O-RAN.WG2.AIML-v01.01

Technical Report

O-RAN Working Group 2
AI/ML workflow description and requirements

Revision History

Date	Revision	Author	Description
2020.02.16	01.01.00	R. Jana	Clean Baseline for v01.01.00
2020.02.16	01.01.01	Q.Sun	Adding approved CR for ML model deployment, Sec 7.2 2019-11-11-CMCC-CR-ML model deployment.docx
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2020.03.09	01.01	R. Jana	For approval v01.01

Contents

Chapter 1 Introduction

1.1 Scope

This Technical Report (TR) has been produced by O-RAN Alliance. TRs are informative but they can contain potential functional requirements that will feed into Techincal Specifications (TS) eventually.

The contents of the present document are subject to continuing work within O-RAN WG2 and may change following formal O-RAN approval. In the event that O-RAN Alliance decides to modify the contents of the present document, it will be re-released by O-RAN Alliance with an identifying change of release date and an increase in version number as follows:

Release x.y.z

where:

x the first digit is incremented for all changes of substance, i.e. technical enhancements, corrections, updates, etc. (the initial approved document will have x=01).

y the second digit is incremented when editorial only changes have been incorporated in the document.

z the third digit included only in working versions of the document indicating incremental changes during the editing process.

The current document addresses the overall architecture and solution for AI/ML related requirements for the use-cases described in O-RAN WG2 UCR doc [O-RAN-WG2.UCR.02.00.00]. The document provides the terminology, workflow, and requirements, related to AI/ML model training, and its distribution and deployment in the Radio Access Network (RAN).

1.2 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 Release 16.

[1] 3GPP TR 21.905: “Vocabulary for 3GPP Specifications”

[2] 3GPP TS 38.401: "NG-RAN; Architecture description".

[3] "O-RAN: towards an Open and smart RAN", O-RAN white paper, https://www.o-ran.org/s/O-RAN-Use-Cases-and-Deployment-Scenarios-Whitepaper-February-2020.pdf

[4] O-RAN WG2 Use Case and Requirements v02.00

[5] O-RAN WG1 O-RAN Architecture Description - v01.00

[6] Intelligent Transportation Systems (ITS), ETSI TS 102 637-2 v1.2.1

1.3 Definitions and Abbreviations

1.3.1 Definition

For the purposes of the present document, the terms and definitions 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].

NMS: A Network Management System

O-DU: O-RAN Distributed Unit: a logical node hosting RLC/MAC/High-PHY layers based on the 7-2x fronthaul split defined by O-RAN.

O-RU: O-RAN Radio Unit: a logical node hosting Low-PHY layer and RF processing based on the 7-2x fronthaul split defined by O-RAN.

Non-RT RIC: O-RAN non-real-time RAN Intelligent Controller: a logical function that enables non-real-time control and optimization of RAN elements and resources, AI/ML workflow including model training and updates, and policy-based guidance of applications/features in Near-RT RIC.

Near-RT RIC: O-RAN near-real-time RAN Intelligent Controller: a logical function that enables near-real-time control and optimization of RAN elements and resources via fine-grained data collection and actions over E2 interface.

O1: Interface between orchestration & management entities (Orchestration/NMS) and O-RAN managed elements, for operation and management, by which FCAPS management, Software management, File management and other similar functions shall be achieved.

A1: Interface between Non-RT RIC and Near-RT RIC to enable policy-driven guidance of Near-RT RIC applications/functions, and support AI/ML workflow.

E2: Interface between Near-RT RIC and underlying RAN functions (CU-CP, CU-UP, and DU).

1.3.2 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].

eNB	eNodeB (applies to LTE)
gNB	gNodeB (applies to NR)

O-DU	O-RAN Distributed Unit
O-RU	O-RAN Radio Unit
O-CU	O-RAN Central Unit
RIC	O-RAN RAN Intelligent Controller
Non-RT RIC	Non-real-time RIC
Near-RT RIC	Near-RT RIC
QoE	Quality of Experience
KQI	Key Quality Indicator
KPI	Key performance indicator
CNN	Convolutional neural network
PCA	principal components analysis
RL	reinforcement learning
DRL	deep reinforcement learning
GPU	graphics processing unit
KNN	k nearest neighbors
LSTM	long short-term memory
ML	machine learning
NN	neural network
RL	reinforcement learning
RNN	recurrent neural network
SMO	service management and orchestration
SVM	support vector machine

Chapter 2 Machine Learning

Machine learning is a field of study that provides computers the ability to learn without being explicitly programmed. The ability to learn useful information from input data can help improve RAN or network performance. For example, convolutional neural networks and recurrent neural networks can extract spatial features and sequential features from time-varying signal strength indicators (e.g., RSSI).

This chapter introduces some of the common terminology related to AI/ML based use-cases development in context of O-RAN architecture.

2.1 Common terminology and Definitions

Table 1 - Common terminology

Definitions	Note/example
Application: An application is a complete and deployable package, environment to achieve a certain function in an operational environment. An AI/ML application is one that contains some AI/ML models.	Generally, an AI/ML application should contain a logically top-level AI/ML model and application-level descriptions
ML-assisted solution: A solution which addresses a specific use case using Machine-Learning algorithms during operation.	As an example, video optimization using ML is an ML-assisted solution.
ML model: The ML methods and concepts used by the ML-assisted solution. Depending on the implementation a specific ML model could have many sub-models as components and the ML model should train all sub-models together.	ML models include supervised learning, unsupervised learning, reinforcement learning, deep neural network, and depending on use-case, appropriate ML model has to be chosen. Separately trained ML models can also be chained together in a ML pipeline during inference.
ML workflow: A ML workflow is the process consisting of data collection and preparation, model building, model training, model deployment, model execution, model validation, continuous model self-monitoring and self-learning/retraining related to ML-assisted solutions	Based on ML model chosen, some or all of the phases of workflow will be included.

ML (model) life-cycle: The life-cycle of the ML model includes deployment, instantiation and termination of ML model components.	These are operational phases: the initial training, inference, possible re-training
ML pipeline: The set of functionalities, functions, or functional entities specific for an ML-assisted solution.	a ML pipeline may consist of one or several data sources in a data pipeline, a model training pipeline, a model evaluation pipeline and an actor.
ML training host: The network function which hosts the training of the model	Non-RT RIC can also be a training host. ML training can be performed offline using data collected from the RIC, O-DU and O-RU.
ML inference host: The network function which hosts the ML model during inference mode (which includes both the model execution as well as any online learning if applicable).	The ML inference host often coincides with the Actor. The ML-host informs the actor about the output of the ML algorithm, and the Actor takes a decision for an action.
Actor: The entity which hosts an ML assisted solution using the output of ML model inference.	
Action: An action performed by an actor as a result of the output of an ML assisted solution.	
Subject of action: The entity or function which is configured, controlled, or informed as result of the action.	
Model training information: Information needed for training the ML model.	This is the data of the ML model including the input plus optional labels for supervised training
Model inference information: Information needed as input for the ML model for inference.	The data needed by an ML model for training and inference may largely overlap, however they are logically different.

Figure 1 depicts the use of the ML components and terminologies as described in Table 1.

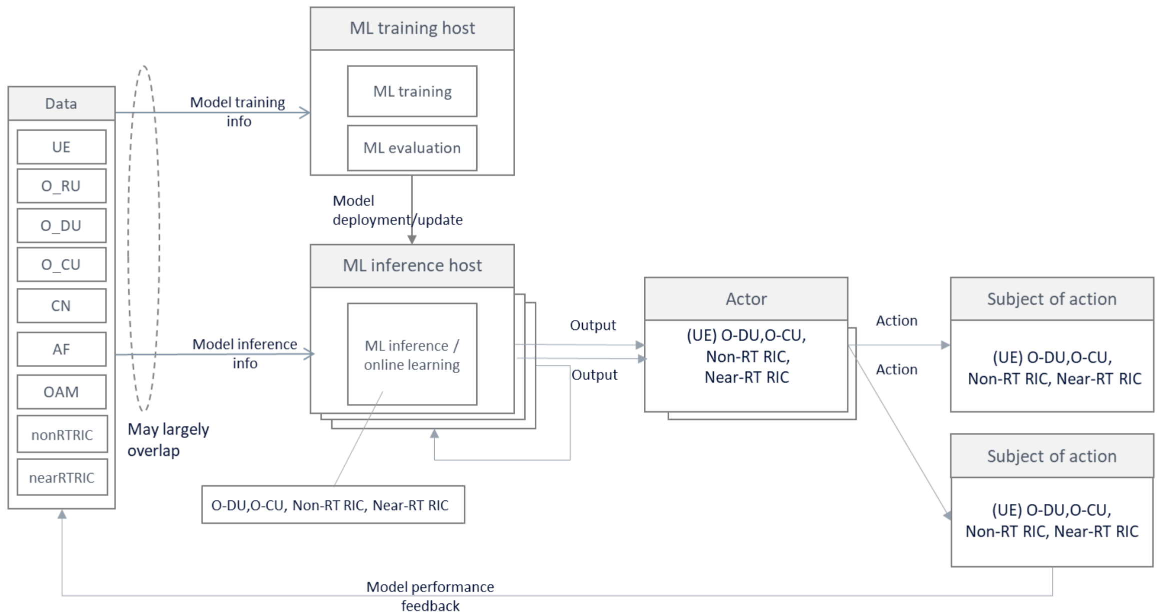


Figure 1 - ML modeling terminology

2.2 General principles

Principle 1: In O-RAN we will always have some offline learning as a proposed best practice (even for reinforcement learning type of scenarios). In the current document, offline training means a model is first trained with offline data, and trained model is deployed in the network for inference. Online training refers to scenarios such as reinforcement learning, where the model 'learns' as it is executing in the network. However, even in the latter scenario, it is possible that some offline training may happen.

Principle 2: A model needs to be trained and tested before deploying in the network. A completely untrained model will not be deployed in the network.

Principle 3: As a best practice, it would be useful if ML Applications are designed in a modular manner that are decoupled from one another. This includes their ability to share data without knowing each other's data needs. It also implies that they need not understand the location or nature of a data source. For example, an ML Application that is consuming RAN data need not know whether that data is being provided directly via E2, or by some other ML Application on the same Inference Host that is consuming and re-publishing that RAN data. Sections 4.2 and 4.3 describe this in more detail.

