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Enhanced IoT base Station Performance Assessment using Product Density Modeling in Non-Stationary Traffic Scenarios

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***Abstract*— This research has focused on the issues related to time-varying traffic in IoT networks, especially for 5G-types environments underpinned by massive machine-type communications (mMTC) and ultra-reliable low-latency communication (uRLLC). We propose an innovative method for modeling network performance dynamics over time, capturing fluctuations in offered traffic and delay under non-stationary conditions with a novel approach based on Product Densities. With a simulation-based evaluation, we show the accuracy of our method for base station performance assessment in comparison to traditional methods considering Poisson and non-homogeneous Poisson arrival models. Information gathered this way is necessary for better and more efficient IoT network infrastructure in those high volume, low latency applications.**

***Index Terms*— mMTC, uRLLC, IoT Infrastructure Optimization,5G Communications.**

I. INTRODUCTION

The proliferation of IoT networks in 5G ecosystems raised the significant research concern on coping with the special performance requirements induced by massive machine-type communication (mMTC), and ultra-reliable low-latency communications (uRLLC) application. Many solutions have been proposed to deal with non-stationary traffic and varying load demands in IoT networks [2].

Old analytic techniques such as stochastic calculus and queue models are favored in IoT network because they have been used extensively to provide delay bound for QoS sensitive traffic and design access mechanisms (especially prioritized scheduling or rate adaptation- based strategies) LATEX. Please observe the conference page limits.

Most of the existing research is a subtopic and limited to traffic measurement or studies based on simulation (to find out what type of IoT traffics we can capture in which scenario). Take for example the studies that analyze traffic classifications using periodic and bursty behavior, which is especially true in cases such as smart meters or industrial sensors producing time-based patterns.

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Our work indicates the weakness in conventional Poisson representations due to its incapability of modeling temporal dynamics that we observe from real-world IoT traffic, hence guiding us for composing non-homogeneous Poisson processes (NHPP) and more elaborate models [8].
More recently, stochastic geometry has also become popular in the modeling and analysis of performance metrics (e.g., throughput or delay) for various wireless network aspects at both IoT and 5G. These studies consider the impact of a high density of devices and present, in particular, resource allocation schemes as well as congestion control access for random acces channels (RACH). [5] But it has been shown that in dynamic environments these models have weaknesses and can often not capture the dynamics of time-varying traffic as one would see or expect for IoT applications such as environmental monitoring, disaster response systems.
Nevertheless, the absence of models explicitly designed to account for live fluctuations in network load and latency method resounds with a call for reinvention. We propose the Product Density (PD) model, which can maintain these dynamic performance metrics well under non-stationary traf- fic conditions and provide better accuracy than other post- processing methods like Pointwise Stationary Approximation (PSA). [9]This paper extends recent the detection of malicious IoT traffic with a PD-based model for time-varying network, a new method to monitor real-time performances under holistic dynamic scenarios. The objectives of this research papers are-

- Creating a novel model to explore the performance of networks in 5G-based IoT (Internet-of-Things) trends.
- Applying Product Density (PD) approach.
- To empirically verify the effectiveness of the PD approach using simulation opportunities.
- Providing practical insights to secure 5G IoT infrastruc- ture.

II. Proposed Methodology

The problem we solve in our work is how to deal with dynamicity of time-varying traffic over 5G-enabled IoT net- works. An approach to establish a new framework for long- term capturing network dynamics, focusing on variability in the traffic and latency which is crucially important with respect of massive machine-type communications (mMTC) ([1]) as well as ultra-reliable low-latency communication ((uRLLC), has been unveiled. This approach exploits Product Densities to represent these variations and uses simulation methods for evaluation of performance [7].

