

Pathloss-Based Uplink Sector Emissions Model for LTE Aggregate Interference Prediction

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Abstract—Accurate aggregate interference prediction is key to successful spectrum sharing between cellular networks and Department of Defense receivers. This paper describes the Pathloss-Based Sector Uplink Emissions Model, a model that predicts uplink emissions with a sector-centric, rather than UE-centric, architecture. In doing so, it provides a higher fidelity model with demonstrated performance improvements for LTE aggregate interference prediction.

Keywords—spectrum sharing, aggregate interference, cellular, LTE

I. INTRODUCTION

To facilitate spectrum sharing between commercial and government systems in AWS-3 Spectrum (1755-1780 MHz), the Defense Information Systems Agency (DISA) Defense Spectrum Organization (DSO) has been seeking accurate methods for assessing the impact of potential Long Term Evolution (LTE) Uplink (UL) emissions on Department of Defense (DoD) receivers occupying the same frequencies. Such assessments require predicting the aggregate interference at the victim receiver caused by emissions from LTE User Equipment (UE) spread out over a large geographic region [1]. The accurate modeling of LTE UL emissions is a critical part of this process.

Prior to the 2015 AWS-3 auction, the Commerce Spectrum Management Advisory Committee (CSMAC) convened a diverse stakeholder group to identify an approach to modeling LTE UL emissions [2]. In 2015, DSO established the Spectrum Sharing Testing and Demonstration (SSTD) program, which created an LTE Working Group (WG) to identify improvements to the existing model. The SSTD LTE WG has since recommended numerous refinements which have led to higher fidelity predictions. However, the fundamental approach defined by CSMAC is still used today.

Currently, interference contributions from individual UEs are considered independently and the contributions from all UEs are summed to obtain the aggregate interference. While this UE-centric architecture is intuitive, it makes simplifying assumptions regarding the number of simultaneous UE

emissions and the correlated emission powers among UEs from the same LTE sector.

In 2021, the SSTD LTE WG identified the advantage of transitioning from a UE-centric architecture to a sector-centric architecture. A sector-centric architecture computes aggregate interference as a sum of contributions from LTE sectors rather than UEs. This enables more accurate modeling of interference contributions by eliminating the independence assumption regarding UE emissions originating from the same sector. Different models could be used in a sector-centric architecture to capture intra-sector dynamics based on mission priorities.

This paper introduces the Pathloss-Based Sector Uplink Emissions Model (PBSUEM) as a model for predicting total sector-wide interference contributions of UE emissions in AWS-1/AWS-3 sectors. PBSUEM uses sector emulation to empirically model sector-wide interference contributions by matching pathloss statistics from real-world networks. It can be used for sector-centric aggregate interference modeling.

II. BACKGROUND

A. Aggregate Interference Link Budget

In this work, no changes are made with respect to the link budget equation used to compute the aggregate interference to the receiver from individual interference sources. 0 describes the link budget currently used for aggregate interference calculation. In the current UE-centric architecture, the Effective Isotropic Radiated Power (EIRP) is per each UE source. In the sector-centric architecture, the EIRP represents the total power from all the emitting UEs within a sector.

$$I = Q - L_{cl} - L_p - FDR + G_r - L_{pol} - L_s$$

I = Interfering signal level at the victim receiver (i. e. aggregate interference contribution)
 Q = Effective Isotropic Radiated Power (EIRP) from the interference source
 L_{cl} = Total Clutter loss between interference source and victim receiver
 L_p = Propagation loss between interference source and victim receiver
 FDR = Frequency Dependent Rejection at the victim receiver
 G_r = Victim receiver antenna gain in the direction of the interference source
 L_{pol} = Victim receiver antenna polarization mismatch loss
 L_s = Victim receiver antenna system loss

Fig. 1. Link budget used for computing aggregate interference.

Due to the stochastic nature of real-world environments, many of the terms in the aggregate interference link budget are random variables. Since aggregate interference is the sum of interference contributions from many sources, the Central Limit Theorem suggests it will take the form of a Gaussian distribution. Furthermore, the relative size of the standard deviation with respect to the mean will fall as the number of interference sources increases. In many applications, it is therefore sufficient to consider only the mean value of each random variable. However, the models described in this paper will define EIRP as a random variable for completeness.

B. CSMAC-Motivated UE Uplink Emissions Model

The current aggregate interference model adopts the UE-centric architecture motivated by the CSMAC recommendations from 2012. EIRP distributions are assigned to individual UEs, and interference contributions are assessed using the link budget defined in 0. The aggregate interference is computed as the sum of the contributions from all the UEs. Fig. 2 illustrates the block diagram for the UE-centric architecture. UEs are assumed to have EIRPs that are mutually independent in each 1-millisecond LTE transmissions time interval (TTI) [2].

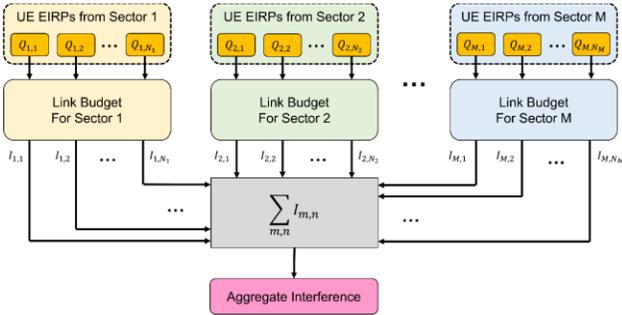


Fig. 2. Aggregate interference calculation using a UE-centric architecture.

