# 5G Link-Level Simulator for Multicast/Broadcast Services

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***Abstract*—The evolution toward the promising 5G Multicast-Broadcast Services (5G-MBS) implies multiple simulation stages at different levels to optimize the proposed solutions. This paper presents an open-source link-level simulator (LLS) to facilitate the upcoming studies on 5G-MBS. The proposal combines unicast/multicast/broadcast capabilities over terrestrial and airborne network deployments, link computation for ATSC 3.0 broadcasting, and device-to-device (D2D) communications. The tool is mainly oriented to recreating heterogeneous networks (HetNet) with multiple users under diverse mobility patterns and requesting differentiated unicast and group-oriented services. The implemented channel models support highly directional communications with multiple antennas. The proposal includes estimating channel quality indication for link adaptation based on a tailored Exponential Effective SINR Metric (EESM). The assessment process comprises multiple simulation results and the comparison with Simu5G, an OMNeT++-based model library.**

***Index Terms*—5G MBS, ATSC 3.0, D2D, EESM, Link Level Simulator**

## I. Introduction

5G Multicast Broadcast Services (5G-MBS) is one of the most promising functionalities of the upcoming development state of the 5G standard [1]. This novel capability will imply the development of multiple features and functionalities to efficiently cope with the expected 5G and beyond requirements [2]. The envisaged 5G-MBS will take advantage of ultra-dense heterogeneous networks (HetNet), integrating terrestrial and non-terrestrial infrastructures (TNs/NTNs) and coexisting with other broadcast technologies such as ATSC 3.0 [3].

In this context, multiple research will be conducted, where the emerging solutions must be thoroughly assessed and optimized. Nevertheless, due to the complexity and heterogeneity of existing mobile broadband technologies, realistic experimental and measurement-based approaches for benchmark data collection are costly, time-consuming, and practically infeasible in the early stages of development [4], [5]. Therefore, a practical approach is to iteratively test and tune the solution through numerical simulations based on mathematical models.

Wireless communication systems' physical (PHY) link layer is typically modeled through link-level simulators (LLSs). LLSs are used to simulate point-to-point communication links with a detailed link characterization and evaluate metrics such as bit/block error rate (BER/BLER) and signal-to-interference and noise ratio (SINR) (typically used as reference inputs to system-level simulators (SLS)) [6]. Multiple research fields take advantage of LLS, such as radio resource management, interference management, channel estimation, Multiple-Input Multiple-Output (MIMO), and Adaptive Modulation and Coding (AMC) scheme.

In the last years, multiple LLS and SLS have been developed. In [4], the authors propose an open-source link-level evaluator for studies on the physical layer of 6G. The proposal aims to bridge the gap between physical layer simulations of sensing and communication applications. In [7], the methodology of two new LLS and SLS for the sidelink Cooperative-Vehicle-to-Everything (C-V2X) Communication is presented. In [8], the authors propose the Vienna 5G LLS, a MATLAB-based simulation tool oriented to facilitate research and development in mobile communications. In [7], the 5G-air-simulator, an open-source SLS, is presented to model the New Radio (NR) critical elements such as massive MIMO, extended multicast and broadcast, and NB-IoT under different mobility patterns, traffic load, and deployment configurations.

In [9] is presented an OMNeT++ library for end-to-end performance evaluation of 5G networks, called Simu5G. This tool simulates the data plane of 5G NR deployments, including all protocol layers. Moreover, in [10], the authors present a full-stack mmWave module for the open-source ns–3 simulator. The solution has modular and highly customizable PHY and Medium Access Control (MAC) layers, including detailed statistical channel models and the ability to incorporate real measurements or ray-tracing data. A detailed cross-comparison among several LLS and SLS can be found in [4], [11], [12].

