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This paper describes an emulation approach using commercial and carrier-grade equipment to characterize aggregate uplink emissions from any realistic Long Term Evolution (LTE)-based cellular deployment scenario. The modeling approach described here can be used to understand the feasibility of coexistence between LTE networks and other systems such as weather satellites in any given spectrum band such as the Advanced Wireless Services 3 (AWS-3) band. We also establish the accuracy of the proposed approach by comparing the results from emulation to field measurements from an active cellular deployment.

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A Novel Approach to Characterize Aggregate Inference from LTE-Based Cellular Deployments

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***Abstract*—This paper describes an emulation approach using commercial and carrier-grade equipment to characterize aggregate uplink emissions from any realistic Long Term Evolution (LTE)-based cellular deployment scenario. The modeling approach described here can be used to understand the feasibility of coexistence between LTE networks and other systems such as weather satellites in any given spectrum band such as the Advanced Wireless Services 3 (AWS-3) band. We also establish the accuracy of the proposed approach by comparing the results from emulation to field measurements from an active cellular deployment.**

***Index Terms*—Long Term Evolution (LTE), 5G, Advanced Wireless Services 3 (AWS-3), Spectrum Relocation, Spectrum Auctions, Spectrum Sharing, Commercial Cellular, Test Bed Development, Modeling and Simulation**

I. INTRODUCTION

The rapidly increasing demand for spectrum to support wireless technology use in all sectors has created the need to re-evaluate the way spectrum is allocated among different users. The United States Department of Defense (DoD) is the largest Federal spectrum user in the Nation, and performs hundreds of mission-critical activities daily that are enabled by wireless technology, whether it be communications, radar, telemetry, or sensing. The recent Advanced Wireless Services 3 (AWS-3) Auction repurposed and auctioned 65 MHz of spectrum from Federal use to commercial cellular use. The 65 MHz of spectrum includes: 1695-1710 MHz, 1755-1780 MHz, and 2155-2180 MHz. The auction details can be found in the Federal Communications Commission (FCC) Report and Order (R&O) (FCC 14-31) from March 2014 [1].

The 25 MHz of spectrum impacted by the AWS-3 auction, 1755-1780 MHz, was used primarily by DoD systems. DoD incumbent systems in this band were given a 10-year period to vacate the band, except for a small number of DoD systems that were granted indefinite access. Furthermore, the demand for this spectrum is so great that the FCC allowed commercial technologies to enter the band early if they can determine that there is minimal risk to the federal systems yet to vacate the band. The DoD determined existing modeling of cell network aggregate interference was insufficient to make a satisfactory risk assessment, and allocated funding to research improved characterization of cellular deployment radiation.

The AWS-3 spectrum rules require commercial operators to operate in the Frequency Division Duplex (FDD) configuration in the AWS-3 bands. The band under study covered by this paper is the uplink band. Characterizing uplink interference in particularly challenging because traffic generation from User Equipment (UE), most commonly known as cell phones, are moving constantly and transmitting from unknown locations. The distributed nature of the UEs, along with agreements to protect user privacy, make collecting real-world data to reconstruct the UEs emissions and traffic unfeasible. Therefore, the most practical approach is to collect representative data in a laboratory environment and from this data create a probabilistic model of UE emissions.

This paper proposes a new methodology to re-create aggregate UE emissions from a representative commercial cellular network, building upon the initial modeling parameters agreed upon by the Consumer Spectrum Management Advisory Committee (CSMAC). [2] Key Performance Indicators (KPI) are provided by the commercial cellular carrier operating the network under study. The enabling technology of this method is a

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laboratory testbed, the Multi-UE LTE Emulator (MULE) [3], developed by MITRE for the Defense Information Systems Agency (DISA) Defense Spectrum Organization (DSO) Spectrum Sharing Test and Demonstration (SSTD) program [4]. The MULE uses commercial grade eNodeB (aka: base station) and UE hardware to re-create traffic and channel conditions observed in field measurements of representative commercial cellular network deployments. This approach consists of two parts:

1) A method to emulate traffic observed (measured) in the field based on carrier-provided KPIs in MITRE's MULE testbed to derive a per-sector EIRP distribution
2) A Monte Carlo simulation process to place the emissions characterized in the lab in the geography of the deployment and propagate them to a receiver in order to create an aggregate interference distribution

The methodology presented in this study is novel because, first, it treats the aggregate UE emissions in one sector as the random variable instead of the individual UE interference contribution. Second, the testbed uses real UE and eNodeB hardware, so deviations of UE and eNodeB behavior from the specification will be represented in the model produced from the emulated traffic. We argue that this approach arrives at an accurate aggregate interference prediction because it captures the behavior of the eNodeB scheduler and accounts for the difference in behavior of an individual UE in sectors under different network loads.

