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| 3GPP TR 38.843 V0.1.0 (2023-05) |
| Technical Report |
| 3rd Generation Partnership Project;Technical Specification Group Radio Access Networks;Study on Artificial Intelligence (AI)/Machine Learning (ML) for NR air interface(Release 18) |
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Contents

Foreword 4

Introduction 5

1 Scope 6

2 References 6

3 Definitions of terms, symbols and abbreviations 6

3.1 Terms 6

3.2 Symbols 6

3.3 Abbreviations 7

4 General AI/ML Framework 7

4.1 Description of the stages of Machine Learning 10

4.2 Collaboration levels 10

4.3 ML model Life Cycle Management 11

5 Use cases 12

5.1 CSI feedback enhancement 13

5.2 Beam Management 14

5.3 Positioning accuracy enhancements 16

6 Evaluations 17

6.1 Common evaluation methodology and KPIs 17

6.2 CSI feedback enhancement 18

6.2.1 Evaluation assumptions, methodology and KPIs 18

6.2.2 Performance results 26

6.3 Beam Management 37

6.3.1 Evaluation assumptions, methodology and KPIs 37

6.3.2 Performance results 43

6.4 Positioning accuracy enhancements 45

6.4.1 Evaluation assumptions, methodology and KPIs 45

6.4.2 Performance results 51

7 Potential Specification Impact Assessment 53

7.1 General observations 53

7.2 Physical layer aspects 53

7.2.1 Common framework 53

7.2.2 CSI feedback enhancement 53

7.2.3 Beam management 55

7.2.4 Positioning accuracy enhancements 56

7.3 Protocol aspects 58

7.3.1 Common framework 59

7.3.2 CSI feedback enhancement 59

7.3.3 Beam management 59

7.3.4 Positioning accuracy enhancements 59

7.4 Interoperability and testability aspects 59

7.4.1 Common framework 59

7.4.2 CSI feedback enhancement 59

7.4.3 Beam management 59

7.4.4 Positioning accuracy enhancements 59

8 Conclusions 59

Annex <X> : Change history 60

For definitive guidance on drafting 3GPP TSs and TRs, see [3GPP TS 21.801](http://www.3gpp.org/DynaReport/21801.htm) supplemented by the 3GPP web page <http://www.3gpp.org/specifications-groups/delegates-corner/writing-a-new-spec>.

Ensure all blue guidance text is removed before submitting the TS/TR to the TSG for approval.

# Foreword

This clause is mandatory; do not alter the text in any way other than to choose between "Specification" and "Report".

This Technical Specification|Report has been produced by the 3rd Generation Partnership Project (3GPP).

The contents of the present document are subject to continuing work within the TSG and may change following formal TSG approval. Should the TSG modify the contents of the present document, it will be re-released by the TSG with an identifying change of release date and an increase in version number as follows:

Version x.y.z

where:

x the first digit:

1 presented to TSG for information;

2 presented to TSG for approval;

3 or greater indicates TSG approved document under change control.

y the second digit is incremented for all changes of substance, i.e. technical enhancements, corrections, updates, etc.

z the third digit is incremented when editorial only changes have been incorporated in the document.

In drafting the TS/TR, pay particular attention to the use of modal auxiliary verbs! TRs shall not contain any normative provisions.

In the present document, modal verbs have the following meanings:

**shall** indicates a mandatory requirement to do something

**shall not** indicates an interdiction (prohibition) to do something

The constructions "shall" and "shall not" are confined to the context of normative provisions, and do not appear in Technical Reports.

The constructions "must" and "must not" are not used as substitutes for "shall" and "shall not". Their use is avoided insofar as possible, and they are not used in a normative context except in a direct citation from an external, referenced, non-3GPP document, or so as to maintain continuity of style when extending or modifying the provisions of such a referenced document.

**should** indicates a recommendation to do something

**should not** indicates a recommendation not to do something

**may** indicates permission to do something

**need not** indicates permission not to do something

The construction "may not" is ambiguous and is not used in normative elements. The unambiguous constructions "might not" or "shall not" are used instead, depending upon the meaning intended.

**can** indicates that something is possible

**cannot** indicates that something is impossible

The constructions "can" and "cannot" are not substitutes for "may" and "need not".

**will** indicates that something is certain or expected to happen as a result of action taken by an agency the behaviour of which is outside the scope of the present document

**will not** indicates that something is certain or expected not to happen as a result of action taken by an agency the behaviour of which is outside the scope of the present document

**might** indicates a likelihood that something will happen as a result of action taken by some agency the behaviour of which is outside the scope of the present document

**might not** indicates a likelihood that something will not happen as a result of action taken by some agency the behaviour of which is outside the scope of the present document

In addition:

**is** (or any other verb in the indicative mood) indicates a statement of fact

**is not** (or any other negative verb in the indicative mood) indicates a statement of fact

The constructions "is" and "is not" do not indicate requirements.

# Introduction

This clause is optional. If it exists, it shall be the second unnumbered clause.

# 1 Scope

This clause shall start on a new page.

The present document …

# 2 References

The following documents contain provisions which, through reference in this text, constitute provisions of the present document.

- References are either specific (identified by date of publication, edition number, version number, etc.) or non‑specific.

- For a specific reference, subsequent revisions do not apply.

- For a non-specific reference, the latest version applies. In the case of a reference to a 3GPP document (including a GSM document), a non-specific reference implicitly refers to the latest version of that document *in the same Release as the present document*.

[1] 3GPP TR 21.905: "Vocabulary for 3GPP Specifications".

[2] RP-213599: “New SI: Study on Artificial Intelligence (AI)/Machine Learning (ML) for NR Air Interface”, Qualcomm (Moderator).

[3] 3GPP TR 38.901: "Study on channel model for frequencies from 0.5 to 100 GHz".

[4] 3GPP TR 38.857: "Study on NR positioning enhancements".

[5] 3GPP TR 38.802: "Study on new radio access technology Physical layer aspects".

…

[x] <doctype> <#>[ ([up to and including]{yyyy[-mm]|V<a[.b[.c]]>}[onwards])]: "<Title>".

It is preferred that the reference to 21.905 be the first in the list.

# 3 Definitions of terms, symbols and abbreviations

This clause and its three subclauses are mandatory. The contents shall be shown as "void" if the TS/TR does not define any terms, symbols, or abbreviations.

## 3.1 Terms

For the purposes of the present document, the terms given in 3GPP TR 21.905 [1] and the following apply. A term defined in the present document takes precedence over the definition of the same term, if any, in 3GPP TR 21.905 [1].

Definition format (Normal)

**<defined term>:** <definition>.

**example:** text used to clarify abstract rules by applying them literally.

Table 3.1-1 presents a list of terminology relevant for this study and possibly future 3GPP work in the area.

Table 3.1-1: List of Terminologies

|  |  |
| --- | --- |
| Terminology | Description |
| AI/ML Model | A data driven algorithm that applies AI/ML techniques to generate a set of outputs based on a set of inputs.  |
| AI/ML model delivery | A generic term referring to delivery of an AI/ML model from one entity to another entity in any manner.Note: An entity could mean a network node/function (e.g., gNB, LMF, etc.), UE, proprietary server, etc. |
| AI/ML model Inference | A process of using a trained AI/ML model to produce a set of outputs based on a set of inputs |
| AI/ML model testing | A subprocess of training, to evaluate the performance of a final AI/ML model using a dataset different from one used for model training and validation. Differently from AI/ML model validation, testing does not assume subsequent tuning of the model. |
| AI/ML model training | A process to train an AI/ML Model [by learning the input/output relationship] in a data driven manner and obtain the trained AI/ML Model for inference |
| AI/ML model transfer | Delivery of an AI/ML model over the air interface in a manner that is not transparent to 3GPP signalling, either parameters of a model structure known at the receiving end or a new model with parameters. Delivery may contain a full model or a partial model. |
| AI/ML model validation | A subprocess of training, to evaluate the quality of an AI/ML model using a dataset different from one used for model training, that helps selecting model parameters that generalize beyond the dataset used for model training. |
| Data collection | A process of collecting data by the network nodes, management entity, or UE for the purpose of AI/ML model training, data analytics and inference |
| Federated learning / federated training | A machine learning technique that trains an AI/ML model across multiple decentralized edge nodes (e.g., UEs, gNBs) each performing local model training using local data samples. The technique requires multiple interactions of the model, but no exchange of local data samples. |
| Functionality identification | A process/method of identifying an AI/ML functionality for the common understanding between the NW and the UE.Note: Information regarding the AI/ML functionality may be shared during functionality identification. Where AI/ML functionality resides depends on the specific use cases and sub use cases.  |
| Model activation | enable an AI/ML model for a specific function |
| Model deactivation | disable an AI/ML model for a specific function |
| Model download | Model transfer from the network to UE |
| Model identification | A process/method of identifying an AI/ML model for the common understanding between the NW and the UE.Note: The process/method of model identification may or may not be applicable.Note: Information regarding the AI/ML model may be shared during model identification. |
| Model monitoring | A procedure that monitors the inference performance of the AI/ML model |
| Model parameter update | Process of updating the model parameters of a model |
| Model selection | The process of selecting an AI/ML model for activation among multiple models for the same AI/ML enabled feature.Note: Model selection may or may not be carried out simultaneously with model activation.  |
| Model switching | Deactivating a currently active AI/ML model and activating a different AI/ML model for a specific function |
| Model update | Process of updating the model parameters and/or model structure of a model |
| Model upload | Model transfer from UE to the network |
| Network-side (AI/ML) model | An AI/ML Model whose inference is performed entirely at the network |
| Offline field data | The data collected from field and used for offline training of the AI/ML model |
| Offline training | An AI/ML training process where the model is trained based on collected dataset, and where the trained model is later used or delivered for inference.Note: This definition only serves as a guidance. There may be cases that may not exactly conform to this definition but could still be categorized as offline training by commonly accepted conventions. |
| One-sided (AI/ML) model | A UE-side (AI/ML) model or a Network-side (AI/ML) model |
| Online field data | The data collected from field and used for online training of the AI/ML model |
| Online training  | An AI/ML training process where the model being used for inference) is (typically continuously) trained in (near) real-time with the arrival of new training samples. Note: the notion of (near) real-time vs. non real-time is context-dependent and is relative to the inference time-scale.Note: This definition only serves as a guidance. There may be cases that may not exactly conform to this definition but could still be categorized as online training by commonly accepted conventions.Note: Fine-tuning/re-training may be done via online or offline training. (This note could be removed when we define the term fine-tuning.) |
| Reinforcement Learning (RL) | A process of training an AI/ML model from input (a.k.a. state) and a feedback signal (a.k.a. reward) resulting from the model’s output (a.k.a. action) in an environment the model is interacting with. |
| Semi-supervised learning  | A process of training a model with a mix of labelled data and unlabelled data |
| Supervised learning | A process of training a model from input and its corresponding *labels*.  |
| Two-sided (AI/ML) model | A paired AI/ML Model(s) over which joint inference is performed, where joint inference comprises AI/ML Inference whose inference is performed jointly across the UE and the network, i.e, the first part of inference is firstly performed by UE and then the remaining part is performed by gNB, or vice versa. |
| UE-side (AI/ML) model | An AI/ML Model whose inference is performed entirely at the UE |
| Unsupervised learning | A process of training a model without labelled data. |

The present study considers “proprietary-format models” and “open-format model” as two separate AI/ML model format categories defined as follows:

**Proprietary-format models**: ML models of vendor-/device-specific proprietary format, from 3GPP perspective. They are not mutually recognizable across vendors and hide model design information from other vendors when shared. Note: An example is a device-specific binary executable format.

**Open-format models**: ML models of specified format that are mutually recognizable across vendors and allow interoperability, from 3GPP perspective. They are mutually recognizable between vendors and do not hide model design information from other vendors when shared.

## 3.2 Symbols

For the purposes of the present document, the following symbols apply:

Symbol format (EW)

<symbol> <Explanation>

## 3.3 Abbreviations

For the purposes of the present document, the abbreviations given in 3GPP TR 21.905 [1] and the following apply. An abbreviation defined in the present document takes precedence over the definition of the same abbreviation, if any, in 3GPP TR 21.905 [1].

AI Artificial Intelligence

BM Beam Management

CIR Channel Impulse Response

CNN Convolutional Neural Network

CSI Channel State Information

DL Downlink

EVM Evaluation Methodology

FLOPS Floating Point per Second

GCS Generalized Cosine Similarity

KPI Key Performance Indicator

LCM Life Cycle Management

LLS Link Level Simulations

ML Machine Learning

NMSE Normalized Mean Square Error

PDP Power Delay Profile

RNN Recurrent Neural Network

SGCS Squared Generalized Cosine Similarity

SLS System Level Simulations

UPT User Perceived Throughput

# 4 General AI/ML Framework

The purpose of this section is to identify common notation and terminology for AI/ML related functions, procedures and interfaces.

Note: the work done for FS\_NR\_ENDC\_data\_collect is considered when appropriate.

## 4.1 Description of AI/ML stages

[In this section, the defining stages of AI/ML related algorithms and associated complexity are characterized, namely:

* Model generation, e.g., model training (including input/output, pre-/post-process, online/offline as applicable), model validation, model testing, as applicable
* Inference operation, e.g., input/output, pre-/post-process, as applicable

In addition, the treatment of dataset(s) for training, validation, testing, and inference is documented.]

*Editor’s notes: This section should cover the introduction model training, model inference, model monitoring. FL to have a* ***figure*** *for description. Each box has a one-liner description with details elaborated in section 4.4.*

## 4.2 AI/ML model Life Cycle Management

In this section, the lifecycle management of AI/ML model is characterized, e.g., model training, model deployment, model inference, model monitoring, model updating.

The following aspects, including the definition of components (if needed) and necessity, are studied in Life Cycle Management:

* Data collection
	+ Note: This also includes associated assistance information, if applicable.
* Model training
* [Model registration]
* Model deployment
	+ Note: Terminology is to be defined.
* [Model configuration]
* Model inference operation
* Model selection, activation, deactivation, switching, and fallback operation.
	+ Including: Decision by the network (either network initiated or UE-initiated and requested to the network), decision by the UE (event-triggered as configured by the network, UE’s decision reported to the network, or UE-autonomous either with UE’s decision reported to the network or without it)
* Model monitoring
* Model update
	+ Note: Terminology is to be defined. This includes model finetuning, retraining, and re-development via online/offline training.
* Model transfer
* UE capability

Notes: Some aspects in the list may not have specification impact. Aspects with square brackets are tentative and pending terminology definition. More aspects may be added as study progresses.

The LCM procedure is studied on the basis that an AI/ML model has a *model ID* with associated information and/or *model functionality* at least for some AI/ML operations.

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*Editor’s note: consider breaking paragraphs below into new subsection under 4.2 (possibly above too).*

For UE-side models and UE-part of two-sided models:

* For *AI/ML functionality identification*
	+ Reuse legacy 3GPP framework of Features as a starting point for discussion.
	+ UE indicates supported functionalities/functionality for a given sub-use-case.
		- UE capability reporting is taken as starting point.
* For *AI/ML model identification*
	+ Models are identified by model ID at the Network. UE indicates supported AI/ML models.

In *functionality-based* LCM, network indicates activation/deactivation/fallback/switching of AI/ML functionality via 3GPP signalling (e.g., RRC, MAC-CE, DCI). Models may not be identified at the Network, and UE may perform model-level LCM. Whether and how much awareness/interaction NW should have about model-level LCM will be studied. For functionality identification, there may be either one or more than one Functionalities defined within an AI/ML-enabled feature, whereby AI/ML-enabled Feature refers to a Feature where AI/ML may be used.

For *AI/ML functionality identification* and *functionality-based LCM* of UE-side models and/or UE-part of two-sided models, *functionality* refers to an AI/ML-enabled Feature/FG enabled by configuration(s), where configuration(s) is(are) supported based on conditions indicated by UE capability. Correspondingly, *functionality-based LCM* operates based on, at least, one configuration of AI/ML-enabled Feature/FG or specific configurations of an AI/ML-enabled Feature/FG.

After *functionality identification*, necessity, mechanisms, for UE to report updates on applicable functionality(es) among [configured/identified] functionality(es), where the applicable functionalities may be a subset of all [configured/identified] functionalities are studied.

In *model-ID-based* LCM, models are identified at the Network, and Network/UE may activate/deactivate/select/switch individual AI/ML models via model ID.

For *AI/ML model identification* and *model-ID-based LCM* of UE-side models and/or UE-part of two-sided models, *model-ID-based LCM* operates based on identified models, where a model may be associated with specific configurations/conditions associated with UE capability of an AI/ML-enabled Feature/FG and additional conditions (e.g., scenarios, sites, and datasets) as determined/identified between UE-side and NW-side.

From RAN1 perspective, an AI/ML model identified by a model ID may be *logical*, and how it maps to physical AI/ML model(s) may be up to implementation. The term *logical AI/ML model* refers to a model that is identified and assigned a *model ID*, the term *physical AI/ML model(s)* refers to an actual implementation of such a model.

After model identification, necessity, mechanisms, for UE to report updates on applicable UE part/UE-side model(s), where the applicable models may be a subset of all identified models are studied.

*Data collection:*

Data collection may be performed for different purposes in LCM, e.g., model training, model inference, model monitoring, model selection, model update, etc. each may be done with different requirements and potential specification impact.

## 4.3 Collaboration levels

In this section, various levels of collaboration between UE and gNB are identified as found pertinent to the selected use cases, e.g.,

* No collaboration: implementation-based only AI/ML algorithms without information exchange [for comparison purposes]
* Various levels of UE/gNB collaboration targeting at separate or joint ML operation

The following network-UE collaboration levels are considered as one aspect for defining collaboration levels

1. **Level x**: No collaboration.
2. **Level y**: Signalling-based collaboration without model transfer. Note: this level includes cases without model delivery.
3. **Level z**: Signalling-based collaboration with model transfer.

Level x/y boundary is understood such as Level x is implementation-based AI/ML operation without any dedicated AI/ML-specific enhancement (e.g., LCM related signalling, RS) collaboration between network and UE. (Note: The AI/ML operation may rely on future specification not related to AI/ML collaboration. The AI/ML approaches can be used as baseline for performance evaluation for future releases.)

