Parameterizable mobile workloads for adaptable base station optimizations

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***Abstract*—Recent works on 5G baseband processing systems address the optimization of applications with different requirements of quality of service (QoS). The volume and heterogeneity of applications that have to be processed on a base station are growing and 5G introduces new use cases that push system designers towards more flexible and adaptable approaches. To investigate future network challenges of mobile communications, a good methodology for the generation of realistic workloads, that allows target optimizations of different traffic scenarios, is required. In this paper, we study the variation of real traffic data on multiple base stations and identify the main sources for the high variation of the 5G workloads. We propose a methodology for parameterizable workload generation for users with different QoS requirements that enables optimization techniques in baseband processing systems. We demonstrate the feasibility of our approach based on a virtual base station using a heterogeneous hardware model and various state-of-the-art mapping policies.**

***Index Terms*—mobile traffic, baseband processing, 5G network**

I. Introduction

With the increasing number of wireless devices, as well as the wide range of applications they can offer, adaptivity in upcoming telecommunication standards becomes essential to accomplish optimized performance. The global data traffic is expected to increase by a factor of 10,000 by 2030 [1], which represents a significant impact on global energy consumption. Additionally, the difference in network requirements needed by different applications like remote medical surgery, virtual and augmented reality (VAR) or low-complexity internet of things (IoT) devices shows the need for flexible protocols that support different latency, reliability and data rate values for the different users. The 5G standard already provides three different use cases, which are classified as enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable and low-latency communications (URLLC) [2]. However, the fast development of emerging technologies and applications indicates that 5G will reach its limits by 2030 [3]. Therefore, Wittig et al. [4] argue about the need of a formal approach for modem design that includes well-defined semantics for adaptivity. Moreover, recent research [5]–[7] has focused on developing adaptable baseband processing systems, since they are a promising solution to cope with the growing flexibility of the standards while providing good energy efficiency.

The heterogeneity of the traffic loads on mobile base stations is defined not only by the specific use case (e.g., video or sensor data) but also by the geographic location. Authors in [8] show how the traffic volume changes accordingly with the population density of 4 different area scenarios: dense urban, urban, suburban and rural areas. For each of the area scenarios, both the population and the base station density can vary within a wide range, e.g. the population per base station ranges from 490 to 2200 inhabitants. Communication in very crowded areas can be limited by the cell capacity rather than the cell range, opposite to what happens in rural areas. Similarly, authors in [9] propose a clustering model, by analysing the data traffic on base stations that share similar behaviour. For example, the activity on a network placed near commercial buildings will be reduced during the weekends, which is the opposite case of public parks. The volatility of the mobile traffic is also reflected in Figure 1, which shows the mean traffic in Mbits of 23 base stations during a few minutes in the same city. The different base stations present a significant difference in the workloads that varies in a range of 0.25-18.5 Mbits. Having a system that captures the heterogeneity of the workloads and produces data traffic that includes detailed information about every single user for a target area scenario is a key enabler to explore optimization algorithms.

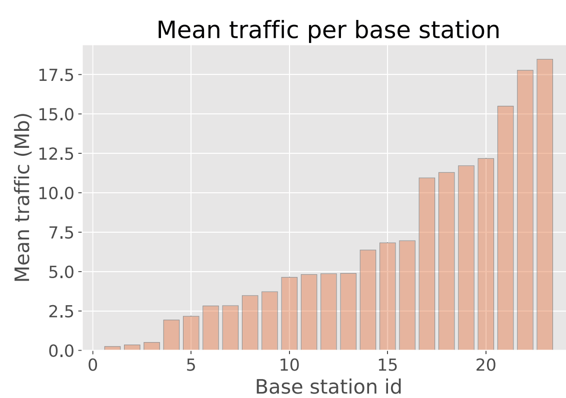

Fig. 1: Mean amount of data traffic on different base stations during the same range of time.