Principle 4: Given that the criteria for determining the deployment scenario for a given ML Application may differ between service providers, as a best practice, it should be possible for a Service Provider to decide whether an ML Application should be deployed to a Non-RT RIC or a Near-RT RIC as its Inference Host. See Section 5.2 for a discussion on the types of criteria that may be weighed differently by different providers.

Chapter 3 Types of Machine Learning algorithms

This section provides a view of how the different ML algorithms can be deployed and realized in O-RAN architecture. It does not detail or recommend the various machine learning algorithms available or recommend specific ML algorithms that should be applied to the use-cases realized in O-RAN architecture.

3.1 Supervised learning

Input data is called training data and has a known label or result. Supervised learning is a machine learning task that aims to learn a mapping function from the input to the output, given a labeled data set.

1. Regression: Linear Regression, Logistic Regression
2. Instance-based Algorithms: k-Nearest Neighbor (KNN)
3. Decision Tree Algorithms: CART
4. Support Vector Machines: SVM
5. Bayesian Algorithms: Naive Bayes
6. Ensemble Algorithms: Extreme Gradient Boosting, Bagging: Random Forest

Supervised learning can be further grouped into Regression and Classification problems. Classification is about predicting a label whereas Regression is about predicting a quantity.

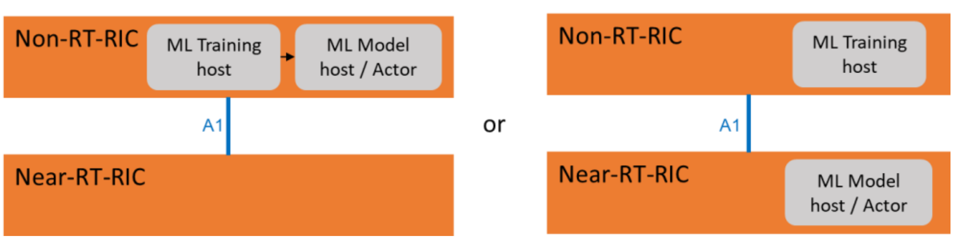


Figure 2 - Supervised learning model training and actor locations

In supervised learning (see Figure 2), Non-RT RIC is part of the SMO and thus is part of the management layer. ML training host and ML model host/actor can be part of Non-RT RIC or Near-RT RIC.

3.2 Unsupervised learning

Input data is not labeled and does not have a known result. Unsupervised learning is a machine learning task that aims to learn a function to describe a hidden structure from unlabeled data. Some examples of unsupervised learning are K-means clustering and principal component analysis (PCA).

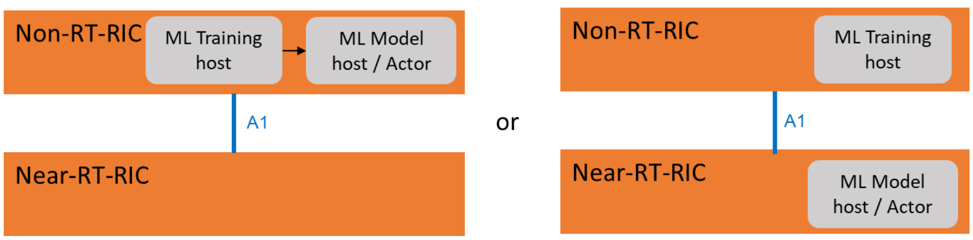


Figure 3 - Unsupervised learning model training and actor locations

In unsupervised learning (see Figure 3), ML training host and ML model host/actor can be part of Non-RT RIC or Near-RT RIC.

3.3 Reinforcement learning

A goal-oriented learning based on interaction with environment. In reinforcement learning (RL), the agent aims to optimize a long-term objective by interacting with the environment based on a trial and error process. There are several RL algorithms

- Q-learning
- Multi-armed bandit learning
- Deep RL

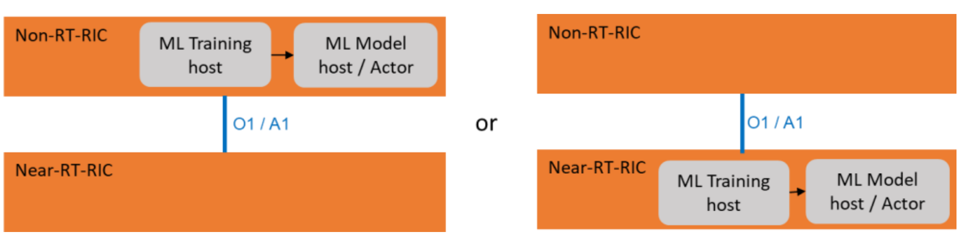


Figure 4- Reinforcement learning model training and actor locations

In reinforcement learning (see Figure 4), ML training host and ML model host/actor shall be co-located as part of Non-RT RIC or Near-RT RIC.

3.4 Mapping AI/ML functionalities into O-RAN control loops

There are three types of control loops defined in O-RAN. ML assisted solutions fall into the three control loops. Time scale of O-RAN control loops depend on what is being controlled, e.g. system parameters, resources or radio resource management (RRM) algorithm parameters. For example, if O-RAN control loop adapts the parameters of RRM algorithms, its time scale is slower than that of the RRM algorithm.

Loop 1 deals with per TTI msec level scheduling and operates at a time scale of the TTI or above. Loop 2 operates in the near RT RIC operating within the range of 10-500 msec and above (resource optimization). Loop 3 operates in the Non-RT RIC at greater than 500 msec (policies, orchestration). It is not expected that these loops are hierarchical but can instead run in parallel.

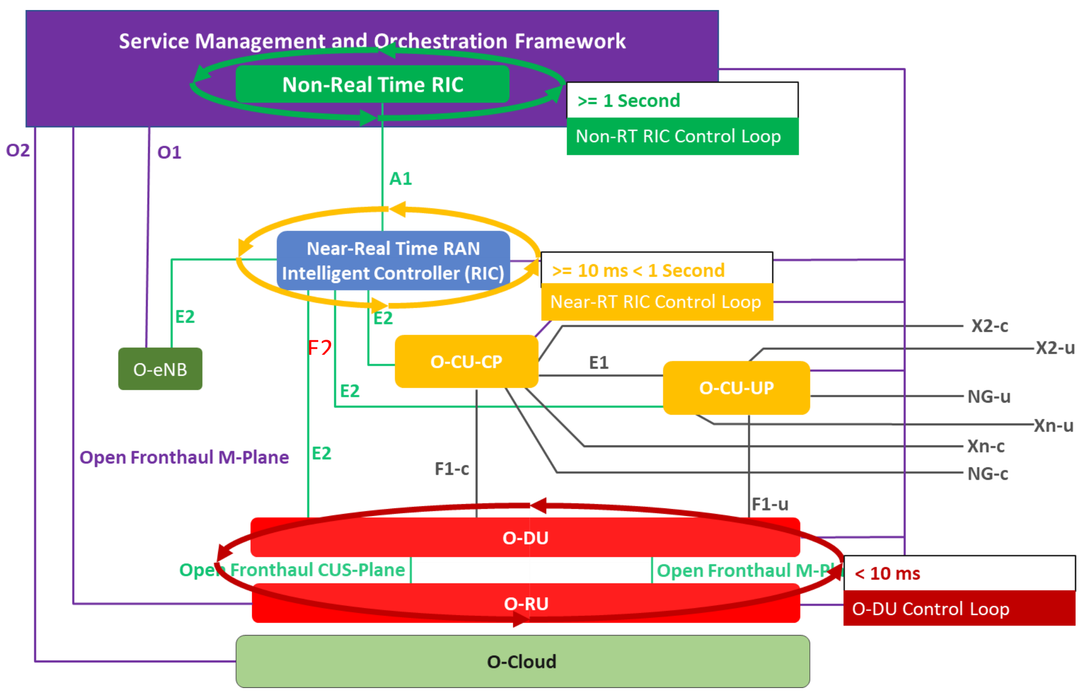


Figure 5 - Control loops in O-RAN

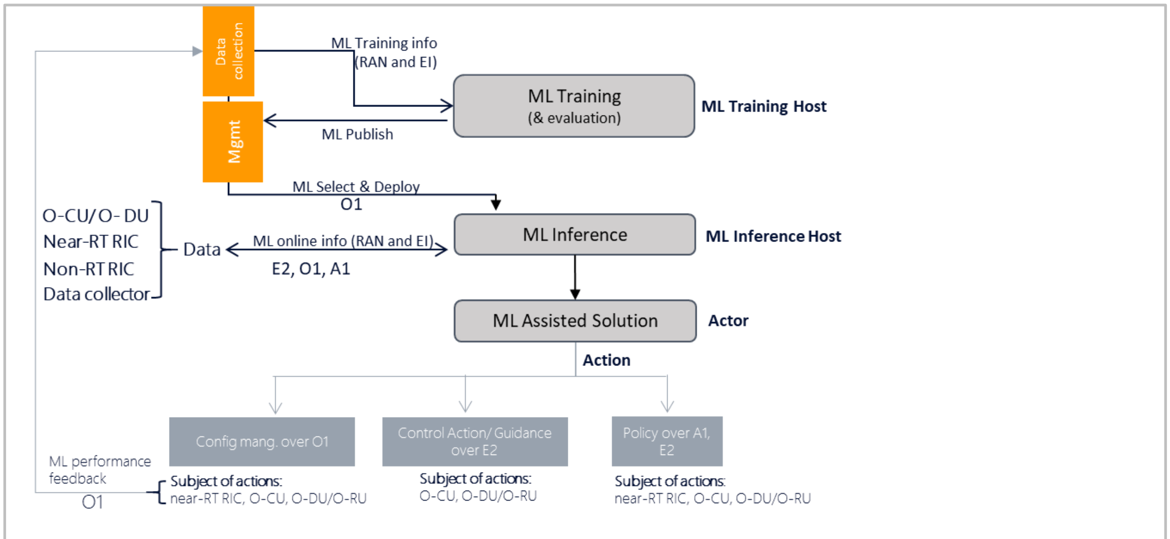
Figure 5 shows the three control loops in O-RAN architecture. AI/ML related functionalities can be mapped into the three loops. The location of the ML model training and the ML model inference for a use case depends on the computation complexity, on the availability and the quantity of data to be exchanged, on the response time requirements and on the type of ML model. For example, online ML model for configuring RRM algorithms operating at the TTI time scale could run in O-DU, while the configuration of system parameters such as beamforming configurations requiring a large amount of data with no response time constraints can be performed in the Non-RT RIC and Orchestration and management layer where intensive computation means can be made available.