Nevertheless, none of the above simulators is specifically oriented to recreate 5G-MBS use cases integrating TN with NTN based on the unmanned aerial vehicle (UAV) and coexisting with other broadcast technologies such as ATSC 3.0. Moreover, it is essential to simulate device-to-device (D2D) or reflective intelligent surface (RIS) links as a multicast relay to improve the performance of the multicast/broadcast use cases. Therefore, to facilitate upcoming research activities, we propose an open-source LLS oriented to, but not exclusively, simulate 5G-MBS use cases that combine TN and NTN

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based on UAV deployments and ATSC 3.0 broadcasting. The proposal includes the possibility of link computation for D2D communication and RIS as a relay for multicast applications.

The tool aims to recreate HetNet with multiple users under diverse mobility patterns, possible group-oriented distributions, and requesting differentiated unicast and multicast/broadcast services. The tool's outputs are the respective SINR of each end user concerning the simulated radio access technology, the corresponding BLER or BER, the channel quality information (CQI) feedback, and the coordinates and speed of each one. The implemented channel models support highly directional communications with multiple antennas. The proposal includes CQI estimation for link adaptation based on a tailored Exponential Effective SINR Metric (EESM).

This paper is organized as follows. Section II presents the structure of the LLS, including initialization, link computation, and link to system adaptation. The validation and corresponding analysis are presented in Section III. Finally, the conclusions are presented in Section IV.

## II. Simulator Description

This section encompasses the structure and main properties of the proposal. Our open-source LLS is wholly programmed in Python language with a modular structure and flow process according to Fig. 1. In the following subsection, we present the main modules and characteristics of the simulator regarding the initialization process, link computation, and link to system adaptation.

### A. LLS Inizialization

The first step of the simulation setup is the initialization of the parameters, such as simulation time, resolution, type and the number of users, the number of base stations (BSs), BSs' scenarios, and selection of the available modes, according to Table II-A. The simulator allows recreating diverse HetNet use cases combining 5G links modes such as point-to-point (PTP), point-to-multipoint (PTM), D2D communication, RIS, and ATSC 3.0 broadcasting. The TNs' scenarios could be set as urban macro-station (Uma), urban micro-station (Umi), and Street Canyon as defined in 3GPP TR 38.901 [13]. When using a UAV as BS, the scenario is set as urban aerial-to-ground (Urban-AG) as described [14].

The second step is to define the simulation grid, including the size, the nodes' initial position as $(x,y)$ coordinates, and mobility models. As specified in Table I, the simulator implements the available mobility patterns according to the Python library *Pymobility* defined in [17]. The available flexibility in mobility and grid scalability allows recreating multiple 5G-MBS use cases where the mobility pattern is a critical parameter. The simulator can play stationary users as sensors for multicast software updates, high-velocity trains or cars, or group-oriented with different mobility behaviors and requesting the same multicast content [18]. In the simulator, mobility is not only limited to the end-users. The BSs can be configured with any specific mobility model. Particularly, the UAVs acting

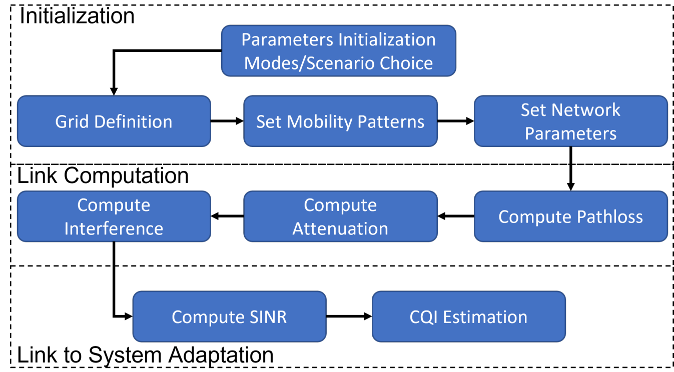


Fig. 1. 5$G$ LLS abstraction model.

