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# Temporal Modelling of Mobile Data Traffic Applications for Network Optimisation

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**Electrical and Computer Engineering**

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*To my beloved family*

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# Abstract

The increasing usage and diversity of data applications, in cellular mobile networks, is changing traffic consumption patterns. Studying and gaining a broader understanding of how impactful people's daily lives are in application utilisation, device preferences, operating systems' share, and network resource demands, in the time domain, for both weekdays and weekends, is key to increasing efficient resource usage, network optimisation, and reducing the operators' costs. The purpose of this work is to statistically characterise the observed data by providing visual aids and mathematical models, thus highlighting patterns and better realising the implicit behaviours associated to a live cellular network. This document includes a background on UMTS, LTE, services and applications. A review of the state of the art on the matters of the study is featured. The entities in analysis are the number of active users and traffic usage, for both download and upload. A statistical modelling methodology is used to fit traffic usage, and 8 regression models are obtained, for each study case, and then compared and ranked based on goodness of fit statistics' results, so that the models that best approximated the data are selected. The regression results suggest that a model resembling a tree stump, with 3 sections, is an adequate representation of the average traffic usage, for both download and upload, considering weekdays and weekends, for the streaming application, the smartphone device, and the Android and iOS operating systems.

# Keywords

UMTS; LTE; Mobile Services; Data Applications; Mobile Network Design and Optimisation; Statistical Modelling; Temporal Traffic Models.

# Resumo

O consumo de tráfego na rede móvel tem demonstrado alterações dos padrões de utilização dos serviços e aplicações de dados. Os utilizadores geram diferentes tipos de tráfego, dependendo das suas preferências, da altura do dia e da semana. O desenvolvimento de modelos, com recurso a informação proveniente da rede móvel, vai permitir caracterizar a utilização de tráfego, as preferências de terminal e de sistema operativo, no domínio do tempo, tanto para os dias de semana como de fim de semana; o que pode contribuir para a eficiência da utilização de recursos, otimização da rede móvel, e redução de custos para o operador. O propósito deste trabalho é caracterizar estatisticamente os dados observados, fornecendo ferramentas visuais e modelos analíticos. Este documento aborda as redes de UMTS e LTE, serviços e aplicações; e inclui o estado da arte que motiva o trabalho. As entidades em análise são o número de utilizadores e o tráfego, em download e upload. Uma metodologia de modelação estatística é usada para ajustar 8 modelos de tráfego aos dados, compará-los e ordená-los, de acordo com os resultados das estatísticas para a qualidade do ajustamento, por forma a selecionar os modelos que melhor explicam os dados. O resultado do ajuste de curvas, sugere que um modelo que se assemelha a um tronco de árvore, representa adequadamente a utilização média de tráfego, para streaming, smartphone, Android, e iOS, tanto para download como upload, considerando tanto os dias de semana, como de fim de semana.

# Palavras-chave

UMTS; LTE; Serviços Móveis; Aplicações de Dados; Otimização e Dimensionamento de Redes Móveis; Modelação Estatística; Modelos de Tráfego no Tempo.

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# List of Acronyms

| | |
|---|---|
| 1G | 1st Generation |
| 2G | 2nd Generation |
| 3G | 3rd Generation |
| 3GPP | 3rd Generation Partnership Project |
| 4G | 4th Generation |
| 5G | 5th Generation |
| ACD | Adjusted Coefficient of Determination |
| ANACOM | Autoridade Nacional de Comunicações |
| App | Applications |
| BS | Base Station |
| CA | Carrier Aggregation |
| CAGR | Compound Annual Growth Rate |
| CD | Coefficient of Determination |
| CDF | Cumulative Distribution Function |
| CI | Confidence Interval |
| CN | Core Network |
| CP | Control Plane |
| CS | Circuit Switch |
| D2D | Device-to-Device |
| DCT | Discrete Cosine Transform |
| DDGM | Data Double Gaussian Model |
| Dev | Devices |
| DGM | Double-Gaussian Model |
| DL | Download Link |
| DS-CDMA | Direct-Sequence Code Division Multiple Access |
| DTrM | Data Trapezoidal Model |
| EDGE | Enhanced Data rates for GSM Evolution |
| EPC | Evolved Packet Core |
| EPS | Evolved Packet System |
| E-UTRAN | Evolved UTRAN |
| FDD | Frequency Division Duplex |
| FiTr | File Transfer Applications |
| FTP | File Transfer Protocol |
| GGSN | Gateway General Packet Radio System Support Node |
| GMSC | Gateway Mobile Services Switching Centre |
| GOF | Goodness Of Fit |

| | |
|---|---|
| GPRS | General Packet Radio System |
| GSM | Global System for Mobile Communications |
| HLR | Home Location Register |
| HSDPA | High Speed Downlink Packet Access |
| HSPA | High Speed Packet Access |
| HSS | Home Subscription Service |
| HSUPA | High Speed Uplink Packet Access |
| HTTP | Hypertext Transfer Protocol |
| IM | Instant Messaging |
| IMS | IP Multimedia Sub-System |
| InMe | Instant Messaging Applications |
| IoT | Internet of Things |
| IP | Internet Protocol |
| KPI | Key Performance Indicator |
| LCR | Low Chip Rate |
| LTE | Long Term Evolution |
| LTE-A | Long Term Evolution - Advanced |
| M2M | Machine-to-Machine |
| MBMS | Multimedia Broadcast Multicast Services |
| MBR | Maximum Bit Rate |
| ME | Mobile Equipment |
| MGBR | Minimum Guaranteed Bit Rate |
| MIMO | Multiple Input and Multiple Output |
| MM | Mobility Management |
| MME | Mobility Management Entity |
| MMS | Multimedia Messaging Service |
| MNO | Mobile Network Operator |
| MSC | Mobile Services Switching Centre |
| MSE | Mean Squared Error |
| MSISDN | Mobile Subscriber Integrated Service Digital Network Number |
| MT | Mobile Terminal |
| NU | Number of Active Users |
| OFDMA | Orthogonal Frequency Division Multiple Access |
| OpS | Operating Systems |
| P2P | Peer-to-Peer |
| PC | Personal Computer |
| PCC | Policy and Charging Control |
| PCRF | Policy and Charging Rules Function |
| PDA | Personal Digital Assistant |
| PDF | Probability Density Function |

| | |
|---|---|
| PDN | Packet Data Network |
| P-GW | Packet Data Network Gateway |
| PLMN | Public Land Mobile Network |
| PS | Packet Switch |
| PyM | Pyramid Model |
| QAM | Quadrature Amplitude Modulation |
| QCI | QoS Class Identifier |
| QoS | Quality of Service |
| QPSK | Quadrature Phase Shift Keying |
| RAN | Radio Access Network |
| RMSE | Root Mean Squared Error |
| RNC | Radio Network Controller |
| RNS | Radio Network Subsystem |
| RRM | Radio Resource Management |
| SAE | System Architecture Evolution |
| SC-FDMA | Single Carrier Frequency Division Multiple Access |
| SGSN | Serving General Packet Radio System Support Node |
| S-GW | Serving Gateway |
| SIM | Subscriber Identity Module |
| SIP | Session Initiation Protocol |
| SMS | Short Messaging Service |
| SNS | Social Networking Services |
| SPPP | Spatial Poisson Point Process |
| SwM | Swing Model |
| TCP | Transmission Control Protocol |
| TDD | Time Division Duplex |
| TE | Terminal Equipment |
| TrM | Trapezoidal Function Model |
| TSM | Tree Stump Model |
| UE | User Equipment |
| UL | Upload Link |
| UMTS | Universal Mobile Telecommunications System |
| UP | User Plane |
| USIM | Universal Subscriber Identity Module |
| UTRAN | UMTS Terrestrial Radio Access Network |
| VLR | Visitor Location Register |
| VoIP | Voice over Internet Protocol |
| WAP | Wireless Access Protocol |
| WCDMA | Wideband Code Division Multiple Access |
| WD | Weekdays |

| | |
|---|---|
| WE | Weekends |
| WebAp | Web Applications |
| Wi-Fi | Wireless Fidelity |

# List of Symbols

| | |
|---|---|
| $\alpha$ | level of significance |
| $\Delta R_n$ | percent change |
| $\sqrt{\overline{\varepsilon^2}}$ | root mean squared error |
| $\overline{\mu}$ | global average |
| $\mu_K$ | average |
| $\mu_i$ | average of the $i^{th}$ observation |
| $\overline{\sigma}$ | average standard deviation |
| $\sigma_i$ | standard deviation of the $i^{th}$ observation |
| $\sigma_K$ | dispersion factor |
| $\tau_1$ | first gaussian deviation |
| $\tau_2$ | second gaussian deviation |
| $a_{mdl}$ | auxiliary model coefficient 2 |
| $a_{gauss}$ | double gaussian model |
| $a_{trd1}$ | first exponential initial value |
| $a_{trd2}$ | second exponential initial value |
| $b_{mdl}$ | auxiliary model coefficient 1 |
| $b_{trd1}$ | first exponential decay factor |
| $b_{trd2}$ | second exponential decay factor |
| $b_K$ | initial value |
| $c$ | collection |
| $c_K$ | vertical offset |
| $c_{trd}$ | linear constant value |
| $c_{trd2}$ | second exponential offset |
| $d$ | day |
| $D_{Lilliefors}$ | Lilliefors' test statistic |
| $E$ | entity |
| $h$ | hour |
| $f$ | auxiliary model |
| $f_{exp\,K}$ | exponential equation |
| $f_{gauss\,K}$ | gaussian equation |
| $f_{lin\,K}$ | linear equation |
| $f_n$ | traffic model for the $n^{th}$ case |
| $f_{trapdata}$ | data trapezoidal model |
| $f_{DOUBLE\ GAUSSIAN}$ | double gaussian model |
| $f_{TRIPLE\ GAUSSIAN}$ | triple gaussian model |
| $f_{GAUSSIAN}$ | gaussian model |

| | |
|---|---|
| $f_{PYRAMID}$ | pyramid model |
| $f_{THORNL}$ | thorn left model |
| $f_{THORNR}$ | thorn right model |
| $f_{TRAPZOID}$ | trapezoid model |
| $f_{TREE\ STUMP}$ | tree stump model |
| $F$ | auxiliary function |
| $F_X$ | theoretical CDF |
| $\hat{F}_X$ | empirical CDF |
| $k_K$ | decay rate |
| $l$ | link |
| $m_K$ | scope |
| $n$ | case |
| $N$ | number of observations |
| $N_D$ | number of days |
| $N_H$ | number of hours |
| $N_n$ | number of cases |
| $N_S$ | number of samples |
| $N_u$ | number of active users |
| $p$ | profile |
| $p_1$ | first gaussian amplitude |
| $p_2$ | second gaussian amplitude |
| $P$ | number of predictors |
| $R^2$ | coefficient of determination value |
| $R^2_{adj}$ | adjusted coefficient of determination value |
| $R_n$ | input ratios |
| $R_{obs}$ | observed input |
| $R_{ref}$ | reference input |
| $\bar{R}_w$ | weighted average |
| $t$ | shifted hour time |
| $t_1$ | morning shifted peak hour |
| $t_2$ | afternoon shifted peak hour |
| $t_K$ | translation in time |
| $t_l$ | shifted lunch hour |
| $t_{trd1shift}$ | first breakpoint shifted hour value |
| $t_{trd2shift}$ | second breakpoint shifted hour value |
| $T$ | traffic usage |
| $T_G$ | global traffic model |
| $T_n$ | maximum traffic for the $n^{th}$ case |
| $u_K$ | scaling factor |
| $v_K$ | vertical offset |
| $w_n$ | weight |

| | |
|---|---|
| $\overline{w_h^E}$ | average hour weight, for the $h$ hour, and $E$ entity |
| $\overline{w_{H\ h,n}^E}$ | average hourly ratio, for the $h$ hour, $n$ case, and $E$ entity |
| $\overline{w_{D\ h,n}^E}$ | average daily ratio, for the $h$ hour, $n$ case, and $E$ entity |
| $\overline{w_n^E}$ | average aggregated daily ratio, for the $n$ case, and $E$ entity |
| $\bar{y}$ | average of the observed values |
| $y_{const}$ | normalisation constant |
| $y_i$ | $i^{th}$ observed value (data set) |
| $\hat{y}_i$ | $i^{th}$ predicted value (model) |
| $y_j$ | $j^{th}$ sample |
| $y_{j_{Norm}}$ | normalised observed values |

# List of Software

| | |
|---|---|
| MATLAB R2016a | Numerical simulation software |
| Microsoft Excel 2016 | Spreadsheet software |
| Microsoft Visio 2016 | Diagramming and vector graphics software |
| Microsoft Word 2016 | Word processor software |

# Chapter 1

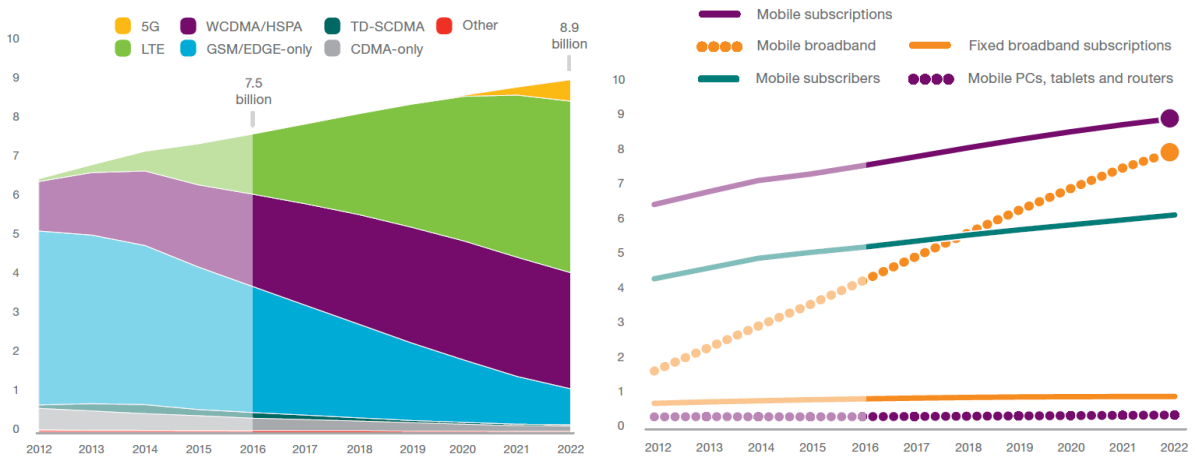
# Introduction

The present chapter establishes the framework of the thesis and presents an overview on the current mobile communications scenario. The motivations are addressed, the problem definition is presented, and the structure for the thesis is provided.

## 1.1 Overview and Motivation

The continuous work and advances in mobile communications, which translates into the development of new technologies, provide continuity to the evolving systems, and allow existing equipment to stay at use; these efforts are grouped into generations. The aim of each new generation is to release features and functionalities that can deliver higher data rates and Quality of Service (QoS), with increased cost efficiency [1]. Introduced in the 1980s, the 1st Generation (1G) of mobile communications only provided voice, with some supplementary services, and consisted of independent analogue systems. The analogue systems had limitations which restricted the general use of mobile devices. The introduction of digital systems allowed an increase in QoS, and the possibility to develop more compact devices. The Global System for Mobile Communications (GSM), introduced in the 1990s, was the first digital mobile communication system, and is known as the 2nd Generation (2G) of mobile communications. The services introduced with 2G, included the Short Message Service (SMS), e-mail and other service applications, at very low data rates. Originally, the system only supported circuit switching, and was improved over time to include data communications through packet transmission, with the development of the General Packet Radio System (GPRS), latter complemented with the radio interface improvements in Enhanced Data rates for GSM Evolution (EDGE). The success of packet transmission services propelled the search and development of solutions for the provision of better QoS and improved capacity. The 3rd Generation Partnership Project (3GPP) was created to unify and standardise the mobile communications systems' development, while assuring compatibility with the previous systems. The 3rd Generation (3G) of mobile communications, Universal Mobile Telecommunications System (UMTS), was introduced in the beginning of the new millennium, with significant improvement of the radio interface. Long Term Evolution (LTE), the 4th Generation (4G) of mobile communications, was designed to provide improved data rates, reduced latency, reduced cost-per-bit, simplified architecture with an all Internet Protocol (IP) network, and improved spectrum efficiency; while allowing compatibility with previous systems. LTE-Advanced (LTE-A), introduced Carrier Aggregation (CA), enabling multiple LTE carriers to be used together to provide higher data rates; relaying, for enhancing both coverage and capacity; and, compatibility for heterogeneous networks. Since the development of EDGE, peak data rates have increased more than 600 times. The 5th Generation (5G) of mobile communications is currently under development, and aims at providing higher capacity, allowing a higher density of mobile broadband users, supporting Device-to-Device (D2D) communications, and the increasing number of Machine-to-Machine (M2M) communications. For better implementation of the Internet of Things (IoT), 5G is being designed to provide lower latency and lower battery consumption, than previous generations [1].

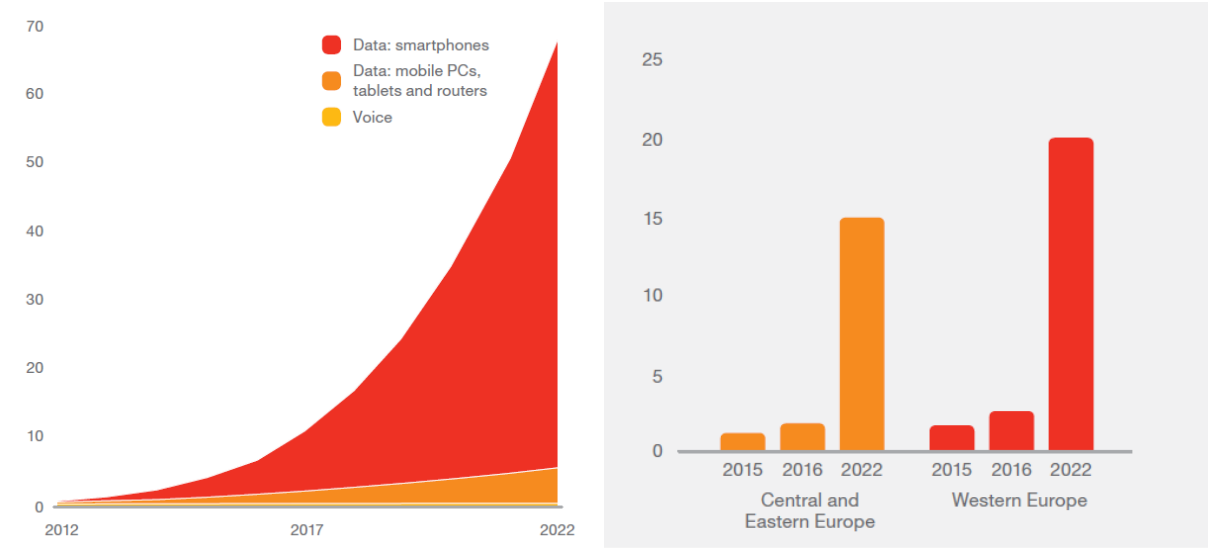
Figure 1.1 (a) depicts the number of mobile subscriptions by mobile communication technology. LTE is anticipated to become the dominant mobile access technology in 2019. 5G networks are expected to be available, and introduced by most operators, by 2020; and, by the end of 2022, the number of 5G subscribers is expected to reach around 550 million. As seen in Figure 1.1 (b), from 2016 to 2022, an increase of 1.5 billion new mobile subscribers is anticipated; and, by 2022, mobile broadband subscriptions are expected to account for 90% of all mobile subscriptions [2].




(a) Mobile subscriptions by technology (billion). (b) Subscriptions and subscribers (billion).

Figure 1.1 – Mobile subscriptions outlook (adapted from [2]).

Total mobile data traffic is expected to increase at a Compound Annual Growth Rate (CAGR) of around 45%. Between 2016 and 2022, total mobile traffic for all devices is expected to increase by 8 times, and smartphone traffic by 10 times, see Figure 1.2 (a). By 2022, smartphones will generate more than 90% of the mobile data traffic. Western Europe, is set to reach more than 2.7 GB per month, per smartphone, from 2016 onwards. In 2022, see Figure 1.2 (b), monthly mobile data traffic per active smartphone, in Europe, will reach values between 15 and 20 GB [2].



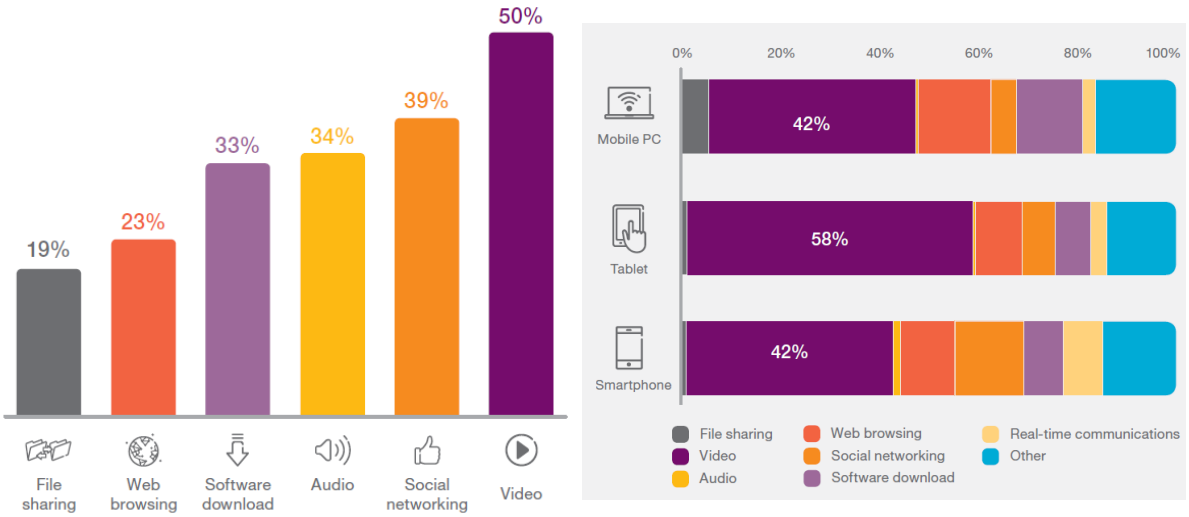

(a) Global mobile traffic (EB per month). (b) Data traffic per smartphone (GB per month).

Figure 1.2 – Mobile traffic outlook (adapted from [2]).

New mobile data services and smart devices have brought mobile operators a large number of new subscribers, causing an increase in traffic usage and service demand. Mobile operators must find strategies for resource management, to meet the ever-increasing network capacity requirements. Smartphones have led to explosive growth in traffic over cellular networks; both in volume, and traffic characteristics diversity. New mobile Internet applications differ from traditional ones, such as web browsing and File Transfer Protocol (FTP), in that they may use always-on connectivity, and generate

a large amount of signalling traffic, leading to significant changes in the observed traffic patterns [3], [4].

Between 2016 and 2022, mobile video traffic is expected to become increasingly dominant and show the highest annual growth, regardless of device type, see Figure 1.3. The growth in the video category, forces the relative share of overall traffic, associated with the remaining applications, to decrease [2]. Larger device screens, higher resolution, and new platforms for live streaming, cause an increase of the use of embedded video in social media and web pages, which contributes to the growth of video traffic usage. Tablets and smartphones are expected to be used equally for watching short video content [2]. The increase in traffic usage in download, must be followed by a low time-to-content in upload, since if the upload speed drops too low, it will limit the speed content can be transferred.




(a) Mobile traffic by application category CAGR 2016-2022 (percent).

(b) Mobile data traffic volumes by application category and device type (percent).

Figure 1.3 – Mobile traffic by application category (adapted from [2]).

Mobile phones have been the fastest growing segment among devices; the M2M segment is expected to experience a boom in the years to come, and IoT devices, may include connected cars, machines, meters, wearables and other consumer electronics. By 2020, around 26 billion connected devices are expected, of which, almost 15 billion will be phones, tablets, laptops and PCs [5]. Figure 1.4 illustrates the expected evolution of the number of connected devices, between 2012 and 2020.

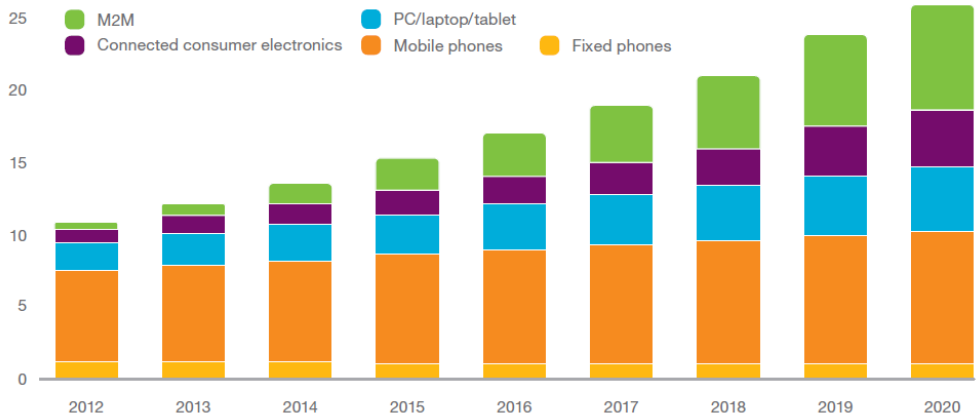



Figure 1.4 – Connected devices (billions) (adapted from [5]).

## 1.2 Problem Definition and Content

Mobile communications systems were firstly designed for voice services. Nowadays, data applications are the main source of traffic in a mobile network. Mobile Network Operators (MNO) have to constantly adapt and upgrade their network to keep up with the increasing demands of network resources, while managing infrastructures and looking for efficient resource usage measures.

Studying and gaining a broader understanding of how impactful people's daily lives, and routines, are in application utilisation, device and operating system preferences, and network resource demands, is a step towards knowing which measures to take, and changes to implement, towards network optimisation. The purpose of this work is to characterise and represent the observed data, by providing visual aids and mathematical models; thus, highlighting patterns and recognising the implicit behaviours associated with the number of active users, traffic usage, weekdays, weekends, applications, devices, and operating systems. The data used for this work was collected at the core level of the Vodafone Portugal network, in Portugal, Lisbon.

This study focuses on 10 applications, 6 devices, and 4 operating systems, adding up to 20 distinct cases. An exploratory data analysis is performed, for each case, regarding the number of active users and traffic usage, for both the download link and upload link, while considering two temporal scenarios, weekdays and weekends, in a total of 40 study cases. Data characterisation, from a statistical viewpoint, is performed, for each case, regarding the traffic usage, for both the download link and upload link, while considering the weekdays and weekends separately, in a total of 80 study cases. Four scenarios are considered: download traffic usage during weekdays; upload traffic usage during weekdays; download traffic usage during weekends; and, upload traffic usage during weekends.

For each one of the 80 study cases, statistical modelling is performed, and 8 regression models obtained. The regression models used are referred to as: Trapezoid; Tree Stump; Pyramid; Thorn Left; Thorn Right; Gaussian; Double Gaussian; and, Triple Gaussian. Each model can be viewed as a combination of sections, up to a maximum of three, which can be represented by Exponential equations, Gaussian equations, and/or Linear equations. A total of 640 models are obtained; the models are checked and tested against two distinct sets of data, a training set, and a validation set.

Three goodness of fit statistics, the Root Mean Squared Error (RMSE), the Coefficient of Determination (CD), and the Adjusted Coefficient of Determination (ACD), are computed, for each section of the 8 models. Concerning the 640 models, and the three goodness of fit statistics, a total of 1920 values are examined and compared, by inspection of results tables, to rank the 8 models associated with each study case. With this process, the two best ranked models are identified, for a total of 160 models, from the initial 640; and one general model is elected, for a total of 80 models, from the initial 640. Each general model is inspected to gather features of daily life and peoples' routines; and, by combining the individual results of each study case, a global traffic curve is uncovered, and overall traffic usage is studied.

The thesis is comprised of five chapters: Introduction, Fundamental Concepts, Model Development and

Implementation, Results Analysis, and Conclusions; complementary results and additional materials may be found in the annexes at the end of this thesis.

Chapter 1, the present chapter, establishes the framework of the thesis and presents an overview on the current mobile communications scenario. The motivations are addressed, the problem definition is presented, and the structure for the thesis is provided. Chapter 2 provides a background on the fundamental concepts of UMTS and LTE networks, detailing the architectures and radio interfaces; and the assigned frequency bands. The quality of service is addressed for both UMTS and LTE. Service classes and popular applications are briefly mentioned. The characterisation of traffic models is discussed. The state of the art gathers the research that motivates the exploratory data analysis and the development of models. Chapter 3 comprises the development framework and the implementation description, used in the exploratory analysis of the number of active users and traffic usage, and to obtain the models for the statistical characterisation of traffic usage, from a live cellular network. The data is structured and analysed. The models are compared and ranked based on goodness of fit statistics' criteria. The regression results are found at the end. Chapter 4 includes the models' assessment and the traffic usage analysis for the obtained models. The impact daily life and peoples' routines have on network resources is presented for applications, devices and operating systems. Recommendations and considerations are addressed for network optimisation and efficient resource usage. Chapter 5 summarises the development, implementation, and results of the work done, and contains recommendations and suggestions for the applicability of the accomplished work.

# Chapter 2

# Fundamental Concepts

This chapter provides a background on the fundamental concepts of UMTS and LTE networks, detailing the architectures and radio interfaces. The quality of service is addressed for both UMTS and LTE. Service classes and popular applications are briefly mentioned. The characterisation of traffic models is discussed. The state of the art gathers the research that motivates the exploratory data analysis and the development of models.

## 2.1 UMTS

The UMTS architecture is divided into 3 modules: User Equipment (UE), UMTS Terrestrial Radio Access Network (UTRAN) and Core Network (CN). The Radio Interface, Uu, connects the UE to the UTRAN; and the CN-UTRAN interface, Iu, connects the UTRAN to the CN [6]. Figure 2.1 depicts the network architecture.

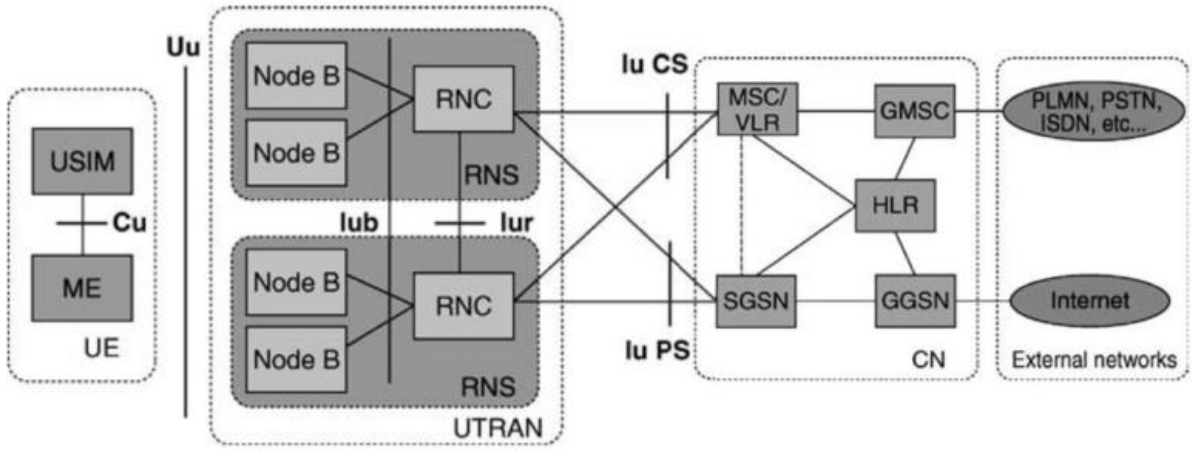



Figure 2.1 – UMTS network architecture (adapted from [7]).

The UE aggregates the Mobile Equipment (ME) and the Universal Subscriber Identity Module (USIM). The ME is the Mobile Terminal (MT) used for radio communication over the Uu interface. The USIM is a smartcard that holds the subscriber identity, performs authentication algorithms, stores authentication and encryption keys, and information needed at the terminal. The Cu interface enables the communication between the USIM and the ME.

The UTRAN is composed of several Radio Network Subsystems (RNS). Each RNS includes a Radio Network Controller (RNC) and the NodeBs. The Iub interface connects the RNC to the NodeB's. The Node B, which represents the Base Station (BS), converts the data flow between the Iub and the Uu interfaces, and participates in the Radio Resource Management (RRM). The RNC controls the NodeB's connected to it, and also executes the RRM. The Iur interface enables the connection between RNCs. The RRM assures the outer loop power control, the packet scheduling, and the handover control. The UTRAN functions are handover; provision of radio coverage; RRM and control; system access control; security and privacy.

The CN aggregates the Packet Switch (PS) network and the Circuit Switch (CS) network. The first is responsible for switching and routing calls and data to external networks, and the second is responsible for the public switched telephone network. The CN gathers the Home Location Register (HLR), the Mobile Services Switching Centre/Visitor Location Register (MSC/VLR), the Gateway MSC (GMSC), the Serving General Packet Radio System (GPRS) Support Node (SGSN), and the Gateway GPRS Support Node (GGSN). The HLR is a database where the operator subscriber's information is stored, such as allowed services, user location for routing calls, and preferences. The MSC/VLR is the switch (MSC) and database (VLR) which serves the UE in its location CS services. The GMSC is where all

incoming and outgoing CS connections are carried by; it is the switch, at the point where UMTS Public Land Mobile Network (PLMN) is connected to external CS network. The SGSN has similar functionalities to MSC/VLR, but is normally used for PS services. The GGSN functionality is analogous to that of GMSC but is in relation to PS services. The CN functions are mobility management; operations, administration and maintenance; switching allowance; service availability; transmission of MT traffic between UTRAN(s) and/or fixed network(s).

The UMTS air interface technology is based on WCDMA, a wideband Direct-Sequence Code Division Multiple Access (DS-CDMA) system. In order to reduce interference between users, the codes are orthogonal to each other. UMTS operates in the Frequency Division Duplex (FDD) mode. For Portugal, UMTS-FDD uses the assigned frequency ranges: [1920, 1980] MHz for the Upload Link (UL), and [2110, 2170] MHz for the Download Link (DL) [8]. UMTS has a channel separation of 5 MHz, a chip rate of 3.84 Mcps, and a 4.4 MHz channel bandwidth. The user data rates may vary on many factors, such as the link quality, the service, and release; the theoretical data rates are comprised in Table 2.1.

Table 2.1 – Data rates in UMTS (extracted from [9]).

| **Service** | **Release** | **Data rate [kbps]** | |
|---|---|---|---|
| | | **Uplink** | **Downlink** |
| **Voice** | 99 | 12.2 | 12.2 |
| **Data** | 99 | < 64.0 | < 384.0 |
| | 5 (HSDPA) | < 384.0 | < 14 400.0 |
| | 6 (HSUPA) | < 5 800.0 | < 14 400.0 |
| | 7 (HSPA+) | < 11 500.0 | < 28 000.0 |

## 2.2 LTE

As a result of 3GPP work on the LTE standard, the System Architecture Evolution (SAE) is a flat Radio Access Network (RAN) architecture, organised in four domains: UE, Evolved Packet Core (EPC), Evolved UTRAN (E-UTRAN), and Services. The IP Connectivity Layer, also known as the Evolved Packet System (EPS), gathers the UE, the E-UTRAN and the EPC [10], [11].

The UE includes the Terminal Equipment (TE) and the Universal Subscriber Identity Module (USIM), used to authenticate and identity the user; it communicates with the network in order to establish, maintain, and remove, its connection. IP is the protocol used to transport all services; therefore, the EPC does not have a circuit-switched domain.

The EPC ensures the overall control of the UE, and is responsible for the bearers' establishment; it is composed by the Mobility Management Entity (MME), the Serving Gateway (S-GW), the Packet Data Network Gateway (PDN Gateway, P-GW), the Policy and Charging Rules Function (PCRF), and the Home Subscription Service (HSS). The MME is the main Control Plane (CP) element in the EPC, and processes the signalling between the UE and the EPC. It supports functions related to connection management, and handles the inter-working with other networks. The S-GW ensures the User Plane (UP) tunnel management and switching; this node acts as a local mobility anchor between evolved

Nodes B (eNodeBs), and collects information and statistics necessary for charging. The P-GW connects the EPC to external packet data networks; it deals with the allocation of the IP address for each terminal, as well as QoS enforcement, and flow-based charging. The PCRF provides the Policy and Charging Control (PCC), deciding on the QoS associated with each service. The HSS is a database server that records the location and all permanent data from the user.

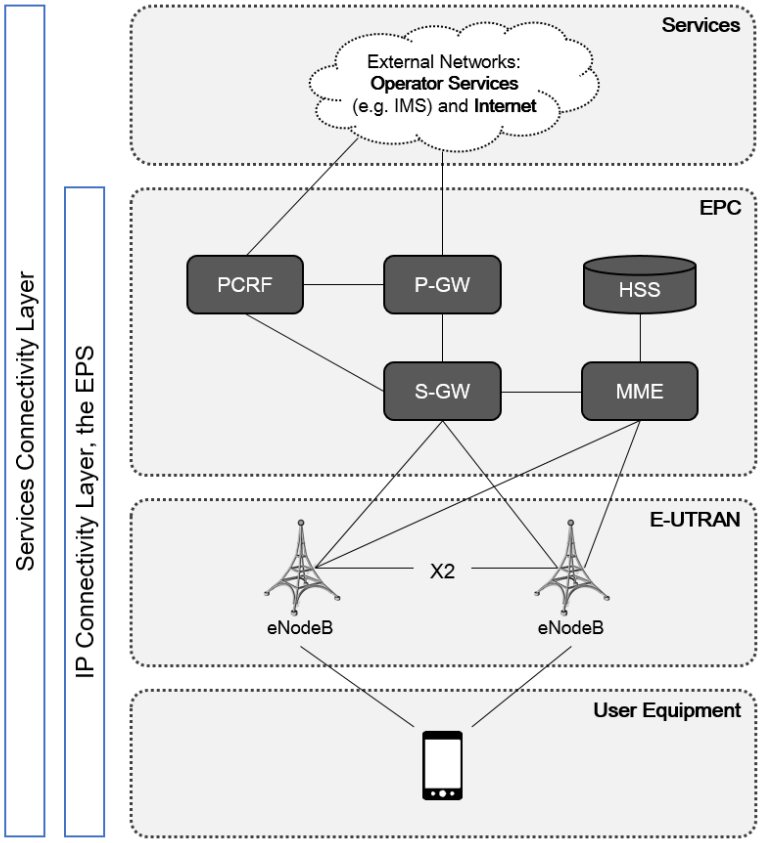



Figure 2.2 – System architecture for an E-UTRAN only network (extracted from [12]).

