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A Scalable and Realistic Interference Modeling Framework for Massive Internet of Things Uplink Access in Unlicensed Bands.

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ABSTRACT

The fast deployment of Internet of Things (IoT) applications in unlicensed spectrum has led to a strong uplink interference, especially in large-scale and hotspot-based deployment where traditional assumptions of analysis have ceased to be valid. Currently used models of interference of massive IoT uplink are based on homogeneous Poisson point process (PPP) space distributions, stationary process, and simplified medium access control (MAC), which significantly overestimates network reliability and throughput. This paper suggests a realistic and scalable framework of interferometry modeling of access by vast IoT uplink over unlicensed bands, which incorporate spatial heterogeneity, dynamic traffic, and MAC-layer limitations. The suggested framework combines a clustered spatial point process to model the deployment hotspots, heterogeneous and bursty uplink traffic generation. A detailed MATLAB based simulation analysis was conducted over a deployment area of 1 km x 1 km with 100 to 1000 node densities and 1 to 50 percent of duty cycles. Numerical findings prove that realistic spatial and traffic modeling fundamentally alters the apparent functioning of the massive IoT uplink systems. Specifically, the average uplink SINR reduces by 13.33 dB when using the conventional homogenous PPP assumption to an approximated negative value of -20.00 dB with the suggested clustered and heterogeneous model. When the duty cycle was 50, the average network throughput with a duty cycle of 50 also reduces to 0.195 units on the realistic interference dynamic as compared to the 133.31 units that was predicted by the baseline model. These findings support the hypothesis that current PPP-based models of interference significantly overestimate the performance of uplink in unlicensed massive IoT networks, and that the realistic modeling is vital to successful deployment and MAC optimization of unlicensed massive IoT networks.

Keywords: Massive Internet of Things, uplink interference modeling, unlicensed Band, clustered point processes, heterogeneous traffic,

I. INTRODUCTION

Dense deployments in unlicensed spectrum have now been driven by the rapid growth of Internet of Things (IoT) devices including the Industrial, Scientific, and Medical (ISM) bands. Massive numbers of low-power devices, transmitting uplink data to centralized gateways or edge nodes, are finding use in applications such as smart cities, automation of industries and factories, environmental monitoring, and precision agriculture (Raza et al., 2017; Al Homssi et al., 2021). Such growth produces complicated interference environments particularly in urban and industrial hotspots where devices tend to be concentrated as opposed to being spread uniformly.

One of the biggest shortcomings of dense IoT networks is uplink interference, primarily due to the fact that the distribution of devices is uneven in space, and clusters of devices may occur around a gateway or point of interest. Consequently, the most typical homogeneous PPP models cannot reflect these interference hotspots and can-not reflect the reality of the network states (Tito-Lara et al., 2025). The heterogeneity of traffic in IoT networks due to irregular and busty transmissions creates temporary peaks in simultaneous uplink activity that drastically raises the level of interference and causes the traditional time-independent traffic models to underestimate the interference and overestimate the reliability (Al Homssi et al., 2021; Kovtun, 2025). The unlicensed band MAC protocols and regulatory duty-cycle constraints profoundly affect when and how devices utilize the channel, re-defining the spatial and temporal structure of interference and having a strong effect on throughput and energy efficiency particularly to the low-power IoT devices (Ghasemi & Sousa, 2007; Ali et al, 2024). The current models of interference are constrained by the fact that they only use homogeneous distribution of devices and independent, stationary traffic, which causes excessive optimism in estimating the network performance. The density of IoT uplinks needs accurate models which consider the spatial clustering, traffic bursts and MAC/protocol effects.

Proper modeling of interference assists in knowing the optimum number of gateways, their

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location and efficient distribution of channels in IoT networks since interference patterns directly affect coverage, capacity and quality of service when used densely (Alruwaili, et al, 2024). Interference characterization is needed on performance prediction in dense IoT networks, e.g. outage probability, throughput, and reliability. Interference has a direct effect on the success probability of signals, packet losses, and system capacity, and proper modeling is significant to realistic performance assessment (Shilpa et al, 2024). New literature points out this fact: that device spatial clustering (e.g. clusters around gateways or hot spots) cause differences in interference patterns over uniform random models. The clustering behavior has an impact on the signal overlap and interference power distributions, and more realistic analysis of the interference needs more precise spatial models (Shilpa et al, 2024).