In the first phase of O-RAN, ML model training will be considered in the Non-RT RIC and ML model inference will be considered in loops 2 and 3. For loop2, the ML inference is typically running in Near-RT RIC. For Loop 1, the ML model inference is typically running in an O-DU. ML workflow on loop 1 is FFS. While ML model implementation in O-RU could be envisaged, it is presently not supported in O-RAN.

Chapter 4 Procedure/Interface framework, Data/Evaluation pipelines

4.1 AI/ML General Procedure and Interface Framework

This chapter first provides the general framework of AI/ML procedure and interfaces, which addresses the ML components rather than network functions (non/Near-RT RIC, etc.). The potential mapping relationship between the ML components and network functions, interfaces defined in O-RAN are also illustrated in Figure 6.



Note: ML capabilities are stored in the management system. Query and Discovery of ML capabilities are terminated in the management system but not shown

Figure 6 - ML training host and inference locations

Note: *ML capabilities shall be stored in the management system (FFS). Query and Discovery of ML capabilities are terminated in the management system but not shown. ML inference host often coincides with the actor*

The deployment scenarios that are considered for ML architecture/framework in O-RAN architecture are

1. Deployment Scenario 1.1: Non-RT RIC acts as both the ML training and inference host
2. Deployment Scenario 1.2: Non-RT RIC acts as the ML training host and the Near-RT RIC as the ML inference host
3. Deployment Scenario 1.3: Non-RT RIC acts as the ML training host and the O-CU/O-DU as the ML inference host (for FFS)

In addition, for reinforcement learning based ML model-based deployment, both ML training and ML interference host shall be co-located on same MF.

Table 2 shows the various deployment scenarios and interfaces.

Table 2 - AI/ML deployment scenarios

Deployment Scenario	**ML Training Host**	**ML Inference Host**	**Interface for ML model deployment / update**	**Subject of Action**	**Action from inference host to subject**		**Enrichment data for inference**
					Config Mgmt. (CM)	**Policy / Control**	
Scenario 1.1	SMO/Non-RT RIC	Non-RT RIC	SMO internal	Near-RT RIC	O1	A1 (policy)	SMO internal
				O-CU, O-DU, O-RU	O1	N/A	SMO internal
Scenario 1.2	SMO/Non-RT RIC	Near-RT RIC	O1, O2	Near-RT RIC	near-RT RIC internal	near-RT RIC internal	A1
				O-CU, O-DU, O-RU	N/A	E2 (control/policy)	E2 (if applicable)
Scenario 1.3 (FFS)	SMO/Non-RT RIC	O-CU / O-DU	O1, O2	O-CU, O-DU, O-RU	FFS	FFS	FFS

Note: Configuration management for scenario 1.2 via E2 is FFS; Non-RT RIC can use SMO internal interfaces to trigger configuration changes over O1

Based on the framework, some key phases of machine learning are expected to be applied to any ML-assisted solution planned in O-RAN architecture. Any use case defined for ML-assisted solution shall have one or more phases (as applicable) and the phases are defined below:

1. **ML model capability query/discovery**

This procedure shall be executed whenever AI/ML model is to be used for ML-assisted solution. This procedure can be executed at start-up or run-time (when a new ML model is to be executed or existing ML model is to be updated). The SMO will discover various capabilities and properties of the ML inference host, such as:

a) Processing capability of HW where ML model is going to be executed (for example: resources available such as CPU/GPU, memory etc. that can be allocated for ML model inference).

b) Properties such as supported ML model formats and ML engines (for example: Protobuf, JSON, or any ONAP specific VES data formats).

c) NFVI based architecture support in MF to run ML model(s)

d) Data-sources available to run ML-pipeline (for example: support for data streams, data lake, or any specific database access)

This discovery of the capabilities shall be used to check if a ML model can be executed in the target ML inference host (MF), and what number and type of ML models can be executed in the MF.

Note: Exact mechanism and contents of capabilities discovery is FFS.

2. **ML model Selection and Training**

This procedure corresponds to design time selection and training of a ML model in relation with a specific ML-assisted solution (use case) to be executed. The ML designer will select and onboard the ML model and relevant meta data into the SMO environment. Utilizing on the ML training data collection, the ML training host will initiate the model training. Once the model is trained and validated, it is published back in the SMO catalogue.

At this stage, the ML designer can check whether the trained model can be deployed in the ML inference host, by mapping the ML model requirements to HW and performance properties discovered from Step 1. Upon successful validation, ML designer will inform the SMO to initiate model deployment.

3. **ML model Deployment and Inference**

The AI/ML model that is selected for the use case can be deployed via containerized image to MF where ML model shall be executing. This also includes configuration of ML inference host with AI/ML model description file.

Note: The O1 interface mechanism for ML model deployment is being specified by WG1.

Once the ML model is deployed and activated, ML online data shall be used for inference in ML-assisted solutions, which includes:

a) 3GPP specific events/counters (across all different Managed Elements) over O1/E2 interface
    a. Events: 3GPP 32.423
    b. Counters: 3GPP 32.425

b) Non-3GPP specific events/counters (across all different Managed Elements) over O1/E2 interface (to be defined in O-RAN WGs)

c) Enrichment information from non-RT RIC over A1 interface (to be defined in O-RAN WGs)

Based on the output of the ML model, the ML-assisted solution will inform the Actor to take the necessary actions towards the Subject. These could include CM changes over O1 interface, policy management over A1 interface, or control actions or policies over E2 interface, depending on the location of ML inference host and Actor.

4. **ML model performance monitoring**

The ML inference host is expected to feedback or report the performance of the ML model to the ML training host so that the ML training host can monitor the performance of the ML model and potentially update the model. Based on the use-case, specific set of data as applicable for use-case shall be used for ML model re-training. Based on the performance evaluation, either some guidance can be provided to use a different model in the ML inference host, or a notification can be sent indicating the need for retraining the model.

Note: Feedback mechanism and how the ML model switching can occur at runtime is FFS.

5. **ML model redeploy/update**

Based on the feedback and data received from various MFs, the ML performance evaluation module can inform the ML designer that an update is required to the current model. The ML designer will initiate the model selection and training step, but with the existing trained model. Once a new model has been trained, it will be deployed as described in Step 3, and the updated model will be used for ML inference.

4.2 Model Design and Composition

ML model design is the first step to conceiving the initial model. This requires connecting to data sources, parsing messages and tokenizing to create and select features. This activity is offline and requires data exploration mechanisms to help the model designer.

One question to address for complex problem spaces is whether to design the solution as a single model with many inputs, or as a chain of modular models. These two approaches can be seen in the figures below.

A chain of models provides a more modular solution that can facilitate reusability. For example, another model X may be shown to produce a better prediction *A-out* by considering an additional input *m*. In such a case, model A can be replaced with model X without the need for retraining or otherwise modifying models B or C.

On the other hand, in a chaining approach any errors in the prediction *A-out* will be propagated to model C, perhaps resulting in a less accurate prediction C-out than produced by the Single model approach shown below.

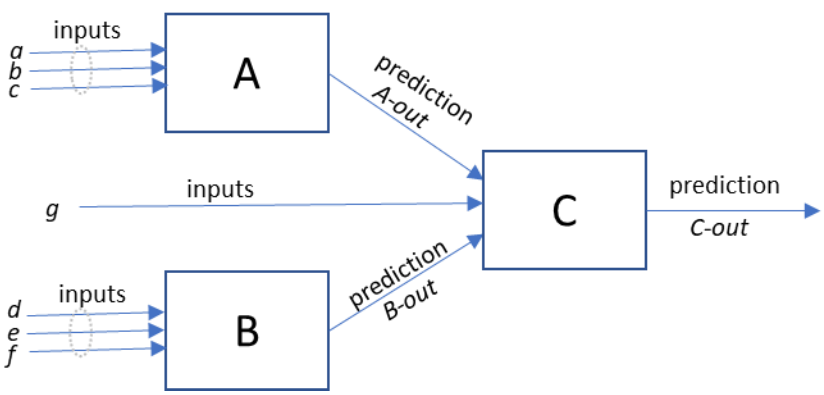


Figure 7 – Chained modular models.

A single model allows machine learning to have access to all inputs, which can detect unexpected data relationships and perhaps lead to a more accurate overall model.

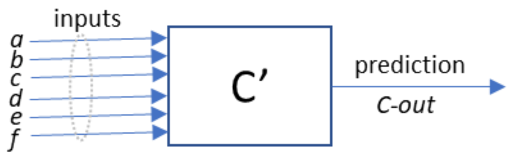


Figure 8 – Single model with many inputs.

Note that the predicted values *A-out* and *B-out* are not directly available to the single model C' whereas they are available to the chained model C. However, the model C' could be designed to derive these in the same way models A and B did in the chained approach.

Note also that inputs *a*, *b*, *c*, *d*, *e* and *f* are not directly available to as inputs to model C, only the predicted values *A-out* and *B-out*. If they are not needed, then the chained approach may work well and achieve the desired modularity. In this case on would expect models C and C' to produce equivalent "*C-out*" predictions. If, however, it turns out that the raw variables *c* and *d* are also useful for a good prediction by model C, then the chained approach may not yield as good a prediction as the single model C' approach might which has access to those inputs. Of course such a problem could be mitigated by also providing input values *c* and *d* to model C as shown below.