The E-UTRAN is a mesh of eNodeBs; the eNodeBs are connected within the mesh by means of the X2 interface, and to the EPC through the S1 interfaces. The eNodeBs handle the RRM, the Mobility Management (MM), the IP header compression, and the ciphering of user data streams. The RRM controls the usage of the radio interface, by allocating resources according to requests, performing UL/DL scheduling in accordance with the required QoS and is continuously monitoring the resources availability. The MM performs handover decisions based on the analysis of radio signal level measurements, executed both at the UE and at the eNodeB, and deals with the exchange of handover signalling between eNodeBs and the MME. The IP header compression allows an efficient use of the radio interface. The ciphering of user data streams is done as a security measure. The services are provided by the mobile network operator or via Internet.

In Portugal, the adopted LTE bands are: 800 MHz, 1 800 MHz, and 2.6 GHz [13]. The current spectrum allocation for LTE-FDD in Portugal [13] is as follows: LTE 800, [832, 862] MHz for the UL, and [791, 821] MHz for DL; LTE 1800, [1805, 1880] MHz for the UL, and [1710, 1785] MHz for DL; LTE 2600, [2630, 2690] MHz for the UL, and [2510, 2570] MHz for DL.

In what concerns multiple access techniques, LTE uses Orthogonal Frequency Division Multiple Access

(OFDMA) in DL, and Single Carrier Frequency Division Multiple Access (SC-FDMA) in UL. LTE allows up to six different bandwidths for the radio channels, as shown in Table 2.2, depending on the number of sub-carriers allocated, in a period of time, to a user.

Table 2.2 – Relationship between the bandwidth, the number of sub-carries and the number of resource blocks (extracted from [9]).

| **Bandwidth [MHz]** | 1.4 | 3 | 5 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|
| **Number of sub-carries** | 72 | 180 | 300 | 600 | 900 | 1200 |
| **Number of Resource Blocks** | 6 | 15 | 25 | 50 | 75 | 100 |

In what concerns modulation, LTE uses both Quadrature Phase Shift Keying (QPSK) and Quadrature Amplitude Modulation (QAM). For DL one has QPSK, 16QAM or 64QAM; and, for UL, only UE of category 5, 7 or 8 allow a modulation up to 64QAM. The first five categories are present in Release 8, 9 and 10; categories 6, 7 and 8 were introduced in Release 10; furthermore, not all UE categories support MIMO, which will restrain the peak throughput achievable by a UE. Nonetheless, considering the maximum allowed modulation scheme and MIMO support, if available, one can obtain the peak throughput of UE, per category, as presented in Table 2.3, for UL and DL.

Table 2.3 – UE's categories in LTE (adapted from [14])

| **UE Category** | **Peak throughput [Mbps]** | |
|---|---|---|
| | **UL** | **DL** |
| **1** | 5 | 10 |
| **2** | 25 | 50 |
| **3** | 50 | 100 |
| **4** | 50 | 150 |
| **5** | 75 | 300 |
| **6** | 50 | 300 |
| **7** | 150 | 300 |
| **8** | 1500 | 3000 |

## 2.3 Services and Applications

In UMTS, traffic is classified into four QoS classes: Conversational, Streaming, Interactive, and Background; following 3GPP specifications. The QoS classes are compared in Table 2.4, based on their performance requirements; the distinguishing factors are the traffic delay, the guaranteed bit rate, and the services priorities. The delay sensitivity is highlighted as the major differentiating factor. The Conversational class corresponds to the traffic with the highest delay sensitivity; while, the Background class corresponds to the lowest one.

In the Conversational class, the emphasise goes to speech; due to its conversational nature, the real time conversation scheme is characterised by a low transfer time. The human perception of video and audio conversation, limits the acceptable communication delay. This class has maximum priority over network resources; the maximum transfer delay must be met in order to guaranty QoS; and, traffic is assumed to be symmetric. Voice over Internet Protocol (VoIP), is an example of a conversational service, characterised by a constant bit rate. For the Streaming class, when the MT uses real time audio

and video, the real time streams scheme applies. Multimedia streaming is a technique for transferring data that enables the end user to access the data before the transfer is completed. Most of the streaming services are asymmetric, and more delay tolerant; nonetheless, the delay variation must be limited, to preserve the time relations of the end-to-end flow. In the Interactive class, traffic is assumed to be asymmetric, and the message is expected to arrive within a certain time; also, the content of the packets must be transferred transparently, with low bit error rate. The service is provided to a MT, either a machine or a human, which requests data from a remote equipment; examples of human interaction are web browsing, Social Networking Services (SNS), Instant Messaging (IM), and FTP; and, an example of machines interaction is automatic data base enquiries. For the Background class, traffic is asymmetric, and the destination does not expect the data within a certain interval, and immediate action is not required; in other words, transmission delay is not critical. The delay variation is more flexible, ranging from seconds, to minutes, to hours. This range of services gives priority to other classes. Examples of background applications are SMS, and background delivery of emails.

Table 2.4 – UMTS QoS Classes (adapted from [9]).

| | | **Service Class** | | | |
|---|---|---|---|---|---|
| | | Conversational | Streaming | Interactive | Background |
| **Main Attributes** | Real time | Yes | Yes | No | No |
| | Symmetric | Yes | No | No | No |
| | Guaranteed Rate | Yes | Yes | No | No |
| | Delay | Minimum Fixed | Minimum Variable | Moderate Variable | High Variable |
| | Buffer | No | Yes | Yes | Yes |
| | Bursty | No | No | Yes | Yes |
| | Example | Voice | Video Streaming | Web Browsing | Email, SMS |

Some examples of always-on background applications include Facebook, Skype and Messengers; keep-alive messages are short and frequent, and one of the main components of background traffic. Background traffic mainly consists of traffic from unattended phones with applications not in active stage; and can be classified either as light or heavy background traffic. Light background traffic, is generally associated with lower mean data rates and lower mean number of packets per second, as well as less packets in a burst, and represents a small contribution for signalling overhead and UE battery consumption; heavy background traffic, corresponds to the opposite situation. Facebook and Skype are examples of light and heavy background traffic, respectively. In the case of Skype, a Peer-to-Peer (P2P) structure is used, and even if the user is not using the application, the smartphone's computational and bandwidth resources may be used for background signalling. In the case of persistent Transmission Control Protocol (TCP) based applications, the exchange of keep-alive messages maintains the TCP connection; TCP applications running on a smartphone, produce independent keep-alive messages, and with more applications installed, the total packet number rapidly increases [4], [15].

In LTE, all provided services are packet based, and applications with distinct QoS requirements can operate simultaneously in a UE. In order to cover all requirements, different bearers are set within the EPS, to reflect the QoS they assure. According to [11], those bearers can be classified into two categories: the Minimum Guaranteed Bit Rate (GBR) bearer, and the Non-GBR bearers. The GBR, is used for applications with an associated GBR value, for which dedicated transmission resources are permanently allocated, at bearer establishment or modification. Bit rates higher than the GBR may be

allowed if resources are accessible, which entails the definition of a Maximum Bit Rate (MBR) parameter, that sets an upper limit to the available bit rate. The Non-GBR, can be used for applications that require no guarantees in terms of bit rate, such as web browsing or FTP transfer; therefore, no bandwidth resources are allocated, in a permanent way, for these bearers. Each bearer has an associated QoS Class Identifier (QCI), characterised by priority, packet delay budget, and acceptable packet loss ratio. The QCI determines the corresponding QoS to be ensured in the access network, by the eNodeB. The standardisation of QCIs allows for vendors to have a uniform understanding of the underlying service characteristics, regardless of the manufacturer of the eNodeB equipment. The standardised QCIs and their characteristics are shown in Table 2.5. In Table 2.6 each service is characterised by its minimum, average, and maximum bit rate; and also, its duration or size. As shown in Table 2.7, mobile internet applications may be categorised as VoIP, Video Call, streaming, FTP, web browsing, SNS, IM, cloud, email, gaming and M2M. Some of the more popular data applications are highlighted in Table 2.8.

Table 2.5 – Standardised QCIs for LTE (extracted from [16]).

| QCI | Resource Type | Priority | Packet Delay Budget [ms] | Packet Error Loss Ratio | Example Services |
|---|---|---|---|---|---|
| 1 | GBR | 2 | 100 | $10^{-2}$ | Conversational Voice |
| 2 | | 4 | 150 | $10^{-3}$ | Conversational Video (Live Streaming) |
| 3 | | 3 | 50 | $10^{-3}$ | Real Time Gaming |
| 4 | | 5 | 300 | $10^{-6}$ | Non-Conversational Video (Buffered Streaming) |
| 5 | Non-GBR | 1 | 100 | $10^{-6}$ | IMS Signalling |
| 6 | | 6 | 300 | $10^{-6}$ | Video (Buffered Streaming), TCP-based (e.g. www, email, chat, FTP, P2P file sharing, progressive video, etc.) |
| 7 | | 7 | 100 | $10^{-3}$ | Voice, Video (Live Streaming), Interactive Gaming |
| 8 | | 8 | 300 | $10^{-6}$ | Video (Buffered Streaming), TCP-based (e.g. www, email, chat, FTP, P2P file sharing, progressive video, etc.) |
| 9 | | 9 | | | |

Table 2.6 – Services characteristics (adapted from [17]).

| Service | | Service Class | Bit Rate [Mbit/s] | | | Duration [s] | Size [kB] |
|---|---|---|---|---|---|---|---|
| | | | Min. | Average | Max. | | |
| VoIP | | Conversational | 0.005 | 0.012 | 0.064 | 60 | - |
| Streaming | | Streaming | 0.016 | 0.064 | 0.160 | 90 | - |
| FTP | | Interactive | 0.384 | 1.024 | - | - | 2042.00 |
| Web Browsing | | Interactive | 0.031 | 0.500 | - | - | 180.00 |
| SNS | | Interactive | 0.024 | 0.384 | - | - | 45.00 |
| Email | | Background | 0.010 | 0.100 | - | - | 300.00 |
| M2M | Smart Meters | Background | - | 0.200 | - | - | 2.50 |
| | e-Health | Interactive | - | 0.200 | - | - | 5611.52 |
| | ITS | Conversational | - | 0.200 | - | - | 0.06 |
| | Surveillance | Streaming | 0.064 | 0.200 | 0.384 | - | 5.50 |
| Video | Calling | Conversational | 0.064 | 0.384 | 2.048 | 60 | - |
| | Streaming | Streaming | 0.500 | 5.120 | 13.000 | 3600 | - |

Table 2.7 – Mainstream mobile internet categories characteristics (adapted from [18]).

| Category | Description | Typical Application | Characteristic |
|---|---|---|---|
| **IM** | Sending or receiving instant messaging | WhatsApp, WeChat, iMessage | Small packets, less frequently |
| **VoIP/Video Call** | Audio and video calls | Viber, Skype, Tango, Face Time, WhatsApp | Small/large packets, continuously |
| **Streaming** | Streaming media such as HTTP audios, HTTP videos, and P2P videos | YouTube, Youku, Spotify, Pandora, PPStream | Big packets, continuously |
| **SNS** | Social networking websites | Facebook, Twitter, Sina Weibo | Small packets, less frequently |
| **Web Browsing** | Web browsing including Wireless Access Protocol (WAP) page browsing | Typical web browsers are Safari and UC Browser | Big packets, less frequently |
| **Cloud** | Cloud computing and online cloud applications | Siri, Evernote, iCloud | Big packets |
| **Email** | Webmail, Post Office Protocol 3 (POP3), and Simple Mail Transfer Protocol (SMTP) | Gmail | Big packets, less frequently |
| **FTP** | File transfer including P2P file sharing, file storage, and application download and update | Mobile Thunder, App Store | Big packets, continuously |
| **Gaming** | Mobile gaming such as social gaming and card gaming | Angry Birds, Draw Something, Words with Friends | Big packets, less frequently |
| **M2M** | Machine Type Communication | Auto meter reading, mobile payment | Small packets |

Table 2.8 – Data applications characterisation.

| Application | Service Class | Service |
|---|---|---|
| **Skype** | Interactive | IM, FTP |
| | Conversational | VoIP, Video call |
| | Background | Keep-alive messages |
| **WhatsApp Messenger** | Interactive | IM, FTP |
| | Conversational | VoIP |
| | Background | Keep-alive messages |
| **Youtube** | Streaming | Video |
| **Spotify** | Streaming | Music |
| **Netflix** | Streaming | Video |
| **Twitter, Instagram** | Interactive | SNS |
| **Facebook** | Interactive | IM, FTP, SNS |
| | Background | Keep-alive messages |

## 2.4 Traffic Models

Traffic usage is shaped by people's daily lives, and routines; thus, for different times of the day and week, and different places and regions, the traffic usage behaviour may change. One should acknowledge the diversity of applications, services and traffic usage, for both spatial and temporal domains; geographical areas can be classified into rural, suburban, urban and dense urban; time may be sectioned into different intervals, such as hours, weekdays, weekends, months, seasons, or even the school and holiday periods. It may also be of value to distinguish residential and business usage.

Geographical characterisation reflects the broad range of radio environments and data traffic

requirements. Taking into consideration collected data from the Portuguese census of 2011, concerning population density, the locality granularity is classified into four geotypes: dense urban, urban, suburban and rural [19], as portrayed in Table 2.9.

Table 2.9 – Geotypes characterisation (adapted from [20]).

| **Geotype** | **Population density** $(\mathrm{pop/km^2})$ |
|---|---|
| Dense Urban | $d > 14000$ |
| Urban | $1100 < d < 14000$ |
| Suburban | $100 < d < 1100$ |
| Rural | $d < 100$ |

The areas that belong to a certain geotype share common radio propagation profiles. The dense urban geotype is characterised by high proportion of population in a small area, which requires a network deployment of cells with small radii; in the opposite end, the rural geotype has less population density and cells with larger radii [21], [22].

Applying the aforementioned classification for granularity, the dense urban and urban geotypes represent 1.6% of the Portuguese territory, and more than 50% of the voice and data traffic; while most of the territory is classified as rural, and is only responsible for roughly 10% of traffic [20]. These results are summarised in Table 2.10. High population density is associated with smaller radii cells, as shown in Table 2.11, where the theoretical coverage radii for each spectrum band is presented.

Table 2.10 – Area, population and mobile traffic by geotype in Portugal (adapted from [20]).

| **Geotype** | **Area** [%] | **Population (2011 census)** [%] | **Voice traffic** [%] | **Data traffic** [%] |
|---|---|---|---|---|
| Dense urban | 0.01 | 1.54 | 3.89 | 3.05 |
| Urban | 1.59 | 38.75 | 54.00 | 49.26 |
| Suburban | 17.07 | 42.03 | 31.95 | 36.91 |
| Rural | 81.32 | 17.67 | 10.15 | 10.79 |
| Total | 100.00 | 100.00 | 100.00 | 100.00 |

Table 2.11 – Theoretical cell radius (km) (adapted from [20]).

| **Geotype** | **800MHz** | **900MHz** | **1800MHz** | **2100MHz** | **2600MHz** |
|---|---|---|---|---|---|
| Dense urban | 0.55 | 0.45 | 0.40 | 0.38 | 0.35 |
| Urban | 1.96 | 1.61 | 1.43 | 1.39 | 1.27 |
| Suburban | 5.42 | 4.46 | 3.95 | 3.84 | 3.50 |
| Rural | 6.01 | 4.95 | 4.38 | 4.31 | 3.89 |

Traffic is unevenly distributed among geotypes; these differences may be related with the fact that urban areas are characterised by higher data and voice consumption, and easier access to technology and network resources; also, companies and business offices, with high traffic demands, usually are concentrated in these areas, where state of the art technologies and network solutions are firstly deployed [21]. To reflect the everyday quotidian activities, a geographic locality can be classified into residential, business or commercial area [23]. Residential areas are characterised by dwellings or blocks of apartments, showing more activity in the morning and end of the day, with a possible increase during the lunch break [24]. Urban centres are mostly characterised by business and commercial activity. Business areas represent higher communication needs, and are mostly active during the workday, from 8:00 to 19:00, with a slight decrease at lunch break [21]. Commercial areas experience larger afflux during mealtime, with a peak at lunch break, and also on weekends or holiday periods [25], [24]. Within

these areas, there are clusters that require specific attention; namely, schools, universities, hospitals, concert and festival arenas, and sport stadiums.

Suggestions for modelling voice and data traffic are presented for the temporal domain, for the duration of the day, in the literature. Voice traffic is well represented by a Double Gaussian curve; and, data traffic usage resembles a tree stump shape. In [26], a voice traffic model, referred to as Double Gaussian Model, is proposed; the model consists of two sections, representing the morning and afternoon peaks, and is defined by two adjusted gaussian functions, as depicted in Figure 2.3 (a), and expressed by,

$$a_{gauss\,(t)} = \begin{cases} p_1 e^{-\frac{(t-t_1)^2}{2\tau_1^2}}, & t < t_l \\ \min\left(p_1 e^{-\frac{(t-t_1)^2}{2\tau_1^2}}\,;\, p_2 e^{-\frac{(t-t_2)^2}{2\tau_2^2}}\right), & t = t_l \\ p_2 e^{-\frac{(t-t_2)^2}{2\tau_2^2}}, & t > t_l \end{cases} \tag{2.1}$$

where:

- $t$: shifted hour time, 5 hours earlier, to obtain a simple analytical model;
- $p_1$: first gaussian amplitude;
- $t_1$: morning shifted peak hour;
- $\tau_1$: first gaussian deviation;
- $t_l$: shifted lunch hour;
- $p_2$: second gaussian amplitude;
- $t_2$: afternoon shifted peak hour;
- $\tau_2$: second gaussian deviation.

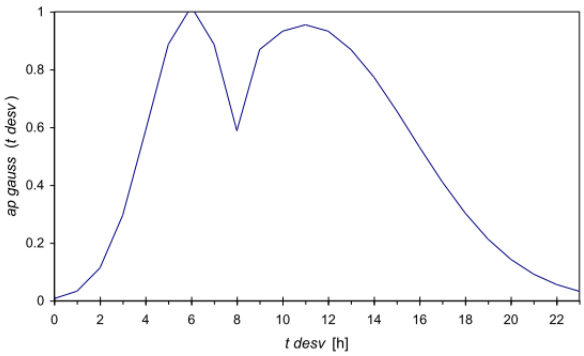
In [27], a data traffic model, referred to as Data Trapezoidal Model, is proposed; the model consists of two exponentials, with a linear function between them, as depicted in Figure 2.3 (b), and expressed by,

$$f_{trapdata}\left(t_{shift}\right) = \begin{cases} a_{trd1} e^{b_{trd1} t_{shift}}, & t_{shift} < t_{trd1shift} \\ c_{trd}, & t_{trd1shift} \le t_{shift} \le t_{trd2shift} \\ c_{trd2} + a_{trd2} e^{b_{trd2} t_{shift}}, & t_{shift} > t_{trd2shift} \end{cases} \tag{2.2}$$

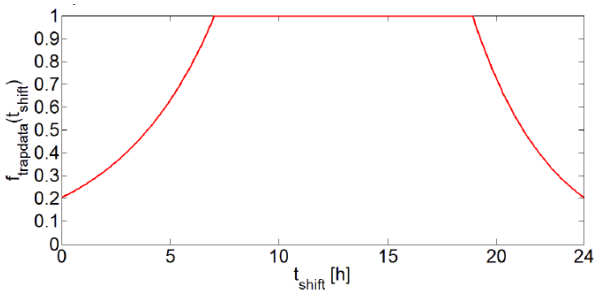
with: $c_{trd} = a_{trd1} e^{b_{trd1} t_{shift}} = a_{trd2} e^{b_{trd2} t_{shift}}$;
where:

- $a_{trd1}$: first exponential initial value;
- $b_{trd1}$: first exponential decay factor;
- $t_{trd1shift}$: first breakpoint shifted hour value;
- $c_{trd}$: linear constant value;
- $t_{trd2shift}$: second breakpoint shifted hour value;
- $a_{trd2}$: second exponential initial value;
- $b_{trd2}$: second exponential decay factor;
- $c_{trd2}$: second exponential offset.

The modelling process should resort to nonlinear regression methodologies, as linear regression might be unable to characterise the intrinsic behaviours of the traffic usage. Nonlinear regression is an iterative procedure, for adjusting a model, as closely as possible to a data set, by finding fit values for the model's parameters. Nonlinear regression is based on the assumption that the scatter of data around the average curve should follow a normal distribution, as this would indicate that the data follows a recognisable pattern [28].




(a) Double Gaussian Voice Traffic Model (adapted from [26]).




(b) Trapezoidal Data Traffic Model (adapted from [27]).

Figure 2.3 – Voice and data traffic models extracted from the literature.

## 2.5 State of the Art

This section gathers some of the literature research, on the topics of the thesis. In [29], based on the analysis of real data from a mobile network operator, in one large city of China, the authors propose a model to characterise the spatial traffic pattern: the Truncated two-dimensional DCT (Discrete Cosine Transform) model, in opposition with the existing spatial traffic models, which are based on ideal assumptions. Other models mentioned and evaluated are Spatial Poisson Point Process (SPPP) distribution model, log-norm distribution model, exponential distribution model, and Gaussian distribution model. Recommendations for the traffic spatial distribution models, for different types of regions, and key parameters, are presented, which will work as the foundation for the theoretical analysis and computer simulation, of cellular network's performance. Furthermore, the modelling results for three typical regions, see Figure 2.4, are compared: dense urban, urban, and suburban; showing that the parameters of the model, are different for each region. For dense urban, traffic fluctuates over space; and, for suburban, traffic is smoother.

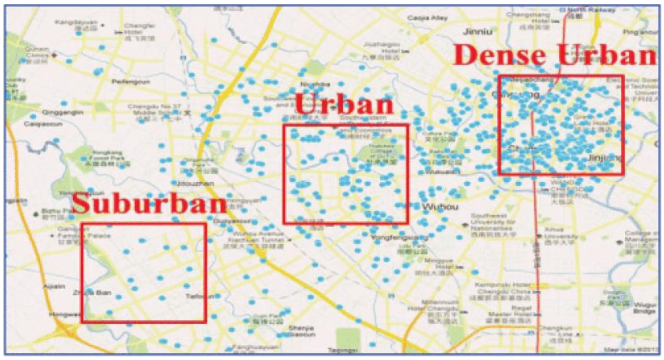



Figure 2.4 – Distribution map of BSs, depicting different regions (extracted from [29]).

In [30], the authors investigated the effect of a new mobile communication service, LTE service, on the number of subscribers and traffic volume of the traditional 3G service, in Korea. Two methods for forecasting 3G data traffic, assuming that LTE service is not launched yet, are investigated. In the first

method, the data traffic is estimated based on the real 3G traffic data for a time period. In the other method, 3G data traffic is separated into two factors: number of subscribers, and data traffic per subscriber. The first method is considered not appropriate to forecast the data traffic; the latter one, which separates the 3G traffic volume into two factors, was chosen as the more appropriated method.

In [3], it is introduced a methodology of data analytics and modelling, to evaluate LTE network performance, based upon traffic measurements and service growth trends. The authors propose an analytical model, to derive the relationships between measured LTE network Key Performance Indicators (KPIs), and forecasted network resources. Other methods are referred, and it is mentioned that there are disadvantages to them, as they cannot analyse how the network resources are quantitatively consumed, by various applications or users; and, user and service behaviours are lost, such as user behaviours to consume traffic, diversity of traffic consumption between services, and seasonality of traffic consumption. In other words, causality was not taken into account; and to overcome these shortcomings, different model strategies are described. In what concerns the forecast of LTE traffic and network resources, the model considers four components: trend component, for a long term; seasonality component, for a given period; burst component, for a significant change from normal trend, caused by external factors; and, random component. Individual predictions are obtained for each component, to reflect the variations in behaviours, and user numbers, as different intervals of time are considered. The method is indicated as able to be generalised, to study other networks such as UMTS.

In [15], the authors propose a novel traffic generation framework for LTE network evolution study, to obtain heterogeneous application traffic flows, including both typical smartphone applications and keep-alive messages, generated from always-on applications, and categorise application level traffic growth forecast. The use of the proposed traffic modelling, is exemplified, with a case study for radio resource consumption, of voice traffic and keep-alive messages, in a realistic LTE network scenario. Ultimately, the purpose of the paper is to provide guidelines to LTE network evolution studies. The traffic generation framework begins with the description of the statistical features of single applications, including keep-alive messages, and typical internet applications running on smartphone, such as web-browsing, FTP, e-mail, and buffered video streaming. A general traffic pattern, for a single smartphone user, is obtained, by focusing on the busy hour, when 8% of overall daily traffic is thought to be concentrated, and assuming statistical stationarity during this period. The increasing trend of traffic load of smartphones is considered in scenario development, with the integration of the traffic growth forecast into the traffic source model, achieved by mapping the growth trend into parameters of each application traffic source, to assure that the traffic demand can be aligned with the prediction. Table 2.12 shows the forecast of traffic load, per user, per month, and presents the share of each application, based on measurements from a real LTE network. Simulations are ran in order to evaluate the resource consumption, in both data plane and control plane, for normal and heavy scenarios. Simulation results are compared with the measurements of a real network.

In [4], the authors investigate traffic characteristics of popular applications, in Android based smartphones, by studying the characteristic of these applications, when they are running without user intervention. In this work, it is presented and discussed various types of applications; the description of

the experiments performed, for diverse data applications, and the results obtained, are presented. An analysis on traffic characteristics, for applications such as Facebook, Skype, and persistent TCP based applications, is also presented. For each case, suggestions and guidelines to mend the limitations identified during the analysis, are enumerated.

Table 2.12 – Application level traffic growth forecast (adapted from [15]).

| Year | Traffic Load per user (GB per month) | Percentage [%] | | | | | |
|---|---|---|---|---|---|---|---|
| | | Keep-alive | VoIP | Web | FTP | Email | Streaming |
| 2016 | 9.60 | 0.02 | 1.80 | 9.0 | 12.6 | 3.0 | 73.5 |
| 2017 | 13.45 | 0.01 | 1.29 | 8.0 | 11.2 | 2.5 | 77.0 |
| 2018 | 18.82 | 0.01 | 0.92 | 7.0 | 10.1 | 2.0 | 80.0 |

In [26], the authors analyse the generation of the voice traffic, for the urban area of Lisbon, Portugal. The modelling is performed for the temporal domain, and the duration of the day, using a double-gaussian and a trapezoidal function. The first, displays the morning and afternoon rush hour peaks, and a lunch hour breakpoint; and, for the second, the traffic volume trace has a constant behaviour for the majority of the day, or for when there are more than two high peaks. In [31], the authors analyse a urban region, grouping the cells with similar characteristics: cell size, number of channels, and daily traffic variation trace. Distinct activity areas, to which there is a specific traffic trace, are defined: urban centre, residential area, and suburban area. It is studied the voice traffic volume along the day, for workdays and weekends, for two of those regions. In [32], the authors consider the daily data traffic, from several European cities, when obtaining a data traffic variation profile, for the duration of the day. The only peak corresponds to the late night period; and, for the lunch hours, there is no decrease in traffic. In [33], it is obtained a daily data traffic variation, based on the accumulated volume of traffic, normalised over 24 hours; the busy hour occurs around 9pm. Comparing the average volume of traffic, during the weekends and the weekdays, the former is lower than the latter.

In [25], the author addresses diurnal usage profiles for a GSM network. It is stated that the diurnal profile is important, when dimensioning the network capacity; and that in particular, one should know the busy hour load, in order to determine the maximum capacity needed in the network. Based on the measurements performed, the diurnal profile was modelled, for application usage. The usage follows a typical diurnal profile, with lower intensity at night, and higher during the day; establishing a visible night and day profile. The diurnal profile of the data volume per application, indicates a distinct usage profile for the different applications considered. Figure 2.5, depicts the diurnal profile of the data volume, for a number of applications, presenting the relative data volume per application, over the day, and averaged over 10-minute intervals.

In [34], the authors present an analysis of data services, based on a 3G data network trace, collected from one of the largest cellular network service providers in North America. It is stated, this is the first work to study data service usage patterns, user access behaviours, and network performance issues, based on measurements from such a large cellular carrier; and, that it differentiates from previous studies, on the scale of the trace, and the multi-dimension analysis. The paper describes the work data trace collection methodology, presents the usage characteristics of data services from distinct perspectives, and concludes with some recommendations for developers and designers of 3G data

networks. Device types and diurnal characteristics, are taken into account, in other to characterise the usage profile; also, data service usage is examined. From the application breakdown, distinct service types can be observed from the trace, and are used by different users, with different patterns, at different time periods. More specifically, the work examines different 3G data services diurnal patterns, on a daily basis, showing different usage patterns between HTTP, MMS and SIP services. Different device types have distinct application usage profiles; namely, laptop users and mobile phone users. Figure 2.6 shows the popularity of different applications for each device type, and each bar shows the percentage of users.

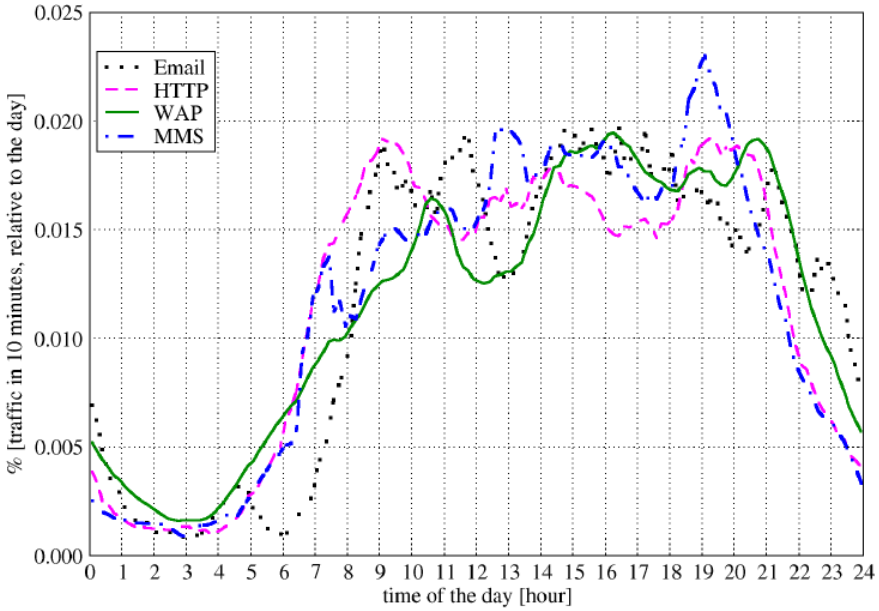



Figure 2.5 – Diurnal application usage profile (extracted from [25]).

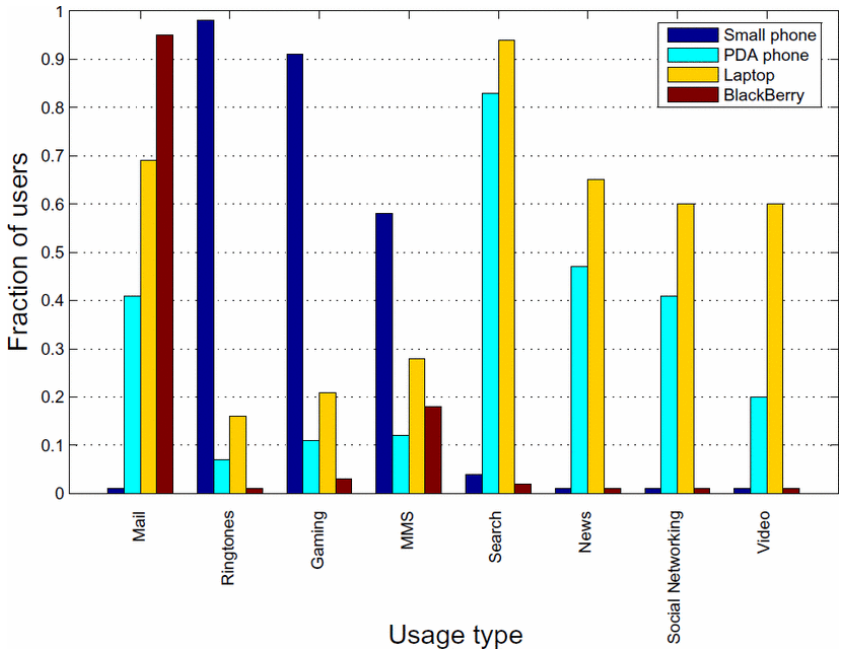



Figure 2.6 – Usage profiles for each device type (extracted from [34]).

In [23], the authors study the usage of the Google Wi-Fi network, deployed in Mountain View, CA. It is stated that the aggregate usage of the Google Wi-Fi network, is composed of distinct user populations,

characterised by distinct traffic, usage patterns, and mobility. The users are the focus of the study, in opposition to the focus being the networks themselves. Various classes of active clients, in the Google Wi-Fi network, are analysed; and, the application workload these clients place on the network, is characterised. There are distinct peaks on weekdays: morning rush hour, lunch time, and the end of evening rush hour; the weekends present a smoother behaviour. The dependency with the client device type, and geographic locality, is also analysed. The usage falls into three classes, based on client device type, which are the traditional laptop users, fixed-location access devices, and PDA-like smartphone devices. Each of these classes, for representative time periods, experiences a certain usage according to the geographic locality, being it on residential, commercial or transportation areas of the city. In what concerns the overall aggregate network activity, Figure 2.7 shows the number of active clients using the network, and their average activity time, over 15-minute intervals.

In [35], the authors compile information on mobile traffic, and provide forecasts and trends, for the period between 2010 and 2020. The focus areas include market trends, mobile broadband services and applications, key growth markets, spectrum, regulation, technology, and implementation. The report deals with penetration rates, voice and data traffic, and services that are expected to be used for mobile networks. Regarding the mobile data traffic, the growing number of mobile devices is shown, considering tablets, dongles, smartphones, connected devices, and M2M. Based on the segmented categories of devices, using mobile networks, it is examined the development of a mobile market model, for the evolution of mobile traffic and services, with future potential. There is a mention to observed data traffic, and daily traffic distributions. Global traffic forecasts are considered for different continents and countries, showing various consumption rates and traffic behaviours, for certain periods of time; also, some operators' expectations, and anticipated results, are stated. For Europe, a daily network traffic consumption is presented; Figure 2.8 depicts the network aggregate traffic profile for Europe.

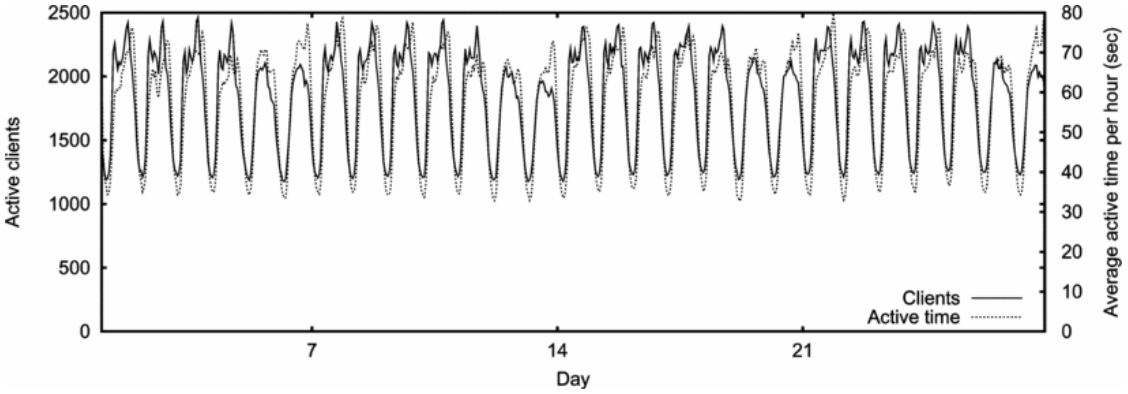



Figure 2.7 – Usage of the Google Wi-Fi network, for a month (extracted from [23]).

In [24], it is addressed the issue of dimensioning user traffic, in 4G networks; the author introduces the topic of 4G, and summarises the main appealing subjects and characteristics. Guidelines and parameters, for the characterisation of user data traffic, are presented. Collected data on user applications, concerning typical user data traffic, is presented for different time intervals, with differentiation on the user terminal. Temporal traffic distribution is analysed, by comparing information on traffic, from residential and business areas. Analysing the DL curve, for the residential case, three peaks are visible, corresponding to the early morning, the lunch time, and the end of the day; the DL

curve, for the business case, has high usage within the work day, with a decrease peak at lunch time. The residential and business cases are represented by the temporal traffic variation, across the day, for each hour of the day, as shown in Figure 2.9.