Initiatives like the one in [10], where participants are encouraged to design a neural network for fast recognition of

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modulation scheme classification on mobile workloads, make use of the RadioML 2018.01A dataset [11] which contains state-of-the-art schemes. In 5G, new modulation schemes are needed to support large-scale heterogeneous traffic. An overview of potential new modulation schemes for 5G is presented in [12]. A methodology to automatically generate new datasets that include futuristic scenarios for design space exploration (DSE), would potentiate current ongoing research on baseband optimization.

Generating meaningful datasets is challenging since (i) it is difficult to obtain access to real data from network operators due to privacy reasons, and (ii) because of the high degree of parameterization of baseband processing. The latter means that deep insight into the algorithms is needed to automatically generate meaningful parameter combinations depending on a given network scenario. In this paper, we present a methodology for the automatic generation of parameterizable workloads for mobile networks. Our methodology allows describing new traffic scenarios for the design and testing of new optimization techniques for baseband processing. Moreover, we test the generator by using an open-source framework for prototyping of base stations and compare different scheduling policies with changing traffic scenarios at runtime. We show how by tuning the multiple parameters involved in mobile workloads we can profile the power consumption of a baseband processing system, providing a better benchmarking system for future research on system-level optimizations.

II. Workload parameterization for 5G and beyond

Radio access networks (RANs) have evolved over the years to address the flexibility challenge in mobile communications. Typically, a RAN architecture is a distributed system where local base stations are composed of mainly two components, a remote radio-head (RRH) in the front-end and a baseband unit (BBU) performing signal processing [13]. The introduction of cloud RANs (cRANs), where BBUs are placed into a centralised pool of BBUs, enabled a more efficient utilization of the resources by sharing the available BBUs among the different RRHs [14]. Then, virtualized RANs (vRANs) extended the flexibility and scalability by leveraging the use of programmable general purpose architectures [15]. Moving towards software-based solutions made it possible to reduce time-to-market and optimise the overall energy consumption of the wireless systems. However, given the advances in mobile communications, the current systems are facing again an increasing demand for more flexibility but more importantly, for energy-efficient approaches. Baseband systems have to evolve towards more adaptable solutions that address these problems.

In LTE, baseband processing in the physical layer is one of the most intensive tasks of the protocol. In uplink communication, every user equipment (UE) that communicates to an LTE base station is allocated with a frequency band that ranges from 1.4 to 20 MHz [16]. The frequency is allocated as a concatenation of physical resource blocks (PRBs). Every PRB is formed by 12 subcarriers (SC) of 15 kHz. The total bandwidth of a PRB is 180 kHz and the maximum number of PRBs allocated to a single UE is 100. In the time domain, the transmission is organized as a sequence of frames containing data transmitted by up to 10 UEs. Every frame has a length of 10 ms and is composed of 10 subframes of length 1 ms. Every subframe is divided into two slots of 0.5 ms each and each slot consists of 7 OFDM symbols. One PRB is equivalent to one subframe in the time domain. The amount of data carried on each symbol depends on the used modulation scheme (MOD) which is determined by the SNR of the transmission. A higher-order modulation rate can provide a higher data transmission rate. Moreover, baseband systems use multiple input multiple output (MIMO) technologies to increase data rates. The MIMO technique allows UEs to transmit information through multiple spatial layers (LAYs) where multiple independent streams of data are sent in order to increase the channel capacity [17].

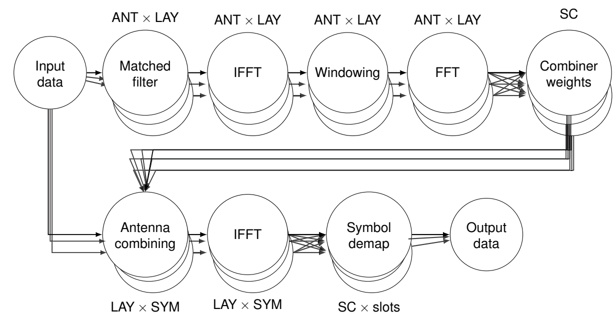

Fig. 2: Block diagram of a baseband receiver.