In the coming sections, we will present this modeling approach in the following parts:

1) The advantages of a sector-based emission model over UE-based emission modeling. Past modeling efforts have modeled individual UE emission distributions, and matched deployment-specific characteristics by varying the location and quantity of transmitting UEs. However, UE transmissions are governed by the scheduler of the eNodeB managing the available spectrum resources of the sector, so a model of the scheduler filling the resource grid will better account for a sector's power than a model of an individual UE
2) Using carrier KPIs to re-create activity of one sector at one specific datetime interval in the field. MITRE has developed a process to create an emulation environment in MULE that closely matches observed field behavior and creates dense 1ms resolution data of UE scheduling and reported power from sparse carrier data. This section will describe the KPI matching process that MITRE has developed to emulate these sectors.
3) Extracting a sector-wide EIRP distribution from the data generated from one MULE run, and how it is extended to a deployment wide Monte-Carlo simulation capable of producing a highly detailed aggregate interference distribution as observed at the modeled collection site.

Following the detailed description of the aggregate interference modeling process, we will discuss the extension of this methodology to future 5G deployments, and its immediate impact on LTE modeling.

II. SELECTING FACTORS TO CHARACTERIZE UPLINK EMISSIONS

Previous work [2] to characterize UE emissions have primarily proposed models that use an EIRP distribution for a single UE, then populate each simulated sector with identical UEs all emitting power with the same probability distribution. Different sectors may use different UE EIRP distributions depending on their location, but all UEs transmit with the same behavior within one sector. Under this approach, the factors used to characterize a sector's emissions are:

- The number of UEs per transmission time interval (TTI) that will be transmitting
- The per-UE EIRP distribution of the UEs in the sector

This approach has certain limitations, specifically that the representation of network load is constrained to either integer numbers of UEs per TTI or fractions of UEs, and that there is no way to capture the changes in scheduler behavior in a sector under different traffic loads.

We propose an alternate approach where individual UEs are not directly represented, and we instead define a distribution for the total emissions radiated by all UEs in a sector. The scheduler allocates physical resource blocks (PRBs) to UEs that request them, and the PRBs allocated will not exceed the maximum available in the sector. With this method, the factors used to scharacterize emissions in one sector are:

- The number of active PRBs per TTI
- The per-PRB EIRP distribution of UEs in the sector

This method better represents the behavior of the eNodeB scheduler, however there is a loss in accuracy in where to place the transmitting UEs within a sector. For the application of this study, we argue that at a sufficient receiver distance the loss in granularity of individual UE transmission locations should not affect the prediction in aggregate and all UEs can be placed at the tower base or some other single location within the sector.

A. *Characterizing Network Load Using Active PRBs per TTI*

A sector's aggregate power does not scale closely with the number of active UEs per TTI. Given a simplified (i.e. ignoring α and other intricacies of power control) UE physical uplink shared channel (PUSCH) power control equation as follows:

$$P_{PUSCH} = \min(P_{max}, \frac{N_{PRB} P_{0_{PUSCH}}}{L_{path}}) \tag{1}$$

the power a UE transmits at, P_{PUSCH}, is approximately the product of the number of resource blocks assigned (N_{PRB}), times the power required to reach P_0 at the tower (P_o times path loss), not to exceed the maximum power of the UE. Thus, when accounting for the total power radiated by a sector, the increase in power attributed to an increase in network activity may be better represented by the total PRBs active per subframe. A sector's total PRB utilization is often readily accessible in KPI reports recorded by the sectors at regular intervals during all hours of operation. This makes PRB utilization a great candidate for a model variable representative of total cell activity.