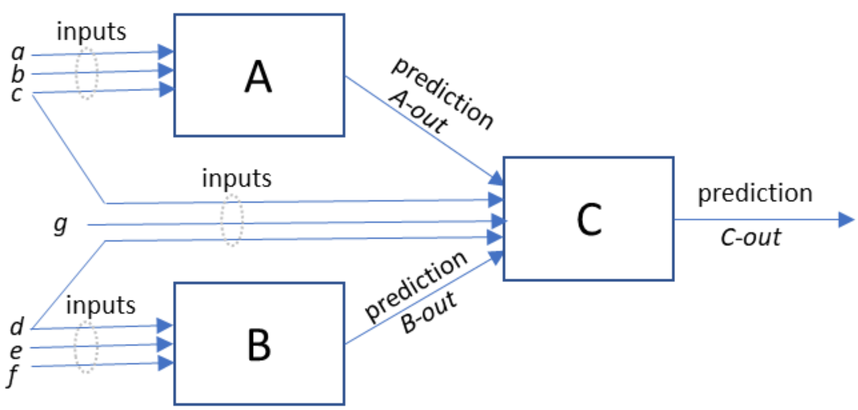


Figure 9 – Chained modular models with common inputs.

As an example of a chained model, consider a business problem that attempts to predict when a UE's serving cell QoE will deteriorate to an unacceptable level, and also predicts when each of the neighbor cell's QoE reaches an acceptable level. Such a prediction would be used it to determine when to trigger a handover, as well as to select among the various handover cell options.

One way to design such a solution would be as follows:

- A: RF signal strength predictor – Predicts RF signal KPIs a UE would experience with a neighbor cell at the current time "x", as well as predict the signal strength that same UE would experience with both its current serving cell and its neighbor cells at time "x+Δ".
- B: Cell utilization predictor – Predicts the cell utilization KPIs for both the serving and neighbor cells above at time "x+Δ".

- C: QoE predictor – Predicts the QoE KPIs that a UE would experience at time “x+Δ” for both its current serving and neighbor cells.

Such a modular approach could be desirable in that other uses for RF signal strength prediction and cell utilization prediction might be envisioned other than to predict UE future QoE. Also, a modular approach would allow each of the prediction models to evolve separately. For example, cell utilization predictor “B” might be improved by including as input trending information or venue schedule information among its inputs without having to retrain a single model “C’”. Or an RF signal prediction model might be improved based on inputs capturing the UEs predicted travel path based on commute patterns.

However, in order for such a chained approach to work, the variables available to the QoE predictor must be carefully considered. Whether a chained or a single model approach would be better for solving such a business problem would require analysis that is beyond the intended scope of this paper and will be left as an exercise for the reader.

4.3 Model Runtime Access to Data

In the prior section we noted that the value of chaining models is the modularity which can be realized. In Figure 9 for example, the models A, B, and C could be improved upon and replaced independent of each other. Such modularity could facilitate a marketplace whereby different vendors produce different modular solutions in the predictive space, allowing service providers to select from among the various models with the best predictive abilities for their specific environment. Because such marketplace vendors would want to provide complete solutions and not simply ML models, we will extend the concepts in the last section to apply also to applications. We will thus in this section re-interpret figures 7, 8 and 9 as representing applications A, B, C and C’ which contain the models in question.

Extending the discussion of the prior section, there can be scenarios in which two separate applications require access to the same data. This was seen in Figure 9 with applications A and C sharing input c and B and C sharing input d. Because such sharing of inputs may be common it would be wise to avoid an approach in which applications are seen as “owning” data. In addition, independence of the applications is impacted if one is aware of the inputs required of the other. For example, in Figure 9 as drawn, application A can be seen as knowing that application C requires Predication A-out as input. If application C was changed to no longer require Prediction A-out as input, then application A would need to be appropriately modified. Such coupling of applications negatively impacts overall solution modularity.

Rather, a better paradigm might be one in which data is commonly held by all applications, those applications being granted access to the data that they require. This common repository for the data along with the mechanism for making that data accessible to each application through some mechanism can be thought of as being the “platform” that underlies the “applications.”

Figure 10 illustrates a re-imaging of Figure 9 with such an approach in mind

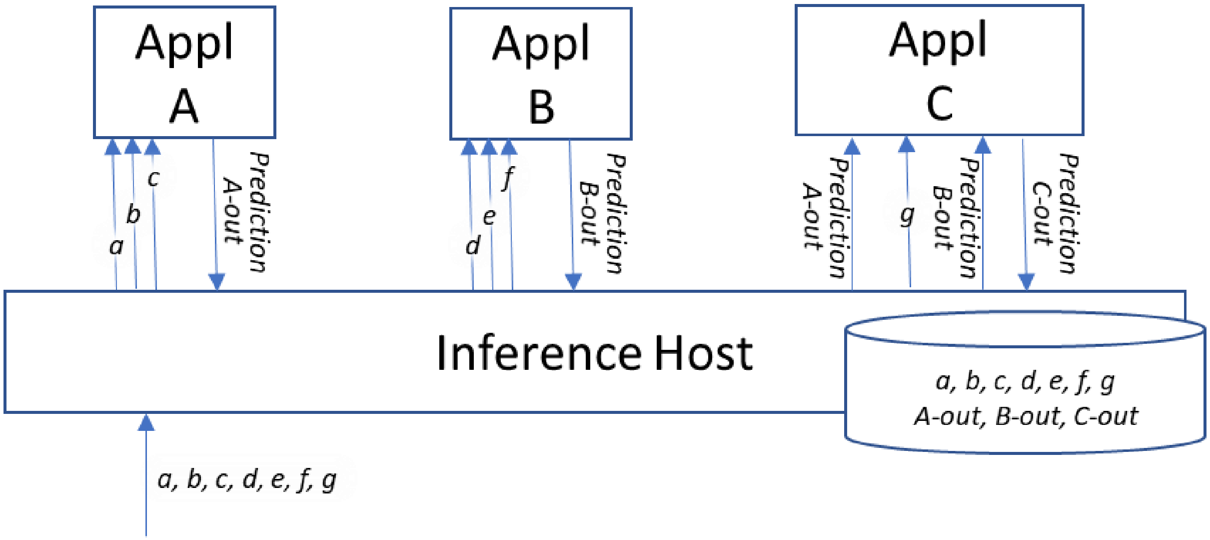


Figure 10 – Chained modular models with common inputs.

With such an approach, applications can be created independently with their own independent descriptors. When an application is loaded, it could "register" with the Platform to declare what types of data it consumes and what types of data it produces.

For example, when application A is loaded, its descriptor would be used to declare that it consumes as input variables *a*, *b* and *c* and that it writes Prediction *A-out*. If the consumed variables are standard attributes that the Platform knows how to obtain (e.g., E2 data), it could respond that those input variables are available through the Platform. Later application A could send a formal "subscription" request with more information (such as the specific geographic "scope" from which to collect that input) to have the Platform actually start providing those values. Regarding the produced variables (e.g., *A-out*), the Platform could assign some space in the common data repository for that output to be written. The Platform might also perform some added value validations to ensure that no other registered application also produces/writes that same variable, or if it does to ensure that the two application instances work within different "scopes" (e.g., geography).

Extending our example, when application C is loaded its descriptor would be used to declare that it reads as input variables *g*, *Prediction A-out* and *Prediction B-out*. Variable *g*, being standard in our example, would be treated as described above. The Platform could also respond that input variable *Prediction A-out* is also available through the Platform. However, if application B had not yet been loaded and registered, the Platform would respond that no source for *Prediction B-out* can be found. Perhaps application C has been written such that *Prediction B-out* is optional input. In this case application C would respond as such and processing would proceed. When application B was later loaded and registered, the Platform could notify all applications of new functionality being available. At that point application C could decide to re-register, again asking for a source for *Prediction B-out*, this time with favorable results.

Thus, the Platform could provide some added value services to ensure that applications are loaded and registered in the proper order.

The above described Platform responsibilities with respect to application registration. Now we can address data subscription.

Let's return to our example in the prior section whereby application A is an RF signal predictor, application B a cell utilization predictor and application C a UE QoE predictor. Perhaps the service provider considers cell utilization prediction to be a fundamental need that should be always "on" for all cells. The service provider would thus configure application B or provide it some policy (e.g., received across an A1-P interface) to generate these predictions, specifying the prediction interval. Application B would then send a "subscribe" request to the Platform asking for variables *d*, *e* and *f* including the desired measurement interval. As part of this "subscription" request Application B would also indicate that it will begin writing *Prediction B-out* with a certain measurement interval. The Platform would determine if these variables are already in the common data repository or not, and if not the Platform would go about securing them (e.g., by sending an E2 SUBSCRIBE request to the appropriate RAN network functions). The Platform would forward to application B the data content found in the data respository that matches that application's subscription request. Upon having secured its input data, application B would continuously be writing *Prediction B-out* to the common data repository.

For applications A and C, however, perhaps the service provider only wants prediction for a certain set of UEs. One way to accomplish this is for service provider to configure application C or provide it some policy describing the UE set of interest as well as the prediction interval. Application C subscription of its input variable *g* would proceed with the Platform in the same way as was described above for Application B. Application C would also subscribe to input variables *Prediction A-out* and *Prediction B-out* with a certain measurement interval, the former including a descriptor of the UE set of interest. For *Prediction B-out*, the Platform would determine that those values are already in the common data repository with the desired measurement interval and forward that content to application C.

For *Prediction A-out*, however, the Platform would determine that there is no data in the common data repository, nor is there any application that has subscribed to write it. The Platform would then identify the application that has registered for writing this data type, in this case application A, and forward to it the subscription request information to that application A. (Note that this is the local equivalent functionality of the Platform sending the E2 SUBSCRIBE request to the RAN for the application B subscription request.)

Application A would receive the *Prediction A-out* subscription request, including the measurement interval and UE set of interest, and determine what the implications are for its own data needs. It would then send to the Platform a subscription request asking for variables *a*, *b* and *c* along with the measurement interval and UEs of interest. It would also declare its intention to begin writing *Prediction A-out* with a certain measurement interval. Assuming that the Platform does not find this data already in the common data repository, it would go about securing it (e.g., via an E2 SUBSCRIBE request), forwarding the resultant data values to application A. At that point application A would begin writing Prediction A-out to the common data repository, which the Platform would in turn begin forwarding to application C.

4.4 Data, Model Training and Model Evaluation pipeline

This section describes the data, model training and evaluation pipelines.