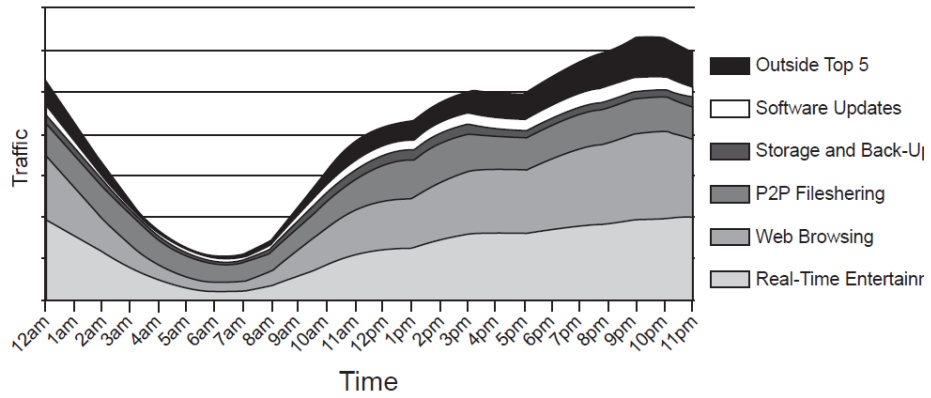



Figure 2.8 – Daily traffic consumption in Europe (extracted from [35]).

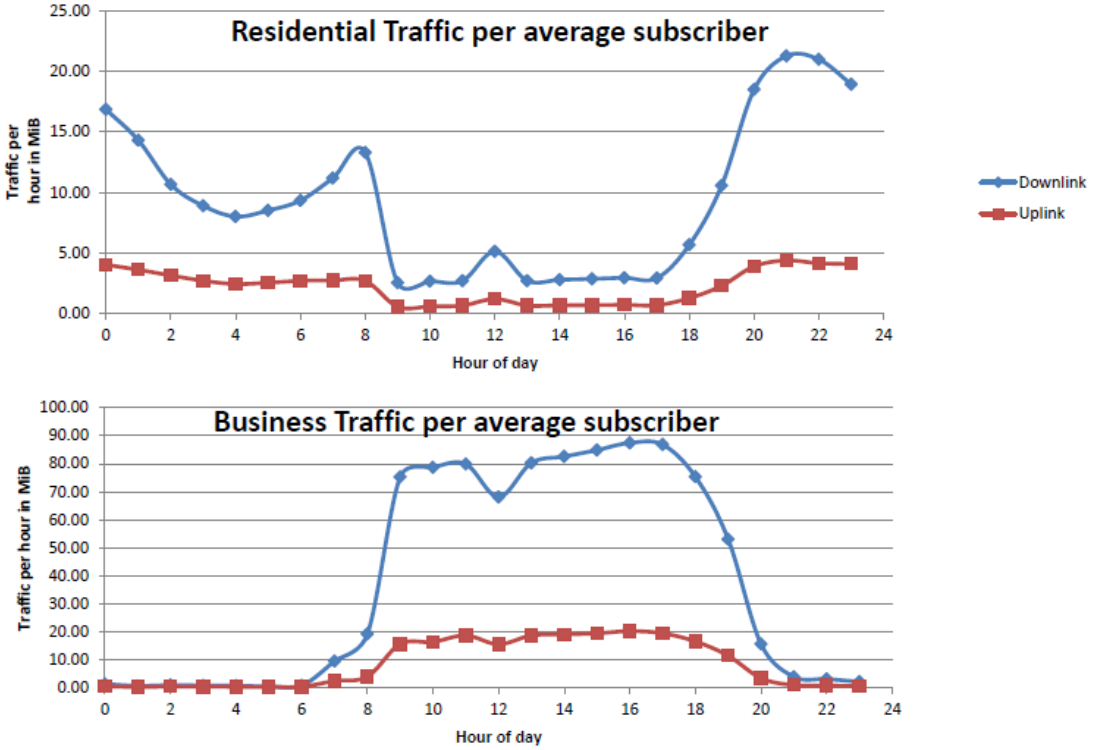



Figure 2.9 – Daily traffic profiles (extracted from [24]).

In [36], the authors explore the usage patterns of smartphone applications, via network measurements, from a cellular network provider, in the US. This paper addresses the sparse understanding of how, where, and when, applications are used, compared to traditional web services; presenting results on applications usage. Regarding user base and geographic area, the work examines the spatial and temporal prevalence, locality, and correlation, of applications at a national scale; contrary to studying small areas, or small populations of users. Traffic from distinct applications is identified, based on HTTP signatures. According to the authors, this study is the first to investigate, the diverse usage behaviours of individual mobile applications, at scale. The study of usage patterns for the aggregate results, is done

from a spatial, temporal, user, and device perspective. An analysis of the diurnal patterns, across various genres of smartphone applications, is presented; for smartphones, despite diversity, applications that have high likelihood of being used at the same time, show similarities in usage. News applications are more frequently used in the early morning, while sports applications are more utilised in the evening. The authors' findings suggest that cloud platforms, that host mobile application servers, can leverage distinct usage patterns in classes of applications, in order to maximise resource utilisation; and, network operators may optimise their network, for distinct applications, and periods of the day. Figure 2.10 shows the normalised traffic volume, across the day, at hourly intervals.

In [37], the authors present a study on GSM network utilisation; the experimental analysis focused on the duration of calls. The traffic peak hour is obtained, for a typical North American GSM network. For the daily voice traffic curve, there are two peaks; the first one, corresponds to the lunch break; and, the second peak, corresponds to the time preceding the end of the working day. The study provides evidence of traffic increase, along the week, from Monday to Friday; and of differentiation of traffic, between weekdays and weekends. It is introduced a traffic forecasting model, using a regression analysis. Figure 2.11 represents the measured average durations of calls, for every hour, of the daily voice traffic, for weekdays and weekends.

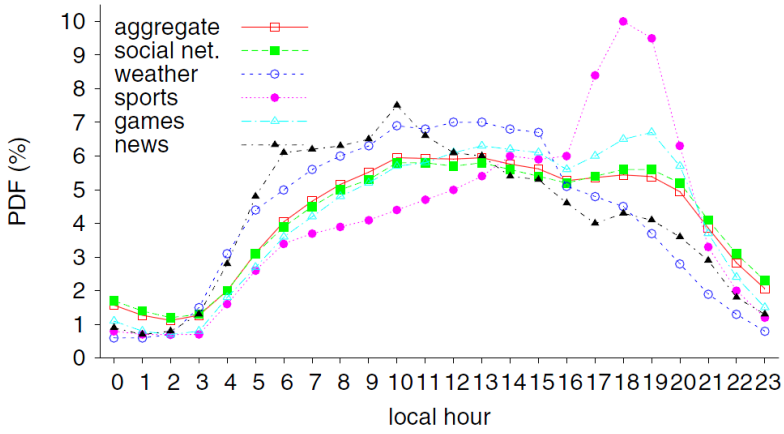



Figure 2.10 – Diurnal patterns for different genres of smartphone applications (extracted from [36]).

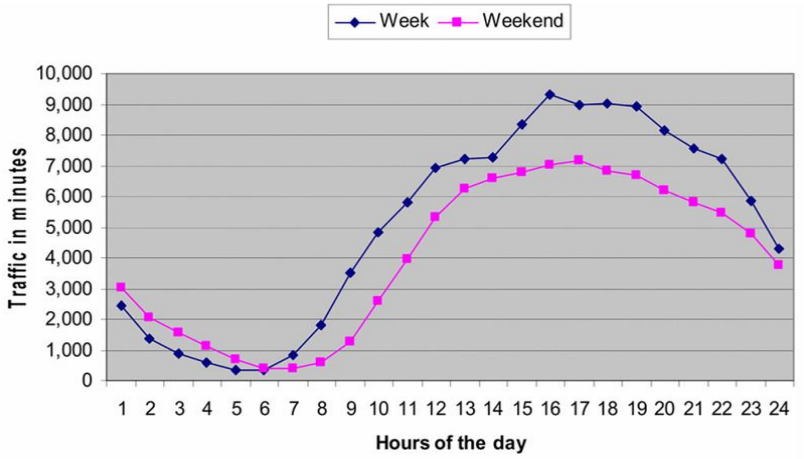



Figure 2.11 – Traffic in minutes during weekday and weekends (extracted from [37]).

# Chapter 3

# Model Development and Implementation

This chapter comprises the development framework and the implementation description, used in the exploratory analysis of the number of active users and traffic usage, and to obtain the models for the statistical characterisation of traffic usage, from a live cellular network. The data is structured and analysed. The models are compared and ranked based on goodness of fit statistics' criteria. The regression results are found at the end.

## 3.1 Data Collection

Studying and gaining a broader understanding of how impactful people's daily lives, and routines, are in application utilisation, device preferences, and network resource demands, is relevant for network optimisation. Data from live cellular mobile networks, can be used to characterise usage behaviours, from a statistical viewpoint, in order to gather recommendations and guidelines for efficient resource usage. A data set, collected from a mobile network, can be divided between a training set and a validation set, if the number of observations is large enough. The training set is used in the fitting process, to find prediction models; and, the validation set is used to validate the fitted models, with an independent set of observations. One should pay attention and check if the data was carefully selected, in order to avoid introducing systematic errors, or overly fitting the models to a very specific setting.

### 3.1.1 Training Data Set

The input data set, to function as training set, was collected at the core level of the Vodafone Portugal network, in Portugal, Lisbon, and contains 583885 observations. The observation period, from 2016/03/12 to 2016/04/19, includes 39 days, in which 26 are weekdays, 12 are weekend days, and 1 is a national holiday day. The national holiday days are considered as weekend days.

Sunrise and sunset time changes daily, due to the variations of the daytime, which is the period a given point of the Earth experiences natural light, making the day length fluctuate. The length of day is the elapsed time between sunrise and sunset. For the Lisbon area, the length of day increases from 2016/03/12 to 2016/04/19, going from 11h47m of daytime, to 13h21m. During this observation period, on 2016/03/27, a Sunday, a time shift occurs, with clocks turning forward one hour.

Table 3.1 – Length of day for March and April, for the Lisbon area.

| **Date** | **Sunrise** | **Sunset** | **Length of day** |
|---|---|---|---|
| **2016/03/12** | 06:52 | 18:39 | 11h47min |
| **2016/03/26** | 06:31 | 18:53 | 12h22min |
| Spring Time Shift | | | |
| **2016/03/27** | 07:29 | 19:54 | 12h24 min |
| **2016/04/01** | 07:21 | 19:59 | 12h37 min |
| **2016/04/19** | 06:55 | 20:16 | 13h21 min |

The input spreadsheet file is organised into 9 fields: date, time, APP_GROUP, DEV_TYPE, OP_SYS, USERS, DOWNLOAD, and UPLOAD:

- The date and time fields define the observation timestamp. The time field takes values from 00:00 to 23:00; and, the time unit is expressed in top-of-the-hour.
- The APP_GROUP field designates the different application labels; data applications with similar features are identified, in the spreadsheet, with the same application label.
- The DEV_TYPE field designates the type of device used.
- The OP_SYS field designates the type of operating systems used by the device.
- The USERS field designates the number of distinct Mobile Subscriber Integrated Service Digital Network Numbers (MSISDNs). The MSISDN is the telephone number associated with a SIM,

and identifies the mobile subscriber.

- The DOWNLOAD field indicates the traffic usage, in the download link, measured in Bytes.
- The UPLOAD field indicates the traffic usage, in the upload link, measured in Bytes.

The training set information is summarised in Table 3.2.

Table 3.2 – Training set description.

| Classes | Subclasses | Observations | Observations [%] |
|---|---|---|---|
| APP_GROUP | E-Mail | 55259 | 9.46 |
| | File Systems | 32694 | 5.60 |
| | File Transfer | 54152 | 9.27 |
| | Games | 45877 | 7.86 |
| | Instant Messaging | 56177 | 9.62 |
| | Other | 59712 | 10.23 |
| | P2P | 46252 | 7.92 |
| | Streaming | 52996 | 9.08 |
| | Terminal Transactions | 62340 | 10.68 |
| | VoIP | 56140 | 9.61 |
| | Web Applications | 62129 | 10.64 |
| | Legacy Protocols | 157 | 0.03 |
| **Total** | | 583885 | 100.00 |
| DEV_TYPE | Hotspots | 43093 | 7.38 |
| | Others | 93327 | 15.98 |
| | Pens | 57150 | 9.79 |
| | Routers | 80976 | 13.87 |
| | Smartphone | 212324 | 36.36 |
| | Tablet | 97015 | 16.62 |
| **Total** | | 583885 | 100.00 |
| OP_SYS | Android | 157027 | 26.89 |
| | Blackberry | 33635 | 5.76 |
| | Others | 211669 | 36.25 |
| | iOS | 78601 | 13.46 |
| | Symbian | 27732 | 4.75 |
| | Windows | 75221 | 12.88 |
| **Total** | | 583885 | 100.00 |

Data entries of applications with similar features, are gathered and assigned, to the same APP_GROUP label designation. The APP_GROUP applications are: E-mail; File Transfer (FiTr); Games; Instant Messaging (InMe); M2M; Other; P2P; Streaming; VoIP; Web Applications (WebAp); and, Legacy Protocols. M2M groups the data entries from Terminal Transactions and File Systems observations. The Legacy Protocols will be left out since they only represent 0.03% of the observations, which is a negligible number and would not provide meaningful results.

The DEV_TYPE devices are: Hotspots; Others; Pens & Datacards, which in the future will be referred to as Pens; Routers; Smartphone; and, Tablet. Hotspots are Wi-Fi terminals of high mobility, that allow connectivity for many devices at the same time [38], while Pens only allow connectivity for one device [39]. Routers are Wi-Fi fixed terminals, that allow connectivity for many devices at the same time [40].

The OP_SYS operating systems are: Android; Others; Windows; iOS; BlackBerry; and, Symbian. BlackBerry and Symbian will be left out, since they both have a small representation in the data set, and are neglectable in comparison with other operating systems.

### 3.1.2 Development Overview

The initial stage of the work goes through identifying the key fields of the file, checking the content options, and establishing the target collections to analyse. Once this initial data inspection is completed, it is possible to define the profiles, entities and links, included in the original raw data, from the training set. The purpose of this work is to characterise and represent the observed data, by providing visual aids and mathematical models, thus highlighting patterns, and better realising the implicit behaviours, associated to the distinct entities, profiles, and collections. Curve fitting is used to obtain the regression models that best approximate the data; there is a group of model hypothesis to test and check how good of a fit they are, when compared against the observed data. It is important to select statistics that allow for the comparison of results, so that adequate and more suitable hypothesis are chosen as the better ones. After obtaining and listing the selected models, a new data set is introduced, to assess the reliability and prediction capacity of these models. It is possible to check the expected results against the ones observed for the validation data set, using the selected statistics and resorting to a Global Traffic Model. The obtained models are later used to portray global traffic predictions scenarios. The framework is illustrated in Figure 3.1, and a detailed development overview is presented in Figure 3.2.

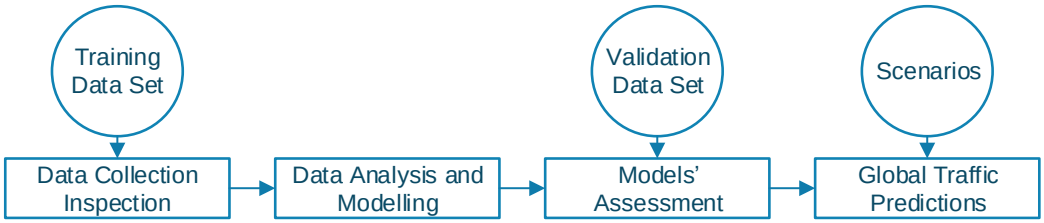



Figure 3.1 – Framework.

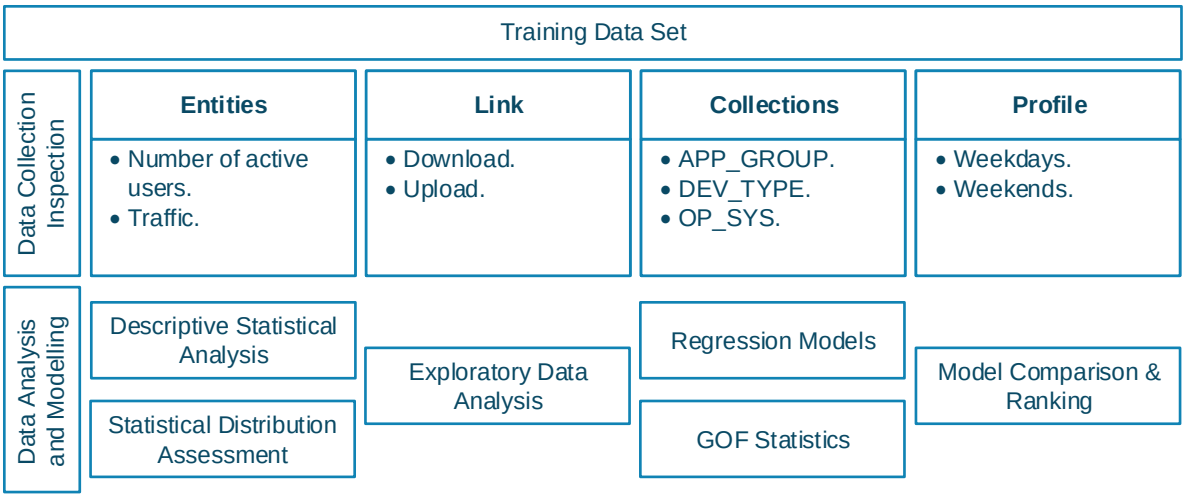



Figure 3.2 – Development overview.

The data collection inspection returns the entities, links, collections, and profiles, found in the data, that are used to structure and organise the raw data. The data analysis and modelling, gather the conclusions taken about the data, the fitting process, and the regression results. The approach adopted starts with the employment of a descriptive statistical analysis, and a data statistical distribution assessment, to check if the data samples have a normal distribution. The exploratory data analysis

makes use of graphical and numerical results for an accessible and compact representation of the data related to the different collections, profiles, entities, and links. The fitting process, uses a model catalogue that lists the models, used as the set of hypotheses for the regression process. The list of tested models has 8 possible models, and each model is composed of one or more sections, represented by linear, exponential, and gaussian equations.

The regression models are obtained by estimating the coefficients of each section, by means of a nonlinear least-squares algorithm, while ensuring continuity between the sections, and the initial and final points of the model. To decide on the better regression models, goodness of fit statistics are used to implement a criteria, for comparing and ranking the hypothesis, on how well they approximate the data, and respective average curves. The validation data set is used for the models' and predictions' assessments. With the listing of the selected models, the models' assessment is performed to test the fitting, of the obtained regression models, with a new data set. The Global Traffic Model, set from 00:00 to 24:00, is used to show the expected traffic usage, to compare against the observed one; and is used for scenarios' predictions.

To maintain the confidentiality of the collected information, the data is presented normalised.

### 3.1.3 Descriptive Statistical Analysis

For each $i^{th}$ top of the hour, or observation, there are $N_S$ samples of data. The average of the $i^{th}$ observation is defined as [41],

$$\mu_i = \frac{1}{N_S}\sum_{j=1}^{N_S} y_j \tag{3.1}$$

where:

- $N_S$: number of samples;
- $y_j$: $j^{th}$ sample.

Each $\mu_i$value defines a point of the average curve, and has a global average defined as,

$$\bar{\mu} = \frac{1}{N}\sum_{i=1}^{N} \mu_i \tag{3.2}$$

where:

- $N$: number of observations.

The standard deviation, associated with each $\mu_i$value, quantifies the sample dispersion as [41],

$$\sigma_i = \sqrt{\frac{1}{N_S}\sum_{j=1}^{N_S} (y_j - \mu_i)^2} \tag{3.3}$$

The average standard deviation about the average curve is defined as,

$$\bar{\sigma} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \sigma_i^2} \tag{3.4}$$

The normalisation of data, and average curves, is performed by dividing the sample values, by a normalisation constant. The normalised observed values are defined as,

$$y_{j\,Norm} = \frac{y_j}{y_{const}} \tag{3.5}$$

where:

- $y_{const}$: normalisation constant.

To weigh the results, with respect to the share each input has in the data set, the weighted average is,

$$\bar{R}_w = \sum_{n=1}^{N_n} w_n \cdot R_n \tag{3.6}$$

where:

- $n$: case index;
- $N_n$: number of cases;
- $w_n$: weight;
- $R_n$: input ratios.

The percent change measures the relative increase, or decrease, between the reference and the observed inputs,

$$\Delta R_{n\,[\%]} = \frac{R_{obs} - R_{ref}}{R_{ref}} \times 100 \tag{3.7}$$

where:

- $R_{ref}$: reference input;
- $R_{obs}$: observed input.

### 3.1.4 Goodness of Fit Tests

There are two possible outcomes as a result of a hypothesis, either the result is consistent with the hypothesis, which is retained, or in case of inconsistency, the hypothesis is rejected. One cannot prove an hypothesis, one can only falsify or disprove an hypothesis [42]. To know the underlying distribution of data samples, one tests for goodness of fit, to check if a hypothesised distribution is rejected or not. The null hypothesis is the hypothesis under test, and the hypothesis test result either states that the null hypothesis was, or was not, rejected at a $\alpha$ level of significance [41]. The Lilliefors Test for Normality is especially designed to assess if the statistical distribution is a normal distribution. The null hypothesis, $H_0$, is that the sample comes from a normal distribution. This test performs like the Kolmogorov-Smirnov test, but the Lilliefors test standardises the data using the sample estimates of the average, and of the standard deviation. The Lilliefors test measures the goodness of fit between the empirical Cumulative Distribution Function (CDF) of the data, and the theoretical CDF of the hypothesised distribution, with parameters estimated from the data. The Lilliefors test rejects the null hypothesis at a level $\alpha$ of significance, if $D_{Lilliefors}$ is larger than the critical value [43], [44], and [45]. The Lilliefors' test statistic is,

$$D_{Lilliefors} = \max_X \left| \hat{F}_X(x) - F_X(x) \right| \tag{3.8}$$

where:

- $\hat{F}_X$: empirical CDF;
- $F_X$: theoretical CDF (hypothetical distribution).

The *lillietest* MATLAB command [43], returns a test decision for a $\alpha$ level of significance. The hypothesis test result, either takes the value 1, which indicates the rejection of the null hypothesis, or takes the value 0, which indicates a failure to reject the null hypothesis.

### 3.1.5 Goodness of Fit Statistics

The Goodness Of Fit (GOF) statistics are used in the comparison and ranking of regression models, with the objective of finding the better fitting models, that best approximate each data case; and, to assess and validate those models, as good prediction models.

The RMSE gives an indication of how different two sets of values are, by quantifying the error between the reference or observed, values; and, the predicted or estimated, values [46]. The closer the two sets of values are, the smaller the value of the RMSE will be. For fitting purposes, a lower RMSE value indicates a better prediction, and a value closer to 0 is preferable when evaluating and comparing results. The RMSE, as an estimate of the standard deviation of the error, is preferable to the Mean Squared Error (MSE), since it is expressed in the same units of the original values [44]. This statistic only takes positive values, and is defined as,

$$\sqrt{\overline{\varepsilon^2}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \tag{3.9}$$

where:

- $\hat{y}_i$: $i^{th}$ predicted value (model);
- $y_i$: $i^{th}$ observed value (data set).

The CD, or R-square, is useful when judging the adequacy of a regression model, and is referred to as the amount of variability in the data, explained by the model [46]. This statistic takes values between 0 and 1, and is dimensionless. For fitting purposes, a model with a higher CD value indicates a better prediction, and a value closer to 1 is preferable when evaluating and comparing results. For a CD of 0.95, the model accounts for 95% of the variability in the data [41], [47], and [28]. However, it is possible to obtain a high CD value and find that the model is unsatisfactory. An increase of the model's number of variables, or coefficients, leads to a higher CD value; nonetheless, adding variables to the model requires caution, as the quality and accuracy of the regression, as a prediction model, can become compromised [41]. Exceptionally, the CD may take negative values, when the average of the observed values is a better model, for explaining the data, than the obtained regression. The CD is defined as,

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{3.10}$$

where:

- $\bar{y}$: average of the observed values.

The ACD, or Adjusted R-square, is helpful in assessing how reliable the CD measure is [46]. Adding new independent variables to the model may either increase, or decrease, the ACD value, in opposition with what happens with the CD. This statistic takes into consideration the number of variables of the model, against the number of observations. It takes values between 0 and 1, it is also dimensionless, and its value is less than, or equal to, the CD value. A sign that the regression model is a good prediction model, is having both measures be very similar; having a high value for the ACD reinforces the accuracy of the CD. For fitting purposes, a model is more trustworthy if both statistics have values closer to 1. The ACD may take a negative value if the respective CD is very low. The ACD is defined as,

$$R^2_{adj} = 1 - \frac{(1 - R^2)(N - 1)}{N - P - 1} \quad (3.11)$$

where:

- $P$: number of predictors (model coefficients).

When evaluating and comparing different regression models, with similar goodness of fit statistics results, the coefficient's Confidence Interval (CI) can be a deciding factor. The coefficients' CIs give a sense of the trust one can put, in the values obtained for the coefficients. The further apart the lower and upper bounds are, the less assurance one can have on the results; regression models that are characterised by very wide CIs should be disregarded. For fitting purposes, a narrow interval is preferable, and indicates more adequate coefficients.

The RMSE and the CD, are not the sole indicators of how well a regression model fits the data, and must be complemented by the ACD. The most favourable scenario is to have the regression model show low RMSE; high and similar, CD and ACD; and, narrow CIs widths. A good prediction model is one which is able to adequately approximate the set of observations. It is possible that many reasonable predictions can be obtained, so deciding on the more suitable one, also should have into consideration the underlying behaviour aspects of the data. These statistics and recommendations, are used as criteria and guidelines, in deciding, out of a model catalogue, which model better fits each data case.

# 3.2 Development Conditions and Considerations

## 3.2.1 Data Collection Analysis

Three collections, out of the original data collection, are studied and analysed separately, with the objective of obtaining models able to describe and predict the underlying data behaviours. The first is the Applications (App) collection, and refers to the APP_GROUP data; the second is the Devices (Dev) collection, and refers to the DEV_TYPE data; and the third is the Operating Systems (OpS) collection, and refers to the OP_SYS data: $c = \{App, Dev, OpS\}$. The entities in analysis are the number of active users, and traffic usage: $E = \{N_u, T_{[GB]}\}$. Both entities, $E$, are defined in terms of an hour of the day, $h$; a day, $d$; a collection, $c$, with $n$ cases; a profile, $p$; a link, $l$; as: $E(h, d, c|n, p, l)$. In a period of a day, there are 24 top of the hours: $h = \{1, \dots, 24\}$. Each collection is sorted into two profiles, weekdays and weekends, with $p = \{WD, WE\}$; and, $WD|d = \{1, \dots, 26\}$, and $WE|d = \{1, \dots, 13\}$. Furthermore, traffic usage is considered for both DL and UL links, $l = \{DL, UL\}$. The App collection has 10 cases, the Dev collection has 6 cases, and the OpS collection has 4 cases:

$c = App$, $n = \{Email, FiTr, Games, InMe, M2M, Other, P2P, Streaming, VoIP, WebAp\}$;

$c = Dev$, $n = \{Hotspots, Others, Pens, Routers, Smartphone, Tablet\}$;

$c = OpS$, $n = \{Android, Others, Windows, iOS\}$.

Four scenarios are established, $\{WD, DL\}$; $\{WD, UL\}$; $\{WE, DL\}$; and, $\{WE, UL\}$.

Originally, the data set is a record of data entries for 39 days. After retrieving the data entries for each day, and each top of the hour, it is possible to start structuring the raw data set, into the different data collections, profiles, entities, and cases. Figure 3.3 depicts the normalised total traffic for the 39 day observation period, distinguishing WD from WE. Once the data is structured, one gains access to all collections, profiles, entities, and cases, independently. The difference in behaviour and traffic load, between WD and WE, is noticeable from inspecting the figure.

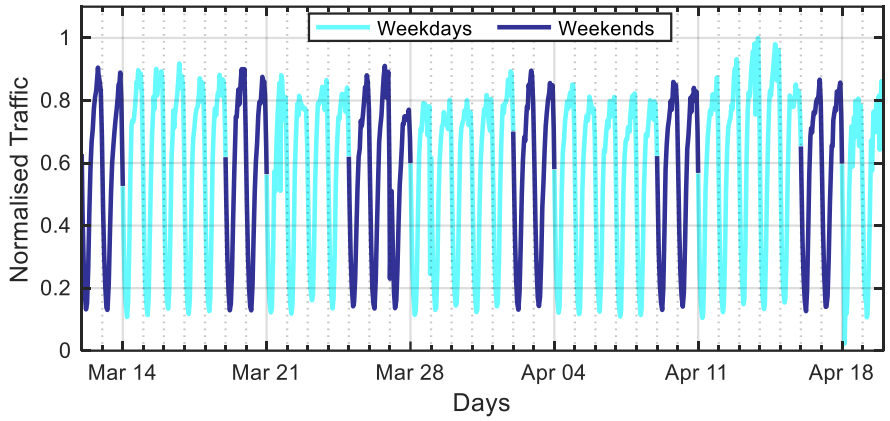
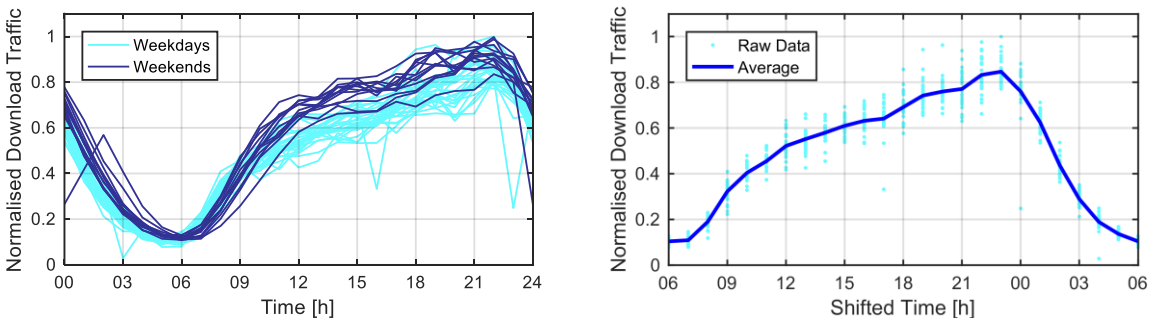



Figure 3.3 – Traffic usage data observations over 39 days, from 2016/03/12 to 2016/04/19.

Figure 3.4 (a) displays the normalised DL traffic usage, for the Streaming case, for both WD and WE. The temporal window represents a day period, with a precision of a measurement of one hour, and 24 top of the hour observations. Each hour is defined by its top of the hour; and, one observation designates the samples for a top of the hour. There are 24 observations in total, and each has as many samples as the profile's number of days; WD have 26 samples per observation, and WE have 13.

The average curve is obtained by averaging the samples for each top of the hour. For each top of the hour, samples have a different dispersion pattern about the average, quantified by the standard deviation, see Figure 3.4 (b). The average standard deviation is the outcome of averaging the standard deviations of each observation. The display of the average curve, and the average standard deviation region about the average, provide insight on the data for each observation, and over the day period. The data samples, of each observation, only take positive values, due to the nature of the data of the three entities. Figure 3.4 (b) displays the average curve, and the sample scatter about the average, for the Streaming case, for WD and DL. The data and the average curve experience a shift translation, and its values are normalised; normalisation is done in reference to the maximum value of the observations.




(a) Download Data Observations.

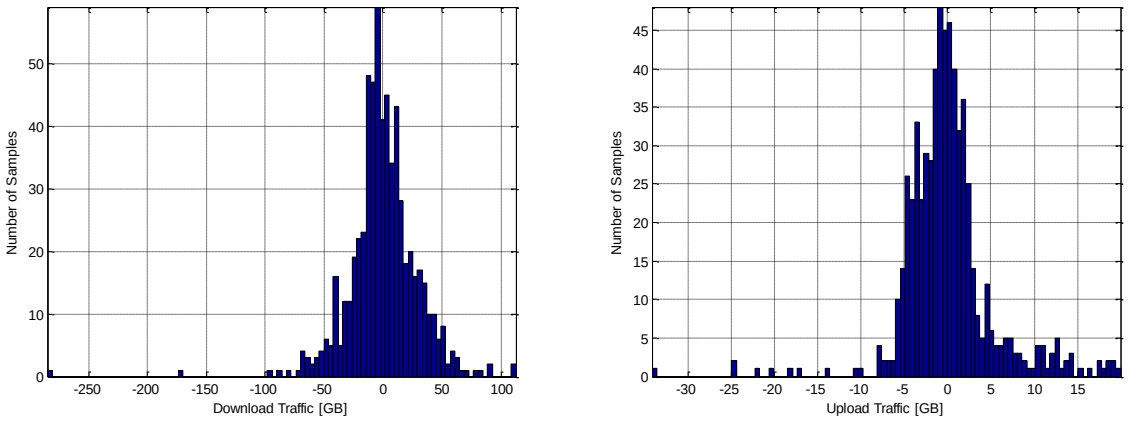
(b) Weekdays Download.

Figure 3.4 – APP_GROUP Streaming.

## 3.2.2 Data Statistical Distribution Assessment

It is important to understand how well behaved the distribution of scatter about the average is, and if one can consider the scatter, of each hour, to have a normal distribution. It is more straightforward to fit, and find, a good regression model, if the scatter distribution about the average, for each top of the hour, is well-behaved. Examining the scatter distribution about the average against the normal distribution, for each top of the hour, gives an indication of how well-behaved the samples about the average are. The normal distribution is symmetric about the average; and, for any normal distribution, there is a 68.3% chance a sample is within the one standard deviation region about the average; a 95.45% chance a sample is within the two standard deviation region; and a 99.73% chance a sample is within the three standard deviation region [41]. For each top of the hour, one assesses if the statistical distribution of the samples about the average is normal. In truth, the samples only take positive values, therefore the more appropriate distribution to use is the truncated normal distribution; however, the normal distribution can be used since, while a sample from the normal distribution can take a positive or negative value, if the average is large enough, in comparison with the standard deviation, then the chance of finding a sample with negative value, within the three standard deviation region, is negligible [48]. The Lilliefors goodness of fit test is used to assess if the samples' scatter about the average has a normal distribution. The Lilliefors test is performed for a 5% level of significance.

A histogram is a column diagram, and a visual inspection of the graph provides an initial understanding of the data distribution about the average [49], in anticipation of the goodness of fit normality tests. For the Streaming case, two visual aids are provided to illustrate a good, Figure 3.5 (a), and a worst, Figure 3.5 (b), situations of data distribution about the average. For WD and DL, the percentage of non-rejected decisions is 83.33%; and, for WD and UL, the percentage of non-rejected decisions is 41.67%.




(a) Weekdays Download. (b) Weekdays Upload.

Figure 3.5 – APP_GROUP Streaming Histogram.

The Lilliefors test is performed for a 5% level of significance. The Lilliefors test assesses the normality of the traffic distribution about the average traffic curve, for each case, for all four scenarios, and three collections. The test decisions, which return a rejection of the null hypothesis, with a test statistic value surpassing less than 10% of the critical value, are considered as failure to reject the null hypothesis. For WD the critical value is 0.1698, and for WE is 0.2333. The percentages of non-rejected decisions, in the

assessment at 5% level, of the goodness of fit to the normal distribution, using the Lilliefors goodness of fit test, are presented in Table 3.3, Table 3.4, and Table 3.5. The weighted average is the product between the weight of the traffic, for each case, and the respective result for the Lilliefors test.

Regarding the App collection, the better overall results are achieved for VoIP, and the worst ones for Other. The lowest percentage of non-rejected decisions is obtained for Other, UL and WD; and, for Streaming, UL and WE; and, the highest percentage of non-rejected decisions is obtained for M2M, DL and WE; and for VoIP, UL and WE. The weighted average of the percentages of non-rejected decisions has a minimum of 74.15%, for UL and WD, and a maximum of 93.25%, for DL and WE. Regarding the Dev collection, the better overall results are achieved for the Routers, and the worst ones for Others. The lowest percentage of non-rejected decisions is obtained for the Routers, UL and WE; and, the highest percentage of non-rejected decisions is obtained for Others, DL and WD. The weighted average of the percentages of non-rejected decisions has a minimum of 77.32%, for UL and WD, and a maximum of 94.71%, for UL and WE. Regarding the OpS collection, the better overall results are achieved for iOS, and the worst ones for Windows. The lowest percentage of non-rejected decisions is obtained for Windows, UL and WD; and, the highest percentage of non-rejected decisions is obtained for Android and iOS, UL and WE. The weighted average of the percentages of non-rejected decisions has a minimum of 76.46%, for DL and WD, and a maximum of 93.70%, for UL and WE.