The modeling of UE EIRP in each TTI is determined by the UL emission model illustrated in Fig. 3. A set of pre-defined baseline EIRP distributions and a network loading factor (NL) are mapped to each UE according to a sector-level category model (see Section II.C). A UE's assessed EIRP for a given TTI is computed by drawing from its baseline EIRP distribution and then scaling by its NL value. Using this approach, a fixed number of UEs are modeled for every sector, three per every 5 MHz of UL channel bandwidth [2].

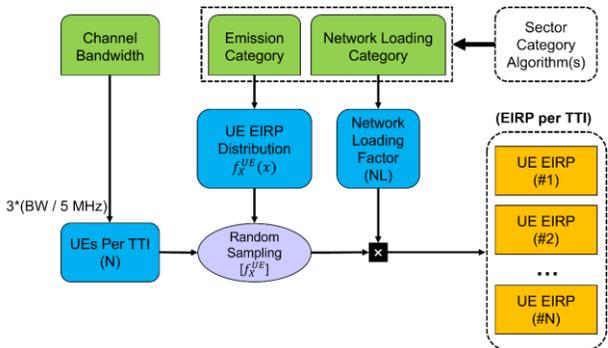


Fig. 3. Block diagram of the uplink emission model currently used in the business process.

In this paper, the UE UL emissions model described in Fig. 3 applied within the context of the UE-centric architecture described in Fig. 2 will be referred to as the CSMAC-Motivated UE Uplink Emissions Model (CMUUEM).

CMUUEM makes several simplifying assumptions which do not accurately reflect UE emissions in real-world sectors. Most notably, CMUUEM assumes UEs transmitting in the same TTI are independent and each have full access to all available frequency resources. In reality, the total frequency resources in a TTI are limited. Therefore, the resources available to a UE is limited by the resources reserved for other UEs already scheduled in the same TTI. Varying traffic demands will cause the number of UEs transmitting in each TTI to vary over time, and the emission powers of simultaneously transmitting UEs will be correlated.

Since its inception, CMUUEM has undergone several refinements which improved methods for modeling components of the link budget, the sector categories, the NL factor, and the baseline UE EIRP curves [1]. This has led to improved aggregate interference predictions, but the fundamental assumptions of the model have remained unchanged. Achieving higher fidelity aggregate interference predictions ultimately requires a change in model assumptions so that the inaccuracies caused by simplifying assumptions can be reduced.

C. Sector Categories

CMUUEM categorizes sectors into two different morphologies with different network loading:

1. A sector located in a region designated as “urban” by the United States Census Bureau is in the urban/suburban morphology. All UEs associated with an urban sector are assigned a 26% network loading (i.e. a NL factor of 0.26) [3].
2. All sectors that are not in the urban/suburban morphology are in the rural morphology. UEs associated with these sectors are assigned a 16% network loading (i.e. a NL factor of 0.16) [3].

These network loading values have been validated against typical values seen in real world data networks (See Section II.E). Under the SSTD LTE WG recommendations predating 2021, UEs are categorized into four different emission categories, two for macro cell sectors and two for small cell sectors:

1. Sectors with antenna height greater than 10 meters are considered macro cell sectors.
 - Macro cell sectors with an urban/suburban network loading category are assigned an urban/suburban UE EIRP distribution.
 - Macro cell sectors with rural network loading category are assigned a rural UE EIRP distribution.
2. Sectors with antenna height less than or equal to 10 meters are considered small cell sectors.
 - Small cell sectors within the coverage area of an approved macro sector are cochannel and their

contributions to aggregate interference are ignored because it is accounted for by the covering macro sector.

- Small cell sectors not within the coverage area of an approved macro sector are non-cochannel and are assigned a small cell UE EIRP distribution.

The SSTD LTE WG 2021 recommendations included a transition of macro cell sector categories from the current morphology (“urban/suburban” and “rural”) model to one based on inter-sector distance (ISD) [4]. This recommendation was motivated by the belief that the size of a sector correlates with UE EIRP dynamics to a greater extent than the morphology of the sector. Five representative ISD categories were defined. These categories are chosen based on trends seen in real world networks.

The SSTD LTE WG recommended a “nearest neighbor” algorithm for assigning a sector to an ISD category. A sector’s nearest neighbor is the closest (not co-located) sector that resides in the line of sight of the sector’s 3dB beamwidth [4]. The sector’s ISD category is obtained by binning the distance between a sector and its nearest neighbor to the closest representative ISD value associated with each of the ISD categories.

While ISD categories are useful when describing sectors in a network, individual sectors can also be categorized by defining a “sector radius” corresponding to the furthest distance from which UEs can consistently connect to the cell. Assuming nearby sectors have roughly equal footprints, each ISD category can be associated with a corresponding sector radius defined by half the representative ISD value. TABLE I. summarizes the ISD categories and the associated sector radius categories.