B. Characterizing UE Path Loss Within a Sector Using Reference Symbol Received Power (RSRP)

The power transmitted by a UE per PRB is dictated by the path loss component of the PUSCH power control equation. The distribution of per PRB power is proportional to the UE path loss distribution in each sector, and mostly independent of network activity, at least in the context of our model. Given that the power per PRB is representative of the distribution of UE location and losses within a cell, and the PRB occupancy is representative of the total activity, then we propose that the total emissions in a cell may be approximated as the number of active PRBs times the per PRB power. The exception to this rule is that UEs that cannot transmit all their PRBs at the assigned power because they will exceed the maximum power of 200mW (23dBm). A device in this state, referred to as negative power headroom, will divide the 200mW evenly among all the PRBs in its grant. In most scenarios, path loss will be equal to the reference symbol power transmitted at the base station minus the reference symbol recieved power (RSRP). Because the RSRP values reported by the UEs to the base station are often recorded by the carrier, one can easily calculate the path loss of from given UE to the bast station antenna from its RSRP using this data.

If a model closely matches the number of active PRBs per TTI and the power per PRB in a cell, the total power accounted for by the model should match closely with what is observed in the field without the need to model individual UEs. A shortcoming of this approach is placing individual UEs in a cell sector is not straightforward, however this scenario is concerned with receivers at large distances away from the UEs that it is likely sufficient to place all transmitters at the base of the tower.

III. CARRIER KPI MATCHING TO EMULATE SECTORS IN THE LAB

MITRE's MULE is a flexible, scalable, and cost-efficient testbed built from commercial-off-the-shelf network elements which can be used to accurately characterizes the aggregate emissions from an LTE/5G sector. A block diagram of the testbed is shown in figure 1. The testbed consists of 24 UEs split between three RF shield boxes connected to an eNodeB by direct conduction through a channel emulator. The UEs execute scripts outlining prescribed network activity, and test data is collected through a protocol analyzer and the UE chipset logs on a per-TTI resolution (1ms).

The goal of the experiments is to replicate the real-world conditions that lead to the aggregate interference from UE emissions. Because it is infeasible to measure aggregate interference at every location for all time, the KPIs provide a mean to validate lab conditions against field conditions. If the KPIs from the lab match the KPIs from the field eNodeB within some margin of error, the UE emissions are considered to be a match and can be used in the calculation of aggregate interference.

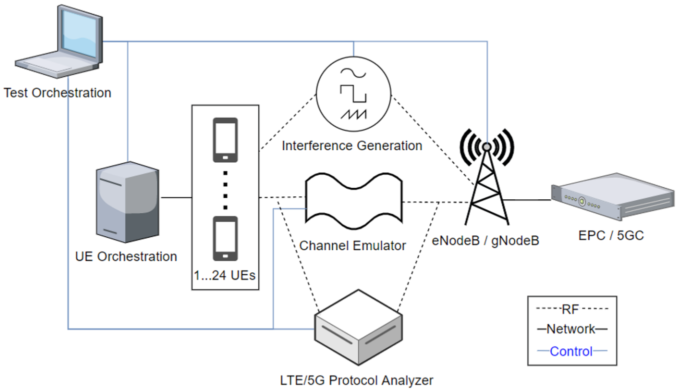

Fig. 1. MULE block diagram.

To match the field conditions observed from KPIs, a series of factors are adjusted in MULE, shown in table I. The variable attenuator is adjusted such that the path loss distribution of UEs in the emulated cell match the path loss distribution reported in the KPI of the sector being emulated. The UEs execute scripts where the payload size in bytes and the delay between transmission is adjustable in order to generate traffic where the overall PRB occupancy matches the KPI. A data transmission script will not always result in the same PRB utilization because the number of resource blocks required to transmit the uplink data will not only depend on the number of bytes the UE needs, but also the modulation and coding scheme (MCS) that the eNodeB assigns to the UE. It is difficult to predict what MCS will be assigned to a UE beforehand, and it may change throughout the run, so it may be necessary to repeat a series of runs where the UE scripts are incrementally adjusted until the PRB utilization matches the field KPI.

