AIMM

CELTIC-NEXT

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AI for Radio Resource Optimisation

Executive Summary

AIMM is a two-year European collaborative research and development project targeting radical performance improvements and efficiency dividends for beyond-5G/6G Radio Access Network (RAN), through novel multiple-input multiple-output (MIMO) enhancements and features, powered through and managed by the latest advancements in Artificial Intelligence (AI)/Machine Learning (ML).

This document provides an outline of the work on AI for Radio Resource Optimisation as part of the AIMM Work-Package 4 (WP4). The technologies of interest target physical (PHY) layer based use cases on Channel Estimation and MIMO Detection, User Localisation and Channel Charting, Channel State Information (CSI) Acquisition in Frequency Division Duplex (FDD) Massive MIMO, and RF Anomaly Detection, all of which involving the adoption of AI/ML for systems operation and optimisation.

AIMM in PHY

In 5G New Radio (NR), MIMO plays an ever-present role, for both improving performance in congested sub-6 GHz bands and also serving as a key enabler in facilitating operation in higher frequency bands. Despite the great success of MIMO to date, further innovation is critical for bridging the MIMO performance gap in theory versus practice in future wireless systems. This is the motivation behind AIMM, a two-year collaborative European research and development project defined in the area of end-to-end RAN delivery chain with six tightly coupled work-packages, as shown in Figure 1.

The AIMM project WP4, titled "AI for Radio Resource Optimisation", focuses on the development of AI/ML-based solutions for various air-interface focused use cases. These use cases comprise real-time PHY layer functionalities, including Channel Estimation, User Detection and Rate Adaptation, as well as those with less stringent timing requirements, such as User Scheduling and Localisation. Also, the task of CSI acquisition for (multiuser) precoding in FDD (frequency-division-duplex) Massive MIMO systems as well as RF anomaly detection of adversary devices are being investigated in AIMM.

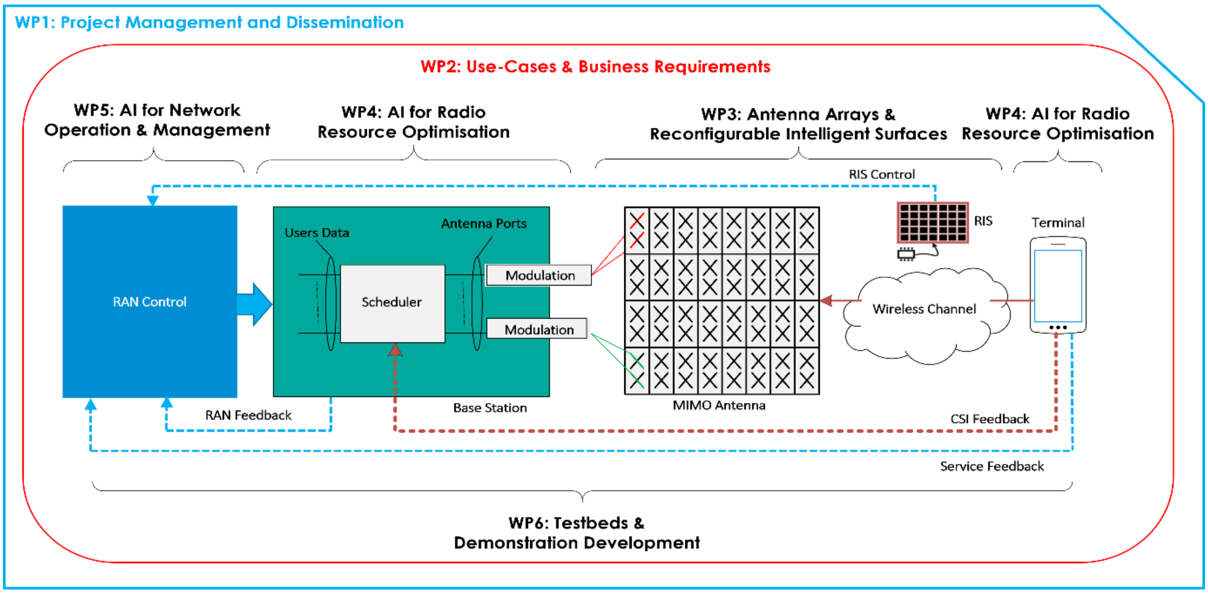

Figure 1. AIMM project structure.