TABLE I. FIVE ISD/RADIUS CATEGORIES

Index Number	Representative ISD	ISD Bin Range	Representative Sector Radius	Radius Bin Range
1	500m	$0m \leq ISD < 750m$	250m	$0m \leq Radius < 375m$
2	1000m	$750m \leq ISD < 1366m$	500m	$375m \leq Radius < 683m$
3	1732m	$1366m \leq ISD < 2366m$	866m	$683m \leq Radius < 1183m$
4	3000m	$2366m \leq ISD < 5000m$	1500m	$1183m \leq Radius < 2500m$
5	7000m	$5000m \leq ISD$	3500m	$2500m \leq Radius$

The ISD categories recommended by the SSTD LTE WG can be used for both the CMUUEM and the PBSUEM models [1]. New UE EIRP distributions were generated for each of these ISD categories for use in CMUUEM. Details are not contained in this paper but can be found in [4].

D. Multi-UE LTE Emulator Testbed

The PBSUEM model was developed using MITRE’s Multi-UE LTE Emulator (MULE), a testbed that enables LTE experimentation and performance and behavior monitoring in a tightly controlled environment. MULE is a complex system that includes commercial UEs, commercial grade LTE base stations (eNodeBs), equipment that emulates the RF path between each UE and the eNodeB, a centralized controller that drives the UEs according to predefined scripts, and a custom-built orchestration

tool that initiates tests and collects result data. A detailed description of MULE and how it operates is provided in Appendix F of [5] (MULE is referred to as MUSE in this reference). A high-level system diagram of MULE is shown in Fig. 4.

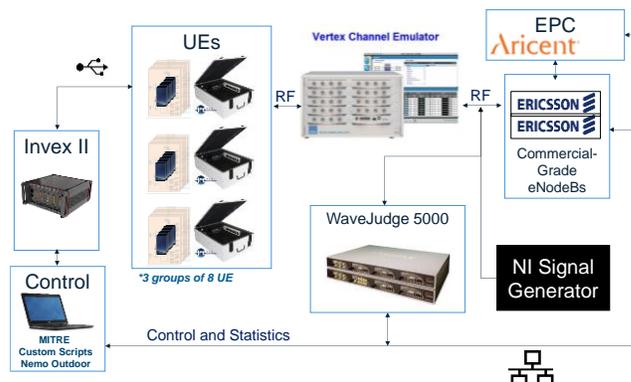


Fig. 4. System Diagram of MULE.

MULE enables high-fidelity emulation of real-world LTE sectors parameterized by key performance metrics that are provided in advance. Given a sector-wide target UL pathloss distribution and average UL network loading, MULE can be used to emulate UE emissions which are consistent with the target sector being emulated. Various measurements of UE and eNodeB performance are collected in each MULE emulation. These include detailed UL emission information which indicates at which LTE TTI each UE transmitted, with what total power, and over what LTE physical resource blocks (PRBs).

E. AWS-1 Multi-Market Data

The work in this paper leveraged data gathered from live AWS-1 networks in 2020. AWS-1 and AWS-3 are adjacent blocks of spectrum. For this reason, it is assumed that metrics derived from real-world AWS-1 networks would be representative to those observed in real-world AWS-3 networks. No AWS-3 network data was made available to the SSTD LTE WG.

The AWS-1 data used in this work was provided by a single mobile network operator (MNO). The data contains statistics collected from eight different regional markets in the contiguous U.S. states and is referred to as “multi-market data” in this paper.

The content of the multi-market data set can be broken down into two categories:

- Sector Configuration and Location Data – Information about the physical towers as well as the radio heads, antennas, and configuration information associated with each sector.
- Key Performance Indicators (KPIs) – Counters and computed performance metrics collected by the eNodeB for each sector.

The KPI data include metrics for estimating the average physical layer network loading for each sector. This was used to validate the current network loading assumptions [6]. Also included in the KPI data are metrics which can be used to

estimate the distribution of UE connection distances from the base station radio. Finally, the KPI data include metrics which enable the estimation of an UL pathloss distribution, corresponding to the distribution of the pathloss associated with each UL transmission in the sector.

III. PATHLOSS-BASED SECTOR UPLINK EMISSIONS MODEL

PBSUEM is an UL EIRP model which uses sector emulation to address the correlation present among the EIRP of UEs transmitting simultaneously within a sector. These correlations are difficult to capture mathematically because they depend on processes involving the base station scheduler and performance requirements imposed by higher layers in the protocol stack. In CMUUEM, they are ignored completely, and UE emissions are modeled as independent and identically distributed random variables.

A. Sector-Centric Architecture

PBSUEM is intended to be used in a sector-centric aggregate interference model. Fig. 5 illustrates the block diagram for aggregate interference computation within the sector-centric architecture. The link budget equation is the same one used for the CMUUEM, but applied to individual sectors instead of UEs. The key component to this architecture is the “Emission Model for Total Sector EIRP” block, which is the UL emission model that predicts UL EIRP contribution from individual sectors.

The sector-centric architecture is a paradigm shift which generalizes the existing UE-centric architecture used by CMUUEM. With an appropriate choice of UL emission model, it is possible to define a sector-centric aggregate interference model which produces the same results as CMUUEM. However, this architecture enables the use of other UL emission models that can achieve higher fidelity with real-world sector emissions. PBSUEM is an example that uses empirical data and sector emulation to obtain an improved emissions model based on the sector categories given in Section II.C.