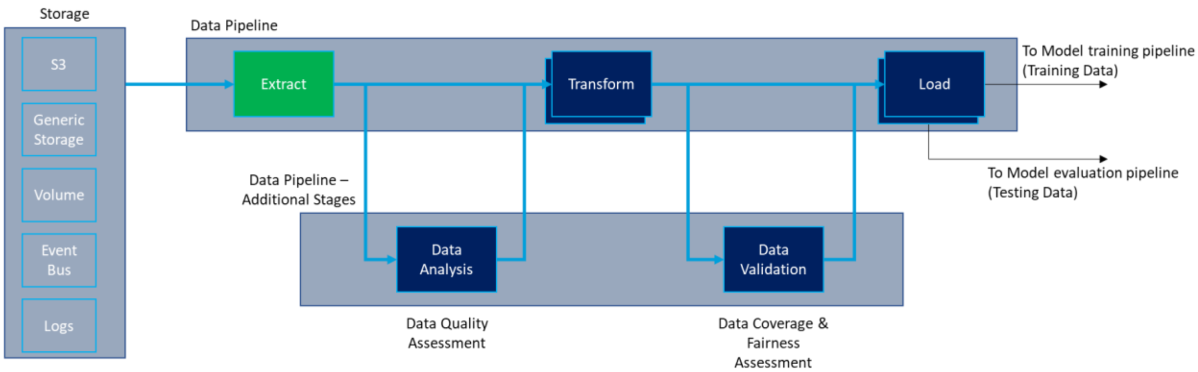


Figure 11- Data pipeline

Figure 11 defines the data pipelines. The "extract-transform-load" (ETL) process describes how data can be extracted from storage, transformed and loaded into training and testing sets. Additional data quality and validation stages can be inserted into the ETL pipeline. Data cleaning can also be part of the Transform block. This is outside the scope of WG2.

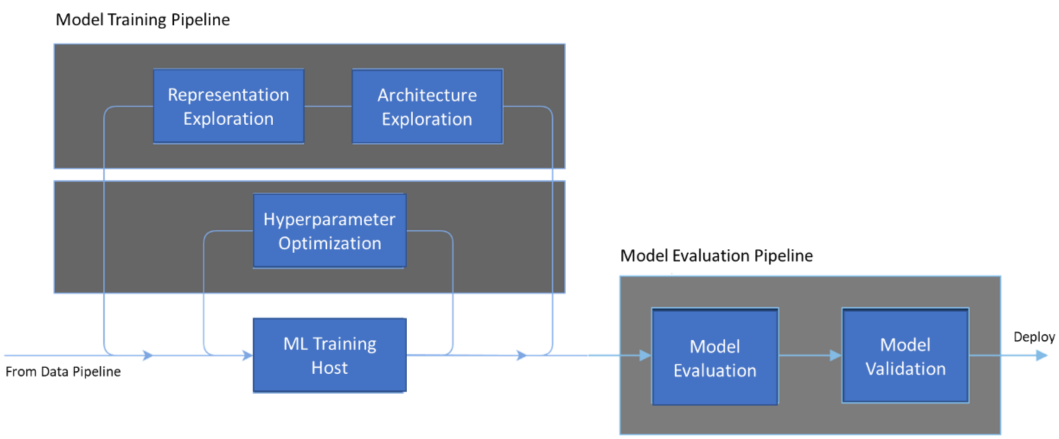


Figure 12 - Model training and evaluation pipelines

Figure 12 shows the model training and evaluation pipelines. Model training pipeline may change with model types. Model evaluation pipeline, however, is a more generic process. Model evaluation can be used to evaluate a single model or extended to select the best model from a range of models.

The end-to-end training process includes the following

- Fulfills the data requirements of the model (format, sample distribution, extent)
- Connects with requisite data via Data Pipeline (simplest ex: a data broker)
- Partitions data into appropriate sets (training, validation, testing, sample)
- Keeps Training data cached for error recovery and subsequent usage

- Manages model training though all phases
- Implements training by invoking a Model Training Pipeline
- Training Client tunes model parameters during training phases
- Scoring client monitors performance in order to declare training phase complete
- Communicates with license manager for usage and versioning

4.5 ML Model Lifecycle Implementation Example

The section provides an example (see Figure 13) of ML model lifecycle implementation example and key phases involved in the design and deployment in O-RAN architecture.

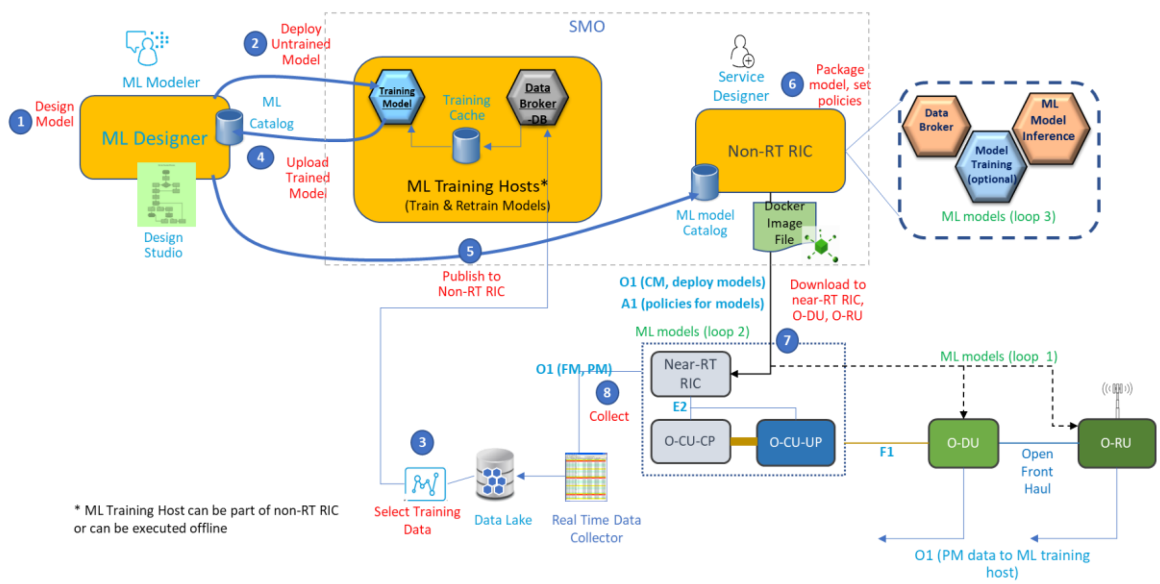


Figure 13 - ML model lifecycle (an implementation example)

Note: ML Model capability query and discovery can occur in ML designer and Non-RT RIC.

The typical steps involved in AL/ML based use-case application in O-RAN architecture is shown in Figure considering supervised/unsupervised learning ML models. The steps for reinforcement model could vary with respect to ML training host and the related interaction flows.

1. ML Modeler uses a designer environment along with ML toolkits (e.g., scikit-learn, R, H2O, Keras, TensorFlow) to create the initial ML model
2. The initial model is sent to training hosts for training

3. The appropriate data sets are collected from the Near-RT RIC, O-CU and O-DU to a data lake and passed to the ML training hosts.
4. The trained model/sub models are uploaded to the ML designer catalog (one such open source catalog platform is AcumosAI). The final ML model is composed.
5. The ML model is published to Non-RT RIC along with the associated license and metadata.
6. Non-RT RIC creates a containerized ML application containing the necessary model artifacts (when using AcumosAI, the ML model's container is created in Acumos catalog itself).
7. Non-RT RIC deploys the ML application to the Near-RT RIC, O-DU and O-RU using the O1 interface. Policies are also set using the A1 interface.
8. PM data is sent back to ML training hosts from Near-RT RIC, O-DU and O-RU for retraining.

Note that Near-RT RIC can also update ML model parameters at runtime (e.g., gradient descent) without going through extensive retraining. Training hosts and ML designers can also be part of Non-RT RIC.

Chapter 5 Deployment Scenarios

This chapter describes the high-level architecture of deployment scenarios defined in Section 5.1 and also captures the sequence diagrams to show end-to-end flows.

The current version captures the deployment scenarios 1.1 (see Figure 14) and 1.2 (see Figure 15) only, and scenario 1.3 is not in current scope of document and are FFS.

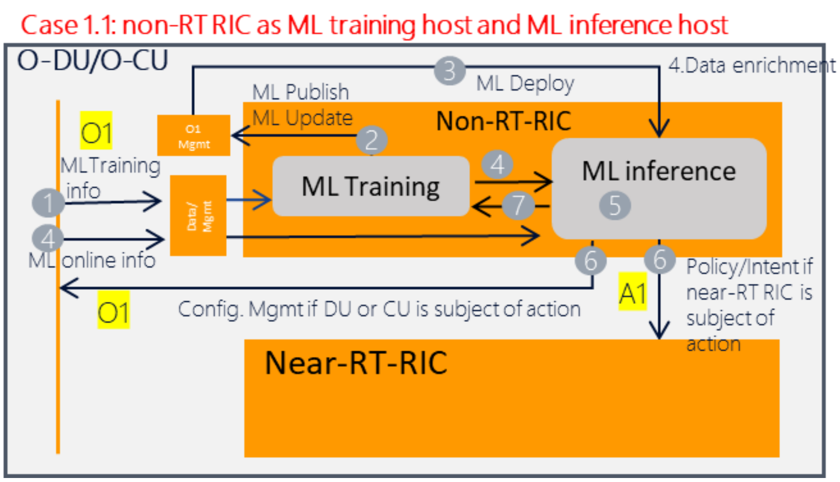


Figure 14 – Deployment scenario 1.1 - ML training and inference host locations

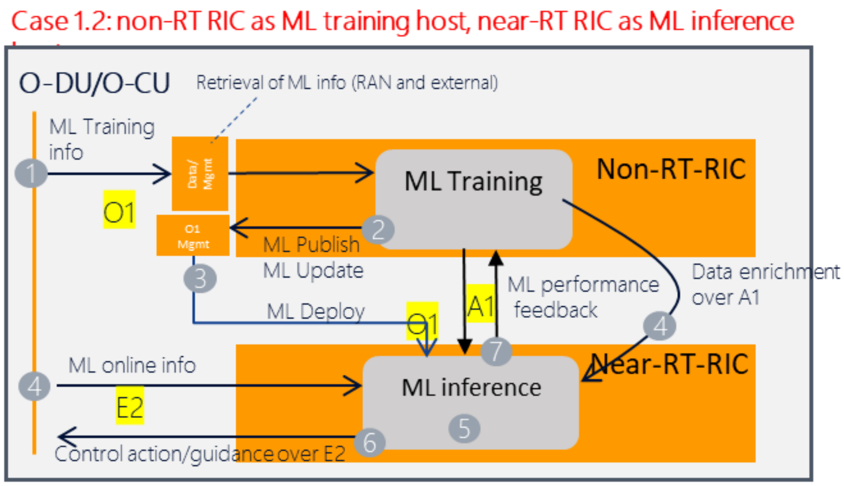


Figure 15 - Deployment scenario 1.2 - ML training and inference host locations

5.1 Sequence Diagram for Deployment Scenarios 1.1 and 1.2

The sequence diagram (see Figure 16) for Deployment Scenario-1.1 (SMO/Non-RT RIC for model training, Non-RT RIC for model inference host) and Deployment Scenario-1.2 (SMO/Non-RT RIC for model training, Near-RT RIC as model inference host) is captured below

