apple [21]
  + Observation: The AI/ML model trained with Dataset 1 does not generalize well to Dataset 2:
    - where
      * Dataset 1 is with d\_V=0.5,d\_H=0.5.
      * Dataset 2 is with d\_V=0.8,d\_H=0.4.
    - With mismatched AI model, the AI performance with set B beam at 16 beams is worse than the AI performance with set B at 8 beams without mismatched AI model.
* Samsung [24]
  + Observation # 12: For DL TX beam prediction and beam pair prediction, AI/ML model performs the best when the training and testing dataset are drawn from the same UE speed. However, performance degradation is observed when the training dataset and testing datasets are drawn from different UE speed.
  + Observation # 13: For DL TX beam prediction and beam pair prediction, training a model with a mixture of dataset drawn from a range of UE speeds allows the model to perform well over a range of UE speeds.

# AI/ML related assumptions

## 4.1 (on hold) Inputs of AI/ML models

In RAN 1 #110, the following alternatives were agreed.

|  |
| --- |
| **Agreement**  *For* the sub use case BM-Case1 and BM-Case2, further study the following alternatives for the predicted beams:   * Alt.1: DL Tx beam prediction * Alt.2: DL Rx beam prediction * Alt.3: Beam pair prediction (a beam pair consists of a DL Tx beam and a corresponding DL Rx beam) * Note1: DL Rx beam prediction may or may not have spec impact |

In this section, further discussion on inputs for each alternative. The following observations/proposals were provided in contributions:

* Huawei [2]
  + Observation 1: For the AI/ML-based beam prediction mechanism, Option 2 (DL Tx beam prediction) may also achieve best Tx-Rx beam combination by DL Tx beam prediction and legacy Rx beam sweeping.
  + Proposal 1: For the evaluation of AI/ML-based beam prediction mechanism,
    - Option 2 (DL Tx beam prediction) should be considered as the starting point.
      * Both Case A (best Rx beam) and Case B (same specific Rx beam) can be adopted and reported by companies
    - Option 1 (Tx-Rx beam pair prediction) can be also evaluated to justify the additional performance gain over Option 2.
    - Option 3 (DL Rx beam prediction) can be considered with lower priority.
* ZTE [3]
  + Observation 3: With a same sampling rate on the whole beam space, the Tx beam prediction obtains a better performance than that of the Tx-Rx beam pairs prediction.
  + Proposal 5: Whether to choose Alt 1 or Alt 4 needs further discussion according to the beam pattern selection.
    - *Note by FL0: Alt 1: only RSRP; Alt 4: RSRP and beam IDs*
* Vivo [5]
  + *DL Tx beam prediction*
  + Observation 11: Significant performance deterioration can be observed in two-step beam prediction with non-best Rx beam, even for the 2nd best Rx beam.
  + Observation 12: The performance of two-step beam prediction with the best Rx beam provides considerable improvement, as decreased prediction difficulty from predicting 256 beam pairs to 32 beam pairs by acquiring precise best Rx beam of each sample.
  + Observation 13: Large performance deterioration can be observed if the Rx beam assumptions of training and inference are different for DL Tx beam prediction scheme.
  + Proposal 21: Study DL Tx beam prediction with different Rx beam assumptions as one of the solutions for generalization to different number of Tx/Rx beams in BM-Case1.
* OPPO [8]
  + For BM-Case1 and BM-Case2, at least support beam pair prediction (Alt.3) as the key feature of representative sub use cases.
  + Observation 1 The input of AI/ML model for beam prediction are element-wise sensitive, therefore the L1-RSRPs of Tx and/or Rx beams in Set B should be input in proper order.
  + Proposal 3: For BM-Case1 and BM-Case2, suggest to adopt L1-RSRP measurement based on Set B as input of AI/ML model.
  + FL0: can be discussed in 9.2.3.2
* CATT [12]
  + *Beam pair prediction:*
  + Observation 2: For Beam pair prediction, additional Beam ID input have significant performance gain compared with beam prediction accuracy with random pattern using L1-RSRP input only.
  + *DL Tx beam prediction:*
  + Observation 3: For DL Tx beam prediction, beam prediction accuracy with fixed pattern has better performance than random pattern, since beam ID is implicit in the fixed pattern.
  + Observation 4: For DL Tx beam prediction, additional Beam ID input have significant performance gain compared with beam prediction accuracy with random pattern using L1-RSRP input only.
  + Proposal 2: For AI/ML based beam management, DL Tx and/or Rx beam ID is supported as an additional input besides L1-RSRP measurement based on Set B.
  + FL0: Some clarification on inputs can be discussed in 9.2.3.2
* Xiaomi [17]
  + Observation 1: AI based beam prediction in spatial domain can provide good performance. And the performance can be further improved by inputting corresponding beam pair ID in addition to measured L1-RSRP or by inputting L1-RSRP of same beam pair IDs.
  + FL0: Some clarification on inputs can be discussed in 9.2.3.2
* Mediatek [20]:
  + Proposal 9: For AI/ML-based spatial domain beam prediction evaluation, adopt the RSRP of beams in Set B as the AI/ML model inputs. Additional information to the input of AI/ML model is not excluded.
  + Proposal 10: Adopt one of the following as the output of AI/ML model: (i) beam index of highest RSRP Set A of beams. (ii) RSRPs of all the Set A of beams.
* Samsung [24]
  + Proposal # 3: Deprioritize the study of Rx beam prediction in this study item for AI/ML in beam management.
  + Proposal # 4: At least for BM Case 1, the following options can be further studied and potential down selection as the inputs of AI model:
    - Option 1: For Tx-Rx beam pair prediction:
      * L1-RSRP measurements of Tx-Rx beam pairs in Set B
        + FFS on the selection of Tx-Rx beam pairs in Set B
    - Option 2: For DL Tx beam prediction
      * L1-RSRP measurements of Tx beams in Set B, measured by one or multiple Rx beam(s), FFS:
        + The Rx beam is “best” Rx beam based on historical measurements
        + The Rx beam(s) is by UE implementation FFS fixed Rx beam or different Rx beam for measuring different Tx beams in Set B
        + FFS: The Rx beam(s) is fixed and configured by gNB or chosen by UE implementation
      * FFS on the number of Rx beams
    - FFS on other information as AI inputs
  + Proposal # 5: For AI inference at gNB side, DL Tx beam prediction is prioritized, and focus on the L1-RSRP measurements of Tx beams in Set B with explicit or implicit Tx beam ID as AI inputs.
* Qualcomm [26]:
  + Proposal 7: For both spatial and temporal prediction evaluation, consider the following options as inputs to AI/ML models for the study and potential down selection:
    - Option 1: For Tx-Rx beam pair prediction:
      * L1-RSRP of Tx-Rx beam pairs in Set B
    - Option 2: For DL Tx beam prediction
      * L1-RSRP of Tx beams in Set B, measured by a (set of) Rx beam(s) selected by UE
        + FFS on selection criteria of (set of) Rx beam(s) by UE
    - Option 3: For DL Rx beam prediction,
      * L1-RSRP of Rx beams in Set B (where Set B of beams is for Rx beam)
    - Note: DL Rx beam prediction may or may not have spec impact
    - Other inputs (e.g., CIR) are not preluded.
    - Note 1: Other assistance information is not precluded
    - Note 2: Options 1 and 3 are applicable to UE-side AI/ML models.

FL 0: Wait for the clarification in 9.2.3.2 on whether implicit beam ID is included or not, as well as some other discussions.

## 4.2 Number of beams Tx and/or Rx beams for Set A and Set B

* Huawei/HiSi [2]:
  + Proposal 5: For the evaluation of AI/ML-based beam management, for the construction of Set A, a DFT codebook with 64 DFT Tx beams and a denser codebook with 256 Tx beams should be considered.
  + Proposal 16: For the evaluation of beam prediction, RAN1 should study Set A with size of 64 and 256 beams to improve beam management related system performance, complexity and coverage over the legacy baseline.
  + Another issue is the number of beams in Set B. Since one of the main motivations to employ sparse beam sweeping is to save overhead compared to an exhaustive sweep, it can be considered to limit the number of beams in Set B relatively to the number of beams in Set A, e.g., number of beams in Set B should not exceed one fourth of the number of beams in Set A.
* Spreadtrum [4]:
  + Proposal 1: For both BM-Case1 and BM-Case2, unifying the number of beams contained in set A and set B should be considered.
* Vivo [5]
  + Proposal 1: Slightly prefer Alt 1 in evaluation assumption of Tx beam number, but we can live with Alt 2.
  + Proposal 2: Support 4 Rx beams per UE panel used at UE side for the evaluation of both temporal and spatial domain beam prediction.
* OPPO [8]
  + Observation 11: For spatial and temporal domain beam prediction, the longer gap between measurement on Set B and prediction among Set A, the deeper performance loss can be observed.
* LGE [10]
  + Proposal 3. It is preferred to fix the number of beams in Set A.
* Ericsson [11]
  + Observation 2: For NW-sided model, the variable number of beams could be due to UE only reporting a subset of the measured beams.
  + Proposal 4: Define the number of beams in set B as a fraction of beams in set A
* Nokia [19]
  + Proposal 1: For BM-Case1, given the current agreed NW antenna configuration, the number of DL Tx beams in Set A should be 32 or 64.
  + Observation 1: For BM-Case1, a large number of beams in Set B (e.g., 32) may not improve the prediction accuracy and the system throughput. Therefore, ML-based beam selection should consider a Set B with a maximum of 16 beams when Set A has 64 beams, hence Set B should have a max of ¼ of Set A beams.
  + Observation 2: For BM-Case1, a “sparse” Set B, or a random Set B pattern design, may cause throughput loss, especially for the cell-edge UE.
  + Observation 3: For BM-Case1, Set B RSRP may not be sufficient for beam prediction input in certain cases.
  + Proposal 2: For BM-Case1, RAN1 further study the case of Set A/B are DL Tx and Set B is a subset of Set A.
    - When Set B is a subset of Set A, RAN1 should consider a Set B with a maximum number of DL Tx beams that is ¼ of Set A beams.
  + Observation 4: For BM-Case1, the ML model using as input only RSRP measurements has performances that reduce significantly changing the number of RSRP measurements from 8 to 4, i.e. further down sampling Set A, from a ratio of ¼ to a ratio of 1/8.
* CEWiT [27]
  + Observation 2: When the size of Set B is increased, the performance of the AI/ML model improves.

