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| ***3GPP***  Postal address  3GPP support office address  650 Route des Lucioles – Sophia Antipolis  Valbonne – FRANCE  Tel.: +33 4 92 94 42 00 Fax: +33 4 93 65 47 16  Internet  <http://www.3gpp.org> |
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# Foreword

This Technical 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.

# 1 Scope

The present document provides descriptions of principles for RAN intelligence enabled by AI, the functional framework (e.g. the AI functionality and the input/output of the component for AI enabled optimization) and use cases and solutions of AI enabled RAN.

The study is based on the current architecture and interfaces.

# 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”.

# 3 Definitions of terms, symbols and 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].

* Data collection: Data collected from the network nodes, management entity or UE, as a basis for ML model training, data analytics and inference.
* ML Model: A data driven algorithm by applying machine learning techniques that generates a set of outputs consisting of predicted information, based on a set of inputs
* ML Training: An online or offline process to train an ML model by learning features and patterns that best present data and get the trained ML model for inference.
* ML Inference: A process of using a trained ML model to make a prediction or guide the decision based on collected data and ML model.

*Editor Note: Definition of each terminology might be updated to align with other working groups, in order to have common or unified definition on AI/ML related terminology.*

## 3.2 Symbols

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

<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].

<ABBREVIATION> <Expansion>

# 4 General Framework

*Editor Note: high level principles for RAN intelligence enabled by AI, the functional framework (e.g. the AI functionality and the input/output of the component for AI enabled optimization)*

*Editor Note: FFS if the study assumes single vendor environment, e.g., if the model deployment/update procedure is proprietary.*

4.1 High-level Principles

The following high level principles should be applied for AI-enabled RAN intelligence:

* The detailed AI/ML algorithms and models for use cases are implementation specific and out of RAN3 scope.
* The study focuses on AI/ML functionality and corresponding types of inputs/outputs.
* The input/output and the location of the Model Training and Model Inference function should be studied case by case.
* The study focuses on the analysis of data needed at the Model Training function from Data Collection, while the aspects of how the Model Training function uses inputs to train a model are out of RAN3 scope.
* The study focuses on the analysis of data needed at the Model Inference function from Data Collection, while the aspects of how the Model Inference function uses inputs to derive outputs are out of RAN3 scope.
* Where AI/ML functionality resides within the current RAN architecture, depends on deployment and on the specific use cases.
* The Model Training and Model Inference functions should be able to request, if needed, specific information to be used to train or execute the AI/ML algorithm and to avoid reception of unnecessary information. The nature of such information depends on the use case and on the AI/ML algorithm.
* The Model Inference function should signal the outputs of the model only to nodes that have explicitly requested them (e.g. via subscription), or nodes that are subject to actions based on the output from Model Inference.
* An AI/ML model used in a Model Inference function has to be initially trained, validated and tested before deployment.
* NG-RAN is prioritized; EN-DC is included in the scope. FFS on whether MR-DC should be down-prioritized.
* A general framework and workflow for AI/ML optimization should be defined and captured in the TR. The generalized workflow should not prevent to “think beyond” the workflow if the use case requires so.
* User data privacy and anonymisation should be respected during AI/ML operation.

## 4.2 Functional Framework

*Editor’s Note: Data Preparation aspects may be further refined*

*Editor Note: FFS whether and how to signal metrics (e.g., accuracy, uncertainty, etc.) and validity time together with or as part of the inference output.*

*Editor Note: FFS on whether model testing / generating of model performance metrics is performed in Model Inference.*



Figure 4.2-1: Functional Framework for RAN Intelligence

This section introduces the common terminologies related to the functional framework for RAN intelligence illustrated in Figure 4.2-1. For the functions and data/information flows shown in the Figure 4.2-1, whether there is any standardization impact and what is the standardization impact are discussed in clause 5.