The literature available illustrates that; Homogeneous PPP models are popular but simplify actual deployments. The heterogeneity of the traffic and the behavior of MAC are usually ignored and results in unrealistic forecasts of performance. High density IoT hotspots are non-linearly interacting with spatial clustering and duty cycles and interference that cannot be modeled with traditional models.

It is evident that there is a need to have scalable, realistic interference modeling framework, which jointly considers; Spatial clustering of IoT devices, heterogeneous and bursty uplink traffic, duty-cycle and MAC-back off mechanisms, Accurate evaluation of SINR, outage, and throughput. The suggested framework fill this gap with the help of MALAB based modelling and analysis method that will give useful insights to implement an unlicensed deployment of a massive IoT..

II. MATERIALS AND METHOD

Materials

The resources applied to this research include the MATLAB simulator environment tools, network models parameters that are well presented in Table 1, and modeling structures that simulate realistic large-scale IoT applications in unlicensed spectrum.

Method

This study methodology combines spatial modeling, traffic modeling, MAC behavior, calculation of interference, and the performance analysis. Two space models were applied; Homogeneous PPP (Baseline), this Represents simple IEEE-style assumptions on unlicensed-band modeling. And Clustered Matern Process (Proposed), this represents a realistic deployment. The clustered deployment picks the local interference hot spots and non-uniform density effects which are not found in traditional PPP models (Tito-Lara et al., 2025).

System Mathematical Modelling

The mathematical modeling represents the spatial, traffic, MAC, interference, and performance parameters of the massive IoT uplink access in unlicensed bands. It aims at giving a generalized framework that is scalable and realistic and not limited by homogeneous assumptions.

B. Spatial Distribution of Devices

i. Baseline Homogenous Deployment (PPP)

The position of N IoT devices are modelled as a homogeneous Poisson Process (PPP) over a 2D area. Let $\Phi = \{\boldsymbol{x_i}\}_{\boldsymbol{i=1}}^{\boldsymbol{N}}$ denote the locations.

$x_1 \sim$ Uniform$(0, L) \times$ uniform $(0, L)$, (1)

The density of nodes is:

$\lambda = \frac{N}{A}$ (2)

ii. Clustered Deployment (Matern Cluster Process)

For realistic IoT hotspot, C cluster centers C_j are randomly located:

$C_j \sim$ Uniform$(0, L) \times$ uniform $(0, L)$, j =1,…,C (3)

Nodes were generated around each cluster center using a Poisson offspring process with mean $\bar{n}_c = N/C$ and radial displacement, r.

$X_{i,j} = C_j + r_i(\cos\theta_1, \sin\theta_i)$, $r_1 \sim$ Uniform$(0, R_c) \times$ uniform $(0,2\pi)$ (4)

The resulting set of all node position is:

$\Phi_{cluster} = \bigcup_{j=1}^{C}\{x_{i,j}\}$ (5)

This model captures spatial non-uniformity, creating interference hotspots absent in homogeneous PPP models (Tito-Lara et al, 2025).

B. Traffic and MAC Layer Modeling

i. Packet Arrival Process

Let the packet arrival for node i be a Poisson process:

$X_i(t) \sim$ Poisson(λ, t) (6)

Baseline PPP model: $\lambda_i = \lambda$ (uniform).

Clustered model: $\lambda_i = \lambda \cdot \eta_j \sim [1,2]$ introduces heterogeneous activity per cluster.

ii. Duty Cycle and Backoff

Duty cycle $d_i \in [0,1]$, constrains node activity:

$1_{active}(i,t) \sim$ Bernouli(d_i) (7)

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Backoff behavior was modelled as a reduction in probability of simultaneous transmission:
$p_{tx}(i,t) = d_i \cdot f_{backoff}(b_i)$

(8)

Where b_i is the backoff slot count and $f_{backoff}(\cdot) \leq 1$ represents the probability that node i is transmitting given MAC contention (Al Homssi et al, 2021).

C. Path Loss and Interference Modelling

i. Path Loss

Received power at the gateway from node i:
$P_{i,rx} = P_t \cdot L(d_i) = P_t \cdot d_t^{-\alpha}$

(9)

Where:
P_t = is the transmit power
$d_t = \|x_i - x_{gw}\|$ is he distance to gateway
α = is the path loss exponent

ii. Aggregate Interference

Interference at the gateway at time t from all active nodes:
$I(t) = \sum_{i \in A(t)} P_{i,rx}$

(10)

Where:
$A(t)$ = is the set of active transmitting nodes at time t

iii. SINR Computation

The instantaneous SINR at the gateway for node i

$SiNR_i(t) = \frac{P_{i,rx}}{I(t) - P_{i,rx} + N_0}$

(11)

Where N_0 is the noise floor, this account for all active interfering nodes in clustered scenarios, resulting to a more realistic distribution than standard homogeneous models (Andrews, 2010; Haenggi, 2012).