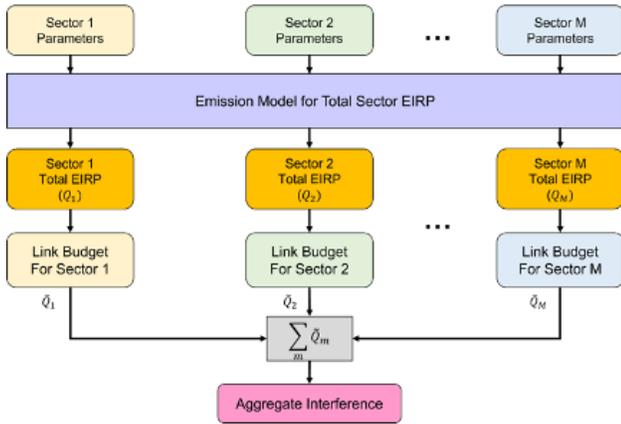


Fig. 5. Aggregate interference calculation using a sector-centric architecture.

B. PBSUEM Overview

The high-level block diagram of PBSUEM is provided in Fig. 6. PBSUEM assumes there exists category algorithms which can classify any given sector into an emission category and a network loading category. It also assumes the channel

bandwidth of the sector is known. Once a sector has been categorized, a corresponding TTI Activity Rate (TAR) and Sector EIRP Distribution (SED) is determined from a table of pre-generated values.

- TAR – Specifies the probability that the sector has at least one transmitting UE in a randomly chosen TTI.
- SED – Specifies a random variable which models the combined EIRP of one or more UEs transmitting in the same TTI within a sector.

The TAR and SED for each category are generated using high fidelity sector emulation parameterized by real-world data. The bandwidth is used to determine a scaling factor that needs to be applied when modeling cells of different bandwidths than the one used in the reference emulation.

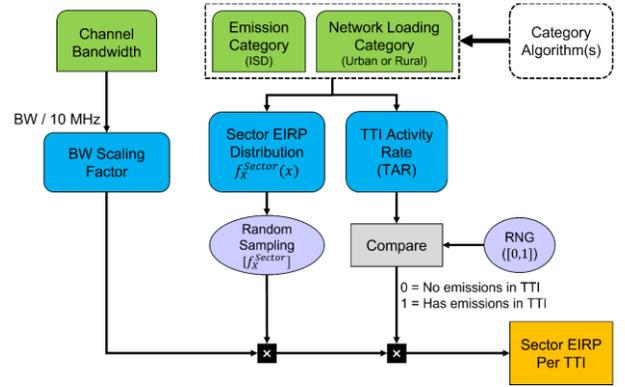


Fig. 6. Block diagram of PBSUEM.

Note the similarity in structure between the UE-centric emission model of CMUUEM (Fig. 3) and the sector-centric emission model of PBSUEM (Fig. 6). In particular, there appears to be a functional correspondence between the TAR in PBSUEM with that of the NL factor in CMUUEM.

The NL factor in CMUUEM is a term with ambiguous real-world meaning. It is a factor that rescales the effective number of UEs that is assumed to be always transmitting on a sector. This procedure was adopted to compensate for the inaccurate network loading assumptions built into the UE EIRP distribution. Network loading in real-world sectors is complicated since it is largely driven by user demand within the sector and the base station scheduler. There could be some TTIs that are completely empty of UL emissions. TTIs could also have disproportionately allocated frequency resources when multiple UEs are transmitting due to differences in UE traffic.

In contrast, the TAR factor in PBSUEM directly corresponds to the probability that a given TTI in the sector is empty. It can be interpreted as the time-dimension loading, while the frequency-dimension loading is captured within the sector-wide EIRP distribution. By leveraging sector emulation using commercial equipment PBSUEM is able to separate the two dimensions of network loading.

C. PBSUEM Parameters for 2021 SSTD-recommended Macro-Cell Sector Categories

In support of the goals of the SSTD LTE WG, a specific set of SED and TAR values were generated to be used with the five ISD categories and the two morphology categories defined in Section II.C. This enables PBSUEM to be compatible with the 2021 SSTD-recommended algorithm for categorizing AWS-3 LTE sectors. TAR and SED values were generated for each of the 10 possible combinations of emission and network loading categories using the MULE testbed (Section II.D) and AWS-1 multi-market data (Section II.E). The details of this process are described in Section IV. A summary of the TAR values is provided in TABLE II, and the corresponding SED values are illustrated in Fig. 7.

TABLE II. PBSUEM TTI ACTIVITY RATES FOR DIFFERENT ISD AND MORPHOLOGY CATEGORIES

	Urban/Suburban	Rural
500m ISD	0.70	0.61
1000m ISD	0.73	0.68
1732m ISD	0.76	0.67
3000m ISD	0.78	0.73
7000m ISD	0.83	0.78