TABLE I
5$G$ LLS PARAMETERS.

| Parameters | 5G LLS |
|---|---|
| Link Modes | 5G: PTP, PTM, D2D, RIS<br>ATSC 3.0 Broadcasting |
| Scenarios | Uma, Umi-Street Canyon,<br>Urban-AG, ATSC 3.0 |
| Network Topology | Single Cell or Multicell (with any combination of modes and scenarios) |
| User type | Sensor, vehicle, pedestrian users |
| Frequency range (GHz) | 0.5-100 |
| Path Loss and Large Scale Fading Models | Based on 3GPP TR 38.901 [13], [15] |
| Propagation conditions | O2O (LOS/non-LOS)<br>and O2I (below 6GHz) |
| Small Scale Fading Models | Rayleigh, Jakes [16] |
| Link Adaptation | CQI Estimation - EESM |
| MIMO support | Yes |
| Interference consideration | Yes |
| Antenna | Omnidirectional or Sectorial with 120° |
| Mobility Models | Stationary, Linear, Random Walk, Random Waypoint, Random Direction, Truncated Levy Walk, Gauss-Markov, Reference Point Group Mobility |
| Output parameters | BLER, SINR, CQI,<br>nodes coordinates, speed |
| Other functionalities | Grid and nodes movement visualization |

as BSs can dynamically adjust their coordinates, including the altitude, to improve the network capacity and user perception. Additionally, the grid and nodes' movement can be visualized, which can be an essential feature for several applications, such as proximity multicast services using D2D communication as a relay or dynamic relay-RIS deployment (e.g., mounted in a UAV) according to the specific user distribution [19].

After initializing the general simulation parameters and the grid, it is necessary to define the specific network parameters according to the particular network scenarios and link modes. These network parameters must be determined from the perspective of the BSs and the end-user, such as height, transmission and reception power, antenna gain, operating frequency, numerology, bandwidth, noise figure, and cable loss. Moreover, the parameters must be configured according to the enabled scenarios, such as building height and street width. These parameters are configured subject to 3GPP TR

38.901 [13]. In the specific case of the BS antennas, it can be configured as omnidirectional or three sectors with 120 grades. The antenna follows the simplified antenna pattern given in ITU-R M.2135 as defined in [13]. For the MIMO modeling, we consider a planar antenna array comprising MgNg panels, with Mg being the number of panels in a column and Ng being the number in a row with elements uniformly spaced as defined in [13].

### B. Link Computation

Once the simulator's initialization and resource pool selection is finalized, it starts the iterative link computation for all the simulation time. The links are computed among BSs and end-users with the same link mode enabled at each time step. In the case of a multicast session, the link is calculated concerning all multicast group (MG) members to obtain the CQI feedback further. In the case of 5G-MBS, this dynamic link computation and CQI feedback are crucial for investigating dynamic multicast resource allocation, adaptative modulation coding scheme (MCS), and subgrouping. The link can be computed in both senses, downlink (DL) and uplink (UL). The path loss model applied for 5G TNs is detailed in [13], whereas the model for UAV AG-link can be founded in [15], [20]. The links can be computed as outdoor-to-outdoor (O2O) with line-of-sight (LOS) and non-LOS and outdoor-to-indoor (O2I). The O2I mode is only defined for simulations below the 6 GHz band and following O2I building penetration loss model defined in [13]. In the specific case of ATSC 3.0 path loss computation, we follow [21] for O2O and O2I.

In all the above cases, we compute the LOS probability and the corresponding shadowing attenuation at simulation time $t = 0$, then recalculate it s.t. the defined correlation distance (by default as 50m). Such correlation distance is defined in the horizontal plane. The distribution of the shadow fading is log-normal, with zero means (around the mean path loss (PL)) and a standard deviation for each scenario given in Table 7.4.1-1 in [13]. The small-scale fast fading model is implemented following the Realistic Channel Model implemented in Simu5G [9] according to a Jakes [16] model with adjustable RMS delay spread, and compliant with [13]. The small and large-scale fading can be enabled or disabled independently in the simulations. Finally, the computed attenuation values (including O2I penetration loss) are added to the PL in the log scale. In the case of the D2D link computation in both senses between two specific users, the shadowing value is considered equal if the distance between the users is lower than the correlation distance, and the fast fading is computed independently.