#### FL1: Number of Tx and Rx beams

**Proposal 4-2-1a:**

* **Adopt the following proposals as working assumption:**
* **For the evaluation of both BM-Case1 and BM-Case 2, 32 or 64 [or 256] Tx beams are used at NW side.** 
  + **Other values are not precluded and can be reported by companies.**
* **For the evaluation of both BM-Case1 and BM-Case 2, 4 Rx beams per UE panel are used at UE side.** 
  + **Other values are not precluded and can be reported by companies.**

|  |  |
| --- | --- |
| Supporting companies |  |
| Objecting companies |  |

**Please provide your view Proposal 4-2-1a, if any.**

|  |  |
| --- | --- |
| Company | Comments |
| FL0 | The above number of beams are used/proposed by majority of companies. I understand that some company may have different number in the assumption. The door is not closed.  In FL’s view, it is good to align the assumption for further evaluation results collection.  Generalization is discussed separately, other values are not precluded. |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |

#### FL1: Number beams(pairs) in Set B

**Proposal 4-2-2a:**

* **For evaluation for DL Tx beam prediction in BM-Case1, when Set B is a subset of Set A, the number of beams(pairs) in Set B is no more than ¼ of beams (pairs) in Set A.**

|  |  |
| --- | --- |
| Supporting companies |  |
| Objecting companies |  |

**Please provide your view Proposal 4-2-1, if any. And the views of following questions:**

**A:** whether to provide list of number of beams, e.g., 1/8 or 1/4 of Set A beams

**B:** the ratio of Set B beam pairs and Set A beam pairs

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |
|  |  |

## 4.3 Selection of Set B of beams(pairs)

RAN 1 #110 agreed three options of the selection of Set B of beams(pairs).

|  |
| --- |
| **Agreement**   * **Study the following options on the selection of Set B of beams (pairs)**    + **Option 1: Set B is fixed across training and inference**     - **FFS on the beams of Set B**   + **Option 2: Set B is variable (e.g., different beams (pairs) patterns in each report/measurement during training and/or inference)**      - **FFS on fixed or variable number of beams (pairs)**     - **FFS on the details**   + **Other options are not precluded.**   + **FFS on the number of beams (pairs) in Set B**   + **Note: This does not preclude the alternative that Set B is different from Set A.** |

The following were discussed or assumed in the assumption for the evaluation of AI for BM:

* Futurewei [1]
  + Option 1: Fixed Beam Pattern
    - In this option, a defined fixed beam pattern with M select beams out of all the available beam pairs is applied for all the input samples. In our experiment, we use even-space sampling to pick M beam pairs (M  {4, 8, 12, 16, 20, 24, 28, 32}) from the total 256 beam pairs.
  + Option 2: Random Beam Patterns
    - In this option, we randomly select M beam (M  {4, 8, 12, 16, 20, 24, 28, 32}) from all available beams as input for each sample.
  + Option 3: Pre-configured Beam Patterns
    - In this option, we pre-defined a set of N (N = 5) different beam patterns, each with M selected beam pairs (M  {4, 8, 12, 16, 20, 24, 28, 32}), then one of them will be randomly chosen as input for each sample.
  + Observation 1: The performance of spatial-domain beam prediction using either fixed beam pattern sampling or pre-configured beam patterns sampling is improving when the training dataset size is increasing.
  + Observation 3: Performance of pre-configured beam patterns sampling is more sensitive to training dataset size increase compared to fixed beam pattern sampling.
  + Proposal 1: For AI/ML based spatial beam prediction, when using pre-configured beam patterns sampling approach, further study the trade-off between training dataset size and performance.
* Huawei/HiSi [2]:
  + Observation 2: For the selection of Set B, under Option 2 (variable Set B), it is more realistic for the gNB to vary among semi-fixed Set B including a limited number of deterministic Set B patterns rather than varying over totally random beams in Set B.
  + Proposal 6: For BM-Case-1 and Case-2, for the selection of Set B, consider Option 1 (Set B is fixed across training and inference) as a starting point.
    - For Option 2 (Set B is variable), semi-fixed Set B can be assumed in the evaluation, which includes a limited number of deterministic Set B patterns.
* Spreadtrum [4]:
  + Proposal 4: Set B to be a subset of set A for spatial domain beam prediction can be used as baseline,
    - If AI/ML inference is at NW side, beams in Set B can be determined by NW implementation.
    - If AI/ML inference is at UE side, beams in Set B can be determined with a fix pattern.
  + Proposal 6: For temporal beam prediction, evaluate and further study “Set A and Set B are the same” as the baseline.
* Vivo [5]:
  + (Option 1): only one pre-defined subset with fixed pattern in Set B is used in option 1 across training and inference stage,
  + while option 2 brings much more selection schemes in Set B, such as,
    - one fixed subset for training and another fixed subset for inference,
    - variable subsets with random patterns in Set B for training and inference, and
    - variable subsets with semi-random patterns in Set B for training and inference.
  + One fixed set B in Option 1 may show good performance in theory, but it lacks flexibility as in practical implementation, a particular beam or beam pair may suffer performance loss due to unexpected channel variation like blockage, and may cause large interference. Hence it is needed to study option 2 and make sure it can provide comparable performance as option 1 with higher flexibility.
  + ***Fixed beams:***
  + Observation 1: Fixed subset selection scheme with different fixed patterns brings tremendous performance difference.
  + Observation 2: Better performance gain can be obtained for one fixed subset selected by well-designed rule or enumerated with predefined searching criterion.
  + Observation 3: The performance with different training and validation fixed subsets is quite poor and not acceptable, i.e., fixed set B selection scheme suffers serious generalization issue.
  + Proposal 13: Unless an excellent generalization performance can be proved in option 1, i.e. a fixed subset in Set B for training and same fixed subset in Set B for validation, fixed set B selection scheme should be deprioritized.
  + ***Random subset selection***
  + Observation 4: Fixed beam subset in Set B can have good performance in ideal scenarios but it lacks flexibility. Issues like blockage and inter-cell interference can bring negative impact on the performance of fixed subset.
  + Observation 5: Random subset selection scheme, which allows multiple random subsets in training, can improve generalization performance as well as beam management related performance if compared to mismatched subset with always using one subset in training.
  + Observation 6: Set 5 with random beam subset still suffers tremendous performance deterioration due to huge number of combinations of selecting a target number of beams from total beam pairs.
  + Observation 7: Compared with Set 5, assistance information brings considerable gain in random subset selection scheme, especially for Tx/Rx beam angle as assistant information.
  + *Semi-random subset selection:*
  + Observation 8: To restrict the selection of random subset from the best X beam subsets can improve the performance of BM Case 1 prediction. Such semi-random selection with Tx/Rx beam angle information as input barely suffers performance loss compared with the best beam subset.
  + Observation 9: Semi-random beam subset scheme has potential to approach the performance upper bound, i.e. the best fixed subset, if the performance of each subset in top-N best subsets has similar performance of top-1 best subset.
  + Proposal 16: Support option 2 for Set B selected by semi-random beam subset selection scheme with both Tx and Rx beam information as AI input.
* OPPO [8]
  + Proposal 1: Apply fixed Set B across training and inference phases for BM-Case1 and BM-Case2.
* LGE [10]
  + Proposal 4. Option 1 can be considered as a baseline for selection of Set B of beams.
* CATT [12]
  + *Beam pair prediction:*
  + Observation 1: For Beam pair prediction, beam prediction accuracy with fixed pattern has better performance than random pattern, since beam ID is implicit in the fixed pattern.
  + Observation 2: For Beam pair prediction, additional Beam ID input have significant performance gain compared with beam prediction accuracy with random pattern using L1-RSRP input only.
  + *DL Tx beam prediction:*
  + Observation 3: For DL Tx beam prediction, beam prediction accuracy with fixed pattern has better performance than random pattern, since beam ID is implicit in the fixed pattern.
  + Observation 4: For DL Tx beam prediction, additional Beam ID input have significant performance gain compared with beam prediction accuracy with random pattern using L1-RSRP input only.
* Fujitsu [13]
  + Proposal 1: For selection of Set B of beams (pairs), it is suggested that the beams of fixed Set B are constructed with an even-spacing sampling rate from beams of Set A.
  + Proposal 2: For selection of Set B of beams (pairs), it is suggested that the beams of variable Set B are constructed with different even-spacing sampling rates from beams of Set A.
* Intel [14]
  + Proposal 2: The variability of Set B can only be due to updating the L1 measurements corresponding to beams or beam-pairs in Set B at different intervals. The cardinality of the set should not change across training and inference.
* Lenovo [15]
  + Allow set B to have variable number of beams at each instant of time during training and/or inference and allow the beams in set B to be variable and change across time during training and/or inference.
* Xiaomi [17]
  + Proposal 2: Adopt the evaluation methodologies listed below for spatial domain beam prediction:
    - Set B is a subset of set A.
    - AI model:
      * Input:
        + Scheme 2: L1-RSRP of beam pairs selected randomly and corresponding beam pair IDs
        + Scheme 3: L1-RSRP of beam pairs with fixed beam pair IDs
      * Output
        + L1-RSRP of all beam pairs with ascending order of beam pair ID
* Nokia [19]
  + Proposal 4: For BM-Case1, RAN1 further study Set B to be a fixed pattern.
  + Proposal 5: For BM-Case1 model inference applies at the NW side, with DL Tx beams considered for Set A and Set B, the training a model with random Set B is not needed.
  + Observation 8: For BM-Case1\_(DL Tx) model inference in UE side, training model with random Set B may reduce model switching/indication/ transferring overhead for UE. But the benefit of BM-Case1\_(DL Tx) model inference on the UE side is not yet clear.
  + Proposal 6: For BM-Case1 model inference applies at the UE side, with DL Tx beams considered for Set A and Set B, the training a model with random Set B can be further studied.
  + Observation 9: For Set B is different to Set A with Set B is wide beam, the KPI for the wide beam codebook design should be both prediction accuracy and throughput performance.
  + Proposal 7: For BM-Case1, RAN1 may further study the case of Set A/B are DL Tx and Set B/Set A are different.
    - Set B is a wide beam codebook and Set A is a refined beam codebook
    - Advance Set B designs are needed to provide sufficient refined beam prediction performance.
  + Observation: For DL Tx-Rx beam pair prediction, the prediction target space . And it requires a large number of measurements to have good beam pair prediction.
  + Proposal 8: RAN1 further investigates the comparison between independent Tx beam, Rx beam prediction, and joint Tx-Rx beam pair prediction.
  + Proposal 13: For BM-Case2, support Method 3 as the main scenario while other methods can be further studied :
    - Method 1: Set B is a fixed subset of Set A
    - Method 2: Set B is a variable subset of Set A
    - Method 3: Set B is the same as Set A
    - Methods 1 or 3 + Assistance Info: ML model input consists of L1-RSRP measurement based on Set B and assistance information
* MediaTek [20]:
  + Observation 9: With a greater number of beams in Set B, both models achieve higher Top-k accuracy. However, greater number of beams in Set B requires more beam RSRP measurements.
  + Proposal 8: Study the tradeoff between the beam measurement overhead and prediction accuracy for different number of beams in Set B.
  + Observation 10: The selection of beams in Set B will affect the prediction accuracy of the AI/ML-based spatial beam prediction.
  + Proposal 11: For AI/ML-based spatial domain beam prediction evaluation, study the subset selection (number and combination) if Set B is variable (Option2 on the selection of Set B of beams in the RAN1 #110 agreement).
  + Observation 11: The spatial beam prediction by using multi-arm beam design in Set B performs better than using subset beam design in Set B.
  + Observation 12: The spatial beam prediction by using wide beam design in Set B does not outperforms the performance by using subset beam design in Set B.
  + Proposal 12: Study and evaluate a more comprehensive Set B design, including joint designing the number of beams in Set B and their beam shape for spatial beam prediction.
* Samsung [24]
  + *DL Tx beam*
  + Observation # 1: Using the L1-RSRP of the “best” Rx beam with exhaustive beam sweep as inputs can provide the best performance for the accuracy of Top-1/N beam prediction than fixed or randomly selected one or two Rx beams with fixed or random Tx beams for BM-Case 1.
  + Observation # 2: With L1-RSRPs of fixed Rx beam(s) as AI inputs can provide better performance than L1-RSRP of random Rx beam(s) for DL Tx beam prediction for BM-Case 1.
  + Observation # 3: With L1-RSRP of fixed Tx beams in Set B of beams as AI inputs can provide better performance than with random Tx beam in Set B of beams for DL Tx beam prediction for BM-Case 1.
  + Observation # 7: For DL Tx beam prediction in BM-Case 1, L1-RSRPs with implicit Tx beam index as AI inputs and best Tx beam as AI outputs and can provide a better performance than with L1-RSRPs with implicit Tx beam index and Rx beam index as AI inputs and best Tx-Rx beam pair as AI outputs.
  + *Beam pair*
  + Observation # 4: Using the L1-RSRP of the “best” Rx beam with exhaustive beam sweep as inputs can provide the best performance for the accuracy of Top-1/N beam prediction than fixed one Rx beam or randomly selected one or two Rx beams with fixed or random Tx beams for DL Tx-Rx beam pair prediction for BM-Case 1.
  + Observation # 5: With L1-RSRPs of fixed Rx beam(s) as AI inputs can provide better performance than L1-RSRP of random Rx beam(s) for DL Tx-Rx beam pair prediction for BM-Case 1.
  + Observation # 6: For beam pair prediction for BM-Case 1, AI with inputs as L1-RSRPs of fixed Tx beams and implicit beam ID information can provide better performance than non-AI based approach.
* CEWiT [27]
  + Observation 1: When Set B is fixed, i.e., when fixed beam pattern is used, spatial domain beam prediction achieves sufficiently high performance with 50% overhead reduction.
  + Observation 2: When the size of Set B is increased, the performance of the AI/ML model improves.