We use the LTE PHY benchmark [18] as a baseline reference to extract a dataflow model of an LTE application. Figure 2 shows the dataflow graph of an LTE application for a single UE in uplink communication. Typically, baseband processing consists of computation kernels such as matched filter, fast Fourier transform (FFT), windowing, inverse FFT (IFFT), antenna combining, combiner weights calculation, and soft symbol demaping. In the LTE standard, the runtime characteristics of the kernels show already a high degree of parameterization. Each of these kernels has multiple parallel instances specified by the numbers in the figure. The parallelization factor as well as the latency for the kernels are defined by the number of allocated PRBs, the total number of layers (LAY), the number of antennas (ANT), sub-carriers (SC), symbols (SYM), and the modulation scheme (MOD).

In the new global standard for mobile communication 5G New Radio (NR), new sources of parameterization are introduced. More specifically, three usage scenarios are defined according to their quality of service (QoS) attributes. eMBB, URLLC, and mMTC are intended to cover scenarios with different requirements on throughput, reliability, latency, and availability. This means also that different use cases are assigned with different expected error ratios, adding some constraints to the deadline within a user request has to be processed. Moreover, 5G NR introduces spectrum flexibility by supporting subcarrier spacing ranging from 15kHz up to

240kHz depending on the frequency band. Which also means a variable number of slots per subframe on the time domain [19]. This set of variables is a key source of the flexibility of modern and upcoming wireless communication standards.

III. A FLEXIBLE TRAFFIC GENERATOR

Understanding the high heterogeneity of the network loads on mobile base stations is a key enabler to explore optimization techniques that target different traffic scenarios. Current 5G networks combine cells of multiple sizes (e.g., macrocells or microcells) which feature different coverage and frequency bands. A macrocell is usually deployed through large towers placed outdoors to provide a wide range of coverage for many users. Small cells, in turn, cover a smaller range and are usually deployed indoors near where the connection is required. Since nearly 80% of the mobile traffic is expected from indoor connectivity [20], we focus on small base stations.

As detailed in Section II, the computational load generated by every single user depends on multiple parameters. The exact amount of traffic generated by a single user can be calculated with the method presented in [21]. Since every physical resource block contains 12 subcarriers with 7 OFDM symbols and a duration of two slots of 0.5 milliseconds each, it means that the number of bits per PRB per slot is equal to $12x7 = 84$. Moreover, given that the number of bits per subcarrier is calculated as $log2(M)$, where M is the QAM order, the total traffic T generated by a single user can be calculated as shown in Equation 1.

$$T = (num\_PRBs * 12 * 7 * log2M * num\_slots)/1ms \quad (1)$$

To be able to emulate realistic mobile workloads on a base station by generating UE requests at every millisecond (i.e., at every subframe) as in a real system, the subframes should contain detailed information about the parameters of every single user. In order to do that we first describe the target geographic location by leveraging existing models of mobile traffic. Many traffic models have been proposed that capture the waveform of the mean traffic volume during one day [9], [22]. All of them show similar behaviour on the waveform with the lowest point of activity around 5:00 a.m. and the highest peak around 9:00 p.m. To define the area scenarios we took the model proposed in [23] where the traffic is represented as a superposition of sinusoidal waves. These models represent the mean data traffic of the specified scenario. Our framework adds noise to the underlying profile to create more realistic scenarios. Figure 3 shows the generated waveforms for a business district (BC) and a park area scenarios in an urban region during a normal weekday, we set 12Mbits as the highest traffic volume. We characterize the different scenarios by modifying the parameters of the phase and amplitude of the sinusoids. In the example, we added random variability sampling from a normal distribution with a standard deviation of 0.5.

The main challenge for a flexible workload generation to test 5G baseband processing systems is to derive realistic

Fig. 3: Traffic model of a base station in a dense urban area.

frame traces based on high-level traffic profiles like the one described above. To this end, we extract and leverage the statistics of real-life use case dependent traces to generate information at the subframe level. Figures 4 and 5, 6 show the probability density functions (PDFs) for the number of active users per subframe and the number of PRBs allocated per user and the number of bits per symbol per user respectively. The PDFs were calculated based on observations of real traffic data extracted from a set of 24 base stations placed in a dense urban area during a five-hour period. We use the extracted PDFs to generate random values that will be used to parameterize the generated UE requests.

