**3GPP TSG-RAN WG3 Meeting #114-eR3-216224**

**Online meeting, 1st Nov – 11th Nov 2021**

Agenda Item: 18.3

Source: Ericsson

Title: AI/ML Load Balancing TP

Document for: Discussion and Agreement

# TP to TR 37.817 for Load Balancing use case

# 5 Use Cases and Solutions for Artificial Intelligence in RAN

## 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.

* 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.

//////////////////////////////////////////// FIRST CHANGE /////////////////////////////////////////

### 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.

Note: gNB is also allowed to continue model training based on AI/ML model trained in the OAM. Other possible locations of the 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.

To increase the awareness of the traffic dynamics and enable more improved traffic steering decisions it is possible to complement load measurements currently exposed over RAN interfaces with information related to predicted load from neighbouring RAN nodes as well as UE measurements and information.

* An NG-RAN node can also predict its own load. This can be achieved by considering the own load and load information received from neighbour RAN nodes. Load predictions can be signalled between RAN nodes.
* An NG-RAN node can also derive load prediction using UE measurements and information, for example MDT and RRM measurements, or UE location information (e.g. velocity, position). For the aspects concerning the configuration and the reporting of UE measurements and information the impacted protocol is RRC. RAN2 needs to be consulted for details during the normative phase.

Signalling of information used to derive Model Inference outputs may be achieved over the Xn interface by reusing existing or new procedures. The details are to be discussed during normative work.

A high-level signalling flow for the AI/ML use case related to Load Balancing is shown in Figure 5.2-2-1 below.



Figure 5.2-2-1: AI/ML for Load Balancing use case

Step 1: an AI/ML Model Training is located at NG-RAN node 1. NG-RAN node 2 is assumed to have capabilities in providing NG-RAN node 1 with useful input information, such as predicted resource status and/or mobility predictions.

Steps 2-3: NG-RAN node 1 can request and obtain UE measurements and location information (e.g. RRM measurements, MDT measurements, velocity, position).

Step 4-5: NG-RAN node 1 can request Resource Status information from the neighbouring NG-RAN node 2. Details and name of the procedure are FFS.

Step 6: NG-RAN node 1 can perform Mobility Load Balancing predictions (e.g. for cells of NG-RAN node 1).

Step 7: NG-RAN node 1 takes Mobility Load Balancing decision and UEs are moved from NG-RAN node 1 to NG-RAN node 2.

Step 8: NG-RAN node 2 sends Feedback to NG-RAN node 1 (e.g. resource status updates after load balancing). It is FFS whether “Feedback” is signalled after receiving a Feedback Request.

5.2.2.1 Input of AI/ML-based Load Balancing

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

From the local node:

* Own resource status information (e.g. per cell, per SSB Area): e.g., this can be calculated using predictions of some or all of the resource information specified in current XnAP
* Predicted own resource status information: e.g., this can be calculated using predictions of some or all of the resource information specified in current XnAP

From the UE:

* UE location information (e.g. from RLF reports, SCG Failure Information, Successful Handover Report)
* UE Radio Measurements, e.g., RSRP, RSRQ, SINR
* UE Mobility History Information

From neighbour NG-RAN Nodes:

* Neighbour resource status information (e.g. per cell, per SSB Area): it may include, e.g., some or all of the resource information in current Xn: Resource Status Update procedure
* Predicted neighbour resource status information: this can be calculated using, e.g., predictions of some or all of the resource information specified in current XnAP

Editor’s Note: FFS other input information required for AI/ML-based load balancing.

5.2.2.2 Output of AI/ML-based Load Balancing

AI/ML-based load balancing model can generate following information as output:

* Selection of target cell for mobility load balancing
* Predicted own resource status information: this can be calculated using, e.g., predictions of some or all of the resource information specified in current XnAP
* Predicted resource status information signalled from neighbor NG-RAN node(s): this can be calculated using, e.g., predictions of some or all of the resource information specified in current XnAP
* Validity time for the Model Inference output predictions. FFS whether validity time is applied to all outputs produced by the Model Inference function.

Editor’s Note: FFS other output information expected from AI/ML-based load balancing.

5.2.2.3 Feedback of AI/ML-based Load Balancing

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

* UE performance information from target NG-RAN (for those UEs handed over from the source NG-RAN node)
* Resource status information updates from target NG-RAN

Editor’s Note: FFS other feedback expected from AI/ML-based load balancing.

///////////////////////////////////////////// END OF CHANGES //////////////////////////////////////////////