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Smartphone User's Traffic Characteristics and Modelling

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ABSTRACT

The proliferation of smartphones and the demand for all-day connectivity has brought exponential growth of global mobile data traffic. To survive the explosive progression and best serve their customers, mobile network operators need to have a better understanding of the nature of traffic carried by cellular networks. Understanding the characteristics of this traffic is important for network design, traffic modelling, resource planning, and network control. In this work we investigate the basic characteristics of smartphone traffic, identifying and understanding the impact of context (location, time, physical interface) on smartphone usage for calls, messages and data traffic. In order to identify and characterize patterns in the user traffic generated by smartphone devices in the mobile networks, we employ naturalistic logging methodology based on non-obtrusive background data collection while aiming for a highly diverse study participant's backdrop. Our statistical results present a comprehensive analysis on user habits while using their smartphones on a daily or weekly basis. By taking advantage of the gathered user logs and the statistical analysis of the traffic characteristics, we attempt to design a mobile traffic generator that will create synthetic voice, message and data traffic according to the observed real life traffic characteristics. The generated mobile traffic scenarios can be used not only for modelling the mobile operators' network (such as 3G and 4G), but also WiFi, mobile ad hoc and sensor networks.

Keywords: Smartphone traffic patterns, mobile user behaviour, analysis and modelling, traffic generator.

1. INTRODUCTION

The mobile evolution, driven by video, cloud-based services, and the Internet, changes how people behave and how they leverage mobility to communicate and to improve their daily lives, using existing and new services. Today users demand ubiquitous connectivity anywhere and anytime. The driving forces of these trends also include new affordable smartphones, and the vast number of new connected devices on the market. The total number of mobile subscriptions globally will reach around 9 billion in 2017 [1]. With an increased number of subscriptions, smart devices and all-day connectivity, the global mobile data traffic is expected to grow 15 times by the end of 2017. Approximately 35-40% of all mobile phones sold in the first quartile of 2012 were smartphones, compared to around 30% for the full year 2011 [2]. Only around 10-15% of the worldwide base of subscriptions uses smartphones, which means that there is considerable room for further uptake [3].

Because of rapidly growing subscriber populations, advances in mobile communication technology, increasingly capable smartphones, and the expanding range of mobile applications; mobile networks have experienced a significant increase in data traffic [4]. Mobile data subscriptions grow strongly, and drive the growth in data traffic along with a continuous increase in the average data volumes per subscription. Mobile voice traffic also continues to grow at a smaller steady rate. To cope with this explosive growth and best serve their customers, operators need to have a better understanding of the nature of traffic carried by cellular networks. Understanding the characteristics of this traffic is important for network design, traffic modelling, resource planning, and network control.

However, little is known about the characteristics of the traffic generated from smartphones. Some recent studies ([5]-[9]) have tried to analyse the characteristics of smartphone data traffic to shed light on the topic. The time between the user interactions was observed in [5] and it was shown that if the users were inactive for a longer period, than it is less probable that they would start a new interaction. The research was based on two data sets of 33 Android and 22 Windows users across different demographics. The results show that users interact with their smartphones from 10 to 200 times a day. The duration of one session can vary highly, but most of the sessions were short. The conclusion that was drawn from the data traffic was that quantity of the data traffic generated from smartphones nowadays is similar to the one generated by the computers few years ago. In [6] the authors have analysed the application usage on a national level using data from a network operator. The traffic was collected in the period of one week and distinct marketplace apps were identified using HTTP signatures. The results obtained from this research can be used to optimize the content delivery in LTE and WiFi networks, i.e. which content can be stored on servers close to the clients. Another conclusion was that the daily cyclic models of different types of applications were quite different. For instance, news applications were used more in the morning hours, while some other applications were used throughout all the day. Surprisingly, most of the traffic that the users generated in this research came from the application for personalized radio (3 TB in one week or 50% from the total traffic). In addition, there were big discrepancies between the applications concerning the consumed traffic. The amount of traffic and the access time have been shown to increase linearly with the number of users. However, because of the high variation in this correlation, it is difficult to model the traffic amount and the access time based on the number of users. The authors made additional analysis on which types of application were more used during the day or night and if the applications' use depends on the smartphone model the users possessed.

In [7] the authors present the characteristics of the mobile http-based traffic, by using stamps on packet level from a large mobile network. The main results from this work show the comparison from the dataset obtained from the wireless set of data in one mobile network and wired set obtained from one local network. 15% of the applications have generated more traffic in the mobile network, whereas 70% in the wired network. The conclusion was that the traffic in the mobile network was a lot more bursty and in smaller packets. Similar data traffic analysis was done in [8]. The authors show that the daily amount of data traffic depends on the smartphone platform and whether or not the users use WiFi. Their focus of investigation is how the data traffic impacts the battery life and the proper use of the available bandwidth (because of the additional headers from the layers below). This research also showed the users habits concerning the use of mobile and WiFi networks. Most of the traffic that the 39 users made during 5 weeks was on the WiFi network (~527 MB), compared to ~90 MB on the mobile network.

The authors in [9] have investigated how SMS messages and voice traffic are connected to the social networks' contacts. Their results show that participants in the study have dialled 57% of their contacts, while they messaged only 19%. However, the number of SMSs was increasing, whereas the number of calls was reducing during the time. The SMSs that were sent to the social network contacts were shorter, while the call duration was longer, comparing to other contacts. A different kind analysis, which tries to capture the characteristics of the users' movement by using the localization data from their smartphones was done in [10]. For instance, the results show that the users in Los Angeles traverse more than the people in San Francisco or Manhattan. This research also focused on determining the possibility for traffic jams as well as the sizes of carbon footprints of urban areas.

Yet, many unanswered questions in this area remain. Thus, one of the goals in this paper is to investigate the basic characteristics of smartphone traffic, identifying and understanding the impact of context (location, time, physical interface) on smartphone usage for calls, messages and data traffic. Though call data records (CDRs) from cellular operators are a valuable source of data for mobility studies that could benefit society at large, obtaining such data is extremely difficult due to operator regulations and the need for individual privacy preservation. On the other hand, user collected data from cellular telephone networks can help study mobile traffic patterns easily and inexpensively, as well as on an as needed frequency basis. Smartphone logging can provide tremendous access to communications data from real environments. Using this approach, special care must be taken in order to preserve naturalistic user behaviours so that the logs are true reflections of the actual everyday activity [11]. Thus, in order to identify and characterize patterns in the user traffic generated by smartphone devices in 3G mobile networks, we utilized logs of user data packets captured at the device via a specially designed nonintrusive application. Volunteer measurements were obtained by deploying a background based measurement tool. Throughout our work, we have taken measures to preserve individual privacy.

In the case of 3G terminals all of the traffic is packet-based traffic. Studying this traffic allows identification of traffic characteristics and patterns described as series of events. An event in this context is the sending or reception of a packet. If it is possible to identify patterns in the traffic and find correlations between events, researchers could exploit knowledge of these patterns and correlations on both the network and user sides. As commented earlier, an improved understanding of user-smartphone traffic patterns would yield insight into a variety of important societal and networking issues [12]. For example, evaluating the effect of traffic patterns on the network capacity depends on knowing how typical mobile users communicate during their daily lives.

Although results show that there is immense diversity among users and their traffic patterns, one common factor is the vast amount of data that is being generated by smartphone devices. Therefore, network operators have to properly dimension their networks by estimating the required capacity of the nodes and links such that they are able to carry the actual amount of traffic that the link experiences, while optimizing expenses. This optimizing of expenses implies that mechanisms to properly dimension packet switched networks are needed. In order to propose a suitable mechanism, it is desirable to evaluate the response of the network to a given set of circumstances, and this is frequently made through simulations.

Networking research has long relied on simulation as the primary vehicle for demonstrating the effectiveness of proposed algorithms and mechanisms. A simulation model is a representation of the key elements of the network. Typically one constructs either a network testbed and conducts experiments with actual network hardware and software, or one simulates network hardware and software in software and conducts experiments via simulation of the network. In either case, experimentation proceeds by simulating the use of the real or simulated network by a population of users with applications that generate representative traffic.

Source traffic generators are used to inject synthetic traffic into the network according to a model that describes the behaviour of the corresponding applications or users. The need for a realistic traffic model is not exclusive to cellular network simulations only. The growing set of diverse applications developed for MANETs and other similar mobile wireless networks, demand for far more complex traffic patterns than the simple traffic pattern of the uniform random generators [13]. Hence, the simple traffic models widely used in previous simulation studies have become inadequate in reflecting the relative performance of these networks when deployed in real life scenarios. A traffic model is a stochastic process that represents the actual traffic measured in a network in a simulation model. Traffic models are used to predict the behaviour of actual traffic streams, so ideally they should preserve all the statistical properties of the original traffic. There are some desirable properties for a traffic model, such as: it should be defined by a small number of parameters, its first and second order statistics should match those of the actual measured traffic, and if the traffic were fed through the model the results should accurately predict those of the real traffic stream fed into an actual network.