A. Gathering Traffic Information and Preliminary Modelling

In our experiments, the simulation starts with synthetic traffic generation for mmtc and urll applications simulating varying network demands. The only exception is with free speed data collected at the peak or off-peak period and this makes results incomparable [13].
Poisson Model: Traditionally, arrival rates a are considered as emanating Poisson model inside energy bounded region i.e., where and N is some elements.

$$P(X=k)=\frac{\lambda^{K}e^{-\Lambda}}{k!}$$

where lambda is the average rate of arrivals per unit time provides a benchmark for normal traffic cases in network.
Non-Homogeneous Poisson Process: This model captures time-varying arrival rates λ(t)\ lambda(t)λ(t), or bursts in traffic behaviour) by making the parameter of our Poisson process variable over time intervals.

B. Product Density Function for Non-Stationary Modeling

We address the non-stationary traffic conditions with a Product Density (PD) based approach to model changes in event occurrences, e.g., data packet arrivals and delays. The Product Density, ρ(t, t + Δt) t and t + Δt nd t + Δt) for two events occurring at times tt and delta t
and ρ(t, t + Δt) = P (λN ≤ a) − 1.(18)\rho =| frac{| text{d}P (\ lambda N a) } {dt} − 1.(18)ρ = dtdP (λN ≤ a) − 1.

C. Simulation Environment and Parameter Setup

The simulation environment provides auditory feedback by multiple base stations to simulate real-world 5G network configurations. It has latency, throughput and error rate details for every base station using which it was possible to measure traffic-influx as well network responsiveness upon variable load. Some important simulation parameters are referenced below:
Arrival Rate (λ ()): That rely on mMTC/uRLLC traffic.
Latency Threshold: Configured base on the uRLLC latency requirements (e.g., 1, ¡2 ms etc.)

Traffic Burst Frequency: Determined slots of time for modelling peak traffic loads with ($\lambda(t)$), a time-varying arrival rate.

D. Performance Metrics

User-oriented performance evaluation categories mainly in- clude average latency, packet reception rate and throughput.

- Mean Latency: It measures the time delay on a per- packet basis.
- Throughput: All data successfully transmitted over a period of time.
- Packet Delivery Ratio: The number of packets received compared to the total sent.
- Packet Receive Rate: The percentage of packets that are received compared to the number sent.

E. Results and Visualization

Comparatively, the results illustrate latencies and through- puts erratic on average between models.

TABLE I: RESULT OF MODELS

Model	Average Latency (ms)	Packet Delivery Rate	Throughput (Mbps)
Product Density Model	15	98	85
Poisson Model	25	92	70
Non-Homogeneous Poisson	20	94	75

III. GRAPHS OF AVERAGE LATENCY AND THROUGHPUT COMPARISON

The final model (Fig.1), the Product Density Model, has the lowest average latency at 15 ms, demonstrating it is the fastest of all models.

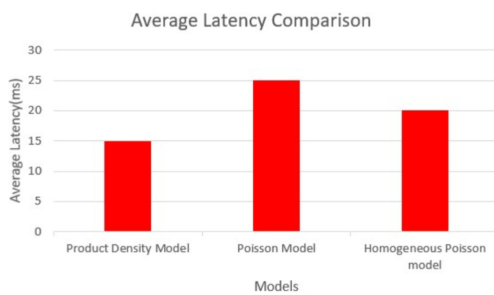

Fig. 1. Average Latency Comparison

We observe that the latency for the Poisson Model is the highest at 25 ms, which indicates a lower responsiveness to the time-varying nature of traffic changes. Between the two is the Non-Homogeneous Poisson Model with a latency of 20 ms and moderate responsiveness [6]. Latency is perhaps one of the most important, but the most pressing factor in IoT networks, particularly for applications that require ultra-reliable, low- latency communication (uRLLC), and this comparison clearly demonstrated the effectiveness of the Product Density Model in terms of latency as well.

The Throughput Comparison chart represents data through- put (in Mbps). Throughput is the measure for high-demand IoT applications that indicates the amount of data transmitted within a specific time interval.