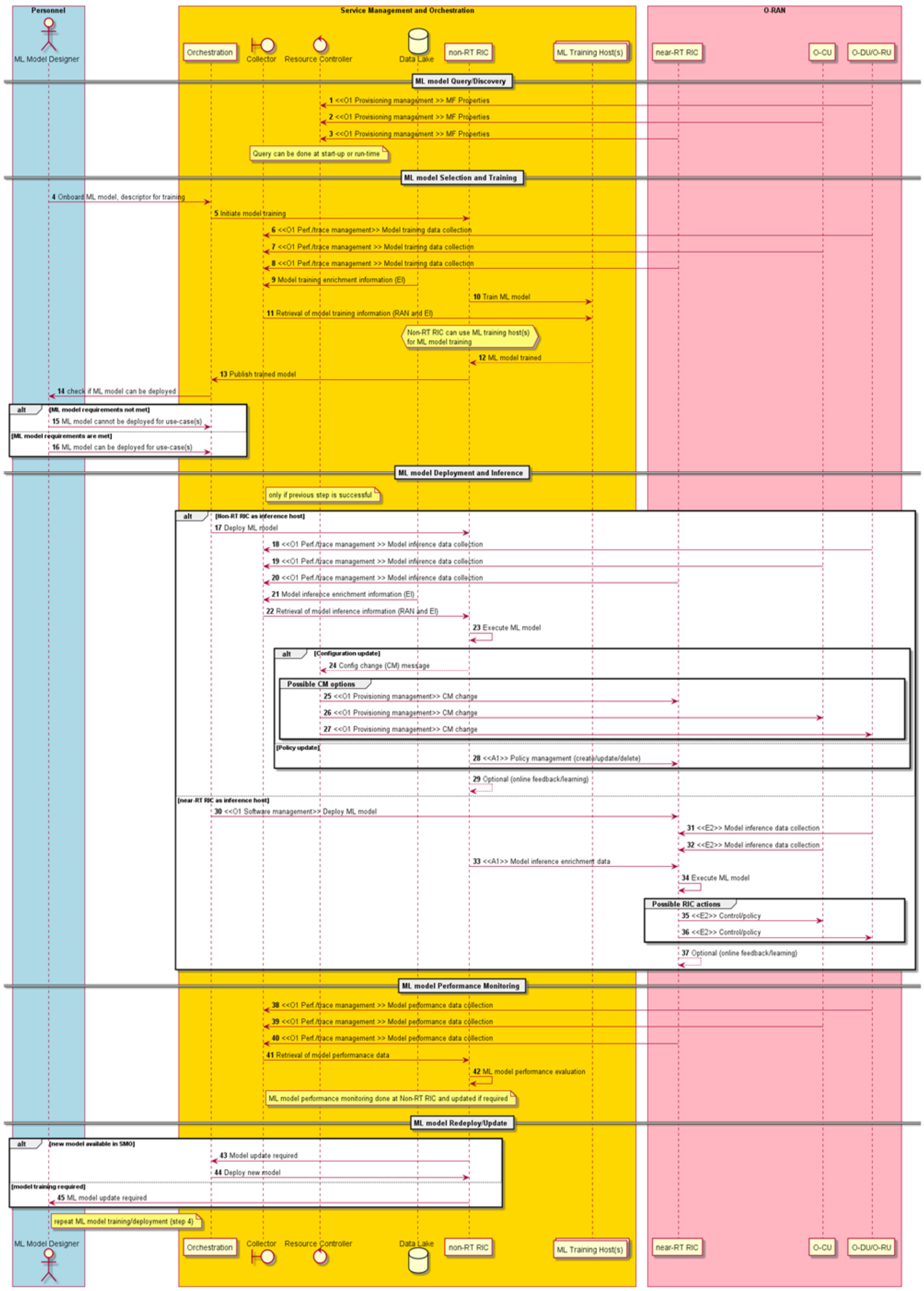


Figure 16 - Non-RT RIC as ML training host, Non-RT RIC or Near-RT RIC as ML inference host (Note that the SMO components are defined in WG1 OAM architecture, Appendix B [i.x9])

5.2 Criteria for Determining Deployment Scenario (Options)

This section discusses some criteria that can be used to decide whether an ML Application should execute in a Non-RT RIC or Near-RT RIC Inference Host. It also discusses some criteria for whether an ML Model within such an ML Application should be initially trained (offline learning) in a Non-RT RIC as its Training Host, or in a more centralized or remote location. (Note that subsequent online learning would be expected to occur in the execution environment.) Considerations for these decisions relate to the amount of data that is required by the ML Model both in training as well as in execution, as well as latency considerations in execution. It is assumed in this section that the type of data that an ML Model requires at runtime will also be required, perhaps in aggregated form, during training.

It is assumed that the Near-RT RIC would not be a suitable candidate for offline Training Host. Initial training would typically require a large pool of compute and storage resources. The very nature of the Near-RT RIC as a Network Function is geared towards high performance runtime processing with a small footprint. It is unlikely to have sufficient compute and storage resources to also handle initial offline learning. In addition, offline learning at the Near-RT RIC would also introduce complexity into its design to provide the assurances that ML training would not affect its runtime network function processing. The Non-RT RIC functionality of the SMO, a management (as opposed to a network) function, seems better suited to host initial training.

Regarding the Inference Host decision, criteria include:

1. The availability of data across a given interface. For example, if the data needed at execution time is available only across the E2 interface, then either the ML Application that includes this ML Model must either consider the Near-RT RIC as its Inference Host, or a Near-RT RIC function must be employed to forward across the O1 interface that E2 data to the Non-RT RIC as Inference Host. If the data needed at execution time is available only across the O1 interface, then the ML Application would need to consider the Non-RT RIC as its Inference Host, or a Non-RT RIC function must be employed to forward that O1 data to the Near-RT RIC with its own O1 interface. Clearly some of these options are very inefficient and likely undesirable.
2. The cost of data movement. Obviously the data movement costs of the various choices described in #1 above differ from one another. Ideally, if an ML Model requires E2 data, the Inference Host of its associated ML Application would be the Near-RT RIC. Similarly, if an ML Model requires O1 data, the Inference Host of its associated ML Application would be the Non-RT RIC. If an ML Model requires E2 data but considers the Non-RT RIC to be its Inference Host, then some function within the Near-RT RIC would need to be used as a vehicle to forward that E2 data to the Non-RT RIC. This would obviously be inefficient and costly. However, if the Non-RT RIC is also the Training Host for ongoing learning of that ML Model, then perhaps this inefficiency and cost would be warranted. Less understandable would be using the Non-RT RIC as a vehicle to forward O1 data to the Near-RT RIC acting as Inference Host.
3. Latency considerations. The data latency associated with the various choices described in #1 above differ from one another, and the Loop 2 versus Loop 3 considerations will factor heavily into whether a ML Model consider its Inference Host to be a Near-RT RIC or a Non-RT RIC.
4. Compute resource availability considerations. The Near-RT RIC may run in an "edge" location where compute resources are very limited and hence expensive. The Non-RT RIC may more likely run in a location with more ready access to compute resources, such as a data center.

Regarding the initial Training Host decision, criteria include:

1. The local versus general significance of the data. A data lake will be required in order to train an ML Model. Assuming that a typical Service Provider will have more than one Non-RT RIC instance, if that training data lake coincides with the Non-RT RIC then the data lake will contain data of only local significance. Only by merging this "local data" from many locales into a "central data lake" could future ML applications perhaps find unexpected correlations within data that was incorrectly assumed to be of only local significance.
2. The cost of data movement. While the previous item discussed the benefits of a "central data lake", transporting "local data" to such a central location is not without its costs.

Thus the decision as to whether to use a "local" Non-RT RIC as an initial (offline) Training Host or not in large part depends on the service provider's assessment of the value of that training data for more general purposes. The results of such an assessment can clearly differ from one service provider to another.

Looking at the criteria above, one can see how the decision as to whether the appropriate Inference Host for an ML model is a Non-RT RIC or a Near-RT RIC can reasonably differ between Service Providers. For example, consider two service providers below in their assessment of how to deploy a ML Application "X" that takes large volumes of E2 data to calculate some "enrichment information" regarding UEs (e.g., the UE's predicted QoE on various cells measured on the order of seconds), which can be used by a different "traffic steering" application (perhaps not ML-enabled) to appropriately drive handovers of those UEs. Assume that the "traffic steering" application would run at the Near-RT RIC using E2 mechanisms to drive handovers. Service Provider A and Service Provider B may come to quite different conclusions of how to deploy such an ML Application "X":

	Service Provider A	**Service Provider B**
"X" Data Source	E2	E2
"X" Data Movement Cost	Very High Volume, Very High Cost to Move Data over Distance	Very High Volume, Very High Cost to Move Data over Distance
"X" Latency Consideration	Loop 3 acceptable	Loop 3 acceptable
"X" Training data evaluation	This E2 data is of only local significance.	This E2 data is of potential global significance. Willing to pay to move data to a central data lake.
Pertainent Business Considerations	Minimize data transport costs for data with only local significance. Reserve Near-RT RIC for applications requiring Loop 2 latency	Any application requiring E2 data should run on the Near-RT RIC. Do not use Near-RT RIC as a data relay to the Non-RT RIC.
Inference Host Decision	Because "X" requires only Loop 3 latency, deploy it as an ML Application using the Non-RT RIC as its Inference Host. "X" will communicate with the "traffic steering" application via A1-EI.	Because it requires E2 data, "X" will run as an ML Application using the Near-RT RIC as its Inference Host. "X" will communicate with the "traffic steering" application via Near-RT RIC internal mechanisms.