Level y/z boundary is defined based on whether model delivery over the air interface in a manner that is not transparent to 3GPP signalling. Note: other procedures than model transfer/delivery of an AI/ML model over the air interface in a manner that is not transparent to 3GPP signalling.

The following Cases further detail the different options for model delivery/transfer to UE, training location, and model delivery/transfer format combinations for UE-side models and UE-part of two-sided models:

|  |  |  |  |
| --- | --- | --- | --- |
| **Case** | **Model delivery/transfer** | **Model storage location** | **Training location** |
| **y** | model delivery (if needed) over-the-top | Outside 3gpp Network | UE-side / NW-side / neutral site |
| **z1** | model transfer in proprietary format | 3GPP Network | UE-side / neutral site |
| **z2** | model transfer in proprietary format | 3GPP Network | NW-side |
| **z3** | model transfer in open format | 3GPP Network | UE-side / neutral site |
| **z4** | model transfer in open format of a known model structure at UE | 3GPP Network | NW-side |
| **z5** | model transfer in open format of an unknown model structure at UE | 3GPP Network | NW-side |

## 4.4 Functional Framework Details

*Editor’s note: RAN2 to complete this section.*

# 5 Use cases

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 AI/ML approaches for the selected sub use cases need to be diverse enough to support various requirements on the gNB-UE collaboration levels

Note: the selection of use cases for this study solely targets the formulation of a framework to apply AI/ML to the air-interface for these and other use cases. The selection itself does not intend to provide any indication of the prospects of any future normative project.

## 5.1 CSI feedback enhancement

***Finalization of representative sub-use cases*:**

The following are selected as representative sub-use cases:

* Spatial-frequency domain CSI compression using two-sided AI model. Note: All pre-processing/post-processing, quantization/de-quantization are within the scope of the sub use case.
	+ The study of AI/ML based CSI compression should be based on the legacy CSI feedback signalling framework.
* Time domain CSI prediction using UE sided model

Considered AI/ML model training collaborations include:

* Type 1: Joint training of the two-sided model at a single side/entity, e.g., UE-sided or Network-sided.
* Type 2: Joint training of the two-sided model at network side and UE side, respectively.
* Type 3: Separate training at network side and UE side, where the UE-side CSI generation part and the network-side CSI reconstruction part are trained by UE side and network side, respectively.
* Note: Joint training means the generation model and reconstruction model should be trained in the same loop for forward propagation and backward propagation. Joint training could be done both at single node or across multiple nodes(e.g., through gradient exchange between nodes).
* Note: Separate training includes sequential training starting with UE side training, or sequential training starting with NW side training [, or parallel training] at UE and NW
* Note: training collaboration Type 2 over the air interface for model training (not including model update) is concluded to be deprioritized in Rel-18 SI.

## 5.2 Beam Management

***Finalization of representative sub-use cases*:**

The following are selected as representative sub-use cases:

* BM-Case1: Spatial-domain Downlink beam prediction for Set A of beams based on measurement results of Set B of beams
	+ Consider: Alt. 1): AI/ML model training and inference at NW side. Alt. 2): AI/ML model training and inference at UE side.
	+ Consider: Alt. i): Set A and Set B are different (Set B is NOT a subset of Set A). Alt. ii): Set B is a subset of Set A. Note: Set A is for DL beam prediction and Set B is for DL beam measurement. The beam patterns of Set A and Set B can be clarified by companies.
	+ AI/ML model input: Alt 1): Only L1-RSRP measurement based on Set B; Alt.2): L1-RSRP measurement based on Set B and assistance information; Alt. 3): CIR based on Set B; Alt. 4): L1-RSRP measurement based on Set B and the corresponding DL Tx and/or Rx beam ID.
* BM-Case2: Temporal Downlink beam prediction for Set A of beams based on the historic measurement results of Set B of beams
	+ Consider: Alt. 1): AI/ML model training and inference at NW side. Alt. 2): AI/ML model training and inference at UE side.
	+ Consider: Alt. i): Set A and Set B are different (Set B is NOT a subset of Set A). Alt. ii): Set B is a subset of Set A (Set A and Set B are not the same). Alt. iii): Set A and Set B are the same.
	+ AI/ML model input: measurement results of K (K≥1) latest measurement instances with the following alternatives: Alt. 1): Only L1-RSRP measurement based on Set B; Alt 2): L1-RSRP measurement based on Set B and assistance information; Alt. 3): L1-RSRP measurement based on Set B and the corresponding DL Tx and/or Rx beam ID.
	+ AI/ML model output: F predictions for F future time instances, where each prediction is for each time instance. At least F=1.

Set B is a set of beams whose measurements are taken as inputs of the AI/ML model.

Note: Beams in Set A and Set B can be in the same Frequency Range.

For both sub-use cases, the following alternatives are studied for the predicted beams:

* Alt.1: DL Tx beam prediction
* Alt.2: DL Rx beam prediction (deprioritized)
* Alt.3: Beam pair prediction (a beam pair consists of a DL Tx beam and a corresponding DL Rx beam)

Note: DL Rx beam prediction may or may not have spec impact

The following alternatives for AI/ML model output are studied:

* Alt.1: Tx and/or Rx Beam ID(s) and/or the predicted L1-RSRP of the N predicted DL Tx and/or Rx beams
	+ e.g., N predicted beams can be the top-N predicted beams
* Alt.2: Tx and/or Rx Beam ID(s) of the N predicted DL Tx and/or Rx beams and other information
	+ e.g., N predicted beams can be the top-N predicted beams
* Alt.3: Tx and/or Rx Beam angle(s) and/or the predicted L1-RSRP of the N predicted DL Tx and/or Rx beams
	+ e.g., N predicted beams can be the top-N predicted beams

Notes: It is up to companies to provide other alternative(s). Beam ID is only used for discussion purposes. All the outputs are “nominal” and only for discussion purpose. Values of N is up to each company. All of the outputs in the above alternatives may vary based on whether the AI/ML model inference is at UE side or gNB side. The Top-N beam IDs might have been derived via post-processing of the ML-model output.

## 5.3 Positioning accuracy enhancements

***Finalization of representative sub-use cases*:**

The following are selected as representative sub-use cases:

* Direct AI/ML positioning:
	+ AI/ML model output: UE location
	+ e.g., fingerprinting based on channel observation as the input of AI/ML model
* AI/ML assisted positioning:
	+ AI/ML model output: new measurement and/or enhancement of existing measurement
	+ e.g., LOS/NLOS identification, timing and/or angle of measurement, likelihood of measurement

More specifically, the following Cases are considered for the study:

* Case 1: UE-based positioning with UE-side model, direct AI/ML or AI/ML assisted positioning
* Case 2a: UE-assisted/LMF-based positioning with UE-side model, AI/ML assisted positioning
* Case 2b: UE-assisted/LMF-based positioning with LMF-side model, direct AI/ML positioning
* Case 3a: NG-RAN node assisted positioning with gNB-side model, AI/ML assisted positioning
* Case 3b: NG-RAN node assisted positioning with LMF-side model, direct AI/ML positioning

One-sided model whose inference is performed entirely at the UE or at the network is prioritized in Rel-18 SI.

For the model input used in evaluations of AI/ML based positioning, if time-domain channel impulse response (CIR) or power delay profile (PDP) is used as model input in the evaluation, companies report the input dimension NTRP \* Nport \* Nt, where NTRP is the number of TRPs, Nport is the number of transmit/receive antenna port pairs, Nt is the number of consecutive time domain samples. If N’t (N’t < Nt) samples with the strongest power are selected as model input, with remaining (Nt ‒ N’t) time domain samples set to zero, then companies report value N’t in addition to Nt. It is also assumed that timing info for the N’t samples need to be provided as model input. For evaluations, companies to report assumed sampling period.

If the model input is the CIR, then each input value of the CIR is a complex number, i.e., it contains two real values, either {real, imaginary} or {magnitude, phase}. If the model input is the PDP, then each input value of the PDP is a real value. Optionally companies can use delay profile (DP) as a type of information for model input. DP is a degenerated version of PDP, where the path power is not provided.

Note: CIR and PDP may have different dimensions. Companies to provide details on their assumption on how PDP is constructed and how (if applicable) it is mapped to Nt samples.

For both the direct AI/ML positioning and AI/ML assisted positioning, the model input is studied, considering the trade-off among model performance, model complexity and computational complexity:

* The type of information to use as model input. The candidates include at least: time-domain CIR, PDP.
* The dimension of model input in terms of NTRP, Nt, and Nt’.
* Note: For the direct AI/ML positioning, model input size has impact to signalling overhead for model inference

At least for model inference of AI/ML assisted positioning, evaluate and report the AI/ML model output, including:

1. the type of information (e.g., ToA, RSTD, AoD, AoA, LOS/NLOS indicator) to use as model output,
2. soft information vs hard information,
3. whether the model output can reuse existing measurement report (e.g., NRPPa, LPP).

# 6 Evaluations

In this section, performance benefits of AI/ML based algorithms for the agreed use cases in the final representative set are evaluated:

The evaluation methodology is 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

Common KPIs and corresponding requirements for the AI/ML operations are to be determined. Also, use-case specific KPIs and benchmarks of the selected use-cases are to be determined.

* 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.

## 6.1 Common evaluation methodology and KPIs

3GPP channel models (TR 38.901) are used as the baseline for evaluations. Note: additional results based on dataset other than that generated by 3GPP channel models are allowed.

**Common KPIs** (if applicable):

* 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 signalling
* Inference complexity, including complexity for pre- and post-processing
	+ Computational complexity of model inference: TOPs, FLOPs, MACs
	+ Computational complexity for pre- and post-processing
	+ Model complexity: e.g., the number of parameters and/or size (e.g., Mbyte)
	+ Complexity shall be reported in terms of “*number of real-value model parameters*” and “*number of real-value operations*” regardless of underlying model arithmetic
* Training complexity
* LCM related complexity and storage overhead
	+ Storage/computation for training data collection
	+ Storage/computation for training and model update
	+ Storage/computation for model monitoring
	+ Storage/computation for other LCM procedures, e.g., model activation, deactivation, selection, switching, fallback operation

## 6.2 CSI feedback enhancement

### 6.2.1 Evaluation assumptions, methodology and KPIs

For the performance evaluation of the AI/ML based CSI feedback enhancement, *system level simulation* approach is adopted as baseline. *Link level simulations* are optionally adopted.

For calibration purposes on the dataset and/or AI/ML model across companies, companies were encouraged to align the parameters (e.g., for scenarios/channels) for generating the dataset in the simulation as a starting point.

For the evaluation of the AI/ML based CSI feedback enhancement, for ‘Channel estimation’, ideal DL channel estimation is optionally taken into the baseline of evaluation methodology for the purpose of calibration and/or comparing intermediate results (e.g., accuracy of AI/ML output CSI, etc.). Up to companies to report whether/how ideal channel is used in the dataset construction and performance evaluation/inference.

Note: Eventual performance comparison with the benchmark release and drawing SI conclusions should be based on realistic DL channel estimation.

Performing intermediate evaluations on AI/ML model performance can be considered to derive the intermediate KPI(s) (e.g., accuracy of AI/ML output CSI) for the purpose of AI/ML solution comparison. CSI accuracy is calculated using the target CSI from ideal channel and the output CSI from the realistic channel estimation. The target CSI from ideal channel equally applies to AI/ML based CSI feedback enhancement, and the baseline codebook.

***KPIs and Evaluation metrics*:**

* Capability/complexity: Floating point operations (FLOPs), AI/ML model size, number of AI/ML parameters
	+ Reported separately for the CSI generation part and the CSI reconstruction part (for CSI compression sub-use case)
	+ When reporting the computational complexity including the pre-processing and post-processing, the complexity metric of FLOPs may be reported separately for the AI/ML model and the pre/post processing. While reporting the FLOPs of pre-processing and post-processing the following boundaries are considered:
		- Estimated raw channel matrix per each frequency unit as an input for pre-processing of the CSI generation part.
		- Precoding vectors per each frequency unit as an output of post-processing of the CSI reconstruction part.
* AI/ML memory storage in terms of AI/ML model size and number of AI/ML parameters is adopted as part of the ‘Evaluation Metric’, and reported by companies who may select either or both.
* CSI compression: Intermediate KPIs: SGCS and/or NMSE to evaluate the accuracy of the AI/ML output CSI
	+ For rank>1 cases, SGCS calculation/extension methods are to be reported:
		- SGCS separately calculated for each layer (e.g., for K layers, K SGCS values are derived respectively, and comparison is performed per layer). Companies to ensure the correct calculation of SGCS and to avoid disorder issue of the output eigenvectors. Note: Eventual KPI can still be used to compare the performance.
	+ The granularity of the frequency unit for averaging operation is assumed to be:
		- For 15kHz SCS: For 10MHz bandwidth: 4 RBs; for 20MHz bandwidth: 8 RBs
		- For 30kHz SCS: For 10MHz bandwidth: 2 RBs; for 20MHz bandwidth: 4 RBs
		- Other frequency unit granularities not precluded.
	+ The intermediate KPI results are in the form of absolute value and the gain over a given benchmark, e.g., in terms of “absolute value (gain over benchmark)”. SGCS is to be expressed in linear domain, while NMSE in dB domain.
* CSI compression: Intermediate KPI: monitoring mechanism considered as:
	+ Step 1: Generate test dataset including K test samples.
	+ Step 2: For each of the K test samples, a bias factor of monitored intermediate KPI (KPI*Diff*) is calculated as a function of KPI*Diff* = *f* ( KPI*Actual* , KPI*Genie* ), where KPI*Actual* is the actual intermediate KPI, and KPI*Genie* is the genie-aided intermediate KPI.
		- KPI*Diff* is considered for:
			* Case 1: NW side monitoring of intermediate KPI, where the monitoring accuracy is evaluated for a given ground-truth CSI format (e.g., quantized ground-truth CSI with 8 bits scalar, R16 eType II-like method, etc.) or SRS measurements, where
				+ KPI*Actual* is calculated with the output CSI at the NW side and the given ground-truth CSI format or SRS measurements.
				+ KPI*Genie* is calculated with output CSI (as for KPI*Actual*) and the ground-truth CSI of Float32
				+ Note: if Float32 is used for KPI*Actual*, the monitoring accuracy is 100% if KPI*Actual* and KPI*Genie* are based on the same CSI sample.
			* Case 2: UE side monitoring of intermediate KPI with a proxy model, where the monitoring accuracy is evaluated for the output of the proxy model at UE:
				+ Case 2-1: the proxy model is a proxy CSI reconstruction part, and KPI*Actual* is calculated based on the inference output of the proxy CSI reconstruction part at UE and the ground-truth CSI. Note: if the proxy CSI reconstruction model is the same as the actual CSI reconstruction model at the NW, the monitoring accuracy is 100%.
				+ Case 2-2: the proxy model directly outputs intermediate KPI (KPI*Actual*)
				+ KPI*Genie* is calculated with the output CSI at the NW side and the same ground-truth CSI.
		- KPI*Diff* = *f* ( KPI*Actual* , KPI*Genie* ) can take the following forms:
			* Option 1: Gap between KPI*Actual* and KPI*Genie*, i.e. KPI*Diff* = (KPI*Actual* - KPI*Genie*); Monitoring accuracy is the percentage of samples for which | KPI*Diff*| < KPI*th 1*, where KPI*th 1* is a threshold of the intermediate KPI gap.
			* Option 2: Binary state where KPI*Actual* and KPI*Genie*, have different relationships to their threshold(s), i.e., KPI*Diff* = (KPI*Actual* > KPI*th 2*, KPI*Genie* > KPI*th 3*) OR (KPI*Actual* < KPI*th 2*, KPI*Genie* < KPI*th 3*), where KPI*th 2* can be the same or different from KPI*th 3*. Monitoring accuracy is the percentage of samples for which KPI*Diff* = 0.
	+ Step 3: Calculate the statistical result of the KPI*Diff* over K test samples which represents the monitoring accuracy performance.
	+ Note: the complexity, overhead and latency of the monitoring scheme are to be reported.
* CSI prediction: Intermediate KPIs: calculated for each predicted instance if AI/ML model outputs multiple predicted instances
	+ The intermediate KPI results are in the form of absolute value and the gain over a given benchmark, e.g., in terms of “absolute value (gain over benchmark)”.
	+ If collaboration level x is reported as the benchmark, the EVM to distinguish level x and level y/z based AI/ML CSI prediction is considered from the generalization aspect, e.g., collaboration level y/z based CSI prediction is modelled as the fine-tuning case or generalization Case 1, while collaboration level x based CSI prediction is modelled as generalization Case 2 or Case 3.
* Throughput including: average UPT, 5%-ile UE throughput, and CDF of UPT

***Model generalization*:**

In order to study the verification of generalization, the following aspects are encouraged to be reported:

* The configuration(s)/scenario(s) for training dataset, including potentially the mixed training dataset from multiple configurations/scenarios
* The configuration(s)/scenario(s) for testing/inference

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:

* Various deployment scenarios (e.g., UMa, UMi, InH)
* Various outdoor/indoor UE distributions for UMa/UMi (e.g., 10:0, 8:2, 5:5, 2:8, 0:10)
* Various carrier frequencies (e.g., 2GHz, 3.5GHz)
* Other aspects of scenarios are not precluded, e.g., various antenna spacing, various antenna virtualization (TxRU mapping), various ISDs, various UE speeds, etc.
* Companies to report the selected scenarios for generalization verification

To verify the generalization/scalability performance of an AI/ML model over various configurations (e.g., which may potentially lead to different dimensions of model input/output), the *set of configurations* are considered focusing on one or more of the following aspects:

* Various bandwidths (e.g., 10MHz, 20MHz) and/or frequency granularities, (e.g., size of subband)
* Various sizes of CSI feedback payloads, FFS candidate payload number
* Various antenna port layouts, e.g., (N1/N2/P) and/or antenna port numbers (e.g., 32 ports, 16 ports)
* Various UE speeds (e.g., 10km/h, 30km/h, 60km/h, 120km/h, etc.) for CSI prediction sub use case
* Other aspects of configurations are not precluded, e.g., various numerologies, various rank numbers/layers, etc.
* Companies to report the selected configurations for generalization verification
* Companies are encouraged to report the method to achieve generalization over various configurations to achieve scalability of the AI/ML input/output, including pre-processing, post-processing, etc

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

* 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

For evaluating the generalization/scalability over various configurations for **CSI compression**, to achieve the scalability over *different input/output dimensions*, companies to report which case(s) are evaluated from the following list:

* Case 0 (benchmark for comparison): One CSI generation part with fixed input and output dimensions to 1 CSI reconstruction part with fixed input and output dimensions for each of the different input and/or output dimensions.
* Case 1: One CSI generation part with scalable input and/or output dimensions to N>1 separate CSI reconstruction parts each with fixed and different output and/or input dimensions
* Case 2: M>1 separate CSI generation parts each with fixed and different input and/or output dimensions to one CSI reconstruction part with scalable output and/or input dimensions
* Case 3: A pair of CSI generation part with scalable input/output dimensions and CSI reconstruction part with scalable output and/or input dimensions

For CSI compression, to achieve the scalability over *different input dimensions* of CSI generation part (e.g., different bandwidths/frequency granularities, or different antenna ports), the generalization cases are elaborated as follows:

* Case 1: The AI/ML model is trained based on training dataset from a fixed dimension X1 (e.g., a fixed bandwidth/frequency granularity, and/or number of antenna ports), and then the AI/ML model performs inference/test on a dataset from the same dimension X1.
* Case 2: The AI/ML model is trained based on training dataset from a single dimension X1, and then the AI/ML model performs inference/test on a dataset from a different dimension X2.
* Case 3: The AI/ML model is trained based on training dataset by mixing datasets subject to multiple dimensions of X1, X2,..., Xn, and then the AI/ML model performs inference/test on a single dataset subject to the dimension of X1, or X2,…, or Xn.
* Note: For Case 2/3, the solutions to achieve the scalability between Xi and Xj, are reported by companies, including, e.g., pre-processing to angle-delay domain, padding, additional adaptation layer in AI/ML model, etc.