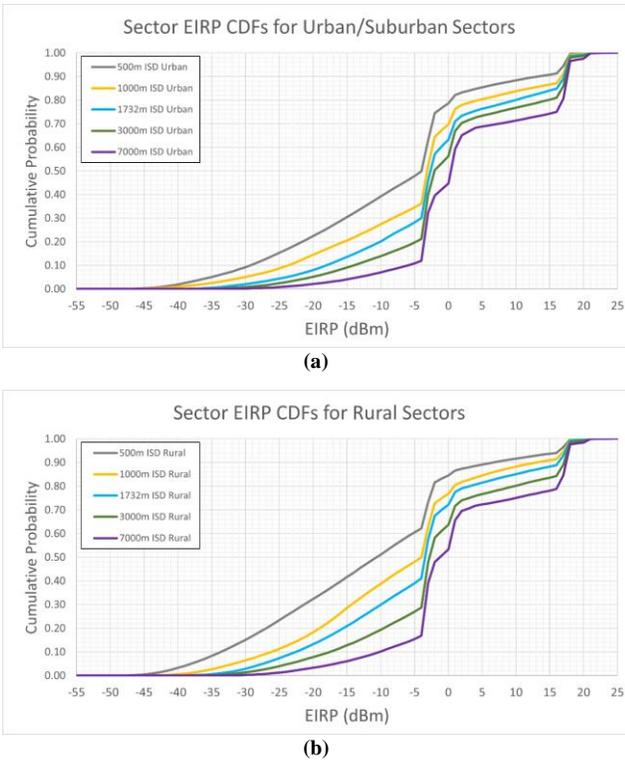


Fig. 7. Sector EIRP Distributions (CDFs) for PBSUEM. (a) Urban/Suburban network loading sectors, (b) Rural network loading sectors.

IV. PROCEDURE FOR OBTAINING MODEL PARAMETERS

This section describes how the AWS-1 multi-market data and the MULE testbed were used to produce the PBSUEM SED and TAR parameters introduced in Section III.C. At a high level, it consists of three steps:

1. For each ISD category, compute a representative UL pathloss distribution from the multi-market data by considering the average distribution from all sectors belonging to the same category.
2. Use the representative pathloss distribution, along with representative network loading levels, as forcing parameters to drive accurate sector emulation using MULE.
3. Use detailed UL emission information from MULE emulation to generate representative SED (and TAR) parameters for each category pairing of ISD and network loading.

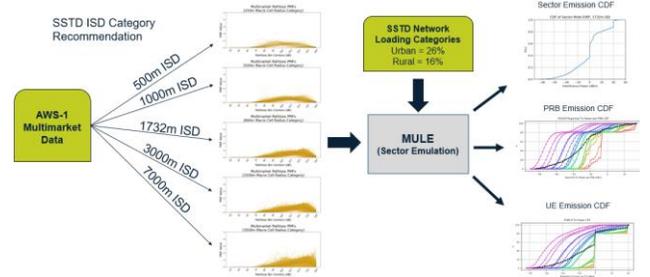


Fig. 8. Flow chart describing the generation of EIRP distributions using MULE.

A. Representative Uplink Pathloss Distributions

One of the key assumptions of PBSUEM is that UL pathloss is strongly correlated with UL emission power. This is motivated by the LTE power control equation [7], which specifies that UE transmit power (in dBm) is proportional to the estimated pathloss (in dB scale). UE pathloss is estimated by the eNodeB to inform scheduling decisions, and statistics about the UL pathloss in each TTI can be recorded as a KPI.

The MULE testbed uses commercial equipment, so it can collect the same KPIs as those on commercial networks. Therefore, it is possible to configure and drive the equipment in MULE so that it generates KPIs that are very similar to those from real-world sectors. If MULE can match an UL pathloss distribution that is representative of those from a real-world sector, then it is likely the associated UE transmit powers from MULE are also consistent with those in a real-world sector.

To create representative UL pathloss distributions from the multi-market dataset, each sector is assigned an ISD category based on the 90th percentile of its UE connection distances. The 90th percentile value was chosen over the max distance to filter out unrealistic, erroneous samples that are sometimes present in the data, and to be consistent with the metric used to validate the nearest neighbor category algorithm in SSTD's category recommendation [4]. The category assignment scheme is shown in TABLE III.

A time-independent estimate of each sector's typical UL pathloss distribution was obtained by aggregating each sector's UL pathloss distributions over all KPI collection times and normalizing by the number of samples. Finally, a single representative distribution was obtained for each ISD category by aggregating the distributions over all sectors in the category

and normalizing by the number of sectors. The resulting representative UL pathloss distributions are shown in Fig. 9 as dotted black lines. Fig. 9 also shows the individual time-independent estimates of each sector’s typical UL pathloss distribution as gold lines. It can be observed that the representative distributions shift towards higher path loss in categories of increasing ISD. This fits the intuition that the typical pathloss in a sector should increase if more UEs are connecting from farther away.

TABLE III. ISD CATEGORY ASSIGNMENT SCHEME

90 th Percentile of UE Connection Distance (m)	ISD Category (m)	Representative Sector Radius
≤375	500	250m
(375, 683]	1000	500m
(683, 1183]	1732	866m
(1183, 2500]	3000	1500m
>2500	7000	3500m