There have been many research efforts to find a traffic model that fits the properties and particularities of packet based networks. Some of the proposed models are presented in [14] and briefly described here. In on-off models, a traffic source alternates between two states, „on" and „off". During an on period, traffic is generated at a constant rate, and during an off period there is no traffic. The lengths of on and off periods are independent. It has been shown that as the number of aggregated on-off sources increases, the resulting process approaches the server occupancy of an $M/G/\infty$ queue [15]. The Poisson-Pareto Burst Process (PPBP) uses a model with bursts arriving according to a Poisson process, and whose durations are Pareto distributed. PPBP can be considered as the limiting process for a large number of independent on-off sources aggregated together [16].

In this work, using logging methodologies as proposed in [11], we are trying to capture the users' mobile traffic characteristics. We are concerned with three different types of events: voice, messages and data. Our statistical results for these types of events present a comprehensive analysis on user habits when using their smartphones on a daily or weekly basis. By taking advantage of the gathered user logs and the statistical analysis of the traffic characteristics, we attempt to design a mobile traffic generator that will create voice, message and data synthetic traffic according to the observed real life traffic characteristics. Since the task at hand is hardly straightforward, we discuss possible approaches and their benefits and drawbacks. The first approach is based on the overall statistical traffic characteristics that we translate into probability distributions for different types of events. Using these distributions, which are the basis for random sampling for our generator, we try to represent the originally observed user behaviour. The second approach, proposed in this work, is to imitate the behaviour of a chosen user. Finally, we expect that using these results we will be able to build a first order approximation that should provide more realistic mobile traffic.

Furthermore, we elaborate the additional possibilities and mappings in order to obtain traffic scenarios even closer to the observed traffic patterns, such as adding social dimension by measuring the influence mapping between the social and the underlying communication network, determining the correlation between the user location and time of day in order to map the user behaviour in different environments. As already discussed, the resulting mobile traffic scenarios generated in this way will be of great significance not only for modelling the mobile operators' network (such as 3G and 4G), but also WiFi, mobile ad hoc and sensor networks.

Please note that in the rest of the paper, unless otherwise specifically noted, when using the term mobile network and mobile traffic we restrict to the network and traffic of cellular telephone network operators.

The rest of this paper is organized as follows. In Section 2 we present and analyse the gathered smartphone user traffic data from our logging application. The presented results are focused on three different traffic types: voice calls, short messages and Internet data traffic. We analyse the users' behaviour in different time contexts (during their daily and weekly activities) for each of the concerned traffic types. In addition, in the last subsection we include the results that rank the applications used by the users, by their popularity and by the Internet data traffic that they have consumed. In Section 3 we present a design for a mobile traffic generator based on two different approaches, statistical and averaged, which can be used for generating traffic scenarios with the three types of events. We also discuss some additional possibilities and mappings that could make the traffic generation model even more realistic and accurate. Section 4 concludes this work.

2. SMARTPHONE USERS' TRAFFIC CHARACTERISTICS

Logging methodologies have addressed many of the concerns about the observer effects on natural user behaviour by employing technology to do the observations. These methodologies provide access to data that can be collected without the presence of observer or a requirement for users to provide self-reports. Data can be pulled from study participants' daily activities on familiar interfaces within normal contexts. Thus, data collected from loggers are typically considered more objective, accurate, and realistic. Smartphone logging of communications data is a recent trend. The logged data gathered under these constraints can be used for advanced research in order to establish empirical models, development of theories and for testing different hypothesis. Although logging has been applied effectively to a number of research aims, no specific intentions where applied to preserve naturalistic behaviours. For instance, many of the previous logging studies mentioned above have reminded participants they are being measured by requiring them to report data, have introduced novel interfaces, or collected data considered private.

In order to provide a more systematic approach while preserving natural user behaviour, as part of this research we designed a background smartphone Android application, which logs different types of events (voice calls, SMS messages and Internet data). Following [11] we have implemented a naturalistic methodology for logging events, taking into account: different variables, users' privacy, participant selection, and the length of the research, level of intrusiveness, the user interface, user tasks and technology.

Thus, first we have selected the participants and we have explained which variables will be used from their smartphones. All of the chosen variables do not threaten the users' privacy. The only suspicious data, i.e. telephone numbers, were replaced by randomly chosen unique identifiers during the logging process. The users did not have any specially appointed tasks, except to install the logging application and to accept the terms of use and export the data at the end of the observation period. During the process of accepting the terms of use, all users where briefed in detail on the types of data that are logged and on the ways employed to ensure their privacy. Upon installation, the application works as a background process and does not disturb the users at any moment. The application logged voice calls, SMS messages and Internet traffic from 18 users of Android phones in the time period of over 3 months. Special attention was given for the chosen users not to be significantly correlated by choosing users with different age, city of origin, profession, smartphone generation (2.3.3 Gingerbread to 4.1 Jelly Bean) and brand (i.e. HTC, Samsung, Sony and others) and mobile operators and packages (prepaid and post-paid). This research was with medium length, thus we claim that the obtained results are realistic. Before deployment of the application, extensive accuracy testing were done in order to ensure the correctness of the gathered data.

From the obtained logs we have divided the traffic events into three separate groups: voice traffic, message traffic and data traffic. The logging variables for the three event types are as follows: 1) calls – type, caller ID, timestamp, call duration; 2) messages – type, caller ID, timestamp; 3) data – interface, application, connection ID, connection start, connection duration, number of received and sent packets in KB. In order to expand our data set, upon installation of the application, the logger crawls all past call and message logs and records the history data. Also, it is important to emphasise that records for VoIP applications that are fully integrated into the OS native call interfaces (e.g. Viber) are considered as voice calls and the corresponding data traffic is not being logged.

In the rest of this Section we summarize the characteristics of the voice, message and data traffic on a fine and coarse time scale. The analysis and results from this Section will be used as a basis for the mobile traffic modelling, presented in Section 3.

2.1 Voice traffic characteristics

Table 1 summarises the main voice call characteristics and the obtained diversity between different call types. We differentiate between 5 call types: incoming, incoming rejected (i.e. incoming calls with duration 0 s), incoming missed, outgoing rejected and missed (i.e. outgoing calls with duration 0 s), and outgoing calls.

Table 1 Voice traffic characteristics

Property	Incoming	Incoming rejected	Missed	Outgoing rejected and missed	Outgoing calls
Average number of calls	4.4	0.3	1.8	2.7	5.1
Average call duration	108.1 s	-	-	-	109.3 s
Standard deviation of the call duration	176.6	-	-	-	188.3
Maximal deviation of the call duration	2821.9	-	-	-	3643.6
Average call duration on daily basis	477.4 s	-	-	-	561.6 s

On a daily basis, the users on average had more outgoing calls (5.1 calls) than incoming calls (4.4 calls). In addition, the average of outgoing rejected and missed calls (2.7 calls) is bigger than the number of incoming rejected and missed (2.1 calls). The average call duration on a daily basis for the outgoing calls is 9.4 minutes, whereas for the incoming calls is around 7.9 minutes. However, the standard deviation and the maximal deviation of the call duration, for both the incoming and the outgoing, is quite high, which shows the diversity of the call data amplified by the heterogeneity of the study participants. The diversity of the results is expected, as it is noted in several previous attempts (see the previous section for more details). The grand scale of the user diversity is becoming a major difficulty that needs to be crossed when designing a synthetic traffic generator.

Comparing our results with the results published by the ITU [4] one can conclude that in US the number of outgoing calls is slightly bigger (8 vs. 5 in our analysis), whereas comparing them with the results from the national agency for electronic communications [17] the observed users have spoken longer than average national citizen (9.4 vs. 5.1 minutes), with a little bit longer average duration of outgoing calls (1.82 vs. 1.75 minutes).

By making an analysis of the number of calls and the call duration in the different hours of the day as well as different days in the week we attempt to capture the basic properties of the users' temporal habits concerning the voice traffic. In Figure 1, we present the average number of calls per hour.

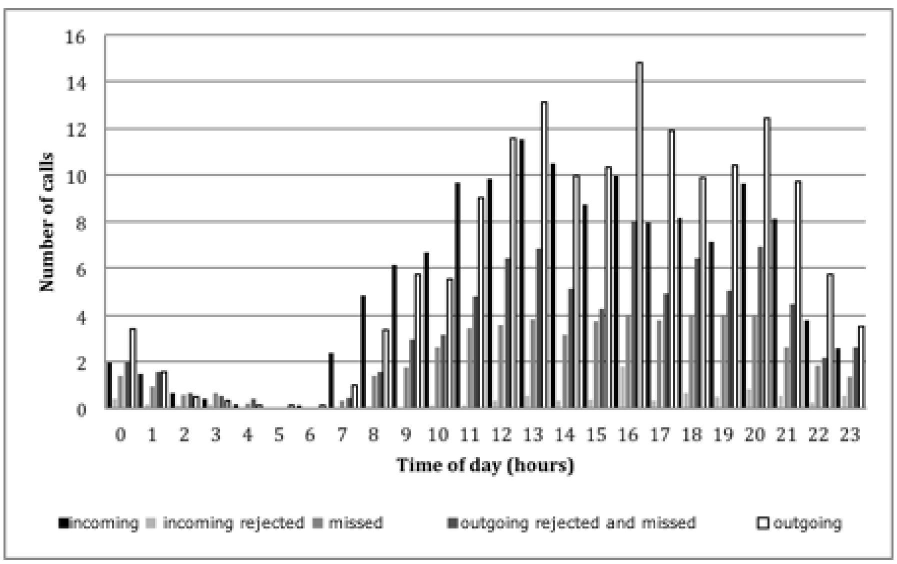


Figure 6: Number of calls distributed in different hours of the day

The average number of all types of calls is heightened in the interval between 7 AM till 1 AM, especially in the period between 12 PM and 8 PM. The maximum is reached during the typical last working hour (i.e. 4 PM). The users' activity then decreases till 6 PM, and gradually increases between 6 PM and 8 PM, which is possibly connected to the users' evening arrangements or preparation for the working activities for the next day. The incoming calls have maximum at 1 PM.