Table 3.3 – Percentages of non-rejected decisions, for APP_GROUP, in the assessment at 5% level of significance, to the normal distribution, using the Lilliefors test.

| App Collection | Non-rejected decisions [%] | | | |
|---|---|---|---|---|
| | Download | | Upload | |
| | Weekdays | Weekends | Weekdays | Weekends |
| (1) E-Mail | 70.83 | 83.33 | 79.17 | 87.50 |
| (2) FiTr | 45.83 | 91.67 | 70.83 | 83.33 |
| (3) Games | 45.83 | 62.50 | 79.17 | 91.67 |
| (4) InMe | 70.83 | 79.17 | 83.33 | 91.67 |
| (5) M2M | 87.50 | 100.00 | 75.00 | 91.67 |
| (6) Other | 54.17 | 91.67 | 50.00 | 79.17 |
| (7) P2P | 83.33 | 95.83 | 95.83 | 91.67 |
| (8) Streaming | 83.33 | 91.67 | 41.67 | 50.00 |
| (9) VoIP | 95.83 | 83.33 | 95.83 | 100.00 |
| (10) WebAp | 87.50 | 95.83 | 87.50 | 87.50 |
| Weighted Average | 80.65 | 93.25 | 74.15 | 78.64 |

Table 3.4 – Percentages of non-rejected decisions, for DEV_TYPE, in the assessment at 5% level of significance, to the normal distribution, using the Lilliefors test.

| Dev Collection | Non-rejected decisions [%] | | | |
|---|---|---|---|---|
| | Download | | Upload | |
| | Weekdays | Weekends | Weekdays | Weekends |
| (1) Hotspots | 87.50 | 87.50 | 58.33 | 87.50 |
| (2) Others | 50.00 | 95.83 | 70.83 | 87.50 |
| (3) Pens | 91.67 | 91.67 | 79.17 | 91.67 |
| (4) Routers | 87.50 | 91.67 | 87.50 | 100.00 |
| (5) Smartphone | 79.17 | 91.67 | 79.17 | 95.83 |
| (6) Tablet | 95.83 | 95.83 | 58.33 | 91.67 |
| Weighted Average | 84.07 | 90.82 | 77.32 | 94.71 |

Table 3.5 – Percentages of non-rejected decisions, for OP_SYS, in the assessment at 5% level of significance, to the normal distribution, using the Lilliefors test.

| OpS Collection | Non-rejected [%] | | | |
|---|---|---|---|---|
| | Download | | Upload | |
| | Weekdays | Weekends | Weekdays | Weekends |
| (1) Android | 79.17 | 91.67 | 83.33 | 95.83 |
| (2) Others | 70.83 | 87.50 | 70.83 | 91.67 |
| (3) Windows | 62.50 | 79.17 | 20.83 | 50.00 |
| (4) iOS | 83.33 | 91.67 | 87.50 | 95.83 |
| Weighted Average | 76.46 | 89.80 | 78.16 | 93.70 |

The weighted average, of the percentages of non-rejected decisions, is superior to 74%, for the App collection; to 77%, for the Dev collection; and, to 76%, for the OpS collection.

## 3.3 Exploratory Data Analysis

Exploratory data analysis makes use of graphical and numerical results, to show previously inaccessible information, from the original raw data. The visual aids and tables allow for a compact representation, and an easy consultation, of the disclosed information. The entities in analysis are the Number of Active Users (NU) and traffic usage.

### 3.3.1 Data Ratios

The entity, for the $h$ hour, in a $d$ day, for a $n$ case, is the result of combining all file entries in those conditions. The entity, for the 12:00 top of the hour, for the first day of WD set, for DL, when considering the App collection, for the Streaming case, is as follows,

$$E(h = 12, d = 1, c = App, p = WD, l = DL, n = 8) \tag{3.12}$$

The entity, for the $h$ hour, in a $d$ day, is the result of combining all $n$ case contributions in those conditions. The entity, for the 12:00 top of the hour, for the first day of WD set, for DL, when considering the App collection for all 10 cases, is as follows,

$$E(h = 12, d = 1, c = App, p = WD, l = DL) = \sum_{n=1}^{N_n} E(h = 12, d = 1, c = App|n, p = WD, l = DL) \tag{3.13}$$

where:

- $N_n$: number of cases.

The Total Entity, for a full day, considers all $n$ cases contributions, for each one of the 24 top of the hours, for the chosen collection, profile, and link. The entity, for all 24 top of the hour, for the first day of WD set, for DL, when considering the App collection with 10 cases, is as follows,

$$E(d = 1, c = App, p = WD, l = DL) = \sum_{h=0}^{N_H} \sum_{n=1}^{N_n} E(h, d = 1, c = App|n, p = WD, l = DL) \tag{3.14}$$

where:

- $N_H$: number of hours.

The Average Hour Weight, for the $h$ hour, is the average over all days of the profile set, for all $n$ cases contributions, for the $h$ top of the hour, pondered to all cases and all hours contributions of that day. The ratio, for the $E$ entity, for the 12:00 top of the hour, pondered to all 24 top of the hour, for each $d$ day of WD set, for DL, when considering the App collection with 10 cases, is,

$$\overline{w^{E}_{h=12}} = \frac{1}{N_D}\left[\sum_{d=1}^{N_D} \frac{\sum_{n=1}^{N_n} E(h=12,d,c=App|n,p=WD,l=DL)}{\sum_{h=0}^{N_H}\sum_{n=1}^{N_n} E(h,d,c=App|n,p=WD,l=DL)}\right] \quad (3.15)$$

where:

- $N_D$: number of days.

This quantifies the average weight each hour has in the duration of one day. All collections, for the same entity, profile, and link, have equal hour weights. For the graphical representation, the sum of all top of the hour contributions (columns) adds up to 100%.

The Entity Average Hourly Ratio, for the $n$ case, is the average over all days of the profile set, of one case contribution, for the $h$ top of the hour, pondered to all cases contributions of that $h$ top of the hour for each day. The ratio, for the $E$ entity, for the 12:00 top of the hour, the Streaming case is pondered to all cases, for each of the days of WD set, for DL, when considering the App collection, is,

$$\overline{w^{E}_{H\ h=12,n=8}} = \frac{1}{N_D}\left[\sum_{d=1}^{N_D} \frac{E(h=12,d,c=App,p=WD,l=DL,n=8)}{\sum_{n=1}^{N_n} E(h=12,d,c=App|n,p=WD,l=DL)}\right] \quad (3.16)$$

This quantifies the average weight each case has for each hour, for the 24 top of the hours. Each collection, for each entity and selected profile set, link, and case, has a different hourly weights distribution. For the graphical representation, the sum of each top of the hour contributions (column) adds up to 100%.

The Entity Average Daily Ratio, for the $n$ case, uses the average weight of each hour, and the average weight of a case for that hour, to obtain the weight of each case, per hour, for a day; it is the Entity Weighted Average Hourly Ratio, for the $n$ case. The ratio, for the $E$ entity, for the 12:00 top of the hour, and the Streaming case, for the selected profile set, and link, when considering the App collection, is,

$$\overline{w^{E}_{D\ h=12,n=8}} = \overline{w^{E}_{h=12}} \cdot \overline{w^{E}_{H\ h=12,n=8}} \quad (3.17)$$

This quantifies the average weight each case, in each top of the hour, has in the duration of one day. Each collection, for each entity, selected profile set, link, and case, has a different daily weights distribution. For the graphical representation, the sum of all top of the hour contributions (columns) adds up to 100%.

For a $n$ case, the Entity Average Aggregated Daily Ratio, combines all Entity Weighted Average Daily Ratios, obtained for the duration of one day. The ratio, for the $E$ entity, for all 24 top of the hour, and the Streaming case, for the selected profile set, and link, when considering the App collection, is,

$$\overline{W^{E}_{n=8}} = \sum_{h=0}^{N_H} \overline{W^{E}_{D\ h,n=8}} \tag{3.18}$$

This quantifies the average weight each case has in the duration of one day. For the graphical representation, the sum of all contributions (columns) adds up to 100%.

The data set is assessed for the NU and the traffic usage, for both DL and UL, using the previously explained data ratios, with results expressed in percentage. The results display the share of the entity related to each top of the hour, in the period of a day; the share of the entity each case of a collection shows, for each one of the 24 top of the hours; the share of the entity associated to a certain case of a collection, weighted to a specific top of the hour; and, for the entire day, the share of the entity which portrays a certain case of a collection.

## 3.3.2 Global Results

The distribution of each entity, along the period of 24 hours, for both WD and WE, is analysed. The hour weights for each entity and a selected profile, either WD or WE, yield the same results for all collections.

Regarding WD, see Figure 3.6, all entities show an increase in the morning; the NU, shows a decrease in the afternoon, starting around 19:00, and throughout the night and early morning, until hitting a minimum between the hours of 3 and 6 in the morning, also, it takes the highest values between the hours of 9 and 20, with a maximum around 14:00 and 18:00; the DL traffic, shows a very steep progression between the hours of 7 and 10, and, only shows a decrease in the late night, after midnight, and hits minimum values between the hours of 3 and 6 in the morning, also, it takes the highest values between the hours of 11 and 23, with peaks at 18:00 and 22:00; the UL traffic, shows a steady progression between the hours of 7 and 10, and, starts showing a decrease after 19:00, and hits minimum values between the hours of 3 and 6 in the morning, also, it takes the highest values between the hours of 11 and 22, with a maximum around 17:00.

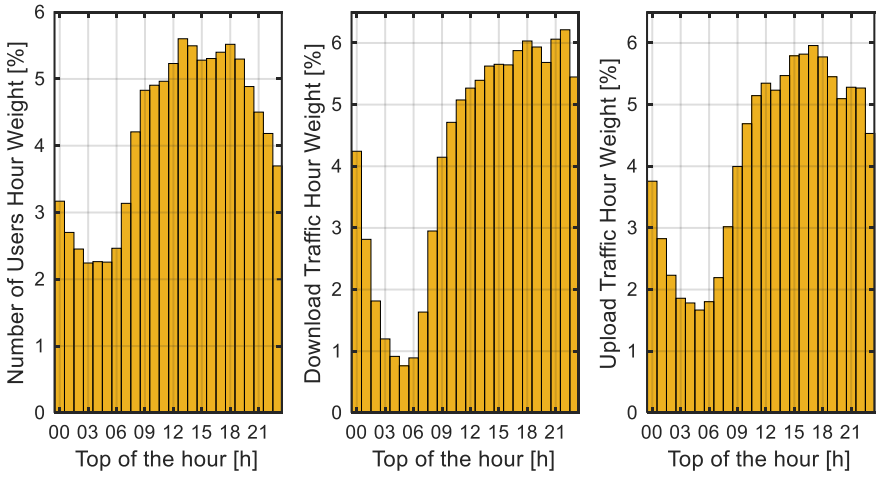


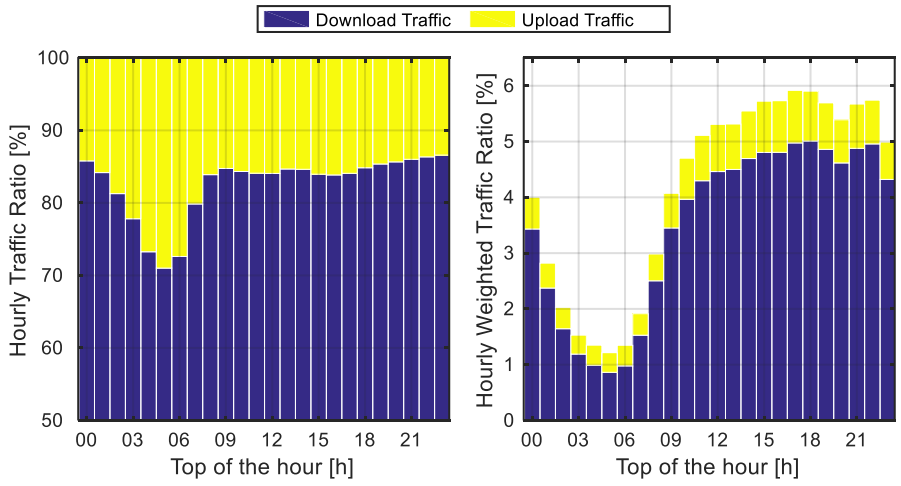

Figure 3.6 – Weekdays Hour Weights.

Regarding WE, the NU, shows a more gradual increase in the morning, starting around 8:00, and, starts to slowly decrease around 20:00, until hitting a minimum between the hours of 3 and 7 in the morning,

also, it takes the highest values between the hours of 11 and 21, with a maximum between 15:00 and 18:00; the DL traffic, shows a steeper progression than WD, between the hours of 8 and 12, and, only shows a decrease in the late night, after midnight, and hits minimum values between the hours of 4 and 7, also, it takes the highest values between the hours of 15 and 23, with a maximum between the hours of 17 and 22; the UL traffic, shows a steady progression between the hours of 8 and 12, and, a slow decrease starting around 22:00, hitting minimum values between the hours of 4 and 7 in the morning, also, it takes the highest values between the hours of 15 and 22, with a peak around 19:00. WE shows a visible delay to the start of the day, which agrees with the fact that a large group of people has WE off, and do not go to work, initiating daily activities latter. All entities show a smoother evolution on WE.

The relation between traffic usage, for DL and UL, along the period of 24 hours, for both WD and WE, is analysed. For WD, in Figure 3.7, two approaches are displayed alongside; in Figure 3.7 (a), for each top of the hour, the share of DL and UL traffic is displayed with a scale from 50% to 100%, and, in Figure 3.7 (b), the shares are now weighted to the traffic weight each top of the hour has. The results of the two approaches are the same for all collections, for both WD and WE.

Regarding WD, the first approach, see Figure 3.7 (a), for the hours from 8:00 in the morning, to 2:00 in the next morning, the DL traffic, takes values higher than 80%; and, the UL traffic, takes values lower than 20%; and, for the hours between 3 and 7, the DL traffic share decreases and takes values between 70% and 80%; and, the UL traffic share increases, complementarily; the second approach, see Figure 3.7 (b), the traffic, for both DL and UL, shows an increase between the hours of 7 and 9, and a decrease in the late night, after 23:00, and hits minimum values between the hours of 3 and 6 in the morning, also, it takes the highest values between the hours of 10 and 22, only slightly varying.




(a) Hourly Ratios. (b) Daily Ratios.

Figure 3.7 – Weekdays Traffic Ratios.

Regarding WE, the first approach, for the hours from 8:00 in the morning, to 3:00 in the next morning, the DL traffic, takes values higher than 80%; and, the UL traffic, takes values lower than 20%; and, for the hours between 4 and 7, the DL traffic share decreases and takes values between 70% and 80%; and, the UL traffic share increases, complementarily; the second approach, the traffic, for both DL and UL, now shows a more gradual and slow increase, for the hours from 8 to 15, and a decrease in the late

night, after 23:00, hitting the minimum values between the hours of 4 and 7, and taking the highest values between the hours of 15 and 23.

### 3.3.3 Applications Results

The distribution of each entity, through the applications, is shown for all 24 top of the hour, for both WD and WE. Two analyses are represented, firstly, the share of entity associated to each one of the applications is displayed, taking values between 0% and 100% for each top of the hour, see Figure 3.8 for WD; later, the shares are weighted to the entity weight each top of the hour has, and all hours have to add up to 100%, see Figure 3.9 for WD. The first analysis helps to grasp the impact each application has for each hour, and how it changes along the day. The second one, displays the actual contributions each application represents in the day.

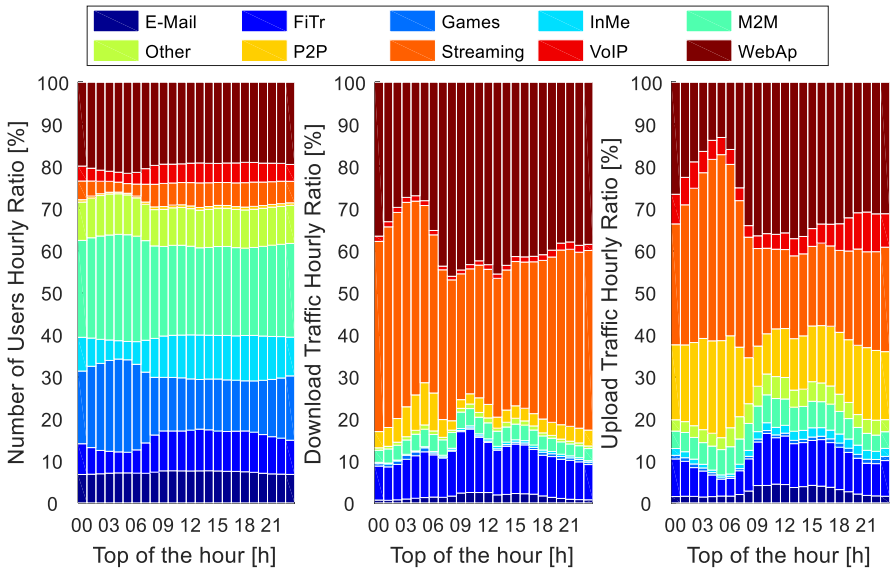



Figure 3.8 – Weekdays APP_GROUP Hourly Ratios.

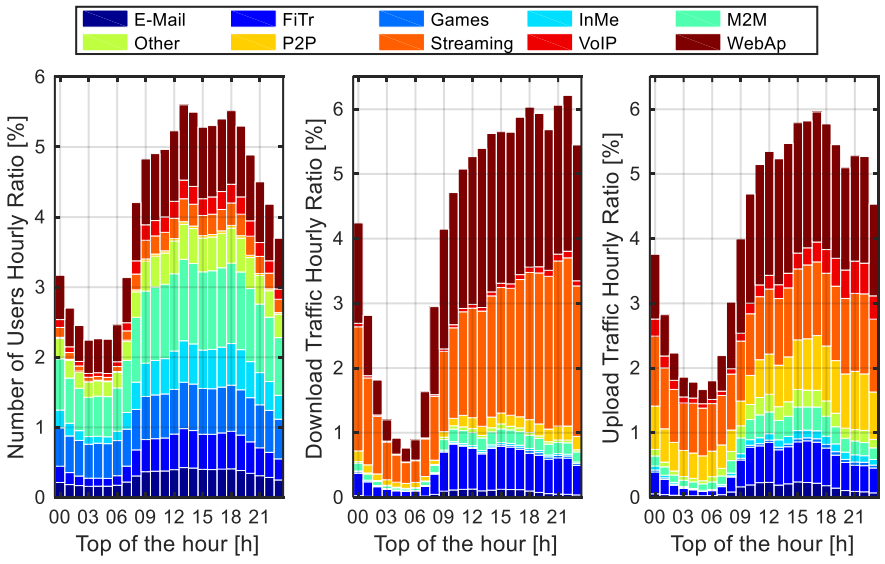



Figure 3.9 – Weekdays APP_GROUP Daily Ratios.

Comparing WD against WE, some subtle changes are visible; in particular, applications associated with business activities, show a reduction during WE; and, an application used all week, but showing an increase on WE, suggests that it is often used for personal and free time. The outside contours of Figure 3.9, equal the ones seen in Figure 3.6, but now with the applications' contribution. These visual aids allow to gain some understanding on the behaviours evolution along the day, and give an insight to which equations and models to use to describe and predict these behaviours. The differences between WD and WE, for the daily ratios, were discussed for the hour weights and the App hourly ratios.

Regarding the App collection and WD, see Figure 3.10, the NU, for M2M and WebAp, takes values higher than 15%; for E-mail, FiTr, Games, InMe, Other and Streaming, takes values between 15% and 5%; and, for P2P and VoIP, takes values lower than 5%; the DL traffic, for Streaming and WebAp, takes values higher than 35%; for FiTr, takes a value between 15% and 5%; for M2M and P2P, takes values between 5% and 2%; and, for E-mail, Games, InMe, Other and VoIP, takes values lower than 2%; the UL traffic, for Streaming and WebAp, takes values higher than 20%; for FiTr, M2M, P2P and VoIP, takes values between 15% and 5%; for E-mail and Other, takes values between 5% and 2%; and, for Games and InMe, takes values lower than 2%. Although E-mail, Games, InMe and M2M correspond to around 53% of the NU, combined only represent 6% of DL traffic and 11% of UL traffic; in contrast, Streaming and WebAp only correspond to around 25% of the NU, and add up to 78% of DL traffic and to 55% of UL traffic. For WE, the NU are around the same values, and the traffic usage, for both DL and UL, vary slightly, with the biggest change occurring for Streaming, which increases.

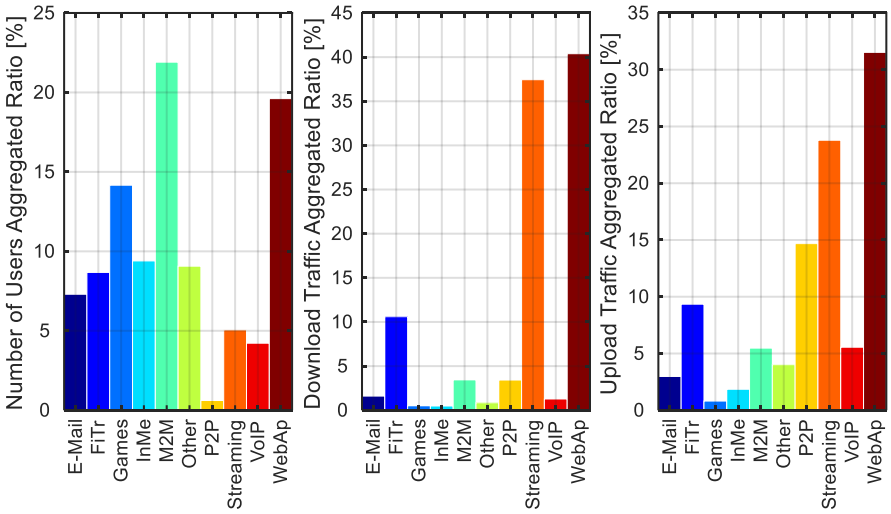



Figure 3.10 – Weekdays APP_GROUP Aggregated Daily Ratios.

## 3.3.4 Devices Results

The distribution of each entity through the devices is shown for all 24 top of the hour, for both WD and WE. Two analysis are represented, firstly, the share of entity associated to each one of the devices is displayed, taking values between 0% and 100% for each top of the hour, see Figure 3.11 for WD; later, the shares are weighted to the entity weight each top of the hour has, and all hours have to add up to 100%, see Figure 3.12 for WD. The first analysis helps to grasp the influence each device has for each hour, and how it changes along the day. The second one, displays the concrete contributions each

device represents in the day.

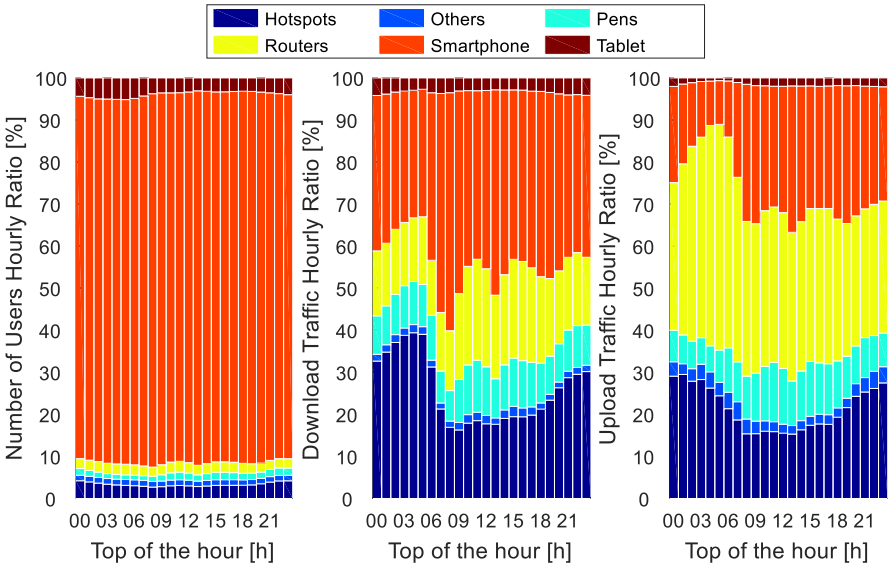



Figure 3.11 – Weekdays DEV_TYPE Hourly Ratios.

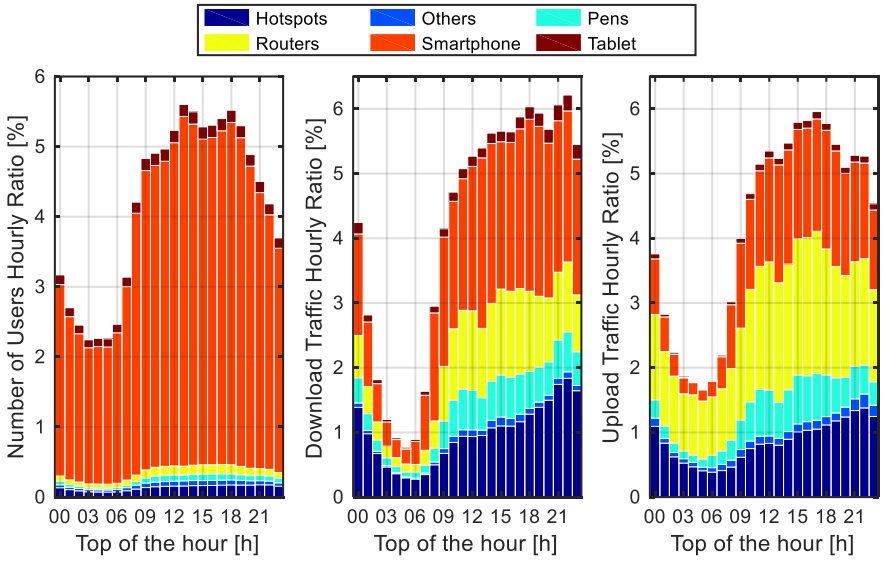



Figure 3.12 – Weekdays DEV_TYPE Daily Ratios.

Comparing WD against WE, the most visible difference is that WE have smother evolutions throughout the day. The outside contours of Figure 3.12, equal the ones seen in Figure 3.6, but now displaying the devices' contributions. These visual aids allow to gain some understanding on the device preference along the day, and give an insight to which equations and models to use to describe and predict these behaviours. The differences between WD and WE, for the daily ratios, were discussed for the hour weights and the Dev hourly ratios. Regarding the Dev collection and WD, see Figure 3.13, the NU, for Smartphone, takes a value higher than 85%; for Hotspots, Others, Pens, Routers and Tablet, takes values lower than 5%; the DL traffic, for Smartphone, takes a value higher than 40%; for Hotspots, Pens and Routers, takes values between 25% and 10%; for Others and Tablet, takes values lower than 5%; the UL traffic, for Routers, takes a value higher than 35%; for Hotspots and Smartphones, takes values between 30% and 20%; for Pens, takes values between 15% and 5%; and, for Others and Tablets,

takes values lower than 5%. Although Smartphone corresponds to around 88% of the NU, it only represents 42% of DL traffic and 28% of UL traffic; in contrast, Hotspots, Pens and Routers correspond to around 7% of the NU, and add up to 53% of DL traffic and to 67% of UL traffic. For WE, the NU are around the same values, and the traffic usage, for both DL and UL, vary slightly; Hotspots, Smartphones and Tablets show an increase.

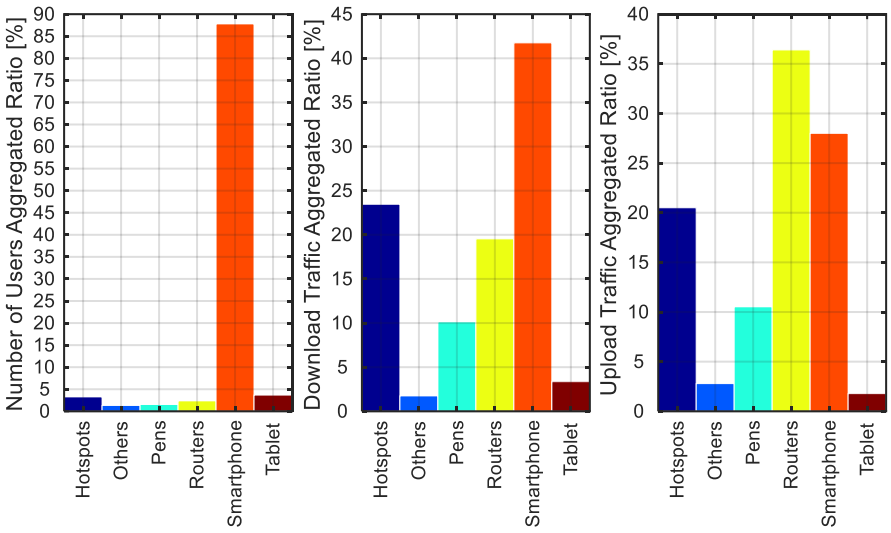



Figure 3.13 – Weekdays DEV_TYPE Aggregated Daily Ratios.

## 3.3.5 Operating Systems Results

The distribution of each entity through the operating systems is shown for all 24 top of the hour, for both WD and WE. Two analysis are represented, firstly, the share of entity associated to each one of the operating systems is displayed, taking values between 0% and 100% for each top of the hour, see Figure 3.14 for WD; later, the shares are weighted to the entity weight each top of the hour has, and all hours have to add up to 100%, see Figure 3.15 for WD. The first analysis helps to grasp the share each operating system has for each hour, and how it changes along the day. The second one, displays the contributions each operating system represents in the day.

Comparing WD against WE, the most visible difference is that WE have smother evolutions throughout the day. The outside contours of Figure 3.15, equal the ones seen in Figure 3.6, but now displaying the operating systems' contributions. These visual aids allow to gain some understanding on the operating systems reach along the day, and give an insight to which equations and models to use to describe and predict these behaviours. The differences between WD and WE, for the daily ratios, were discussed for the hour weights and the OpS hourly ratios. Regarding the OpS collection and WD, see Figure 3.16, the NU, for Android and iOS, takes values higher than 40%; and, for Others and Windows, takes values lower than 10%; the DL traffic, for Android and Others, takes values higher than 30%; for iOS, takes a value between 25% and 20%; and, for Windows, takes a value lower than 2%; the UL traffic, for Android and Others, takes values higher than 40%; for iOS, takes a value around 15%; and, for Windows, takes a value lower than 2%. Android and iOS add up to roughly 90% of the NU, and represent around 56% of DL traffic and UL traffic. For WE, the NU and the traffic usage, for both DL and UL, are roughly maintained the same.

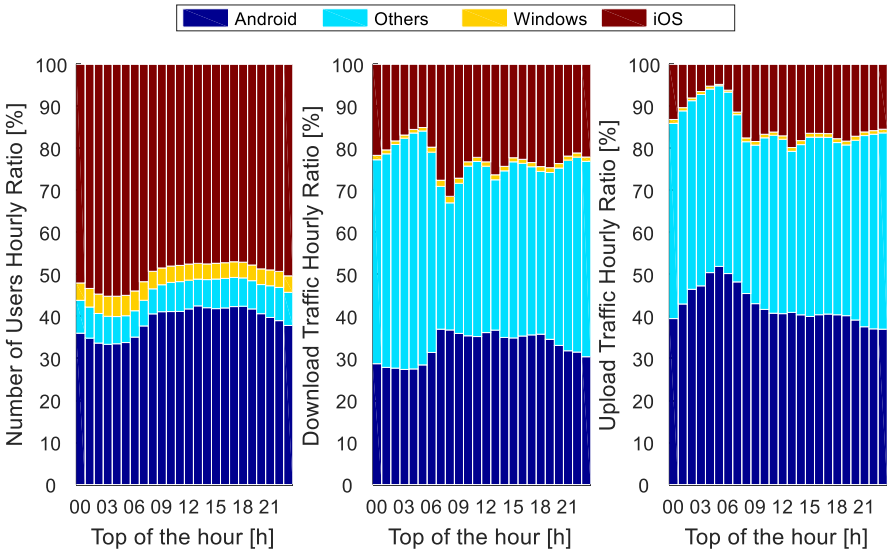



Figure 3.14 – Weekdays OP_SYS Hourly Ratios.

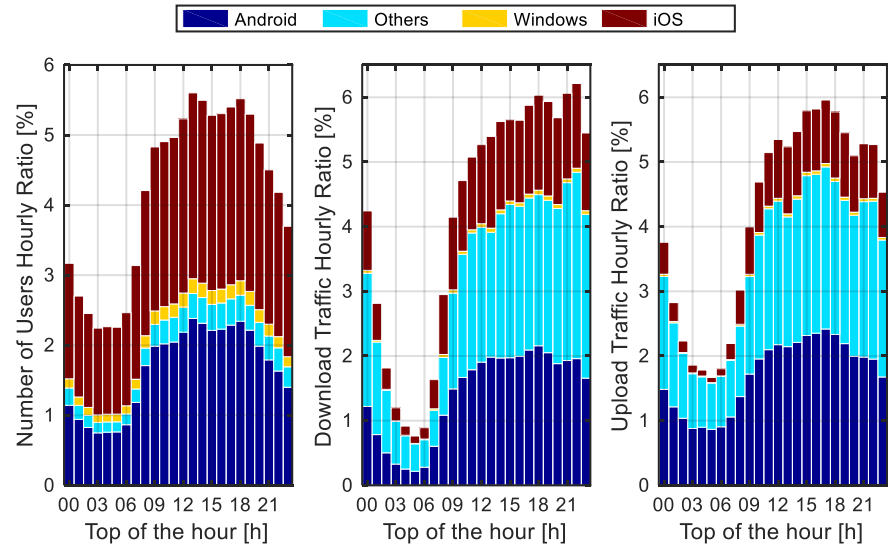



Figure 3.15 – Weekdays OP_SYS Daily Ratios.

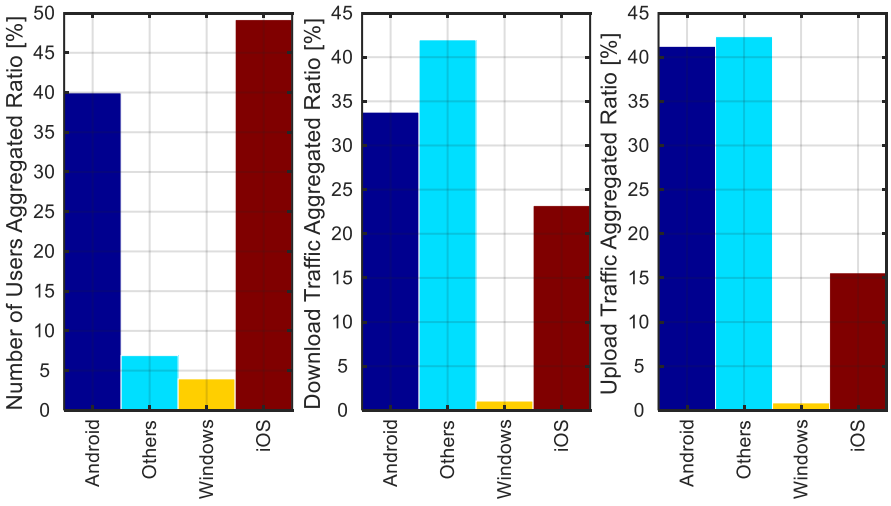



Figure 3.16 – Weekdays OP_SYS Aggregated Daily Ratios.

### 3.3.6 Maximum Traffic Percent Change

To have a better understanding of the traffic variations between WD and WE, for both DL and UL; and between DL and UL, for both WD and WE, these variations are quantified with the maximum traffic change. The maximum traffic change is used in two angles, in comparing WD against WE, and, in comparing DL against UL. Percent changes are obtained for both DL and UL, when comparing WD against WE; and, for both WD and WE, when comparing DL against UL; a total of four situations are analysed. The maximum traffic change considers as the reference and observed values, the maximum traffic $T_{[GB]}$ observed for a particular $n$ case of a collection. For the comparison between WD and WE, WD is the reference value and WE is the observed one; and, for the comparison between DL and UL, DL is the reference value and UL is the observed one. A decrease, symbolised with the minus sign, means that the maximum DL traffic is higher than the maximum UL traffic, whereas an increase means the opposite. Each one of these variations is presented, for each collection, and for each one of the respective $n$ cases, in Table 3.6 for the App collection, in Table 3.7 for the Dev collection, and in Table 3.8 for the OpS collection.

Regarding the App collection, when comparing WD against WE, for DL, the highest percent change is obtained for E-mail, at a decrease of 63.62%, and the lowest one is obtained for WebAp, at a decrease of 2.02%; when comparing WD against WE, for UL, the highest percent change is obtained for E-mail, at a decrease of 61.44%, and the lowest one is obtained for Streaming, at an increase of 1.99%. For both DL and UL there is a percent change decrease for E-mail, FiTr, M2M, Other, VoIP and WebAp; and a percent change increase for Games, InMe, P2P and Streaming. E-mail shows a large decrease, from WD to WE, which is in accordance with the fact that it is mainly used in a work environment and for labour activities. Games, InMe, P2P and Streaming show a slight increase, from WD to WE, which suggests and supports that these are applications are for personal and free time use.

Regarding the App collection, when comparing DL against UL, for WD, the highest percent change is obtained for Streaming, at a decrease of 91.12%, and the lowest one is obtained for VoIP, at a decrease of 12.25%; when comparing DL against UL, for WE, the highest percent change is obtained for Streaming, at a decrease of 91.6%, and the lowest one is obtained for VoIP, at a decrease of 8.54%. For both WD and WE, the maximum DL traffic is always higher than the maximum UL traffic. The percent change for DL against UL varies between a decrease of 63% and 92%, with the exceptions of InMe, Other, P2P, and VoIP for which it varies between a decrease of 8% and 39%. VoIP can be considered a symmetric conversational service, with a percent change for DL against UL, at a decrease of 12.25% for WD, and at a decrease of 8.54% for WE. InMe is an interactive service often used for dialogue purposes, which explains the low percent changes obtained. For both WD and WE, the highest percent changes are obtained for Streaming, and the lowest ones are obtained for VoIP.

Regarding the Dev collection, when comparing WD against WE, for DL, the highest percent change is obtained for Others, at a decrease of 32%, and the lowest one is obtained for Hotspots, at an increase of 0.16%; when comparing WD against WE, for UL, the highest percent change is obtained for Pens, at a decrease of 32.47%, and the lowest one is obtained for Smartphone, at a decrease of 1.78%. For both DL and UL there is a percent change decrease for Others, Pens and Routers; and a percent change

increase for Hotspots and Tablet; with the exception of Smartphone that has a percent change at an increase of 0.60% for DL, and at a decrease of 1.78% for UL. Hotspots and Smartphones, for DL, have a percent change of nearly 0%, and for UL, have an increase of 3.25% and a decrease of 1.78%, respectively, which suggests an overall usage independent of WD or WE. Tablet shows an usage increase on WE, for both DL and UL, suggesting that this device is used for personal and leisure times.

Regarding the Dev collection, when comparing DL against UL, for WD, the highest percent change is obtained for Tablet, at a decrease of 91.20%, and the lowest one is obtained for Routers, at a decrease of 69.27%; when comparing DL against UL, for WE, the highest percent change is obtained for Tablet, at a decrease of 90.35%, and the lowest one is obtained for Others, at a decrease of 69.07%. For both WD and WE, the maximum DL traffic is always higher than the maximum UL traffic. The percent change for DL against UL varies between a decrease of 69% and 92%; and, for each one of the devices, the obtained values for WD and WE are very similar.