Summary on the views on the different options for Set B of beams(pairs)

* Fixed beams
  + Huawei, Spreadtrum (as baseline), OPPO, LGE(baseline), Intel, xiaomi, Nokia(network side BM-Case 1 and BM-Case 2)
  + Concerns on generalization by vivo.
* Random beams
  + Lenovo(?), xiaomi
  + Intel (not preferred. only be due to updating the L1 measurements)
* Pre-configured beam patterns
  + Futurewei, Huawei, vivo, Nokia (UE side only), Nokia(network side BM-Case 2)

#### FL1: Set B of beams (Pairs)

**Please provide your views on the following questions:**

**Q1:** Whether fixed Set B of beams (Pairs) lacks of flexibility and may suffer from performance loss?

* Vivo: One fixed set B in Option 1 may show good performance in theory, but it lacks flexibility as in practical implementation, a particular beam or beam pair may suffer performance loss due to unexpected channel variation like blockage, and may cause large interference. Hence it is needed to study option 2 and make sure it can provide comparable performance as option 1 with higher flexibility.

**Q2:** Whether to support fixed beams across training and inference can be the baseline for BM-Case 1 and inference at gNB side?

**Q3:** For option 2, which of options do you support and which cases it needed, e.g., inference at UE side, Temporal domain prediction?

Opt A: Set B is variable with a pre-configured pattern in each time instant (e.g., for BM-Case 2) for each training

Opt B: Set B is randomly changed among pre-configured patterns (with fixed or variable number of beams(pairs)) in each report/measurement during training and/or inference

Opt C: Set B is randomly changed among Set A beams (pairs) (with fixed or variable number of beams(pairs)) in each report/measurement during training and/or inference

**D:** other comments

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |
|  |  |

## 4.4 Assumption of time domain information for BM-Case 2

There were some discussions/proposals/disclosures of assumption on the beam sweeping and RS pattern:

* Huawei/HiSi [2]
  + Proposal 19: Considering the robustness of AI/ML against longer prediction time instances and higher UE speeds, CSI-RS patterns for the observation/prediction window should be assumed with a large time domain distance between observation/prediction instances, for example 80ms or 160ms.
* vivo [5]
  + BM evaluation metrics are calculated based on difference between decided/predicted best beam pair and real best beam pair in T2. For comparison, non-AI and AI based 2-step scheme are evaluated. For AI based 2-step scheme, best pair is predicted based on P2+P3 procedure, and for non-AI 2-step scheme, best pair is decided based on measurement in P2+P3 procedure without prediction. Time duration T1 is fixed to 8\*40ms, and time duration T2 is equal to 1\*40ms, 4\*40ms or 8\*40ms respectively.
* Ericsson [11]
  + The NN’s inputs at training and inference are the L1-RSRPs selected from 5 consecutive time instances. So, the observation duration T1=5\*40ms=200ms. Prediction is at the time instance immediately following the last observation window time instance, and also a prediction at 160ms ahead for comparison. Hence the time duration for the best beam evaluation is T2= 40 ms or 160 ms.
* Xiaomi [17]
  + Observation 5: AI based beam prediction scheme 1 and scheme 2 in time domain can provide good performance.
    - Scheme 1 assumes same periodicity for history measurement instance and future time instance.
    - Scheme 2 assumes longer periodicity for history measurement instance than that of future time instance. It can reduce more RS overhead than scheme 1.
  + Proposal:
    - Set A and set B are the same set.
    - The periodicity of future time instance can be 80ms/160ms
    - The periodicity of future time instance can be same or different from that of history measurement instance
    - AI model:
      * Input:
        + L1-RSRP of set B in 4 history measurement instances
      * Output
        + Top K beams of set A in 1/2/4 future instances
* Nokia [19]:
  + CSI measurement/report periodicity: 40ms or 80ms
  + Observation window: 200, Prediction window: 40 80ms
* Mediatek [20]:
  + Proposal 3: Evaluate the impact of different observation and prediction window sizes to the performance of AI/ML temporal beam prediction.
  + Observation 2: By fixing the observation window size, the accuracy performance becomes better when prediction window size is lower.
  + Observation 3: By fixing the prediction window size, the accuracy performance increases when the observation window size increases. However, the performance will saturate.
  + Proposal 5: When the prediction window size is fixed, evaluate and study the optimal observation window size in terms of prediction accuracy and RS overhead.
* DoCoMo [25]
  + Proposal 3: Both Pattern 1 and Pattern 2 should be considered in the BM-Case 2 for both evaluation and study on specification impact.
    - Pattern 1: The sequence of inputs of AI/ML model has different periodicity and time scale from that of the sequence of outputs (Input: large; Output: small).
    - Pattern 2: The sequence of inputs of AI/ML model has the same periodicity and time scale as that of the sequence of outputs.
* 
* **Figure 3.** Illustration of pattern 1
* 
* **Figure 4.** Illustration of pattern 2