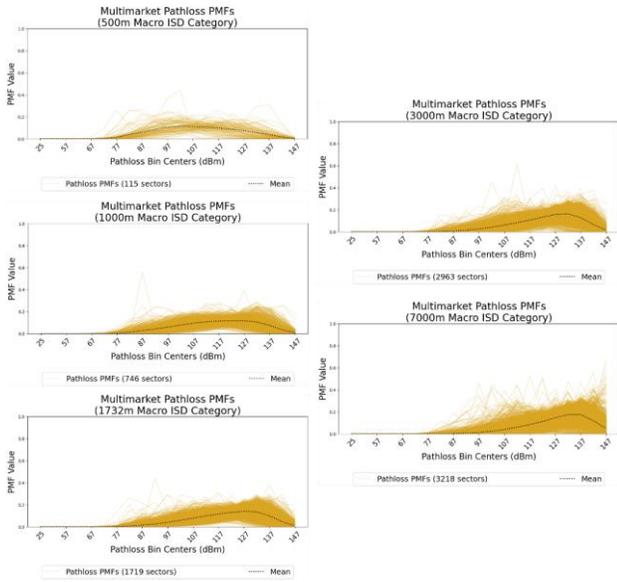


Fig. 9. Plots of the UL PL distributions in the multimarket data for each of the five ISD categories.

B. Representative Network Loading

The physical layer UL network loading is defined as the mean rate of UL PRBs used in the sector in each TTI. Network loading is influenced by UE traffic needs, the RF environment, and the eNodeB scheduling algorithm. In an operational environment, network loading is a metric that is measured after-the-fact and can be derived from an eNodeB’s PRB utilization KPI.

A sector’s total UL EIRP is dependent on the network loading since a higher utilization of PRBs creates the possibility of higher total power being emitting from the sector. This is because UE transmit power scales with the number of PRBs being used for transmission [7]. For this reason, the UL network loading recorded by MULE must be consistent with those of real-world sectors to produce accurate estimates of the total sector EIRP.

In developing the SEDs for PBSUEM, it is assumed that sectors located in rural areas have a typical network loading of 16% while sectors in urban or suburban areas have a typical network loading of 26%. The designation of urban and rural morphology is based on the United States Census Bureau data as described in Section II.C. This is consistent with the values for the network loading factor recommended in [3]. These network loading values have been determined to be appropriately conservative based on analysis of the AWS-1 multi-market KPI data [6].

C. Sector Emulation with MULE

The MULE testbed was leveraged to generate the required SEDs and TARs for model sectors parameterized by KPIs from the multi-market dataset and DSO’s previously recommended network loading factors [3]. The SED and TAR for each model sector is derived from data obtained from a MULE emulation. A MULE emulation is the instrumented operation of MULE’s components for a KPI collection interval (typically 15 minutes) which results in KPIs that match the desired metrics of the model sector being emulated.

The Cartesian product of the five representative UL pathloss distributions and the two network loading values defines the set of 10 MULE emulations required to produce the SED and TAR values for the desired model sectors. MULE was configured using the same parameters for all emulations. TABLE IV. summarizes the key parameters.

TABLE IV. MULE CONFIGURATION FOR ISD CATEGORY MODEL EMULATIONS

Parameter	Value
Number of Physical UEs	21
Number of Cells	1
Carrier UL Center Frequency	1710 MHz
Carrier Bandwidth	10 MHz
Alpha	0.8
PO PUSCH	-90dBm
Number of PUSCH Resource Bocks	46
Number of PUCCH Resource Bocks	4
Channel Model	3GPP EPA5

A valid emulation must simultaneously match the target UL pathloss distribution as well as the target network loading. This was done by adjusting the pathloss experienced by each UE as well as the application traffic required by each UE.

Matching both UL pathloss distribution and network loading is difficult because the two metrics are interdependent. The UL pathloss distribution is derived from a histogram that accumulates one sample per uplink emission. UEs with more traffic will have more emissions and contribute more UL pathloss samples. UEs with high pathloss are also more likely to use more resources due to lower signal-to-noise ratios caused by limited maximum transmit power. For this reason, each MULE emulation is an iterative process. The UL pathloss distribution is matched first, and then the aggregate traffic is incrementally adjusted to tune the network loading on the sector while preserving the UL pathloss distribution.

1) Matching Uplink Pathloss Distributions

MULE cannot alter the pathloss experienced by a UE on a TTI-by-TTI basis. Therefore, it is necessary to assign each UE an average pathloss such that the resulting distribution matches the target distribution as closely as possible. This is achieved by multiplying each pathloss bin's relative frequency by the number of UEs in the emulation and rounding the product to the nearest integer, resulting in a count of UEs to be assigned to each pathloss. If there are remaining UEs, the pathloss bins with UE counts of zero are sorted by their relative frequencies, and a UE is assigned to the pathloss having the largest relative frequency.

As a numerical example of this process, consider a pathloss bin with a relative frequency of 0.07. The value 0.07 is multiplied by the number of UEs in the emulation, for example, 21, resulting in a product of 1.47. The product is then be rounded down to 1 and consequently the pathloss is assigned to one UE.

The pathloss assignments are realized by adjusting the attenuation on the RF path between the UEs and eNodeB such that the RSRP measured by the UEs reflect the pathloss assignments. A channel model is also used to modulate the pathloss of each UE over time. In this manner, the average pathloss of a UE may be fixed, but its pathloss at each TTI can vary.