The simulator allows computing the background cell interference if enabled. In the case of D2D, the simulator calculates the D2D link among all the users independently of their distance. This information can be used for D2D cluster formation, selecting the multicast relay users, or interference consideration for dynamic power or resource adjusting, assuming several users operate in the same band. This interference consideration allows for more realistic approaches, crucial for D2D communications developments.

After path loss computation, the total received power at the end-user, $P_{rx,pl}$ is computed as

$$P_{rx,pl} = P_{tx} G_{tx} G_{rx} PL^{-1}(d), \tag{1}$$

where $G_{tx}$ and $G_{rx}$ are the transmit $(tx)$ and receive $(rx)$ antenna gain, respectively. $PL(d)$ is the path loss, where $d$ is the 3D distance between $tx$ and $rx$. In the specific case that the RIS link mode is enabled, $PL(d)$ is equal to $PL(d_{\text{tx2r}})PL(d_{\text{r2rx}})$, where $d_{\text{tx2r}}$ and $d_{\text{r2rx}}$ are the distances from the $(tx)$ to the RIS and from the RIS to the $(rx)$. The resulting total received power at an end-user through the RIS can be computed as in [22]:

$$P_{rx,pl} = \left( \sum_i \sqrt{\frac{P_{tx}|\Gamma_i| G_{tx} G_{rx}}{PL(d_{\text{tx2r}})PL(d_{\text{r2rx}})}} e^{j\phi_i} \right)^2, \tag{2}$$

where $\phi_i$ is the phase delay of the signal received through the $i$-th reflective element of the RIS, and $\Gamma_i$ is the $i$-th reflection coefficient. Additional details about the followed RIS link implementation and assumption can be found in [22], [23]. The final total received power at the $u$-th end-user and the $r$-th sub channel $(P_{rx,u,r})$ is computed as:

$$P_{rx,u,r}|dB = (P_{rx,pl,u,r} + T_u + S_u + H_{u,r})|dB, \tag{3}$$

where $T_u$, $S_u$, and $H_{u,r}$ are the penetration attenuation component, shadowing fading, and the fast fading, respectively (expressed in decibels (dB)).

### C. Link to System Adaptation: CQI Estimation-EESM

After the link computation, the link channel quality is evaluated in terms of the SINR measured over each sub-channel $r$ [24]:

$$SINR_{u,r} = \frac{P_{rx,u,r}}{I + (FN_0 B_r)}, \tag{4}$$

where $F$, $N_0$, and $B_r$ are the configured noise figure, the noise spectral density (with a default value of -174 dBm/Hz), and the bandwidth of the sub-channel. $I$ is the sum of interference components if enabled. The SINR computation is the first step of the link to the system's mapping process throughout the CQI estimation and BLER computation. The following subsection presents the CQI estimation process.

The frequency selectivity that characterizes the wireless channel implies that in the link computation over a specific bandwidth, the different sub-bands (as can be the resource blocks available in multicast section with $B_r$ equal to 180 kHz) may have different characteristics resulting in different SINR values. Therefore, we need an SINR value to reflect the channel behavior to evaluate the overall channel state. Traditionally, two main functions, EESM and mutual information effective SINR metric (MIESM), are used to map the SINR measured over each sub-channel $r$, $SINR_{u,r}$, to an effective SINR value, $SINR_{eff}$. This $SINR_{eff}$ will reflect in the single AWGN channel the complex behavior of the real channel [25].