The average call duration in different time of the day is presented in Figure 2. The duration of the user calls is longer after work (from 4 PM till 8 PM) compared to the working hours from 7 AM till 4 PM. The results show that users tend to make more, but shorter calls while working. As expected, the call duration is smallest during early hours after 1 AM till 7 AM. The outgoing calls reach their maximum at 4 PM, while the incoming at 8 PM. The users received more calls than they dialled to.

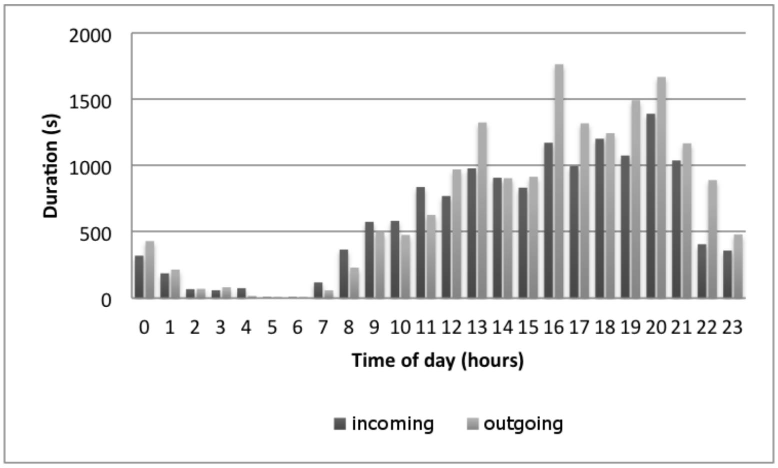


Figure 7: Average call duration in different hours of the day

For an analysis on a more coarse time scale, the average number of calls for every day of the week is illustrated in in Figure 3. It is noticeable that the users' call activity is biggest on Tuesdays, whereas the users mostly tend to reject the incoming calls on Fridays. The voice calls get more sporadic during the weekend, while the peak for missed calls is reached after the weekend.

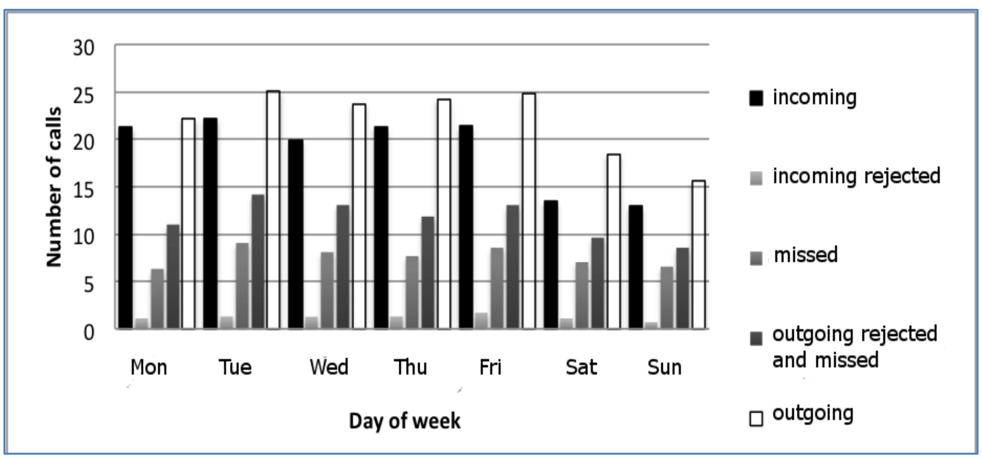
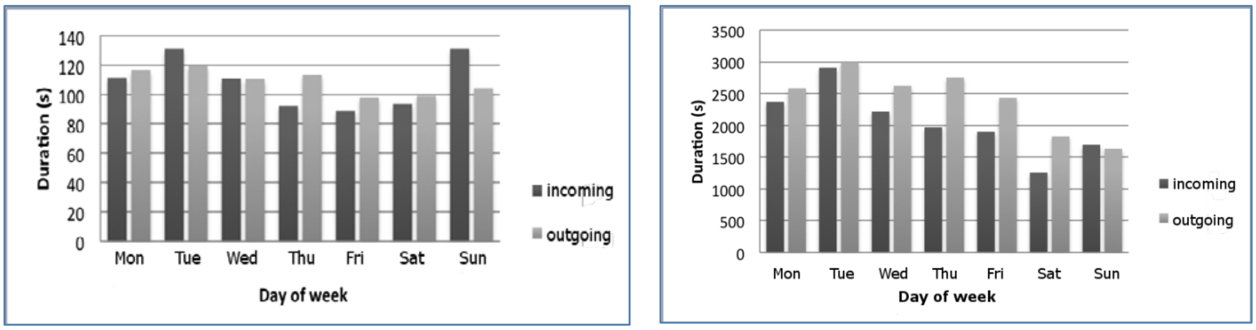


Figure 8: Number of calls in different days of the week

Regarding the call duration on different days of the week, the situation is a little bit different compared to the number of calls. Users tend to have long incoming and outgoing calls on Tuesdays. Please note that this behaviour has been reported in some of the related research studies mentioned previously. However, the duration of the incoming calls is also long on Sundays, while the number of outgoing calls is smallest during the weekends (see Figure 4(a)).

The longer, but fewer calls on Sundays can be due to the fact that the users tend to have long conversations only with their close relatives and friends on Sundays and while the short business related ones with their co-workers are not present. The duration of the incoming and the outgoing calls is shortest on Fridays.

The overall duration of all calls in different days of the week is given in Figure 4(b). By deeper inspection and comparative analysis, one can draw a number of conclusions about the user behaviour: users talk more in general during the working days. As the incoming calls duration becomes shorter towards the end of the working part of the week, the outgoing calls lessen as the week progresses but with lesser intensity. The top talk day is Tuesday for both incoming and outgoing calls.



(a) (b)

Figure 9; (a) Average call duration in different days of the week, (b) Overall call duration in different days of the week

The obtained results also show the diversity in the users' behaviour regarding the number of calls that they have made. For instance, the range of the number of calls per user varies between 8% and 63% of the total number of calls made by all the users.

Another type of analysis conducted in this research is dealing with the social aspect of user interaction. For instance, from the voice call data we have obtained it is evident that most of the users talk to a repetitive small group of contacts, while a small part of the users talk to a larger set of contacts. All users tend to make most of the calls to their top contacts when considering the number of calls and duration of calls also. However, these results are preliminaries and can be further used for mapping and research of the mutual influence between the social and underlying communication network.

2.2 Message traffic characteristics

In the following subsection, we present our analysis on the users' habits concerning sending and/or receiving SMS on different time scales.

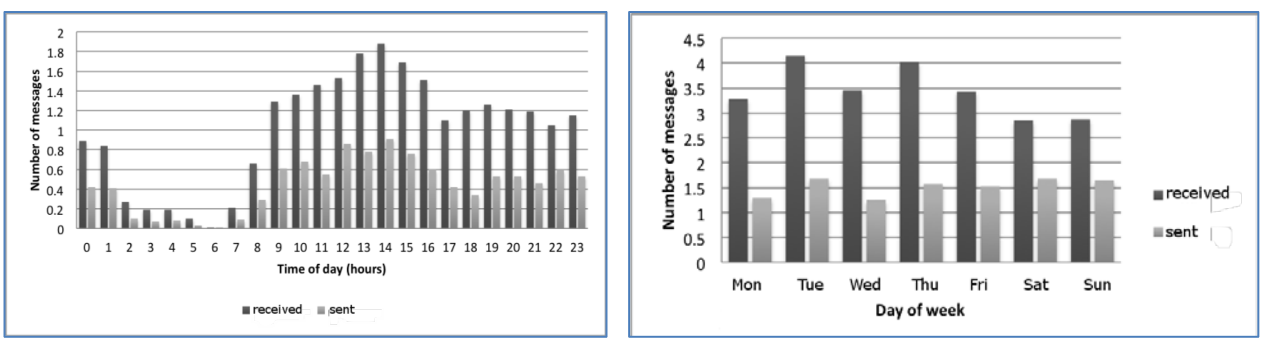
On a monthly basis, users have received 24 messages on average, while they have sent around 10.5 messages. Compared to daily basis, users receive on average around 0.8 and send around 0.35 messages (see Table 2). The obtained results exhibit similar ratio between sent and received SMS on daily basis if compared to the results from ITU (1 versus 1.15) 17]. However, when comparing the results with the national agency for electronic communications the users have sent fewer messages than an average national user (10.5 vs. 18 SMS) [17]. In unison with the comparison made for the voice calls, we can draw a conclusion that smartphone users tend to talk more compared to writing SMS, which seems to be more accepted for users with traditional older mobile phones. This could be due to the inclination towards more cheap means of communication (via SMS) for users that cannot afford smartphones.