TABLE I
LAB VARIABLES USED TO EMULATE FIELD FACTORS

Field Factor	***MULE Emulation Method***
Path loss	Variable attenuator
PRB utilization	UE ping script delays
Channel fading and Doppler shift *	Channel emulator
P_0, α*	COTS eNb configuration
Scheduling algorithm *	Inherent to COTS eNb

*Not changed based on KPIs

Due to limitations in KPI granularity, there is an infinite number of combinations over a 15-minute KPI collection period that could result in the same KPI numbers. However, if the path loss KPI is reported on a per transport block basis the impact of coarse KPI reporting intervals is mitigated because the proportion of transmissions coming from UEs with low RSRPs will limit the number of transmissions coming from users with high RSRPs.

In the tests, the UEs are all given approximately the same data load because users are assumed not to change their behavior based on their phone's signal strength. UEs transmit resource blocks proportional to their signal quality due adjustments to the MCS. If the proportion of transmissions made at each path loss is consistent, and the sector-wide resource block utilization matches, the resulting transmission powers will be representative of the field conditions.

IV. USING MULE DATA IN SIMULATION TO PREDICT INTERFERENCE

MULE reports an extensive suite of data after each run, however for interference prediction the UEs' chipset logs are analyzed. Each UE connected to the cell generates a log containing the reported transmit power of every transmission. MULE synchronizes these logs so the resource grid of the PUSCH can be completely reconstructed and populated with the power of each resource block as reported at the UE antenna port. The result is a $M \times N$ array, where M in the number of PRBs in the PUSCH, and N is the number of TTIs in the run. Then the dataset of sector wide EIRP, as measured at each UEs antenna power, is constructed as shown below:

```
Given an $M \times N$ array representing the PUSCH resource grid for UE $i$
for TTI $n$ in 1 to N do
    $EIRP_n^i \leftarrow \sum_{m=1}^{M} EIRP_{PRBm}^i$
end for
```

Based on the assumptions above, a distribution of sector wide per-TTI power for the sector being emulated on the testbed can be calculated as the sum of the total power reported by each UE that transmitted during each TTI. Because the traffic and UE path loss distribution in the sector match the factors determined to be most important in characterizing aggregate emissions, the total power across all UEs in this emulated sector will be representative of the sector in the field from which the KPI data originated.

A. Aggregate Interference Scenario

The modeling process is designed to predict the aggregate interference of one deployment on the scale of a city or large urban area as received at a distant receiver with a known gain pattern and azimuth, at a specific time of day. Before running the simulation, KPIs would be collected from every sector in the deployment in 15-minute intervals throughout the duration that aggregate interference would be evaluated. The receiver may be located anywhere, but for testing and evaluation purposes the modeled receiver would be placed at the same location and have the same antenna gain pattern as a receiver that was used to measure the real aggregate interference of the deployment over the same duration that the KPIs were collected. The primary location specific factors that must be modeled to predict aggregate interference are the path loss between the transmitter and receiver, and the clutter loss, which is additional propagation loss doe to foliage and buildings. To predict path loss, terrain elevation data must be available covering the area of the deployment, and all paths between the sectors under test and the receiver. Then the path loss can be computed for all points using a rough terrain propagation model like Longley-Rice or Terrain Integrated Rough Earth Model (TIREM) [5] [6]. Clutter loss, in this context, is additional loss beyond what would be predicted by a rough terrain model, for example fading from buildings and foliage between the UEs and the receiver. The modeler may measure these losses in the location under test for their receiver specifically or use clutter distributions derived from land use data or census designations. Both approaches are used in practice, and it is worth considering that while the latter approach may be less accurate, it will produce a model that does not require any physical access to the location in order to produce a prediction.

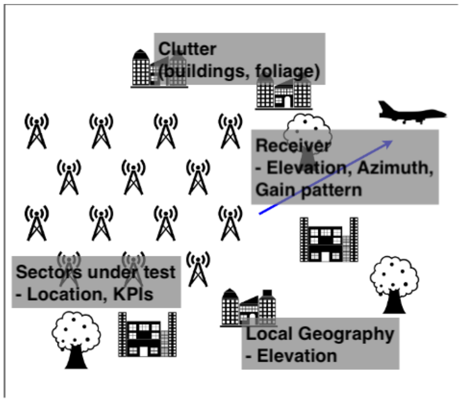

Fig. 2. Aggregate interference scenario.