Table 3.6 – APP_GROUP Traffic Percent Change.

| App Collection | Maximum Traffic Change [%] | | | |
|---|---|---|---|---|
| | Weekdays vs Weekends | | Download vs Upload | |
| | Download | Upload | Weekdays | Weekends |
| (1) E-Mail | -63.62 | -61.44 | -65.29 | -63.21 |
| (2) FiTr | -26.30 | -25.12 | -83.20 | -82.94 |
| (3) Games | 23.76 | 9.34 | -74.12 | -77.14 |
| (4) InMe | 13.78 | 13.02 | -26.63 | -27.12 |
| (5) M2M | -17.15 | -36.67 | -67.28 | -74.99 |
| (6) Other | -47.88 | -27.58 | -38.66 | -14.77 |
| (7) P2P | 12.99 | 17.43 | -21.94 | -18.87 |
| (8) Streaming | 8.28 | 1.99 | -91.12 | -91.64 |
| (9) VoIP | -6.70 | -2.76 | -12.25 | -8.54 |
| (10) WebAp | -2.02 | -13.55 | -84.83 | -86.61 |

Table 3.7 – DEV_TYPE Traffic Percent Change.

| Dev Collection | Maximum Traffic Change [%] | | | |
|---|---|---|---|---|
| | Weekdays vs Weekends | | Download vs Upload | |
| | Download | Upload | Weekdays | Weekends |
| (1) Hotspots | 0.16 | 3.25 | -85.91 | -85.48 |
| (2) Others | -32.00 | -25.58 | -71.74 | -69.07 |
| (3) Pens | -9.98 | -32.47 | -78.24 | -83.68 |
| (4) Routers | -20.68 | -19.93 | -69.27 | -68.97 |
| (5) Smartphone | 0.60 | -1.78 | -87.16 | -87.46 |
| (6) Tablet | 17.96 | 29.34 | -91.20 | -90.35 |

Regarding the OpS collection, when comparing WD against WE, for DL, the highest percent change is obtained for iOS, at an increase of 8.90%, and the lowest one is obtained for Windows, at an increase of 0.42%; when comparing WD against WE, for UL, the highest percent change is obtained for Windows, at an increase of 25.31%, and the lowest one is obtained for iOS, at an increase of 1.42%. For both DL and UL there is a percent change decrease for Android and Others; and a percent change increase for Windows and iOS. The percent change for WD against WE varies between an increase of 0% and 26%, and a decrease of 2 and 13%.

Regarding the OpS collection, when comparing DL against UL, for WD, the highest percent change is

obtained for iOS, at a decrease of 86.87%, and the lowest one is obtained for Android, at a decrease of 79.17%; when comparing DL against UL, for WE, the highest percent change is obtained for iOS, at a decrease of 87.77%, and the lowest one is obtained for Android, at a decrease of 80.25%. For both WD and WE, the maximum DL traffic is always higher than the maximum UL traffic. The percent change for DL against UL varies between a decrease of 79% and 88%; and, for each one of the operating systems, the obtained values for WD and WE are very similar. For both WD and WE, the highest percent changes are obtained for iOS, and the lowest ones are obtained for Android.

Table 3.8 – OP_SYS Traffic Percent Change.

| OpS Collection | Maximum Traffic Change [%] | | | |
|---|---|---|---|---|
| | Weekdays vs Weekends | | Download vs Upload | |
| | Download | Upload | Weekdays | Weekends |
| (1) Android | -7.54 | -12.32 | -79.17 | -80.25 |
| (2) Others | -2.11 | -2.65 | -83.73 | -83.82 |
| (3) Windows | 0.42 | 25.31 | -85.47 | -81.86 |
| (4) iOS | 8.90 | 1.42 | -86.87 | -87.77 |

## 3.4 Model Catalogue

The model catalogue contains the models used as the set of hypotheses when looking for regression models to explain the data. The list of tested models is: Trapezoid model, Tree Stump model, Pyramid model, Thorn model, Gaussian model, Double Gaussian model and Triple Gaussian model. Three types of equations are chosen as the basis to all models, they are the linear equation, the exponential equation and the gaussian equation. Each model can assemble one or more sections.

Linear equation,

$$f_{lin\ K}(x) = m_K\, x + b_K \tag{3.19}$$

where:

- $m_K$: slope;
- $b_K$: initial value;
- $K$: section index.

Exponential equation,

$$f_{exp\ K}(x) = c_K + e^{\frac{(x - t_K)}{k_K}} \tag{3.20}$$

where:

- $c_K$: vertical offset;
- $t_K$: translation in time;
- $k_K$: decay rate.

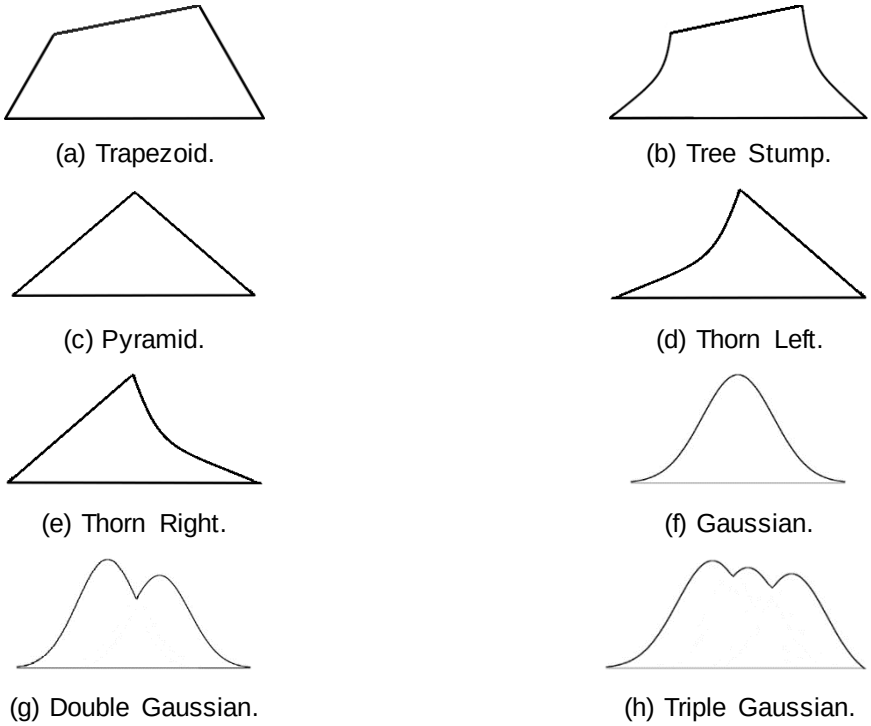
Gaussian equation,

$$f_{gauss\ K}(x) = v_K + u_K \frac{1}{\sqrt{2\pi\,\sigma_K{}^2}} e^{\frac{-(x-\mu_K)^2}{2\sigma_K^2}} \tag{3.21}$$

where:

- $v_K$: vertical offset;
- $u_K$: scaling factor;
- $\sigma_K$: dispersion factor;
- $\mu_K$: average.

A visual aid for the model catalogue is presented in Figure 3.17, showing how many sections each model has, and with which equations is built.



(a) Trapezoid. (b) Tree Stump.

(c) Pyramid. (d) Thorn Left.

(e) Thorn Right. (f) Gaussian.

(g) Double Gaussian. (h) Triple Gaussian.

Figure 3.17 – Model Fitting Options.

The initial and final points of the model, $X_i$ and $X_f$, limit to the left the first section and to the right the last section of the model, respectively. If the model has more than one section, the breakpoints between sections are $X_1$, section limit one, and $X_2$, section limit two.

The Trapezoid model has three linear sections,

$$f_{TRAPZOID}(x) = \begin{cases} f_{lin\ 1}(x), & X_i \le x \le X_1 \\ f_{lin\ 2}(x), & X_1 \le x \le X_2 \\ f_{lin\ 3}(x), & X_2 \le x \le X_f \end{cases} \quad (3.22)$$

The Tree Stump model has three sections, two exponential sections and a linear section, between them,

$$f_{TREE\ STUMP}(x) = \begin{cases} f_{exp\ 1}(x), & X_i \le x \le X_1 \\ f_{lin\ 2}(x), & X_1 \le x \le X_2 \\ f_{exp\ 3}(x), & X_2 \le x \le X_f \end{cases} \quad (3.23)$$

The Pyramid model has two linear sections,

$$f_{PYRAMID}(x) = \begin{cases} f_{lin\ 1}(x), & X_i \le x \le X_1 \\ f_{lin\ 2}(x), & X_1 \le x \le X_f \end{cases} \quad (3.24)$$

The Thorn Left model has two sections, an exponential followed by a linear section,

$$f_{THORNL}(x) = \begin{cases} f_{exp\,1}(x), & X_i \le x \le X_1 \\ f_{lin\,2}(x), & X_1 \le x \le X_f \end{cases} \quad (3.25)$$

The Thorn Right model has two sections, a linear followed by an exponential section,

$$f_{THORNR}(x) = \begin{cases} f_{lin\,1}(x), & X_i \le x \le X_1 \\ f_{exp\,2}(x), & X_1 \le x \le X_f \end{cases} \quad (3.26)$$

The Gaussian model has one gaussian section,

$$f_{GAUSSIAN}(x) = f_{gauss}(x), \quad X_i \le x \le X_f \quad (3.27)$$

The Double Gaussian model has two gaussian sections,

$$f_{DOUBLE\ GAUSSIAN}(x) = \begin{cases} f_{gauss\,1}(x), & X_i \le x \le X_1 \\ f_{gauss\,2}(x), & X_1 \le x \le X_f \end{cases} \quad (3.28)$$

The Triple Gaussian model has three gaussian sections,

$$f_{TRIPLE\ GAUSSIAN}(x) = \begin{cases} f_{gauss\,1}(x), & X_i \le x \le X_1 \\ f_{gauss\,2}(x), & X_1 \le x \le X_2 \\ f_{gauss\,3}(x), & X_2 \le x \le X_f \end{cases} \quad (3.29)$$

Each model is identified as follows: Trapezoid (T); Tree Stump (TS); Pyramid (P); Thorn Left (TL); Thorn Right (TR); Gaussian (G); Double Gaussian (DG); Triple Gaussian (TG).

## 3.5 Implementation Methodology

The data is organised and categorised so information about each study case can be accessed. The different collections, profiles, entities, links, and cases of each collection, add up to 120 distinct study cases. A statistical modelling methodology is implemented in MATLAB, to obtain regression models that characterise the study cases.

### 3.5.1 Data Structuring and Processing

The Data Processing, see Figure 3.19, starts with loading the raw data from the file, into a table in MATLAB; retrieving the names of the applications, devices and operating systems; and defining a data structure. Profile definition, see Figure 3.21, establishes the WD and WE, and separates the date logs between the two profiles. The data is structured as depicted in Figure 3.22. For each profile, either WD or WE, one uses the profile indexes to identify the respective rows in the raw data table; the raw data table entries are then loaded into the data structure. Next, for each entity, the raw data table entries are loaded into the data structure; for each profile, the respective date logs and time logs are drew; and, for each day, one obtains the total data for a specific hour, by combining all data entries with the same date log and time log. The 583885 raw data entries are organised into the data structure that has 24 entries, one for each top of the hour, and as many columns as the profile's number of days, 26 for WD and 13 for WE. In case the original file may be missing some entry log, the data set undergoes a process that checks for and corrects any faults detected. The implementation assumes that each day entry (column)

has 24 sequential hour entries (rows); the training data set file has two types of faults: 8 days are missing one hour log, and 1 day has one data log filled under an hour log different from the top of the hour. Knowing the value each time log must have, and the right order in which it appears, it is possible to identify the time logs missing in the days at fault. The detected faults are corrected by applying linear interpolation to the data set, using the *interp1* command in MATLAB [50].

For the descriptive statistical analysis, one obtains the average of each hour and the average standard deviation. The data points and the average curves undergo a time shift. The shift implementation begins with the task of finding the global minimum of the average curve. The objective behind shifting and rearranging the data, is making it easier to visually recognise shapes and the sections' limits; but also, to facilitate the fitting process. The global minimum is shifted to the left limit of the time window; the same shift is applied to the rest of the data points, and to the average curves. Data shifting is equivalent to performing a translation of the time logs. Histograms provide an initial understanding of the data scatter distribution about the average; and, the *lillietest* MATLAB command is performed for a 5% level of significance to assess if the data statistical distribution can be considered normal. The shifted data and the shifted average curve are normalised to the maximum value of the average curve.

## 3.5.2 Fitting Process

For the Fitting Process, see Figure 3.20, the initial guess, or the starting values of the coefficients affects the convergence of the fitting algorithm. The data is not approximated by a single function; the model is obtained by assembling the section's equation results. Sectioning the model creates added difficulties, from defining the limits of each section, to guaranteeing the continuity at the breakpoints between sections; and, since the data has a cyclic daily window, there is also the need to guarantee the continuity between the left and right limits of the model.

The 3 equations types are defined, the model catalogue is listed, and each one of the 8 models is built by assembling the respective sections' equations. Each model has a different number of sections and different types of section's equations, which influence the number of coefficients estimated for each model. The *fit* MATLAB command performs curve fitting for one fitType at a time, using a nonlinear least-squares algorithm [51], but is unable to yield a discontinuity free model; many manually set attempts would have to be tested, without knowing if a viable model could be found. Preventive measures must be taken so only models suitable to the data, and with positive values, can be obtained. The section's limits, and options for the coefficients values, can be appointed from inspecting the average curves, but is not practical to individually defined each, due to the large number of study cases and unknows. The starting values, for initialisation, and upper and lower bounds, are established for each one of the model's coefficients, and breakpoints between sections. At the same time, continuity between adjacent sections, and the initial and final points of the model, must be ensured.

One assumes the amplitude, for the left and right section limits of a $K^{th}$ section, as $Y_{left}^{K}$ and $Y_{right}^{K}$, respectively. To ensure continuity for a model with only one section, one only needs to guaranty that the initial and final amplitudes of the model, $Y_{left}^{1}$ and $Y_{right}^{1}$, are equal; for a model with two sections, one

needs to guaranty that $Y_{left}^{1} = Y_{right}^{2}$ and $Y_{right}^{1} = Y_{left}^{2}$; and, for a model with three sections, one needs to guaranty that $Y_{left}^{1} = Y_{right}^{3}$ , $Y_{right}^{1} = Y_{left}^{2}$ and $Y_{right}^{2} = Y_{left}^{3}$. To fulfil these conditions, an Auxiliary Model $f(X)$, is introduced. Each one of the three types of equations, used as the basis to all models, can be regarded as a variant of the auxiliary model, with an allied Auxiliary Function $F(X)$.

The Auxiliary Model,

$$f(X) = b_{mdl}\, F(X) + a_{mdl} \tag{3.30}$$

where:

- $b_{mdl}$: auxiliary model coefficient 1;
- $F(X)$: auxiliary function;
- $a_{mdl}$: auxiliary model coefficient 2.

The Linear Auxiliary Function, with $b_{mdl} = m_K$ and $a_{mdl} = b_K$,

$$F(X) = X \tag{3.31}$$

The Exponential Auxiliary Function, with $b_{mdl} = 1$ and $a_{mdl} = c_K$,

$$F(X) = e^{\frac{(X-t)}{k}} \tag{3.32}$$

The Gaussian Auxiliary Function, with $b_{mdl} = u_K$ and $a_{mdl} = v_K$,

$$F(X) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-(X-\mu)^2}{2\sigma^2}} \tag{3.33}$$

For each section, a two-equation system is used to define the left limit, $(X_1, Y_1)$, and the right limit, $(X_2, Y_2)$. The system's solutions are $a_{mdl}$ and $b_{mdl}$.

$$\begin{cases} f(X_1) = Y_1 \\ f(X_2) = Y_2 \end{cases} \Leftrightarrow \begin{cases} b_{mdl}\, F(X_1) + a_{mdl} = Y_1 \\ b_{mdl}\, F(X_2) + a_{mdl} = Y_2 \end{cases} \tag{3.34}$$

$$a_{mdl} = \frac{Y_1 F(X_2) - Y_2 F(X_1)}{F(X_2) - F(X_1)} \tag{3.35}$$

$$b_{mdl} = \frac{Y_2 - Y_1}{F(X_2) - F(X_1)} \tag{3.36}$$

The Exponential equation sections are the exception. To obtain reasonable values for the estimations of the coefficients, and for the width of the coefficient's CI, one coefficient is fixed, specifically $b_{mdl} = 1$; the quality of the fitting adjustment is not compromised. For the exponential auxiliary function, the system's solutions are $t_{mdl}$ and $k_{mdl}$.

$$t_{mdl} = \frac{X_1 \log(Y_2 - a_{mdl}) - X_2 \log(Y_1 - a_{mdl})}{\log(Y_1 - a_{mdl}) - \log(Y_2 - a_{mdl})} \tag{3.37}$$

$$k_{mdl} = \frac{X_1 - X_2}{\log(Y_1 - a_{mdl}) - \log(Y_2 - a_{mdl})} \tag{3.38}$$

For the rest of the points where continuity must be ensured, the same approach applies. Depending on what type of section equation it is, different system's solutions are used. The expressions for $a_{mdl}$, $b_{mdl}$, $t_{mdl}$, and $k_{mdl}$, are placed into the original models, from the model catalogue, in accordance with each section's equation. At the end of the fitting process, the coefficient's values are retrieved based on the same respective expressions.

For the actual fitting process, not all coefficients' estimations, and resulting models, are suitable for the respective study case. A method must be in place to discard unwanted results. A limit of 10 viable model hypotheses is established, for each one of the 8 catalogue models, and from which the best hypothesis is selected. The coefficients' and breakpoints' initialisation values, and upper and lower bounds, are used to reduce the range of possibilities, when testing a hypothesis, and avoid senseless results. An iterative condition is implemented, that establishes the coefficient's CI width to a minimum of 1, and, if the *fit* MATLAB command is unable to return an estimation, increments the width until a solution is reached. Each time a hypothesis is obtained, its results are compared against the ones from the previously obtained hypothesis, and the better one prevails to be compared again against the ones from the next obtained hypothesis, until 10 have been tested.

The CD results, obtained from comparing each model hypothesis against the average curve, are used as criteria to decide which hypothesis is better, between the two; the better option is the one with higher CD. This process is completed when, within the stated conditions, all 8 models are obtained. For each one of the 8 models, the GOF statistics' results are obtained per section, from comparing the model against data; and from comparing the model against the data's average curve, as seen in Figure 3.18.

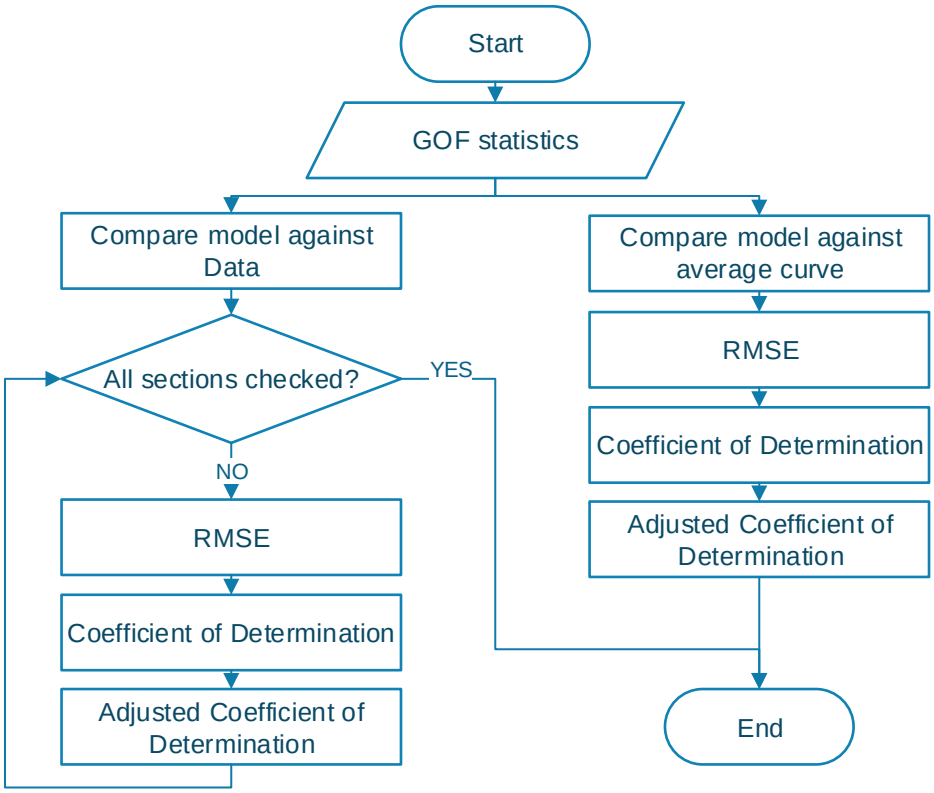



Figure 3.18 – Goodness of fit statistics.

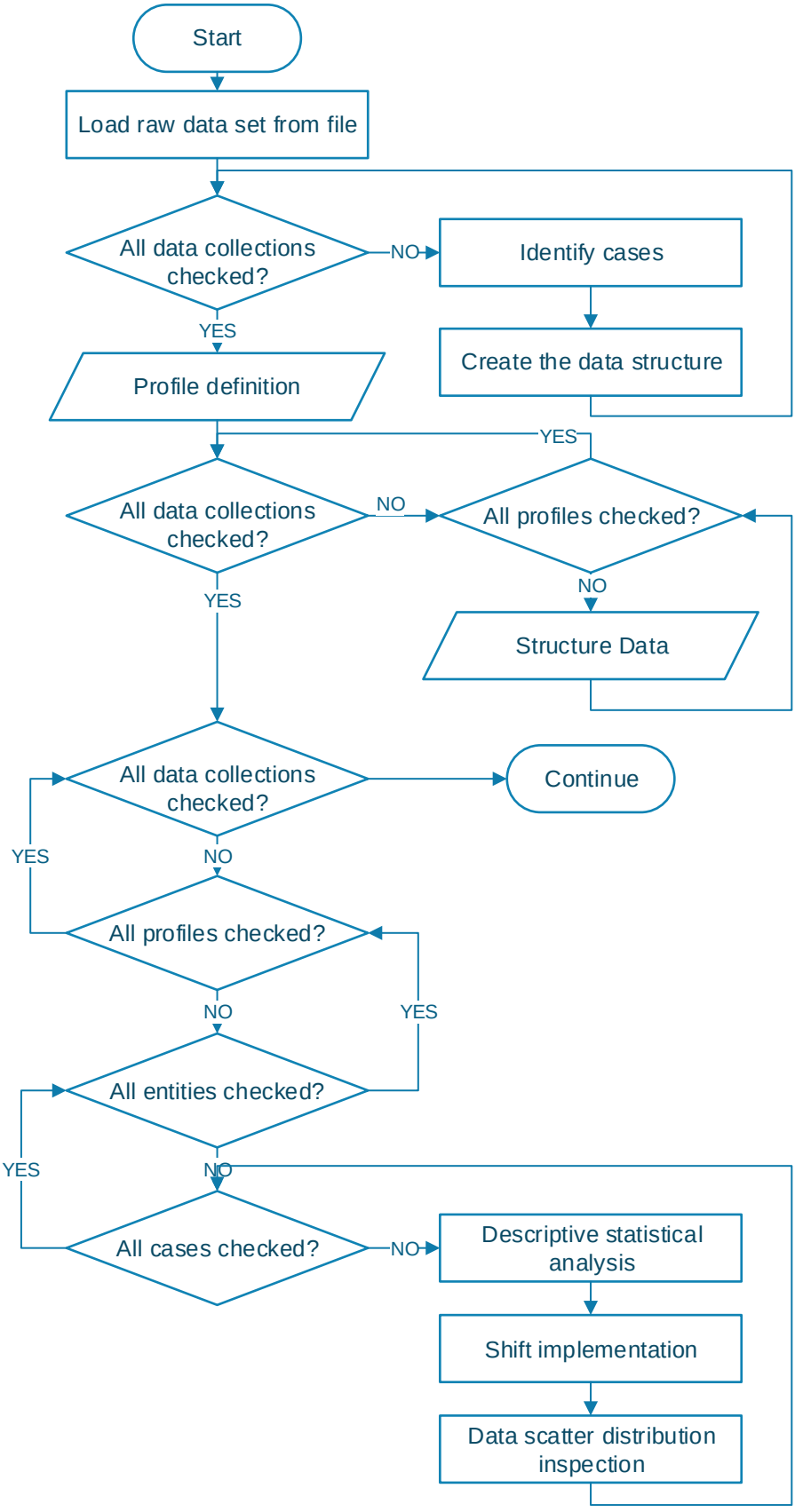



Figure 3.19 – Data Processing.

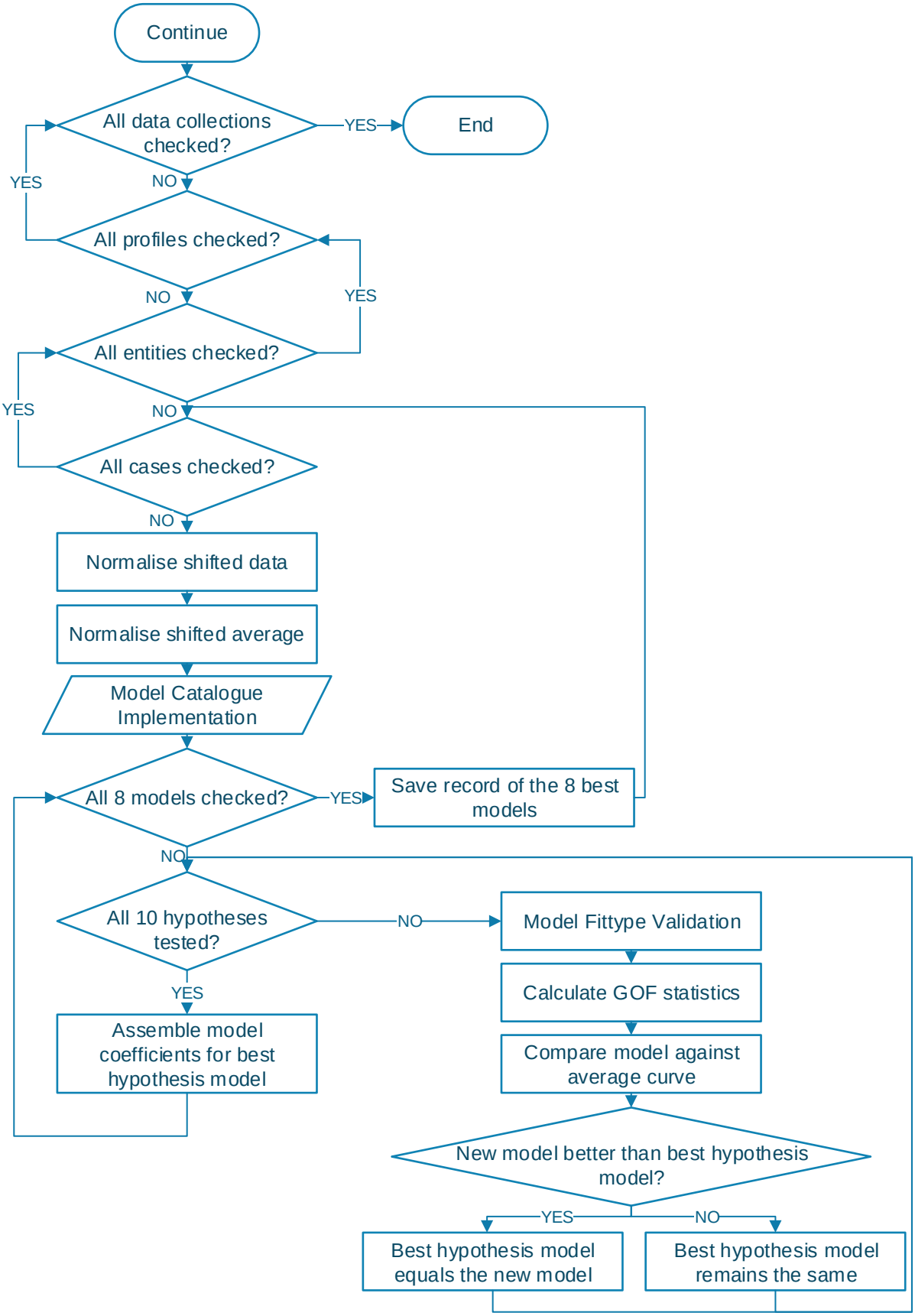



Figure 3.20 – Fitting Process.

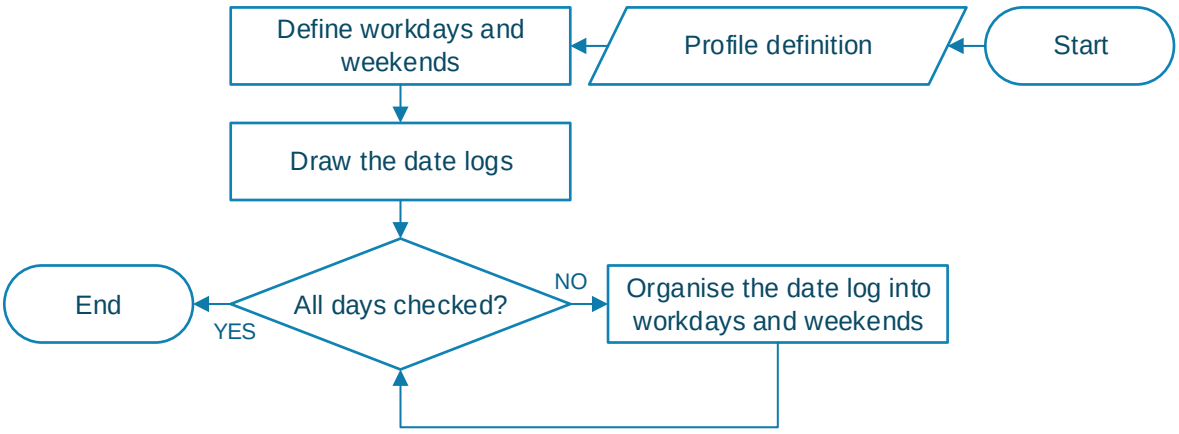



Figure 3.21 – Profile definition.

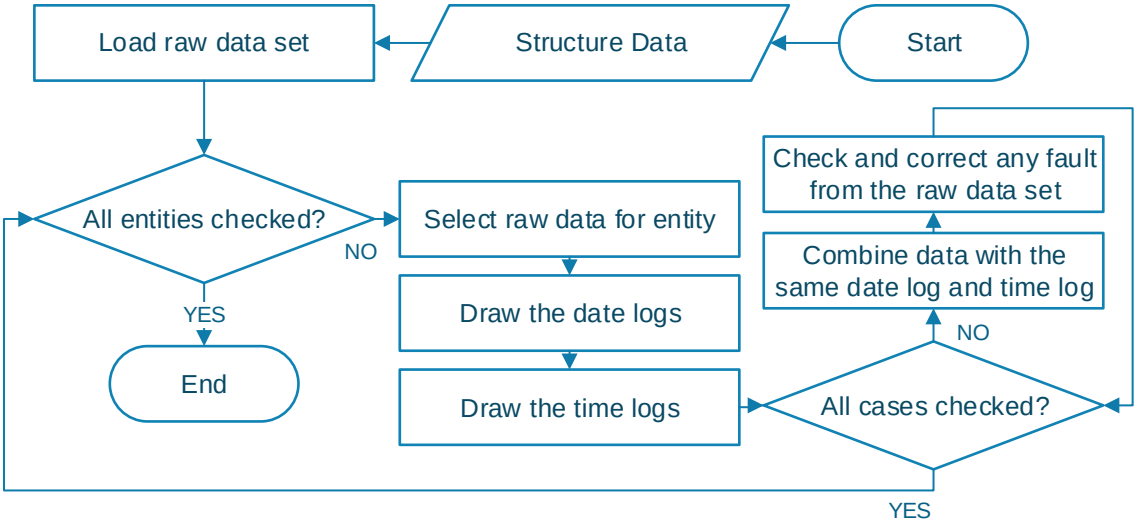


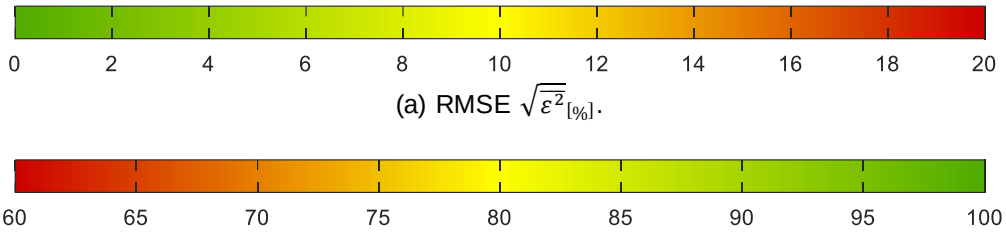

Figure 3.22 – Structure data.

## 3.6 Model Comparison and Ranking

### 3.6.1 Goodness of Fit Statistics Results

The statistics' results are obtained from comparing the normalised shifted models with the respective normalised shifted average curves. The goodness of fit statistics are used to evaluate the fit of the obtained models against the respective data curves. The RMSE, the CD and the ACD are used as criteria of comparison, and ranking, between the obtained models. The goal is to find the models that fulfil the most number of criteria. A model fulfils each criteria if the statistics' results are closer to the preferable ones, than the results obtained for the other model hypothesis. For more accurate and meaningful results, only eligible models that guaranty a RMSE lower than 10%, and a CD and an ACD

higher than 90% will be used to represent each data collection. A colour criteria scheme is implemented to aid in the survey and comparison of the results, see Figure 3.23. For the RMSE, the lowest values, starting in 0%, are coloured in green, becoming lighter until a middle point at 10%, with yellow, and then becoming darker up to red, at an established maximum of 20%. For the CD and the ACD, the highest values, up to 100%, are coloured in green, becoming lighter until the values lower to 80%, with yellow, and then becoming darker up to red at an established minimum of 60%. The break points at 10% and 80%, respectively, define the value after which the results must be taken with extra caution. Values higher than 20% for the RMSE, and values lower than 60% for both the CD and the ACD, are considered unreliable results and are to be discarded, and the respective models are found questionable in its ability to predict the data. Models that are good approximations for the data often have very similar values in the range between [90,100]%; this highlights the models that are to be considered as the hypothesis for Best and General models.




(a) RMSE $\sqrt{\overline{\varepsilon^2}}_{[\%]}$.

(b) CD $R^2_{[\%]}$; ACD $R^2_{adj\ [\%]}$.

Figure 3.23 – Goodness of fit statistics' colour criteria.

The combination of each of the three tables allows to compare the models, and helps rank them in agreement with the established criteria, with the objective of finding the Best and General models. For each case of a collection (one column of the tables), each section of the table is analysed and the models ranked, and then the criteria decisions are combined. This procedure is repeated for each column of the four scenarios: WD, DL; WD, UL; WE, DL; WE, UL. The criteria decisions require ordering the models in ascendant order for the RMSE, and in descendent order for both the CD and the ACD.

For the App collection, and the scenario WD, DL, when comparing the results of the 8 models, see Table 3.9, regarding the RMSE, the lowest value is obtained for M2M and VoIP, with the TG model, at 1.9%, and the highest one is obtained for WebAp, with the TR model, at 16.2%; regarding the CD, the highest value is obtained for M2M and VoIP, with the TG model, at 99.6%, and the lowest one is obtained for P2P, with the TL model, at 65.3%; and, regarding the ACD, the highest value is obtained for M2M and VoIP, with the TG model, at 99.3%, and the lowest one is obtained for P2P, with the TL model, at 60.1%.

For the App collection, and the scenario WD, UL, when comparing the results of the 8 models, regarding the RMSE, the lowest value is obtained for VoIP, with the TG model, at 1.7%, and the highest one is obtained for WebAp, with the TR model, at 13.1%; regarding the CD, the highest value is obtained for VoIP, with the TG model, at 99.6%, and the lowest one is obtained for Streaming, with the TL model, at 80.6%; and, regarding the ACD, the highest value is obtained for VoIP, with the TG model, at 99.3%, and the lowest one is obtained for Streaming, with the TL model, at 77.7%.

For the App collection, and the scenario WE, DL, when comparing the results of the 8 models, regarding

the RMSE, the lowest value is obtained for InMe, with the TG model, at 1.0%, and the highest one is obtained for Streaming, with the TL model, at 13.5%; regarding the CD, the highest value is obtained for InMe, with the TG model, at 99.9%, and the lowest one is obtained for Streaming, with the TL model, at 79.0%; and, regarding the ACD, the highest value is obtained for InMe, with the TG model, at 99.8%, and the lowest one is obtained for Streaming, with the TL model, at 75.8%.

For the App collection, and the scenario WE, UL, when comparing the results of the 8 models, regarding the RMSE, the lowest value is obtained for VoIP and WebAp, with the TS and TG models, respectively, at 1.4%, and the highest one is obtained for WebAp, with the TL model, at 12.5%; regarding the CD, the highest value is obtained for WebAp, with the TG model, at 99.8%, and the lowest one is obtained for WebAp, with the TL model, at 83.3%; and, regarding the ACD, the highest value is obtained for WebAp, with the TG model, at 99.7%, and the lowest one is obtained for WebAp, with the TL model, at 80.7%.