AI/ML-based Channel Estimation and MIMO Detection

Channel estimation and symbol detection are of utmost importance for Massive MIMO systems. However, state-of-the-art (SOTA) algorithms for both problems come at tremendous implementation complexities which render their practical use prohibitive. Tools from AI/ML provide a different approach to both problems with the potential to achieve close to or even beyond SOTA performance with reduced complexity. The AIMM partners are developing new ML-based solutions to channel estimation and symbol detection with evaluations under realistic conditions, that is, channels generated through simulations (using 3GPP-compliant channel models), raytracing, and importantly over-the-air measurements. An emphasis is placed on the problems of online learning, that is, training ML models in the field, and transfer learning, that is, how ML models can be adapted from one cell to the other with minimal retraining.

The wireless channel of a multicarrier system is high-dimensional, in sense of frequency, time and spatial domains with individual characteristics, which makes the complexity of a conventional joint channel estimator be extremely high. ML provides an alternative solution to estimate the channel for one of these domains, denoted as 1-Dimensional (1D) neural network (NN)-based estimator. An iterative ML based channel estimator, referred to as Turbo-AI is being developed, which can estimate the wireless channel through frequency, time and spatial domains with reduced complexity. After integrating a universal interpolation approach to Turbo-AI in sense of strong adaptability even for ultra high user mobility, the conventional Turbo-AI can support discrete pilots based channel estimation, namely with Demodulation Reference Signal (DMRS). The following figure demonstrates a snapshot for SNR at 0dB, in which DMRS-Turbo-AI is exploited for estimating the channel response of a user, moving with supersonic speed approximately at 1260km/h.

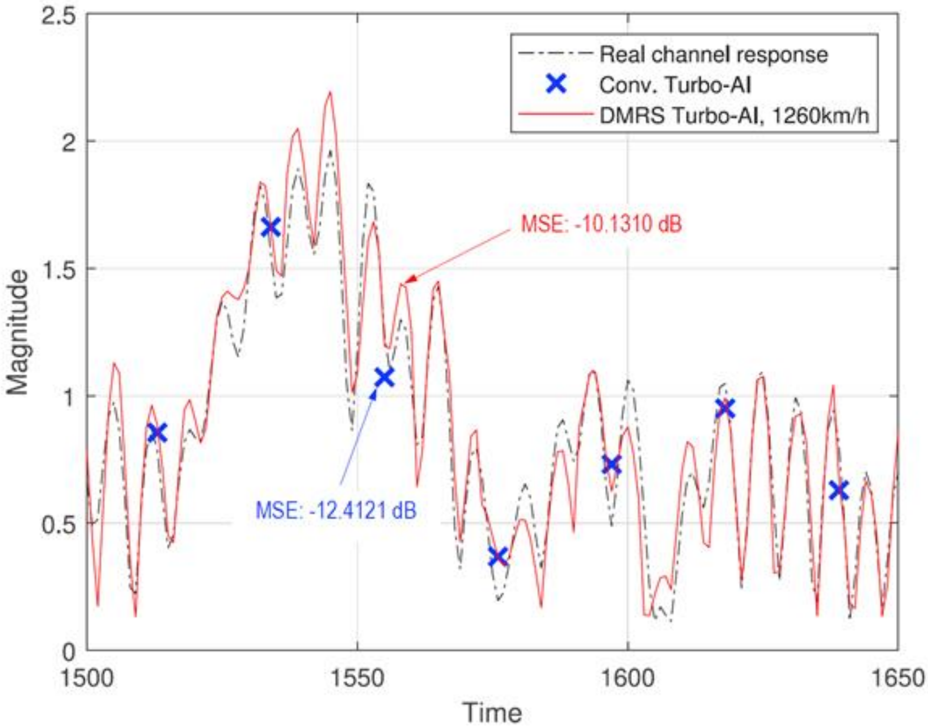

Figure 2. Snapshot of channel tracking in DMRS-Turbo-AI for 1260km/h, SNR 0dB.

User Localisation and Channel Charting Using AI/ML

User localisation through radio signals is becoming increasingly important and it is expected that further location accuracy will be major requirement for B5G/6G systems, similar to latency and throughput. While model-based approaches work well in line-of-sight propagation conditions, their precision typically suffers in complex indoor and urban outdoor environments. For this reason, various groups have leveraged ML for user localisation based on CSI that is already available at Massive MIMO receivers. The biggest practical challenge related to such approaches is the need for large quantities of labelled training data, that is, CSI with precise location information, which might be difficult to acquire in large or fast-changing environments. The aim of this task is to carry out research on ML solutions to CSI-based user localisation which require less training data. One approach is that of channel charting, but also methods from self-supervised learning through smart data augmentation as well as online learning techniques are being investigated.