B. Interference Prediction Process

To produce a prediction, MULE first produces the reported power, grant size, time, and location for every UE in each sector in the deployment under evaluation. MULE is configured using KPIs collected from these sectors at the time of day for which the prediction is needed. Before the simulation is run, a sector-wide distribution of EIRP as measured at the UE antenna port for each of these sectors is prepared using the algorithm shown at the start of this section. Then, the Monte Carlo simulation re-samples each of these distributions and places the transmissions in the modeled geography of the deployment, and propagates the power to the receiver, taking into account the direction gain of the receive antenna and losses in the signal path. Each of these samples is summed at the receiver to produce one aggregate sample, and the Monte Carlo process is repeated until sufficient samples are collected to create a final distribution of aggregate interference. A block diagram of the process is shown in figure 3.

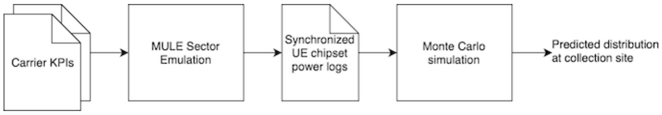

Fig. 3. Interference Modeling Process.

In order to arrive at a total aggregate interference distribution, we collected sector-wide EIRP distributions generated from the MULE tests for each sector in the scenario, and resampled the distributions in a Monte Carlo simulation and propagated the emissions to the receiver at the collection site. However, an additional loss, L_{indoor}, must be applied to the UE power to account for UEs located indoors. The RSRP distributions that MULE matches to account for indoor UEs because they are matched to real field RSRPs, however this loss will not be accounted for when we propagate the transmissions to the collection site so we must approximate it. In this scenario, we assumed 80% of UEs were indoors, and that all indoor transmissions are attenuated by 20db (a linear loss of 100).

The Monte Carlo sampling algorithm for N samples measured at a receiver located at latitude and longitude ϕ_{Rx}, λ_{Rx} is as follows:

```
while $n < N$ do
    aggregate sample $AI_n \leftarrow$ 0mW
    for sector $i$ in study do
        draw sector EIRP sample $EIRP_i$
        draw $p$ from $U(0,1)$
        $L_{indoor} \leftarrow \begin{cases} 100, p <= 0.8, \\ 1, p > 0.8 \end{cases}$
        $AI_i \leftarrow \frac{EIRP_i \times G_{Rx}(\theta_{i,Rx})}{L_{indoor} \times L_{path}(\phi_i,\lambda_i,\phi_{Rx},\lambda_{Rx}) \times L_{clutter}(\phi_i,\lambda_i)}$
        $AI_n \leftarrow AI_n + AI_i$
    end for
    add aggregate sample $AI_n$ to distribution
end while
```

This process produces samples defining a distribution of aggregate power at the receiver, which is often presented in a cumulative distribution function (CDF).

V. RESULTS

In order to assess the accuracy of this analysis, we gathered the following data:

- A 24-hour field collection of 10 second samples at 5-minute intervals at a known measurement site with an antenna of a known gain pattern
- 15-minute KPIs from over 80 sectors operating in the area immediately surrounding the collection site, focused within the main lobe of the antenna
- 5-meter resolution terrain elevation data of the surrounding area
- A drive test measurement of the clutter loss between the collection site and locations along the drive test path

The exact location and market of the towers under test is omitted as it is competition sensitive data from the MNO.

The following are cumulative density functions (CDFs) of an aggregate interference distribution generated by the Monte Carlo simulation using the KPIs from these sectors, and the field collection recorded at the same time as the KPIs used to configure the MULE tests. The selected times were 5:00-5:15 PM (high traffic volume) and 6:30-6:45 AM (low traffic volume). An arbitrary offset in power has been applied to x-axis of figures 5 and 4 to obscure the exact values of the field collection data.