Table 3.9 – Weekdays Download APP_GROUP.

| | (1) E-Mail | (2) FiTr | (3) Games | (4) InMe | (5) M2M | (6) Other | (7) P2P | (8) Streaming | (9) VoIP | (10) WebAp |
|---|---|---|---|---|---|---|---|---|---|---|
| RMSE $\sqrt{\overline{\varepsilon^2}}$ [%] | | | | | | | | | | |
| T | 9.5 | 7.2 | 4.5 | 7.6 | 5.4 | 8.9 | 7.9 | 4.0 | 6.7 | 6.8 |
| TS | 4.1 | 3.5 | 4.2 | 6.0 | 4.2 | 9.8 | 4.3 | 2.5 | 2.8 | 4.4 |
| P | 10.1 | 13.3 | 5.5 | 11.2 | 10.8 | 10.4 | 12.3 | 8.0 | 8.1 | 14.3 |
| TL | 10.2 | 12.3 | 6.1 | 14.3 | 12.5 | 10.9 | 13.5 | 11.9 | 11.8 | 16.1 |
| TR | 12.3 | 15.9 | 5.9 | 12.7 | 13.3 | 9.7 | 8.6 | 6.4 | 4.1 | 16.2 |
| G | 10.5 | 13.2 | 6.7 | 9.1 | 10.1 | 11.2 | 9.6 | 10.6 | 11.7 | 12.3 |
| DG | 4.4 | 8.1 | 3.8 | 6.3 | 6.8 | 8.9 | 6.7 | 5.7 | 6.0 | 11.5 |
| TG | 2.9 | 3.2 | 3.0 | 3.0 | 1.9 | 8.4 | 5.5 | 2.1 | 1.9 | 4.3 |
| CD $R^2$[%] | | | | | | | | | | |
| T | 92.5 | 94.6 | 97.2 | 95.4 | 96.9 | 87.8 | 88.2 | 98.0 | 94.6 | 95.9 |
| TS | 98.6 | 98.7 | 97.6 | 97.2 | 98.2 | 85.2 | 96.4 | 99.2 | 99.1 | 98.3 |
| P | 91.5 | 81.4 | 95.9 | 90.0 | 87.6 | 83.3 | 71.4 | 91.8 | 92.1 | 81.8 |
| TL | 91.3 | 84.1 | 94.9 | 83.8 | 83.5 | 81.6 | 65.3 | 81.8 | 83.2 | 77.2 |
| TR | 87.5 | 73.6 | 95.2 | 87.3 | 81.4 | 85.3 | 85.8 | 94.7 | 97.9 | 76.9 |
| G | 90.8 | 81.7 | 94.0 | 93.5 | 89.3 | 80.5 | 82.3 | 85.5 | 83.4 | 86.7 |
| DG | 98.4 | 93.1 | 98.0 | 96.8 | 95.1 | 87.7 | 91.4 | 95.8 | 95.7 | 88.4 |
| TG | 99.3 | 98.9 | 98.8 | 99.3 | 99.6 | 89.2 | 94.2 | 99.4 | 99.6 | 98.3 |
| ACD $R^2_{adj}$ [%] | | | | | | | | | | |
| T | 90.9 | 93.5 | 96.6 | 94.5 | 96.2 | 85.3 | 85.7 | 97.6 | 93.4 | 95.0 |
| TS | 98.1 | 98.3 | 96.7 | 96.2 | 97.5 | 79.9 | 95.1 | 98.9 | 98.7 | 97.7 |
| P | 90.7 | 79.7 | 95.5 | 89.1 | 86.4 | 81.7 | 68.7 | 91.0 | 91.4 | 80.1 |
| TL | 90.0 | 81.7 | 94.1 | 81.3 | 81.0 | 78.8 | 60.1 | 79.1 | 80.6 | 73.7 |
| TR | 85.6 | 69.6 | 94.5 | 85.4 | 78.6 | 83.1 | 83.7 | 93.9 | 97.6 | 73.4 |
| G | 89.4 | 79.0 | 93.1 | 92.5 | 87.7 | 77.6 | 79.6 | 83.3 | 81.0 | 84.7 |
| DG | 97.8 | 90.7 | 97.3 | 95.7 | 93.4 | 83.3 | 88.4 | 94.3 | 94.1 | 84.3 |
| TG | 98.8 | 98.1 | 97.8 | 98.7 | 99.3 | 80.9 | 89.7 | 99.0 | 99.3 | 97.1 |

For the App collection, the RMSE varies between 1% and 16.2%; the CD varies between 99.9% and 65.3%; and, the ACD varies between 99.8% and 60.1%.

For WD, DL, concerning the Streaming case, going back to Table 3.9, regarding the RMSE, the lowest values are obtained with the TG model, at 2.1%, and with the TS model, at 2.5%; regarding the CD, the highest values are obtained with the TG model, at 99.4%, and with the TS model, at 99.2%; and, regarding the ACD, the highest values are obtained with the TG model, at 99.0%, and with the TS model,

at 98.9%. A model that presents the best results for a statistic fulfils the criteria for that statistic. A model with statistics results closer to the preferable ones for the three statistics, fulfils the three criteria the best, and is ranked first, which is what happens with the TG model. The TS model is ranked second, as it is the second best model to satisfies all three criteria. It is possible to guaranty a RMSE lower than 3%, a CD higher than 99%, and an ACD higher than 98%. The same procedure is repeated for the remaining applications, for all scenarios.

For the Dev collection, and the scenario WD, DL, when comparing the results of the 8 models, regarding the RMSE, the lowest value is obtained for Hotspots, with the TG model, at 1.9%, and the highest one is obtained for Pens, with the TR model, at 17.5%; regarding the CD, the highest value is obtained for Pens, with the TG model, at 99.6%, and the lowest one is obtained for Pens, with the TR model, at 70.5%; and, regarding the ACD, the highest value is obtained for Pens, with the TG model, at 99.3%, and the lowest one is obtained for Pens, with the TR model, at 66.1%.

For the Dev collection, and the scenario WD, UL, when comparing the results of the 8 models, regarding the RMSE, the lowest value is obtained for Routers, with the TG model, at 1.5%, and the highest one is obtained for Tablet, with the TR model, at 15.4%; regarding the CD, the highest value is obtained for Tablet, with the TG model, at 99.6%, and the lowest one is obtained for Others, with the G model, at 46.9%; and, regarding the ACD, the highest value is obtained for Tablet, with the TG model, at 99.3%, and the lowest one is obtained for Others, with the G model, at 39.0%.

For the Dev collection, and the scenario WE, DL, when comparing the results of the 8 models, regarding the RMSE, the lowest value is obtained for Hotspots, with the TS model, at 1.5%, and the highest one is obtained for Tablet, with the TL model, at 15.8%; regarding the CD, the highest value is obtained for Hotspots, with the TS model, at 99.7%, and the lowest one is obtained for Tablet, with the TL model, at 71.3%; and, regarding the ACD, the highest value is obtained for Hotspots, with the TS model, at 99.6%, and the lowest one is obtained for Tablet, with the TL model, at 67.0%.

For the Dev collection, and the scenario WE, UL, when comparing the results of the 8 models, regarding the RMSE, the lowest value is obtained for Smartphone, with the TG model, at 0.9%, and the highest one is obtained for Others, with the TL model, at 17.1%; regarding the CD, the highest value is obtained for Smartphone, with the TG model, at 99.9%, and the lowest one is obtained for Others, with the TL model, at 68.5%; and, regarding the ACD, the highest value is obtained for Smartphone, with the TG model, at 99.8%, and the lowest one is obtained for Others, with the TL model, at 63.8%.

For the Dev collection, the RMSE varies between 0.9% and 17.5%; the CD varies between 99.9% and 46.9%; and, the ACD varies between 99.8% and 39.0%.

For WD, DL, concerning the Smartphone case, regarding the RMSE, the lowest values are obtained with the TS model, at 5.2%, and with the T model, at 6.7%; regarding the CD, the highest values are obtained with the TS model, at 97.2%, and with the T model, at 95.5%; and, regarding the ACD, the highest values are obtained with the TS model, at 96.2%, and with the T model, at 94.5%. A model that presents the best results for a statistic fulfils the criteria for that statistic. A model with statistics results closer to the preferable ones for the three statistics, fulfils the three criteria the best, and is ranked first,

which is what happens with the TS model. The T model is ranked second, as it is the second best model to satisfies all three criteria. It is possible to guaranty a RMSE lower than 7%, a CD higher than 95%, and an ACD higher than 94%. The same procedure is repeated for the remaining devices, for all scenarios.

For the OpS collection, and the scenario WD, DL, when comparing the results of the 8 models, regarding the RMSE, the lowest value is obtained for Others, with the TG model, at 2.1%, and the highest one is obtained for Windows, with the TL model, at 16.8%; regarding the CD, the highest value is obtained for Android, with the TG model, at 99.1%, and the lowest one is obtained for Windows, with the TL model, at 68.2%; and, regarding the ACD, the highest value is obtained for Others, with the TG model, at 99.0%, and the lowest one is obtained for Windows, with the TL model, at 63.4%.

For the OpS collection, and the scenario WD, UL, when comparing the results of the 8 models, regarding the RMSE, the lowest value is obtained for Others, with the TG model, at 0.9%, and the highest one is obtained for iOS, with the TL model, at 13.7%; regarding the CD, the highest value is obtained for Others, with the TG model, at 99.9%, and the lowest one is obtained for Others, with the TR model, at 81.4%; and, regarding the ACD, the highest value is obtained for Others, with the TG model, at 99.8%, and the lowest one is obtained for Others, with the TR model, at 78.6%.

For the OpS collection, and the scenario WE, DL, when comparing the results of the 8 models, regarding the RMSE, the lowest value is obtained for Others, with the TS model, at 1.5%, and the highest one is obtained for Android, with the TL model, at 13.7%; regarding the CD, the highest value is obtained for Others, with the TS and TG models, at 99.7%, and the lowest one is obtained for Android, with the TL model, at 80.4%; and, regarding the ACD, the highest value is obtained for Others, with the TS model, at 99.6%, and the lowest one is obtained for Android, with the TL model, at 77.5%.

For the OpS collection, and the scenario WE, UL, when comparing the results of the 8 models, regarding the RMSE, the lowest value is obtained for iOS, with the TG model, at 1.0%, and the highest one is obtained for Windows, with the TR model, at 12.1%; regarding the CD, the highest value is obtained for iOS, with the TG model, at 99.9%, and the lowest one is obtained for Windows, with the TR model, at 81.7%; and, regarding the ACD, the highest value is obtained for iOS, with the TG model, at 99.8%, and the lowest one is obtained for Windows, with the TR model, at 78.9%.

For the OpS collection, the RMSE varies between 0.9% and 16.8%; the CD varies between 99.9% and 68.2%; and, the ACD varies between 99.8% and 63.4%.

For WD, DL, concerning the Android case, regarding the RMSE, the lowest values are obtained with the TG model, at 3.1%, and with the TS model, at 4.0%; regarding the CD, the highest values are obtained with the TG model, at 99.1%, and with the TS model, at 98.4%; and, regarding the ACD, the highest values are obtained with the TG model, at 98.3%, and with the TS model, at 97.8%. A model that presents the best results for a statistic fulfils the criteria for that statistic. A model with statistics results closer to the preferable ones for the three statistics, fulfils the three criteria the best, and is ranked first, which is what happens with the TG model. The TS model is ranked second, as it is the second best model to satisfies all three criteria. It is possible to guaranty a RMSE lower than 4%, a CD higher than

98%, and an ACD higher than 97%. The same procedure is repeated for the remaining devices, for all scenarios.

## 3.6.2 Best Ranked Models

The number of fulfilled criteria ranges between a maximum of three fulfilled criteria and a minimum of 1, with a colour scale of green for three, yellow for two, and red for 1. A model that presents the best results for a statistic fulfils the criteria for that statistic. A model that fulfils the three criteria with ranking one is the model that best satisfies all three criteria. The following tables are the product of the inspection and comparison of the GOF statistics tables. The focus is on the first and second ranked models. The Best Models guaranty a $\sqrt{\overline{\varepsilon^2}} \leq 10\%$, a $R^2 \geq 95\%$ and a $R^2_{adj} \geq 90\%$, with a more narrow and restricted range of results for the CD than the ones set initially.

For the App collection, and the scenario WD, DL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, see Table 3.10, the TG model is ranked as first, for 8 out of 10 cases, and ranked as second for 2; the TS model is ranked as first for 2 cases, and ranked as second for 6; the DG and T models are ranked as second. For 7 out of 10 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics; and for 3 cases, only two criteria are fulfilled for both.

Table 3.10 – Weekdays Download APP_GROUP Best Models.

| | (1) E-Mail | (2) FiTr | (3) Games | (4) InMe | (5) M2M | (6) Other | (7) P2P | (8) Streaming | (9) VoIP | (10) WebAp |
|---|---|---|---|---|---|---|---|---|---|---|
| Ranking | | | | | | | | | | |
| 1º | TG | TG | TG | TG | TG | TG | TS | TG | TG | TS |
| 2º | TS | TS | DG | TS | TS | T | TG | TS | TS | TG |
| Number of Fulfilled Criteria | | | | | | | | | | |
| 1º | 3 | 2 | 3 | 3 | 3 | 2 | 3 | 3 | 3 | 2 |
| 2º | 3 | 2 | 3 | 3 | 3 | 2 | 3 | 3 | 3 | 2 |

For WD, DL, concerning the FiTr case, going back to Table 3.9, the TG model shows better statistic results for the RMSE and the CD, than the TS model, with the exception of the ACD, for which the TS model shows better results; in this way, the TG and TS models do not fulfil one of the criteria for first and second rank, respectively, attaining both two criteria checked for their rank, see Table 3.10, regarding the number of fulfilled criteria. Similar conditions happen for Other and WebAp.

For the App collection, and the scenario WD, UL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, the TG model is ranked as first, for 7 out of 10 cases, and ranked as second for 1; the TS model is ranked as first for 1 case, and ranked as second for 3; the DG model is ranked as first for 2 cases, and ranked as second for 5; the T model is ranked as second. For 9 out of 10 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics; and for 1 case, only two criteria are fulfilled for both.

For the App collection, and the scenario WE, DL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, the TG model is ranked as first, for 5 out of 10 cases, and ranked as second for 3; the TS model is ranked as first for 3 cases, and ranked as second for 6; the DG model is

ranked as first for 1 case, and ranked as second for 1; the T model is ranked as first. For 7 out of 10 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics; for 2 cases, the first fulfils all three criteria and the second only two; and for 1 case, only two criteria are fulfilled for both.

For the App collection, and the scenario WE, UL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, the TG model is ranked as first, for 7 out of 10 cases, and ranked as second for 1; the TS model is ranked as first for 2 cases, and ranked as second for 2; the DG model is ranked as second for 5 cases; the T model is ranked as first for 1 case, and ranked as second for 1. For 7 out of 10 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics; for 2 cases, the first fulfils all three criteria and the second only two; and for 1 case, only two criteria are fulfilled for both.

For the Dev collection, and the scenario WD, DL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, see Table 3.11, the TG model is ranked as first, for 3 out of 6 cases, and ranked as second for 1; the TS model is ranked as first for 3 cases, and ranked as second for 3; the DG and T models are ranked as second. For 5 out of 6 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics; and for 1 case, the first fulfils all three criteria and the second only two.

Table 3.11 – Weekdays Download DEV_TYPE Best Models.

| | (1) Hotspots | (2) Others | (3) Pens | (4) Routers | (5) Smartphone | (6) Tablet |
|---|---|---|---|---|---|---|
| Ranking | | | | | | |
| 1º | TG | TG | TG | TS | TS | TS |
| 2º | TS | TS | TS | DG | T | TG |
| Number of Fulfilled Criteria | | | | | | |
| 1º | 3 | 3 | 3 | 3 | 3 | 3 |
| 2º | 3 | 2 | 3 | 3 | 3 | 3 |

For the Dev collection, and the scenario WD, UL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, the TG model is ranked as first, for all 6 cases; the TS model is ranked as second for 4 cases; the DG model is ranked as second for 2 cases. For all 6 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics.

For the Dev collection, and the scenario WE, DL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, the TG model is ranked as first, for 3 out of 6 cases, and ranked as second for 2; the TS model is ranked as first for 3 cases, and ranked as second for 1; the DG and T models are ranked as second. For all 6 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics.

For the Dev collection, and the scenario WE, UL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, the TG model is ranked as first, for 4 out of 6 cases, and ranked as second for 2; the TS model is ranked as first for 2 cases; the DG model is ranked as second for 4 cases. For 5 out of 6 cases, the first and second best models fulfil all three criteria for having the statistics

results closer to the preferable ones for the three statistics; and for 1 case, the first fulfils all three criteria and the second only two.

For the OpS collection, and the scenario WD, DL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, see Table 3.12, the TG model is ranked as first, for 2 out of 4 cases; the TS model is ranked as first for 2 cases, and ranked as second for 2; the T model is ranked as second. For 9 out of 10 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics; and for 1 case, only two criteria are fulfilled for both. For all 4 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics.

Table 3.12 – Weekdays Download OP_SYS Best Models: Ranking.

| | (1)<br>Android | (2)<br>Others | (3)<br>Windows | (4)<br>iOS |
|---|---|---|---|---|
| Ranking | | | | |
| 1º | TG | TG | TS | TS |
| 2º | TS | TS | T | T |
| Number of Fulfilled Criteria | | | | |
| 1º | 3 | 3 | 3 | 3 |
| 2º | 3 | 3 | 3 | 3 |

For the OpS collection, and the scenario WD, UL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, the TG model is ranked as first, for all 4 cases; the TS model is ranked as second for 1 case; the DG and T models are ranked as second. For 3 out of 4 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics; and for 1 case, only two criteria are fulfilled for both.

For the OpS collection, and the scenario WE, DL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, the TG model is ranked as first, for 3 out of 4 cases, and ranked as second for 1; the TS model is ranked as first for 1 case, and ranked as second for 3. For 3 out of 4 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics; and for 1 case, the first fulfils all three criteria and the second only two.

For the OpS collection, and the scenario WE, UL, when ranking and attaining the number of fulfilled criteria for the models hypothesis, the TG model is ranked as first, for all 4 cases; the TS model is ranked as second for 1 case; the DG and T models are ranked as second. For all 4 cases, the first and second best models fulfil all three criteria for having the statistics results closer to the preferable ones for the three statistics.

Regarding the best ranked models, for the App collection, the more used models are TG, TS and DG; for the Dev collection, the more used models are TG, TS and DG; and, for the OpS collection, the more used models are TG and TS.

## 3.6.3 General Models

For some cases, even though a model is not ranked in the best models, its statistic values are within

the intended and satisfactory range to obtain a reliable model. General Models guaranty a $\sqrt{\overline{\varepsilon^2}} \leq 10\%$, a $R^2 \geq 95\%$ and a $R^2_{adj} \geq 90\%$, with a more narrow and restricted range of results for the CD than the ones set initially.

For the App collection, and the scenario WD, DL, the attributed General model, see Table 3.13 , is a TS model for 5 out of 10 cases; is a TG model for 4 cases; is a DG model for 1 case; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 4.4\%$, a $R^2 \geq 96.4\%$ and a $R^2_{adj} \geq 95.1\%$, with the exception of Other, for which the best results are $\sqrt{\overline{\varepsilon^2}} = 8.4\%$, $R^2 = 89.2\%$ and $R^2_{adj} = 80.9\%$. E-mail and Games, use models that are not ranked as first or second, but these guarantee the desired statistic values.

Table 3.13 – Weekdays Download APP_GROUP General Model.

| | (1) E-Mail | (2) FiTr | (3) Games | (4) InMe | (5) M2M | (6) Other | (7) P2P | (8) Streaming | (9) VoIP | (10) WebAp |
|---|---|---|---|---|---|---|---|---|---|---|
| | DG | TG | TS | TG | TG | TG | TS | TS | TS | TS |

For the App collection, and the scenario WD, UL, the attributed General model, is a TS model for 5 out of 10 cases; is a TG model for 4 cases; is a DG model for 1 case; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 5.4\%$, a $R^2 \geq 96.3\%$ and a $R^2_{adj} \geq 94.9\%$. VoIP uses a model that is not ranked as first or second, but it guarantees the desired statistic values.

For the App collection, and the scenario WE, DL, the attributed General model, is a TS model for 6 out of 10 cases; is a TG model for 3 cases; is a P model for 1 case; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 4.8\%$, a $R^2 \geq 96.2\%$ and a $R^2_{adj} \geq 95.8\%$. Games uses a model that is not ranked as first or second, but it guarantees the desired statistic values.

For the App collection, and the scenario WE, UL, the attributed General model, is a TS model for 5 out of 10 cases; is a TG model for 3 cases; is a TR model for 2 cases; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 5.7\%$, a $R^2 \geq 95.3\%$ and a $R^2_{adj} \geq 93.7\%$. Games, M2M and P2P, use models that are not ranked as first or second, but these guarantee the desired statistic values.

For the App collection, and General models, the RMSE varies between 1.0% and 5.7%; the CD varies between 99.9% and 95.3%; and, the ACD varies between 99.8% and 93.7%.

For the Dev collection, and the scenario WD, DL, the attributed General model, see Table 3.14, is a TS model for 5 out of 6 cases; is a TG model for 1 case; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 8.9\%$, a $R^2 \geq 96.7\%$ and a $R^2_{adj} \geq 95.5\%$.

Table 3.14 – Weekdays Download DEV_TYPE General Model.

| | (1) Hotspots | (2) Others | (3) Pens | (4) Routers | (5) Smartphone | (6) Tablet |
|---|---|---|---|---|---|---|
| | TS | TG | TS | TS | TS | TS |

For the Dev collection, and the scenario WD, UL, the attributed General model, is a TS model for 5 out of 6 cases; is a TG model for 1 case; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 6.4\%$, a $R^2 \geq 95.2\%$ and a $R^2_{adj} \geq 93.4\%$. Pens uses a model that is not ranked as first or second, but it guarantees the desired statistic

values.

For the Dev collection, and the scenario WE, DL, the attributed General model, is a TS model for all 6 cases; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 5.5\%$, a $R^2 \geq 96.4\%$ and a $R^2_{adj} \geq 95.2\%$. Others and Smartphone, use models that are not ranked as first or second, but these guarantee the desired statistic values.

For the Dev collection, and the scenario WE, UL, the attributed General model, is a TS model for all 6 cases; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 6.5\%$, a $R^2 \geq 95.0\%$ and a $R^2_{adj} \geq 93.2\%$. Pens, Routers, Smartphone and Tablet, use models that are not ranked as first or second, but these guarantee the desired statistic values.

For the Dev collection, and General models, the RMSE varies between 1.5% and 8.9%; the CD varies between 99.7% and 95.0%; and, the ACD varies between 99.6% and 93.2%.

For the OpS collection, and the scenario WD, DL, the attributed General model, see Table 3.15, is a TS model for all 4 cases; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 5.5\%$, a $R^2 \geq 96.6\%$ and a $R^2_{adj} \geq 95.5\%$.

Table 3.15 – Weekdays Download OP_SYS General Model.

| | (1)<br>Android | (2)<br>Others | (3)<br>Windows | (4)<br>iOS |
|---|---|---|---|---|
| | TS | TS | TS | TS |

For the OpS collection, and the scenario WD, UL, the attributed General model, is a TS model for all 4 cases; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 7.1\%$, a $R^2 \geq 95.4\%$ and a $R^2_{adj} \geq 93.8\%$. Android, Windows and iOS use models that are not ranked as first or second, but these guarantee the desired statistic values.

For the OpS collection, and the scenario WE, DL, the attributed General model, is a TS model for all 4 cases; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 4.5\%$, a $R^2 \geq 98.0\%$ and a $R^2_{adj} \geq 97.3\%$.

For the OpS collection, and the scenario WE, UL, the attributed General model, is a TS model for all 4 cases; and is guaranteed a $\sqrt{\overline{\varepsilon^2}} \leq 6.2\%$, a $R^2 \geq 95.2\%$ and a $R^2_{adj} \geq 93.5\%$. Android, Windows and iOS use models that are not ranked as first or second, but these guarantee the desired statistic values.

For the OpS collection, and General models, the RMSE varies between 1.5% and 7.1%; the CD varies between 99.7% and 95.2%; and, the ACD varies between 99.6% and 93.5%.

## 3.7 Regression Results

The entity to model is traffic usage, for both links, DL and UL, for all four scenarios: WD, DL; WD, UL; WE, DL; WE, UL. The regression models allow to describe mathematically the data variations throughout the day. The resulting models are used to describe the training data set, and to predict the behaviour of new data for different input situations. The time unit is expressed in top of the hours. The models are obtained for shifted and normalised data and average curves. The maximum value of the

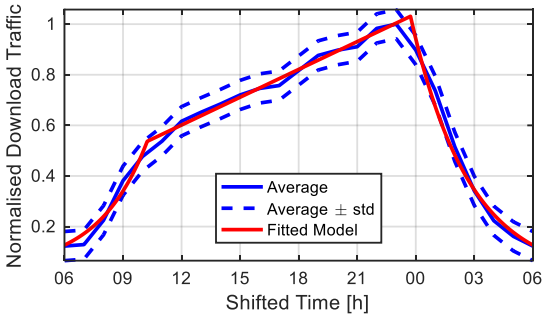
average curve is used to normalise all results. The model, the average curve and the average standard deviation region about the average are displayed shifted and normalised. Although the models are obtained for the data set, the average curves provide an adequate representation of the data. Displaying the obtained model next to the average curve gives insight to how well the model describes the behaviour and matches the overall data observations. The average standard deviation expresses the dispersion of data samples about the average. If the obtained model is contained by the average standard deviation region about the average, then the regression model is more likely to provide a good representation of the data. The final model representation is displayed for the interval between 00:00 and midnight, and is normalised to the maximum value the model may take.

The models are composed of sections characterised by linear, exponential, and gaussian equations; each type of equation has a different set of coefficients that is estimated. The narrower the 95% coefficients' CIs are, the more the results can be trusted. The coefficient values are obtained for each one of the model's sections, with the respective CIs and GOF statistics. The GOF statistics are presented for each one of the model's section to better assess the fit of the model to the data, and also, an overall assessment is obtained by comparing the model with the average curve.

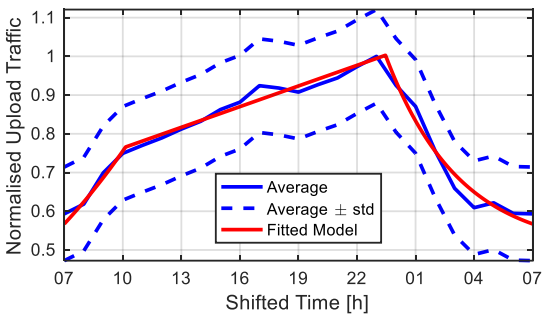
The best models are the ones which fulfil the highest number of criteria for having the statistics' results closer to the preferable ones. The general models are the ones that either are classified as best, or guarantee a $\sqrt{\overline{\varepsilon^2}} \leq 10\%$, a $R^2 \geq 95\%$ and a $R^2_{adj} \geq 90\%$. The general models are assessed in regards to its quality and capacity of prediction against a new data set, and scenarios.

An illustrative set of results is presented for the App, Dev and OpS collections, focusing on the general models. Regarding the App collection, for Streaming, see Figure 3.24, a general model is presented for each one of the four scenarios. The general models are all contained by its respective average standard deviation region about the average; for DL traffic the region is very narrow, while for UL traffic is larger. The average curve, in blue, is well match by all the models, in red. For WD, DL, the Streaming general model is a TS, see Figure 3.24 (a), and has an average standard deviation lower than 6%. The first section corresponds to the period between the hours of 6 and 10, and is associated to an exponential equation; all coefficients show very narrow CIs, with width smaller than 1; and the GOF statistics' results guarantee a $\sqrt{\overline{\varepsilon^2}} \leq 4.4\%$, a $R^2 \geq 90.8\%$ and a $R^2_{adj} \geq 90.7\%$. The second section corresponds to the period between the hours of 10 and 24, and is associated to a linear equation; all coefficients show very narrow CIs, with width smaller than 2; and the GOF statistics' results guarantee a $\sqrt{\overline{\varepsilon^2}} \leq 7.2\%$, a $R^2 \geq 78.4\%$ and a $R^2_{adj} \geq 78.3\%$. The third section corresponds to the period between the hours of 24 and 6, and is associated to an exponential equation; all coefficients show very narrow CIs, with width smaller than 2; and the GOF statistics' results guarantee a $\sqrt{\overline{\varepsilon^2}} \leq 7.1\%$, a $R^2 \geq 93.8\%$ and a $R^2_{adj} \geq 93.7\%$. The comparison between the model against the average curve, guarantees a $\sqrt{\overline{\varepsilon^2}} \leq 2.5\%$, a $R^2 \geq 99.2\%$ and a $R^2_{adj} \geq 98.9\%$. Having a high value for the ACD reinforces the accuracy of the CD. The final model representation is displayed for the interval between 00:00 and midnight, and is normalised to the maximum value the model may take. For WD and DL traffic, the Streaming final model, see Figure 3.25 (a), shows an increase in the morning, and a decrease starting around midnight, until hitting a minimum

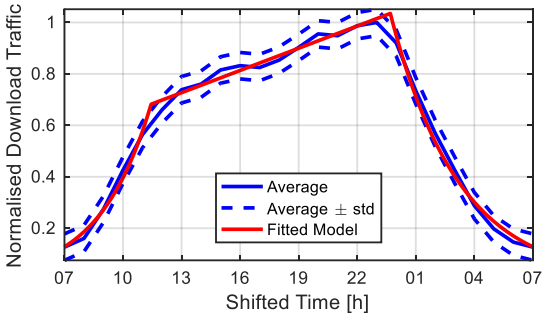
at 6 in the morning, also, it takes the highest values, busy hours, between the hours of 10 and 24, where it gradually increases.



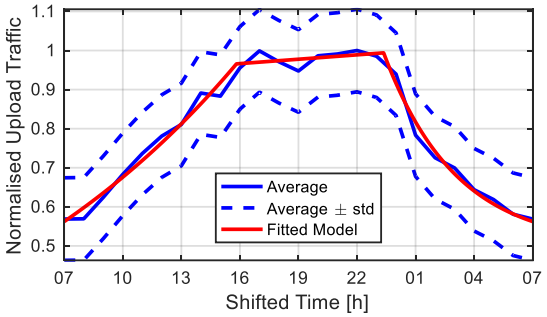

(a) Weekdays Download plot.




(b) Weekdays Upload plot.

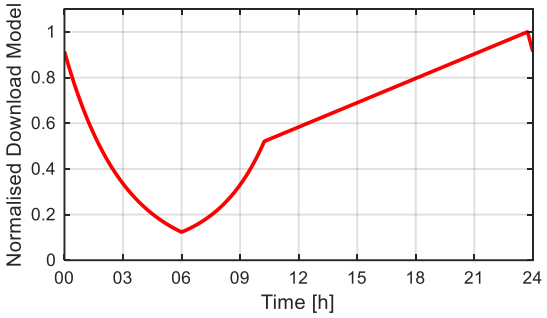



(c) Weekends Download plot.

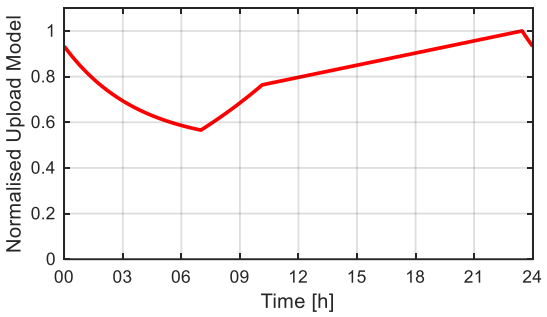



(d) Weekends Upload plot.

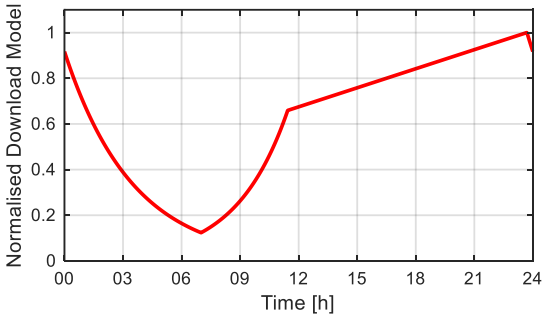
Figure 3.24 – APP_GROUP Streaming General Model.



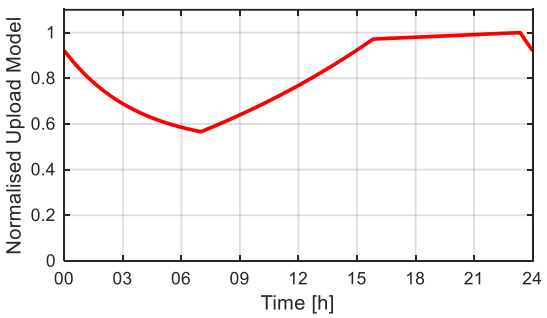

(a) Weekdays Download plot.




(b) Weekdays Upload plot.




(c) Weekends Download plot.




(d) Weekends Upload plot.

Figure 3.25 – APP_GROUP Streaming General Model 00:00 – 24:00.

For the App collection, and the scenario WD, DL, the obtained General models are presented, indicating the name, the average standard deviation, the section number, the time period, the corresponding equation type, and the respective coefficient values. The hours with the highest traffic usage observed, in the models' curves, are the busy hours of the day. The E-mail model, in Table 3.16, has the busy hours from 10:00 to 14:00, and from 14:00 to 19:00, with a reduction of activity around 14:00. The FiTr model, in Table 3.17, has the busy hours from 10:00 to 13:00, from 13:00 to 21:00, and from 21:00 to 24:00, with a reduction of activity around 13:00 and 21:00. The Games model, in Table 3.18, has the busy hours from 18:00 to 24:00. The InMe model, in Table 3.19, has the busy hours from 10:00 to 24:00, with a minor reduction of activity around 13:00 and 22:00. The M2M model, in Table 3.20, has the busy hours from 10:00 to 13:00, from 13:00 to 21:00, and from 21:00 to 24:00, with a reduction of activity around 13:00 and 21:00. The Other model, in Table 3.21, has the busy hours from 10:00 to 24:00. The P2P model, in Table 3.22, has the busy hours from 12:00 to 24:00. The Streaming model, in Table 3.23, has the busy hours from 10:00 to 24:00. The VoIP model, in Table 3.24, has the busy hours from 10:00 to 23:00. The WebAp model, in Table 3.25, has the busy hours from 10:00 to 24:00.