#### FL1: Assumptions for BM-Case 2

**Proposal 4-4-1a:**

* **At least for BM-Case 2, consider the following assumptions for evaluation**
  + **Periodicity of time instance for each measurement/report:**
    - **[20ms], 40ms, 80ms, 160ms**
    - **Other values can be reported by companies.**
  + **Number of time instances for measurement/report:** 
    - **4, [5], 8**
    - **Other values can be reported by companies.**
  + **Time instance(s) for prediction:**
    - **[20ms], 40ms, 80ms, 160ms, [1440ms] after the last [time instance/measurement/report]**
    - **Other values can be reported by companies.**

**Please provide your view Proposal 4-4-1a, if any.**

|  |  |
| --- | --- |
| Company | Comments |
| FL1 | * The intention is to align the assumption for evaluation results collection. * The numbers proposed/used by single company are put in bracket. * The definition of time instance(s) for prediction needs to be discussed, e.g., after the last time instance, or measurement or report. * In FL’s view, with separated periodicity for measurement and prediction, DoCoMo’s proposal can be covered. |
|  |  |
|  |  |
|  |  |
|  |  |

## 4.5 (on hold) Assistance information

Assistance information were discussed and some observations are summarized:

* Huawei [2]
  + Observation 3: For the AI/ML-based beam prediction, the provision of some assistance information may be infeasible due to the concern of disclosing proprietary information or privacy to the other side. For a NW-side model, this includes Rx beam angle or boresight direction, Rx beam shape, and FFS the UE speed and UE position. For a UE-side model, a list of infeasible assistance information includes at least the Tx beam angle or boresight direction, 3dB beamwidth, and Tx beam shape.
    - The meaning and method to obtain expected Tx/Rx beam information, LOS probability may need to be clarified before discussing.
* ZTE[3]
  + We also note that other assistance information such as beam shape or beam usage are not evaluated since they are implementation-related information of the gNB or UE, which may be difficult to be disclosed to the opposite node
* Vivo [5]:
  + Observation 7: Compared with Set 5, assistance information brings considerable gain in random subset selection scheme, especially for Tx/Rx beam angle as assistant information.
  + Proposal 14: Assistance information, such as Tx/Rx beam ID or angle in connection with input RSRPs, should be used as AI input with random subset selection for both BM-Case1 and BM-Case2.
  + Proposal 15: Suggest to use both Tx and Rx beam information as assistance information for further performance improvement in random subset selection.
  + Proposal 23: Further study assistance information, such as beam shape pattern, 3dB beam width, etc., as model input to address performance deterioration for generalization of different beam shapes in BM-Case1.
  + ***BM-Case 2: with different beam shape patterns***
  + Observation 18: For the case using local beam ID as model input, beam loss and accuracy degenerate significantly compared to the performance of AI model training and inference with beam pointing angle.
  + Proposal 27: Further study assistance information, such as beam shape pattern, 3dB beam width, etc., as model input to address performance deterioration for generalization of different beam shapes in BM-Case2.
  + Proposal 28: Suggest to use beam pointing angle or global beam ID as assistance information for AI model input.
* OPPO [8]
  + Proposal 4: For the assistance information of BM-Case1 and BM-Case2, suggest to
    - Justify the performance benefits if assistance information
    - Study whether assistance information would expose beamforming implementation and proprietary information at NW or UE.
* Nokia [19]
  + Observation 4: For BM-Case1, the ML model using as input only RSRP measurements has performances that reduce significantly changing the number of RSRP measurements from 8 to 4, i.e. further down sampling Set A, from a ratio of ¼ to a ratio of 1/8.
  + Observation 5: For BM-Case1, when the ML model use the UE angle as the assistance information, it has a better performance than all the other variants.
  + Observation 6: For BM-Case1, the ML model using as input RSRP measurements and UE Position has performances that outweigh the performance of the ML model using only RSRP.
  + Observation 7: For BM-Case1, using assistance information like Beam Angle and Beam ID related to the measured beams may not significantly improve the performance of the ML model using as input only RSRP with a fixed pattern.
  + Proposal 3: For BM-Case1, RAN1 further study the use of assistance information at the ML model input. The following assistance information can be prioritized:
    - the beam angle and/or the beam boresight direction for the measured DL Tx beams from NW to UE.
    - the UE position information.
    - the UE’s angle relative to a panel array of the gNB
* MediaTek [20]:
  + Observation 6: Temporal beam prediction by adding additional UE angle information directly to the input of the model did not show significant gains compared to predicting without UE angle information.
  + Proposal 6: Study more scenarios where additional information may improve the temporal beam prediction performance
  + Observation 13: The spatial prediction accuracy does not improve much by using UE angles directly as the additional input, at least for the ratio of Set B and Set A sizes is between 1/6 to 1.
  + Observation 14: The spatial prediction accuracy does not improve much by using UE angles directly as the additional input, under various selections of Set B.

## 4.6 Others

Some other input/output related discussion:

* Futurewei [1]
  + Observation 1: The performance of spatial-domain beam prediction using either fixed beam pattern sampling or pre-configured beam patterns sampling is improving when the training dataset size is increasing.
  + Observation 3: Performance of pre-configured beam patterns sampling is more sensitive to training dataset size increase compared to fixed beam pattern sampling.
* Vivo [5]:
  + Proposal 5: At least AI model inputs/outputs and training/validation dataset should be reported per sub-use case by companies. Other parameters, such as NN architecture type, loss function, and data post/pre-processing method, are encouraged to be reported.
* Ericsson [11]
  + To help enable reproducibility, companies should report relevant information about the AI/ML model architecture, data pre- and post-processing, loss functions, and training procedures using an academic style paper and/or pseudocode.

|  |
| --- |
| **Agreement**   * Companies are encouraged to report the following aspects of AI/ML model in RAN 1 #110. FFS on whether some of aspects need be defined or reported.   + Description of AI/ML model, e.g, NN architecture type   + Model inputs/outputs (per sub-use case)   + Training methodology, e.g.     - Loss function/optimization function     - Training/ validity /testing dataset:       * Dataset size, number of training/ validity /test samples       * Model validity area: e.g., whether model is trained for single sector or multiple sectors       * Details on Model monitoring and model update, if applicable   + Others related aspects are not precluded |

#### FL1: Other assumptions

**Q: Any other assumption needs to be aligned/reported for evaluation results collection? E.g., amount of training/testing data set?**

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |
|  |  |

# Evaluation results for AI/ML in beam management

#### FL1: Results collection:

**Proposal 5-1a:**

For both BM-Case1 and BM-Case 2, the following table is adopted as **working assumption** for reporting the evaluation results.

**Table X. Evaluation results for AI/ML model deployed on [UE or network]-side without model generalization**

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| AI/ML model Input/output | | Data size | | AI/ML model | | | Evaluation results | | | | | |
| [Beam prediction accuracy (%)] | | [L1-RSRP Diff] | [System performance] | | |
| Model input | Model output | Training | testing | [Short model description] | Model inference complexity | Computational complexity | KPI A | KPI B… | [Average L1-RSRP diff] | [RS overhead] | [UCI report] | [UTP]  … |
|  |  |  |  |  |  |  |  |  |  |  |  |  |

To report the following in table caption:

* + - * Which side the model is deployed

Further info for the columns:

* Model input: input type, e.g., L1-RSRP
* Model output: output type, e.g., the best DL Tx beam ID
* Dataset size, both the size of training/validation dataset and the size of test dataset
* Short model description: e.g., CNN, LSTM
* AI/ML complexity: both model complexity in terms of “number of model parameters”, and computational complexity in terms of FLOPs
* Evaluation results: agreed KPIs

Note: To report other simulation assumptions, if any.

**Please provide your views on the template for result collection**

|  |  |
| --- | --- |
| Company | Comments |
|  |  |
|  |  |
|  |  |
|  |  |

## (on hold) Evaluation results for BM-Case 1

The following observations were provided in contributions:

* Futurewei [1]:
  + Observation 2: The performance of AI/ML-based beam prediction has achieved significantly better performance when comparing with sparse beam sweeping approach.
* Huawei/HiSi [2]:
  + Observation 4: For spatial domain beam prediction, AI/ML-based schemes under the 64-DFT codebook outperform the legacy approach in most of the cases in terms of beam selection accuracy, e.g.,:
    - AI/ML-based Top-5 prediction reaches almost the upper performance bound with a prediction accuracy of 94.95% but with an overhead reduction of 67.17%. On the other hand, for the same overhead reduction, the established legacy Baseline approach can only achieve a prediction accuracy of 55.3%
    - With AI/ML-based Top-3 prediction, the overhead compared to the legacy Baseline approach can be further reduced by another 8%, while the prediction still is much higher (89.2% as opposed to 55.3%)
  + Observation 5: For spatial domain beam prediction, AI/ML-based schemes under the 64-DFT codebook outperform the legacy approach in most of the cases in terms in terms of average L1-RSRP difference, e.g.,:
    - For AI/ML-based Top-5 prediction, the L1-RSRP difference compared to genie-aided beam prediction in Exhaustive 64 is as low as 0.03 dB, with an overhead reduction of 67.17%. On the other hand, for the same overhead reduction, the established legacy Baseline approach can only achieve an average L1-RSRP difference of 1.02dB
    - With AI/ML-based Top-3 prediction, the overhead compared to the legacy Baseline approach can be further reduced by another 8%, while the average L1-RSRP difference is still is much smaller (0.08dB as opposed to 1.02dB)
  + Observation 6: It can be observed that better prediction accuracy is achieved when Set B is a subset of Set A compared to the case where Set B is a wide beam set, especially when K=1; with the increase of K, the gap between two options becomes narrower.
* ZTE [3]:
  + Proposal 3: The AI/ML model can be utilized for spatial domain beam prediction, which can greatly reduce the RS overhead for measurement while maintain a high beam prediction accuracy.
* Interdigital [6]
  + Observation 7: AI aided beam selection achieves more than 95% selection accuracy when error margin is larger than 0.5 dB by consuming 50%/33% of the measurement overhead for the exhaustive measurement.
  + Observation 8: AIML-based RSRP estimation always outperforms the baseline especially when less RSRP measurements are available as it achieves a higher selection accuracy by 35% when error margin is 0.5 dB.
* China Telecom [7]
  + Observation 1: Modelling the spatial beam prediction task as a classification model provides better performance with less training overhead.
* OPPO [8]
  + Spatial domain beam prediction can yield beam prediction accuracy (at least 80%) while overhead/latency reduction rate is 75%.
  + The system level metric, i.e. spectrum efficiency or throughput, is not sensitive to the L1-RSRP difference introduced by spatial domain beam prediction.
  + For 80% of the incorrect spatial domain beam prediction cases, the L1-RSRP difference can be kept within 2dB.
  + When beam prediction accuracy is high (at least 80%) and L1-RSRP difference is small (within 1 dB), the system-level performance, i.e. spectrum efficiency or throughput, may only provide non-essential insight, therefore focusing on L1-RSRP for beam prediction would be good enough.
* Ericsson [11]
  + *Tx beam prediction (with RSRP from best Rx beam)*
  + Observation 3: In outdoor scenarios, AI/ML can reduce beam spatial-domain beam prediction overhead substantially while maintaining good accuracy, both for 4x8 (30 beams in Set A) and 8x16 arrays (168 beams in Set A).
  + Observation 4: In scenarios with primarily indoor UEs, spatial-domain beam predication is more challenging.
  + *Tx/Rx beam prediction*
  + Observation 5: Joint TX/RX prediction can give good performance while significantly reducing RS overhead compared to measurements of all RX beams for each TX beam in Set B.
  + *System level performance*
  + Observation 6: The gains from AI/ML over baseline algorithm in terms of basic KPIs translate well to gains in full-buffer system-level evaluations.
  + *Reporting overhead*
  + Observation 7: By allowing variable number of reported beams via UE pre-processing of measurements, the reporting overhead can be substantially reduced with little performance degradation.
    - We consider a scheme with gNB-side inference where the UE measures a fixed set of beams, but only reports beams with RSRP exceeding a certain threshold relative to the strongest beam, i.e. only beams with an RSRP at most X dB below the RSPR of the strongest measured beam are reported.
* CAICT [16]
  + Observation 1: AI-based solution could achieve good performance for beam pair prediction with same training and validation set configurations.
* CMCC [18]
  + Observation 1: The increase of K significantly improves the prediction accuracy while leading to a small degree of increased beam sweeping overhead.
  + Observation 2: Compared with baseline option 1, AI based spatial beam prediction has minor loss of prediction accuracy for top-K beam pair but has large beam sweeping overhead reduction.
  + Observation 3: Compared with baseline option 2, AI based spatial beam prediction significantly enhances prediction accuracy for top-K beam pair under the same beam sweeping overhead.
* Rakuten Symphony [22]
  + Observation 1: The probability of one of the K beams being the best beam is more than 95% for K = 4.
  + Proposal 1: Consider a two-step beam management procedure where legacy beam management mechanism is used to choose the best beam from a set of beam recommendations from the AI/ML model.
* NVDIA [22]:
  + Observation 2: AI/ML-based algorithms for beam prediction in spatial domain can achieve performance comparable to that of exhaustive beam search, while the reference signal overhead, measurement effort, reporting overhead, and latency can be much reduced.
* Samsung [24]:
  + Observation # 10: For spatial domain prediction, AI can provide better performance in terms of beam prediction accuracy than non-AI based scheme with the measurements of a given subset of beams to select a best beam among a full set of beams.
  + Observation # 11: With the help of AI, SSB/RS overhead for measurements, UE measurement efforts, reporting overheads can be reduced to achieve a target performance for beam selection.
  + Observation # 12: For spatial domain prediction, AI can provide better performance in terms of beam prediction accuracy than non-AI based scheme with the measurements of a set of wide beams and a subset of narrow beams to select a best beam among a full set of narrow beams.
  + Observation # 13: For spatial domain prediction, AI can predict the best narrow beam based on the measurements of wide beams only with decent performance.
  + Observation # 14: For spatial domain prediction, AI can help gNB to predict the best narrow beam set that including the best narrow beam for UE to measure with high probability.

## (on hold) Evaluation results for BM-Case2

The following observations were provided in contributions:

* Huawei/HiSi [2]:
  + Observation 7: The AI/ML-based beam prediction based on the Set A with 256 beams (Type-2) provides a considerable gain over the legacy upper bound Exhaustive 64 (Type-1) in achievable L1-RSRP for a small fraction of the overhead associated with an Exhaustive 64 sweep.
  + Proposal 17: For AI/ML-based temporal domain beam prediction, regarding the relationship between Set A and Set B:
    - The size of Set B smaller than Set A should be considered as baseline.
      * Both can be considered in evaluations: Set B is a subset of Set A; Set B contains wide beams with full direction which are different from Set A with narrow beams.
    - Set B equal to Set A can be optionally used for performance comparison in evaluations.
  + Observation 8: For temporal beam prediction, AI/ML based methods are more robust than legacy approaches to variations of the UE speed.
    - When the time instance is 0.08s in the observation and prediction window, for UE speed 30km/h, the AI/ML Top-8 approach is 42% better than for the legacy baseline but for a UE speed of 90 km/h, the AI/ML Top-8 prediction accuracy is 47% better than for the legacy baseline
    - When the time interval is 0.16s in the observation and prediction window, for UE speed 30km/h, the AI/ML Top-8 approach is 48% better than for the legacy baseline but for UE speed 90 km/h, the AI/ML Top-8 prediction accuracy is 77% better than for the legacy baseline.
  + Observation 9: For temporal beam prediction, lower spatial consistency has more impact on the prediction accuracy achieved by the legacy approach than on accuracy achieved by the AI/ML-based methods. This can be seen from the results when different time instances are evaluated.
    - For UE at 30km/h, the accuracy of AI/ML Top-8 degrades 3.35% but the baseline degrades 4.8% when stretching the two prediction instances from 0.08s to 0.16s
    - For UE at 90km/h, the accuracy of AI/Ml Top-8 degrades 0.93% but the baseline degrades 9.56% when stretching the two prediction instances from 0.08s to 0.16s
* ZTE [3]:
  + Observation 5: A better beam prediction accuracy is achieved if more measured RSRPs are input to the AI model. However, for a NW-side model, more measured RSRPs used as AI input also means increasing of the UE reporting overhead.
  + Observation 6: Compared with the selected non-AI method, a more significant performance gain is observed if the beam set for measurement is a subset of the beam set for prediction.
* Vivo [5]:
  + Observation 15: For BM-Case2, compared with non-AI scheme, beam pair prediction scheme improves beam prediction accuracy and reduces average L1-RSRP difference significantly.
  + Proposal 24: Further study beam pair prediction scheme with expected information as AI input for improving generalization performance in BM-Case2.
* Interdigital [6]
  + Observation 9: AIML-based beam selection achieves more than 95% selection accuracy when error margin is larger than 0.5 dB by consuming 50% of the measurement overhead of the exhaustive measurement and it also shows better accuracy when the error margin is low.
  + Proposal 14: Further study benefits of AI/ML aided beam prediction.
* OPPO[8]
  + Temporal domain beam prediction can provide beam prediction accuracy (at least 77%) while overhead/latency reduction can be up to 50% (for the case of K = 4 and F = 4).
  + Beam predication accuracy slightly decreases from 87.1% to 77.1% (the case of Top-1) when F increases from 1 to 4, but strongly increases from 77.1% to 98.8% (the case of F = 4) when predicted beam number increases from Top-1 to Top-4.
  + For 80% of the incorrect temporal domain beam prediction cases, the L1-RSRP difference is lower than 3.5dB which may not strongly impact the spectrum efficiency.
  + Spatial and temporal domain beam prediction can provide beam prediction accuracy (at least 74.4%) while overhead/latency reduction can be up to 87.5% (for the case of K = 4, F = 4 and Set B = 32 beam pairs, Set A = 128 beam pairs).
  + Spatial and temporal domain beam prediction can provide beam prediction accuracy (at least 64.5%) while overhead/latency reduction can be up to 87.5% (for the case of K = 8, F = 8 and Set B = 32 beam pairs, Set A = 128 beam pairs).
* Ericsson [11]
  + Observation 10 The observed prediction performance improvement over baseline when number of beams in set B is <=8 is mainly due to the spatial domain prediction ability
  + Observation 11 With set A equal to set B and having 30 km/h straight line moving UEs with no rotation, AI/ML temporal prediction at T2=40ms shows no gain over baseline method due to the slow-varying channel.
* Xiaomi[17]
  + Observation 6: Set B < set A causes much more performance degradation compared to set B=set A for temporal beam prediction.
* Nokia[19]
  + Observation 18: For BM-Case2, the ML model using as input only RSRPs has performance that decreases when Set B is a subset of Set A and if no advanced algorithm is applied for beam selection in Set B.
  + Observation 19: For BM-Case2, the ML model using as input only RSRPs has performance that decreases when increasing the length of the prediction window.
  + Observation 20: For BM-Case2, additional algorithm (i.e. Bayesian Optimization) should be applied for choosing the beam measurements in Set B for the scenario of Set B is a subset of Set A.
  + Proposal 14: For BM-Case2, with Set B is a subset of Set A, measurement instances K and prediction instances F shall be carefully investigated prior supporting the sub-use case.
* Mediatek [20]:
  + *Performance between different models*
  + Observation 4: Transformer performs better than LSTM in terms of Top-k accuracy, and it requires less observation window size than LSTM does to achieve the same level of RSRP difference.
  + Observation 5: The computing complexity of Transformer is larger than LSTM, furthermore, the computing complexity increases with the observation window for both models.
  + Proposal 4: For different choices of prediction and observation window sizes, study the optimal model for to use, considering their computing complexity, UE’s computational and storage capacity.
  + Observation 7: Tx beam prediction’s Top-k performance is better than beam pair prediction’s Top-k performance. However, beam pair prediction doesn’t require UE Rx beam sweeping during the prediction windows.
  + Proposal 7: Study the tradeoff between using Tx beam prediction or beam pair prediction mechanisms considering their prediction Top-k accuracy, and corresponding beam management overhead.
* NVIDIA [23]
  + Observation 3: AI/ML-based algorithms for beam prediction in time domain can simply use a history of the best beam index to perform the prediction.
  + Observation 4: AI/ML-based algorithms for beam prediction in time domain can help lower reference signal overhead and reduce UE’s measurement requirement.
* Samsung [24]
  + Observation # 17: For time and spatial domain prediction, AI can provide better performance in terms of beam prediction accuracy than non-AI based scheme with the measurements of a subset of narrow beams to select a best beam among a full set of narrow beams.
* DoCoMo [25]
  + Observation 2: AI/ML could improve the beam prediction accuracy in time-domain, and the performance gain is higher in the high UE speed scenario.
  + Observation 3: The performance of AI/ML-based beam prediction is good even if Rx-sweeping periodicity (P) is large (>>20ms).
  + Proposal 4: Discuss the different performance gain for different UE speed for BM-Case 2, and consider the target scenario/speed for BM-Case 2 .