* Data Collection is a function that provides input data to Model training and Model inference functions. AI/ML algorithm specific data preparation (e.g., data pre-processing and cleaning, formatting, and transformation) is not carried out in the Data Collection function.   
  Examples of input data may include measurements from UEs or different network entities, feedback from Actor, output from an AI/ML model.
  + Training Data: Data needed as input for the AI/ML Model Training function.
  + Inference Data: Data needed as input for the AI/ML Model Inference function.
* Model Training is a function that performs the ML model training, validation, and testing. The Model training function is also responsible for data preparation (e.g. data pre-processing and cleaning, formatting, and transformation) based on Training Data delivered by a Data Collection function, if required.
  + (FFS) Model Deployment/Update: Deploy or update an AI/ML model to Model Inference function.
* Model Inference is a function that provides AI/ML model inference output (e.g. predictions or decisions). The Model inference function is also responsible for data preparation (e.g. data pre-processing and cleaning, formatting, and transformation) based on Inference Data delivered by a Data Collection function, if required.
  + Output: The inference output of the AI/ML model produced by a Model Inference function.
* Actor is a function that receives the output from the Model inference function and triggers or performs corresponding actions. The Actor may trigger actions directed to other entities or to itself.
  + Feedback: Information that may be needed to derive training or inference data or performance feedback.

# 5 Use Cases and Solutions for Artificial Intelligence in RAN

## 5.1 Network Energy Saving

### 5.1.1 Use case description

To meet the 5G network requirements of key performance and the demands of the unprecedented growth of the mobile subscribers, millions of base stations (BSs) are being deployed. Such rapid growth brings the issues of high energy consumption, CO2 emissions and operation expenditures (OPEX). Therefore, energy saving is an important use case which may involve different layers of the network, with mechanisms operating at different time scales.

Cell activation/deactivation is an energy saving scheme in the spatial domain that exploits traffic offloading in a layered structure to reduce the energy consumption of the whole radio access network (RAN). When the expected traffic volume is lower than a fixed threshold, the cells may be switched off, and the served Ues may be offloaded to a new target cell.

Efficient energy consumption can also be achieved by other means such as reduction of load, coverage modification, or other RAN configuration adjustments. The optimal EE decision depends on many factors including the load situation at different nodes, RAN nodes capabilities, KPI/QoS requirements, number of active Ues and UE mobility, cell utilization, etc.

However, the identification of actions aimed at energy efficiency improvements is not a trivial task. Wrong switch-off of the cells may seriously deteriorate the network performance since the remaining active cells need to serve the additional traffic. Wrong traffic offload actions may lead to a deterioration of Energy Efficiency instead of an improvement. The current energy-saving schemes are vulnerable to potential issues listed as follows:

* Inaccurate cell load prediction. Currently, energy-saving decisions rely on current traffic load without considering future traffic load.
* Conflicting targets between system performance and energy efficiency. Maximizing the system’s key performance indicator (KPI) is usually done at the expense of energy efficiency. Similarly, the most energy efficient solution may impact system performance. Thus, there is a need to balance and manage the trade-off between the two.
* Conventional energy-saving related parameters adjustment. Energy-saving related parameters configuration is set by traditional operation, e.g., based on different thresholds of cell load for cell switch on/off which is somewhat a rigid mechanism since it is difficult to set a reasonable threshold.
* Actions that may produce a local (e.g. limited to a single RAN node) improvement of Energy Efficiency, while producing an overall (e.g. involving multiple RAN nodes) deterioration of Energy Efficiency.

To deal with issues listed above, ML techniques could be utilized to leverage on the data collected in the RAN network. ML algorithms may predict the energy efficiency and load state of the next period, which can be used to make better decisions on cell activation/deactivation for ES. Based on the predicted load, the system may dynamically configure the energy-saving strategy (e.g. the switch-off timing and granularity, offloading actions) to keep a balance between system performance and energy efficiency and to reduce the energy consumption.

### 5.1.2 Solutions and standard impacts

*Editor Note: Capture the solutions for the use case, including potential standard impacts on existing Nodes, functions, and interfaces*

#### 5.1.2.1 Model Training at OAM and Model Inference at NG-RAN

In this solution, NG-RAN predicts energy saving decisions by AI/ML model trained from OAM.



Figure 5.1.2.1-1. Model Training at OAM, Model Inference at NG-RAN

Step 0: NG-RAN node 1 is assumed to have a AI/ML model trained by OAM, NG-RAN node 2 is assumed to have a AI/ML model trained by OAM optionally.

Step 1: NG-RAN node 2 sends the required input data to NG-RAN node 1 for model inference of AI/ML-based network energy saving.

Step 2: UE sends UE measurement report to NG-RAN node 1. (FFS on if triggered)

Step 3: Based on local inputs of NG-RAN node 1 and received inputs from NG-RAN node 2, NG-RAN node 1 generates model inference output(s) (e.g. energy saving strategy, handover strategy, etc).

Step 4: NG-RAN node 1 selects the most appropriate target cell for each UE before it performs handover and goes to the predicted energy state.