2) Matching Network Loading

Once the UL pathloss distribution is matched as closely as possible, the network loading is matched. The sector's network loading is adjusted by tuning the traffic bitrate on each UE in an iterative manner. The first iteration is a baseline in which each UE transmits at the same average bitrate. After the network loading for the baseline run is calculated, control scripts are modified to increase or decrease the aggregate bitrate for a set of UEs. Because network loading is based on PRBs instead of bits, the modification logic considers the average amount of useful data per transport block and may increase or decrease the bitrate more than expected to push the eNodeB scheduler to assign more or fewer PRBs to transmit. This process is repeated until the KPIs indicate network loading is within 5% of the target value.

D. Creation of EIRP Distributions from MULE Data

The output data of each MULE emulation includes information regarding the transmit power and resource allocations of every UL emission from each UE. Different EIRP distributions can be generated using the fine-grain information collected during an emulation.

1) UE Transmit Power Adjustment

To create EIRP distributions, the recorded UE transmit powers must be adjusted to reflect real-world characteristics that are not reflected by the emulation. Antenna loss is subtracted from the reported power to account for the reduction in radiated power due to non-ideal antennas on UEs. To account for the presence of indoor UEs in the sector and the effect of building penetration losses, a percentage of UE transmission powers are reduced accordingly, generally by a constant amount. For this work, the following adjustments were made:

- 3 dB was subtracted as antenna loss.

- A random 80% of all transmissions were chosen to be emissions from indoor UEs, and an additional 20 dB was subtracted from those emissions. This is consistent with assumptions made in 3GPP working group simulations [8].

2) Construction of Sector EIRP Distributions

3GPP standards specify that uplink transmissions have the same average transmit power over all allocated frequency resources (i.e., PRBs) [9]. Using this information, it is possible to construct a time-frequency resource grid that indicates the theoretical EIRP present in each PRB of each TTI in the MULE emulation.

Fig. 10 illustrates the concept of an EIRP resource grid. In this example, the total number of PRBs is 16, and the total number of TTIs elapsed is 12. In each TTI (i.e., column), the colored tiles indicate PRB resources occupied by UE emissions. The EIRP of each occupied PRB is given by the numbers in the corresponding tile of the grid. Contiguous blocks of the same color within each TTI correspond to emissions from the same UE. Purple blocks correspond to a total EIRP of 10mW (10 dBm); red blocks correspond to a total UE EIRP of 8mW (9 dBm); and gold blocks correspond to a total UE EIRP of 2mW (3 dBm).

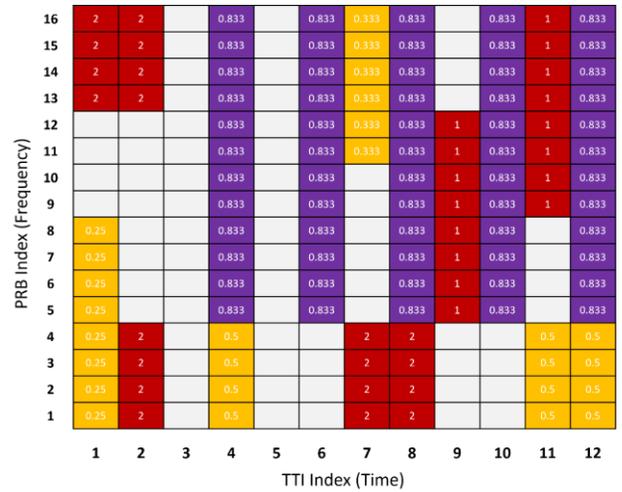


Fig. 10. Cartoon illustration of an EIRP resource grid. EIRP given in units of milliwatts.

EIRP modeling can be thought of as compressing the information contained in the EIRP resource grid obtained from a representative MULE emulation. There are three different ways of modeling total sector EIRP using the granular emission information provided by MULE: per-UE, per-PRB, and sector-wide.

- The per-UE model considers the total sector EIRP as the sum of independent UE EIRPs per TTI. This is consistent with the UE-centric architecture for aggregate interference.
- The per-PRB model considers total sector EIRP as the sum of independent PRB EIRPs per TTI.

- The sector-wide model considers the total sector EIRP as a single random variable per TTI.

PBSUEM is a sector-wide model parameterized by the TAR and SED as defined in Section III.B. The computation of TAR and SED can be explained as a series of operations applied to the EIRP resource grid:

1. The EIRP per PRB is summed over all PRBs in each TTI to obtain the total EIRP contribution from all the UEs in the emulated sector at each TTI. Fig. 11 illustrates this computation using the example grid from Fig. 10.
2. The TAR is computed by dividing the number of TTIs with non-zero contributions (highlighted in green in Fig. 11) by the total number of TTIs.
3. The SED is computed by creating a normalized histogram of the non-zero values of total EIRP contributions (Fig. 12).

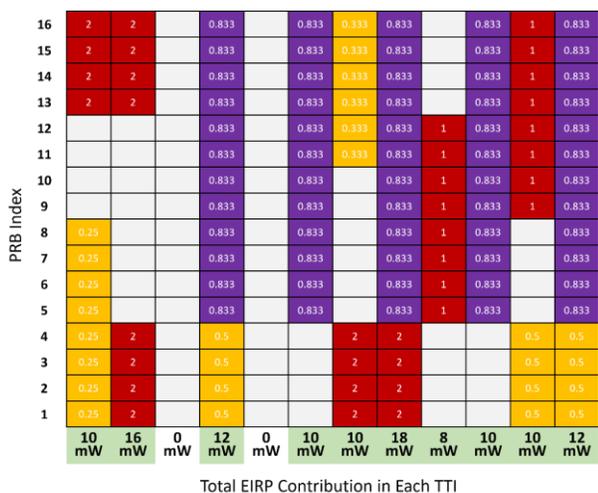


Fig. 11. Illustration of total EIRP contribution in each TTI. TAR = 10/12 = 0.833.

