3GPP TSG RAN Rel-18 workshop **RWS-210448**
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Title: Views on studies on AI/ML for PHY

Agenda item: 4.3

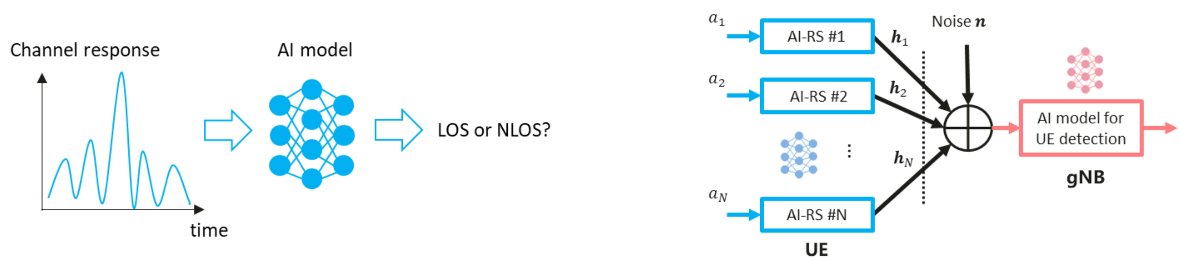
Document for: Discussion and decision

1. Introduction

In recent years, artificial intelligence (AI) and machine learning (ML) have made great success in the fields of computer vision, natural language processing, automotive driving, just to name a few. Applying AI/ML to wireless networks are also being discussed in many standardization organizations, e.g. 3GPP and ITU. In the Rel-17 of 3GPP RAN3, there is an ongoing study item "Study on enhancement for data collection for NR and ENDC" studying the functional framework for RAN intelligence, and some higher layer use cases for AI/ML have also been identified, i.e., load balancing, network energy saving, mobility, traffic steering [1]. In RAN#91-e, companies also showed interests in applying AI/ML for physical layer use cases [2][3][4][5][6]. In this contribution, we present our views on the potential study of AI/ML for physical layer.

2. Motivations of AI/ML for physical layer

Applying AI/ML in 5G networks has received much attention in 3GPP. In the RAN3 led study item, general functional framework, potential use cases and related standardization impacts for RAN intelligence are being discussed. With the discussion, 3GPP RAN community are getting some common understanding on the concept and general procedures of AI/ML approaches, i.e., model training, and model inference. Nonetheless, the discussion is limited to high layer use cases, and no detailed evaluation of AI/ML schemes is performed.



(a). AI/ML for LOS/NLOS identification (b). AI/ML for RS design and channel estimation

Figure 1. Examples of AI/ML for physical layer

Applying AI/ML for physical layer use cases was on the table for discussion before also but with no consensus achieved yet. One potential motivation on AI/ML for physical layer is to handle the design problems that are *hard-to-model* via traditional approaches. Current NR networks are mainly designed with precise mathematical models developed from Shannon theory, detection theory, queueing theory, and so on. However, due to high randomness and diversity of wireless environments, there are many problems hard to find precise mathematical models. Although some approximated models are proposed, the performance of corresponding solution can be far from optimal. To tackle this issue, AI/ML may provide a new solution by leveraging its capability of learning the wireless environments. For example, wireless positioning relies on line-of-sight (LoS) signals for accurate ranging, while identifying LoS and non-line-of-sight (NLoS) signal based on channel responses lacks of effective modelling methodology. As shown in Figure 1(a), AI/ML can be a solution to this problem due to the strength in classification by learning the distinct patterns of LoS and NLoS channel responses.

Observation 1: AI/ML may potentially solve hard-to-model problems in physical layer use cases.

Another potential motivation to apply AI/ML on physical layer is for the complexity reduction towards the problems that are *hard-to-solve*. For many physical layer use cases in wireless networks, the design problems often scale fast with the system parameters, e.g., the number of transmit and receive antennas, the number of UEs, the number of TRPs, the bandwidth, and so on. Although with precise mathematical models, it would still be extremely difficult to find the optimal solution, as finding the optimal solution via exhaustive searching and iterative heuristic algorithms is normally costly and unacceptable. Recently, the advances in AI/ML shed a light on this challenge. As AI/ML model is theoretically able to fit any optimization problem with a reasonable number of neurons and AI/ML model can be efficiently optimized, a welltrained AI/ML model can fit a physical layer design problem and predict the optimal solution immediately depends on inputs, circumventing inefficient searching from the large feasible set. For example, when there are massive UEs for uplink grant-free transmission in the same resource, much more than the number of orthogonal DMRS ports, the problem of RS design and UE detection becomes quite complicated. As shown in Figure 1(b), AI/ML can be applied to find the RS pool and corresponding UE detection algorithm efficiently, without the need of searching and testing all candidate RS patterns and sequences.

Observation 2: AI/ML may potentially provide efficient solutions to hard-to-solve problems in physical layer use cases.