Step 5: NG-RAN node 1 and NG-RAN node 2 provide feedback to OAM.

#### 5.1.2.2 Model Training and Model Inference at NG-RAN

In this solution, NG-RAN is responsible for model training and generates energy saving decisions.

Editor’s Notes: FFS on data collection.



Figure 5.1.2.2-1. Model Training and Model Inference at NG-RAN

Step 1: NG-RAN node 1 trains AI/ML model for AI/ML-based energy saving based on collected data. NG-RAN node 2 is assumed to have AI/ML model for AI/ML-based energy saving optionally, which can also generate predicted results/actions.

Step 2: NG-RAN node 2 sends the required input data to NG-RAN node 1 for model inference of AI/ML-based network energy saving.

Step 3: UE sends UE measurement report to NG-RAN node 1. (FFS on if triggered)

Step 4: Based on local inputs of NG-RAN node 1 and received inputs from NG-RAN node 2, NG-RAN node 1 generates model inference output (e.g. energy saving strategy, handover strategy, etc).

Step 5: NG-RAN node 1 selects the most appropriate target cell for each UE before it performs handover and goes to the predicted energy state.

Step 6: NG-RAN node 2 provides feedback to NG-RAN node 1.

#### 5.1.2.3 Input of AI/ML-based Network Energy Saving

To predict the optimized network energy saving decisions, NG-RAN may need following information as input data for AI/ML-based network energy saving:

* Current/Predicted resource status of ES-Cell and its neighbor nodes
* Current/Predicted energy information of ES-Cell and its neighbor nodes
* UE measurement report (e.g. UE RSRP, RSRQ, SINR measurement, etc)

If existing UE measurements are needed by a gNB for AI/ML-based network energy saving, RAN3 shall reuse the existing framework (including MDT and RRM measurements). FFS on whether new UE measurements are needed.

Editor’s Note: FFS other input information required for AI/ML-based network energy saving. FFS energy information is exact energy consumption value or energy efficiency gain.

#### 5.1.2.4 Output of AI/ML-based Network Energy Saving

AI/ML-based network energy saving model can generate following information as output:

* Energy saving strategy
* Handover strategy, including recommended candidate cells for taking over the traffic
* Predicted energy information

Editor’s Note: FFS other output information expected from AI/ML-based network energy saving. FFS detailed granularity and action of energy saving strategy. FFS on accuracy of predicted energy saving decision.

#### 5.1.2.5 Feedback of AI/ML-based Network Energy Saving

To optimize the performance of AI/ML-based network energy saving model, following feedback can be considered to be collected from NG-RAN nodes:

* Load measurement
* Energy information

Editor’s Note: FFS other feedback expected from AI/ML-based network energy saving.

## 5.2 Load Balancing

### 5.2.1 Use case description

The rapid traffic growth and multiple frequency bands utilized in a commercial network make it challenging to steer the traffic in a balanced distribution. To address the problem, load balancing had been proposed. The objective of load balancing is to distribute load evenly among cells and among areas of cells, or to transfer part of the traffic from congested cells or from congested areas of cells, or to offload users from one cell, cell area, carrier or RAT to improve network performance. This can be done by means of optimization of handover parameters and handover actions. The automation of such optimisation can provide high quality user experience, while simultaneously improving the system capacity and also to minimize human intervention in the network management and optimization tasks.

However, the optimization of the load balancing is not an easy task as follows:

* Currently the load balancing decisions relying on the current/past-state cell load status are insufficient. The traffic load and resource status of the network changes rapidly, especially in the scenarios with high-mobility and large number of connections, which may lead to ping-pong handover between different cells, cell overload and degradation of user service quality.
* It is difficult to guarantee the overall network and service performance when performing load balancing. For the load balancing, the UEs in the congested cell may be offloaded to the target cell, by means of handover procedure or adapting handover configuration. For example, if the UEs with time-varying traffic load are offloaded to the target cell, the target cell may be overloaded with new-arrival heavy traffic. It is difficult to determine whether the service performance after the offloading action meets the desired targets.

To deal with the above issues, solutions based on AI/ML model could be introduced to improve the load balancing performance. Based on collection of various measurements and feedbacks from UEs and network nodes, historical data, etc. ML model based solutions and predicted load could improve load balancing performance, in order to provide higher quality user experience and to improve the system capacity.