Table 3.16 – Weekdays Download APP_GROUP E-Mail General Model.

| $\bar{\sigma}_{[\%]} = 7.371$ | | | | | |
|---|---|---|---|---|---|
| **Model** Double Gaussian | | | | | |
| $\text{Section}_1$ | $[X_i; X_f]_{[h]}$ | $[06;14]$ | $\text{Section}_2$ | $[X_i; X_f]_{[h]}$ | $[14;06]$ |
| Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{gauss}$ | $v_1$ | 0.055 | $f_{gauss}$ | $v_2$ | 0.070 |
| | $u_1$ | 0.225 | | $u_2$ | 0.383 |
| | $\mu_1$ | 0.507 | | $\mu_2$ | 0.680 |
| | $\sigma_1$ | 0.092 | | $\sigma_2$ | 0.176 |

Table 3.17 – Weekdays Download APP_GROUP FiTr General Model.

| $\bar{\sigma}_{[\%]} = 14.323$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Triple Gaussian | | | | | | | | |
| $\text{Section}_1$ | $[X_i; X_f]_{[h]}$ | $[06;13]$ | $\text{Section}_2$ | $[X_i; X_f]_{[h]}$ | $[13;21]$ | $\text{Section}_3$ | $[X_i; X_f]_{[h]}$ | $[21;06]$ |
| Eq. | Coefficients | | Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{gauss}$ | $v_1$ | 0.089 | $f_{gauss}$ | $v_2$ | 0.500 | $f_{gauss}$ | $v_3$ | 0.098 |
| | $u_1$ | 0.194 | | $u_2$ | 0.163 | | $u_3$ | 0.189 |
| | $\mu_1$ | 0.484 | | $\mu_2$ | 0.696 | | $\mu_3$ | 0.923 |
| | $\sigma_1$ | 0.081 | | $\sigma_2$ | 0.153 | | $\sigma_3$ | 0.107 |

Table 3.18 – Weekdays Download APP_GROUP Games General Model.

| $\bar{\sigma}_{[\%]} = 28.164$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| $\text{Section}_1$ | $[X_i; X_f]_{[h]}$ | $[07;19]$ | $\text{Section}_2$ | $[X_i; X_f]_{[h]}$ | $[19;24]$ | $\text{Section}_3$ | $[X_i; X_f]_{[h]}$ | $[00;07]$ |
| Eq. | Coefficients | | Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{exp}$ | $c_1$ | 0.000 | $f_{linear}$ | $b_2$ | 1.674 | $f_{exp}$ | $c_3$ | 0.059 |
| | $k_1$ | 0.284 | | $m_2$ | -0.864 | | $k_3$ | -0.152 |
| | $t_1$ | 0.812 | | | | | $t_3$ | 0.943 |

Table 3.19 – Weekdays Download APP_GROUP InMe General Model.

| $\bar{\sigma}_{[\%]} = 9.526$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Triple Gaussian | | | | | | | | |
| $\text{Section}_1$ | $[X_i; X_f]_{[h]}$ | $[06;13]$ | $\text{Section}_2$ | $[X_i; X_f]_{[h]}$ | $[13;22]$ | $\text{Section}_3$ | $[X_i; X_f]_{[h]}$ | $[22;06]$ |
| Eq. | Coefficients | | Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{gauss}$ | $v_1$ | 0.009 | $f_{gauss}$ | $v_2$ | 0.500 | $f_{gauss}$ | $v_3$ | 0.069 |
| | $u_1$ | 0.255 | | $u_2$ | 0.255 | | $u_3$ | 0.174 |
| | $\mu_1$ | 0.532 | | $\mu_2$ | 0.740 | | $\mu_3$ | 0.927 |
| | $\sigma_1$ | 0.123 | | $\sigma_2$ | 0.200 | | $\sigma_3$ | 0.085 |

Table 3.20 – Weekdays Download APP_GROUP M2M General Model.

| $\bar{\sigma}_{[\%]} = 9.999$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Triple Gaussian | | | | | | | | |
| $\text{Section}_1$ | $[X_i; X_f]_{[h]}$ | $[06;13]$ | $\text{Section}_2$ | $[X_i; X_f]_{[h]}$ | $[13;21]$ | $\text{Section}_3$ | $[X_i; X_f]_{[h]}$ | $[21;06]$ |
| Eq. | Coefficients | | Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{gauss}$ | $v_1$ | 0.088 | $f_{gauss}$ | $v_2$ | 0.400 | $f_{gauss}$ | $v_3$ | 0.120 |
| | $u_1$ | 0.234 | | $u_2$ | 0.305 | | $u_3$ | 0.197 |
| | $\mu_1$ | 0.501 | | $\mu_2$ | 0.698 | | $\mu_3$ | 0.942 |
| | $\sigma_1$ | 0.103 | | $\sigma_2$ | 0.200 | | $\sigma_3$ | 0.109 |

Table 3.21 – Weekdays Download APP_GROUP Other General Model.

| $\bar{\sigma}_{[\%]} = 25.996$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Triple Gaussian | | | | | | | | |
| $\text{Section}_1$ | $[X_i; X_f]_{[h]}$ | $[07;14]$ | $\text{Section}_2$ | $[X_i; X_f]_{[h]}$ | $[14;21]$ | $\text{Section}_3$ | $[X_i; X_f]_{[h]}$ | $[21;07]$ |
| Eq. | Coefficients | | Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{gauss}$ | $v_1$ | 0.037 | $f_{gauss}$ | $v_2$ | 0.429 | $f_{gauss}$ | $v_3$ | 0.110 |
| | $u_1$ | 0.213 | | $u_2$ | 0.100 | | $u_3$ | 0.115 |
| | $\mu_1$ | 0.551 | | $\mu_2$ | 0.677 | | $\mu_3$ | 0.916 |
| | $\sigma_1$ | 0.122 | | $\sigma_2$ | 0.115 | | $\sigma_3$ | 0.108 |

Table 3.22 – Weekdays Download APP_GROUP P2P General Model.

| $\bar{\sigma}_{[\%]} = 23.651$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| $\text{Section}_1$ | $[X_i; X_f]_{[h]}$ | $[09;12]$ | $\text{Section}_2$ | $[X_i; X_f]_{[h]}$ | $[12;24]$ | $\text{Section}_3$ | $[X_i; X_f]_{[h]}$ | $[00;09]$ |
| Eq. | Coefficients | | Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{exp}$ | $c_1$ | 0.196 | $f_{linear}$ | $b_2$ | 0.472 | $f_{exp}$ | $c_3$ | 0.312 |
| | $k_1$ | 0.083 | | $m_2$ | 0.490 | | $k_3$ | -0.079 |
| | $t_1$ | 0.550 | | | | | $t_3$ | 0.977 |

Table 3.23 – Weekdays Download APP_GROUP Streaming General Model.

| $\bar{\sigma}_{[\%]} = 5.763$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| $\text{Section}_1$ | $[X_i; X_f]_{[h]}$ | $[06;10]$ | $\text{Section}_2$ | $[X_i; X_f]_{[h]}$ | $[10;24]$ | $\text{Section}_3$ | $[X_i; X_f]_{[h]}$ | $[00;06]$ |
| Eq. | Coefficients | | Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{exp}$ | $c_1$ | 0.035 | $f_{linear}$ | $b_2$ | 0.162 | $f_{exp}$ | $c_3$ | 0.000 |
| | $k_1$ | 0.104 | | $m_2$ | 0.879 | | $k_3$ | -0.125 |
| | $t_1$ | 0.498 | | | | | $t_3$ | 0.993 |

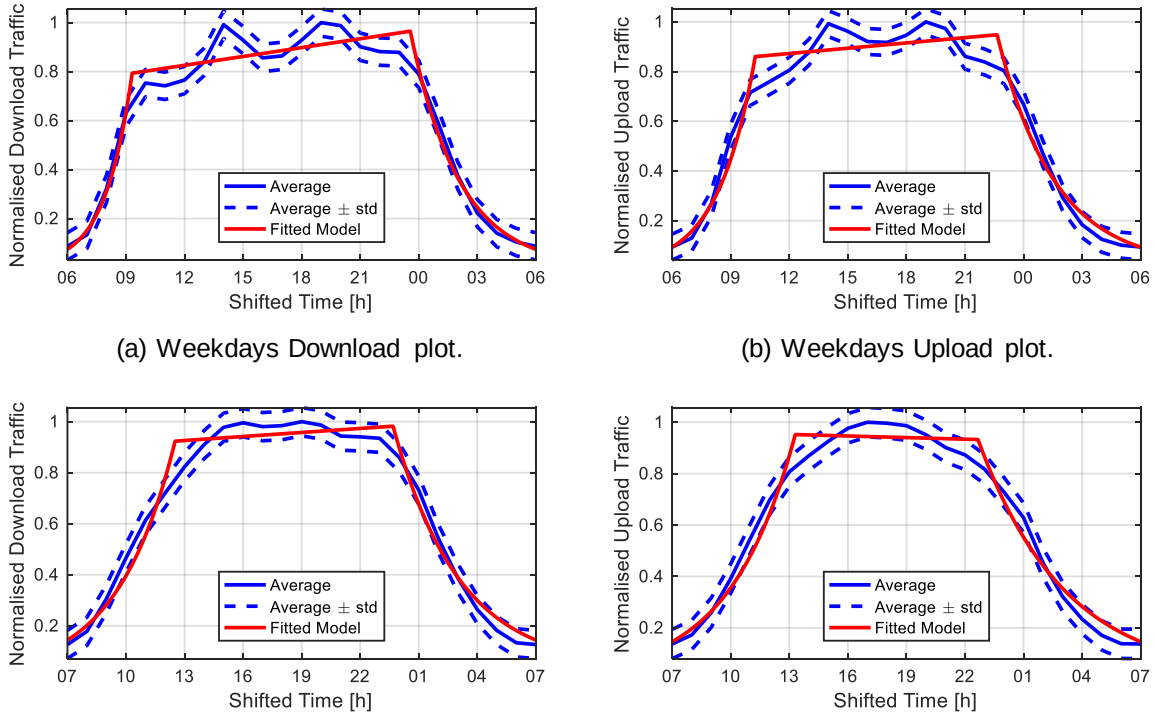
Table 3.24 – Weekdays Download APP_GROUP VoIP General Model.

| $\bar{\sigma}_{[\%]} = 8.366$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_1$ | $[X_i;X_f]_{[h]}$ | $[06;10]$ | Section$_2$ | $[X_i;X_f]_{[h]}$ | $[10;23]$ | Section$_3$ | $[X_i;X_f]_{[h]}$ | $[23;06]$ |
| Eq. | Coefficients | | Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{exp}$ | $c_1$ | 0.044 | $f_{linear}$ | $b_2$ | -0.095 | $f_{exp}$ | $c_3$ | 0.027 |
| | $k_1$ | 0.072 | | $m_2$ | 1.126 | | $k_3$ | -0.092 |
| | $t_1$ | 0.499 | | | | | $t_3$ | 0.971 |

Table 3.25 – Weekdays Download APP_GROUP WebAp General Model.

| $\bar{\sigma}_{[\%]} = 4.992$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_1$ | $[X_i;X_f]_{[h]}$ | $[06;10]$ | Section$_2$ | $[X_i;X_f]_{[h]}$ | $[10;24]$ | Section$_3$ | $[X_i;X_f]_{[h]}$ | $[00;06]$ |
| Eq. | Coefficients | | Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{exp}$ | $c_1$ | 0.000 | $f_{linear}$ | $b_2$ | 0.849 | $f_{exp}$ | $c_3$ | 0.045 |
| | $k_1$ | 0.079 | | $m_2$ | 0.128 | | $k_3$ | -0.090 |
| | $t_1$ | 0.436 | | | | | $t_3$ | 0.983 |

Regarding the Dev collection, for Smartphone, see Figure 3.26, a general model is presented for each one of the four scenarios.




(a) Weekdays Download plot.

(b) Weekdays Upload plot.

(c) Weekends Download plot.

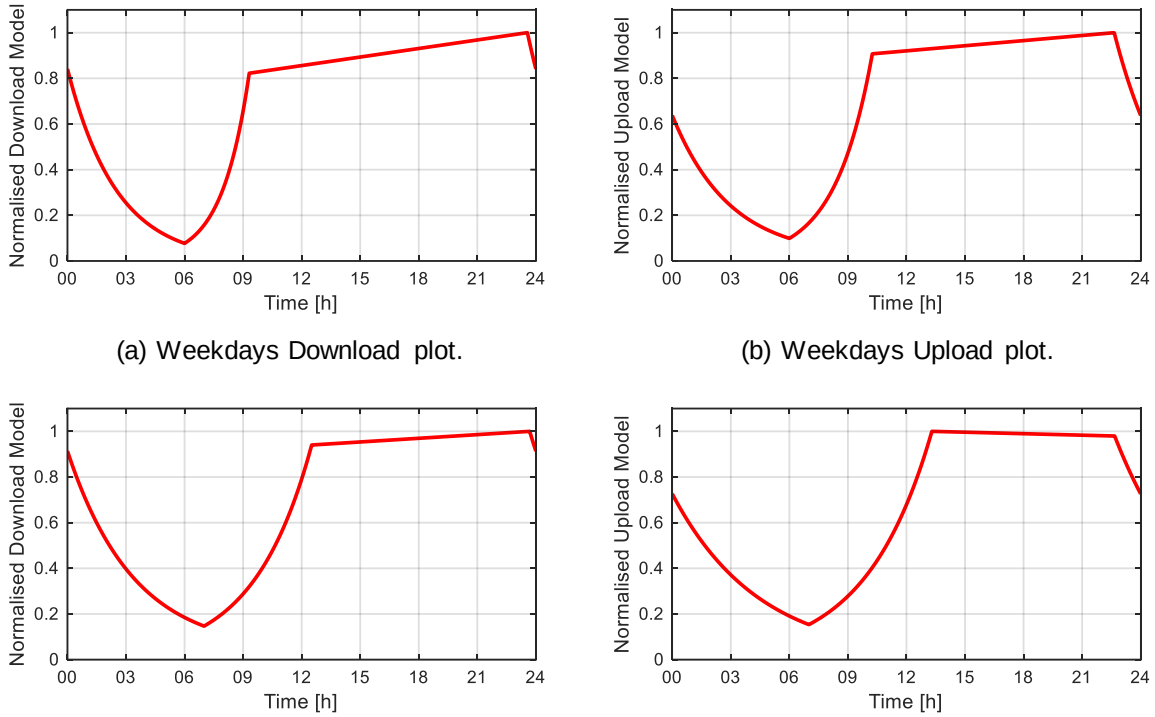
(d) Weekends Upload plot.

Figure 3.26 – DEV_TYPE Smartphone General Model.

The four models are very similar, with only slight changes, which supports that the Smartphone usage pattern is consistent regardless of it being WD or WE. The data behaviour between the hours of 10:00 and 24:00, for WD, can be represented by a linear curve because, although some fluctuations occur,

they can be considered not significant, when compared against the variation between the minimum and maximum values. The right and left sections of the model are mostly contained by a narrow standard deviation region, which reinforces the precision of the model.

For the Dev collection, and the scenario WD, DL, the obtained General model for the Smartphone case is presented, indicating the name, the average standard deviation, the section number, the time period, the corresponding equation type, and the respective coefficient values, in Table 3.26, and has the busy hours from 09:00 to 24:00. The Dev models have the busy hours from around 10:00 to 24:00.




(a) Weekdays Download plot.

(b) Weekdays Upload plot.

(c) Weekends Download plot.

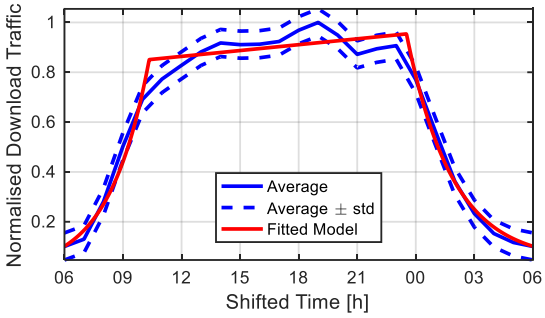
(d) Weekends Upload plot.

Figure 3.27 – DEV_TYPE Smartphone General Model 00:00 – 24:00.

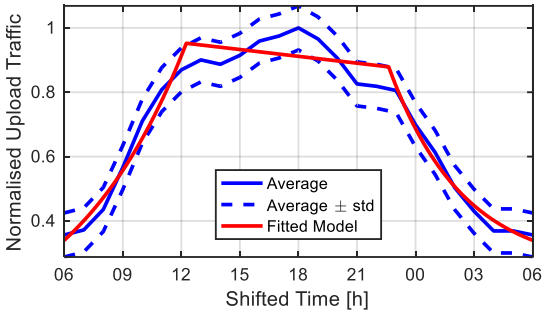
Table 3.26 – Weekdays Download DEV_TYPE Smartphone General Model.

| $\bar{\sigma}_{[\%]} = 5.585$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| $\text{Section}_1$ | $[X_i; X_f]_{[h]}$ | $[06;09]$ | $\text{Section}_2$ | $[X_i; X_f]_{[h]}$ | $[09;24]$ | $\text{Section}_3$ | $[X_i; X_f]_{[h]}$ | $[00;06]$ |
| Eq. | Coefficients | | Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{exp}$ | $c_1$ | 0.000 | $f_{linear}$ | $b_2$ | 0.681 | $f_{exp}$ | $c_3$ | 0.000 |
| | $k_1$ | 0.058 | | $m_2$ | 0.289 | | $k_3$ | -0.105 |
| | $t_1$ | 0.402 | | | | | $t_3$ | 0.978 |

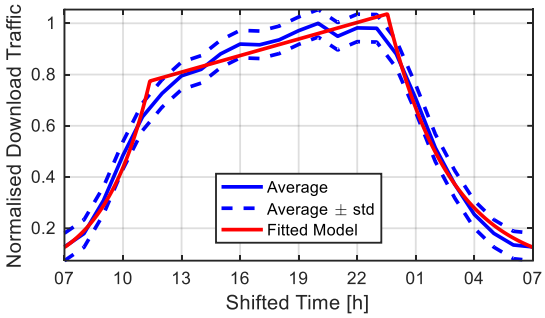
Regarding the OpS collection, for Android, see Figure 3.28, a General model is presented for each one of the four scenarios. The data behaviour between the hours of 10:00 and 24:00, for DL, shows almost no fluctuations, which support a stable usage pattern for the busy hours of the day.



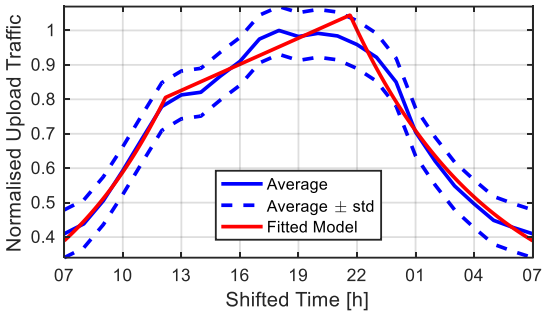

(a) Weekdays Download plot.




(b) Weekdays Upload plot.

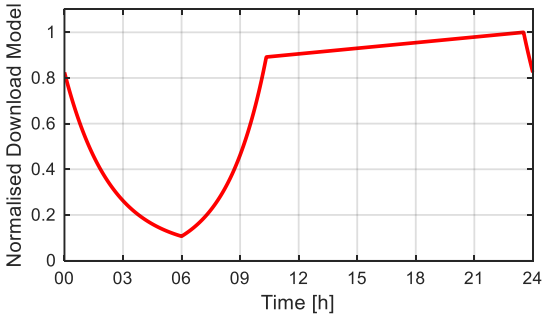



(c) Weekends Download plot.

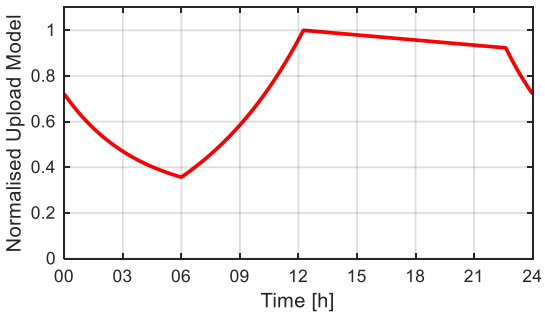



(d) Weekends Upload plot.

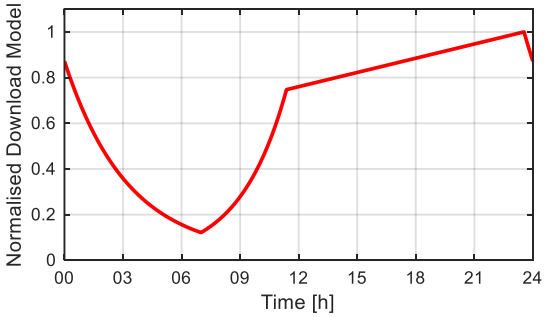
Figure 3.28 – OP_SYS Android General Model.



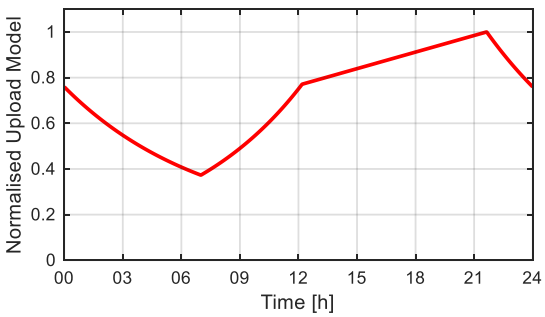

(a) Weekdays Download plot.




(b) Weekdays Upload plot.




(c) Weekends Download plot.




(d) Weekends Upload plot.

Figure 3.29 – OP_SYS Android General Model 00:00 – 24:00.

For the OpS collection, and the scenario WD, DL, the obtained general model for the Android case is presented, indicating the name, the average standard deviation, the section number, the time period, the corresponding equation type, and the respective coefficient values, in Table 3.27. The OpS models have the busy hours from 10:00 to 24:00.

Table 3.27 – Weekdays Download OP_SYS Android General Model.

| $\bar{\sigma}_{[\%]} = 5.439$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| $\text{Section}_1$ | $[X_i; X_f]_{[h]}$ | $[06;10]$ | $\text{Section}_2$ | $[X_i; X_f]_{[h]}$ | $[10;24]$ | $\text{Section}_3$ | $[X_i; X_f]_{[h]}$ | $[00;06]$ |
| Eq. | Coefficients | | Eq. | Coefficients | | Eq. | Coefficients | |
| $f_{exp}$ | $c_1$ | 0.000 | $f_{linear}$ | $b_2$ | 0.770 | $f_{exp}$ | $c_3$ | 0.045 |
| | $k_1$ | 0.085 | | $m_2$ | 0.188 | | $k_3$ | -0.097 |
| | $t_1$ | 0.445 | | | | | $t_3$ | 0.971 |

During the development and implementation stages, one took precaution measures to safeguard the quality of the results and guarantee a good implementation. The data statistical distribution was tested with the goodness of fit Lilliefors test to assess if it has a normal distribution. The regression results were compared against the data for each section, and the average curve of the data sets. The employment of GOF statistics provides criteria to compare and rank the regression models. The visual aids complement the statistics' results and allow for an easy, accessible, and compact way of scrolling through the information and checking for glitches. The Best and General models guarantee a $\sqrt{\overline{\varepsilon^2}} \leq 10\%$, a $R^2 \geq 95\%$ and a $R^2_{adj} \geq 90\%$.

The next stage is to test the results against a new data set. Testing the fitting of the obtained regression models with a new validation data set, and checking the goodness of fit statistics' results, allow to determine if the regression models are good at approximating the validation data set. The previously obtained goodness of fit statistics' results, when evaluating the models against the training set, are taken as a reference, when checking the fit between those same models and the new validation set. The App collection's Other represents less than a 10% share of the NU, and, less than a 1% share of DL traffic; and, the Dev collection's Others represents less than a 2% share of the NU, and, less than a 2% share of DL traffic; these cases are not assessed for the validation data set.

For testing the prediction quality of the regression models, one verifies if the Average Global Traffic curve of the validation set matches well with the Prediction Global Traffic curve, based on the information of the validation set, and the application of the regression models obtained for the training set. The models of the App collection's Other and Dev collection's Others can be used since they have minimal influence on the curve shape, given that these cases do not have a significant share of the NU, and the traffic they generate is negligible.

# Chapter 4

# Results Analysis

This chapter includes the models' assessment and the traffic usage analysis for the obtained models. The impact daily life and peoples' routines have on network resources is presented for applications, devices and operating systems. Recommendations and considerations are addressed for network optimisation and efficient resource usage.

## 4.1 Models' Assessment and Applicability

### 4.1.1 Validation Data Set

The new input data set, to function as validation set, was collected at the core level of the Vodafone Portugal network, in Portugal, Lisbon, and contains 468074 observations. The observation period, from 2016/09/11 to 2016/10/12, includes 32 days, in which 22 are weekdays, 10 are weekend days, and 1 is a national holiday day. National holiday days are considered as weekend days. For the Lisbon area, the length of day diminishes from 2016/03/12 to 2016/04/19, going from 12h33m of daytime, to 11h17m. The input spreadsheet file is organised into the same 8 fields as the training set.

Table 4.1 – Length of day for September and October, for the Lisbon area.

| Date | **Sunrise** | **Sunset** | **Length of day** |
|---|---|---|---|
| **2016/09/11** | 07:15 | 19:49 | 12h33min |
| **2016/10/01** | 07:33 | 19:17 | 11h44min |
| **2016/10/12** | 07:44 | 19:01 | 11h17 min |

To test the fitting of the obtained regression models with a new validation data set, one uses the same statistics as previously, the RMSE, the CD, and the ACD. The statistics' results obtained when evaluating the models against the training set are taken as a reference, when checking the fit between those same models and the new validation set. The normalised validation data is compared against the normalised models obtained for the original training data. The outcomes, for both the General model and the first ranked Best model are verified. Analysing the table results, the combination of each of the three rows concerning each of the models, and the previously established criteria, allows to assess the applicability of the models for the validation data set, and helps to evaluate their prediction capacity for a new data set and a different time of the year. For each case of a collection, the assessment conclusions take into consideration the results of each of the three statistics and its comparison against the preferable values. The models are eligible, and the results reliable, if it is guaranteed that the RMSE is lower than 15%, and the CD and the ACD are higher than 80%. With some reservations, results up to 20% for the RMSE, and down to 70% for the CD and the ACD, are still acceptable and guarantee reliable results. For the last two statistics, if the value goes lower than around 60%, the model must be considered inadequate. These target values will guarantee that the models, obtained for the training data set, are suitable to approximate and represent new information. The testing process compares the normalised regression models against the normalised average curves of the validation data set, for a 24 top of the hour period, and is executed for all four scenarios: WD, DL; WD, UL; WE, DL; WE, UL.

For the App collection, and the scenario WD, DL, and General model results, see Table 4.2, assessing each of the statistics results, regarding the RMSE, the lowest value is obtained for VoIP at 2.0%, and the highest one is obtained for Games at 6.4%, with the exceptions of FiTr and P2P at around 12%; regarding the CD, the highest value is obtained for VoIP at 99.6%, and the lowest one is obtained for Games at 94.4%, with the exceptions of FiTr and P2P at 83.4% and 78.6%, respectively; and, regarding the ACD, the highest value is obtained for VoIP at 99.2%, and the lowest one is obtained for Games at 90.4%, with the exceptions of FiTr and P2P at around 71.5%. When comparing the General and Best

models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 7\%$, a $R^2 > 94\%$ and a $R^2_{adj} > 90$. FiTr and P2P results are the ones which show the worst values, and depart the most from the preferable ones, even so, it is guaranteed a $\sqrt{\overline{\varepsilon^2}} < 12\%$, a $R^2 > 78\%$ and a $R^2_{adj} > 71\%$, signifying that predictions obtained with these models are still reliable. The best overall statistics' results achieved for VoIP validation data, are highly similar to the ones obtained with the training data, and support the regularity and little fluctuation to the behaviour of voice applications for different times of the year.

Table 4.2 – Weekdays Download APP_GROUP.

| | | (1) E-Mail | (2) FiTr | (3) Games | (4) InMe | (5) M2M | (7) P2P | (8) Streaming | (9) VoIP | (10) WebAp |
|---|---|---|---|---|---|---|---|---|---|---|
| General Model | $\sqrt{\overline{\varepsilon^2}}$ | 5.9 | 11.7 | 6.4 | 5.3 | 4.8 | 11.8 | 4.8 | 2.0 | 5.3 |
| | $R^2$ | 96.6 | 83.4 | 94.4 | 97.8 | 97.5 | 78.6 | 97.0 | 99.6 | 97.6 |
| | $R^2_{adj}$ | 94.2 | 71.5 | 90.4 | 96.3 | 95.8 | 71.4 | 94.8 | 99.2 | 96.8 |
| Best Model | $\sqrt{\overline{\varepsilon^2}}$ | 6.6 | 11.7 | 5.9 | 5.3 | 4.8 | 11.8 | 4.5 | 3.0 | 5.3 |
| | $R^2$ | 95.8 | 83.4 | 95.2 | 97.8 | 97.5 | 78.6 | 97.3 | 99.0 | 97.6 |
| | $R^2_{adj}$ | 94.4 | 71.5 | 93.6 | 96.3 | 95.8 | 71.4 | 96.4 | 98.7 | 96.8 |

For the App collection, and the scenario WD, UL, and General model results, assessing each of the statistics results, the RMSE varies between 4.3% and 8.4%, with the exception of Streaming at around 21%; the CD, varies between 98.2% and 91.3%, with the exception of Streaming at around 35%; and, the ACD, varies between 97.2% and 87.6%, with the exception of Streaming at around 13%. When comparing the General and Best models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 9\%$, a $R^2 > 90\%$ and a $R^2_{adj} > 87\%$. The predictions obtained with these models are reliable.

For the App collection, and the scenario WE, DL, and General model results, assessing each of the statistics results, the RMSE varies between 3.5% and 7.2%, with the exceptions of FiTr, P2P and VoIP, varying between 9.2% and 11.1%; the CD, varies between 99.0% and 80.3%; and, the ACD, varies between 98.2% and 84.6%, with the exceptions of Games at 76.4%. When comparing the General and Best models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 12\%$, a $R^2 > 80\%$ and a $R^2_{adj} > 84\%$. The predictions obtained with these models are reliable.

For the App collection, and the scenario WE, UL, and General model results, assessing each of the statistics results, the RMSE varies between 4.8% and 6.6%, with the exceptions of Games, M2M and P2P, varying between 9.2% and 11.0%, and Streaming at around 19%; the CD, varies between 97.6% and 83.6%, with the exception of Streaming at around 56%; and, the ACD, varies between 95.9% and 80.7%, with the exceptions of M2M and Streaming, at 71.9% and 41.2%, respectively. When comparing the General and Best models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 12\%$, a $R^2 > 83\%$ and a $R^2_{adj} > 80\%$. The predictions obtained with these models are reliable.

The Streaming results for UL, for both WD and WE, indicate that the model obtained for the training data set is inadequate to characterise this particular validation data set. A closer inspection to the Streaming curves for the validation data set, shows that the top of the hours associated to the highest traffic usage are unchanged, when compared against the ones observed for the training data set; only the behaviours in the early morning and in the late night differ. Streaming for UL represents a small contribution to the overall traffic usage when compared against the DL contribution, which makes these models' impact negligible in the overall network resources.

Regarding the App collection, for the validation set, the General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 12\%$, a $R^2 > 80\%$ and a $R^2_{adj} > 80\%$; and the exception cases guaranty reliable results.

For the Dev collection, and the scenario WD, DL, and General model results, assessing each of the statistics results, the RMSE varies between 3.6% and 6.6%; the CD, varies between 98.0% and 95.6%; and, the ACD, varies between 96.6% and 92.8%. When comparing the General and Best models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 7\%$, a $R^2 > 95\%$ and a $R^2_{adj} > 92\%$. The predictions obtained with these models are reliable.

For the Dev collection, and the scenario WD, UL, and General model results, assessing each of the statistics results, the RMSE varies between 4.3% and 5.9%, with the exception of Routers at 12%; the CD, varies between 98.0% and 95.7%, with the exception of Routers at 82%; and, the ACD, varies between 96.6% and 92.6%, with the exception of Routers at 69%. When comparing the General and Best models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 6\%$, a $R^2 > 95\%$ and a $R^2_{adj} > 92\%$. Routers results are the ones showing the worst values. The predictions obtained with these models are reliable.

For the Dev collection, and the scenario WE, DL, and General model results, assessing each of the statistics results, the RMSE varies between 4.1% and 6.6%; the CD, varies between 98.3% and 94.5%; and, the ACD, varies between 97.8% and 94.0%. When comparing the General and Best models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 7\%$, a $R^2 > 94\%$ and a $R^2_{adj} > 94\%$. The predictions obtained with these models are reliable.

For the Dev collection, and the scenario WE, UL, and General model results, assessing each of the statistics results, the RMSE varies between 3.5% and 13.4%; the CD, varies between 98.8% and 76.5%; and, the ACD, varies between 97.9% and 59.8%. When comparing the General and Best models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 14\%$, a $R^2 > 76\%$ and a $R^2_{adj} > 59\%$. The results indicate that some of the models must be used with caution when characterising the validation data set used. A closer inspection to the Pens, Routers and Tablet curves, for the validation data set, show wide average standard deviation regions about the average, and its average curves have many fluctuations, in contrast to the ones observed for the training data set which present smoother curves despite, also,

having wide average standard deviation regions about the average. The predictions obtained with these models are still reliable, even though some reservations are advised. UL traffic represents a small contribution to the overall traffic usage when compared against the DL contribution, which makes these models' impact negligible in the overall network resources.

Regarding the Dev collection, for the validation set, the General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 7\%$, a $R^2 > 94\%$ and a $R^2_{adj} > 92\%$; and for the exception cases the results should be used with some reservations.

For the OpS collection, and the scenario WD, DL, and General model results, assessing each of the statistics results, the RMSE varies between 4.0% and 7.4%; the CD, varies between 98.0% and 94.5%; and, the ACD, varies between 96.6% and 90.6%. When comparing the General and Best models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 8\%$, a $R^2 > 94\%$ and a $R^2_{adj} > 90\%$. The predictions obtained with these models are reliable.

For the OpS collection, and the scenario WD, UL, and General model results, assessing each of the statistics results, the RMSE varies between 5.3% and 10.4%; the CD, varies between 96.7% and 89.1%; and, the ACD, varies between 94.3% and 81.3%. When comparing the General and Best models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 11\%$, a $R^2 > 87\%$ and a $R^2_{adj} > 81\%$. The predictions obtained with these models are reliable.

For the OpS collection, and the scenario WE, DL, and General model results, assessing each of the statistics results, the RMSE varies between 4.6% and 7.5%; the CD, varies between 98.0% and 93.9%; and, the ACD, varies between 96.6% and 89.5%. When comparing the General and Best models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 8\%$, a $R^2 > 93\%$ and a $R^2_{adj} > 89\%$. The predictions obtained with these models are reliable.

For the OpS collection, and the scenario WE, UL, and General model results, assessing each of the statistics results, the RMSE varies between 3.5% and 12.1%; the CD, varies between 98.8% and 83.4%; and, the ACD, varies between 98.0% and 83.2%, with the exception of Android at around 71.6%. When comparing the General and Best models' results against each other, no noteworthy difference is detected between the obtained values. The General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 12\%$, a $R^2 > 83\%$ and a $R^2_{adj} > 71\%$. The predictions obtained with these models are reliable.

Regarding the OpS collection, for the validation set, the General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 12\%$, a $R^2 > 83\%$ and a $R^2_{adj} > 71\%$.

For all three collections, the obtained values, for the General and Best models' results, do not show a mentionable difference, supporting the right decision of, in some cases, using another model as the General model instead of the first ranked Best model. To demonstrate the ability of these models to

characterise and predict applications and devices behaviours, and reinforce the reliability of the results, the average global traffic for the validation data set is approximated with the obtained models, using the ratio inputs collected from that same validation data set.

### 4.1.2 Global Traffic Model

The Global Traffic Model combines all the traffic contributions related to a collection, for DL or UL, to obtain the representation of the traffic usage for an average day from 00:00 to 24:00. For the App collection, the traffic contribution of one application is obtained by weighing the respective General model to its NU weight and to the maximum traffic observed for that particular application. The NU weight, for each $n$ case, is provided by the Average Aggregated Daily Ratios, which give the average contributions each case has in the duration of one day; for Streaming it is represented as $\overline{w_{n=8}^{N_u}}$. There can be applications with the NU weight equal to 0, nonetheless, all weights must add up to 1. The maximum traffic value is measured in Bytes, and is visually the highest peak of the regression model; for Streaming it is represented as $T_{n=8}$. The regression models used are the normalised General models, and each represents an average day from 00:00 to 24:00. These models have been normalised to its maximum values. Regarding a data collection, the Global Traffic model, for DL or UL, is,

$$T_G(t) = \sum_{n=1}^{N_n} \overline{w_n^{N_u}}\, T_n\, f_n(t) \tag{4.1}$$

where:

- $f_n(t)$: regression model.

The Global Traffic model can be used for approximating the average global traffic curve of a data collection, using the NU weights and the maximum traffic values observed for that data, and leads to the expected Global Traffic for those inputs; or can also be used for predicting the Global Traffic for established scenarios, with defined NU weights and maximum traffic values, which is useful for studying and understanding the impact the variation of these inputs can have on the resulting Global Traffic curve. These two applications are implemented for the App and Dev collections. Since Android and iOS have similar behaviours, the Global Traffic will not be addressed for the OpS collection.

#### 4.1.2.1 Prediction Global Traffic

To test the prediction capacity of the regression models previously obtained for the training data set, the expected Global Traffic curve, obtained using the NU weights and the maximum traffic values observed for the validation data set, is compared against the average global traffic curve of the validation data. If the expected outcome matches well the real average global traffic curve of the validation data, then the regression models can predict new data sets and have a broad reach of possibilities.

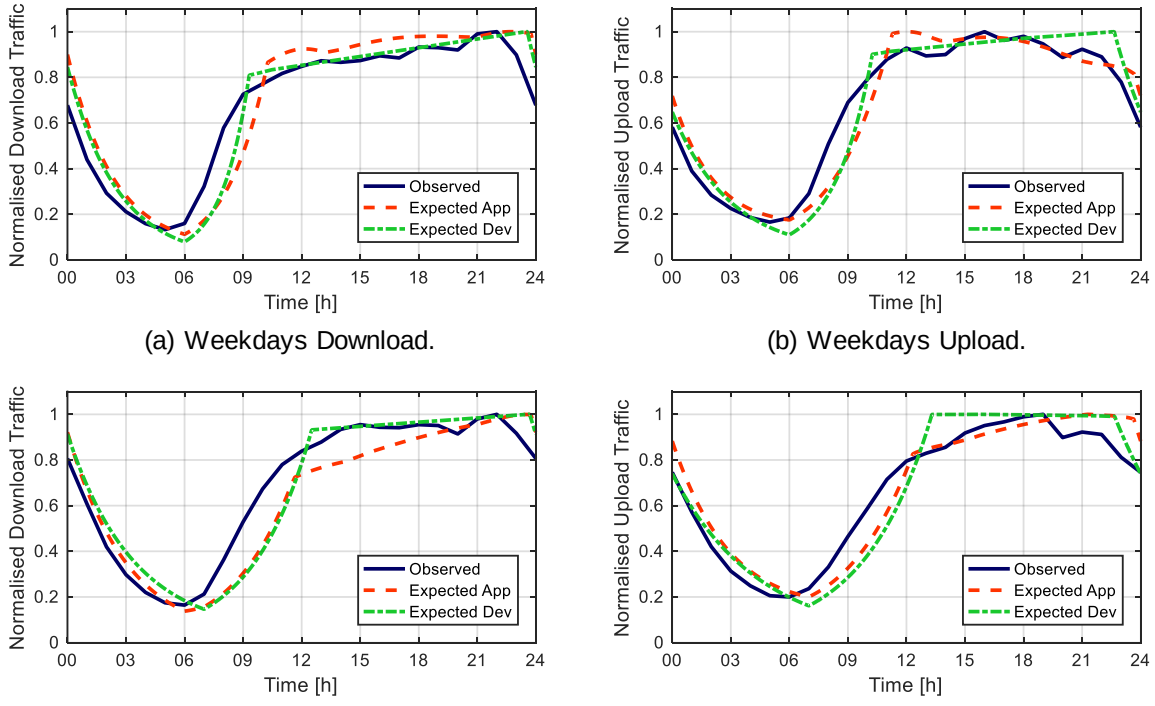
The average Global Traffic curve of the validation data, either for DL or UL traffic, is obtained by adding up all normalised average curves related to a collection, and acts as the observed global traffic curve. The same 10 applications and 6 devices, as the ones for which the regression models were obtained, are considered. The expected global traffic curve is obtained with the Global Traffic model, using the

normalised regression models and the real observed data inputs, $\overline{w_n^{Nu}}$ and $T_n$; and all 10 applications and all 6 devices are considered. The models for the App collection's Other, and Dev collection's Others, have very reduced influence on the curve shape, given that these cases do not have significant share of the NU, and the traffic they generate is negligible. Both the observed and the expected curves cover time from 00:00 to 24:00. The expected Global Traffic curve can also be referred to as Prediction Global Traffic curve. For assessing the prediction quality, when verifying how well the observed and expected curves match, one uses the RMSE and the CD.

For each of the scenarios, the observed curve and the expected curves, for both App and Dev collections, are presented. From an initial inspection of the results, the expected App curve shows more details, making perceptible the influence of the different contributions for the Global Traffic, and a modest variation of the input conditions can alter the shape of the expected curve; the expected Dev curve shows a more uniform behaviour for the hours of highest traffic usage, which arises from the fact that the majority of the General models, that characterise each device, are TS models.