3. High-level Principles

In RAN3 study item, some high-level principles have been discussed for AI/ML. Some high-level principles there should also be applied for the potential study of AI/ML for physical layer. Firstly, it is preferred that detailed AI/ML algorithms and models shall be left for implementation, so that vendors are encouraged to implement their own competitive algorithms and models. AI/ML is a fast developing field, and lots of new AI/ML algorithms models are being proposed by the AI/ML community. Specified AI/ML algorithms and models will limit the power of AI/ML for wireless networks.

Secondly, for AI/ML schemes, plenty of data can be necessary for model training and model inference. It should be ensured that proposed AI/ML schemes shall not impose any privacy concerns from the users. It should be discussed which data is accessible by which logical nodes.

Thirdly, for the potential study, the existing network architecture and interfaces of NR should be reused. This would also mean that new logical nodes or interfaces are not desirable, so that further complicating the system can be avoided, and backward compatibility with legacy gNBs and UEs can be ensured as much as possible.

Proposal 1: For the potential study of AI/ML for physical layer,

- ***Detailed AI/ML algorithms and models shall be left for implementation;***
- ***AI/ML schemes shall not impose any privacy concerns;***
- ***Existing network architecture and interfaces of NR should be reused.***

4. Preliminary considerations for study

4.1 Evaluation methodology

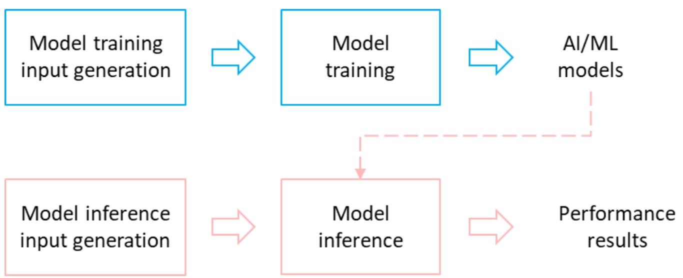


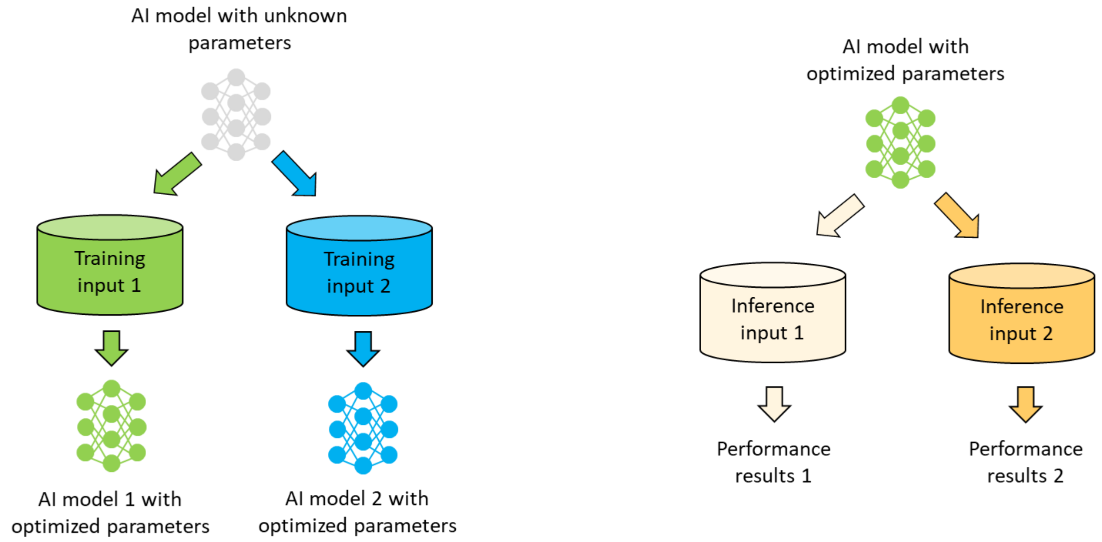
Figure 2. Example of evaluation procedure for AI/ML schemes

For the potential study of AI/ML for physical layer, detailed evaluation is necessary to justify the benefits of AI/ML schemes and necessity of the related standard impacts. As there is no evaluation of AI/ML schemes ever before in 3GPP, the evaluation methodology need to be carefully studied. In general, link-level and system-level simulations are necessary for the performance comparison of AI/ML schemes and traditional schemes. Detailed simulation parameters and performance metrics would depend on the use cases.

Figure 2 shows an example of evaluation procedure for AI/ML schemes. First, the model training input will be generated, then the model training output would be the optimized AI/ML models. Then, the model inference input will be generated, usually independent from the model training input. For model inference, one or multiple physical layer modules are replaced with the optimized AI/ML models by model training. Finally, the performance of AI/ML models can be evaluated. For system-level simulation, physical layer abstraction can be applied for the detection and decoding. If AI/ML models is applied, how to apply the physical layer abstraction may also be considered.

Proposal 2: For the potential study of AI/ML for physical layer, evaluation methodology should be studied.