Observation 4: Similar tendency to pattern 1 could be observed for pattern 2 while the absolute performance gain of AI/ML is lower.

# Others

Some companies suggest to consider multiple scenarios for evaluations.

* Huawei/HiSi: [2]
  + Proposal 7: The evaluation for beam prediction should focus on a one-sided AI/ML model.
  + FL0: will be discussed in 9.2.3.2
* Interdigital [6]
  + Proposal 7: Support ‘Set B is a subset of Set A’ when Set A and Set B are utilized in a same frequency range for both temporal/spatial domain prediction.
  + Proposal 8: Support ‘Set A and Set B are different’ when Set A and Set B are utilized in different frequency ranges for both temporal/spatial domain prediction.
  + Proposal 9: AI/ML based beam management based on association between different frequency ranges should supported for both between FR1 and FR2-1 and between FR2-1 and FR2-2.
  + Proposal 10: For conventional scheme to obtain performance KPIs, current specification for beam management (i.e., up to 4 CRIs with L1-RSRP/SINR or SRS based prediction) should be considered.
  + Proposal 11: Number of beams in Set B should be decided and reported by each company.
  + FL0: Suggest to propose to in 9.2.3.2
* Intel [14]:
  + Proposal 1: For AI/ML evaluation for beam management use cases, including spatial and temporal domain beam management, consider only offline training of AI/ML models.
  + FL0: will be discussed in 9.2.3.2
* Nokia [19]
  + Observation 16: Selecting the beam based on the QoS based model output can improve the throughput performance of each UE by clustering the UEs to a single beam.
  + Observation 17: Even with errors in the input RSRP values of beams which are not in set B, QoS based beam selection can improve the throughput performance of each UE.
  + Proposal 11: For BM-Case1, RAN1 further investigate QoS-based beam prediction with predicted RSRPs of the beams in set A.
  + FL0: Suggest to propose to in 9.2.3.2
* Mediatek [20]:
  + Observation 8: Transformer always outperforms DNN in both datasets under various sizes of Set B. However, Transformer is more complex than DNN in terms of FLOPs.
  + Observation 15: For spatial beam prediction, the prediction performance of the best beam pair by using Transformer is only around 10% worse than predicting the best Tx beam.
  + Observation 16: For spatial beam prediction, the prediction performance of the best beam pair by using DNN is significantly worse than predicting the best Tx beam.
  + Proposal 13: Further study the use of larger size AI/ML model for best Tx/Rx beam pair prediction in spatial beam prediction.
  + FL 0: based on the conclusion in framework, this study does not intend to compare the performance of different AI models.

|  |
| --- |
| **Conclusion**  As indicated in SID, although specific AI/ML algorithms and models may be studied for evaluation purposes, AI/ML algorithms and models are implementation specific and are not expected to be specified. |

# Proposals for GTW on 10/10

**Proposal 3-1-1a: (Same agreements as in 9.2.2.1)**

**The following cases are considered for verifying the generalization performance of an AI/ML model over various scenarios/configurations as a starting point:**

* **Case 1: The AI/ML model is trained based on training dataset from one Scenario#A/Configuration#A, and then the AI/ML model performs inference/test on a dataset from the same Scenario#A/Configuration#A**
* **Case 2: The AI/ML model is trained based on training dataset from one Scenario#A/Configuration#A, and then the AI/ML model performs inference/test on a different dataset than Scenario#A/Configuration#A, e.g., Scenario#B/Configuration#B, Scenario#A/Configuration#B**
* **Case 3: The AI/ML model is trained based on training dataset constructed by mixing datasets from multiple scenarios/configurations including Scenario#A/Configuration#A and a different dataset than Scenario#A/Configuration#A, e.g., Scenario#B/Configuration#B, Scenario#A/Configuration#B, and then the AI/ML model performs inference/test on a dataset from a single Scenario/Configuration from the multiple scenarios/configurations, e.g., Scenario#A/Configuration#A, Scenario#B/Configuration#B, Scenario#A/Configuration#B.**
  + - * **Note: Companies to report the ratio for dataset mixing**
      * **Note: number of the multiple scenarios/configurations can be larger than two**
* **FFS the detailed set of scenarios/configurations**
* **FFS other cases for generalization verification, e.g.,**
  + - * **Case 2A: The AI/ML model is trained based on training dataset from one Scenario#A/Configuration#A, and then the AI/ML model is updated based on a fine-tuning dataset different than Scenario#A/Configuration#A, e.g., Scenario#B/Configuration#B, Scenario#A/Configuration#B. After that, the AI/ML model is tested on a different dataset than Scenario#A/Configuration#A, e.g., subject to Scenario#B/Configuration#B, Scenario#A/Configuration#B.**

**Proposal 2-1-1a:**

* **The definition of beam prediction accuracy (%) for Top-1 and/or Top-K beams:**
  + **Option 1 (optional): The beam prediction accuracy (%) is the percentage of “the Top-1 predicted beam is one of the Top-K genie-aided beams”**
  + **Option 2 (baseline): The beam prediction accuracy (%) is the percentage of “the Top-1 genie-aided beam is one of the Top-K predicted beams”**

**Proposal 1-1-2a:**

* **For system performance related KPI (if supported) [e.g, throughput] evaluation (model inference), companies report the traffic model:**
  + **Option 1: Full buffer**
  + **Option 2: FTP model with detail assumptions (e.g., FTP model 1, FTP model 3)**

**Proposal 1-1-1a:**

* **BS antenna configuration:** 
  + **antenna setup and port layouts at gNB: [4, 8, 2, 1, 1, 1, 1], (dV, dH) = (0.5, 0.5) λ**
  + **Other assumptions are not precluded**
* **BS Tx power:** 
  + **40dB or 34 dBm reported by companies**
  + **Other values are not precluded**
* **UE antenna configuration (Clarification of agreement in RAN 1 #110):** 
  + **antenna setup and port layouts at UE: [1, 4, 2, 1, 2, 1, 1], 2 panels (left, right)**
  + **Other assumptions are not precluded**

**Proposal 4-2-1a:**

* **Adopt the following proposals as working assumption:**
* **For the evaluation of both BM-Case1 and BM-Case 2, 32 or 64 [or 256] Tx beams are used at NW side.** 
  + **Other values are not precluded and can be reported by companies.**
* **For the evaluation of both BM-Case1 and BM-Case 2, 4 Rx beams per UE panel are used at UE side.** 
  + **Other values are not precluded and can be reported by companies.**

**Proposal 2-2-3a: (updated from Agreement in RAN 1 #110)**

* **To evaluate the performance of AI/ML in beam management at least for NW side beam prediction, UCI report overhead can be further studied as one of KPI options.** 
  + **~~FFS:~~ number of UCI reports and/or UCI payload size for each prediction**

# Reference

[1] R1-2208368, Continued discussion on evaluation of AI/ML for beam management, FUTUREWEI

[2] R1-2208431, Evaluation on AI/ML for beam management, Huawei, HiSilicon

[3] R1-2208523, Evaluation on AI for beam management, ZTE

[4] R1-2208549, Evaluation on AI for beam management, Spreadtrum Communications

[5] R1-2208636, Evaluation on AI/ML for beam management, vivo

[6] R1-2210240, Discussion for evaluation on AI/ML for beam management, InterDigital, Inc.