For CSI compression, to achieve the scalability over *different output dimensions* of CSI generation part (e.g., different generated CSI feedback dimensions), the generalization cases of are elaborated as follows

* Case 1: The AI/ML model is trained based on training dataset from a fixed output dimension Y1 (e.g., a fixed CSI feedback dimension), and then the AI/ML model performs inference/test on a dataset from the same output dimension Y1.
* Case 2: The AI/ML model is trained based on training dataset from a single output dimension Y1, and then the AI/ML model performs inference/test on a dataset from a different output dimension Y2.
* Case 3: The AI/ML model is trained based on training dataset by mixing datasets subject to multiple dimensions of Y1, Y2,..., Yn, and then the AI/ML model performs inference/test on a single dataset of Y1, or Y2,…, or Yn.
* Notes: For Case 1/2/3, companies to report whether the output of the CSI generation part is before quantization or after quantization. For Case 2/3, the solutions to achieve the scalability between Yi and Yj, are reported by companies, including, e.g., truncation, additional adaptation layer in AI/ML model, etc.

***Further details on evaluations including training collaboration types***

For the evaluation of the AI/ML based CSI compression sub use cases, a two-sided model is considered as a starting point, including an AI/ML-based CSI generation part to generate the CSI feedback information and an AI/ML-based CSI reconstruction part which is used to reconstruct the CSI from the received CSI feedback information. At least for inference, the CSI generation part is located at the UE side, and the CSI reconstruction part is located at the gNB side.

For the evaluation of an example of Type 3 (Separate training at NW side and UE side), the following procedure is considered for the *sequential training starting with NW side training* (NW-first training):

* Step1: NW side trains the NW side CSI generation part (which is not used for inference) and the NW side CSI reconstruction part jointly
* Step2: After NW side training is finished, NW side shares UE side with a set of information (e.g., dataset) that is used by the UE side to be able to train the UE side CSI generation part
* Step3: UE side trains the UE side CSI generation part based on the received set of information
* Other Type 3 NW-first training approaches are not precluded

For the evaluation of an example of Type 3 (Separate training at NW side and UE side), the following procedure is considered for the *sequential training starting with UE side training* (UE-first training):

* Step1: UE side trains the UE side CSI generation part and the UE side CSI reconstruction part (which is not used for inference) jointly
* Step2: After UE side training is finished, UE side shares NW side with a set of information (e.g., dataset) that is used by the NW side to be able to train the CSI reconstruction part
* Step3: NW side trains the NW side CSI reconstruction part based on the received set of information
* Other Type 3 UE-first training approaches are not precluded

For the evaluation of an example of Type 3 (Separate training at NW side and UE side), the following evaluation cases for sequential training are considered for multi-vendors:

* Case 1 (baseline): Type 3 training between one NW part model and one UE part model
	+ Note 1: Case 1 can be naturally applied to the NW-first training case where 1 NW part model to M>1 separate UE part models
		- Companies to report the dataset used between the NW part model and the UE part model, e.g., whether dataset for training UE part model is the same or a subset of the dataset for training NW part model
	+ Note 2: Case 1 can be naturally applied to the UE-first training case where 1 UE part model to N>1 separate NW part models
		- Companies to report the dataset used between the NW part model and the UE part model, e.g., whether dataset for training NW part model is the same or a subset of the dataset for training UE part model
	+ Companies to report the AI/ML structures for the combination(s) of UE part model and NW part model, which can be the same or different
* Case 2: For UE-first training, Type 3 training between one NW part model and M>1 separate UE part models
	+ Note: Case 2 can be also applied to the M>1 UE part models to N>1 NW part models
	+ Companies to report the AI/ML structures for the M>1 UE part models and the NW part model
	+ Companies to report the dataset used at UE part models, e.g., same or different dataset(s) among M UE part models
	+ Companies to report Dataset construction, e.g., the set of information includes the input and label of the UE side CSI reconstruction part, or includes the input of the UE side CSI reconstruction part only, or other information if applicable. Also, report the Quantization behaviour, e.g., whether the shared input of the UE side CSI reconstruction part is before or after quantization.
* Case 3: For NW-first training, Type 3 training between one UE part model and N>1 separate NW part models
	+ Note: Case 3 can be also applied to the N>1 NW part models to M>1 UE part models
	+ Companies to report the AI/ML structures for the UE part model and the N>1 NW part models
	+ Companies to report the dataset used at NW part models, e.g., same or different dataset(s) among N NW part models
	+ Companies to report Dataset construction, e.g., the set of information includes the input and output of the Network side CSI generation part, or includes the output of the Network side CSI generation part only, or other information if applicable. Also report the Quantization behaviour, e.g., whether the shared output of the Network side CSI generation part is before or after quantization.
* Case 4: 1-on-1 training with joint training: benchmark/upper bound for performance comparison.

***Evaluation assumptions*:**

Table 6.2.1-1 presents the baseline system level simulation assumptions for AI/ML based CSI feedback enhancement evaluations.

Table 6.2.1-1: Baseline System Level Simulation assumptions for AI/ML based CSI feedback enhancement evaluations

|  |  |
| --- | --- |
| Parameter | Value |
| Duplex, Waveform | FDD (TDD is not precluded), OFDM |
| Multiple access | OFDMA |
| Scenario | Dense Urban (Macro only) is a baseline.Other scenarios (e.g., UMi@4GHz 2GHz, Urban Macro) are not precluded. |
| Frequency Range | FR1 only, 2GHz as baseline, optional for 4GHz (if R16 as baseline)FR1 only, 2GHz with duplexing gap of 200MHz between DL and UL, optional for 4GHz (if R17 as baseline) |
| Inter-BS distance | 200m |
| Channel model         | According to TR 38.901 |
| Antenna setup and port layouts at gNB | Companies need to report which option(s) are used between- 32 ports: (8,8,2,1,1,2,8), (dH,dV) = (0.5, 0.8)λ- 16 ports: (8,4,2,1,1,2,4), (dH,dV) = (0.5, 0.8)λOther configurations are not precluded. |
| Antenna setup and port layouts at UE | 4RX: (1,2,2,1,1,1,2), (dH,dV) = (0.5, 0.5)λ for (rank 1-4)2RX: (1,1,2,1,1,1,1), (dH,dV) = (0.5, 0.5)λ for (rank 1,2)Other configuration is not precluded. |
| BS Tx power | 41 dBm for 10MHz, 44dBm for 20MHz, 47dBm for 40MHz |
| BS antenna height | 25m |
| UE antenna height & gain | Follow TR36.873 |
| UE receiver noise figure | 9dB |
| Modulation | Up to 256QAM |
| Coding on PDSCH | LDPCMax code-block size=8448bit |
| Numerology | Slot/non-slot | 14 OFDM symbol slot |
| SCS | 15kHz for 2GHz, 30kHz for 4GHz |
| Simulation bandwidth | 10 MHz for 15kHz as a baseline, and configurations which emulate larger BW, e.g., same sub-band size as 40/100 MHz with 30kHz, may be optionally considered. Above 15kHz is replaced with 30kHz SCS for 4GHz (if R16 as baseline)20 MHz for 15kHz as a baseline (optional for 10 MHz with 15KHz), and configurations which emulate larger BW, e.g., same sub-band size as 40/100 MHz with 30kHz, may be optionally considered. Above 15kHz is replaced with 30kHz SCS for 4GHz (if R17 as baseline) |
| Frame structure | Slot Format 0 (all downlink) for all slots |
| MIMO scheme | SU/MU-MIMO with rank adaptation. Companies are encouraged to report the SU/MU-MIMO with RU.  |
| MIMO layers | For all evaluation, companies to provide the assumption on the maximum MU layers (e.g., 8 or 12) |
| CSI feedback | Feedback assumption at least for baseline scheme- CSI feedback periodicity (full CSI feedback): 5 ms (baseline)- Scheduling delay (from CSI feedback to time to apply in scheduling): 4 ms |
| Overhead | Companies shall provide the downlink overhead assumption (i.e., whether the CSI-RS transmission is UE-specific or not and take that into account for overhead computation) |
| Traffic model | At least, FTP model 1 with packet size 0.5 Mbytes is assumed.Other options are not precluded |
| Traffic load (Resource utilization) | 20/50/70%. Companies are encouraged to report the MU-MIMO utilization.  |
| UE distribution | CSI compression: 80% indoor (3 km/h), 20% outdoor (30 km/h)CSI prediction: 100% outdoor (10, 20, 30, 60, 120 km/h) including outdoor-to-indoor car penetration loss per TR 38.901 if the simulation assumes UEs inside vehicles. No explicit trajectory modeling considered for evaluations.  |
| UE receiver | MMSE-IRC as the baseline receiver |
| Feedback assumption | Realistic |
| Channel estimation          | Realistic as a baseline. Up to companies to choose the error modelling method for realistic channel estimation.FFS ideal channel estimation |
| Evaluation Metric | Throughput and CSI feedback overhead as baseline metrics.The CSI feedback overhead is calculated as the weighted average of CSI payload per rank and the distribution of ranks reported by the UE. * + - For AI/ML based solutions: The above-mentioned “CSI feedback overhead” is calculated as max allowed bits at the given rank.
		- For legacy Type II CB: Option 2b is mandatorily reported by companies, while Option 2a can be optionally reported up to companies if partial NZC report is assumed for the legacy Type II CB
* Option 2a: The above-mentioned “CSI feedback overhead” is calculated as each CSI reported payload with a given rank
* Option 2b: The above-mentioned “CSI feedback overhead” is calculated as max allowed bits at the given rank

Additional metrics, e.g., ratio between throughput and CSI feedback overhead, can be used.Maximum overhead (payload size for CSI feedback)for each rank at one feedback instance is the baseline metric for CSI feedback overhead, and companies can provide other metrics. |
| Baseline for performance evaluation | For CSI compression:Companies need to report which option is used between:- Rel-16 TypeII Codebook as the baseline for performance and overhead evaluation.- Rel-17 TypeII Codebook as the baseline for performance and overhead evaluation.Additional assumptions from R17 TypeII EVM: Same consideration with respect to utilizing angle-delay reciprocity should be considered taken for the AI/ML based CSI feedback and the baseline scheme if R17 TypeII codebook is selected as baseline.Optionally, Type I Codebook (if it outperforms Type II Codebook) can be considered for comparing AI/ML schemes.For CSI-prediction: Companies need to report which option is used between:* The nearest historical CSI without prediction
* Non-AI/ML or AI/ML with collaboration Level x based CSI prediction for which corresponding details would need to be reported

Note: the specific non-AI/ML based CSI prediction is compatible with R18 MIMO; collaboration level x AI/ML based CSI prediction could be implementation based AI/ML compatible with R18 MIMO as an example.For the evaluation of CSI enhancements, companies can optionally provide the additional throughput baseline based on CSI without compression (e.g., eigenvector from measured channel), which is taken as an upper bound for performance comparison. |

Note: the baseline EVM is used to compare the performance with the benchmark release, while the AI/ML related parameters (e.g., dataset construction, generalization verification, and AI/ML related metrics) can be of additional/different assumptions. The conclusions for the use cases in the SI should be drawn based on generalization verification over potentially multiple scenarios/configurations.

Table 6.2.1-2 presents the baseline link level simulation assumptions for AI/ML based CSI feedback enhancement evaluations.

Table 6.2.1-2: Baseline Link Level Simulation assumptions for AI/ML based CSI feedback enhancement evaluations

|  |  |
| --- | --- |
| Parameter | Value |
| Duplex, Waveform  | FDD (TDD is not precluded), OFDM  |
| Carrier frequency | 2GHz as baseline, optional for 4GHz |
| Bandwidth | 10MHz or 20MHz |
| Subcarrier spacing | 15kHz for 2GHz, 30kHz for 4GHz |
| Nt | 32: (8,8,2,1,1,2,8), (dH,dV) = (0.5, 0.8)λ |
| Nr | 4: (1,2,2,1,1,1,2), (dH,dV) = (0.5, 0.5)λ |
| Channel model | CDL-C as baseline, CDL-A as optional |
| UE speed | 3kmhr, 10km/h, 20km/h or 30km/h to be reported by companies |
| Delay spread | 30ns or 300ns |
| Channel estimation | Realistic channel estimation algorithms (e.g., LS or MMSE) as a baseline, FFS ideal channel estimation |
| Rank per UE | Rank 1-4. Companies are encouraged to report the Rank number, and whether/how rank adaptation is applied |

***AI/ML model training collaborations type dependent evaluations*:**

For the evaluations of Type 2 (Joint training of the two-sided model at network side and UE side, respectively), the following evaluation cases are considered for multi-vendors,

* Case 1 (baseline): Type 2 training between one NW part model to one UE part model
* Case 2: Type 2 training between one NW part model and M>1 separate UE part models
	+ Companies to report the AI/ML structures for the UE part model and the NW part model
* Case 3: Type 2 training between one UE part model and N>1 separate NW part models
	+ Companies to report the AI/ML structures for the UE part model and the NW part model

For the evaluation of Type 3 (Separate training at NW side and UE side), the following cases are considered for evaluations:

* Case 1 (baseline): Aligned AI/ML model structure between NW side and UE side
* Case 2: Not aligned AI/ML model structures between NW side and UE side
	+ Companies to report the AI/ML structures for the UE part model and the NW part model, e.g., different backbone (e.g., CNN, Transformer, etc.), or same backbone but different structure (e.g., number of layers)

***CSI compression sub use case specific aspects*:**

For the evaluation of the AI/ML based **CSI compression** sub use case, companies are encouraged to report details of their models, including:

* The structure of the AI/ML model, e.g., type (CNN, RNN, Transformer, Inception, …), the number of layers, branches, real valued or complex valued parameters, etc.
* AI/ML model input (for CSI generation part)/output (for CSI reconstruction part) types for evaluations:
	+ Raw channel matrix (in frequency or delay domain), e.g., channel matrix with dimensions of Tx, Rx, and frequency unit
	+ Precoding matrix (as a group of eigenvectors or an eTypeII-like reporting)
* Data pre-processing/post-processing
* Loss function
* Specific quantization/dequantization method, e.g., vector quantization, scalar quantization, etc, considering the following aspects:
	+ Quantization non-aware training, where the float-format variables are directly passed from CSI generation part to CSI reconstruction part during the training
		- Fixed/pre-configured quantization method/parameters is applied for the inference phase. Companies to report the design of the fixed/pre-configured quantization method/parameters, e.g., quantization resolution, vector quantization codebook, etc
	+ Quantization-aware training, where quantization/dequantization is involved in the training process
		- Case 2-1: Fixed/pre-configured quantization method/parameters are applied during the training phase; the same quantization codebook is applied for the inference phase. Companies to report the design of the fixed/pre-configured quantization method/parameters, e.g., quantization resolution, vector quantization codebook, etc.
		- Case 2-2: The quantization method/parameters are updated in together with the AI/ML models during the training; when training is finished, the final quantization codebook is applied for the inference phase. Companies to report how to update the quantization method/parameters during the training
	+ Quantization methods including uniform vs non-uniform quantization, scalar versus vector quantization, and associated parameters, e.g., quantization resolution, etc.
	+ How to use the quantization methods
	+ Considering performance impact of ground truth quantization in the CSI compression
		- Studying high resolution quantization methods for ground truth CSI, including at least the following options:
			* High resolution scalar quantization with Float32 adopted as the baseline/upper-bound for performance comparisons
			* High resolution codebook quantization, e.g., Rel-16 TypeII-like method with new parameters, in which case companies are to report the R16 Type II parameters with specified or new/larger values to achieve higher resolution of the ground-truth CSI labels, e.g., L,$ p\_{v}$, $β$, reference amplitude, differential amplitude, phase, etc
* For CSI compression sub use case with rank ≥ 1, AI/ML model setting to adapt to ranks/layers to be reported amongst the following options:
	+ Option 1-1 (rank specific): Separated AI/ML models are trained per rank value and applied for corresponding ranks to perform individual inference, any specific model operates on multi-layers jointly.
	+ Option 1-2 (rank common): A unified AI/ML model is trained and applied for adaptive ranks to perform inference, the model operates on multi-layers jointly.
	+ Option 2 (layer specific): Separated AI/ML models are trained per layer value and applied for corresponding layers to perform individual inference.
		- Note: input/output type is Precoding matrix
		- Companies to report the setting is
			* Option 2-1: layer specific and rank common (different models applied for different layers; for a specific layer, the same model is applied for all rank values), or
			* Option 2-2: layer specific and rank specific (different models applied for different layers; for a specific layer, different models are applied for different rank values)
	+ Option 3 (layer common): A unified AI/ML model is trained and applied for each layer to perform individual inference.
		- Note: input/output type is Precoding matrix
		- Companies to report whether the setting is
			* Option 3-1: layer common and rank common (A unified AI/ML model is applied for each layer under any rank value to perform individual inference), or
			* Option 3-2: layer common and rank specific (different models applied for different rank values; for a specific rank, the same model is applied for all layers)
* For CSI compression sub use case with rank >1, for a given configured Max rank=K, the complexity of FLOPs is reported as the maximum FLOPs over all ranks each includes the summation of FLOPs for inference per layer if applicable, e.g.,
	+ Option 1-1 (rank specific): Max FLOPs over K rank specific models.
	+ Option 1-2 (rank common): FLOPs of the rank common model.
	+ Option 2-1 (layer specific and rank common): Sum of the FLOPs of K models (for the rank=K).
	+ Option 2-2 (layer specific and rank specific): Max of the FLOPs over K ranks, k=1,…K, each with a sum of k models.
	+ Option 3-1 (layer common and rank common): K \* FLOPs of the common model.
	+ Option 3-2 (layer common and rank specific): Max of the FLOPs over K ranks, k=1,…K, each with k \* FLOPs of the layer common model.
* For CSI compression sub use case with rank >1, the storage of memory storage/number of parameters is reported as the summation of memory storage/number of parameters over all models potentially used for any layer/rank, e.g.,
	+ Option 1-1 (rank specific)/Option 3-2 (layer common and rank specific): Sum of memory storage/number of parameters over all rank specific models.
	+ Option 1-2 (rank common): A single memory storage/number of parameters for the rank common model.
	+ Option 2-1 (layer specific and rank common): Sum of memory storage/number of parameters over all layer specific models.
	+ Option 2-2 (layer specific and rank specific): Sum of memory storage/number of parameters for the specific models over all ranks and all layers in per rank.
	+ Option 3-1 (layer common and rank common): A single memory storage/number of parameters for the common model

Further, the following aspects are to be studied:

* CQI determination in CSI report, if CQI in CSI report is configured considering the following options:
	+ Option 1: CQI is NOT calculated based on the output of CSI reconstruction part from the realistic channel estimation, including
		- Option 1a: CQI is calculated based on target CSI with realistic channel measurement
		- Option 1b: CQI is calculated based on target CSI with realistic channel measurement and potential adjustment
		- Option 1c: CQI is calculated based on legacy codebook
	+ Option 2: CQI is calculated based on the output of CSI reconstruction part from the realistic channel estimation, including
		- Option 2a: CQI is calculated based on CSI reconstruction output, if CSI reconstruction model is available at the UE and UE can perform reconstruction model inference with potential adjustment
			* Note: CSI reconstruction part at the UE can be different comparing to the actual CSI reconstruction part used at the NW.
		- Option 2b: CQI is calculated using two stage approach, UE derive CQI using precoded CSI-RS transmitted with a reconstructed precoder.
	+ Notes: feasibility of different options should be evaluated. Gap analyses between the UE side CQI calculation results and the NW side results, as well as the impact on the scheduling performance should be evaluated. Complexity of CQI calculation needs to be evaluated, including the computing complexity and potential RS/signaling overhead.
* CSI configuration and report:
	+ NW configuration to determine CSI payload size, e.g., possible CSI payload size, possible rank restriction and/or other related configuration.
	+ How UE determines/reports the actual CSI payload size and/or other CSI related information within constraints configured by the network.
* Support of legacy CSI reporting principles including at least:
	+ The priority rule regarding CSI collision handling and CSI omission
	+ Codebook subset restriction
	+ CSI processing Unit

***CSI prediction sub use case specific aspects*:**

For the evaluation of the AI/ML based **CSI prediction** sub use case, companies are encouraged to report details of their models, including:

* The structure of the AI/ML model, e.g., type (FCN, RNN, CNN,…), the number of layers, branches, format of parameters, etc.
* The input CSI type, e.g., raw channel matrix, eigenvector(s) of the raw channel matrix, feedback CSI information, etc.
	+ Including assumptions on the observation window, i.e., number/time distance of historic CSI/channel measurements
* The output CSI type, e.g., channel matrix, eigenvector(s), feedback CSI information, etc.
	+ Including assumptions on the prediction window, i.e., number/time distance of predicted CSI/channel
* Data pre-processing/post-processing
* Loss function

For SLS, spatial consistency Procedure A with 50m decorrelation distance from TR 38.901 is used (if not used, assumptions used need to be reported). UE velocity vector is assumed as fixed over time in Procedure A modelling.

***Model Fine-tuning*:**

For the evaluation of the potential performance benefits of model fine-tuning of CSI feedback enhancement, which is optionally assessed, the following case is considered:

* 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.
* In this case, the fine-tuning dataset setting (e.g., size of dataset) is to be reported along with the improvement of performance.

### 6.2.2 Performance results

Tables 6.2.2-1 through 6.2.2-4 present the performance results for the evaluation results of AI/ML-based CSI compression without and with generalization/scalability verification for different training assumptions, namely, 1-on-1 joint training, multi-vendor joint training and separate training.

For the evaluation of CSI compression, the specific CQI determination method(s) for AI/ML can be reported by introducing an additional field in the template, e.g.,

* Option 2a: CQI is calculated based on CSI reconstruction output, if CSI reconstruction model is available at the UE and UE can perform reconstruction model inference with potential adjustment.
	+ Option 2a-1: The CSI reconstruction part for CQI calculation at the UE same as the actual CSI reconstruction part at the NW.
	+ Option 2a-2: The CSI reconstruction part for CQI calculation at the UE is a proxy model, which is different from the actual CSI reconstruction part at the NW.
* Option 2b: CQI is calculated using two stage approach, UE derives CQI using precoded CSI-RS transmitted with a reconstructed precoder.
* Option 1a: CQI is calculated based on the target CSI from the realistic channel estimation.
* Option 1b: CQI is calculated based on the target CSI from the realistic channel estimation and potential adjustment.
* Option 1c: CQI is calculated based on traditional codebook.

The following baselines are recommended to facilitate calibration of results:

* Benchmark: R16 eType II CB;
	+ Others can be additionally submitted, e.g., Type I CB.
* Input/Output type: Eigenvectors of the current CSI
	+ Other can be additionally submitted, e.g., eigenvectors with additional past CSI, eType II-like input, raw channel matrix, etc.
* Ground-truth CSI quantization method: Float32, i.e., without quantization
	+ Other high resolution CSI quantization methods can be additionally submitted for comparison, e.g., R16 Type II-like method with new parameters, scalar quantization, etc.
* Rank/layer adaptation settings for rank>1: Option 3-1, i.e., layer common and rank common.
	+ Other rank>1 options can be additionally submitted for comparison, e.g., Option 1-1/1-2/2-1/2-2/3-2.
* Quantization method: quantization-aware training (Case 2-1 or Case 2-2)
	+ Quantization non-aware training can be additionally submitted for comparison
	+ SQ and/or VQ is up to companies; companies are encouraged to provide results of various cases for comparison.
* Performance metric for intermediate KPI: SGCS
	+ NMSE can be additionally submitted

 Table 6.2.2-1: Evaluation results for CSI compression 1-on-1 joint training without model generalization/scalability, [traffic type], [Max rank value], [RU]

|  |  |  |
| --- | --- | --- |
|  | Source 1 | … |
| CSI generation part | AL/ML model backbone |  |  |
| Pre-processing |  |  |
| Post-processing |  |  |
| FLOPs/M |  |  |
| Number of parameters/M |  |  |
| [Storage /Mbytes] |  |  |
| CSI reconstruction part | AL/ML model backbone |  |  |
| [Pre-processing] |  |  |
| [Post-processing] |  |  |
| FLOPs/M |  |  |
| Number of parameters/M |  |  |
| [Storage /Mbytes] |  |  |
| Common description | Input type |  |  |
| Output type |  |  |
| Quantization /dequantization method |  |  |
| Rank/layer adaptation settings for rank>1 |  |  |
| Dataset description | Train/k |  |  |
| Test/k |  |  |
| Ground-truth CSI quantization method (incl. scalar/codebook based quantization, and the parameters) |  |  |
| Overhead reduction compared to Float32 if high resolution quantization of ground-truth CSI is applied |  |  |
| [Other assumptions/settings agreed to be reported] |  |  |
| Benchmark |  |  |
| Benchmark assumptions, e.g., CSI overhead calculation method (Optional) |  |  |
| SGCS of benchmark, [layer 1] | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| SGCS of benchmark, [layer 2] | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| Gain for SGCS, [layer 1] | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| Gain for SGCS, [layer 2] | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| …(other layers) |  |  |  |
| NMSE of benchmark, [layer 1] | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| NMSE of benchmark, [layer 2] | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| Gain for NMSE, [layer 1] | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| Gain for NMSE, [layer 2] | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| …(other layers) |  |  |  |
| Other intermediate KPI (description/value) (optional) |  |  |
| Gain for other intermediate KPI (description/value) (optional) |  |  |
| Gain for Mean UPT (for a specific CSI feedback overhead) | CSI feedback payload A |  |  |
| CSI feedback payload B  |  |  |
| CSI feedback payload C |  |  |
| Gain for 5% UPT | CSI feedback payload A |  |  |
| CSI feedback payload B |  |  |
| CSI feedback payload C |  |  |
| Gain for upper bound without CSI compression over Benchmark – Mean UPT (Optional) | CSI feedback payload A |  |  |
| CSI feedback payload B |  |  |
| CSI feedback payload C |  |  |
| Gain for upper bound without CSI compression over Benchmark – 5% UPT (Optional) | CSI feedback payload A |  |  |
| CSI feedback payload B |  |  |
| CSI feedback payload C |  |  |
| [CSI feedback reduction (%)] |  |  |
| … |  |  |  |
| FFS others |  |  |  |

where, for Max rank = 1 or 2: X ≤ 80 bits; Y = 100 bits – 140 bits; Z ≥ 230 bits and for Max rank = 3 or 4, X ≤ $\left⌈160/υ\right⌉$ bits; Y = $\left⌈200/υ\right⌉$ bits – $\left⌈280/υ\right⌉ $bits; Z ≥ $\left⌈460/υ\right⌉$ bits.

where, CSI feedback payload A ≤ β∙80 bits; B = β∙(100 bits – 140 bits); C ≥ β∙230 bits. Note: β=1 for Max rank = 1 and β = 1.5 for Max rank = 2, 3 or 4.

The CSI feedback reduction is provided for three CSI feedback overhead ranges (RU ≤ 39%, 40% ≤ RU ≤ 69%, RU ≥ 70%) , where for each CSI feedback overhead range of the benchmark, it is calculated as the gap between the CSI feedback overhead of benchmark and the CSI feedback overhead of AI/ML corresponding to the same mean UPT. Note: the CSI feedback overhead reduction and gain for mean/5%tile UPT are determined at the same payload size for benchmark scheme.

Notes: “Benchmark” means the type of Legacy CB used for comparison. “Quantization/dequantization method” includes the description of training awareness (Case 1/2-1/2-2), type of quantization/dequantizaion (SQ/VQ), etc. “Input type” means the input of the CSI generation part. “output type” means the output of the CSI reconstruction part.

Table 6.2.2-2: Evaluation results for CSI compression with model generalization/scalability, [Max rank value], [Scenario/configuration]

|  |  |  |
| --- | --- | --- |
|  | Source 1 | … |
| CSI generation part | AL/ML model backbone |  |  |
| Pre-processing |  |  |
| Post-processing |  |  |
| FLOPs/M |  |  |
| Number of parameters/M |  |  |
| [Storage /Mbytes] |  |  |
| CSI reconstruction part | AL/ML model backbone |  |  |
| [Pre-processing] |  |  |
| [Post-processing] |  |  |
| FLOPs/M |  |  |
| Number of parameters/M |  |  |
| [Storage /Mbytes] |  |  |
| Common description | Input type |  |  |
| Output type |  |  |
| Quantization /dequantization method |  |  |
| Generalization/Scalability method description if applicable, e.g., truncation, adaptation layer, etc. |  |  |
| Input/output scalability dimension if applicable, e.g., N>=1 NW part model(s) to M>=1 UE part model(s) |  |  |
| Dataset description | Ground-truth CSI quantization method |  |  |
| [Other assumptions/settings agreed to be reported] |  |  |
| Generalization Case 1 | Train (setting#A, size/k) |  |  |
| Test (setting#B, size/k) |  |  |
| SGCS, layer 1 | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| SGCS, layer 2 | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| NMSE, layer 1 | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| NMSE, layer 2 | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| …(other settings for Case 1) |  |  |  |
| … |  |  |  |
| Generalization Case 2 | Train (setting#A, size/k) |  |  |
| Test (setting#B, size/k) |  |  |
| …(results for Case 2) |  |  |  |
| …(other settings for Case 2) |  |  |  |
| Generalization Case 3 | Train (setting#A, size/k) |  |  |
| Test (setting#B, size/k) |  |  |
| …(results for Case 3) |  |  |  |
| Fine-tuning case (optional) |  |  |  |
| …(results for Fine-tuning) |  |  |  |
| …(other settings for Fine-tuning) |  |  |  |
| FFS others |  |  |  |

Notes: “Quantization/dequantization method” includes the description of training awareness (Case 1/2-1/2-2), type of quantization/dequantizaion (SQ/VQ), etc. “Input type” means the input of the CSI generation part. “output type” means the output of the CSI reconstruction part.

Table 6.2.2-3: Evaluation results for CSI compression of multi-vendor joint training without model generalization/scalability, [traffic type], [Max rank value], [RU]

|  |  |  |
| --- | --- | --- |
|  | Source 1 | … |
| Common description | Input type |  |  |
| Output type |  |  |
| [Training method] |  |  |
| Quantization /dequantization method |  |  |
| Dataset description | Train/k |  |  |
| Test/k |  |  |
| Ground-truth CSI quantization method (incl. scalar/codebook based quantization, and the parameters) |  |  |
| Case 1 (baseline): NW#1-UE#1 | UE part AI/ML model backbone/structure |  |  |
| Network part AI/ML model backbone/structure |  |  |
| ...(other NW-UE combinations for Case 1) |  |  |  |
| Case 2 (1 NW part to M>1 UE parts) | NW part model backbone/structure |  |  |
| UE#1 part model backbone/structure |  |  |
| UE#1 part training dataset description and size |  |  |
| … |  |  |
| UE#M part model backbone/structure |  |  |
| UE#M part training dataset description and size |  |  |
| Case 3 (N>1 NW parts to 1 UE part) | UE part model backbone/structure |  |  |
| NW#1 part model backbone/structure |  |  |
| NW#1 part training dataset description and size |  |  |
| … |  |  |
| NW#N part model backbone/structure |  |  |
| NW#N part training dataset description and size |  |  |
| Intermediate KPI type (SGCS/NMSE) |  |  |
| FFS other cases |  |  |  |
| Case 1: NW#1-UE#1: Intermediate KPI | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| …(results for other NW-UE combinations for Case 1) |  |  |  |
| Case 2: Intermediate KPI | CSI feedback payload X,  |  |  |
| NW-UE#1 |  |  |
| … |  |  |
| CSI feedback payload X,  |  |  |
| NW-UE#M |  |  |
| Case 3: Intermediate KPI | CSI feedback payload X,  |  |  |
| NW#1-UE |  |  |
| … |  |  |
| CSI feedback payload X,  |  |  |
| NW#N-UE |  |  |
| FFS other cases |  |  |  |
| FFS others |  |  |  |

Notes: “Quantization/dequantization method” includes the description of training awareness (Case 1/2-1/2-2), type of quantization/dequantizaion (SQ/VQ), etc. “Input type” means the input of the CSI generation part. “output type” means the output of the CSI reconstruction par

Table 6.2.2-4: Evaluation results for CSI compression of separate training without model generalization/scalability, [Max rank value]

|  |  |  |
| --- | --- | --- |
|  | Source 1 | … |
| Common description | Input type |  |  |
| Output type |  |  |
| Quantization /dequantization method |  |  |
| Shared output of CSI generation part/input of reconstruction part is before or after quantization |  |  |
| Dataset description | Test/k |  |  |
| Ground-truth CSI quantization method  |  |  |
| [Benchmark: NW#1-UE#1 joint training] | UE part AI/ML model backbone/structure |  |  |
| Network part AI/ML model backbone/structure |  |  |
| Training dataset size |  |  |
| ...(other NW-UE combinations for benchmark) |  |  |  |
| Case 1-NW first training | NW part model backbone/structure |  |  |
| UE#1 part model backbone/structure |  |  |
| UE#1 part training dataset description and size |  |  |
| … |  |  |
| UE#M part model backbone/structure |  |  |
| UE#M part training dataset description and size |  |  |
| [air-interface overhead of information (e.g., dataset) sharing] |  |  |
| Case 1-UE first training | NW#1 part model backbone/structure |  |  |
| NW#1 part training dataset description and size |  |  |
| … |  |  |
| NW#N part model backbone/structure |  |  |
| NW#N part training dataset description and size |  |  |
| UE part model backbone/structure |  |  |
| [air-interface overhead of information (e.g., dataset) sharing] |  |  |
| Case 2-UE first training | UE#1 part model backbone/structure |  |  |
| … |  |  |
| UE#M part model backbone/structure |  |  |
| UE part AI/ML model backbone/structure |  |  |
| NW part training dataset description and size (e.g., description/size of dataset from M UEs and how to merge) |  |  |
| Case 3-NW first training | NW#1 part model backbone/structure |  |  |
| … |  |  |
| NW#N part model backbone/structure |  |  |
| UE part model backbone/structure |  |  |
| UE part training dataset description and size (e.g., description/size of dataset from N NWs and how to merge) |  |  |
| Intermediate KPI type (SGCS/NMSE) |  |  |
| FFS other cases |  |  |  |
| NW#1-UE#1 joint training: Intermediate KPI | CSI feedback payload X |  |  |
| CSI feedback payload Y |  |  |
| CSI feedback payload Z |  |  |
| …(results for other 1-on-1 NW-UE joint training combinations) |  |  |  |
| Case 1-NW first training: Intermediate KPI | CSI feedback payload X, NW-UE#1 |  |  |
| … |  |  |
| CSI feedback payload X, NW-UE#M |  |  |
| CSI feedback payload Y … |  |  |
| CSI feedback payload Z … |  |  |
| Case 1-UE first training: Intermediate KPI | CSI feedback payload X, NW#1-UE |  |  |
| … |  |  |
| CSI feedback payload X, NW#N-UE |  |  |
| CSI feedback payload Y … |  |  |
| CSI feedback payload Z … |  |  |
| Case 2-NW first training: Intermediate KPI | CSI feedback payload X, NW#1-UE |  |  |
| … |  |  |
| CSI feedback payload X, NW#N-UE |  |  |
| CSI feedback payload Y … |  |  |
| CSI feedback payload Z … |  |  |
| Case 3-NW first training: Intermediate KPI | CSI feedback payload X, NW-UE#1 |  |  |
| … |  |  |
| CSI feedback payload X, NW-UE#M |  |  |
| CSI feedback payload Y …CSI feedback payload Z … |  |  |
|  |  |  |
| FFS other cases |  |  |  |
| FFS others |  |  |  |

Notes: “Quantization/dequantization method” includes the description of training awareness (Case 1/2-1/2-2), type of quantization/dequantizaion (SQ/VQ), etc. “Input type” means the input of the CSI generation part. “output type” means the output of the CSI reconstruction part.