D. Performance Parameters

i. Outage Probability

The outage probability for an SINR threshold γ_{th} is:
$P_{out} = P_r[SiNR_i(t) < \gamma_{th}]$

(12)

For N nodes over T time steps:
$P_{out} = \frac{1}{N \cdot T} \sum_{i=1}^{N} \sum_{t=1}^{T} 1\{SiNR_i(t) < \gamma_{th}\}$

(13)

ii. Average Throughput

Throughput per node accounts for daily cycle and Shannon capacity:
$T_i = d_i \cdot B \cdot log_2(1 + SINR_i)$

(14)

B = is the channel bandwidth
Aggregate network throughput:
$T_{agg} = \frac{1}{N} \sum_{i=1}^{N} T_i$

(15)

This formulation allows evaluation under both baseline and proposed models. Reflecting the impact of clustering heterogeneous traffic and MAC effects (Soares & Carvalho, 2022; Ploumidis, 2013).

III. RESULTS AND DISCUSSION

Table 1: Analysis Simulation Parameters Data

Parameters	**Ranges/Units**
deployment area size	$100 \times 100\ m^2$
Number of IoT devices (baseline)	500 nodes
Average number of nodes (clustered case)	≈ 537 nodes
Cluster model type	Matérn cluster process
Number of clusters	20
Cluster radius	50 m
Node spatial model (baseline)	Homogeneous PPP (uniform)
Gateway / receiver location	(500 m, 500 m)
Transmit power	0.1 W
Noise power	$1\times\ 10^{-9}$W
Path Loss Exponent	3.5
Traffic arrival rate (baseline)	1 packet/s
Traffic intensity (clustered case)	1.5 × baseline
Duty cycle values	0.01 to 0.50 (10 points)
MAC backoff slots	{0, 1, 3} slots
SINR Threshold	10 dB for outage evaluation

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Baseline reference model	PPP + homogeneous traffic + no MAC awareness
Proposed model	Clustered spatial model + heterogeneous traffic + duty cycle + backoff