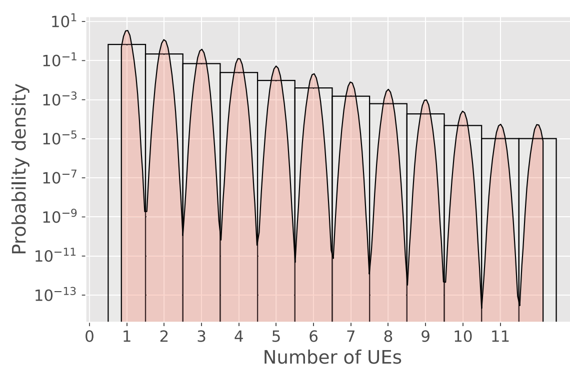

Fig. 4: PDF of number of UEs per BS per subframe.

Currently, our dataset includes three basic modulation schemes but can be easily extended to account for other datasets. The work in [24] presents a 5G trace dataset collected from a major Irish mobile operator. The dataset contains throughput, channel and context information of two mobility patterns across different applications. Among the provided metrics, the dataset contains the values for Channel Quality Indicator (CQI). The CQI is a parameter that encodes the state of a channel and it can be used by the base station to select a suitable modulation scheme for a given UE. State-of-the-art modulation schemes include QPSK, 16QAM and 64QAM with

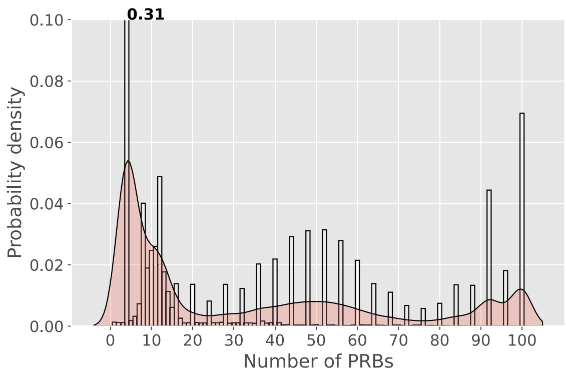

Fig. 5: PDF of number of allocated PRBs per UE.

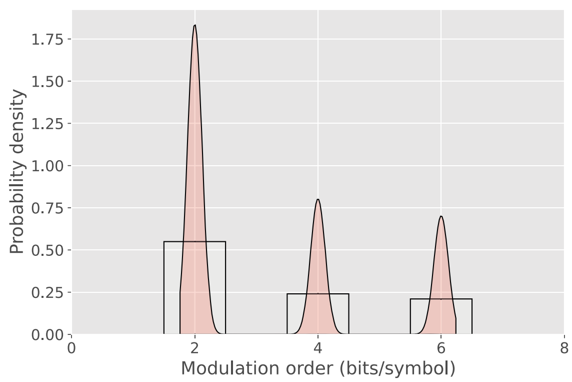

Fig. 6: PDF of number of transmitted bits per symbol per user.

a bit rate of 2, 4 and 6 bits/symbol respectively. We classify the traces in the dataset according to their CQI as shown in Table I, which is based on the SNR-CQI Mapping for 5G Network proposed in [25]. Figure 7 shows the resulting PDF of the modulation schemes for the Irish mobile operator dataset. The distribution of the PDF follows an ascending order for the QPSK, 16QAM and 64QAM modulation schemes, which is the opposite behaviour of our dataset.

TABLE I: CQI mapping.

CQI Region	Modulation scheme
CQI ≤ 6	QPSK
$6 <$ CQI ≤ 9	16QAM
$9 <$ CQI ≤ 15	64QAM

To generate detailed subframe information at a given target hour of the day, our framework has to generate a set of UE requests that collectively add up around the desired traffic predicted by the model. For that, we generate a subframe with a random number of UE requests according to the probability density function (PDF) of each of the parameters. Based on the models in Figures 4–6, our framework then generates time-dependent traces to follow observed base-station profiles. Figure 8 shows the result of generating random subframes to follow the model of the business district with the modulation