Table 2 Message traffic characteristics

Property	Received SMS	Sent SMS
Average number of daily SMS messages	0.8	0.35
Average number of monthly SMS messages	24	10.5

In Figure 5(a) the average number of SMS per user during one day is presented. The users have sent and received most of their SMS messages between 12 PM and 3 PM, with a maximum peak at 2 PM. Another type of analysis is the distribution of average number of SMS for different days of the week. Similarly as in the case for the call duration, the users have received most of their SMS on Tuesdays and during the working days, whereas the users have sent most of their SMS during the weekend, see Figure 5(b) Thus, Tuesday seems to be the overall most "communicative" day of the week, while the weekend shows heightened activity connected with leisure and family.

The diversity in the users' behaviour regarding the maximum number of SMS messages that each study participant have sent and/or received is also prominent. Similarly to the maximum number of calls, the range of the number of SMS per user varies between 8% and 79% of the total number of messages.



(a) (b)

Figure 10: (a) Average SMS in different hours of the day, (b) Average number of SMS in different days of the week

2.3 Data traffic characteristics

The aim of this subsection is to present some of the analysis on the characteristics of the users' data traffic. The Internet data traffic is captured separately on the mobile network and WiFi network interfaces. Table 3 summarizes the main statistical characteristics of the observed traffic.

Table 3 Data traffic characteristics

Property	Mobile network	WiFi network
Average number of daily connections	6.9	5.8
Average overall Internet connection duration (per day)	3878 s	4029 s
Average amount of received traffic (per day)	8748.2 KB	8437.9 KB
Average amount of sent traffic (per day)	1135.2 KB	1046.9 KB
Average number of received packets (per day)	9588	8329
Average number of sent packets (per day)	8525	6675
Average connection duration	564 s	695 s
Standard deviation of connection duration	1878 s	1694 s
Maximal deviation of connection duration	57957 s	32338 s
Average amount of received traffic (per connection)	1271.2 KB	1455.2 KB
Standard deviation of received traffic	4898.4 KB	7702.7 KB
Maximal deviation of received traffic	118941.8 KB	195683.8 KB
Average amount of sent traffic per connection	165 KB	180.5 KB
Standard deviation of sent traffic	385.8 KB	758.3 KB
Maximal deviation of sent traffic	6206 KB	17204.5 KB
Average number of received packets (per connection)	1393	1436
Standard deviation of received packets	4246	6042
Maximal deviation of received packets	99301	138391
Average number of sent packets (per connection)	1239	1151
Standard deviation of sent packets	3753	4542
Maximal deviation of sent packets	96093	99785
Average size of received packets	0.91 KB	1.01 KB
Average size of sent packets	0.13 KB	0.16 KB

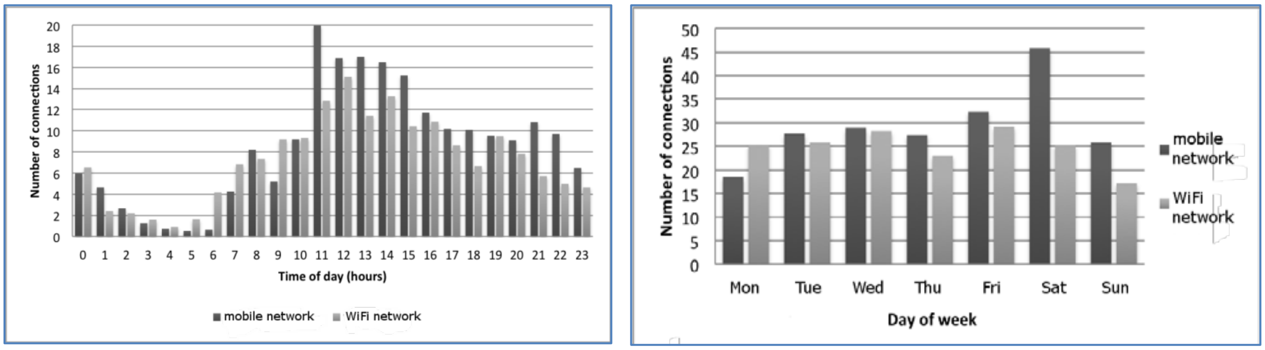
The data from the table shows that the daily number of connections made using the mobile network as carrier is somewhat bigger compared to the number of the connections made using the WiFi network interface (6.9 vs. 5.8). The users spent most of their time in the day on WiFi network (151 s more than in the mobile network), and the duration of one connection made using the WiFi interface is 131 s longer. However, the amount of daily traffic is bigger for the mobile than for the WiFi network. Users have received 310.3 KB and sent 88.3 KB more on mobile network. When observing the number of packets on daily basis, users have sent 1259 more packets, whereas have received 1850 more packets, on WiFi network compared to the mobile network. The average amount of received/sent traffic per connection is also bigger for WiFi network. On WiFi network, users have received 43 packets more per connection, while they have sent 88 packets more on mobile network. The average size of the received and sent packets is moderately equal for both types of interfaces. Please note that compared to previous studies (as discussed in Section 1) these results show that smartphone users tend to use the mobile interface for data traffic even more than just recently starting to surpass the WiFi traffic.

The logging application also differentiated the traffic on the mobile network interface according to the following types of mobile networks: GPRS (2.5G), EDGE (2.75G), UMTS (3G), HSDPA (3.5G) and HSPA (3.5G). The division of the Internet traffic realised on a mobile network, according to the type of the mobile network is shown in Table 4. It can be noticed that the majority of the connections were established on HSPA and HSDPA mobile networks, showing that the users preferred to connect to mobile networks with higher data transfer rates. The number of daily connections and the amount of daily received Internet traffic is bigger for the HSPA network, whereas, the users had longer average connection duration and they sent larger amount of Internet traffic on a daily basis using the HSDPA network. As expected, the users tend to avoid slow connections, such as GPRS, when sending or receiving Internet data. However, the results depend not only on users' habits, but also on the offered type of connection by the mobile operator and the user tariff models.

Table 4 Main characteristics of data traffic depending on the offered service

Property	GPRS (2,5G)	EDGE (2,75G)	UMTS (3G)	HSDPA (3,5G)	HSPA (3,5G)
Average number of daily connections	0,06	0,74	0,25	2,75	3,08
Average overall Internet connection duration (per day)	30 s	501 s	156 s	2298 s	893 s
Average amount of received traffic (per day)	10,7 KB	420,3 KB	89,7 KB	3894,6 KB	4332,9 KB
Average amount of sent traffic (per day)	3,4 KB	82,2 KB	16,6 KB	539,3 KB	493,8 KB
Average number of received packets (per day)	20	552	117	4447	4451
Average number of sent packets (per day)	22	560	112	3962	3869
Average connection duration	468 s	680 s	635 s	835 s	290 s
Standard deviation of connection duration	842 s	1759 s	1988 s	2642 s	655 s
Maximal deviation of connection duration	3491 s	18963 s	20971 s	57686 s	7762 s
Average amount of received traffic (per connection)	165,8 KB	571,3 KB	364,5 KB	1415 KB	1405,4 KB
Standard deviation of received traffic	482,9 KB	1807,9 KB	1035,1 KB	4465,6 KB	5885,5 KB
Maximal deviation of received traffic	2661,2 KB	22647,7 KB	6328,5 KB	94906 KB	118807,6 KB
Average amount of sent traffic per connection	53,1 KB	111,7 KB	67,3 KB	195,9 KB	160,2 KB
Standard deviation of sent traffic	131 KB	341,8 KB	165,5 KB	404,7 KB	391,1 KB
Maximal deviation of sent traffic	738,9 KB	5092,3 KB	1331,7 KB	5078,1 KB	6210,8 KB
Average number of received packets (per connection)	314	750	475	1616	1444
Standard deviation of received packets	702	2008	1188	4010	4956
Maximal deviation of received packets	3125	27354	7802	73978	99250
Average number of sent packets (per connection)	335	761	454	1439	1255
Standard deviation of sent packets	734	2043	1222	3467	4408
Maximal deviation of sent packets	3207	30230	9904	74761	96077
Average size of received packets	0,53 KB	0,76 KB	0,77 KB	0,88 KB	0,97 KB
Average size of sent packets	0,16 KB	0,15 KB	0,15 KB	0,14 KB	0,13 KB

The number of connections in different hours of the day for an average user is presented in Figure 6(a). Users tend to make most of their connections between 11 AM and 2 PM. The maximum number of connections on the mobile network is at 11 AM, while on WiFi is at 12 AM. During the week, via the network operator the users made most of their Internet connections on Friday and Saturday, whereas, using WiFi, the biggest number of connections is on Wednesday and Friday (see Figure 6(b)). Please note the prominent usage of the mobile Internet on Saturdays, which could be due to the users' tendency for more leisure outgoing activities during this day.