[7] R1-2208771, Evaluation on AI/ML for beam management, China Telecom

[8] R1-2208852, Evaluation methodology and preliminary results on AI/ML for beam management, OPPO

[9] R1-2208880, On Evaluation of AI/ML based Beam Management, Google

[10] R1-2208901, Evaluation on AI/ML for beam management, LG Electronics

[11] R1-2208906, Evaluation on AI/ML for beam management, Ericsson

[12] R1-2208969 Evaluation on AI/ML for beam management, CATT

[13] R1-2209013 Evaluation on AI/ML for beam management, Fujitsu

[14] R1-2209049 Evaluations for AI/ML beam management, Intel Corporation

[15] R1-2209122 Evaluation on AI/ML for beam management, Lenovo

[16] R1-2209232 Some discussions on evaluation on AI-ML for Beam management , CAICT

[17] R1-2209279 Evaluation on AI/ML for beam management, xiaomi

[18] R1-2209330 Discussion on evaluation on AI/ML for beam management, CMCC

[19] R1-2209369 Evaluation of ML for beam management, Nokia, Nokia Shanghai Bell

[20] R1-2209508 Evaluation on AI/ML for beam management, MediaTek Inc.

[21] R1-2209578 Evaluation on AI/ML for beam management, Apple

[22] R1-2209613 Evaluation of AI/ML based beam management, Rakuten Symphony

[23] R1-2209627 Evaluation of AI and ML for beam management, NVIDIA

[24] R1-2209724 Evaluation on AI ML for Beam management, Samsung

[25] R1-2209898 Discussion on evaluation on AI/ML for beam management, NTT DOCOMO, INC.

[26] R1-2209978 Evaluation on AI/ML for beam management, Qualcomm Incorporated

[27] R1-2210107 Evaluation on AI/ML for beam management, CEWiT

# Appendix: Agreements

# Agreements in RAN 1 #109e

[**R1-2205269**](file:///C:\Users\feifei.sun\AppData\Local\Temp\Docs\R1-2205269.zip) **Feature lead summary #1 evaluation of AI/ML for beam management Moderator (Samsung)**

From May 17th GTW session

Agreement

* For dataset construction and performance evaluation (if applicable) for the AI/ML in beam management, system level simulation approach is adopted as baseline
  + Link level simulation is optionally adopted

Agreement

* At least for temporal beam prediction, companies report the one of spatial consistency procedures:
  + Procedure A in TR38.901
  + Procedure B in TR38.901

Agreement

* At least for temporal beam prediction, Dense Urban (macro-layer only, TR 38.913) is the **basic** scenario for dataset generation and performance evaluation.
  + Other scenarios are not precluded.
* For spatial-domain beam prediction, Dense Urban (macro-layer only, TR 38.913) is the **basic** scenario for dataset generation and performance evaluation.
  + Other scenarios are not precluded.

Agreement

* At least for spatial-domain beam prediction in initial phase of the evaluation, UE trajectory model is not necessarily to be defined.

Agreement

* At least for temporal beam prediction in initial phase of the evaluation, UE trajectory model is defined. FFS on the details.

[R1-2205270](file:///C:\Users\feifei.sun\AppData\Roaming\Microsoft\Docs\R1-2205270.zip) Feature lead summary #2 evaluation of AI/ML for beam management Moderator (Samsung)

[R1-2205271](file:///C:\Users\feifei.sun\AppData\Roaming\Microsoft\Docs\R1-2205271.zip) Feature lead summary #3 evaluation of AI/ML for beam management Moderator (Samsung)

**Decision:** As per email decision posted on May 20th,

Agreement

* UE rotation speed is reported by companies.
  + Note: UE rotation speed = 0, i.e., no UE rotation, is not precluded.

Agreement

* For AI/ML in beam management evaluation, RAN1 does not attempt to define any common AI/ML model as a baseline.

Conclusion

Further study AI/ML model generalization in beam management evaluating the inference performance of beam prediction under multiple different scenarios/configurations.

* FFS on different scenarios/configurations
* Companies report the training approach, at least including the dataset assumption for training

Agreement

* For evaluation of AI/ML in BM, the KPI may include the model complexity and computational complexity.
  + FFS: the details of model complexity and computational complexity

Agreement

* For spatial-domain beam prediction, further study the following options as baseline performance
  + Option 1: Select the best beam within Set A of beams based on the measurement of all RS resources or all possible beams of beam Set A (exhaustive beam sweeping)
    - FFS CSI-RS/SSB as the RS resources
  + Option 2: Select the best beam within Set A of beams based on the measurement of RS resources from Set B of beams
    - FFS: Set B is a subset of Set A and/or Set A consists of narrow beams and Set B consists of wide beams
    - FFS: how conventional scheme to obtain performance KPIs
    - FFS: how to determine the subset of RS resources is reported by companies
  + Other options are not precluded.

**Decision:** As per email decision posted on May 22nd,

Agreement

* For dataset generation and performance evaluation for AI/ML in beam management, take the parameters (if applicable) in Table 1.2-1b for Dense Urban scenario for SLS

**Table 1.2-1b Assumptions for Dense Urban scenario for AI/ML in beam management**

|  |  |
| --- | --- |
| **Parameters** | **Values** |
| **Frequency Range** | FR2 @ 30 GHz   * SCS: 120 kHz |
| **Deployment** | 200m ISD,   * 2-tier model with wrap-around (7 sites, 3 sectors/cells per site)   Other deployment assumption is not precluded |
| **Channel mode** | UMa with distance-dependent LoS probability function defined in Table 7.4.2-1 in TR 38.901. |
| **System BW** | 80MHz |
| **UE Speed** | * For spatial domain beam prediction, 3km/h * For time domain beam prediction: 30km/h (baseline), 60km/h (optional) * Other values are not precluded |
| **UE distribution** | * FFS UEs per sector/cell for evaluation. More UEs per sector/cell for data generation is not precluded. * For spatial domain beam prediction: FFS:   + Option 1: 80% indoor ,20% outdoor as in TR 38.901   + Option 2: 100% outdoor * For time domain prediction: 100% outdoor |
| **Transmission Power** | Maximum Power and Maximum EIRP for base station and UE as given by corresponding scenario in 38.802 (Table A.2.1-1 and Table A.2.1-2) |
| **BS Antenna Configuration** | * [One panel: (M, N, P, Mg, Ng) = (4, 8, 2, 1, 1), (dV, dH) = (0.5, 0.5) λ as baseline] * [Four panels: (M, N, P, Mg, Ng) = (4, 8, 2, 2, 2), (dV, dH) = (0.5, 0.5) λ. (dg,V, dg,H) = (2.0, 4.0) λ as optional] * Other assumptions are not precluded.   Companies to explain TXRU weights mapping.  Companies to explain beam selection.  Companies to explain number of BS beams |
| **BS Antenna radiation pattern** | TR 38.802 Table A.2.1-6, Table A.2.1-7 |
| **UE Antenna Configuration** | [Panel structure: (M,N,P) = (1,4,2)]   * 2 panels (left, right) with (Mg, Ng) = (1, 2) as baseline * Other assumptions are not precluded   Companies to explain TXRU weights mapping.  Companies to explain beam and panel selection.  Companies to explain number of UE beams |
| **UE Antenna radiation pattern** | TR 38.802 Table A.2.1-8, Table A.2.1-10 |
| **Beam correspondence** | Companies to explain beam correspondence assumptions (in accordance to the two types agreed in RAN4) |
| **Link adaptation** | Based on CSI-RS |
| **Traffic Model** | FFS:   * Option 1: Full buffer * Option 2: FTP model   Other options are not precluded |
| **Inter-panel calibration for UE** | Ideal, non-ideal following 38.802 (optional) – Explain any errors |
| **Control and RS overhead** | Companies report details of the assumptions |
| **Control channel decoding** | Ideal or Non-ideal (Companies explain how it is modelled) |
| **UE receiver type** | MMSE-IRC as the baseline, other advanced receiver is not precluded |
| **BF scheme** | Companies explain what scheme is used |
| **Transmission scheme** | Multi-antenna port transmission schemes  Note: Companies explain details of the using transmission scheme. |
| **Other simulation assumptions** | Companies to explain serving TRP selection  Companies to explain scheduling algorithm |
| **Other potential impairments** | Not modelled (assumed ideal).  If impairments are included, companies will report the details of the assumed impairments |
| **BS Tx Power** | [40 dBm] |
| **Maximum UE Tx Power** | 23 dBm |
| **BS receiver Noise Figure** | 7 dB |
| **UE receiver Noise Figure** | 10 dB |
| **Inter site distance** | 200m |
| **BS Antenna height** | 25m |
| **UE Antenna height** | 1.5 m |
| **Car penetration Loss** | 38.901, sec 7.4.3.2: μ = 9 dB, σp = 5 dB |

Agreement

* For temporal beam prediction, the following options can be considered as a starting point for UE trajectory model for further study. Companies report further changes or modifications based on the following options for UE trajectory model. Other options are not precluded.
  + Option #2: Linear trajectory model with random direction change.
    - UE moving trajectory: UE will move straightly along the selected direction to the end of a~~n~~ time interval, where the length of the time interval is provided by using an exponential distribution with average interval length, e.g., 5s, with granularity of 100 ms.
      * UE moving direction change: At the end of the time interval, UE will change the moving direction with the angle difference A\_diff from the beginning of the time interval, provided by using a uniform distribution within [-45°, 45°].
      * UE move straightly within the time interval with the fixed speed.
    - FFS on UE orientation
  + Option #3: Linear trajectory model with random and smooth direction change.
    - UE moving trajectory: UE will change the moving direction by multiple steps within a~~n~~ time internal, where the length of the time interval is provided by using an exponential distribution with average interval length, e.g., 5s, with granularity of 100 ms.
      * UE moving direction change: At the end of the time interval, UE will change the moving direction with the angle difference A\_diff from the beginning of the time interval, provided by using a uniform distribution within [-45°, 45°].
      * The time interval is further broken into N sub-intervals, e.g. 100ms per sub-interval, and at the end of each sub-interval, UE change the direction by the angle of A\_diff/N.
      * UE move straightly within the time sub-interval with the fixed speed.
    - FFS on UE orientation
  + Option #4: Random direction straight-line trajectories.
    - Initial UE location, moving direction and speed: UE is randomly dropped in a cell, and an initial moving direction is randomly selected, with a fixed speed.
      * The initial UE location should be randomly drop within the following blue area



where d1 is the minimum distance that UE should be away from the BS.