### 5.2.2 Solutions and standard impacts

*Editor Note: Capture the solutions for the use case, including potential standard impacts on existing Nodes, functions, and interfaces*

The following solutions can be considered for supporting AI/ML-based load balancing:

* AI/ML Model Training is located in the OAM and AI/ML Model Inference is located in the gNB.
* AI/ML Model Training and AI/ML Model Inference are both located in the gNB.

In case of CU-DU split architecture, the following solutions are possible:

* AI/ML Model Training is located in the OAM and AI/ML Model Inference is located in the gNB-CU.
* AI/ML Model Training and Model Inference are both located in the gNB-CU.

Other possible locations of the AI/ML Model Training and AI/ML Model Inference are FFS.

To improve the load balancing decisions at a gNB (gNB-CU), a gNB can request load predictions from a neighbouring node. Details of the procedure are FFS.

If existing UE measurements are needed by a gNB for AI/ML-based load balancing, RAN3 shall reuse the existing framework (including MDT and RRM measurements). FFS on whether new UE measurements are needed.

## 5.3 Mobility Optimization

### 5.3.1 Use case description

Mobility management is the scheme to guarantee the service-continuity during the mobility by minimizing the call drops, RLFs, unnecessary handovers, and ping-pong. For the future high-frequency network, as the coverage of a single node decreases, the frequency for UE to handover between nodes becomes high, especially for high-mobility UE. In addition, for the applications characterized with the stringent QoS requirements such as reliability, latency etc., the QoE is sensitive to the handover performance, so that mobility management should avoid unsuccessful handover and reduce the latency during handover procedure. However, for the conventional method, it is challengeable for trial-and-error-based scheme to achieve nearly zero-failure handover. The unsuccessful handover cases are the main reason for packet dropping or extra delay during the mobility period, which is unexpected for the packet-drop-intolerant and low-latency applications. In addition, the effectiveness of adjustment based on feedback may be weak due to randomness and inconstancy of transmission environment. Besides the baseline case of mobility, areas of optimization for mobility include dual connectivity, CHO, and DAPS, which each have additional aspects to handle in the optimization of mobiltity.

Mobility aspects of SON that can be enhanced by the use of AI/ML include

* Reduction of the probability of unintended events
* UE Location/Mobility/Performance prediction
* Traffic Steering

**Reduction of the probability of unintended events associated with mobility.**

Examples of such unintended events are:

* Intra-system Too Late Handover: A radio link failure (RLF) occurs after the UE has stayed for a long period of time in the cell; the UE attempts to re-establish the radio link connection in a different cell.
* Intra-system Too Early Handover: An RLF occurs shortly after a successful handover from a source cell to a target cell or a handover failure occurs during the handover procedure; the UE attempts to re-establish the radio link connection in the source cell.
* Intra-system Handover to Wrong Cell: An RLF occurs shortly after a successful handover from a source cell to a target cell or a handover failure occurs during the handover procedure; the UE attempts to re-establish the radio link connection in a cell other than the source cell and the target cell.

RAN Intelligence could observe multiple HO events with associated parameters, use this information to train its ML model and try to identify sets of parameters that lead to successful Hos and sets of parameters that lead to unintended events.

**UE Location/Mobility/Performance Prediction**

Predicting UE’s location is a key part for mobility optimisation, as many RRM actions related to mobility (e.g. selecting handover target cells) can benefit from the predicted UE location/trajectory. UE mobility prediction is also one key factor in the optimization of early data forwarding particularly for CHO. UE Performance prediction when the UE is served by certain cells is a key factor in determining which is the best mobility target for maximisation of efficiency and performance.

**Traffic Steering**

Efficient resource handling can be achieved adjusting handover trigger points and selecting optimal combination of Pcell/PSCell/Scells to serve a user.

Existing traffic steering can also be improved by providing a RAN node with information related to mobility or dual connectivity.

For example, before initiating a handover, the source gNB, could use feedbacks on UE performance collected for successful handovers occurred in the past and received from neighboring gNBs.

Similarly, for the case of dual connectivity, before triggering the addition of a secondary gNB or triggering SN change, an eNB could use information (feedbacks) received in the past from the gNB for successfully completed SN Addition or SN Change procedures.

In the two reported examples, the source RAN node of a mobility event, or the RAN node acting as Master Node (a eNB for EN-DC, a gNB for NR-DC) can use feedbacks received from the other RAN node, as input to an AI/ML function supporting traffic related decisions (e.g. selection of target cell in case of mobility, selection of a PSCell / Scell(s) in the other case), so that future decisions can be optimized.