Runtime E2 Data Movement	RAN -> E2 -> Near-RT RIC -> O1 -> Non-RT RIC	RAN -> E2 -> Near-RT RIC
Initial (Offline) Training Host Decision	Non-RT RIC will be used for training “X” (local training)	A central off-line location will be used for training “X” (training on a central data lake)
Initial (Offline) Training E2 Data Movement	RAN -> E2 -> Near-RT RIC -> O1 -> Non-RT RIC (leverage the Runtime E2 Data Movement path)	RAN -> Offline Data Collection -> Central Data Lake

Because the mechanism of inter-ML application communication (e.g., A1 versus Near-RT RIC internal) is so sensitive to considerations that can reasonably differ among service providers, it will be useful if the mechanism used were only a deployment decision. This should be kept in mind when the A1 and Near-RT RIC internal interface mechanisms are defined. To illustrate this extending the example above, if the mechanism for having the ML model “X” communicate with the “traffic steering” application is through a data structure capturing predicted QoE for a given UE on various cells, this data structure could be communicated either as “enrichment information” via A1-EI or communicated via a common data repository on the Near-RT RIC (such as described in section 4.3). Such an approach could preserve the service provider’s ability to make the choice of inference host a deployment consideration that does not require extensive refactoring or retraining of the solution components.

Chapter 6 Requirements

6.1 Functional Requirements

This section describes the functional requirements for A1 interface and Non-RT RIC.

[REQ-Non-RT RIC-FUN1]	Non-RT RIC may request/trigger ML model training in training hosts.

Notes: Regardless of where the model is deployed and executed, non-RT RIC should request/trigger ML model training. Note that ML models may be trained and not currently deployed. Implicitly, model re-training and model performance/evaluation.

[REQ-Non-RT RIC-FUN2]	Non-RT RIC shall provide a query able catalog for ML designer to publish/install trained ML models (executable software components) and Non-RT RIC will provide discovery mechanism if a particular ML model can be executed in the target ML inference host (MF), and what number (and type) of ML models can be executed in the MF.

Notes: Non-RT RIC is a component of the SMO framework, i.e., one component of the NMS. The catalogue is not only for external ML market place or platform to publish the models, but also the source for any internal models as well. Non-RT RIC can also connect to external ML catalogues via SMO specific interfaces (interface specification is not in scope of document). There are three types of catalogs namely (design-time catalog (outside non-RT RIC in other ML platforms), training/deployment-time catalog (inside non-RT RIC), and run-time catalog (inside near-RT RIC for scenario 1.2)). In scenario 1.1 where ML models are trained, deployed and executed in non-RT RIC.

[REQ-Non-RT RIC-FUN3]	Non-RT RIC shall support necessary capabilities (enable executable software to be installed, e.g., containers) for ML model inference in support of ML assisted solutions running in non-RT RIC

Notes: ML engines are packaged s/w executable libraries that provide the necessary routines to run the model.

Note: As an example, policies to switch and activate ML model instances under different operating conditions (busy hour vs non-busy hour or seasonal changes, etc.)

[REQ-Non-RT RIC-FUN4]	Non-RT RIC shall be able to access feedback data over O1 interface on ML model performance and perform necessary evaluation.

Note: PM and FM stats for ML model are relayed over O1. If the ML model fails during runtime an alarm can be generated as feedback to non-RT RIC. How well the ML model is performing in terms of accuracy of prediction or other operating statistics it produces can be sent to non-RT RIC over O1.

Note: The following requirements which apply to both the Non-RT RIC and the Near-RT RIC as ML Inference Host are intended to facilitate a Service Provider's ability to consider it a deployment decision whether an ML Application should be run on a Non-RT RIC or a Near-RT RIC as its Inference Host. This is in recognition that the criteria for determining the deployment scenario for a given ML Application may differ between service providers. See Section 5.2 for a discussion on the types of criteria that may be weighed differently by different providers

[REQ-Non-RT RIC-FUN5] [REQ-Near-RT RIC-FUN1]	As part of ML Application "registration", the ML Inference Host shall be able to digest information relating the data type(s) and periodicity thereof that the ML Application produces and consumes. This requirement applies both to the Non-RT RIC function and the Near-RT RIC as ML Inference Host.

Note: The following is the corresponding requirement as applied to ML Applications.

[REQ-Non-RT RIC-FUN6] [REQ-Near-RT RIC-FUN2]	ML Applications shall be able to perform "registration" interactions with the ML Inference Host communicating information relating the data type(s) and periodicity thereof that the ML Application produces and consumes. This requirement applies both to those ML Applications that consider the Non-RT RIC function as ML Inference Host, as well as those ML Applications that consider the Near-RT RIC as ML Inference Host.

Note: "Registration" differs from "subscription" in that "registration" involves only data types and their periodicity, whereas "subscription" involves specific sets of data within a given "scope" (see next requirement).

[REQ-Non-RT RIC-FUN7] [REQ-Near-RT RIC-FUN3]	The ML Inference Host will be able to match data consumption needs with data sources. In this respect a data source could be either an ML Application (i.e., another ML Application's data "produced') or the ML Inference Host itself (e.g., mediating an O1-VES data source via the SMO). The ML Inference Host shall consider it a registration-time validation error if no corresponding source can be matched to an ML application's "consumed data" requirements. This requirement applies both to the Non-RT RIC function and the Near-RT RIC as ML Inference Host.

Note: The following requirements referring to ML Inference Host handling of data "subscription requests" are intended to allow ML Applications to share data without knowing each other's data needs (see sections 4.2 and 4.3). This functionality is seen as an enabler for modularity of ML Applications.

[REQ-Non-RT RIC-FUN8] [REQ-Near-RT RIC-FUN4]	The ML Inference Host shall be able to process scoped data "subscription" requests from ML Applications, working with other neighboring (i.e., SMO, Non-RT RIC function, Near-RT RIC Platform) functions as necessary to set up the corresponding data routing (e.g., routing of O1-VES data to the ML Application, routing of one ML Application's produced data to the consuming ML Application). This requirement applies both to the Non-RT RIC function and the Near-RT RIC as ML Inference Host.

Note: An example of "scope" for a data subscription request would be identifying a specific set of gNBs from which to collect O1 data of a particular data type.

[REQ-Non-RT RIC-FUN9] [REQ-Near-RT RIC-FUN5]	For subscription requests that correspond to data produced by another ML Application, the ML Inference Host function will pass the information content thereof (e.g., data type, scope, periodicity) to that other ML Application for processing. This requirement applies both to the Non-RT RIC function and the Near-RT RIC as ML Inference Host.

[REQ-Non-RT RIC-FUN10] [REQ-Near-RT RIC-FUN6]	ML Applications that produce data shall be able to interact with the ML Inference Host to receive and process scoped subscription requests. The ML Application will be responsible for determining and generating to the ML Inference Host any additional subscription requests needed to produce the requested data. This requirement applies both to those ML Applications that consider the Non-RT RIC function as ML Inference Host, as well as those ML Applications that consider the Near-RT RIC as ML Inference Host.

Note: It is the responsibility of the ML Application to ensure that the periodicity and scope of these "consumed data" subscription request corresponds to that ML Application's needs in producing the requested data, as described in the scoped subscription request that it received from the Inference Host.

[REQ-Non-RT RIC-FUN11] [REQ-Near-RT RIC-FUN7]	The ML Inference Host shall be able to provide data mediation functionality such that, if two separate ML Applications request the same ML Application-produced data, the ML Inference Host will split the data feed without placing a burden on the source ML Application. This requirement applies both to the Non-RT RIC function and the Near-RT RIC as ML Inference Host.

REQ	Description
[REQ-O1-FUN1]	O1 interface shall support deployment and update of the ML models as a packaged s/w executable (e.g., in a container).
[REQ-O1-FUN2]	O1 interface shall support file based ML model deployment and updates.
[REQ-O1-FUN3]	O1 interface shall support PM and FM data collection for ML models, including fine-grained events/counters needed for ML training and inference.

[REQ-O1-FUN4]	O1 interface shall support collection of ML relevant capabilities of the managed function where the model is to be deployed for inference.

6.2 Non-Functional Requirements

This section describes the non-functional requirements for A1 interface and Non-RT RIC, e.g., security.

REQ	Description
[REQ-O1-NONFUN1]	O1 interface shall support scaling ML model instances running in target ML inference host (MF) by observing resource utilization in MF.

Note: The environment where the ML model instance is running will monitor resource utilization (e.g., in O-RAN-SC there is a component call Resource Monitor in near-RT RIC; similarly, in non-RT RIC there needs to be a Resource Monitor that continuously monitors resource utilization). If resources are low or fall below a certain threshold, the runtime environment in near-RT RIC and non-RT RIC needs to provide a scaling mechanism to add more ML instances. K8s runtime environments typically provide auto-scaling feature.

REQ	Description
[REQ-O1-NONFUN2]	ML model instances running in target ML inference hosts shall be automatically scaled by observing resource utilization in MF.

Chapter 7 Key Issues

7.1 AI/ML Models in O-RAN Use Cases

In [4] multiple AI/ML assisted use cases are discussed. This section summarizes the examples of the AI/ML models used in the O-RAN use cases.