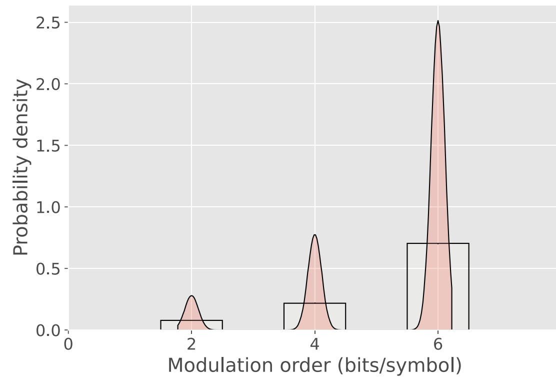

Fig. 7: PDF of number of transmitted bits per symbol per user.

scheme PDF in Figure 6, by tuning the PDF of the number of active users per subframe for every millisecond during a normal day. The presented methodology is flexible and can be easily extended to include new datasets and new parameters introduced in 5G or in upcoming standards. The real mobile traces, together with the extracted PDFs cannot be published due to privacy reasons. However, the traffic generator is open source[i] and includes approximated probabilities for the different parameters that allow the user to generate realistic data.

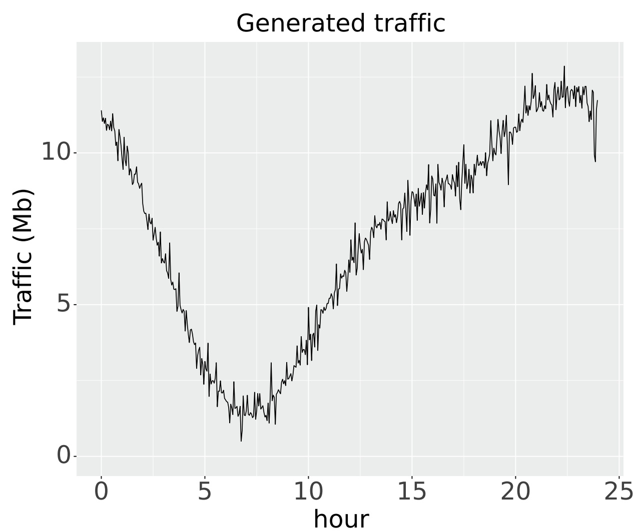

Fig. 8: Generated traffic controlling the number of active users per subframe.

IV. Use Case

In this section, we demonstrate how the traffic generator can be used to evaluate state-of-the-art frameworks for optimizing baseband processing systems. In particular, we reproduce the results of a state-of-the-art framework, originally evaluated only on three concrete load scenarios. We show how our

[i]https://github.com/tud-ccc/mobile-traces

traffic generator can be used for a more extensive and realistic evaluation, at different times of the day.

A. Experimental setup

We use an open-source virtual prototype of a base station, which is a plugin for Mocasin [26]. Mocasin is a framework for rapid prototyping that provides support for a wide range of models of computation, allows to describe customized hardware architectures and includes many scheduling algorithms for fast design space exploration. The plugin describes a virtual heterogeneous hardware platform made of multiple Exynos 5422 chips with a big.LITTLE architecture connected through a hierarchical memory model. Every Exynos contains four ARM Cortex-A15 and four ARM Cortex-A7 cores, with frequencies of 1.8 GHz and 1.5 GHz respectively. The tool describes also an FFT hardware accelerator that is integrated to the platform.

We use the dataflow model provided by the Mocasin plugin for mobile applications, which was described in Section II and apply different scheduling strategies under different traffic scenarios. We use the presented methodology, in order to generate and evaluate 2 different temporal traffic scenarios. To generate the workload we set the same geographic location conditions used in Section III for the business district and generate subframes for 2 different modulation scheme distributions, one based on Figure 6, which will be referred to as $PDF1$, and the other one based on Figure 7, which will be referred to as $PDF2$. We evaluate the performance of the prototype and the impact of using two different scheduling policies. More specifically, we compare the behaviour of the system with a standard work-stealing algorithm and a recently proposed domain-specific hybrid mapping for wireless networks. The description of the Mocasin plugin and the hybrid scheduling can be found in [27].