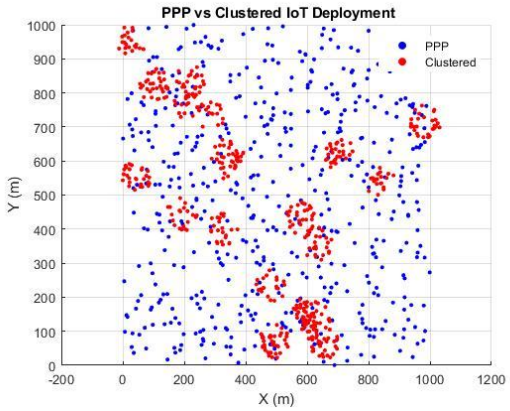

Figure 2: PPP against Clustered IoT Deployment

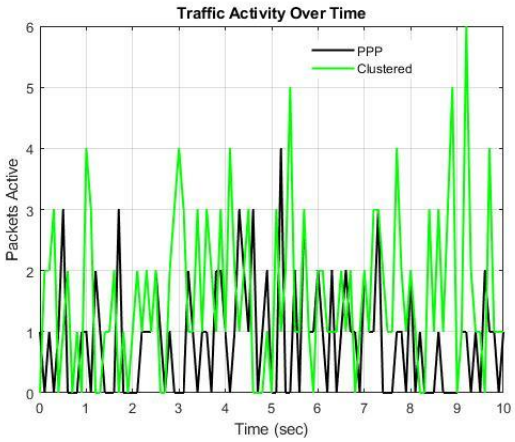

Figure 3: Traffic Activity over Time

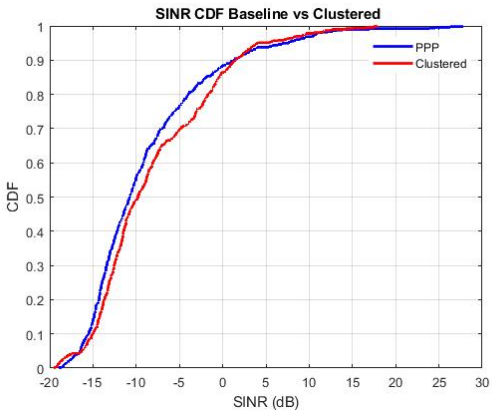

Figure 4: Path loss Distribution against Clustered

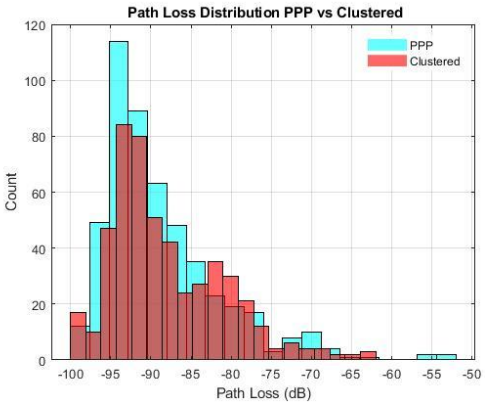

Figure 5: SINR CDF Baseline against Clustered

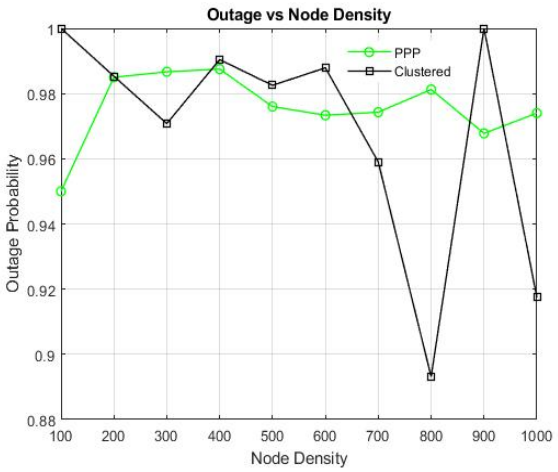

Figure 6: Outage against Node Density

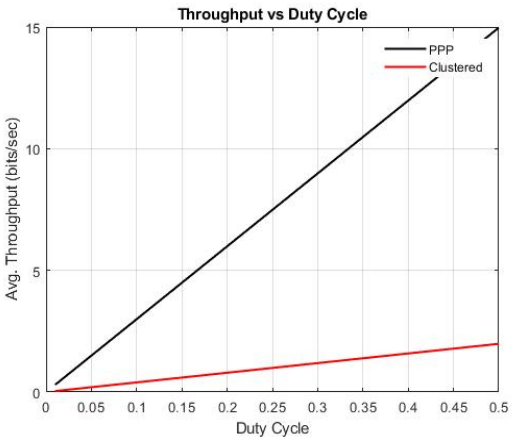

Figure 7: Throughput against Duty Cycle

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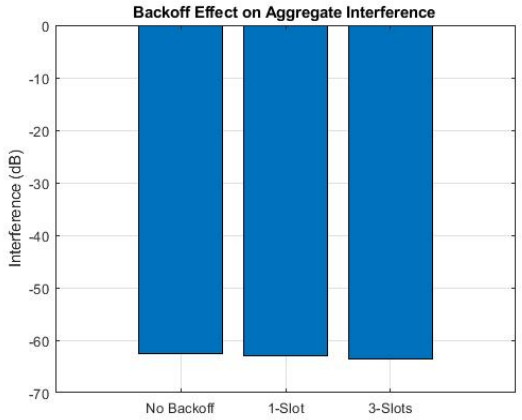