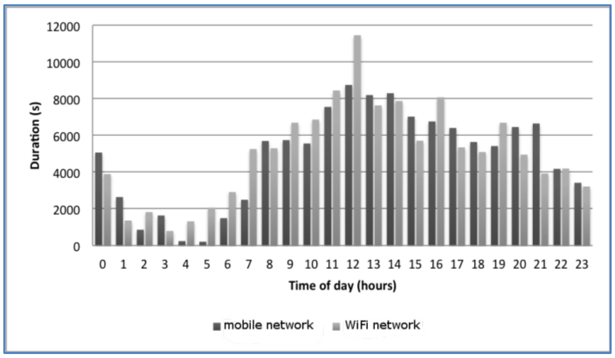


(a) (b)

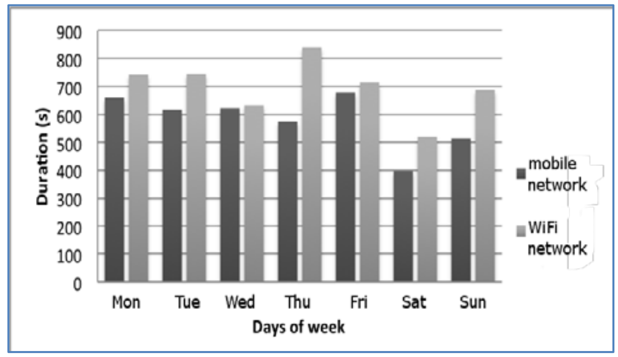
Figure 11: (a) Average number of connections in different hours of the day, (b) Average number of connections in different days of the week

The duration of the connections is longest between 11 AM and 2 PM, reaching its maximum at noon, see Figure 7(a). These results show that the users are most active during their break or lunch time. Similarly, for the average duration of the connection in different days of the week, when using WiFi the users tend to have longest connections on Thursdays, while when using mobile network on Fridays, whereas the shortest duration of the connections is noticed on Saturdays (see Figure 7(b)).

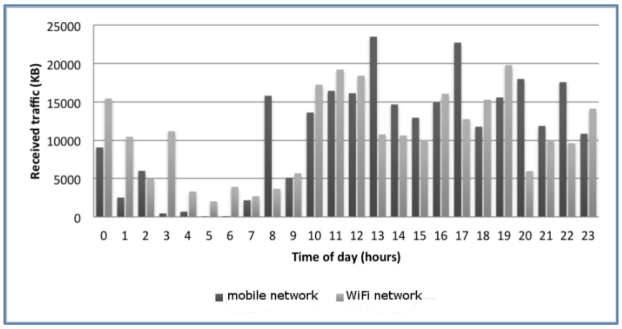
Concerning the amount of traffic, here we present the results for the amount of received and sent traffic using WiFi and mobile network. When connecting via WiFi networks, users have received most of their traffic between 10 AM and 12 AM and the maximum peak was achieved around 7 PM, whereas when the users connect via the mobile network, most of the traffic they have received was at 1 PM, 5 PM and 8 PM. The results are shown in Figure 7(c). If we analyse the behaviour during the different days of the week, most of the received traffic using WiFi network was on Saturdays and Sundays, while using the mobile network on Wednesday, Friday and Saturday. When analysing Figure 7(d), it is noticeable that the users have received more traffic during the weekends and on Fridays, while Monday is the most inert day of the week.



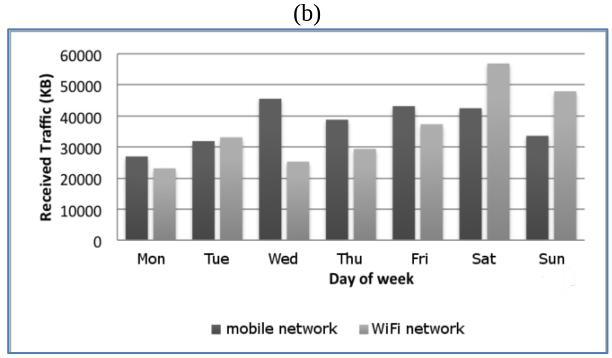
(a)



(b)



(c)



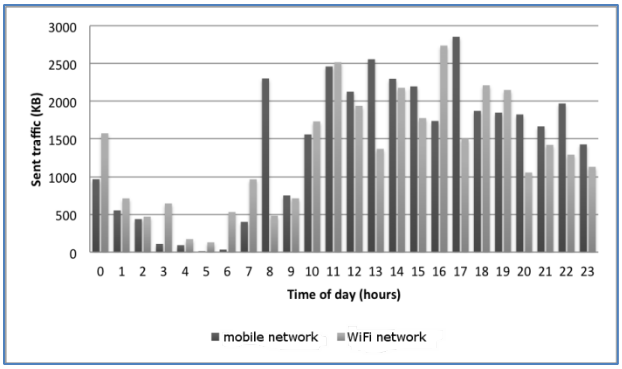
(d)

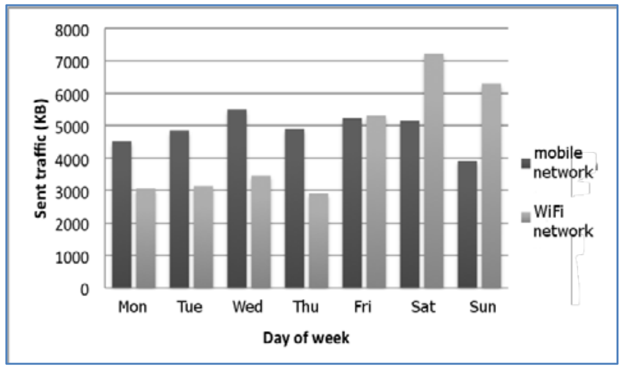
Figure 12: (a) Connection duration for different hours of the day, (b) Connection duration for different days of the week, (c) Received traffic from all connections in different hours of the day, (d) Received traffic from all connections in different days of the week

Similarly to the received traffic, the traffic generated from the users on mobile networks was in its peak at 11 AM, 1 PM and 5 PM. On WiFi networks the peaks were reached at 11 AM, 4 PM and 6 PM (see Figure 8(a)). The results for the sent traffic from the users in different days of the week are quite similar to the results for the received traffic (see Figure 8(b) and Figure 7(d)). While on WiFi, the users have sent most traffic on Sundays and Sundays, while mostly on Wednesdays and Fridays they sent their traffic using the mobile network as carrier towards the Internet gateway.

Our analysis of the Internet traffic also includes data on the usage of different applications. Thus, we measured the relative popularity of mobile applications, similarly to [6]. Overall, the users have used 294 different applications that have generated Internet traffic. On average, 61 app relied on traffic every day. In

Table 5 we show the main characteristics of the applications usage. The average traffic for one app was 231.4 KB of received data and 27.5 KB of sent data.





(a) (b)

Figure 13: (a) Sent traffic from all connections in different hours of the day, (b) Sent traffic from all connections in different days of the week

Table 5 Main characteristics of app usage

Property	sent	received
Average amount of traffic for all app (per day)	14118,7 KB	1678,6 KB
Average amount of traffic for one app	231,4 KB	27,5 KB
Standard deviation of the traffic for one app	1425,2 KB	179,4 KB
Maximal deviation of the traffic for one app	105261 KB	16216,1 KB

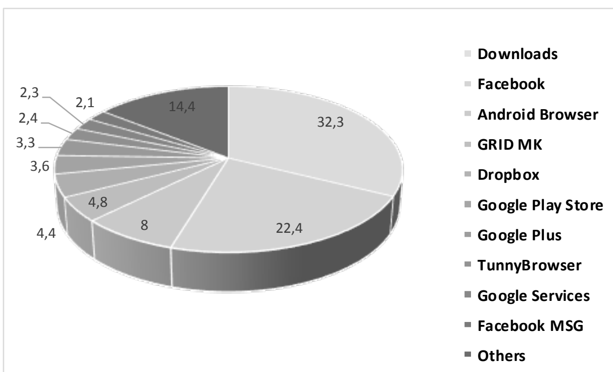


Figure 14: Top 10 data consumption applications

In Figure 9 the top 10 data consuming applications are presented. As expected, applications that are responsible for most of the overall offered traffic were: Downloads, then Facebook, Android Browser, GRID MK (local news aggregator) and Dropbox, see Table 5Usually, the overall traffic is consisted mostly of downstream traffic, i.e. from the operator to the user (around 90%, see Table 5), thus, we have obtained almost identical results for the received traffic as for the overall traffic. Also, applications that used most of the upstream traffic were Facebook, Dropbox, Facebook Messenger, Android Browser and Google Plus.