Table 6.2.2-5 presents the performance results for the evaluation results of AI/ML-based CSI prediction without generalization/scalability verification.

For the evaluation of CSI prediction without model generalization/scalability verification, the following baselines are recommended to facilitate calibration of results:

* UE speed: 10km/h, 30km/h, 60km/h;
	+ Others can be additionally submitted, e.g., 120km/h.
* Input/Output type: Raw channel matrix
	+ Other can be additionally submitted, e.g., eigenvectors.
* Observation window: 5/5ms, 10/5ms
	+ Other observation window configurations can be additionally submitted for comparison, e.g., 3/5ms, 4/5ms, 8/2.5ms, 10/4ms, etc.
* Prediction window: 1/5ms/5ms
	+ Other prediction window configurations can be additionally submitted for comparison, e.g., 3/5ms/5ms, 5/5ms/5ms, 4/2.5ms/2.5ms, 5/4ms/4ms, etc.
* Performance metric for intermediate KPI: SGCS
	+ NMSE can be additionally submitted.
* Spatial consistency configuration (optional): procedure A with 50m decorrelation distance and channel updating periodicity of 1 ms.

 Table 6.2.2-5: Evaluation results for CSI prediction without model generalization/scalability, [traffic type], [Max rank value], [RU]

|  |  |  |
| --- | --- | --- |
|  | Source 1 | … |
| AI/ML model description | AL/ML model backbone |  |  |
| [Pre-processing] |  |  |
| [Post-processing] |  |  |
| FLOPs/M |  |  |
| Parameters/M |  |  |
| [Storage /Mbytes] |  |  |
| Input type |  |  |
| Output type |  |  |
| Assumptions | UE speed |  |  |
| CSI feedback periodicity |  |  |
| Observation window (number/distance) |  |  |
| Prediction window (number/distance [between prediction instances/distance from the last observation instance to the 1st prediction instance]) |  |  |
| Whether/how to adopt spatial consistency |  |  |
| Codebook type for CSI report |  |  |
| Dataset size | Train/k |  |  |
| Test/k |  |  |
| Benchmark 1 |  |  |
| Intermediate KPI #1 of Benchmark 1 |  |  |  |
| Gain for intermediate KPI#1 over Benchmark 1 |  |  |  |
| Intermediate KPI #2 of Benchmark 1 |  |  |  |
| Gain for intermediate KPI#2 over Benchmark 1 |  |  |  |
| Gain for eventual KPI (Benchmark 1) | Mean UPT |  |  |
| 5% UPT |  |  |
| Benchmark 2 |  |  |
| Intermediate KPI #1 of Benchmark 2 |  |  |  |
| Gain for intermediate KPI#1 over Benchmark 2 |  |  |  |
| Intermediate KPI #2 of Benchmark 2 |  |  |  |
| Gain for intermediate KPI#2 over Benchmark 2 |  |  |  |
| Gain for eventual KPI (Benchmark 2) | Mean UPT |  |  |
| 5% UPT |  |  |
| FFS others |  |  |  |

Table 6.2.2-6 presents the performance results for the evaluation results of AI/ML-based CSI prediction with model generalization/scalability verification.

For the evaluation of CSI prediction with model generalization/scalability verification, the following baselines are recommended to facilitate calibration of results:

* Performance metric for intermediate KPI: SGCS
	+ NMSE can be additionally submitted.

Table 6.2.2-6: Evaluation results for CSI prediction with model generalization/scalability [Max rank value]

|  |  |  |
| --- | --- | --- |
|  | Source 1 | … |
| AI/ML model description | AL/ML model description (e.g., backbone, structure) |  |  |
| [Pre-processing] |  |  |
| [Post-processing] |  |  |
| FLOPs/M |  |  |
| Parameters/M |  |  |
| [Storage /Mbytes] |  |  |
| Input type |  |  |
| Output type |  |  |
| Assumptions | CSI feedback periodicity |  |  |
| Observation window (number/distance) |  |  |
| Prediction window (number/distance between prediction instances/distance from the last observation instance to the 1st prediction instanc) |  |  |
| Whether/how to adopt spatial consistency |  |  |
| Generalization Case 1 | Train (setting#A, size/k) |  |  |
| Test (setting#A, size/k) |  |  |
| SGCS (1,…N, N is number of prediction instances) |  |  |
| NMSE (1,…N, N is number of prediction instances) |  |  |
| …(other settings and results for Case 1) |  |  |  |
| Generalization Case 2 | Train (setting#A, size/k) |  |  |
| Test (setting#A, size/k) |  |  |
| SGCS (1,…N, N is number of prediction instances) |  |  |
| NMSE (1,…N, N is number of prediction instances) |  |  |
| …(other settings and results for Case 2) |  |  |  |
| Generalization Case 3 | Train (setting#A, size/k) |  |  |
| Test (setting#A, size/k) |  |  |
| SGCS (1,…N, N is number of prediction instances) |  |  |
| NMSE (1,…N, N is number of prediction instances) |  |  |
| …(other settings and results for Case 3) |  |  |  |
| Fine-tuning case (optional) | Train (setting#A, size/k) |  |  |
| Fine-tune (setting#B, size/k) |  |  |
| Test (setting#B, size/k) |  |  |
| SGCS (1,…N, N is number of prediction instances) |  |  |
| NMSE (1,…N, N is number of prediction instances) |  |  |
| …(other settings and results for Fine-tuning) |  |  |  |
| FFS others |  |  |  |

***Observations***:

**CSI compression**

From the results for the *generalization verification* of AI/ML based CSI compression *over various deployment scenarios*:

15 sources show that compared to the case where the AI/ML model is trained with dataset subject to a certain deployment scenario#B and applied for inference with a same deployment scenario#B, it has degraded performance if the model is trained with deployment scenario#A and applied for inference with a different deployment scenario#B.

e.g., deployment scenario#A is UMa, deployment scenario#B is UMi, deployment scenario#A is UMi, deployment scenario#B is UMa, or deployment scenario#A is InH, deployment scenario#B is UMa/UMi.

6 sources observe that if deployment scenario#A and deployment scenario#B are subject to some certain combinations, the degradation is minor.

e.g., deployment scenario#A is UMa, deployment scenario#B is UMi, or deployment scenario#A is UMi, deployment scenario#B is UMa.

6 sources show that generalized performance of the AI/ML model can be achieved, if the training dataset is constructed with data samples subject to multiple deployment scenarios including deployment scenario#A and deployment scenario#B, and the trained AI/ML model applies inference on either deployment scenario#A or deployment scenario#B.

e.g., deployment scenario#A is InH, deployment scenario#B is UMa and/or UMi.

3 sources show that, compared to the case where the AI/ML model is trained on scenario#A and applied for inference on deployment scenario#B, the generalization performance can be improved, if the AI/ML model, after trained on deployment scenario#A, is updated based on a fine-tuned dataset subject to deployment scenario#B, and performs inference on deployment scenario#B.

e.g., deployment scenario#A is InH, deployment scenario#B is UMa or UMi.

From the results for the *generalization verification* of AI/ML based CSI compression *over various CSI payload sizes*:

Compared to the generalization Case 1 where the AI/ML model is trained with dataset subject to a certain CSI payload size#B and applied for inference with a same CSI payload size#B,

Generalized performance of the AI/ML model can be achieved (0%~5.9% loss) under generalization Case 3 for the inference on either CSI payload size#A or CSI payload size#B, if the training dataset is constructed with data samples subject to multiple CSI payload sizes including CSI payload size#A and CSI payload size#B, and an appropriate scalability solution is performed to scale the dimension of the AI/ML model, shown by 7 sources (6 sources showing 0%~2.2% loss, 3 sources showing 2.35%~5.9% loss). The scalability solution is adopted as follows:

* Pre/post-processing of truncation/padding, adopted by 3 sources, showing 0.2%~5.9% loss.
* Various quantization granularities, adopted by 1 source, showing 1.8%~4.7% loss.
* Adaptation layer in the AL/ML model, adopted by 3 sources, showing 0%~4.05% loss.

The above results are based on the following assumptions:

* Precoding matrix is used as the model input.
* Training data samples are not quantized, i.e., Float32 is used/represented.
* 1-on-1 joint training is assumed.
* Input/output scalability dimension Case 3 is adopted: A pair of CSI generation part with scalable input/output dimensions and CSI reconstruction part with scalable output and/or input dimensions.
* The performance metric is SGCS in linear value for layer 1/2.

**CSI Prediction**

For the AI/ML based CSI prediction,

11 sources show that the AI/ML-based CSI prediction outperforms the benchmark of the nearest historical CSI, wherein

5 sources show the gain of 14% ~ 26.47% using raw channel matrix as input.

2 sources show the gain of 5.64% ~ 9.49% using precoding matrix as input, which is in general worse than using raw channel matrix as input.

Note: spatial consistency is adopted in 1 source and not adopted in 5 sources.

The above results are based on the following assumptions:

* The observation window considers to start as early as 15ms~50ms.
* A future 4ms or 5ms instance from the prediction output is considered for calculating the metric.
* UE speed is 30km/h.
* The performance metric is SGCS in linear value for layer 1.

## 6.3 Beam Management

### 6.3.1 Evaluation assumptions, methodology and KPIs

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

***KPIs*:**

* Model complexity and computational complexity.

Beam prediction accuracy related KPIs, including:

* **Top-1 genie-aided Tx beam** considers the following definitions:
	+ Option A (baseline), the Top-1 genie-aided Tx beam is the Tx beam that results in the largest L1-RSRP over all Tx and Rx beams
	+ Option B (optional), the Top-1 genie-aided Tx beam is the Tx beam that results in the largest L1-RSRP over all Tx beams with specific Rx beam(s)
* **Top-1 genie-aided Tx-Rx beam pair** considers the following definitions:
	+ Option A: The Tx-Rx beam pair that results in the largest L1-RSRP over all Tx and Rx beams
	+ Other options not precluded and can be reported
* Average 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
* Beam prediction accuracy (%):
	+ Top-1 (%): the percentage of “the Top-1 genie-aided beam is Top-1 predicted beam”
	+ Top-K/1 (%): the percentage of “the Top-1 genie-aided beam is one of the Top-K predicted beams”
	+ Top-1/K (%) (Optional): the percentage of “the Top-1 predicted beam is one of the Top-K genie-aided beams”
	+ Where K >1 and values can be reported
* 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”
* Other beam prediction accuracy related KPIs are not precluded and can be reported

Impact of quantization error of inputed L1-RSRP (for training and inference) is to be studied. Existing quantization granularity of L1-RSRP (i.e., 1dB for the best beam, 2dB for the difference to the best beam) is the starting point for evaluation at least for network-sided model.

System performance related KPIs, including:

* UE throughput: CDF of UE throughput, average and 5%-ile UE throughput
* RS overhead reduction for BM-Case1:
	+ Option 1: "RS " OH reduction[%]=1-N/M
		- where N is the number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement for AI/ML
		- where M is the total number of beams (pairs) to be predicted
	+ Option 2: "RS " OH reduction[%]=1-N/M
		- where N is the total number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement for AI/ML, including the beams (pairs) required for additional measurements before/after the prediction if applicable
		- where M is the total number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement for baseline scheme, including the beams (pairs) required for additional measurements before/after the prediction if applicable
		- Companies report the assumption on additional measurements
* RS overhead reduction for BM-Case2:
	+ "RS " OH reduction[%]=1-N/M
		- where N is the total number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement for AI/ML, including the beams (pairs) required for additional measurements before/after the prediction if applicable.
		- where M is the total number of beams (pairs) (with reference signal (SSB and/or CSI-RS)) required for measurement for baseline scheme
		- Companies report the assumption on additional measurements.
		- Companies report the assumption on baseline scheme.
		- Companies report the assumption on T1 and T2.
* Other System performance related KPIs are not precluded and can be reported by companies

Other KPIs, including:

* UCI report overhead, at least for NW side beam prediction
* 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

For AI/ML models, which provide L1-RSRP as the model output, the accuracy of predicted L1-RSRP is to be evaluated. Companies optionally report average (absolute value)/CDF of the predicted L1-RSRP difference, where the predicted L1-RSRP difference is defined as the difference between the predicted L1-RSRP of Top-1[/K] predicted beam and the ideal L1-RSRP of the same beam.

At least for NW side beam prediction, UCI report overhead (e.g., number of UCI reports and UCI payload size) and/or UCI overhead reduction for inference of AI/ML model can be reported:

* UCI overhead reduction = 1- Total UCI payload size for AI/ML/Total UCI payload size of baseline.
* Companies expected to report detailed assumption of UCI for AI/ML and baseline, e.g., including quantization mechanism.

***Model generalization*:**

In the context of model generalization, scenarios may mean various deployment scenarios, various outdoor/indoor UE distributions, various UE mobility assumptions. Similarly, configurations may mean various UE parameters, various gNB settings, Various Set B of beam(pairs). The selected scenarios/configurations for generalization verification may consider the AI model inference node (e.g., @UE or @gNB) and use case (e.g., BM-Case1, or BM-Case2). Specifically, conside the following:

* Scenarios:
	+ Various deployment scenarios, e.g., UMa, UMi and others; e.g., 200m ISD or 500m ISD and others; e.g., same deployment, different cells with different configuration/assumption; e.g., gNB height and UE height;
	+ Various outdoor/indoor UE distributions, e.g., 100%/0%, 20%/80%, and others
	+ Various UE mobility, e.g., 3km/h, 30km/h, 60km/h and others
* Configurations (parameters and settings):
	+ Various UE parameters, e.g., number of UE Rx beams (including number of panels and UE antenna array dimensions)
	+ Various gNB settings, e.g., DL Tx beam codebook (including various Set A of beam(pairs) and gNB antenna array dimensions)
	+ Various Set B of beam (pairs)
	+ T1 for measurement /T2 for prediction for BM-Case2
* Other scenarios/configurations(parameters and settings) are not precluded and can be reported

Companies to report the selected scenarios/configurations for generalization verification. Note: other approaches for achieving good generalization performance for AI/ML-based schemes are not precluded.

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.
* Notes: Companies to report the ratio for dataset mixing. Number of the multiple scenarios/configurations can be larger than two.
* The following case for generalization verification, can be optionally considered by companies:
	+ 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.
		- Companies to report the fine-tuning dataset setting (e.g., size of dataset) and the improvement of performance

***Further details on evaluation assumptions***

The following options are studied on the selection of Set B of beams (pairs):

* Option 1: Set B is fixed across training and inference
* Option 2: Set B is variable (e.g., different beams (pairs) patterns in each time instance/report/measurement during training and/or inference)
	+ - Opt A: Set B is changed following a set of pre-configured patterns
		- Opt B: Set B is randomly changed among pre-configured patterns
		- Opt C: Set B is randomly changed among Set A beams (pairs)
		- Opt D: Set B is a subset of measured beams (pairs) Set C (including Set B = Set C), e.g. Top-K beams(pairs) of Set C
		- The number of beams(pairs) in Set B can be fixed or variable
	+ Companies report the number of pre-configured patterns used in the evaluation for Option 2: Set B is variable if applicable (e.g. Opt A and Opt B)
* Note: BM-Case1 and BM-Case2 may be considered for different option.

Note: This does not preclude the alternative that Set B is different from Set A.