In our proposal, we use the enhanced version of the traditional EESM function based on two adjustment factors $\alpha$ and $\beta$, presented in [26]:

$$EESM_u = -\alpha \times \ln\left(\frac{1}{Rb}\sum_{r=1}^{Rb}\exp\left(\frac{-SINR_{u,r}}{\beta}\right)\right), \quad (5)$$

where $Rb$ is the number of available sub-channels. $\alpha$ and $\beta$ are the adjustment factors to each specific MCS (according to Table 5.2.2.1-3 in [27]) and the corresponding CQI value (from 1 to 15). The goal of training $\alpha$ and $\beta$ is to minimize the difference between the real BLER, $BLER_{real}$, achieved with the $SINR_{u,r}$ array of the real channel and the equivalent BLER, $BLER_{eff}$, in the AWGN channel achieved with $SINR_{eff}$. Another approach could be to minimize the difference between the equivalent SINR in the AWGN channel, $SINR^{*}_{AWGN}$, that ensures the same $BLER_{real}$ and the computed $SINR_{eff}$ through (5). Minimizing such metrics, we ensure that the computed $SINR_{eff}$ can reflect the real channel behavior as best as possible. Then, we could estimate the correct CQI using the BLER curves versus SINR for the AWGN channel, with a CQI estimation error rate as low as possible. The target BLER used for selecting the CQI can be set during the initialization and is typically defined as 0.1.

To find the optimal $\alpha$ and $\beta$ that ensure better compression from the real $SINR_{u,r}$ to the $SINR_{eff}$, we use the particle swarm optimization (PSO) algorithm [28]. The PSO is a metaheuristic algorithm inspired by the behavior of natural swarms, such as flocks of birds or fishes. This algorithm finds the global maximum or minimum in a non-convex optimization problem defined for a specific cost function. For our proposal, we use the PSO to minimize the following cost function ($C_f$):

$$\arg\min_{(\alpha,\beta)} \frac{1}{NcNs}\sum_{c=1}^{Nc}\sum_{s=1}^{Ns}(SINR^{*,s,c}_{AWGN} - SINR^{s,c}_{eff})^2, \quad (6)$$

where $Nc$ is the number of channel realizations and $Ns$ is the number of $SINR_{u,r}$ arrays evaluated for one specific CQI and one channel realization. As presented in [29], the critical range for the CQI estimation is defined from the SINR value corresponding to a BLER of 0.9 ($SINR_{0.9}$) to the SINR value corresponding to a BLER of 0.001 ($SINR_{0.001}$) for a target BLER of 0.1. Therefore, this is the critical training range for $\alpha$ and $\beta$. Then, $Ns$ are the total $SINR^{s,c}_{AWGN}$ values into the limits $SINR^{CQI}_{0.9}$ and $SINR^{CQI}_{0.001}$. The process for finding the optimal calibration of $\alpha$ and $\beta$ and effectively estimating the CQI is shown in algorithm 1.

**Algorithm 1:** Optimal calibration of $\alpha$ and $\beta$ through PSO

```
Input: C_f: CQI, SINR^CQI_0.9, SINR^CQI_0.001, Nc
Input: PSO: Particles, Iter, Bounds, options
Output: (α′, β′)
for c ← 1 to Nc do
    for SINR_AWGN ← (−10 : 0.2 : 40) do
        s = 0
        S = ComputeShadowingAttenuation
        for r ← 1 to Rb do
            H_r = ComputeFastFadingAttenuation
            SINR_r = SINR_AWGN + S + H_r
        end
        BLER_real = GetBlerReal(SINR_r, CQI)
        SINR*_AWGN =
          GetSinrAwgn(BLER_real, CQI)
        if SINR^CQI_0.9 ≤ SINR*_AWGN ≥ SINR^CQI_0.01
         then
            s = s + 1
            SINR^{s,c}_eff =
              ComputeEESM(SINR_r, α, β)
            SINR^{*,s,c}_AWGN = SINR*_AWGN
        else
    end
end
C_f = 1/(NcNs) Σ_{c=1}^{Nc} Σ_{s=1}^{Ns} (SINR^{*,s,c}_AWGN − SINR^{s,c}_eff)^2
(α′, β′) = ExecutePSO(C_f)
```

## III. Simulation and Results

To assess the effectiveness of the proposed LLS for 5G-MBS applications, we first calibrate the implemented channel models against Simu5G. After looking through the Simu5G implementation, the corresponding documentation, and following [13], we identify specific conditions to use Simu5G results as a calibrator and benchmark for our proposal. Moreover, as mentioned above, in our simulator, we implement the small-scale fast-fading model according to the Jakes model implementation of Simu5G.