With a newly developed distributed massive MIMO channel sounder, multiple datasets in different radio environments containing more than 20000 position-tagged CSI vectors each have been captured. Various methods and instruments for producing highly accurate position labels were investigated, including tachymeters, LiDAR, global navigation satellite system (GNSS) receivers and even HTC Vive trackers for indoor positioning. As shown in Figure 3, initial user localisation estimates, generated by deep neural networks, appear very promising with typical estimation errors (compared to tachymeter-based labels) on the order of a few centimetres. The generalizability of these results to different propagation environments and improvements to the network architecture in that regard are subject to our future studies.

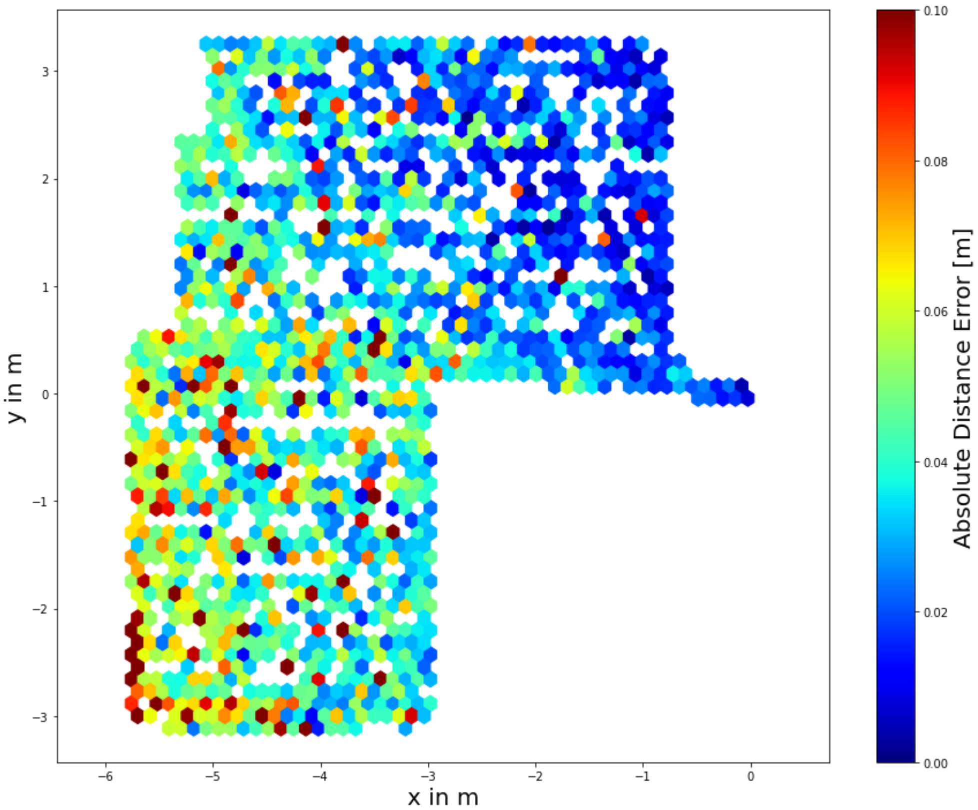

Figure 3. Heat map of absolute localisation error of an indoor office environment dataset.

CSI Compression for FDD Massive MIMO using AI/ML

The advantages of Massive MIMO are best leveraged in time-division-duplex (TDD) mode of operation, where uplink (UL) and downlink (DL) channel use the same frequency band. In the TDD case, due to channel reciprocity, no explicit reporting of DL CSI may be required (from the mobile terminal through the UL to the network), to enable multiuser/massive MIMO precoding. However, in many regulatory domains, UL and DL are put on separate (yet nearby) frequency bands (frequency-division-duplex, FDD), thus putting a huge burden on the terminal to report DL CSI to the network through the UL channel. This task investigates the idea of learning the DL CSI based on the observed UL CSI at the network, using methods from deep learning. It is anticipated that this significantly reduces the UL CSI feedback overhead by either fully inferring on the DL CSI, or, at the least, finding appropriate compression schemes to minimize UL CSI feedback rate.

Inference of the DL channel's CSI purely based on UL channel coefficients without any terminal feedback is currently being investigated. In the single-input single-output (SISO) case illustrated in Figure 4, this approach is somewhat questionable - in a MIMO scenario, however, the spatial dimension provides additional information that a deep neural network may be able to exploit to estimate downlink precoding vectors, i.e. by steering the downlink beam in the same approximate direction that the uplink beam was received from. Compared to various baselines, first results obtained using a dense neural network appear very promising. What remains to be investigated is the generalizability of these results as well as adding neural network-aided feedback compression.