For the evaluation of Option 2: Set B is variable (e.g., different beams (pairs) patterns in each time instance/report/measurement during training and/or inference), study the following options as AI/ML model inputs:

* Alt 1: *Implicit* information of Tx beam ID and/or Rx beam ID
	+ e.g., measurements of Set B of beams together with default values (e.g., 0) for the beams not in Set B are used as AI inputs in a certain order/ matrix/ vector. Detailed assumption can be reported.
* Alt 2: Tx beam ID and/or Rx beam ID is used as inputs of AI/ML *explicitly*

For the purpose of DL Tx beam prediction, consider the following options for Rx beam as AI/ML model input for training and/or inference if applicable:

* Option 1: Measurements of the “best” Rx beam with exhaustive beam sweeping for each model input sample. Companies expected to report how to select the “best” Rx beam(s).
* Option 2: Measurements of specific Rx beam(s).
	+ - Companies expected to report how to select specific Rx beam(s).
* Option 3: Measurements of random Rx beam(s) per model input sample.
* Option 4: Quasi-optimal Rx beam (i.e., not all the measurements as inputs of AI/ML are from the “best” Rx beam) with less measurement/RS overhead compared to exhaustive Rx beam sweeping.
	+ Identify the quasi-optimal Rx beams to be utilized for measuring Set B/Set C based on the previous measurements. Companies can report the time information and beam type (e.g., whether the same Tx beam(s) in Set B) of the reference signal to use. Companies expected to report the measurement/RS overhead together with the beam prediction accuracy, as well as, how to find the quasi-optimal Rx beam with “previous measurement”.
* Other options are not precluded and can be reported by companies

Performance with different types of labels are studied considering the following:

* Option 1a: Top-1 beam(pair) in Set A
* Option 1b: Top-K beam (pair)s in Set A
* Option 2a: L1-RSRPs per beam of all the beams(pairs) in Set A
* Option 2b: Top-K beam(pair)s in Set A and the corresponding L1-RSRPs
* Option 2c: Top-1 beam(pair) in Set A and the corresponding L1-RSRP

***Evaluation assumptions:***

Table 6.3.1-1 presents the baseline system level simulation assumptions for AI/ML in beam management evaluations.

Table 6.3.1-1: Baseline System Level Simulation assumptions for AI/ML in beam management evaluations

|  |  |
| --- | --- |
| Parameter | Value |
| 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 model | 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/hFor time domain beam prediction: 30km/h (baseline), 60km/h (optional) 90km/h (optional), 120km/h (optional)Other values are not precluded |
| UE distribution | 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/cell during data collection (training/testing) is reported by companies if relevant.For spatial domain beam prediction (optional to compare different UE distributions assumptions):* 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 | Antenna setup and port layouts at gNB: (4, 8, 2, 1, 1, 1, 1), (dV, dH) = (0.5, 0.5) λOther assumptions are not precluded. Companies to explain TXRU weights mapping.Companies to explain beam selection.Number of BS beams: 32 or 64 downlink Tx beams (max number of available beams) at NW side. Other values, e.g., 256 not precluded. |
| BS Antenna radiation pattern | TR 38.802 Table A.2.1-6, Table A.2.1-7 |
| UE Antenna Configuration | Antenna setup and port layouts at UE: (1, 4, 2, 1, 2, 1, 1), 2 panels (left, right)Other assumptions are not precludedCompanies to explain TXRU weights mapping.Companies to explain beam and panel selection.Number of UE beams: 4 or 8 downlink Rx beams (max number of available beams) per UE panel at UE side. Other values, e.g., 16 not precluded. |
| 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 | For system performance related KPI (if supported) evaluation (model inference), companies report either of the following traffic model: Option 1: Full buffer Option 2: FTP model with detail assumptions (e.g., FTP model 1, FTP model 3) |
| 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 to explain what scheme is used |
| Transmission scheme | Multi-antenna port transmission schemesNote: Companies explain details of the using transmission scheme. |
| Other simulation assumptions | Companies to explain serving TRP selectionCompanies 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 (baseline)Other values (e.g., 34 dBm) not precluded |
| Maximum UE Tx Power | 23 dBm |
| BS receiver Noise Figure | 7 dB |
| UE receiver Noise Figure | 10 dB |
| Inter site distance | 200 m |
| BS Antenna height | 25 m |
| UE Antenna height | 1.5 m |
| Car penetration Loss | 38.901, sec 7.4.3.2: μ = 9 dB, σp = 5 dB |
| UE measurements/reports | At least for Temporal Downlink beam prediction: * Periodicity of time instance for each measurement/report in T1: 20ms, 40ms, 80ms, [100ms], 160ms, [960ms]. Other values can be reported.
* Number of time instances for measurement/report in T1 can be reported. Time instance(s) for prediction can be reported.
 |
| Scenario | Dense Urban (macro-layer only, TR 38.913) is the basic scenario for dataset generation and performance evaluation. Other scenarios are not precluded.  |
| Spatial consistency  | At least for BM-Case1, companies report the one of spatial consistency procedures: * Procedure A in TR38.901
* Procedure B in TR38.901
 |
| UE trajectory model | UE trajectory model is defined at least for *temporal beam prediction* in initial phase of the evaluation. Further details below. UE trajectory model is not necessarily to be defined at least for *spatial-domain beam prediction* in initial phase of the evaluation. |
| UE rotation | UE speed to be reported. Note: UE rotation speed = 0, i.e., no UE rotation, is not precluded |
| Baseline for performance evaluation | For *temporal beam prediction*: * Option 1: 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 to 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.* 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)
	+ Option 2: Select the best beam within Set A of beams based on the measurement of RS resources from Set B of beams
	+ Other options are not precluded.
 |

For temporal beam prediction, the following options are considered as a starting point for *UE trajectory model*. Companies report further changes or modifications from those. Other options are not precluded. UE orientation can be independently modelled from UE moving trajectory. Other UE orientation model is not precluded:

* Option 1: Linear trajectory model with random direction change.
	+ UE moving trajectory: UE will move straight along the selected direction to the end of an 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 moves straight within the time interval with the fixed speed.
* Option 2: Linear trajectory model with random and smooth direction change.
	+ UE moving trajectory: UE will change the moving direction by multiple steps within an 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 moves straight within the time sub-interval with the fixed speed.
* Option 3: 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 seconds if it is in time, or set as D meter if it is in distance.
	+ The trajectory sampling interval granularity depends on UE speed.
* UE can move straight along the entire trajectory, or
* UE can move straight during the time interval, where the time interval is provided by using an exponential distribution with average interval length ΔT
	+ 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 hits 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.
	+ The length of observation window + prediction window is not fixed and companies can report their values.

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

Table 6.3.1-2 presents the baseline link level simulation assumptions for AI/ML in beam management evaluations.

Table 6.3.1-2: Baseline Link Level Simulation assumptions for AI/ML in beam management evaluations

|  |  |
| --- | --- |
| Parameter | Value |
| Frequency | 30GHz. |
| Subcarrier spacing | 120kHz |
| Data allocation | [8 RBs] as baseline, companies can report larger number of RBsFirst 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 = 100nsNLOS channel: CDL-A/B/C extension, DS = 100nsCompanies to explain 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 down-tilt 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 precludedCompanies 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.  |

### 6.3.2 Performance results

Table 6.3.2-1 presents the performance results.

Table 6.3.2-1: Evaluation results for [BM-Case1 or BM-Case2] without model generalization for [DL Tx beam prediction or Tx-Rx beam pair prediction or Rx beam prediction

|  |  |  |
| --- | --- | --- |
|  | Company A | … |
| Assumptions | Number of [beams/beam pairs] in Set A |  |  |
| Number of [beams/beam pairs] in Set B |  |  |
| Baseline scheme |  |  |
| AI/ML model input/output | Model input |  |  |
| Model output |  |  |
| Data Size | Training  |  |  |
| Testing  |  |  |
| AI/ML model | [Short model description] |  |  |
| Model complexity |  |  |
| Computational complexity |  |  |
| Evaluation results [With AI/ML / baseline] | [Beam prediction accuracy (%)] | [KPI A] |  |  |
| [KPI B]… |  |  |
| [L1-RSRP Diff] | [Average L1-RSRP diff]… |  |  |
| [System performance] | [RS overhead Reduction (%) / RS overhead] |  |  |
| [UCI report] |  |  |
| [UPT]… |  |  |

***Observations***:

*BM-Case1*: Spatial-domain Downlink beam prediction for Set A of beams based on measurement results of Set B of beams

At least for BM-Case1 for inference of DL Tx beam with L1-RSRPs of all beams in Set B, existing quantization granularity of L1-RSRP (i.e., 1 dB for the best beam, 2 dB for the difference to the best beam) causes [a minor loss x%~y%, if applicable] in beam prediction accuracy compared to unquantized L1-RSRPs of beams in Set B.

When *Set B is a subset of Set A*, AI/ML can provide good beam prediction performance with less measurement/RS overhead without considering generalization aspects *with the measurements from the best Rx beam* without UE rotation:

(A)With measurements of fixed Set B of beams corresponding to 1/4 of Set A beams:

* evaluation results [from 4 sources] indicate that, AI/ML can achieve [about 70%~80%] beam prediction accuracy of Top-1 DL Tx beam, evaluation results [from 6 sources] indicate that, AI/ML can achieve [about 80%~90%] beam prediction accuracy of Top-1 DL Tx beam, and evaluation results [from 4 sources] show [more than 90%] beam prediction accuracy of Top-1 DL Tx beam.
* evaluation results [from 8 sources] indicate that, AI/ML can achieve [more than 90%] beam prediction accuracy for Top-1 DL Tx beam with 1dB margin.
* evaluation results [from 8 sources] indicate that, AI/ML can achieve [more than 80%] beam prediction accuracy for Top-2 DL Tx beam. The beam prediction accuracy increases with K.
* evaluation results [from 9 sources] indicate that, the average L1-RSRP difference of Top-1 predicted beam can be [below or about 1dB].

(B) With measurements of fixed Set B of beams corresponding to 1/8 of Set A beams:

* evaluation results [from 2 sources] indicate that, AI/ML can achieve [about 50%] beam prediction accuracy of Top-1 DL Tx beam, evaluation results [from 3 sources] show [about 60%~70%] beam prediction accuracy of Top-1 DL Tx beam, and evaluation results [from 2 sources] show [about 70%~80] beam prediction accuracy of Top-1 DL Tx beam.
* evaluation results [from 4 sources] indicate that, AI/ML can achieve [70%-90%] beam prediction accuracy for Top-1 DL Tx beam prediction with 1dB margin
* evaluation results [from 2 sources] indicate that, AI/ML can achieve [about 70%~ 80%] beam prediction accuracy for Top-2 DL Tx beam, and evaluation results [from 4 sources] indicate that, AI/ML can achieve [more than 80%] beam prediction accuracy for Top-2 DL Tx beam. The beam prediction accuracy increases with K.

Note that ideal measurements are assumed:

* Beams could be measured regardless of their SNR.
* No measurement error.
* Measured in a single-time instance (within a channel-coherence time interval).
* No quantization for the L1-RSRP measurements.
* No constraint on UCI payload overhead for full report of the L1-RSRP measurements of Set B for NW-side models are assumed.

(C) For the case that Set B of beams is changed among pre-configured patterns, evaluation results [from 4 sources] show that the beam prediction accuracy degrades [no more than 5%] in terms of Top-1 beam prediction accuracy compared to when Set B is fixed across training and inference, where the [one source] used [24] pre-configured patterns and the rest of sources use [4 or 5] patterns; evaluation results [from 1 source] show that the beam prediction accuracy degrades [about 10%] in terms of Top-1 beam prediction accuracy compared to when Set B is fixed across training and inference.

Note: the above performance can also be treated as training with mixed patterns of Set B of beam, and testing with mixed patterns Set B of beams. The measurements are obtained from the best Rx beam without UE rotation.

Note that ideal measurements are assumed:

* Beams could be measured regardless of their SNR.
* No measurement error.
* Measured in a single-time instance (within a channel-coherence time interval).
* No quantization for the L1-RSRP measurements.
* No constraint on UCI payload overhead for full report of the L1-RSRP measurements of Set B for NW-side models are assumed.
* This observation is based on Set B patterns that were chosen by each company

## 6.4 Positioning accuracy enhancements

### 6.4.1 Evaluation assumptions, methodology and KPIs

***KPIs*:**

* For all scenarios and use cases, the main KPI is the CDF percentiles of horizonal accuracy
	+ The CDF percentiles to analyse are: 90% (baseline) and {50%, 67%, 80%} (optional)
	+ Vertical accuracy can be optionally reported
	+ Target positioning requirements for horizonal accuracy and vertical accuracy are not defined for AI/ML-based positioning evaluation
* Model complexity and computational complexity, e.g., FLOPS
	+ Reported via the metric of “number of model parameters”. Note: if complex value is used in modelling process, the number of the model parameters is doubled, which is also applicable for other AIs of AI/ML.
* For AI/ML assisted positioning, an intermediate performance metric of *model output*

***Model generalization*:**

To investigate the model generalization capability, at least the following aspect(s) are considered for the evaluation for AI/ML based positioning:

* Different drops: Training dataset from drops {A0, A1,…, AN-1}, test dataset from unseen drop(s) (i.e., different drop(s) than any in {A0, A1,…, AN-1}). Here N>=1.
* Clutter parameters, e.g., training dataset from one clutter parameter (e.g., {40%, 2m, 2m}), test dataset from a different clutter parameter (e.g., {60%, 6m, 2m});
* Network synchronization error, e.g., training dataset without network synchronization error, test dataset with network synchronization error;
* UE/gNB RX and TX timing error: The baseline non-AI/ML method may enable the Rel-17 enhancement features (e.g., UE Rx TEG, UE RxTx TEG).
* InF scenarios, e.g., training dataset from one InF scenario (e.g., InF-DH), test dataset from a different InF scenario (e.g., InF-HH)
	+ If an InF scenario different from InF-DH is evaluated for the model generalization capability, the selected parameters (e.g., clutter parameters) are compliant with TR 38.901 Table 7.2-4 (Evaluation parameters for InF). Note: In TR 38.857 Table 6.1-1 (Parameters common to InF scenarios), InF-SH scenario uses the clutter parameter {20%, 2m, 10m} which is compliant with TR 38.901.
* Other aspects are not excluded.

For AI/ML assisted approach, for a given AI/ML model design (e.g., input, output, single-TRP vs multi-TRP), identify the generalization aspects where model fine-tuning/mixed training dataset/model switching is necessary.

***Evaluation assumptions*:**

The IIoT indoor factory (InF) scenario is a prioritized scenario for evaluation of AI/ML based positioning. Specifically, InF-DH sub-scenario is prioritized for FR1 and FR2.

Reuse the common scenario parameters defined in Table 6-1 of TR 38.857. For evaluation of InF-DH scenario, the parameters are modified from TR 38.857 Table 6.1-1 as shown in Table 6-5. The parameters in the table are applicable to InF-DH at least. If other InF sub-scenario is prioritized in addition to InF-DH, some parameters in Table 6-5 may be updated:

**Table 6-4.1-1: Parameters common to InF scenario (Modified from TR 38.857 Table 6.1-1) for AI/ML based positioning evaluations**

|  |  |  |
| --- | --- | --- |
|  | FR1 specific values | FR2 specific values |
| Channel model | InF-DH | InF-DH |
| Layout | Hall size | InF-DH: (baseline) 120x60 m(optional) 300x150 m |
| BS locations | 18 BSs on a square lattice with spacing D, located D/2 from the walls.- for the small hall (L=120m x W=60m): D=20m- for the big hall (L=300m x W=150m): D=50m |
| Room height | 10 m |
| Total gNB TX power, dBm | 24dBm | 24dBmEIRP should not exceed 58 dBm |
| gNB antenna configuration | (M, N, P, Mg, Ng) = (4, 4, 2, 1, 1), dH=dV=0.5λ according to Table A.2.1-7 in TR 38.802.Note: Other gNB antenna configurations are not precluded for evaluation. | (M, N, P, Mg, Ng) = (4, 8, 2, 1, 1), dH=dV=0.5λ according to Table A.2.1-7 in TR 38.802.One TXRU per polarization per panel is assumed. |
| gNB antenna radiation pattern | Single sector according to Table A.2.1-7 in TR 38.802. | 3-sector antenna configuration according to Table A.2.1-7 in TR 38.802 |
| Penetration loss | 0dB |
| Number of floors | 1 |
| UE horizontal drop procedure | Uniformly distributed over the horizontal evaluation area for obtaining the CDF values for positioning accuracy, The evaluation area should be selected from- (baseline) the whole hall area, and the CDF values for positioning accuracy is obtained from whole hall area.- (optional) the convex hull of the horizontal BS deployment, and the CDF values for positioning accuracy is obtained from the convex hull. |
| UE antenna height | Baseline: 1.5m(Optional): uniformly distributed within [0.5, X2] m, where X2 = 2m for scenario 1 (InF-SH) and X2= *hc* for scenario 2 (InF-DH)  |
| UE mobility | 3km/h  |
| Min gNB-UE distance (2D), m | 0m |
| gNB antenna height | Baseline: 8m(Optional): two fixed heights, either {4, 8} m, or {max(4, *hc*), 8}. |
| Clutter parameters: {density *r*, height *hc*, size *dclutter*} | High clutter density:- {60%, 6m, 2m}- {40%, 2m, 2m} - can be considered optional in the evaluations considering specific AI/ML designs. |
| Channel Estimation | Assumption, e.g., realistic or ideal channel estimation, error models, receiver algorithms should be reported.  |
| Spatial consistency | If enabled for the evaluations:Model at least one of: large scale parameters, small scale parameters and absolute time of arrival, where:* the large scale parameters are according to Section 7.5 of TR 38.901 and correlation distance = *dclutter*/2 for InF (Section 7.6.3.1 of TR 38.901)
* the small scale parameters are according to Section 7.6.3.1 of TR 38.901
* the absolute time of arrival is according to Section 7.6.9 of TR 38.901

Baseline evaluation does not incorporate spatially consistent UT/BS mobility modelling (Section 7.6.3.2 of TR 38.901). It is optional to implement it. |
| Baseline for performance evaluation | Existing Rel-16/Rel-17 positioning methods. Specific existing positioning method (e.g., DL-TDOA, Multi-RTT) used as comparison is to be reported.  |

For the evaluation of AI/ML based positioning, the study of model input due to different number of TRPs include the following approaches. Proponents of each approach are to provide analysis for model performance, signalling overhead (including training data collection and model inference), model complexity and computational complexity.