3. MODELING SMARTPHONE TRAFFIC

One of the first steps when analysing wireless mobile networks, regardless of the different infrastructure-(less) and technological possibilities, is developing a simulation environment that will as closely as possible reflect a real life scenario for the user usage of the network. After deciding on the various protocols on the different network layers, there are two more modelling decisions that need to be made which will greatly influence the obtained results. These are the mobility model that defines the nodes positioning and movement in the observed environment and the traffic model that defines the traffic patterns in terms of packets that are going to be exchanged between different pairs of nodes at given moments. However, in most of the cases these two characteristics are often neglected and overlook, while researchers habitually use a random node movement that does not reflect any realistic human behaviour in combination with a random traffic generator that creates randomly sized packets at random time intervals choosing random destinations in the network. The results obtained with simulations based on this type of modelling of the user behaviour can be very far from the real life applications of the network, thus misleading when trying to analyse the network performances or when inspecting the behaviour of a new control or routing protocol. It is imperative that when designing simulations of wireless mobile networks, wherein it is expected that in real life conditions the network nodes will be devices that will be used by humans, the mobility and traffic patterns are modelled as realistically as possible. Thus, in this section we present how the results from the previous section can be used towards creating a more realistic synthetic traffic pattern for mobile users. Please note that this type of traffic pattern does not necessarily has to be constrained for the purposes of simulation of mobile network operators' networks. Since we observe the traffic pattern on its highest application layer, the same traffic pattern can be applied to any underlining network architecture as long as its goal is to provide peer-to-peer communication between its nodes together with a gateway to the Internet. Thus, the smartphone traffic generator we propose here can be used in simulations of 3G and 4G networks, but also Wi-Fi and mobile ad hoc networks and alike.

The observation and statistical analysis of the behaviour of different smartphone users over an extended period of time can be used as a cornerstone for the creation of a realistic smartphone traffic model that can then be translated into a smartphone traffic generator. In this way, instead of using overly simplified random traffic generators that are a very crude replacement for the real expected traffic between the users, we can try to use the available abundant information on the users created traffic and model the network traffic more realistically. However, it must be taken into consideration that the creation of a traffic generator that will perfectly imitate the user behaviour is an exceedingly tedious task that can hardly capture every aspect of the observed communication pattern between the users in correlation with other factors like time of day, location, social connections, age, etc. Thus, what we propose is a first order approximation that should produce a more human like traffic compared to the pure random generators. One can always build on top of this approximation in order to put an accent on a certain aspect of interest, like for an example, the correlation between the source-destination pairs and the underlying social network of the users.

When deciding on the mechanisms for our synthetic smartphone traffic generator, we define two possible models that make use of the previously gathered user data. The first model is based on the statistical characteristics of the averaged traffic of all of the observed users over the complete period of observation. Following this line of reasoning, we can obtain functions that will represent the statistical distribution of different events of interests and then use these functions as input to random generators that will take samples from the distributions for all different types of events. By combining the samples we can obtain a synthetic traffic representation of the originally observed user behaviour. The second model is to use user emulation instead of synthetic traffic generation. The emulation will provide the basis for imitating the behaviour of the average user. However, in order to use this approach we must first discover who the average user is among the observed set of users. Towards this goal we decided to choose the average user as the user whose obtained traffic pattern characteristics are closest to the average value of the main event characteristic. In the following subsections we will consider both of the proposed models and discuss their positive and negative sides. The output of both of the models will be a traffic pattern scenario that can be fed into a network simulator and will be used to define the traffic that traverses between the nodes in the network on the application level. One must take into account that the traffic patterns for the simulation scenarios that will be provided are going to be based on results obtained using daily traffic, i.e. it will reflect the daily observed patterns of communication between the users. However, by adjusting the time scale, one can easily translate the 24h traffic into a shorter or wider timeframe as necessary.

In order to move towards a synthetic traffic generator based on the gathered data that describes the smartphone traffic pattern created by our sample users, we firstly divide the traffic event into three separate groups that we model with different types of traffic and different type of services and QoS: voice traffic, message traffic and data traffic.

3.1 Voice Traffic Representation

In Figure 10 the cumulative probability distribution function (CDF) for the number of call events per user per day according to the gathered data in our study is presented. Using the distribution function one can draw conclusions on the percentage of users that have made up to a given number of calls (e.g. 66% of the users have made less than 15 calls per day). For our synthetic traffic generation purposes, we can use this function by taking a random sample value for each node in the network that is going to be represented in our simulation. The obtained random sample will define the number of voice call events for the given node. According to our previous analysis (see Section 2, Table 1), 36% of the total number of call events are outgoing calls made by the user. Thus, the traffic generator will decide that during the simulation the given user will need to make 36%*(random sample from CDF) outgoing calls to randomly chosen destination nodes. In order to define the rest of the voice call characteristics, other additional distributions are needed.

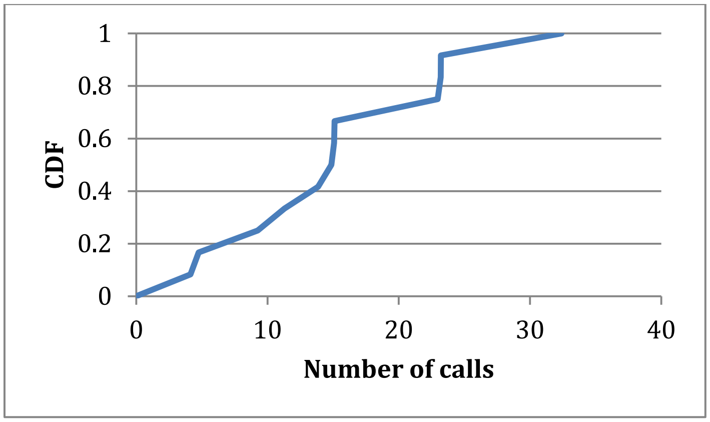


Figure 15: Cumulative distribution function of the number of calls per day

In Figure 11 the CDF for the call duration is presented. According to the results, 90% of the calls last less than 200s. For the purposes of creation of a realistic simulation scenario, each of the call events defined by sampling the previous CDF for the number of calls per day has to be sorted by type using the results given in Table 1, and afterwards for each outgoing call we need to sample the CDF given in 0In this way we obtain the number of outgoing calls per user for each node in the simulation together with the duration of each individual outgoing call. In order to complete all of the necessary information for the voice call events we need the starting moment of the calls. For this parameter we decided to use uniform random distribution that will take samples from the (0, end_time_of_simulation) in order to accommodate, and in a way scale, to any duration of the chosen simulation time. A more realistic approach would be to obtain a third CDF for the call start time, however we believe that this will decrease the usability of the generator since it is very rare that researchers create wireless mobile simulation scenarios with simulation time longer than a few hours.

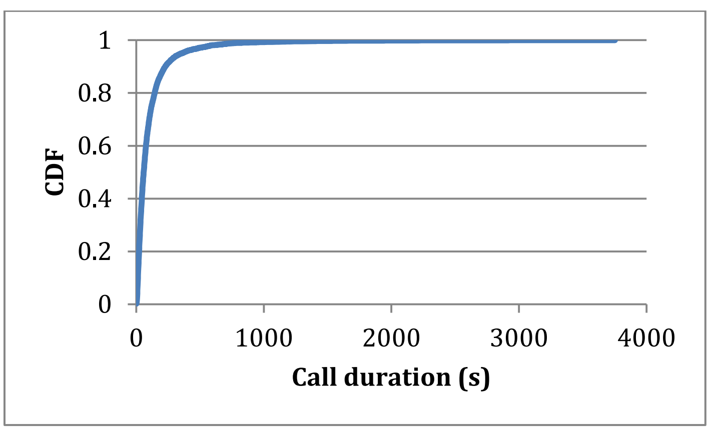


Figure 16 Cumulative distribution function of the call duration per day

The voice events simulation traffic can be created by emulating the data obtained from the user that has the closest average value to the average value of the total calls duration for all users per day. Using this approach, instead of sampling the number of calls and their duration, one simply looks them up in a table and scales each call event (in order to adapt to any given simulation time). Thus, we obtain a traffic pattern scenario wherein we simulate the behaviour of typical "average" nodes in the network. In order to provide more distinct node behaviour, different nodes can reflect the "average" user behaviour from different days randomly chosen from the full set of days that were gathered during the observation period. In this way, the different user behaviour in different days will realistically reflect in the simulation scenario.

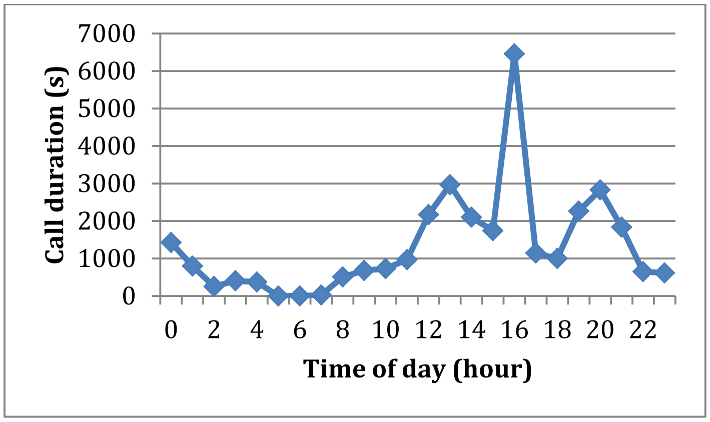


Figure 17 Average call duration in different time of day for the "average" user

Figure 12 presents the average call duration for different time of day of the chosen "average" user. The typical peaks of call duration at 1, 4 and 8 PM will also reflect in the simulation since the generated traffic will be a scaled mirror like version of the users' behaviour.