One of the tested scenarios consists of a single BS configured as Uma with a pedestrian user located at 300 meters with a speed of 3 m/s in a perpendicular direction (in the same ground plane) concerning the initial 300 meters line between the BS and the user. The simulation time was 100 seconds for a whole trajectory of 300 meters, and a final distance regarding the BS of 424 meters. The BS antenna was configured as omnidirectional, with link conditions as O2O with LOS. The main simulation parameters set for both simulators are summarized in Table III.

Fig. 2 presents the simulation results. In the case of Simu5G, we show the result of averaging ten simulation runs, and for our proposal, we plot the average result for 100 simulation runs. During Simu5G simulations as the benchmark, we only consider 10 simulation runs because exporting the data from the OMNeT++ environment to our Python framework for 100 runs becomes complicated. Moreover, increasing the Simu5G simulation runs the curve behavior tends to an AWGN channel losing the contribution of the shadowing and fast fading in the plot. As shown in Fig. 2, our simulator follows the same tendency with a similar standard deviation. In both cases, we can see how the SINR decreases gradually as the user goes far from the BS. As in the previous analysis, the simulation results of the comparison between Simu5G and our proposal validate

TABLE II
MAIN SIMULATION PARAMETERS SET FOR LLS/SIMU5G.

| Parameters | LLS/Simu5G |
|---|---|
| Link Mode | PTP |
| Scenario | Uma |
| Network Topology | Single Cell |
| User type | pedestrian users |
| Frequency range (GHz) | 2 |
| Resource Blocks | 50 (with $B_r$ equal to 180kHz ) |
| Propagation conditions | O2O with LOS |
| Small Scale Fading Models | Jakes |
| BS/UE height (m) | 25/1.5 |
| Tx/Rx power (dBm) | 20/0 |
| Antenna Gain TX/Rx (dB) | 18/0 |
| Interference consideration | Not |
| Antenna | Omnidirectional |
| Mobility Models | Linear (3mps) |
| Correlation distance | 6m |
| delay RMS | 363ns |

the channel implementations and resulting link computations for the different modes and scenarios.

Regarding the CQI estimation validation, we implement the curves of BLER vs. SINR that Simu5G uses for their implemented Jakes channel, as shown in Fig. 3. These curves were used to compute the real BLER ($BLER_{real} = GetBlerReal(SINR_r, CQI)$) during the calibration process.

In Fig. 4, we show the simulated effective SINR, $SINR_{eff}$ mapping over the single AWGN channel and for each CQI (solid lines). The figure shows the effectiveness of the compression process from the real channel, Fig. 3, and the $SINR_r$ array to the AWGN channel. For better visualization of the compression process and validation of the implemented solution, we can see Fig. 5.

Fig. 5 shows the compression process for CQI 5 and 9. We generate real SINR values for this specific simulation to ensure a $BLER_{real}$ less than 0.1, the target BLER for CQI 5 and 9, respectively. As we can see, the compression process generates an equivalent $SINR_{eff}$, with a BLER in AWGN channel less than 0.1, for a correct CQI estimation.

Additional results regarding Urban-AG and ATSC 3.0 link computation will be presented in an extended version of this paper. Moreover, we must follow a thorough link calibration for the different implemented modes as recommended in [11], [13].