* Approach 1: Model input size stays constant as NTRP=18. The number of TRPs (N’TRP) that provide measurements to model input varies. When N’TRP < NTRP, the remaining (NTRP - N’TRP) TRPs do not provide measurements to model input, i.e., measurement value is set to 0.
	+ Approach 1-A. The set of TRPs (N’TRP) that provide measurements is fixed.
	+ Approach 1-B. The set of TRPs (N’TRP) that provide measurements can change dynamically.
	+ Note: for Approach 1, one model is provided to cover the entire evaluation area.
* Approach 2: The TRP dimension of model input is equal to the number of TRPs (N’TRP) that provide measurements as model input. When N’TRP < NTRP, the remaining (NTRP - N’TRP) TRPs are ignored by the given model. For a given AI/ML model, the set of TRPs (N’TRP) that provide measurements is fixed.
	+ For Approach 2: one model can be provided to cover the entire evaluation area, which is equivalent to deploying N’TRP TRPs in the evaluation area for positioning if ignoring the potential inference from the remaining (18 - N’TRP) TRPs.
	+ For Approach 2, if Nmodel (Nmodel >1) models are provided to cover the entire evaluation area, the total model complexity is the summation of the Nmodel models.

In the evaluation of AI/ML based positioning, if N’TRP<18, the set of N’TRP TRPs that provide measurements to model input of an AI/ML model are reported using the TRP indices shown below:



For the evaluation of AI/ML based positioning method, the measurement size and signalling overhead for the model input is reported.

Impact from implementation imperfections is to be studied. Further, how AI/ML positioning accuracy is affected by user density/size of the training dataset is to be also studied. Note: details of user density/size of training dataset to be reported in the evaluation.

*Labels:*

The performance impact from availability of the ground truth labels (i.e., some training data may not have ground truth labels) is to be studied. The learning algorithm (e.g., supervised learning, semi-supervised learning, unsupervised learning) is to be reported by participating companies and, when providing evaluation results, data labelling details need to be described, including:

* Meaning of the label (e.g., UE coordinates; binary identifier of LOS/NLOS; ToA)
* Percentage of training data without label, if incomplete labelling is considered in the evaluation
* Imperfection of the ground truth labels, if any

Whether, and if so how, an entity can be used to obtain ground truth label and/or other training data is to be studied.

For direct AI/ML positioning, the impact of labelling error to positioning accuracy is studied considering:

* The ground truth label error in each dimension of x-axis and y-axis can be modelled as a truncated Gaussian distribution with zero mean and standard deviation of L meters, with truncation of the distribution to the [-2\*L, 2\*L] range. Value L is up to sources.
* [Whether/how to study the impact of labelling error to label-based model monitoring methods]
* [Whether/how to study the impact of labelling error for AI/ML assisted positioning.]

Synthetic dataset generated according to the statistical channel models in TR 38.901 is used for model training, validation, and testing. The dataset is generated by a system level simulator based on 3GPP simulation methodology.

As a starting point, the training, validation and testing dataset are from the same large-scale and small-scale propagation parameters setting. Subsequent evaluations can study the performance when the training dataset and testing dataset are from different settings.

For AI/ML-based positioning evaluation, RAN1 does not attempt to define any common AI/ML model as a baseline. Companies can evaluate the impact of at least the following issues related to measurements on the positioning accuracy of the AI/ML model. The simulation assumptions reflecting these issues are up to companies.

* SNR mismatch (i.e., SNR when training data are collected is different from SNR when model inference is performed).
* Time varying changes (e.g., mobility of clutter objects in the environment)
* Channel estimation error

Details of the training dataset generation are to be reported, including:

* The size of training dataset, e.g., the total number of UEs in the evaluation area for generating training dataset;
* The distribution of UE location for generating the training dataset may be one of the following:
	+ Option 1: grid distribution, i.e., one training data is collected at the center of one small square grid, where, for example, the width of the square grid can be 0.25/0.5/1.0 m.
	+ Option 2: uniform distribution, i.e., the UE location is randomly and uniformly distributed in the evaluation area.

***Sub-use case specific*:**

For AI/ML-assisted positioning, companies report which construction is applied in their evaluation:

1. Single-TRP construction: the input of the ML model is the channel measurement between the target UE and a single TRP, and the output of the ML model is for the same pair of UE and TRP.
2. Multi-TRP construction: the input of the ML model contains N sets of channel measurements between the target UE and N (N>1) TRPs, and the output of the ML model contains N sets of values, one for each of the N TRPs.

Notes: For a measurement (e.g., RSTD) which is a relative value between a given TRP and a reference TRP, the TRP in “single-TRP” and “multi-TRP” refers to the given TRP only. For single-TRP construction, companies report whether they consider same model for all TRPs or N different models for TRPs.

When single-TRP construction is used for the AI/ML model, companies report at least the AI/ML complexity (Model complexity, Computation complexity) for N TRPs, which are used to determine the position of a target UE considering the various constructions in Table 6-6 below.

**Table 6.4.1-2: Model complexity and computational complexity to support N TRPs for a target UE**

|  |  |  |
| --- | --- | --- |
|  | Model complexity to support N TRPs | Computational complexity to process N TRPs |
| Single-TRP, same model for N TRPs | $$P\_{S}$$where $P\_{S}$ is the model complexity for one TRP and the same model is used for N TRPs. | $$N×C\_{S}$$where $C\_{S}$ is the computation complexity of the same model for one TRP. |
| Single-TRP, N models for N TRPs | $$\sum\_{i=1,…N}^{}P\_{S,i}$$where $P\_{S,i}$ is the model complexity for the i-th AI/ML model. | $$\sum\_{i=1,…N}^{}C\_{S,i}$$where $C\_{S,i}$ is the computation complexity for the i-th AI/ML model. |
| Multi-TRP (i.e., one model for N TRPs) | $$P\_{M}$$where $P\_{M}$ is the model complexity for the one model. | $$C\_{M}$$where $C\_{M}$ is the computation complexity for the one model. |

Note: The reported model complexity above is intended for inference and may not be directly applicable to complexity of other LCM aspects

For evaluation of AI/ML assisted positioning, the following intermediate performance metrics are used:

* LOS classification accuracy, if the model output includes LOS/NLOS indicator of hard values, where the LOS/NLOS indicator is generated for a link between UE and TRP;
* Timing estimation accuracy (expressed in meters), if the model output includes timing estimation (e.g., ToA, RSTD).
* Angle estimation accuracy (in degrees), if the model output includes angle estimation (e.g., AoA, AoD).
* Companies provide info on how LOS classification accuracy and timing/angle estimation accuracy are estimated, if the ML output is a soft value that represents a probability distribution (e.g., probability of LOS, probability of timing, probability of angle, mean and variance of timing/angle, etc.)

For AI/ML assisted positioning the following is considered for the various types of model output:

* TOA: the impact of labelling error to TOA accuracy and/or positioning accuracy is studied.
	+ The ground truth label error of TOA is calculated based on location error. The location error in each dimension of x-axis and y-axis can be modelled as a truncated Gaussian distribution with zero mean and standard deviation of L meters, with truncation of the distribution to the [-2\*L, 2\*L] range.
* LOS/NLOS indicator: the impact of labelling error to LOS/NLOS indicator accuracy and/or positioning accuracy is studied.
	+ The ground truth label error of LOS/NLOS indicator can be modelled as m% LOS label error and n% NLOS label error.

***~~Location of Positioning computation vs. AI/ML model location cases~~***~~:~~

* ~~Case 1: UE-based positioning with UE-side model, direct AI/ML or AI/ML assisted positioning~~
* ~~Case 2a: UE-assisted/LMF-based positioning with UE-side model, AI/ML assisted positioning~~
* ~~Case 2b: UE-assisted/LMF-based positioning with LMF-side model, direct AI/ML positioning~~
* ~~Case 3a: NG-RAN node assisted positioning with gNB-side model, AI/ML assisted positioning~~
* ~~Case 3b: NG-RAN node assisted positioning with LMF-side model, direct AI/ML positioning~~

***Model monitoring:***

For AI/ML assisted approach, the performance of model monitoring metrics is studied at least where the metrics are obtained from inference accuracy of model output. Further, the performance of label-free model monitoring methods, which do not require ground truth label (or its approximation) for model monitoring, is to be studied.

For direct AI/ML positioning, the performance of model monitoring methods is studied, including:

* Label based methods, where ground truth label (or its approximation) is provided for monitoring the accuracy of model output.
* Label-free methods, where model monitoring does not require ground truth label (or its approximation).

where at least the following entities are identified to derive monitoring metric

* UE at least for Case 1 and 2a (with UE-side model)
* gNB at least for Case 3a (with gNB-side model)
* LMF at least for Case 2b and 3b (with LMF-side model

***Model Fine-tuning*:**

For evaluation of the potential performance benefits of model finetuning, training dataset setting (e.g., training dataset size necessary for performing model finetuning) and horizontal positioning accuracy (in meters) before and after model finetuning**,** are to be reported.

For both direct and AI/ML assisted positioning methods, investigate at least the impact of the amount of fine-tuning data on the positioning accuracy of the fine-tuned model. The fine-tuning data is the training dataset from the target deployment scenario.

### 6.4.2 Performance results

If fine-tuning is not evaluated, Table 6.4.2-1 presents the performance results.

Evaluation area shall be included in the evaluations reporting template, assuming the same evaluation area is used for training dataset and test dataset. Note that the baseline evaluation area for InF-DH = 120x60 m. If different evaluation areas are used for training dataset and test dataset, they are marked out separately under “Train” and “Test” instead.

**Table 6.4.2-1: Evaluation results for AI/ML model deployed on [UE or network]-side, [with or without] model generalization, [short model description], UE distribution area = [e.g., 120x60 m, 100x40 m]**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Input | Model Output | Label | Clutter parameters | Dataset Size | AI/ML complexity | Horizontal positioning accuracy at CDF=90% (m) |
| Train | Test | Model compl. | Compu compl. | AI/ML |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |

If fine-tuning is evaluated, Table 6.4.2-2 presents the performance results.

**Table 6.4.2-2: Evaluation results for AI/ML model deployed on [UE or network]-side, [with or without] model generalization, [short model description], UE distribution area = [e.g., 120x60 m, 100x40 m]**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model Input | Model Output | Label | Settings (e.g., drops, clutter param, mix) | Dataset Size | AI/ML complexity | Horizontal positioning accuracy at CDF=90% (m) |
| Train | Fine-tune | Test | Train | Fine-tune | Test | Model compl. | Compu compl. | AI/ML |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |

***Observations***:

Direct AI/ML positioning can significantly improve the positioning accuracy compared to existing RAT-dependent positioning methods when the generalization aspects are not considered.

For InF-DH with clutter parameter setting {60%, 6m, 2m}, evaluation results [submitted to RAN1#111] indicate that the direct AI/ML positioning can achieve horizontal positioning accuracy of <1m at CDF=90%, as compared to >15m for conventional positioning methods.

Evaluation of the following generalization aspects show that the positioning accuracy of direct AI/ML positioning deteriorates when the AI/ML model is trained with dataset of one deployment scenario, while tested with dataset of a different deployment scenario.

* The generalization aspects include:
	+ Different drops
	+ Different clutter parameters
	+ Different InF scenarios
	+ Network synchronization error
* Companies have provided evaluation results which show that the positioning accuracy on the test dataset can be improved by better training dataset construction and/or model fine-tuning/re-training.
	+ Better training dataset construction: The training dataset is composed of data from multiple deployment scenarios, which include data from the same deployment scenario as the test dataset.
	+ Model fine-tuning/re-training: the model is re-trained/fine-tuned with a dataset from the same deployment scenario as the test dataset.

Note: ideal model training and switching may provide the upper bound of achievable performance when the AI/ML model needs to handle different deployment scenarios.

For AI/ML based positioning method, companies have submitted evaluation results to show that for their evaluated cases, for a given company’s model design, a lower complexity (model complexity and computational complexity) model can still achieve acceptable positioning accuracy (e.g., <1m), albeit degraded, when compared to a higher complexity model.

For direct AI/ML positioning, for L in the range of 0.25m to 5m, the positioning error increases approximately in proportion to L, where L (in meters) is the standard deviation of truncated Gaussian Distribution of the ground truth label error.

AI/ML assisted positioning can significantly improve the positioning accuracy compared to existing RAT-dependent positioning methods when the generalization aspects are not considered.

* For InF-DH with clutter parameter setting {40%, 2m, 2m}, evaluation results [submitted to RAN1#111] indicate that the AI/ML assisted positioning can achieve horizontal positioning accuracy of <0.4m at CDF=90%, as compared to >9m for conventional positioning method.
* For InF-DH with clutter parameter setting {60%, 6m, 2m}, evaluation results [submitted to RAN1#111] indicate that the AI/ML assisted positioning can achieve horizontal positioning accuracy of <1m at CDF=90%, as compared to >15m for conventional positioning method.

*Model monitoring*

For AI/ML assisted positioning, evaluation results have been provided by sources for label-based model monitoring methods. With TOA and/or LOS/NLOS indicator as model output, the estimated ground truth label (i.e., TOA and/or LOS/NLOS indicator) is provided by the location estimation from the associated conventional positioning method. The associated conventional positioning method refers to the method which utilizes the AI/ML model output to determine target UE location.

For both direct AI/ML and AI/ML assisted positioning, evaluation results have been provided by sources to demonstrate the feasibility of label-free model monitoring methods.

*Generalization*

For both direct AI/ML and AI/ML assisted positioning, evaluation results submitted show that with CIR model input for a trained model,

* For two SNR/SINR values S1 (dB) and S2 (dB), S1 ≥ S2 + 15 dB, positioning error of a model trained with data of S1 (dB) and tested with data of S2 (dB) is more than 5.75 times that of the model trained and tested with data of S1 (dB).
* For two SNR/SINR values S1 (dB) and S2 (dB), S1 ≤ S2 – 10 dB, the generalization performance of a model trained with data of S1 (dB) and tested with data of S2 (dB) is better than the performance of a model trained with data of S2 (dB) and tested with data of S1 (dB). Positioning error of a model trained with data of S2 (dB) and tested with data of S1 (dB) is more than 2.97 times that of the model trained with data of S1 (dB) and tested with data of S2 (dB).

Note: here the positioning error is the horizonal positioning error (meters) at CDF=90%.

For direct AI/ML positioning, based on evaluation results of timing error in the range of 0-50 ns, when the model is trained by a dataset with UE/gNB RX and TX timing error t1 (ns) and tested in a deployment scenario with UE/gNB RX and TX timing error t2 (ns), for a given t1,

* For a case evaluated by a given source, the positioning accuracy of cases with t2 smaller than t1 is better than the cases with t2 equal to t1. For example,
	+ For the case of (t1, t2)=(50ns, 30ns), evaluation results submitted to RAN1#112bis show the positioning error of (t1, t2)=(50ns, 30ns) is 0.82~0.86 times that of (t1, t2)=(50ns, 50ns).
	+ For the case of (t1, t2)=(50ns, 0ns), evaluation results submitted to RAN1#112bis show the positioning error of (t1, t2)=(50ns, 0ns) is 0.80~0.82 times that of (t1, t2)=(50ns, 50ns).
* For a case evaluated by a given source, the positioning accuracy of cases with t2 greater than t1 is worse than the cases with t2 equal to t1. The larger the difference between t1 and t2, the more the degradation. For example,
	+ For the case of (t1, t2)=(0ns, 10ns), evaluation results submitted to RAN1#112bis show the positioning error of (t1, t2)=(0ns, 10ns) is 1.25~18.7 times that of (t1, t2)=(0ns, 0ns).
	+ For the case of (t1, t2)=(0ns, 50ns), evaluation results submitted to RAN1#112bis show the positioning error of (t1, t2)=(0ns, 50ns) is 3.5~18.3 times that of (t1, t2)=(0ns, 0ns).

Note: here the positioning error is the horizonal positioning error (meters) at CDF=90%.

For direct AI/ML positioning, based on evaluation results of network synchronization error in the range of 0-50 ns, when the model is trained by a dataset with network synchronization error t1 (ns) and tested in a deployment scenario with network synchronization error t2 (ns), for a given t1,

* For a case evaluated by a given source, the positioning accuracy of cases with t2 smaller than t1 is better than the cases with t2 equal to t1. For example,
	+ For the case of (t1, t2)=(50ns, 10ns), evaluation results submitted to RAN1#112bis show the positioning error of (t1, t2)=(50ns, 10ns) is 0.74~0.83 times that of (t1, t2)=(50ns, 50ns).
	+ For the case of (t1, t2)=(50ns, 0ns), evaluation results submitted to RAN1#112bis show the positioning error of (t1, t2)=(50ns, 0ns) is 0.73~0.82 times that of (t1, t2)=(50ns, 50ns).
* For a case evaluated by a given source, the positioning accuracy of cases with t2 greater than t1 is worse than the cases with t2 equal to t1. The larger the difference between t1 and t2, the more the degradation. For example,
	+ For the case of (t1, t2)=(0ns, 10ns), evaluation results submitted to RAN1#112bis show the positioning error of (0ns, 10ns) is 1.17~9.5 times that of (0ns, 0ns).
	+ For the case of (t1, t2)=(0ns, 50ns), evaluation results submitted to RAN1#112bis show the positioning error of (0ns, 50ns) is 10~40 times that of (0ns, 0ns).

Note: here the positioning error is the horizonal positioning error (meters) at CDF=90%.

# 7 Potential Specification Impact Assessment

## 7.1 General observations

[Editor’s note: this section is meant to capture general observations on specification impact considering possibly, different timelines (e.g, short-term vs. long-term)]

## 7.2 Physical layer aspects

In this section, aspects related to, e.g., the potential specification of the AI Model lifecycle management, and dataset construction for training, validation and test for the selected use cases are considered.

In addition, use case and collaboration level specific specification impact is documented, such as new signalling, means for training and validation data assistance, assistance information, measurement, and feedback.