B. Evaluation

We use the generated subframes, with the detailed information of the UE requests, and pass them as input to the simulator to generate a profile of the power consumption of the system. Figure 9 shows the power consumption of a base station placed in a business district during a normal weekday. The parameterization of the users alternates between $PDF1$ and $PDF2$ during different periods of the day in order to analyze the behaviour of the system when the quality of the channel presents some pattern variability. The waveform of the power consumption follows the waveform of the data traffic as expected. Although the peak of the input traffic is placed in the period of time 18:00-24:00 hours, the period with more power consumption is between 12:00-18:00, which means that in general, the system shows a better performance for a workload with the $PDF2$ distribution for the modulation schemes. Moreover, the domain-specific scheduling algorithm allows higher power saving compared to the work-stealing algorithm in all the traffic scenarios. A similar analysis was carried out for the number of dropped packages, i.e. every time a UE request misses the deadline within it has to be processed, the request gets discarded. In this case, no significant improvement was displayed by any of the scheduling algorithms, which means that the domain-specific hybrid mapping allows reducing overall power consumption while ensuring a similar QoS. In this case, we consider the variation in only one of the parameters, but changing different parameters during different periods of the day will potentially reveal more opportunities for the optimization of baseband processing systems.

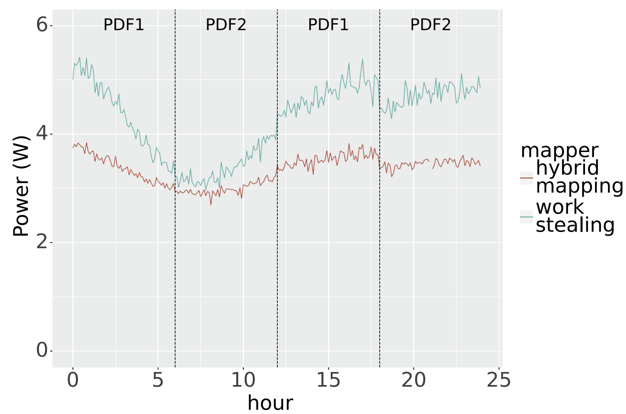

Fig. 9: Base station power consumption.

V. Related Work

The application of predictive analysis is becoming popular in many research areas. Interest in forecasting mobile traffic on LTE cells is essential for the efficiency of the design of future cellular networks. The works in [8], [9], [23] describe traffic models that take into account the spatio-temporal characteristics of traffic from multiple base stations. Cells with similar behaviours are grouped in order to build accurate models that capture the variability of mobile networks. Moreover, the authors in [22] present traffic forecasting by using the fbProphet algorithm developed by Facebook. While the models are of high quality, they alone cannot be used to generate realistic baseband traces at the subframe level. Nevertheless, they can be seen as orthogonal to our method since they can be used as input to desired target traffic.

Mobile base station traffic patterns have been investigated for understanding the various parameters involved in cellular networks. The work in [28] presents an analysis of real traffic data in order to understand usage patterns of LTE networks. They propose a methodology to derive a characterization for the spatio-temporal variation of the LTE traffic. Ding et al. [29] study the capability requirements on connection density and user data rate in order to design base stations with different network capabilities. The authors in [30] target prediction-driven resource allocation for mobile networks. They analyze LTE control channel information to propose an optimization framework that encompasses different forecasting solutions. These works profile different aspects of mobile communication, however, they are not flexible enough to explore different patterns on each of the involved communication parameters.

VI. Conclusion

In this paper, we present a methodology for the generation of parameterizable workloads for mobile networks. The methodology is flexible and allows to describe multiple spatio-temporal mobile traffic scenarios to investigate on optimization techniques for baseband processing systems. We use the traffic generator to reproduce and extend an evaluation of a state-of-the-art framework as a demonstration. Our work can be used to generate new datasets based on previously known traffic behaviours, but also makes it possible to explore speculative scenarios in order to predict the performance of the systems in presence of anomalous patterns or futuristic use cases like new modulation schemes or frequency band allocation.

Acknowledgment

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