## 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. AI/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

#### 5.2.2.1 Locations for AI/ML Model Training and AI/ML Model Inference

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.

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

A high-level signalling flow for the AI/ML use case related to Load Balancing with Model Training in OAM and Model Inference in NG-RAN is shown in Figure 5.2.2-1 below.



 Figure 5.2.2-1 Model Training at OAM, Model Inference at NG-RAN

Step 0: NG-RAN node 2 is assumed to have an AI/ML model optionally, which can provide NG-RAN node 1 with useful input information, such as predicted resource status, etc.

Step 1: The NG-RAN node 1 configures the UE to provide measurements and/or location information (e.g., RRM measurements, MDT measurements, velocity, position).

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

Step 3: The UE reports to NG-RAN node 1 requested measurements and/or location information (e.g., UE measurements related to RSRP, RSRQ, SINR of serving cell and neighbouring cells, velocity, position).

Step 4: NG-RAN node 1 further sends UE measurement reports together with other input data for Model Training to OAM. NG-RAN node 2 also sends input data for Model Training to OAM.

Step 5: AI/ML Model Training is located at OAM. The required measurements and input data from other NG-RAN nodes are leveraged to train the AI/ML model.

Step 6: OAM deploys/updates AI/ML model into the NG-RAN node(s). The NG-RAN node is allowed to continue model training based on the received AI/ML model from OAM.

Note: This step is out of RAN3 Rel-17 scope.

Step 7: The UE collects and reports to NG-RAN node 1 requested measurements or location information.

Step 8: The NG-RAN node 1 receives from the neighbouring NG-RAN node 2 the input information for load balancing model inference.

Step 9: NG-RAN node 1 performs Mobility Load Balancing predictions (e.g. for cells of NG-RAN node 1).

Step 10. The NG-RAN 1 sends the model performance feedback to OAM if applicable.

Note: This step is out of RAN3 scope.

Step 11: NG-RAN node 1 may take Load Balancing actions and the UE is moved from NG-RAN node 1 to NG-RAN node 2.

Step 12: NG-RAN node 1 and NG-RAN node 2 send feedback information to OAM.

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

A high-level signalling flow for the AI/ML use case related to Load Balancing with Model Training and Model Inference in a NG-RAN node is shown in Figure 5.2.2-2 below.



Figure 5.2.2-2: Model Training and Model Inference in a NG-RAN node

Step 0: NG-RAN node 2 is assumed to have an AI/ML model optionally, which can provide NG-RAN node 1 with useful input information, such as predicted resource status, etc.

Step 1: The NG-RAN node 1 configures UE to provide measurements and/or location information(e.g., RRM measurements, MDT measurements, velocity, position).

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

Step 3: The UE reports to NG-RAN node 1 the requested measurements and/or location information (e.g., UE measurements related to RSRP, RSRQ, SINR of serving cell and neighbouring cells, velocity, position).

Step 3: The NG-RAN node 1 requests the neighbouring NG-RAN node 2 the input information for load balancing model training.

Step 4: The NG-RAN node 1 receives from the neighbouring NG-RAN node 2 the input information for load balancing model training.

Step 5: An AI/ML Model Training is located at NG-RAN node 1. The required measurements and input data from other NG-RAN nodes are leveraged to train the AI/ML model.

Step 6: NG-RAN node 1 receives UE measurements and/or location information.

Step7: NG-RAN node 1 can receive from the neighbouring NG-RAN node 2 the input information for load balancing model inference.

Step 8: NG-RAN node 1 performs Mobility Load Balancing predictions (e.g., for cells of NG-RAN node 1).

Step 9: NG-RAN node 1 may take Load Balancing actions and the UE is moved from NG-RAN node 1 to NG-RAN node 2.

Step 10: NG-RAN node 2 sends feedback information to NG-RAN node 1 (e.g. resource status updates after load balancing, etc).

5.2.2.4 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:

* Current/predicted resource status
* UE trajectory prediction
* Current and predicted UE traffic

From the UE:

* UE location information (e.g., coordinates, serving cell ID, moving velocity) interpreted by gNB implementation when available
* UE Mobility History Information
* UE measurement report (e.g. UE RSRP, RSRQ, SINR measurement, etc), including cell level and beam level UE measurements

From neighbouring NG-RAN Nodes:

* Current/predicted resource status
* UE performance measurement at traffic offloaded neighbouring cell

5.2.2.5 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. Model output validity to be discussed in normative phase per inference output.
* The predicted UE(s) selected to be handed over to target NG-RAN node (will be used by RAN node internally)

5.2.2.6 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
* System KPIs (e.g., throughput, delay, RLF of current and neighbours)

5.2.2.7 Standard impact

**Potential Xninterface impact**:

* MDT procedures enhancements (for collecting radio measurements on RRM events, i.e. RSRP, RSRQ, SINR and other UE information identified during SI, i.e. location information, MHI) on improving AI/ML model impacts to be discussed during the normative phase
* New or enhanced existing signaling procedure to request/retrieve predicted resource status information from neighbouring nodes via Xn interface.
* New or enhanced existing signaling procedure to request/retrieve predicted load balancing strategy information from neighbouring nodes via Xn interface.
* New or enhanced existing procedure to request/retrieve feedback information via Xn interface.