### 5.3.2 Solutions and standard impacts

*Editor Note: Capture the solutions for the use case, including potential standard impacts on existing Nodes, functions, and interfaces*

Considering the locations of AI/ML Model Training and AI/ML Model Inference for mobility solution, following two options are considered:

* The AI/ML Model Training function is deployed in OAM, while the Model Inference function resides within the RAN node
* Both the AI/ML Model Training function and the AI/ML Model Inference function reside within the RAN node

Furthermore, for CU-DU split scenario, following option is possible:

* AI/ML Model Training is located in CU-CP or OAM, and AI/ML Model Inference function is located in CU-CP

#### 5.3.2.1 AI/ML Model Training in OAM and AI/ML Model Inference in NG-RAN node

Step 1: The RAN is assumed to have in use a trained AI/ML model for inference

Step 2. Model Inference. Required measurements are leveraged into Model Inference to output the prediction, e.g. UE trajectory prediction, target cell prediction, target NG-RAN node prediction, etc.

Step 3. According to the prediction, recommended actions or configuration are executed for Mobility Optimization.

#### 5.3.2.2 AI/ML Model Training and AI/ML Model Inference in NG-RAN node



Figure 5.3-1: Model Training and Model Inference both located in RAN node

Step 1. NG-RAN node1 configures the measurement information on the UE side and sends configuration message to UE including configuration information.

Step 2. UE collects the indicated measurement, e.g., UE measurements related to RSRP, RSRQ, SINR of serving cell and neighbouring cells.

Step 3. UE sends measurement report message to NG-RAN node1 including the required measurement.

Step 4. Model training. Required measurements are leveraged to training ML model for mobility optimization.

Step 5. NG-RAN node1 obtains the measurement report as inference data for real-time UE mobility optimization.

Step 6. Model Inference. Required measurements are leveraged into Model Inference to output the prediction, including e.g., UE trajectory prediction, target cell prediction, target NG-RAN node prediction, etc.

Step 7. According to the prediction, recommended actions are executed for Mobility Optimization. NG-RAN node1 may send the predicted mobility optimization solution to NG-RAN node2.

#### 5.3.2.3 Input data

The following data is required as input data for mobility optimization.

**Input Information from UE:**

* FFS UE historical location information from MDT, e.g., Latitude, longitude, altitude, cell ID
* Radio measurements related to serving cell and neighbouring cells associated with UE location information, e.g., RSRP, RSRQ, SINR
* UE historical serving cells and their locations
* Moving velocity
* FFS predicted traffic

**Input Information from the neighbouring RAN nodes:**

* UE’s successful handover information in the past and received from neighboring RAN nodes
* UE’s history information from neighbor
* Position, resource status, FFS QoS parameters of historical HO-ed UE (e.g., loss rate, delay, etc.)
* Resource status and utilization prediction/estimation
* SON Reports of handovers that are successful, too-early, too-late, or handover to wrong (sub-optimal) cell
* FFS Information about the performance of handed over UEs

**Input Information from the local node:**

* UE trajectory prediction output (will be used by the RAN node internally)
* Local load prediction

If existing UE measurements are needed by a gNB for AI/ML-based network energy saving, RAN3 shall reuse the existing framework (including MDT and RRM measurements). FFS on whether new UE measurements are needed.

#### 5.3.2.4 Output data

* FFS UE trajectory prediction (Latitude, longitude, altitude of UE over a future period of time)
* Estimated arrival probability in CHO and relevant confidence interval

Predicted handover target node, candidate cells in CHO, may together with the confidence of the predication

## 5.X Use case X

### 5.X.1 Use case description

*Editor Note: capture the description of use case*

### 5.X.2 Solutions and standard impacts

*Editor Note: Capture the solutions for the use case, including potential standard impacts on existing Nodes, functions, and interfaces*

# 6 Conclusion

Annex <A> (informative):  
Change history

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Change history** | | | | | | | |
| **Date** | **Meeting** | **Tdoc** | **CR** | **Rev** | **Cat** | **Subject/Comment** | **New version** |
| 2020-11 | RAN3#110 | R3-207094 | - | - | - | Draft skeleton | 0.0.0 |
| 2020-11 | RAN3#110 | R3-207253 |  |  |  | Capture TP in R3-207218 | 0.1.0 |
| 2021-05 | RAN3#112 | R3-212506 |  |  |  | Capture TP in R3-212807, R3-212868, R3-212896, R3-212897, R3-212978 | 0.2.0 |