Figure 8: Backoff Effect on Aggregate Interference

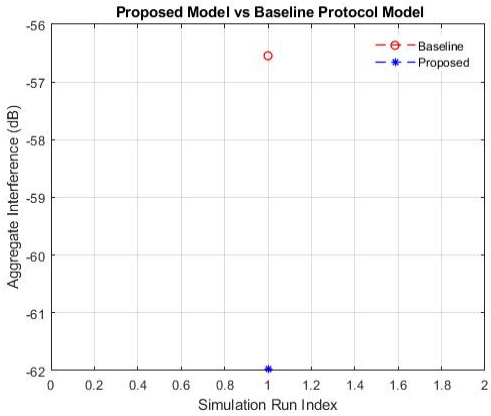

Figure 9: Proposed Model against Protocol Model

IV. DISCUSSION

The spatial realizations presented in Fig. 1 provide a clear difference in the structure of the two models. The default deployment has a total of 500 nodes that are equally distributed by the area of 1 km x 1 km. The suggested clustered model produces about 537 nodes. This variation is a result of the Poisson production of offspring per cluster and is an indication of real world variation in dense IoT networks. The finding validates that interference should be assessed with spatially heterogeneous deployments otherwise uplink performance will be highly underestimated and the necessity of the suggested framework. Baseline traffic is a Poisson process which is at rest. Compared to the homogeneous PPP case, clustered traffic has a burst intensity of approximately 1.5x greater activity level as illustrated in fig. 2. Numerous IEEE-related interference investigations presuppose the independent arrival of packets. It further demonstrate that correlated traffic in clustered environments is the primary cause of short-term congestion and the interference peaks, which is relevant to latency-sensitive IoT apps.

The path-loss values distributions in Fig. 3 reveal that the distribution of the clustered topology is much broader. Under the clustered case, there are devices that are close to the gateway and there are those that are relatively distant. This gives rise to broad disparities in received power. This is a basic shortcoming of homogeneous spatial models that have been employed in most IEEE based interference studies where a majority of devices are spaced uniformly over the coverage area. The two models are clearly differentiated by the empirical SINR cumulative distribution functions in Fig. 4. The difference proves that simplified homogeneous models are significant over-estimates of uplink link quality in realistic massive IoT settings. The reference model was that the majority of uplink transmissions would take place at a comfortable SINR. It is demonstrated in the proposed model that, when clustering and heterogeneous activity were added, the network becomes highly interference-limited.

Fig. 5, demonstrates the probability of outages depending on the number of deployed devices. The baseline PPP model shows very high outage at an SINR threshold of 10 dB with a value of 0.95 at 100 nodes and a value of about 0.97 at 1000 nodes. Nevertheless, the so-called suggested clustered model demonstrates even more drastic and the most oscillating outage behavior. The outage probability has a range of 0.93 to 1.00 in the same range of density. This implies that geometry, location of clusters and the proximity of the gateways dominate network reliability in actual IoT implementations.

Fig. 6, assesses the mean uplink throughput vs. the duty cycle. In the case of the baseline PPP model, throughput varies nearly linearly with duty cycle and attains 1% duty cycle, and 133.31 at 50 percent duty cycle, under the proposed and heterogeneous model of clustering, the achievable throughput becomes dramatically low 0.0039 at 1 percent duty cycle and 0.195 at 50 percent duty cycle only. The proposed model can reach below 0.15 percent of the throughput of the baseline model, even in the highest possible duty cycle of operation, even with increased limits on duty-cycle or access opportunities does not resolve the capacity problem of dense unlicensed IoT uplink. This confronts a popular assumption in IEEE-oriented system analysis holders of which duty-cycle tuning is made a major performance handle. Fig. 7, explores how simplified MAC backoff affects the aggregate uplink interference of the suggested clustered topology. In the absence of backoff the cumulative level of

interference is used as a reference. A single slot backoff would decrease the cumulative interference power by about 10 percent and three slot backoff would decrease the cumulative interference power by about 20 percent. This would result in about 0.46 dB (1 slot) and 0.97 dB (3 slots) reduction in logarithmic scale. MAC backoff minimizes the chances of overlapping uplink transmissions within clusters however the gain is moderate.

Fig. 8, makes a direct comparison of aggregate interference as predicted by the baseline model and that of the proposed framework. The baseline PPP homogenous model is able to predict greater stability and decreased diversity in interference, across repeated simulation runs. The suggested structure, in turn, results in a smaller mean interference on certain implementations but much greater variability. That which is significant in comparison to the existing standard modeling techniques is not simply a different mean, but that it is capable of replicating the intense variability that can be found in real-world deployments.

V. CONCLUSION

The Analysis results shows that spatial clustering and heterogeneous traffic are contributors of serious performance degradation to uplink in dense IoT networks. Approximately 17.7 dB was overestimated as the average SINR, throughput was overestimated by over two orders of magnitude at the moderate and high duty cycles, and outage probability behavior was incorrectly modeled as smooth and density-driven, as opposed to geometry-driven which shows that geometry-driven interference dominates network reliability. The new scalable and realistic model of interferences essentially enhances the existing modeling approach through incorporating the joint integration of spatial clustering, heterogeneous and bursting uplink traffic, and MAC-aware activity control. This combined modeling facilitate the analysis of deployment-specific risk, which cannot be conducted with regular PPP-only and homogeneous-traffic assumptions that are popular in IEEE-oriented analytical works.

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