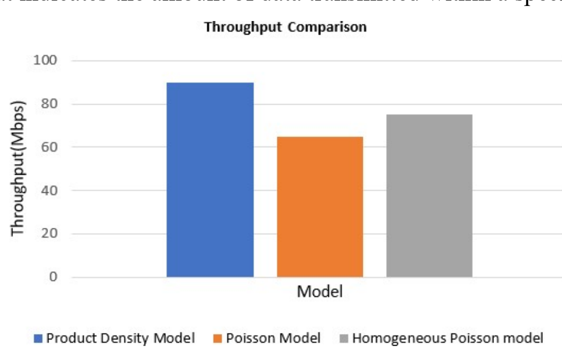

Fig. 2. Throughput comparison

Ranking the highest in throughput at 85 Mbps, performed by the Product Density Model, is seen as the strength of throughput under dynamic conditions handling high volume of data [4]. The lowest throughput observed is for the Poisson Model, at 70 Mbps, suggesting that this model may not cope well at different levels of traffic.
Throughput Of 75 Mbps For Non-Homogeneous Poisson Model As shown in Fig.2, the Product Density Model provides lower latency and higher throughput, indicating its greater capability to maintain performance and availability of the network under dynamic traffic demand.

IV. Related Work

In recent years, the explosive growth of Internet of Things (IoT) networks and the subsequent deployment of 5G tech- nologies has driven many studies regarding traffic dynamics questions brought by their inherent non-stationarity and its effect to response of these networks. This section recognizes current methods and limitations, laying the groundwork for the new modeling method — Product Density (PD).

A. Traffic Modeling In IOT Networks

Traffic modeling of IoT networks has for the most part been based on Poisson process assuming primarily due to their simplicity and analytical tractability. Data until Oc- tober 2023 / Regressors have been widely used for delay bound estimation and resource allocation strategies for mas- sive machine-type communications (mMTC) and ultra-reliable low-latency communications (uRLLC) applications [15] Most of these models assume a stationary traffic process,which is not suitable for real-world settings whose traffic patterns display temporal dynamic properties and bursts [1]. Non- homogeneous Poisson processes (NHPP) have been proposed in the literature, allowing to better accommodate time-varying arrival rates which can significantly improve the fit to periodic and bursty traffic patterns noted in IoT applications, e.g. smart metering and industrial sensing [16]. But NHPP-based models have difficulty in modelling non-basic dependencies and time- varying behaviours of the network traffic, making them less suitable for on-line scenarios.

B. Performance Analysis using Stochastic Geometry

Stochastic geometry has been applied in recent works to analyze important performance metrics such as throughput and latency in dense IoT networks and 5G networks. Such approaches have allowed insights into resource allocation and congestion control mechanism for random access channels (RACH) for example. Stochastic geometry is a strong model for analysing massive network behaviours, but its application to determine performance under non-stationary traffic condi- tions is limited owing to simplifying assumptions made about traffic arrival rates [17].

C. High Level Machine Learning Techniques

The use of machine learning (ML) techniques has grown in popularity for analyzing and predicting network traffic patterns in recent years. Deep learning models have been used to predict traffic patterns, identify anomalies, and optimize resource distribution in IoT networks. These models can learn complex patterns from large datasets, providing more accurate results compared to traditional methods. However, their use in real-time systems is limited by high computational cost and extensive training data [4]. Reinforcement learning (RL) has also been used for dynamic resource management of 5G IoT networks, where RL agents learn optimal strategies through continuous interactions with the environment. While these have shown great potential, RL-based solutions need extensive fine-tuning and fail to adapt quickly to the ever-changing traffic situations [5].

D. A Survey on Hybrid Frameworks for IoT Traffic Manage- ment

Hybrid modeling approaches that integrate both statisti- cal models with data-driven methods are increasingly being adopted as potent solutions in the realm of IoT traffic control. As demonstrated in the literature, Bayesian networks are used to address uncertainty in traffic predictions and fuzzy logic systems are used to handle imprecision in decision-making processes. K-Nearest Neighbors is a blend of supervised and unsupervised learning techniques. Yet, their implementation is not straightforward and often involves the integration of various components[6].