4.2 Model Training and Model Inference

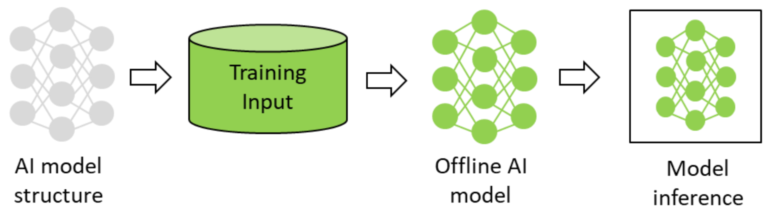


(a). Input/output for model training (b). Input/output for model inference

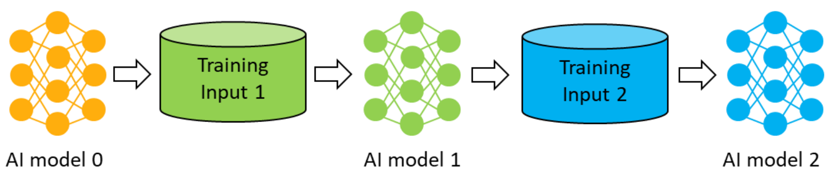
Figure 3. Input/output for model training and model inference

The inputs for model training and model inference is important for the evaluation of AI/ML schemes. For physical layer use cases, the inputs for model training and model inference can be channel response, noise, transmitted symbols, received symbols, CSI measurements, UE positions, and so on. As shown in Figure 3, with different model training inputs, the trained AI/ML models would be different. Similarly, with different model inference inputs, the performance results would also be different. Therefore, the inputs for model training and model inference should be aligned during evaluation.

To generate the inputs for model training and model inference, one option is to apply the 3GPP channel models in TR 38.901, which is simple and easy to calibrate. With the 3GPP channel models and commonly used simulation platform, the inputs with different size can be easily generated, and the distribution will depend on the simulation setting. Note the inputs for model training and model inference should be independent, which can also have different size and distribution. Besides the 3GPP channel models, other options of inputs can also be considered, e.g., field test, generated by other AI/ML models.



(a). Offline model training



(b). Online model training

Figure 4. Offline and online model training

In wireless networks, there can be different ways for model training. As shown in Figure 4, model training can be performed either offline or online. For offline training, input and output of model training are generated offline, without the need of communication between gNBs and UEs. In this case, there will be no limitation on the inputs for model training. Note it should be assumed that the input for model inference is unknown during model training. For online training, the inputs for model training is generated online, which may need the communication between gNB and UEs. There may have some limitation on the inputs of model training. For example, the size of model training input may depend on the constraints on the complexity and signalling overhead, and so on.

Proposal 3: For the potential study of AI/ML for physical layer, the input/output for model training and model inference should be studied.

4.3 Potential Use Cases

Like the RAN3 study item, suitable use cases for AI/ML should be identified for further proceeding. First, the benefits of AI/ML for physical layer should be justified based on the identified use cases. The above evaluation methodology can be applied, and the simulation parameters can be set accordingly. If the benefits of AI/ML for physical layer use cases are confirmed, related standard impacts can be further discussed.

Many use cases have been proposed by companies [2][3][4][5][6], e.g., AI-assisted positioning, RS and channel estimation, CSI feedback, beam management, and so on. 3GPP should carefully select use cases and scenarios to formulate the objectives, such that there is promising commercial value, and the impact on existing implementation could be minimized and duplicate work on the same issue through separate topics is avoided.

Proposal 4: For the potential study of AI/ML for physical layer, use cases should be identified for justifying the benefits of AI/ML schemes and studying the standard impacts.

5. Conclusions

In this contribution, some views on AI/ML on physical layers are provided, with the following observations and proposals.

Observation 1: AI/ML may potentially solve hard-to-model problems in physical layer use cases.

Observation 2: AI/ML may potentially provide efficient solutions to hard-to-solve problems in physical layer use cases.

Proposal 1: For the potential study of AI/ML for physical layer,

- ***Detailed AI/ML algorithms and models shall be left for implementation;***
- ***AI/ML schemes shall not impose any privacy concerns;***
- ***Existing network architecture and interfaces of NR should be reused.***

Proposal 2: For the potential study of AI/ML for physical layer, evaluation methodology should be studied.

Proposal 3: For the potential study of AI/ML for physical layer, the input/output for model training and model inference should be studied.

Proposal 4: For the potential study of AI/ML for physical layer, use cases should be identified for justifying the benefits of AI/ML schemes and studying the standard impacts.

6. References

[1] RP-201620, Study on enhancement for data collection for NR and ENDC, RAN#89e, Sep. 2020.

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[5] RP-210614, Support of Artificial Intelligence Applications for 5G Advanced, ZTE, RAN#91e, Mar. 2021.

[6] RP-210672, On the Scope of Rel-18 PHY Layer Enhancements using AI-based Solutions, InterDigital, RAN#91e, Mar. 2021.