While the second type of modelling using an "average" representative of the pool of user data seems more adequate for more realistic traffic patterns, the biggest problem that arises is choosing the right representative. The results have shown that if we decide on a different parameter (e.g. average number of calls, average call duration, average number of outgoing calls only, etc.) we end up with a different candidate user whose average value is the closest to the total average, i.e. the representative user changes with the change of the observed average parameter. Thus, when deciding on using this method of modelling application traffic, one must first decide on the parameter that is of highest importance in the simulation scenarios, whether it is the number of calls, or the call duration, or some other value.

On the other hand, the average statistical method offers a more straightforward way of integrating a more humanlike behaviour into the traffic pattern scenario for a given simulation. However, the obtained traffic patterns are further away from real life scenarios since they are based on total averaged functions. This is even more pronounced if we come back to the results from the previous section and review that the standard deviation that accompanies the total average has very large values indicating that the users are extremely heterogeneous in their behaviour. Yet, this is still a very good first order approximation that has incorporated this heterogeneous behaviour by having all of the user events values influencing the obtained CDFs.

As for the voice call event itself, it can be modelled using VoIP (over UDP/IP) packets tagged with the highest quality of service (QoS). These will be packets that are sent in uniformly distributed time intervals with different size and data rate depending on the chosen codec [18]. For example, AMR codec, which is often chosen for VoIP, can support 8 different possible data rates starting from 4.5 kbps up to 12.2 kbps. It generates 244 bit packets, which represent 20 ms voice frames. In order to provide high QoS, the packet delay must be less than 150 ms, with packet loss not higher than 1% and jitter less than 25 ms.

3.2 Message Traffic Representation

The modelling of the short message traffic is a bit simpler compared to the voice calls. In this case we need to model the communication that is a short burst of acknowledged information in a given time moment and does not need to be handled with any QoS except offering reliable service. Towards this goal we can model the sending of a message by sending on application level packet to a randomly chosen destination with a random size that can be chosen from the uniformly distributed interval of (10 B, 128B) wherein a message of 128B corresponds to the largest SMS size allowed when using all of the 160 available characters. TCP on the transport layer will reflect the reliable nature of the traffic. In the case of short messages we argue that the parameter of highest importance is the number of messages an average user sends per day and thus for the purposes of message traffic modelling we propose the use of the CDF given in Figure 13. In some special cases, one could also be interested in the specific distribution of moments of sending messages for which cases another CDF is necessary.

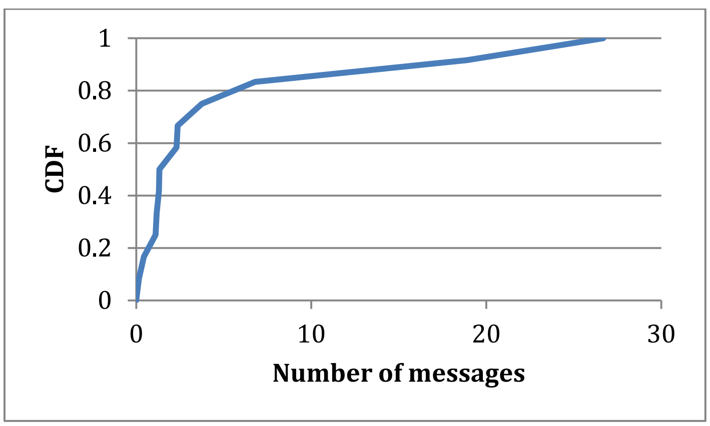


Figure 18: CDF for the number of messages per day

The result presented in Figure 13 also shows that 75% of the users deal with less than 4 messages per day. For the purposes of creating synthetic message traffic, after taking a sample from the presented CDF, we need to decide on the exact number of sent messages by referring to the results presented in Table 2.

Since the amount of traffic of short messages is sparse compared to the voice and data traffic, for modelling of message traffic we would encourage using the second proposed method of emulating an actual user experience by choosing an "average" user from the gathered data. Another interesting observation that comes into light is that the "average" user whose average number of messages per day is closest to the total average of the gathered data is the same "average" user selected for the voice calls traffic. However, since our gathered data set is relatively small we cannot draw a conclusion that this will always be the case. Figure 14 represents the distribution of messages per hour of day for the chosen "average" user whose behaviour will be reflected into the simulation scenario.

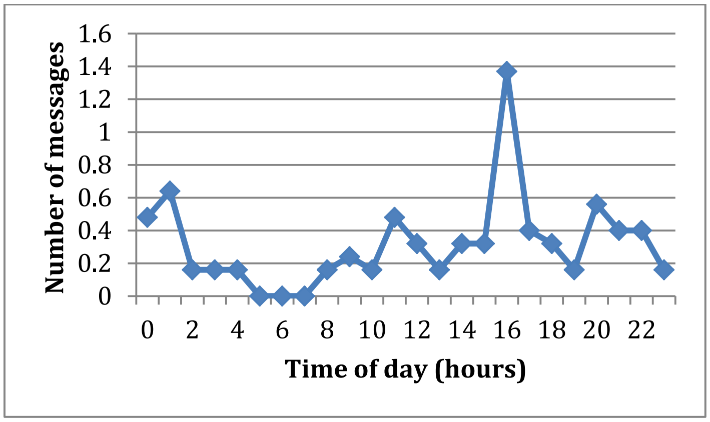


Figure 19: Number of messages per day for the "average" user

3.3 Data Traffic Representation

When simulating data traffic in a wireless mobile network scenario for the purposes of optimizing a protocol or discovering the impact of certain network parameter, researcher seldom use heterogeneous scenarios in which the data traffic can be transferred among the user nodes via different networking technologies. Thus, for the purposes of modelling and generating synthetic data traffic we will not distinguish between the different types of traffic (e.g. WiFi and 3G) and will consider the total data traffic that passes between the users. In order to simplify the simulation scenario we also do not try the divide the traffic according to type on application level, i.e. all traffic that is transferred from/to devices is considered to belong to the same application layer (we merge all applications into one). This simplification can be justified due to the fact that the generated traffic will be similar to the one observed while the application details are hidden in order to make the resulting simulation trace output more readable. Thus, we model all of the data traffic using a number of bidirectional connection channels to a given Internet gateway to/from which we send equally sized packets (the packet size is determined as the average packet size for received and sent packets, respectfully). In order to accommodate for different types of connections, for each connection we can optionally randomly choose the transport protocol (TCP or UDP).

In order to decide on the number of connections as well as the connection duration we need to sample the corresponding CDFs given in Figure 15. After sampling the number of connections for each user, we than independently sample the duration of each connection.

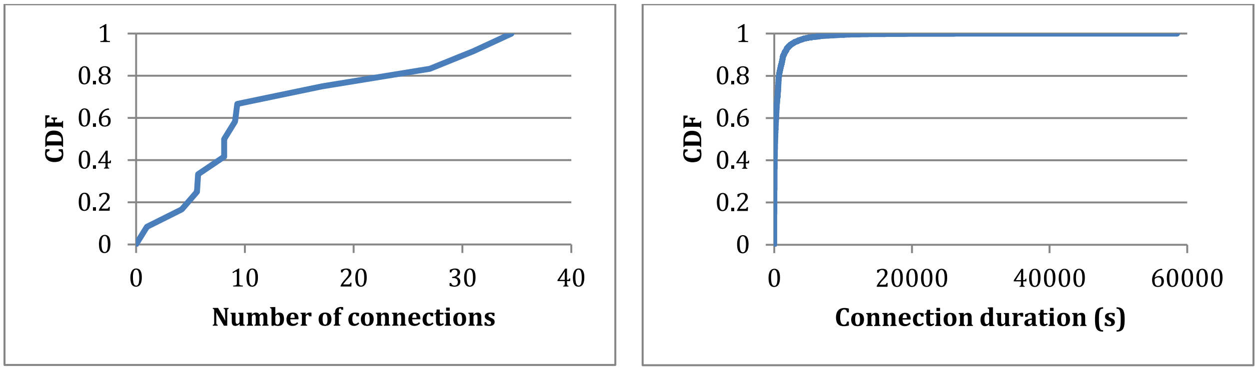


Figure 20: CDFs for the number of connections and connection duration per day

After defining the number of connections and their duration, the next step is to define the dynamic behaviour of the connection in terms of traffic received and sent. This can be done in two possible ways: by using the CDFs that describe the distribution of the amount of received/sent traffic averaged per connection per day, or by utilizing the CDFs that describe the number of packets received/sent averaged per connection per day. For simplicity, sticking to the first order approximation of real life traffic, we incline to using packets with the same size. We argue that the second option of using the CDFs that describe the number of received/send packets per connection will result in a more realistic representation inside the simulator. Thus, as a next step in the process of determining the data traffic that will be defined in the simulation scenario, the traffic generator will take samples from the CDFs that represent the number of received and sent packets per connection, as given in Figure 16, respectively.