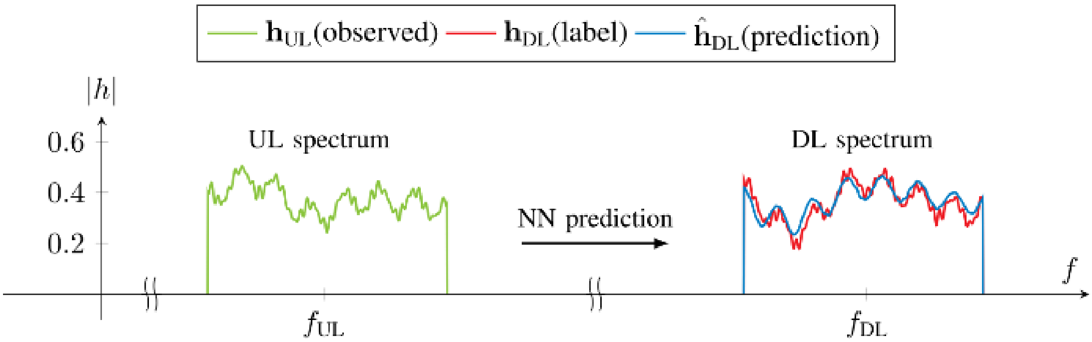

Figure 4. Basic principle of neural network-based downlink channel CSI inference from uplink channel CSI.

Advanced AI/ML Algorithms for RF Detection and Location

Using AI to detect and locate adversarial devices and attacks is a relatively new field in the Cyber Security and Defence domains with several Governments supporting local companies to develop a much needed capability.

This task in AIMM will use state of the art Anomaly Detection algorithms to detect RF signals based on monitoring and analysing RF spectrum in real-time to gain awareness of the surrounding wireless environment in a fashion that was previously prohibitive. The proposed AI technique will detect RF Spectrum anomalies such as jamming, Spectrum Hijacking, as well as malicious cyber threat transmissions from secure facilities. The system will also collect and analyze Spectrum signatures to categories malicious activity for future forensic assessment and Cyber Security based remediation steps that localize, isolate, and mitigate the threat. AI Anomaly Detection Algorithms, such as Auto & Variational Encoders as well as other Probabilistic density models will be Trained and tested against real-world scenarios.

So far work on several steps of the project including modelling, Training and inference detection of single & multi-tone interference (jamming sources) as well as Co-Channel and

Adjacent channel interference typical in many 4G/5G wireless networks have been competed. This represents one of the more challenging aspects of this type of application, since this form of interference can vary across customer scenarios, In addition this class of interference is somewhat stochastic in nature and varies across frequency spectrum, amplitude and time.

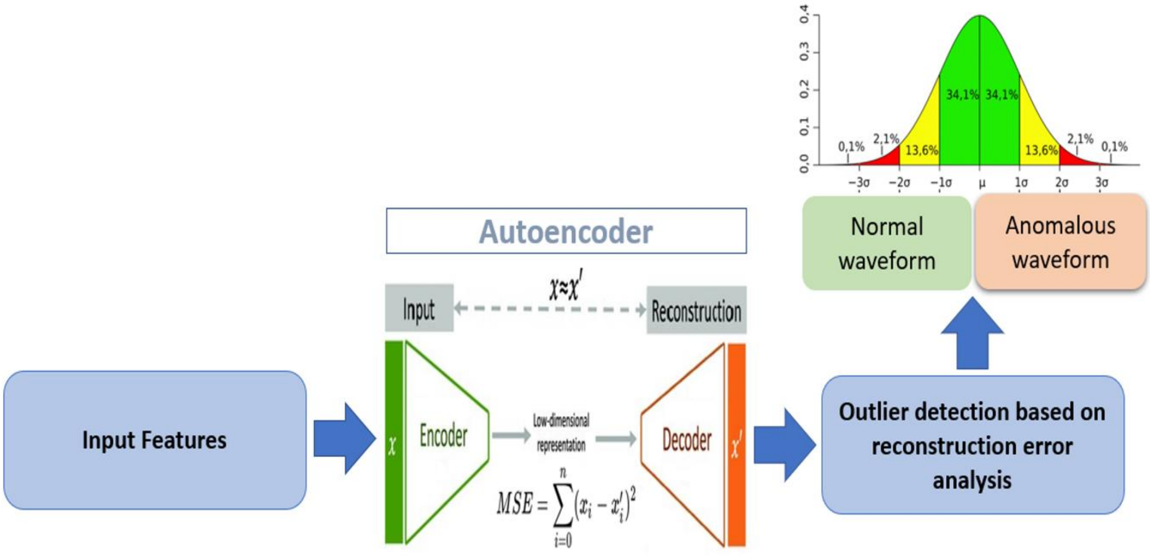

Figure 5. Illustration of AI-based RF anomaly detection in AIMM.

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