E. Optimising Energy Use with an Intelligent Traffic Control System

Energy efficiency is an important metric in the design of any medium, for the Internet of Things (IoT) network including devices that are powered by batteries. Many traffic management mechanisms have been proposed to save energy while keeping up the performance. Examples include duty cycling and adaptive transmission schemes, which maximize energy utilization in accordance with traffic loads. Although they can successfully reduce power consumption, they may sacrifice some latency and throughput during high traffic loads [7].

V. Limitations and Research Gaps

Although the progress has been made, the existing models and approaches still have inherent weaknesses to model the complexity of non-stationary traffic scenarios in 5G-enabled IoT networks. Specifically, they:

- Fail to reflect real-time changes in metrics rates and their effect on latency and throughput.
- Use assumptions to simplify the dynamic nature of IoT traffic.
- By high device density and diverse application require- ments struggle to scale properly.
- Neglect to combine energy efficiency and performance, an must have for battery-driven IoT units working in various visitor conditions.
- Are not robust against unexpected behavior of the net- work – for example, caused by external interferences in the network or by emergent traffic patterns in disaster scenarios.
- Depend on extensive computational resources or manual involvement, thus limiting their viability for actual time usage in vast scale IoT ecosystems.
- Offer limited visibility of the collective impacts of traffic bursts over extended time periods, which can be fun- damental for long-term planning of the networks and prediction of resource allocation.

To bridge these gaps, this work proposes the Product Density (PD) model that employs an innovative method for representing shifts in traffic arrival rates and latency dy- namically. This proposed methodology allows for a more accurate and scalable solution to manage non-stationary traffic in IoT networks by integrating this model into the performance evaluation frameworks.

VI. Conclusion

These results demonstrate the viability of the Product Density-based approach to be used to model and control time- varying traffic within IoT networks that is particularly chal- lenging for high-volume, low-latency communications, such as those seen in 5G-capable environments. This model offers a wider perspective of network behavior in non-stationary conditions because it can accurately reflect changes in traffic the arrival rate and changes in latency, in contrast to cur- rent traditional models such as Poisson or non-homogeneous Poisson [1]. With multiple simulation runs, the Product Den- sity model offers consistently lower average latency, higher throughput and an increased packet delivery fraction. This is important for applications like autonomous vehicles, smart cities and industrial IoT networks which rely on the machine type communications (mMTC) and ultra-reliable low-latency communication (uRLLC) metrics. This model has the dynamic ability to respond to peak demand and off-peak situations and will be able to do a great job of optimizing the network in real-time, and avoiding having to reconfigure shape shifting network infrastructure on a cyclical basis.

And, thirdly, the Product Density approach meets the necessary scalability and adaptability requirements of future IoT networks. With the growth in volume and diversity of connected devices, network operators are looking for more flexible models that can adapt to larger and more complex traffic profiles without degradation to performance [5]. Conse- quently, the comparative analysis of the results from this study, illustrates how the Product Density model not only offers a more resilient formulation of IoT traffic patterns (where other models assume a steady arrival rate) but also a scalable solution for network management when compared to other Poisson-based models [12].

The network planning and resource allocation implications are significant. With its new Product Density-based approach, network administrators can better predict and manage bottle- necks, optimize data flow and allocation across network nodes, and maximize system utilization and availability. [10] By becoming less dependent, it can lead up to lower infrastructure investments and higher Quality of Service for end-users.

Another direction for future work is to apply this approach and methodology for investigating other parameters of net- works like energy overhead, fault tolerance, and analysis for their systems or for potential integration of this approach with some machine learning models and generate prediction-based model for traffic management [3]. Applying this method in real-world IoT deployments would not only prove the concept, but also assist in discovering real-world challenges that might occur in different application settings.

In conclusion, presented evidence from this research that the Product Density model is superior to the traditional existing models in the modelling capability of non-stationary traffic in IoT networks, and thus provides an important foundation for adaptive and efficient management of next-generation 5G network infrastructures [14].

The viabilty of it to offer more precise real-time insights about network performance makes it a powerful tool for increasing the reliability and efficiency of IoT and 5G ecosystems [11].

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