### 7.2.1 Common framework

### 7.2.2 CSI feedback enhancement

***Items considered***:

In **CSI compression** using two-sided model use case:

*Performance monitoring*:

* Model performance monitoring related assistance signalling and procedure.
	+ Metrics/methods including:
		- Intermediate KPIs (e.g., SGCS)
		- Eventual KPIs (e.g., Throughput, hypothetical BLER, BLER, NACK/ACK).
		- Legacy CSI based monitoring: schemes using additional legacy CSI reporting
		- Other monitoring solutions, at least including the following option:
			* Input or Output data based monitoring: such as data drift between training dataset and observed dataset and out-of-distribution detection
* NW-side performance monitoring: NW monitors the performance and make decisions of model activation/ deactivation/updating/switching. Impact to enable performance monitoring using an existing CSI feedback scheme as the reference, including the association between AI/ML scheme and existing CSI feedback scheme for monitoring, are considered. Note: The metric for monitoring and comparison includes intermediate KPI and eventual KPI.
* UE-side performance monitoring: UE monitors the performance and reports to Network, NW makes decisions of model activation/deactivation/updating/switching. Impact on triggering and means for reporting the monitoring metrics, including periodic/semi-persistent and aperiodic reporting, and other reporting initiated from UE, are considered.

*Fallback model*:

* Potential co-existence and fallback mechanisms between AI/ML-based CSI feedback mode and legacy non-AI/ML-based CSI feedback mode

*NW/UE alignment*:

* Alignment of the quantization/dequantization method and the feedback message size between Network and UE, including the following:
	+ For vector quantization scheme, the format and size of the VQ codebook, and the size and segmentation method of the CSI generation model output
	+ For scalar quantization scheme, uniform and non-uniform quantization with format, e.g., quantization granularity, consisting of distribution of bits assigned to each float.
	+ Quantization alignment using 3GPP aware mechanism.

*Model input/output*:

* Output-CSI-UE and input-CSI-NW at least for Precoding matrix
	+ 1a: The precoding matrix in spatial-frequency domain
	+ 1b: The precoding matrix represented using angular-delay domain projection

*UE side data collection*:

* Enhancement of CSI-RS configuration to enable higher accuracy measurement.
* Assistance information for UE data collection for categorizing the data in forms of ID for the purpose of differentiating characteristics of data due to specific configuration, scenarios, site etc.
	+ The provision of assistance information needs to consider feasibility of disclosing proprietary information to the other side.
* Signaling for triggering the data collection

*NW side data collection*:

* Enhancement of SRS and/or CSI-RS measurement and/or CSI reporting to enable higher accuracy measurement.
* Contents of the ground-truth CSI including:
	+ Data sample type, e.g., precoding matrix, channel matrix etc.
	+ Data sample format: scaler quantization and/or codebook-based quantization (e.g., e-type II like).
	+ Assistance information (e.g., time stamps, and/or cell ID, Assistance information for Network data collection for categorizing the data in forms of ID for the purpose of differentiating characteristics of data due to specific configuration, scenarios, site etc., and data quality indicator)
* Latency requirement for data collection
* Signaling for triggering the data collection
* Ground-truth CSI format for model training, including scalar or codebook-based quantization for ground-truth CSI. The number of layers for which the ground truth data is collected, and whether UE or NW determine the number of layers for ground-truth CSI data collection, are considered.

*Intermediate KPI based model monitoring:*

* NW-side monitoring based on the target CSI with realistic channel estimation associated to the CSI report, reported by the UE or obtained from the UE-side.
* UE-side monitoring based on the output of the CSI reconstruction model, subject to the aligned format, associated to the CSI report, indicated by the NW or obtained from the network side.
	+ Network may configure a threshold criterion to facilitate UE to perform model monitoring.
* UE-side monitoring based on the output of the CSI reconstruction model at the UE-side
	+ Note: CSI reconstruction model at the UE-side can be the same or different comparing to the actual CSI reconstruction model used at the NW-side.
	+ Network may configure a threshold criterion to facilitate UE to perform model monitoring.

*Potential specification enhancement on:*

* CSI-RS configurations (not including CSI-RS pattern design enhancements)
* CSI reporting configurations
* CSI report UCI mapping/priority/omission

### 7.2.3 Beam management

***Items considered***:

***Model monitoring***:

For BM-Case1 and BM-Case2 with a UE-side AI/ML model, the following aspects are studied including their necessity or lack thereof:

* NW-side performance monitoring:
	+ Configuration/Signaling from gNB to UE for measurement and/or reporting
	+ UE reporting to NW (e.g., for the calculation of performance metric)
	+ Indication from NW for UE to do LCM operations
	+ Note: At least the performance and reporting overhead of model monitoring mechanism should be considered
* UE-side performance monitoring:
	+ Indication/request/report from UE to gNB for performance monitoring
		- Note: The indictation/request/report may be not needed in some case(s)
	+ Configuration/Signaling from gNB to UE for performance monitoring

*Performance monitoring*:

For BM-Case1 and BM-Case2 with a UE-side AI/ML model:

* NW-side Model monitoring
	+ NW monitors the performance metric(s) and makes decision(s) of model selection/activation/ deactivation/switching/ fallback operation
	+ Beam measurement and report for model monitoring
* Atl1. UE-side Model monitoring
	+ UE monitors the performance metric(s)
	+ UE makes decision(s) of model selection/activation/ deactivation/switching/fallback operation
* Alt3. Hybrid model monitoring
	+ UE monitors the performance metric(s)
	+ NW makes decision(s) of model selection/activation/ deactivation/switching/ fallback operation

For BM-Case1 and BM-Case2 with a NW-side AI/ML model:

* NW-side Model monitoring
	+ UE reporting of beam measurement(s) based on a set of beams indicated by gNB
	+ Signaling, e.g., RRC-based, L1-based
	+ Note: Performance and UE complexity, power consumption should be considered

*L1 signalling:*

For BM-Case1 with a UE-side AI/ML model:

* L1 signalling to report the following information of AI/ML model inference to NW:
	+ The beam(s) that is based on the output of AI/ML model inference.

For BM-Case2 with a UE-side AI/ML model:

* L1 signalling to report the following information of AI/ML model inference to NW:
	+ The beam(s) of N future time instance(s) that is based on the output of AI/ML model inference.

For BM-Case1 and BM-Case2 with a network-side AI/ML model:

* L1 beam reporting enhancement for AI/ML model inference:
	+ UE to report the measurement results of more than 4 beams in one reporting instance
	+ Other L1 reporting enhancements can be considered

For BM-Case1 and BM-Case2 with a UE-side AI/ML model:

* Predicted L1-RSRP(s) corresponding to the DL Tx beam(s) or beam pair(s)
	+ Whether/how to differentiate predicted L1-RSRP and measured L1-RSRP
* Confidence/probability information related to the output of AI/ML model inference (e.g., predicted beams)
* Reporting of best beam(s) obtained by measuring beams of a set of indicated by gNB (e.g., Beams from Set A)
* Reporting of measurements of the predicted best beam(s) corresponding to model output (e.g., comparison between actual L1-RSRP and predicted RSRP of predicted Top-1/K Beams)

*Data collection*

At UE side for UE-side AI/ML model:

* UE reporting to NW supported/preferred configurations of DL RS transmission.
* Trigger to initiate data collection considering:
	+ Option 1: data collection initiated/triggered by configuration from NW.
	+ Option 2: request from UE for data collection.

At NW side:

* Mechanism related to the reporting.
* Additional information for content of the reporting.
* Reporting overhead reduction.

Regarding data collection for NW-side AI/ML model, the following options (including the combination of options) for the contents of collected data are studied:

* Opt.1: M1 L1-RSRPs (corresponding to M1 beams) with the indication of beams (beam pairs) based on the measurement corresponding to a beam set, where M1 can be larger than 4, if applicable.
* Opt.2: M2 L1-RSRPs (corresponding to M2 beams) based on the measurement corresponding to a beam set, where M2 can be larger than 4, if applicable.
* Opt.3: M3 beam (beam pair) indices based on the measurement corresponding to a beam set, where M3 can be larger than 4, if applicable.
* Note: Overhead, UE complexity and power consumption are to be considered for the above options.

*Data collection for model training:*

* Whether and how to initiate data collection
* Configurations, e.g., configuration related to Set A and/or Set B, information on association/mapping of Set A and Set B
* Assistance information from Network to UE (if supported)

*Model Inference related*:

For BM-Case1 and BM-Case2 with a UE-side AI/ML model:

* Indication of the associated Set A from network to UE, e.g., association/mapping of beams within Set A and beams within Set B if applicable
* Beam indication from network for UE reception, which may or may not have additional specification impact (e.g., legacy mechanism may be reused)

### 7.2.4 Positioning accuracy enhancements

***Items considered***:

*AI/ML model indication[/configuration]*:

* Validity conditions, e.g., applicable area/[zone/]scenario/environment and time interval, etc.
* Model capability, e.g., positioning accuracy quality and model inference latency
* Conditions and requirements, e.g., required assistance signalling and/or reference signals configurations, dataset information

*Signalling, report/feedback*:

* Assistance signalling and procedure at least for UE-side model
* Report/feedback and procedure at least for Network-side model
	+ Note: study is applicable to both of the following cases:
		- Model inference and model monitoring at the same entity
		- Entity to perform the model monitoring is not the same entity for model inference
* Details of request/report of label and/or other training data, and to enable delivering the collected label and/or other training data to the training entity when the training entity is not the same entity to obtain label and/or other training data
* Assistance signalling indicating reference signal configuration(s) to derive label and/or other training data
* Request/report of training data: Ground truth label; Measurement corresponding to model input; Associated information of ground truth label and/or measurement corresponding to model input
* Assistance signalling and procedure to facilitate generating training data: Reference signal (e.g., PRS/SRS) configuration(s) and configuration identifier; Assistance information, e.g., between LMF and UE/PRU, for label calculation/generation, and label validity/quality condition, etc.
	+ Note: whether such assistance signalling and procedure can be applied to other aspect(s) of AI/ML model LCM can also be discussed
* Notes: Study may consider different entity to generate training data as well as different types of training data when applicable. Study considers both of the following cases when applicable: when the training entity is the same entity to generate training data, and when the training entity is not the same entity to generate training data

*Training data generation* for AI/ML based positioning:

* The following options of entity and mechanisms to generate ground truth label are identified:
	+ At least PRU is identified to generate ground truth label for UE-based positioning with UE-side model (Case 1) and UE-assisted positioning with UE-side model (Case 2a)
	+ At least LMF with known PRU location is identified to generate ground truth label for UE-assisted/LMF-based positioning with LMF-side model (Case 2b) and NG-RAN node assisted positioning with LMF-side model (Case 3b)
	+ At least network entity with known PRU location is identified to generate ground truth label for NG-RAN node assisted positioning with gNB-side model (Case 3a)
* The following options of entity to generate other training data (at least measurement corresponding to model input) are identified:
	+ For UE-based with UE-side model (Case 1) and UE-assisted positioning with UE-side (Case 2a) or LMF-side model (Case 2b)
		- PRU
		- UE
	+ For NG-RAN node assisted positioning with Network-side model (Case 3a and Case 3b)
		- TRP
* Note: transfer of training data from the entity generating training data to a different entity is not precluded and associated potential specification impact is to be considered

*Training data collection* for AI/ML based positioning:

* Associated information of training data:
	+ Ground truth label at least for model training; report from the label data generation entity
	+ Measurement (corresponding to model input) at least for model training; report from the measurement data generation entity.
	+ Quality indicator for and/or associated with ground truth label and/or measurement at least for model training; report from the label and/or the measurement data generation entity and/or as request from a different (e.g., data collection, etc.) entity.
	+ RS configuration(s) at least for deriving measurement
		- Request from data generation entity (UE/PRU/TRP) to LMF and/or as LMF assistance signalling to UE/PRU/TRP.
		- Note: there may not be any enhancements on top of existing RS configuration(s) or any new RS configuration(s) for positioning measurement.
	+ Time stamp at least for and/or associated with training data for model training; report from data generation entity together with training data and/or as LMF assistance signalling.
		- Separate time stamp for measurement and ground truth label, when measurement and ground truth label are generated by different entities.
		- Note: there may not be any enhancements on top of time stamp in existing positioning measurement report or any new time stamp report for positioning measurement
* Assistance signalling and procedure to facilitate generating/collecting training data:
	+ Potential determination of the UE/PRU/TRP which can provide the training data
	+ Configuration of reference signal (for measurement and/or label)
	+ Signalling other than above 2 for data collection, e.g., requested quality of training data

*Model monitoring*:

* Data for computing monitoring metric:
	+ If monitoring based on model output: e.g., estimated UE location corresponding to model output for direct AI/ML positioning, estimated intermediate parameter(s) corresponding to model output for AI/ML assisted positioning, ground truth label corresponding to model inference output for both direct and AI/ML assisted positioning
	+ If monitoring based on model input: e.g., measurement corresponding to model inference input.
	+ Assistance signalling from LMF to UE/PRU/gNB for UE/gNB-side model monitoring.
	+ Assistance signalling from UE/PRU for network-side model monitoring.
* If certain type of data is necessary for computing monitoring metric:
	+ How an entity can be used to provide the given type of data for calculating monitoring metric: companies requested to report their assumption of the entity (or entities) used to provide the given type of data for calculating monitoring metric for each case
	+ Potential signalling for provisioning of the given type of data for calculating associated monitoring metric
	+ Potential assistance signalling and procedure to facilitate an entity providing data for calculating monitoring metric
	+ Potential UE-network interaction: e.g., model monitoring decision indication between UE and network
* Entity to derive monitoring metric
	+ UE at least for Case 1 and 2a (with UE-side model)
	+ gNB at least for Case 3a (with gNB-side model)
	+ LMF at least for Case 2b and 3b (with LMF-side model)
* If model monitoring does not require ground truth label (or its approximation).
	+ Monitoring metric: e.g., statistics of measurement(s) compared to the statistics associated with the training data.
	+ Note: the measurement(s) may or may not be the same as model input.
	+ Assistance signalling and procedure, e.g., RS configuration(s) for measurement, measurement statistics as compared to the model input statistics of the training data, etc.
	+ report of the calculated metric and/or model monitoring decision
* If model monitoring requires and is provided ground truth label (or its approximation)
	+ Monitoring metric: statistics of the difference between model output and provided ground truth label.
	+ Provisioning of ground truth label and associated label quality.
	+ Assistance signalling and procedure, e.g., from LMF to UE/gNB indicating ground truth label and/or measurement, etc.
	+ report of the calculated metric and/or model monitoring decision

*Model Inference related*:

* For direct AI/ML positioning (Case 2b and 3b), type of measurement(s) as model inference input considering performance impact and associated signaling overhead
	+ Potential new measurement: CIR/PDP
	+ Existing measurement: e.g., RSRP/RSRPP/RSTD
	+ Note: details of potential new measurement and/or potential enhancement to existing measurement is to be studied.
* For AI/ML assisted positioning with UE-assisted (Case 2a) and NG-RAN node assisted positioning (Case 3a), measurement report to carry model output to LMF
	+ New measurement report: e.g., ToA, path phase
	+ Existing measurement report: e.g., RSTD, LOS/NLOS indicator, RSRPP
	+ Enhancement of existing measurement report: e.g., soft information/high resolution of RSTD
* Assistance signalling and procedure to facilitate model inference for both UE-side and Network-side model
	+ RS configurations

*LCM*:

* For AI/ML based positioning accuracy enhancement, at least for Case 1 and Case 2a (model is at UE-side)
	+ which aspects should be specified as conditions of a Feature/FG available for functionality-based LCM.
	+ which aspects should be considered as additional conditions, and how to include them into model description information during model identification for model ID-based LCM.

The specification impact related to the following items is assessed:

* Types of measurement as model inference input
	+ new measurement
	+ existing measurement
* UE is assumed to perform measurement as model inference input for Case 1, Case 2a and Case 2b; TRP is assumed to perform measurement as model inference input for Case 3a and Case 3b
	+ Report of measurements as model inference input to LMF for LMF-side model (Case 2b and Case 3b)
* For AI/ML assisted positioning, new measurement report and/or potential enhancement of existing measurement report as model output to LMF for UE-assisted (Case 2a) and NG-RAN node assisted positioning (Case 3a)
* Assistance signalling and procedure to facilitate model inference for both UE-side and Network-side model
	+ New and/or enhancement to existing assistance signalling
	+ Note: whether such assistance signalling and procedure can be applied to other aspect(s) of AI/ML model LCM can also be discussed

## 7.3 Protocol aspects

In this section, aspects related to, e.g., capability indication, configuration and control procedures (training/inference), and management of data and AI/ML model, per RAN1 input, are considered.

In addition, collaboration level specific specification impact per use case is documented.

### 7.3.2 CSI feedback enhancement

### 7.3.3 Beam management

### 7.3.4 Positioning accuracy enhancements

## 7.4 Interoperability and testability aspects

In this section, requirements and testing frameworks to validate AI/ML based performance enhancements and ensuring that UE and gNB with AI/ML meet or exceed the existing minimum requirements, if applicable, are documented.

The need and implications for AI/ML processing capabilities definition is considered.

### 7.4.1 Common framework

### 7.4.2 CSI feedback enhancement

### 7.3.1 Common framework

### 7.4.3 Beam management

### 7.4.4 Positioning accuracy enhancements

# 8 Conclusions

[Editor’s note: conclusions may include recommendations for subsequent WI(s).]

Annex <X> :
Change history

Use style "Heading 8" in TSs and "Heading 9" in TRs. Do not use "informative" in the title in TRs.

This is the last annex for TS/TSs which details the change history using the following table.
This table is to be used for recording progress during the WG drafting process till TSG approval of this TS/TR.
For TRs under change control, use one line per approved Change Request
Date: use format YYYY-MM
CR: four digits, leading zeros as necessary
Rev: blank, or number (max two digits)
Cat: use one of the letters A, B, C, D, F
Subject/Comment: for TSs under change control, include full text of the subject field of the Change Request cover
New vers: use format [n]n.[n]n.[n]n

|  |
| --- |
| **Change history** |
| **Date** | **Meeting** | **TDoc** | **CR** | **Rev** | **Cat** | **Subject/Comment** | **New version** |
| 2022-05 | RAN1#109e |  |  |  |  | TR skeleton | 0.0.0 |
| 2023-05 | RAN1#113 | R1-23xxxxx |  |  |  | Updated TR 38.843 including RAN1 agreements until RAN1#113 | 0.1.0 |
|  |  |  |  |  |  |  |  |