* + - * + Each sector is a cell and that the cell association is geometry based.
        + During the simulation, inter-cell handover or switching should be disabled.

For training data generation

* + - For each UE moving trajectory: the total length of the UE trajectory can be set as T second if it is in time, of set as D meter if it is in distance.
      * The value of T (or D) can be further discussed
      * The trajectory sampling interval granularity depends on UE speed and it can be further discussed.
    - UE can move straightly along the entire trajectory, or
    - UE can move straightly during the time interval, where the time interval is provided by using an exponential distribution with average interval length
      * UE may change the moving direction at the end of the time interval. UE will change the moving direction with the angle difference A\_diff from the beginning of the time interval, provided by using a uniform distribution within [-45°, 45°]
    - If the UE trajectory hit the cell boundary (the red line), the trajectory should be terminated.
      * If the trajectory length (in time) is less than the length of observation window + prediction window, the trajectory should be discarded.
      * At the current stage, the length of observation window + prediction window is not fixed and the companies can report their values.
    - FFS on UE orientation
* Generalization issue is FFS

Agreement

* For temporal beam prediction, further study the following options as baseline performance
  + Option 1a: Select the best beam for T2 within Set A of beams based on the measurements of all the RS resources or all possible beams from Set A of beams at the time instants within T2
  + Option 2: Select the best beam for T2 within Set A of beams based on the measurements of all the RS resources from Set B of beams at the time instants within T1
    - Companies explain the detail on how to select the best beam for T2 from Set A based on the measurements in T1
  + Where T2 is the time duration for the best beam selection, and T1 is a time duration to obtain the measurements of all the RS resource from Set B of beams.
    - T1 and T2 are aligned with those for AI/ML based methods
  + Whether Set A and Set B are the same or different depend on the sub-use case
  + Other options are not precluded.

Agreement

* For dataset generation and performance evaluation for AI/ML in beam management, take the following assumption for LLS as optional methodology

|  |  |
| --- | --- |
| Parameter | Value |
| Frequency | 30GHz. |
| Subcarrier spacing | 120kHz |
| Data allocation | [8 RBs] as baseline, companies can report larger number of RBs  First 2 OFDM symbols for PDCCH, and following 12 OFDM symbols for data channel |
| PDCCH decoding | Ideal or Non-ideal (Companies explain how is oppler) |
| Channel model | FFS:  LOS channel: CDL-D extension, DS = 100ns  NLOS channel: CDL-A/B/C extension, DS = 100ns  Companies explains details of extension methodology considering spatial consistency  Other channel models are not precluded. |
| BS antenna configurations | * One panel: (M, N, P, Mg, Ng) = (4, 8, 2, 1, 1), (dV, dH) = (0.5, 0.5) λ as baseline * Other assumptions are not precluded.     Companies to explain TXRU weights mapping.  Companies to explain beam selection.  Companies to explain number of BS beams |
| BS antenna element radiation pattern | Same as SLS |
| BS antenna height and antenna array downtile angle | 25m, 110° |
| UE antenna configurations | Panel structure: (M, N, P) = (1, 4, 2),   * 2 panels (left, right) with (Mg, Ng) = (1, 2) as baseline * 1 panel as optional * Other assumptions are not precluded     Companies to explain TXRU weights mapping.  Companies to explain beam and panel selection.  Companies to explain number of UE beams |
| UE antenna element radiation pattern | Same as SLS |
| UE moving speed | Same as SLS |
| Raw data collection format | Depends on sub-use case and companies’ choice. |

**Decision:** As per email decision posted on May 25th,

Agreement

* For UE trajectory model, UE orientation can be independent from UE moving trajectory model. FFS on the details.
  + Other UE orientation model is not precluded.

Agreement

* Companies are encouraged to report the following aspects of AI/ML model in RAN 1 #110. FFS on whether some of aspects need be defined or reported.
  + Description of AI/ML model, e.g, NN architecture type
  + Model inputs/outputs (per sub-use case)
  + Training methodology, e.g.
    - Loss function/optimization function
    - Training/ validity /testing dataset:
      * Dataset size, number of training/ validity /test samples
      * Model validity area: e.g., whether model is trained for single sector or multiple sectors
      * Details on Model monitoring and model update, if applicable
  + Others related aspects are not precluded

Agreement

* To evaluate the performance of AI/ML in beam management, further study the following KPI options:
  + Beam prediction accuracy related KPIs, may include the following options:
    - Average L1-RSRP difference of Top-1 predicted beam
    - Beam prediction accuracy (%) for Top-1 and/or Top-K beams, FFS the definition:
      * Option 1: The beam prediction accuracy (%) is the percentage of “the Top-1 predicted beam is one of the Top-K genie-aided beams”
      * Option 2: The beam prediction accuracy (%) is the percentage of “the Top-1 genie-aided beam is one of the Top-K predicted beams”
    - CDF of L1-RSRP difference for Top-1 predicted beam
    - Beam prediction accuracy (%) with 1dB margin for Top-1 beam
      * The beam prediction accuracy (%) with 1dB margin is the percentage of the Top-1 predicted beam “whose ideal L1-RSRP is within 1dB of the ideal L1-RSRP of the Top-1 genie-aided beam”
    - the definition of L1-RSRP difference of Top-1 predicted beam:
      * the difference between the ideal L1-RSRP of Top-1 predicted beam and the ideal L1-RSRP of the Top-1 genie-aided beam
    - Other beam prediction accuracy related KPIs are not precluded and can be reported by companies.
  + System performance related KPIs, may include the following options:
    - UE throughput: CDF of UE throughput, avg. and 5%ile UE throughput
    - RS overhead reduction at least for spatial-domain beam prediction at least for top-1 beam:
      * 1-N/M,
        + where N is the number of beams (with reference signal (SSB and/or CSI-RS)) required for measurement
        + where (FFS) M is the total number of beams
        + Note: Non-AI/ML approach based on the measurement of these M beams may be used as a baseline
      * FFS on whether to define a proper value for M for evaluation.
    - Other System performance related KPIs are not precluded and can be reported by companies.
  + Other KPIs are not precluded and can be reported by companies, for example:
    - Reporting overhead reduction: (FFS) The number of UCI report and UCI payload size, for temporal /spatial prediction
    - Latency reduction:
      * (FFS) (1 – [Total transmission time of N beams] / [Total transmission time of M beams])
        + where N is the number of beams (with reference signal (SSB and/or CSI-RS)) in the input beam set required for measurement
        + where M is the total number of beams
    - Power consumption reduction: FFS on details

Final summary in R1-2205641.

# Agreement in RAN 1 #110

**Agreement**

**The Following updated based on the agreements in RAN 1 #109-e is adopted**

|  |  |
| --- | --- |
| **Parameters** | **Values** |
| **UE distribution** | * ~~FFS~~ 10 UEs per sector/cell for system performance related KPI (if supported) [e.g,, throughput] for full buffer traffic (if supported) evaluation (model inference). * X UEs per sector/cell for system performance related KPI for FTP traffic (if supported) evaluation (model inference). * Other values are not precluded * Number of UEs per/sector per cell during data collection (training/testing) is reported by companies if relevant * ~~More UEs per sector/cell for data generation is not precluded.~~ |
| **UE Antenna Configuration** | * Antenna setup and port layouts at UE: [1,2,1,4,2,1,1], 2 panels (left, right) * ~~[Panel structure: (M,N,P) = (1,4,2)]~~   + ~~panels (left, right) with (Mg, Ng) = (1, 2) as baseline~~ * Other assumptions are not precluded     Companies to explain TXRU weights mapping.  Companies to explain beam and panel selection.  Companies to explain number of UE beams |

**Agreement**

**The Following updated based on the agreements in RAN 1 #109-e is adopted**

|  |  |
| --- | --- |
| **Parameters** | **Values** |
| **UE Speed** | * For spatial domain beam prediction, 3km/h * For time domain beam prediction: 3km/h(optional), 30km/h (baseline), 60km/h (optional), 90km/h (optional), 120km/h (optional) * Other values are not precluded |
| **UE distribution** | * For spatial domain beam prediction:   + Option 1: 80% indoor ,20% outdoor as in TR 38.901   + Option 2: 100% outdoor * For time domain prediction: 100% outdoor |

**Agreement**

* **If UE orientation is modeled, it can be independently modeled from UE moving trajectory model.** 
  + **This is not precluded that UE orientation coupled with UE moving trajectory model.**

**Agreement**

* **Study the following options on the selection of Set B of beams (pairs)** 
  + **Option 1: Set B is fixed across training and inference**
    - **FFS on the beams of Set B**
  + **Option 2: Set B is variable (e.g., different beams (pairs) patterns in each report/measurement during training and/or inference)** 
    - **FFS on fixed or variable number of beams (pairs)**
    - **FFS on the details**
  + **Other options are not precluded.**
  + **FFS on the number of beams (pairs) in Set B**
  + **Note: This does not preclude the alternative that Set B is different from Set A.**

**Agreement**

* **To evaluate the performance of AI/ML in beam management at least for NW side beam prediction, UCI report overhead can be further studied as one of KPI options.** 
  + **FFS: number of UCI reports and UCI payload size**