## IV. CONCLUSIONS

This article proposes an open-source link-level simulator (LLS) to simulate 5G-MBS use cases that combine TN and NTN based on UAV deployments and ATSC 3.0 broadcasting. Our solution includes the possibility of link computation for D2D communication and RIS as a relay for multicast applications. The tool's capabilities can facilitate upcoming research activities based on multiple users with diverse mobility patterns, with possible group-oriented distributions, and requesting differentiated unicast and multicast/broadcast services. The ATSC 3.0 link computation capability allows the inclusion of services such as alert warning or linear television among the

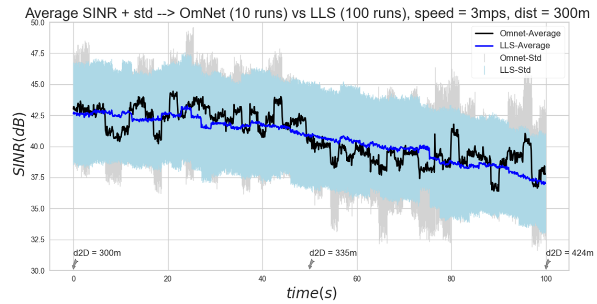


Fig. 2. *SINR* experience by a single user respect to a single Uma in Simu5G and our LLS.

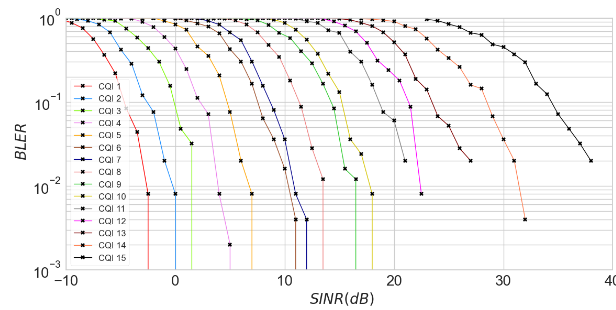


Fig. 3. Curves of BLER vs. SINR for the implemented real channel based on Jakes [9], [16].

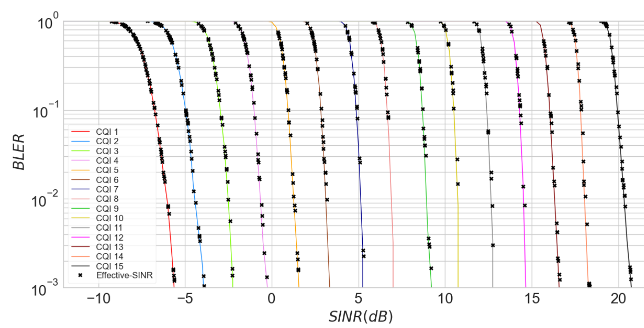


Fig. 4. Effective *SINR* mapping curves from Jakes channel to AWGN.

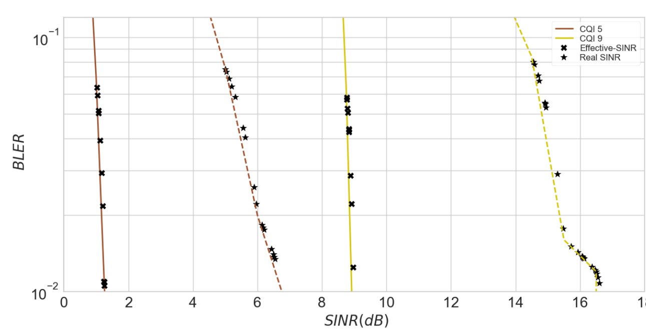


Fig. 5. Compression from Jakes channel to AWGN for *CQI*s 5 and 9.

recreated user requests for studies on future broadband broadcast convergence. After running a simulation, the simulator returns the respective SINR of each end-user concerning the simulated radio access technology, the corresponding BLER or BER, CQI feedback, and the coordinates and speed of each node in the simulated area. The link to the system's mapping process is based on a tailored EESM modeling that uses the PSO algorithm to calibrate the CQI estimation.

The channel models implemented in our proposal were calibrated and validated using as benchmark Simu5G, an OMNeT++ library for end-to-end performance evaluation of the 5G network. Regarding the link to system adaptation, we evaluate the effective compression from a Jakes channel implementation to the AWGN channel for an adequate CQI estimation.

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