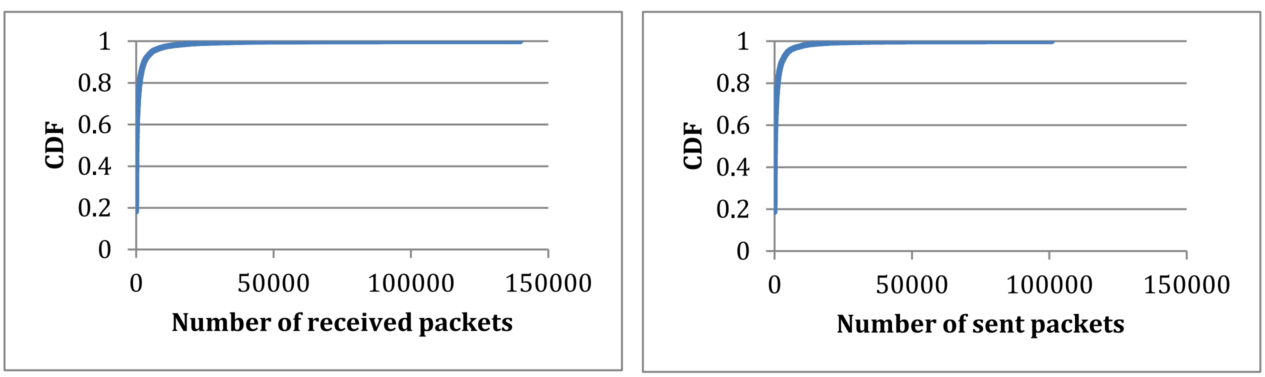


Figure 21: CDFs for the number of received and sent packets per connection

The previous discussion has already hinted that modelling a traffic generator for the observed data traffic is the most difficult task because of the non-homogenous nature of the data traffic. The distributions from which samples can be taken are numerous and which ones will be utilized will depend mostly on the goal and purposes of the simulation. We find that the one example we presented here is useful for general wireless mobile network simulations in which we can observe the network behaviour under realistic traffic on a global macro scale. Due to the highly differential nature of this type of traffic it is extremely difficult to achieve synthetizing traffic that will highly resemble the observed one. The only parameters that will fairly correspond to the real observations are the ones that are chosen to take samples from.

Additionally, the granularity of our gathered data and observations permit for other more complex scenarios that can include heterogeneous scenarios involving different types of data traffic while discerning the network interface used for data transfer, the type of application used, etc. However, for these kinds of especially detailed simulations we propose using the second method of synthetic traffic generation via emulation of an "average" user according to the parameter of interest. In this way, one can fully rely on grasping all of the traffic nuances needed for a realistic simulation scenario. For an example, Figure 17 shows the total amount of traffic received (rx) and sent (tx) for the "average" user chosen as the user closest to the total average traffic.

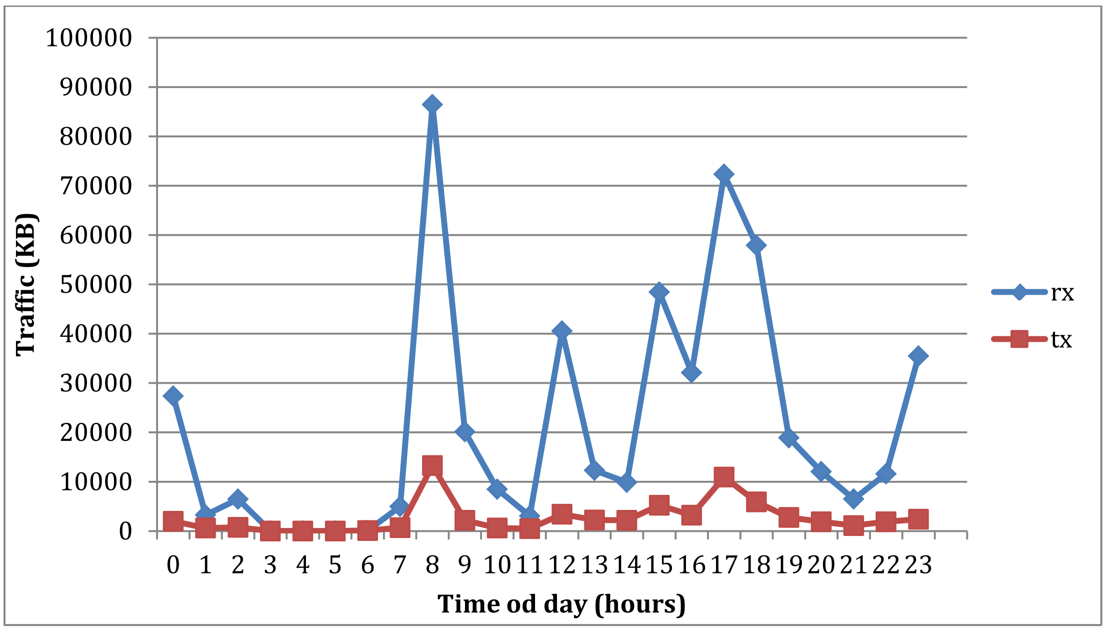


Figure 22: Data traffic exchanged at different time of day by the "average" user

3.4 Additional Possibilities and Mappings

The basic functioning of the synthetic traffic modelling discussed so far offers the possibility of generation of simulation traffic according to two types of modelling (using CDFs or emulation of average users). For each of the chosen modelling type, in order to generate data traffic the generator also needs to be fed with the particular parameters that are of highest interest for modelling. Thus, the resulting traffic scenario becomes a mix of randomly chosen values distributed according to the chosen distributions. As our envisioned generator is continuously connected to the database of gathered data from real life users, with the continuous process of data gathering and user base expansion, the data on which the distributions and emulations are based will become more reliable and will more closely reflect the major traffic properties.

Also, by adding additional mappings to the real life conditions we can obtain traffic scenarios that even closer to the observed traffic patterns. Our future efforts are focused on adding the social dimension to the generator by reverse engineering the social network among the users using the gathered voice call data. With the creation of a social graph of the users we can decide on the destination of every communication more realistically by mapping the communication intensity for each source-destination pair information exchanges.

The gathered data can be used for mapping and researching of the mutual influences between the social and underlying communication networks. The social user interconnection can be represented using a weighted directional graph that will reflect the direction of information flow as well as the frequency and duration. Our preliminary results show that the obtained social graph clearly exhibits the typical social characteristics: a small number of users talk to lots of different users, while the biggest majority call to a standardized smaller group of acquaintances. An interesting observation that arises is that the obtained graph wherein the link weights denote the call frequency and the obtained graph wherein the link weights denote the call duration are almost identical. The differences that occur can pinpoint the users that communicate while not socially acquainted at the same time, while the heavy weighted links reflect strong bonding (family members, friends, etc.).

Other possible mappings we are considering are correlating the user location and time of day in order to conclude his behaviour in different environments (e.g. work, home, out). We expect that this type of correlation should reveal more detailed patterns in the observed traffic. However, our set of users so far have been reluctant about revealing their precise location using GPS and we found that the less accurate positioning using cell towers and WiFi connection info is very coarse and does not reveal significant information so far.

4. CONCLUSION

The proliferation of smart wireless mobile devices has created an enormous and still growing change in the traffic patterns of mobile cellular and WiFi networks. And while the traffic generated from new smartphone and alike devices exponentially grows and surpasses the traditional wired and WiFi PCs networks, the new user demands for high quality wireless connections anytime, anywhere put a lot of pressure on network providers. In order to accordingly adapt to the new demands of today's modern smartphone users, network designers must understand the changes in traffic patterns induced by the smart devices.

Towards this goal, in this paper we investigated the characteristics of the overall traffic (voice calls, messages and Internet data) generated by typical smartphone users. For obtaining our data set we used a background based logging application that was collecting information on all traffic activity on the networking interfaces of the smartphone devices of our selected users. Based on the gathered observations, we have made a statistical analysis of the traffic that is generated during typical user behaviour on a daily basis. Our results have shown different patterns and inclinations of usage that help view the overall traffic characteristics in different time contexts. Thus, we concluded that users tend to use their smartphones over longer periods of interaction during their leisure time (off-work), while business communication over the smartphone is conducted via a greater amount of shorter calls and bursts of data traffic.

We used the results from our statistical analysis as input into a newly designed synthetic mobile traffic generator whose aim is to duplicate the major characteristics of our findings. The proposed generator is intended for use as a source traffic generator for wireless mobile network simulations and modelling in which a more realistic traffic is needed compared to the traditional uniformly random approach. This is especially the case when researchers want to analyse the behaviour of the network, as it would be used in real life scenarios. While designing the traffic model we offer two different approaches: using overall statistics and probability distributions of the major traffic characteristics, or determining the average user among the collected data set and emulating his behaviour. Both approaches have different benefits and pitfalls and can be used for generation of traffic with different characteristics. We also discuss possible extensions of the design that can help overcome some of the unrealistic properties of the initial design. These extensions are mainly based on examining the correlation between the users' traffic and the underlying social network as well as the location. Using these three sets of information (traffic, social connections and location) we can draw conclusions and predict the user behaviour on a very fine level.

However, the main result from our analysis is the high diversity in behaviour of the observed users and their traffic patterns. Large portion of the analysed characteristics shows very high deviations around the averaged value making it difficult to model all users using a simplified one-fits-all model. Thus, in our future work, using comparative statistical and social analysis of the gathered data, we intend to identify groups of similar users. The traffic characteristics of the identified groups can then be used as a basis for an improved socially intelligent and diversified synthetic traffic generator that will be able to capture the real life traffic characteristics in the mobile network with increased fidelity.

ACKNOWLEDGEMENTS

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