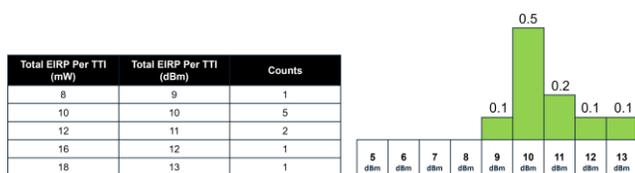


Fig. 12. Sector EIRP Distribution based on cartoon example in Fig. 11.

The SED and TAR values provided in Section III.C were derived in this manner using MULE data sets with roughly 900000 TTIs.

V. VALIDATION AGAINST FIELD MEASUREMENTS

Since 2018, the SSTD program has conducted six Carrier Coordinated Testing (CCT) events to gather data for model development and validation. These tests were performed in collaboration with an MNO at different locations in Colorado

and Virginia. For each CCT event, the MNO provided network information and base station KPIs collected during the time of the testing. Aggregate interference was measured directly at a remote site which overlooks the sectors of interest.

The PBSUEM model was validated against each CCT data set by comparing predictions of mean aggregate interference against actual measured values. Due to the high computational complexity of running many Monte-Carlo simulations, only the mean aggregate interference is computed as a baseline reference. This is sufficient for validation purposes since the CCT events do not reflect real operational scenarios.

In all CCT events, the receiver was located on an elevated point overlooking the test region. This is to emulate the conditions of real operational scenarios. However, in the case of CCT Event 1, there was an unusually high number of base stations close to the receiver location, resulting in larger variations in aggregate interference. In CCT Event 6, dense foliage close to the receiver may have led to more clutter loss than anticipated by the clutter model used to generate the predictions.

TABLE V. summarizes the results of the validation. The “FY21 UE Model Prediction” corresponds to the CMUUEM model with all of the 2021 SSTD recommendations, from all WGs, applied. For almost all the CCT events, the PBSUEM predictions are conservative and within 6 dBm of measured values. PBSUEM predictions are also closer to the measured values in four out of the six CCT events.

TABLE V. PBSUEM PREDICTIONS FOR CCT EVENTS

CCT Event	Measured Value (Mean diurnal peaks)	FY21 UE Model Prediction	PBSUEM Prediction
1	-87 (±3) dBm	-88.1 dBm	-89.4 dBm
2	-82 (±1) dBm	-78.0 dBm	-78.8 dBm
3	-85 (±2) dBm	-75.3 dBm	-74.9 dBm
4	-92 (±1) dBm	-84.5 dBm	-86.2 dBm
5	-85 (±2) dBm	-81.8 dBm	-83.2 dBm
6	-93 (±3) dBm	-78.6 dBm	-79.5 dBm

VI. CONCLUSION

This work introduced a sector-centric architecture for modeling cellular aggregate interference and defined the Pathloss-Based Sector Uplink Emissions Model (PBSUEM) as an example of a sector emission model within that architecture. PBSUEM illustrates that the complicated behavior of UE emissions can be directly captured through real-world emulation informed by empirical data gathered from existing cellular networks. In this manner, higher fidelity emission models can be developed without a dramatic increase in model complexity and, therefore, simple, yet accurate, models for interference prediction can improve spectrum sharing between commercial cellular and US government systems.

VII. REFERENCES

- [1] "FY21 SSTD LTE Working Group Pathloss-Based Sector Uplink Emission Model Recommendation." Spectrum Sharing Testing and Demonstration Working Group recommendation paper, December 2021.
- [2] NTIA, "Commerce Spectrum Management Advisory Committee Final Report: Working Group 1 – 1695-1710 MHz Meteorological-Satellite." January 22, 2013. Web:

https://www.ntia.doc.gov/files/ntia/publications/wg_1_report.pdf.
Accessed: December 12, 2021.

- [3] "SSTD LTE Tiger Team LTE Emissions 'NL/UE' Modeling Improvement Recommendation Language." Spectrum Sharing Testing and Demonstration Working Group recommendation paper, August 2019.
- [4] "FY21 SSTD LTE Working Group UE-based Small Cell & Family of Macro Cell Emission Model Recommendation." Spectrum Sharing Testing and Demonstration Working Group recommendation paper, November 2021.
- [5] Jason Coder et al., "Characterizing LTE User Equipment Emissions: Factor Screening", NIST, September 2019.
- [6] MITRE, "RSRP/Pathloss-Based Advanced Emission Models: Per Sector and Per-PRB & Ensemble Validation." SSTD LTE Characterization Working Group presentation, November 16, 2021.
- [7] 3GPP TS.36.213: "Evolved Universal Terrestrial Radio Access (E-UTRA); Physical layer procedures".
- [8] 3GPP TS 36.872: " Small cell enhancements for E-UTRA and E-UTRAN - Physical Layer Aspects".
- [9] 3GPP TS 36.211: "Evolved Universal Terrestrial Radio Access (E-UTRA); Physical channels and modulation".