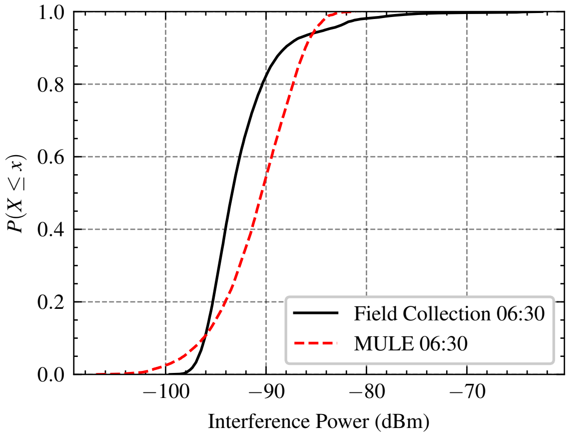

Fig. 4. CDF of Predicted Aggregate Interference at 6:30 AM.

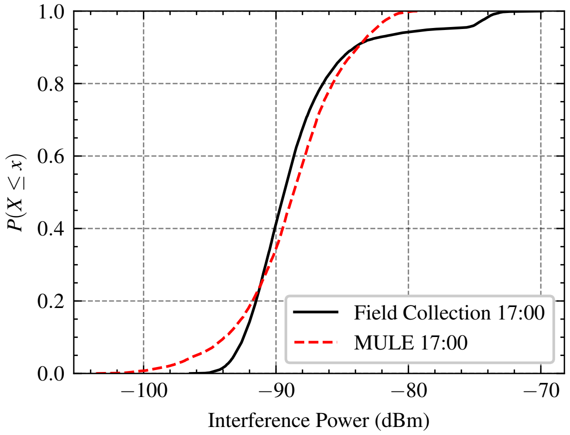

Fig. 5. CDF of Predicted Aggregate Interference at 5:00 PM.

The MULE emulation of the 5pm traffic produced a distribution with a mean 2.53 dB lower than the field collection, whereas the 6:30 AM emulation produced a distribution 0.26 dB higher. The lower traffic distribution had a slightly larger discrepancy from its corresponding field measurement at the $P = 0.5$ point on the CDF and the tails of the higher traffic distribution do not align with the measurement, however, the decrease in overall traffic was clearly captured by MULE. The exact difference in dB between the CDFs at $P = 0.5$ and $P = 0.9$ can be found in table II.

TABLE II
DIFFERENCE BETWEEN MULE CDF AND FIELD CDF AT 0.5 AND 0.9 CDF POINTS

CDF Point	***6:30 AM***	***5:00 PM***
$P = 0.5$	+3.00 dB	+0.65 dB
$P = 0.9$	+2.13 dB	+0.21 dB

VI. EXTENSION TO 5G AND IMPACT ON CELLULAR DEPLOYMENT MODELING

While developing a model of deployment emissions on an individual sector granularity is more cumbersome than more general models that have been proposed in the past, to so closely reproduce a distribution as it is measured in the field is an important result in the broader context of cellular deployment emission prediction. In producing a close match in an omniscient model, where we know the activity in every sector and precise propagation losses, we may use this result to inform more general models that will take less effort to develop.

Neither the methodology presented in this paper nor the geographic spectrum sharing scenario are exclusive to LTE technology. This methodology can be used to predict the uplink channel interference in aggregate of any distributed network of cellular transmitters where similar KPI statistics are collected. This is particularly extensible to future 5G networks, where new spectrum sharing agreements are needed frequently as MNOs negotiate spectrum purchases in the mid-band and mmWave.

Furthermore, the complexities of predicting interference radiated by 5G deployments will likely come from the vastly increased complexity of the scheduler. 5G numerology supports sub-carrier spacing and sub-frame durations that can vary from sector to sector and change dynamically based on network slicing and the current use case. An analytic approach may require significant effort to re-create this complexity, but this emulation approach remains mostly unchanged as long as one can acquire hardware that supports the same configurations used in the field.

VII. CONCLUSIONS

Based on the results of this study, it is clear that modeling individual sectors can produce a distribution closely matched to the field collection originating from the same time window. Because of this, we can conclude the parameters we selected to reproduce in MULE, namely PRB occupancy, RSRP distribution, and negative power headroom, are key factors in determining the amount of aggregate interference a sector will radiate. We look to use this as a baseline to develop a pared down model where we can assign models to sectors without requesting KPIs from the MNOs.

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