Use Case	AI/ML models functionality description	AI/ML algorithms types (example)	Deploy scenarios mapping	Data Input	Data Output
QoE Optimization	service type classification	Supervised learning (e.g., CNN, DNN)	Scenario 1.2	user traffic data	service type
	KQI/QoE prediction (e.g., good, bad or video stall ratio, duration)	Supervised learning (e.g, LSTM, XGboost)	Scenario 1.2	Network data: L2 measurement report related to traffic pattern, e.g., throughput, latency, packets per-second UE level radio channel information, mobility related metrics RAN protocol stack status: e.g. PDCP buffer status Cell level information: e.g. DL/UL PRB occupation rate Application data: e.g., video QoE score, video initial delay	KQI/QoE value e.g., good/bad, stalling ratio, video stalling duration, vMoS value

				stalling detail including the timestamp stalling duration, stalling ratio,	
	Available radio bandwidth prediction	Supervised learning (e.g., DNN)	Scenario 1.2	similar to above	Available radio Bandwidth
Traffic Steering	cell load prediction/user traffic volume prediction	Supervised learning (time series prediction, e.g., SVR, DNN)	Scenario 1.1 / Scenario1.2	load related counters, e.g., UL/DL PRB occupation	same to input
	Radio finger print prediction	supervised learning (e.g., SVR, GBDT)	Scenario 1.2	Intra-frequency MR data and PM counters, e.g., RSRP, RSRQ, MCS, CQI, etc.	Inter-frequency MR data, e.g, RSRP, RSRQ, MCS, CQI, etc.
QoE based Traffic Steering	generate relevant A1 policies to provide guidance on the traffic steering preferences	FFS	Scenario 1.1	FFS	priority order of the cells to be used for downlink data transmission.
	time-series prediction of individual performance metrics or counters	Supervised learning (e.g. lasso regression-based prediction model)	Scenario 1.2	FFS	FFS

	QoE prediction at each neighbor cell for a given targeted user	Supervised learning (e.g., binary classification model using Random Forest)	Scenario 1.2	FFS	QoE good/bad
V2X Handover Managem ent	✓ prediction / detection HO anomalies ✓ discovery of preferred HO sequences	Supervised learning	Scenario 1.2	CAM,,radio cell IDs, connection IDs, and basic radio measurements (RSRP, RSPQ etc.) GPS, direction, velocity	✓ HO anomalies probability ✓ preferred HO sequences

Note: CAM stands for Cooperative Awareness Message, as defined in [6]. It originates from the vehicular UE and terminates in the V2X App Server. It contains the GPS coordinates of the vehicle to a 0.1-1s granularity.

7.2 AI/ML Model Deployment

In deployment scenario 1.2, Non-RT RIC acts as the ML model training host and near-RT RIC acts as the ML model inference host. ML/AI model can be deployed and enabled in Near-RT RIC in different options:

1. Image based deployment: The AI/ML model will be deployed as a xAPP or within a xAPP instance, and also can be updated via the xAPP software update. In this case, the ML inference runtime is self-contained in the image, which simplifies the deployment. This is a generic deployment of ML xAPP – in the sense that ML xAPP is treated no differently from other types of xAPP.

2. File based deployment: The AI/ML model can be deployed based on the AI/ML model file, which is generally decoupled with the xAPP software version, and can be enabled and updated via the xAPP file configuration. For this scenario, a ML model catalog and an inference platform/engine are usually required for the ML model inference host (i.e., Near-RT RIC). The Near-RT RIC may have an unified inference platform/engine, which can help to accelerate the inference efficiency (exploiting native ML capabilities of the platform) and enable greater customization but which requires the ML model file format to be supported by the inference platform.

Figure 77 illustrates an example of image based vs file based ML model deployments.

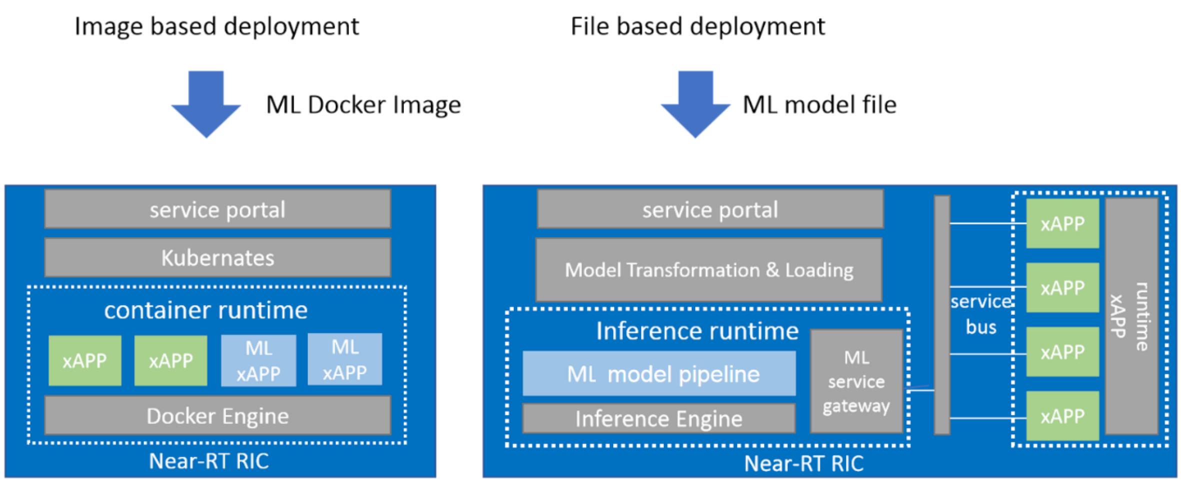


Figure 77 - Examples of image based and file based ML model deployment

Notes: The above figure only shows examples of how Near-RT RIC works under the image based ML model deployment and the file based ML model deployment. It may have different Near-RT RIC internal implementation.

Table 3 compares the Pros and Cons of the two approaches.

Table 3 - Pros and Cons of the image based and file based ML model deployment

Options	Pros	Cons
Opt1: Image Based ML model deployment	Faster and flexible deployment. Less requirements on the ML model inference host, i.e., Near-RT RIC, except for support of container runtime env.	The inference efficiency depends on the container capability.
Opt2: File Based ML model deployment	Better customization and efficiency by exploiting the on-device model optimization and update capabilities. Potential use of standard file formats for ML models.	Additional function requirement for the ML model inference host. Requires the matching of the ML model format and the inference engine.

Annex A (Informative)

A.1 Discussion on A1/O1 clarification

The following table tries to summarize WG2 involved information exchange over O1 and A1 interface based on the UCR doc and AI/ML workflow discussion.

Table 4 - A1 vs O1 information exchange

Information	Interface	Management Services	Remarks
Policy	A1		
Enrichment information	A1		
Policy feedback	A1		Feedback for model state
Non-RT RIC performance data collection	O1	Performance measurement	SMO internal interface to access O1 data
Non-RT RIC Fault data collection	O1	Fault measurement	SMO internal interface to access O1 data
Network parameter configuration	O1	Provisioning management	O1-CM
AI/ML model deployment	O1	Software management	
AI/ML model update	O1	Software management	Containerized, same for xApp update/revision control as per OAM
AI/ML model performance monitoring	O1		Enhancement is needed. How to model the AI/ML in the information model needs further study.

A.2 Examples of ML model capabilities/descriptors

- ML capabilities may include performance aspects of the target network function (e.g. CPU, memory, etc.), support for ML engines and supported libraries..
- These capabilities need to be matched against an ML model descriptor to decide whether a model can be deployed in the target network function.

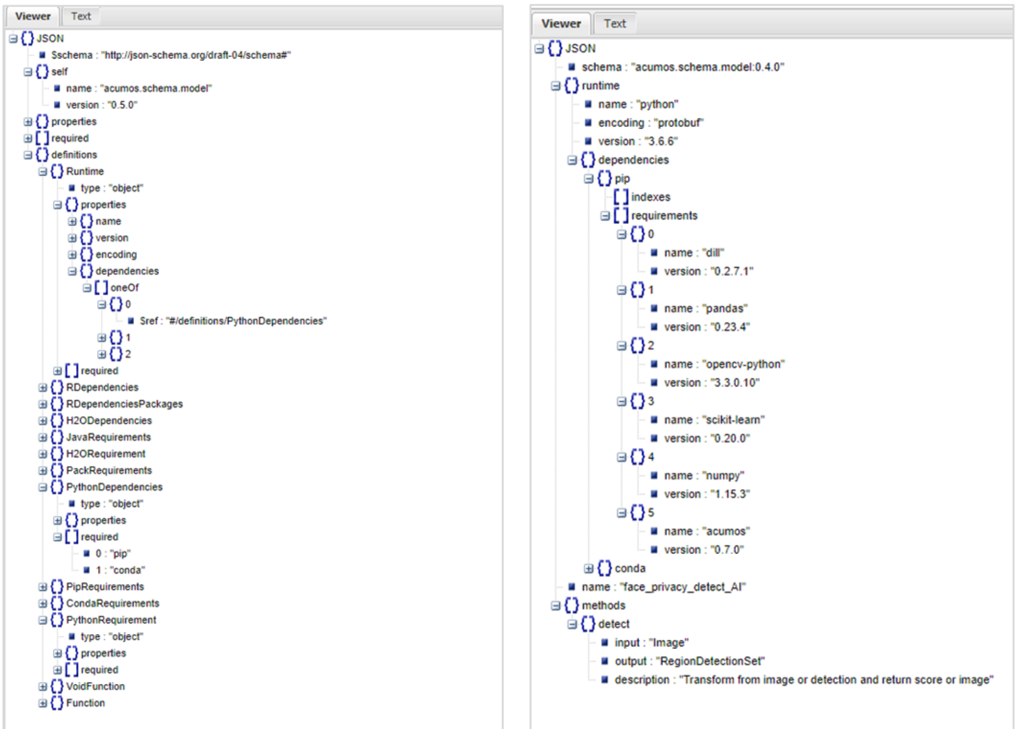


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Figure 18 - Example ML model descriptor schema

Figure 18 provides an example schema for ML models and an illustration for a face_privacy_detection use case. It shows the input/output mapping and a set of ML model runtime dependencies.

Annex Z: O-RAN Adopter License Agreement

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Execution of this Agreement by Adopter in its capacity as a legal entity or association constitutes that legal entity's or association's agreement that its Affiliates are likewise bound to the obligations that are applicable to Adopter hereunder and are also entitled to the benefits of the rights of Adopter hereunder.

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