A breakpoint of the curve is a point in which the curve outline changes behaviour. Three breakpoints are identified: the first one is the point where the traffic usage hits the minimum value; the second one is the point where the traffic usage stops increasing, during the late morning; and, the third one is the point where the traffic usage starts decreasing, at the end of the day.

For the scenario WD, DL, see Figure 4.1 (a), when comparing the observed and expected curves, the first breakpoint occurs nearly at the same time, at around 6:00; the second breakpoint occurs roughly at the same time, between the hours of 9 and 10; and the third breakpoint occurs close to midnight for the expected curves, and slightly before for the observed curve.




(a) Weekdays Download.

(b) Weekdays Upload.

(c) Weekends Download.

(d) Weekends Upload.

Figure 4.1 – APP_GROUP and DEV_TYPE Prediction Assessment.

The statistics' results of comparing each of the expected curves, with the observed curve, are gathered in Table 4.3, for the App collection, and in Table 4.4, for the Dev collection. A prediction's global traffic is reliable if the RMSE is lower than 15%, and the CD is higher than 80%. Regarding the App collection, the expected global traffic curves guarantee a $\sqrt{\overline{\varepsilon^2}} < 12\%$ and a $R^2 > 84\%$; and, regarding the Dev collection, the expected global traffic curves guarantee a $\sqrt{\overline{\varepsilon^2}} < 11\%$ and a $R^2 > 86\%$.

Table 4.3 – APP_GROUP Prediction Assessment.

| Scenarios | | **GOF** [%] | | Scenarios | | **GOF** [%] | |
|---|---|---|---|---|---|---|---|
| Weekdays | DL | $\sqrt{\overline{\varepsilon^2}}$ | 11.64 | Weekends | DL | $\sqrt{\overline{\varepsilon^2}}$ | 10.81 |
| | | $R^2$ | 84.10 | | | $R^2$ | 86.50 |
| | UL | $\sqrt{\overline{\varepsilon^2}}$ | 8.65 | | UL | $\sqrt{\overline{\varepsilon^2}}$ | 8.69 |
| | | $R^2$ | 91.62 | | | $R^2$ | 90.21 |

Table 4.4 – DEV_TYPE Prediction Assessment.

| Scenarios | | **GOF** [%] | | Scenarios | | **GOF** [%] | |
|---|---|---|---|---|---|---|---|
| Weekdays | DL | $\sqrt{\overline{\varepsilon^2}}$ | 8.79 | Weekends | DL | $\sqrt{\overline{\varepsilon^2}}$ | 10.64 |
| | | $R^2$ | 90.91 | | | $R^2$ | 86.92 |
| | UL | $\sqrt{\overline{\varepsilon^2}}$ | 8.62 | | UL | $\sqrt{\overline{\varepsilon^2}}$ | 9.83 |
| | | $R^2$ | 91.65 | | | $R^2$ | 87.49 |

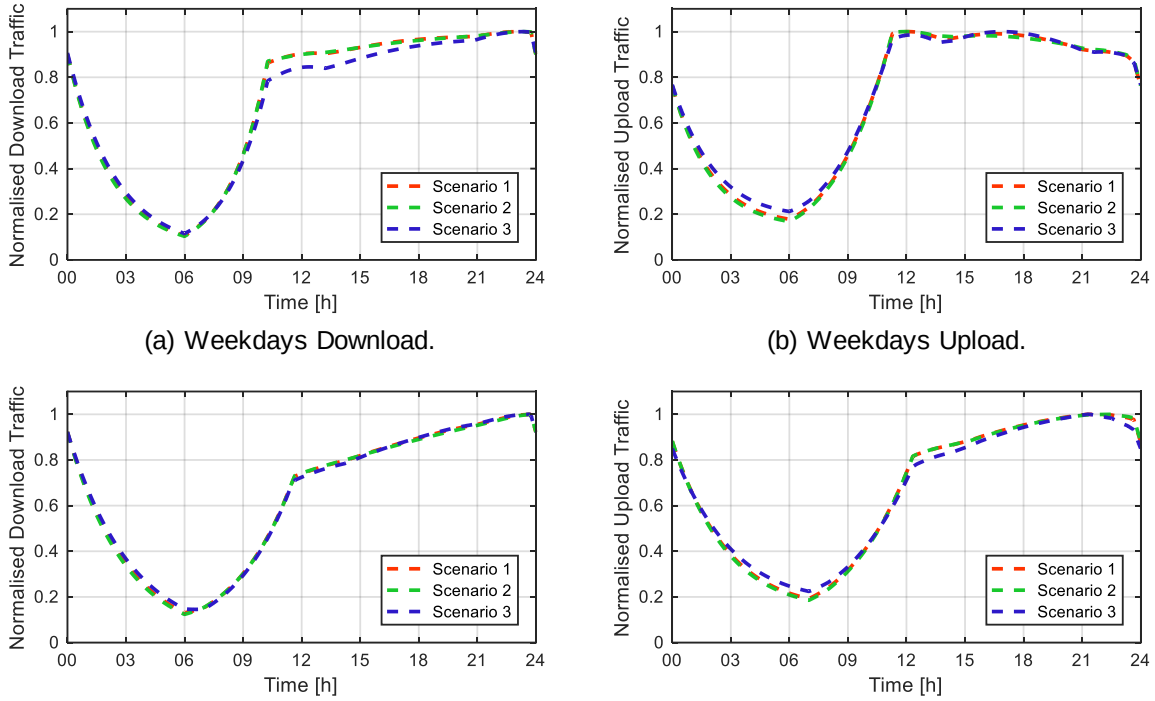
When comparing the expected curves statistics' results for the two collections against each other, for each one of the scenarios, there is no noteworthy difference between the obtained values. Since the statistics' target values are satisfied, the Global Traffic Model returns reliable predictions, and the regression models, that characterise each application or device, are suitable approximations of the behaviours they represent, regardless of the time of the year and origin of the data set.

Although both data sets where collected for the Lisbon area, the length of day increases throughout the days, for the training set, while decreasing for the validation set. The daytime can influence peoples' activity levels, motivation, disposition, and overall health. During WD, people follow a more structured schedule, so the curves are very similar. During WE, some differences can be noted; for the training set, as there is sunlight until later in the day, people stay active until later hours of the night; while, for the validation set, people start the day slightly earlier to seize the natural light, and end up being less active during the later hours of the night.

### 4.1.2.2 Vodafone Scenarios Prediction Global Traffic

A total of three scenarios were proposed, by Vodafone, to check the influence of the obtained models and the prediction Global Traffic Model, in order to assess the implications different scenarios have in the Prediction Global Traffic curve, which are helpful in evaluating the impact a scenario would have in the network resources demands and infrastructures, throughout the day. Concerning the Global Traffic Model, one will refer to $\overline{w_n^{N_u}}\, T_n$ as the scale factor of a model. Concerning the results representation, each global traffic curve has been normalised to its maximum value.

Regarding the App collection, for all three scenarios, the $\overline{w_n^{N_u}}$ are roughly the same, so the differentiating factor between scenarios is the $T_n$ associated to each application. For all four temporal scenarios, see Figure 4.2, WebAp is the dominant application, showing the highest scale factor value, due to having a much higher $\overline{w_n^{N_u}}$ than other applications; because of this, the shape of the curves resemble the ones for WebAp. Although each scenario is associated to different scale factor values for each application, as WebAp shows the highest one, for all three scenarios, the shape of the global traffic curve is identical for all three scenarios.



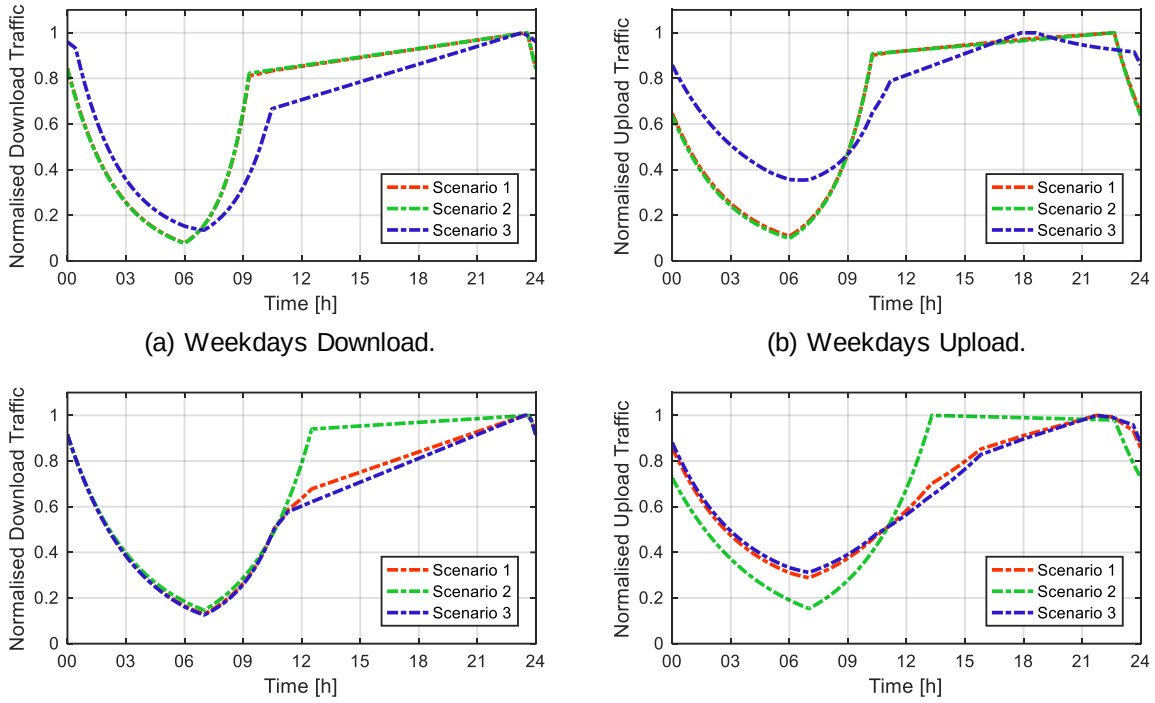

(a) Weekdays Download. (b) Weekdays Upload.

(c) Weekends Download. (d) Weekends Upload.

Figure 4.2 – App Collection Prediction Global Traffic for the General Models.

Regarding the Dev collection, both $\overline{w_n^{N_u}}$ and $T_n$ differ from one scenario to another. For both WD scenarios, see Figure 4.3 (a) and (b), scenario 1 shows that Smartphone represents over 85% of NU and has the highest $T_n$; scenario 2, only considers the device Smartphone, as it represents 99% of NU, and the other devices show $\overline{w_n^{N_u}}$ and $T_n$ near to 0; and, scenario 3, emphasises the influence of Hotspots, Routers and Pens, which add up to around 71% of NU, and represent the highest $T_n$ contributions, while Smartphone is negligible. For scenario 1 and 2, Smartphone shows the highest scale factor value, which explains why both global traffic curves are identical, for both WD scenarios; and, scenario 3 shows the distinct behaviour Hotspots, Routers and Pens have compared with Smartphone. For both WE scenarios, see Figure 4.3 (c) and (d), scenario 1 shows the influence of Hotspots, Routers and Pens, which add up to around 78% of NU, and represent the highest $T_n$ contributions, against the influence of Smartphone, with only around 5% of NU and double the highest $T_n$; scenario 2, only considers the device Smartphone, as the other devices show $\overline{w_n^{N_u}}$ and $T_n$ near to 0; and, scenario 3, emphasises the influence of Hotspots, Routers and Pens, which show the highest scale factor values. For scenario 1 and 3, the global traffic curve shape is mostly influenced by Hotspots, Routers and Pens, which explains why both

global traffic curves are similar, for both WE scenarios; and, scenario 2 shows the Smartphone behaviour. The proposed scenarios allow to illustrate the prediction Global Traffic Model applicability.




(a) Weekdays Download. (b) Weekdays Upload.

(c) Weekends Download. (d) Weekends Upload.

Figure 4.3 – Dev Collection Prediction Global Traffic for the General Models.

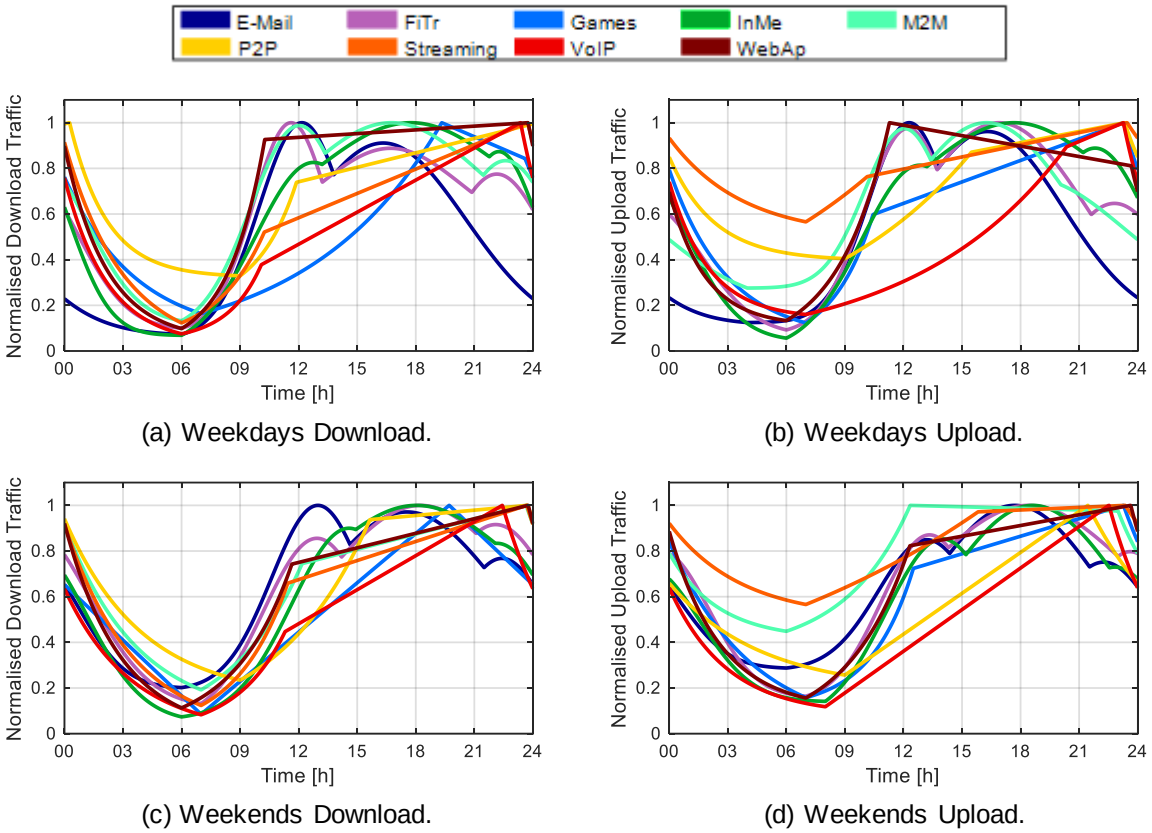
# 4.2 Model Collections

## 4.2.1 Applications Models

A wide range of services and applications is offered for different operating systems, and on various devices. The App collection data shows a broad diversity of behaviours, with a variety of peaks and downs of activity. The obtained models, for all four scenarios, see Figure 4.4, characterise the mobile network traffic usage for the App collection.

A visual inspection of the models' curves show that some applications are more sensitive to daily life. The outline of the curves exhibit two sudden traffic reductions during the busy hours, one about the lunch time, and another, about dinner time. Lunch time varies, depending on if it is WD or WE; starting earlier on WD, around 13:00, from the hours of 12 to 14; and, on WE, around 15:00, from the hours of 13 to 16. Dinner time is the same, for both WD and WE, from 20 to 22, with a minimum around 21. The curves also suggest that, on WD, the day starts earlier, between 7 and 10; while on WE, starts later and slower, from 9 to 12, which can also explain the difference between lunch hours. For both WD and WE, the bulk of activity decreases after 22:00, with a faster reduction after midnight. During the WE, entertainment, leisure and personal purpose applications, either maintain the same overall traffic usage

or show an increase in activity, since it is when most people take time to rest and pursue their interests and hobbies.




(a) Weekdays Download.

(b) Weekdays Upload.

(c) Weekends Download.

(d) Weekends Upload.

Figure 4.4 – App Collection General Models.

Regarding the App collection, VoIP, InMe and P2P reveal symmetric traffic usage, with nearly the same usage of DL and UL; and, E-mail, FiTr, Games, M2M, Streaming and WebAp reveal higher usage of DL than UL.

E-mail, a background service, nowadays, is mostly used for work and business purposes; on WD, DL traffic usage doubles the UL one, with an activity increase early in the morning and busy hours from 10:00 to 19:00; on WE, although it is used along the entire day, the overall traffic usage decreases by half. During meal times, there is a reduction of activity.

VoIP, used for real time conversational communication between users, has DL and UL traffic usage nearly symmetric, with busy hours from 10:00 to 23:00, while more active at the end of the day; and, WD and WE have very similar overall traffic usage.

InMe send short messages, exchanged between users, and are often used for dialogue purposes, what is evident from the fact that DL and UL traffic usage are nearly symmetric, with busy hours from 10:00 to 24:00, and clear decrease in activity during meal time; and, from WD to WE, the overall traffic usage remains the same, which highlights the widespread of this group of applications, and the personal and interactive nature of these communications.

For Games, an interactive service, the user sends signalling, to provide the game status and the play moves thought the UL link, while the DL link is used to receive game updates, scenario changes and

other players moves; DL traffic usage is much higher than the UL one, with busy hours from 10:00 to 24:00, while showing more activity at the end of the day. On WE, as the number of active users increases, so does the overall traffic usage.

P2P is used to facilitate the sharing or distribution of content and files, and the user does both the download and then upload of the information, but also, for sending background signalling and control messages, and continues to occur even in the early hours of the day. DL and UL traffic usage are nearly symmetric, with busy hours from around 12:00 to 24:00; and, WD and WE overall traffic usage are similar, with a slight increase on WE.

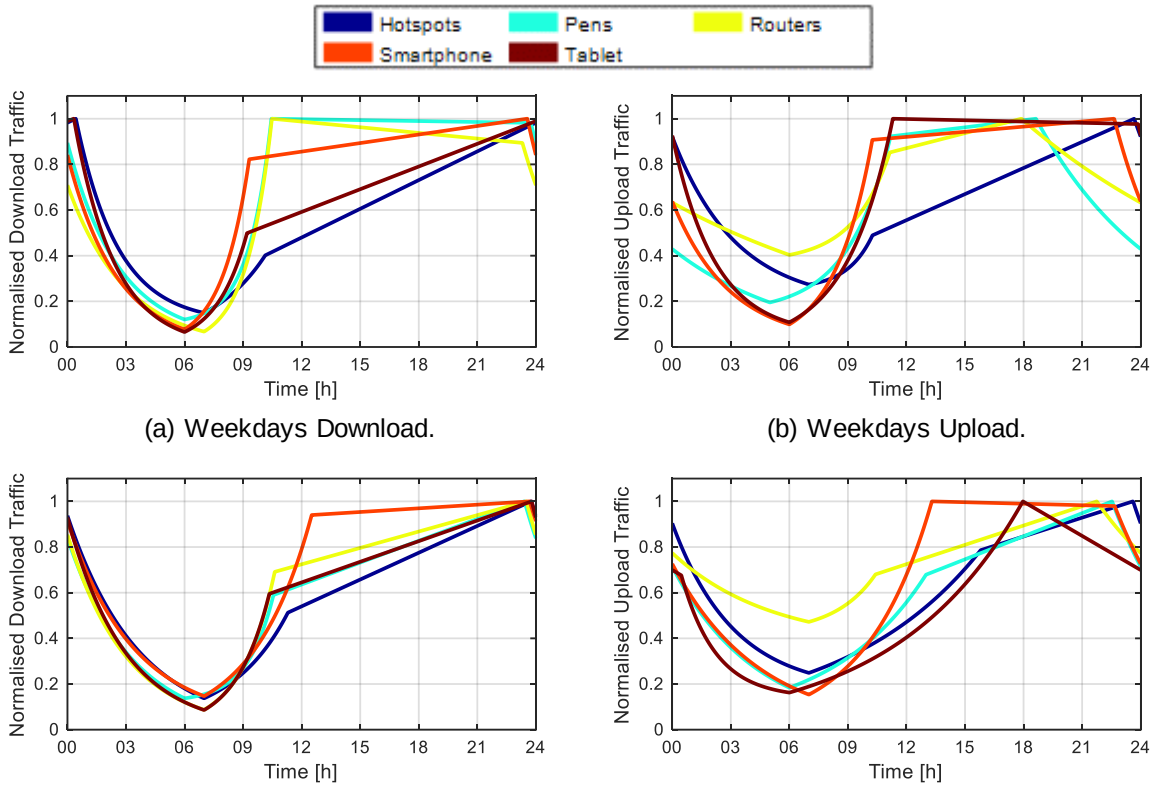
FiTr is used to transfer or storage files, from one location to another, and may include cloud storage and other services. DL traffic is more than five times higher than the UL traffic, with busy hours from around 10:00 to 24:00, and a visible reduction of activity during meal times; and, from WD to WE, the overall traffic usage only slightly decreases.

M2M can include smart meters, surveillance, alarms, terminal transactions, health, and fitness trackers, which represent a variety of behaviours, and a large share of active users, but correspond to a very low overall traffic usage share. During the early hours of the day, due to some of these applications, an exchange of background signalling and status messages is maintained. DL traffic is about two times higher than UL traffic, with busy hours from around 10:00 to 24:00, with a visible reduction of activity during meal times, which shows the impact daily life has in some applications, included in this group, for monitoring and tracking people's habits; and, on WD and WE, the overall traffic usages are similar.

WebAp and Streaming have a quarter share of the active users, and add up to almost 80% of DL traffic, and more than half of UL traffic, making them the most influential and impactful applications when managing and planning the network resources; and the busy hours are from around 10:00 to 24:00, for WD, and from around 12:00 to 24:00, on WE. WebAp, an interactive service, can be personalised to the user, and vary with each person's likes and interest. DL traffic is more than six times higher than UL traffic; and, from WD to WE, the overall traffic usage does not vary, which also emphasises the impact this group of applications generates. Streaming allows for real time broadcast of audio and video, which requires large amounts of data. DL traffic is about ten times higher than UL traffic; throughout the day, traffic activity shows a stable rise; and, on WE, the overall traffic usage increases.

### 4.2.2 Devices Models

Nowadays, it is available an ample selection of devices, with different characteristics, sizes, screen resolutions, and weights; and, the users expect to be able to access and enjoy their applications everywhere and in the most comfortable manner. The obtained models, for all four scenarios, see Figure 4.5, characterise the mobile network traffic usage for the Dev collection. A visual inspection of the models' curves reveals that after midnight, up until 7:00, the traffic activity experiences a fast decrease, which is in agreement with rest and sleep time during the night.




(a) Weekdays Download.

(b) Weekdays Upload.

(c) Weekends Download.

(d) Weekends Upload.

Figure 4.5 – Dev Collection General Models.

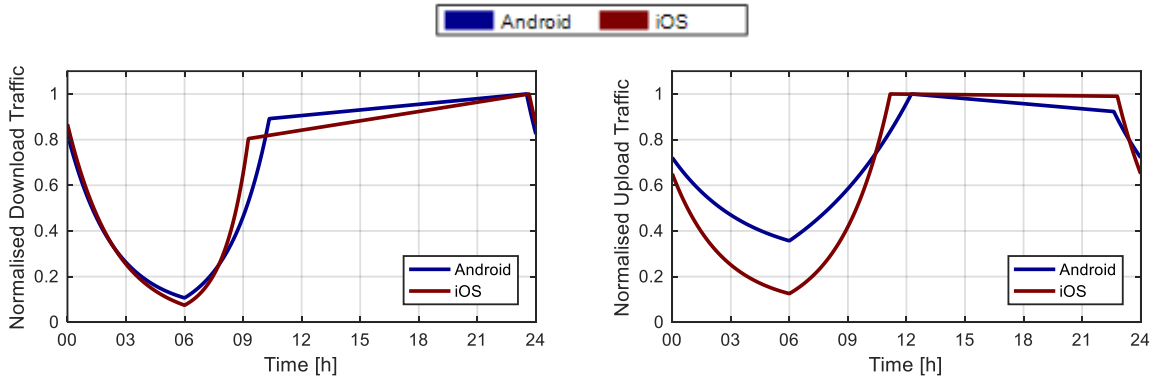
The Smartphone has high mobility and offers flexibility to the user; and, although there are many designs and manufactures from which to choose from, the reality is that, daily live is entwined with the use of Smartphones, as it provides a variety of services and applications, that thrive to adapt to and support peoples' routines and likes. Therefore, is no surprise that the Smartphone represents the highest traffic usage contribution, for both DL and UL, amongst the devices. DL traffic is almost eight times higher than UL traffic; and, from WD to WE, the overall traffic usage remains stable. Tablet is a smaller, lighter, alternative to computers or PCs; it allows the user to move freely and is travel friendly. DL traffic is more than ten times higher than UL traffic; and, on WE, the overall traffic usage increases. The low overall traffic usage is likely due to, the evolution and adaptability of Smartphones, to have larger screens, while maintaining a size that is comfortable to handle and transport, and for, additionally, allowing to perform calls. Hotspots, Pens, Datacards, and Routers, are devices that provide other device terminals with mobile network access; their contributions combined, add up to more than 50% of the traffic usage, for both DL and UL. Pens and Datacards, [39], enable data access to a single terminal equipment, at a time, while allowing mobility. DL traffic is more than four times higher than UL traffic; and, on WE, the overall traffic usage decreases. Hotspots, [38], enable data access to a limited number of terminal equipments, at a time, and, also allow mobility. DL traffic is around seven times higher than UL traffic; and, from WD to WE, the overall traffic usage remains stable, with a minor increase on WE. Routers, [40], enable data access to a large group of terminal equipment, at a time, for a fixed location. DL traffic is around three times higher than UL traffic; and, on WE, the overall traffic usage decreases.

For DL traffic, on WD, all devices show a speedy increase of activity during the early hours of the

morning. Smartphone and Tablet stabilise the earliest, after 9:00; and, during commute times, due to mobility and their compact size, allow the user, to check their e-mail, news, SNS, or read a book, in a quick and simple manner. These types of terminals gather all conveniences in one equipment, and are gradually replacing the paper format. Hotspots, Pens, and Routers stabilise after 10:00. On WE, all devices stabilise later in the morning; and, the devices that experience an increase of the overall traffic usage allow for mobility, Hotspots, Smartphone and Tablet, which can be related with the increase of outdoors and entertainment activities. Independently of it being WD or WE, only at the end of the day, is there a reduction of activity. For UL traffic, some curves maintain activity during the night, which indicate the exchange of signalling and control messages, nevertheless, it represents a small contribution to the overall traffic usage when compared against the DL contribution.

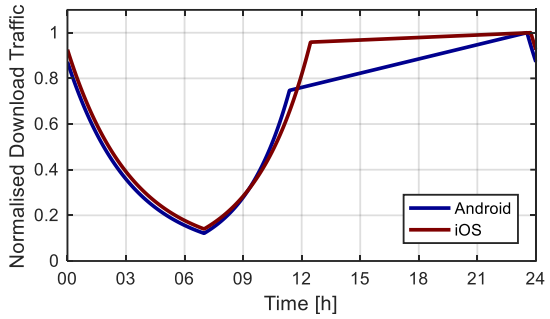
### 4.2.3 Operating Systems Models

Android and iOS operating systems add up to roughly 90% of the active users, and represent more than half of the overall traffic usage. Currently, Android or iOS operating systems are mostly used in smartphones, which is confirmed from comparing the traffic usage associated to both operating systems, with the values observed for Smartphone, and concluding they are very similar. The obtained models, for all four scenarios, see Figure 4.6, enlighten the resemblance, and difference, between Android and iOS traffic usage contributions. An initial inspection to the models' curves reveals identical focal points and alike outline shapes. Android systems generate higher overall traffic than the iOS ones; and, during the lower activity period, after midnight until early morning, due to background signalling, and system and keep-alive messages, Android maintains higher UL traffic. For Android, DL traffic is around five times higher than UL traffic; and, for iOS, DL traffic is more than seven times higher than UL traffic. The overall traffic usage of these operating systems remains nearly the same for the entire week, which emphasises the uniform and permanent, every day, utilisation of smartphones.

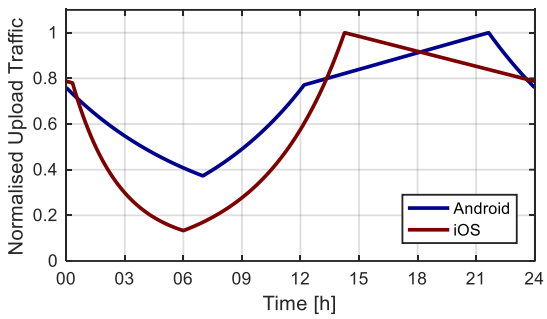



(a) Weekdays Download.

(b) Weekdays Upload.




(c) Weekends Download.




(d) Weekends Upload.

Figure 4.6 – OpS Collection Android and iOS General Models.

For the scenario WD, DL, see Figure 4.6 (a), both curves display nearly the same breakpoints: the minimum value, at 6:00, and the right and left limits of the busy hours section, from around 10:00 to 24:00. These two models show similar outline shape, which emphasises that people have a global activity pattern, regardless of the operating system that is used. The regression models, for DL traffic, are nearly the same, especially for WD, which reveals the existence of a clear and reliable pattern, for representing DL traffic, generated by both operating systems. The biggest differences are observed for UL traffic, which has low impact on the overall network resources.

### 4.2.4 Considerations and Recommendations

Although the regression models where obtained for data collected at the core level of the Vodafone network, for the Lisbon area, daily life and peoples' routines can be considered global and extendable for other regions, and for any time of the year. Combining and cross checking information and results from the three collections, one can determine the global busy hours, as the hours from 10:00 to 24:00 for WD; and keep some reservations regarding WE, which normally present a delayed and slower start to the days' activities. The daytime can influence peoples' activity levels and dispositions, which can alter slightly the busy hours. Knowing the busy hour traffic usage allows to define the maximum traffic capacity the network should guarantee to satisfy all active users. After midnight, up until the early hours of the morning, there is a low activity period, that represent less than 10% of the average daily traffic usage, and so, the available resources and, network managing structures, may be reduced, while still maintaining QoS. To assure QoS for all data applications, different constraints must be imposed to guarantee the different requirements of each service class. Each service class is associated to a level of priority, from conversional, with the highest one; to streaming; to interactive; and, with the lowest priority, background. The obtained regression models can be used to guide and establish target resource values and help define the allocation of data rates, based on the applications included in each service class. If the objective is to know the evolution of traffic usage for a specific application, using a real observed network measure, for a determined hour, allows to scale the model curve for the present reality; and, the models can also be adapted to predict traffic usage for special events and different seasons, by scaling the curves to the maximum expected values. Taking advantage of network virtualisation and centralised managing, different network configurations may be deployed to maintain communications, and increase efficient resource usage, for different periods of the day, with different

requirements. A better management of infrastructures and resources, based on the model prediction of the behaviour of data, reduces the operators' costs. Users want to be able to access a vast range of information, instantaneously, and anywhere. Portable devices gain emphasis as a daily life essential and are replacing the paper format, like books, magazines and planners. Devices and operating systems must be developed with the easiness of use in mind. Applications' and devices' activities, and operating systems preferences, can be used to create custom and user oriented communication planes, but also predict suitable changes to the management of network resources to accommodate the alterations of data usage.

Understanding and being able to model data behaviours and traffic usage is crucial to the design and optimisation of networks, as more and more content is available every day, and users play an important role, as creators and consumers of data.

# Chapter 5

# Conclusions

This chapter summarises the development, implementation, and results of the work done, and contains recommendations and suggestions for the applicability of the accomplished work.

Chapter 1 establishes the framework of the thesis and presents an overview on the current mobile communications scenario. The motivations are addressed, the problem definition is presented, and the structure for the thesis is provided. Chapter 2 provides a background on the fundamental concepts of UMTS and LTE networks, detailing the architectures and radio interfaces. The quality of service is addressed for both UMTS and LTE. Service classes and popular applications are briefly mentioned. The characterisation of traffic models is discussed. The state of the art gathers the research that motivates the exploratory data analysis and the development of models. Chapter 3 comprises the development framework and the implementation description, used in the exploratory analysis of the number of active users and traffic usage, and to obtain the models for the statistical characterisation of traffic usage, from a live cellular network. The data is structured and analysed. The models are compared and ranked based on goodness of fit statistics' criteria. The regression results are found at the end. Chapter 4 includes the models' assessment and the traffic usage analysis for the obtained models. The impact daily life and peoples' routines have on network resources is presented for applications, devices and operating systems. Recommendations and considerations are addressed for network optimisation and efficient resource usage. Chapter 5 summarises the development, implementation, and results of the work done, and contains recommendations and suggestions for the applicability of the accomplished work.

A data set, collected from a mobile network, can be divided between a training set and a validation set, if the number of observations is large enough. The training set is used in the fitting process to find prediction models; and, the validation set is used to validate the fitted models, with an independent set of observations.

Studying and gaining a broader understanding of how impactful people's daily lives are in application utilisation, device preferences, and network resource demands, is relevant for network optimisation. The purpose of this work is to characterise and represent the observed data, by providing visual aids and mathematical models, thus highlighting patterns and better realising the implicit behaviours associated to the distinct entities, profiles, and collections.

The applications, devices and operating systems collections are analysed, a descriptive statistical analysis is employed, and the data statistical distribution is assessed to check if the data samples have a normal distribution. The weighted average of the percentages of non-rejected decisions is superior to 74%, for the App collection; to 77%, for the Dev collection; and, to 76%, for the OpS collection. The exploratory data analysis makes use of graphical and numerical results for an accessible and compact representation of the data; the entities in analysis are the number of active users and traffic usage. Although E-mail, Games, InMe and M2M correspond to around 53% of the users, combined only represent 6% of DL traffic and 11% of UL traffic; in contrast, Streaming and WebAp only correspond to around 25% of the users, and add up to 78% of DL traffic and to 55% of UL traffic. Although Smartphone corresponds to around 88% of the NU, it only represents 42% of DL traffic and 28% of UL traffic; in contrast, Hotspots, Pens and Routers correspond to around 7% of the NU, and add up to 53% of DL traffic and to 67% of UL traffic. Android and iOS add up to roughly 90% of the users, and represent around 56% of DL traffic and UL traffic.

The fitting process is implemented in MATLAB using a statistical modelling methodology, and for each study case, provides 8 regression models, that can assemble one or more sections, with linear, exponential, or gaussian equations, while ensuring continuity between the sections, and the initial and final points, of the model. The obtained regression models are compared against the observed data, and the goodness of fit statistics' results allow for the comparison and ranking of the models, so that the models that best approximated the data are selected.

For the App collection, the RMSE varies between 1% and 16.2%; the CD varies between 99.9% and 65.3%; and, the ACD varies between 99.8% and 60.1%. For the Dev collection, the RMSE varies between 0.9% and 17.5%; the CD varies between 99.9% and 46.9%; and, the ACD varies between 99.8% and 39.0%. For the OpS collection, the RMSE varies between 0.9% and 16.8%; the CD varies between 99.9% and 68.2%; and, the ACD varies between 99.8% and 63.4%.

Regarding the best ranked models, for the App collection, the more used models are TG, TS and DG; for the Dev collection, the more used models are TG, TS and DG; and, for the OpS collection, the more used models are TG and TS.

For the App collection, and General models, the RMSE varies between 1.0% and 5.7%; the CD varies between 99.9% and 95.3%; and, the ACD varies between 99.8% and 93.7%. For the Dev collection, and General models, the RMSE varies between 1.5% and 8.9%; the CD varies between 99.7% and 95.0%; and, the ACD varies between 99.6% and 93.2%. For the OpS collection, and General models, the RMSE varies between 1.5% and 7.1%; the CD varies between 99.7% and 95.2%; and, the ACD varies between 99.6% and 93.5%.

The Best Models and General Models guarantee a $\sqrt{\overline{\varepsilon^2}} \leq 10\%$, a $R^2 \geq 95\%$ and a $R^2_{adj} \geq 90\%$.

A new data set is introduced, to assess the reliability and prediction capacity of the regression models. The General models are compared against the validation data set; and one verifies if the Average Global Traffic curve of the validation set, matches well with the Prediction Global Traffic curve, based on the information of the validation set, and the application of the General models obtained for the training set.

Regarding the App collection, for the validation set, the General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 12\%$, a $R^2 > 80\%$ and a $R^2_{adj} > 80\%$; and the exception cases guaranty reliable results. Regarding the Dev collection, for the validation set, the General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 7\%$, a $R^2 > 94\%$ and a $R^2_{adj} > 92\%$; and for the exception cases the results should be used with some reservations. Regarding the OpS collection, for the validation set, the General and Best models guaranteed a $\sqrt{\overline{\varepsilon^2}} < 12\%$, a $R^2 > 83\%$ and a $R^2_{adj} > 71\%$.

For all three collections, the obtained values, for the General and Best models' results, do not show a mentionable difference, supporting the right decision of, in some cases, using another model as the General model instead of the first ranked best model. To demonstrate the ability of these models to characterise and predict applications and devices behaviours, and reinforce the reliability of the results, the average global traffic for the validation data set is approximated with the obtained models, using the ratio inputs collected from that same validation data set. The Global Traffic model can be used for

approximating the average global traffic curve of a data collection, and leads to the Expected Global Traffic for that data inputs; or can also be used for predicting the Global Traffic for established scenarios, which is useful for studying and understanding the impact the variation to the number of active users, and the maximum traffic values, can have on the resulting Global Traffic curve.

For the Expected Global Traffic, the expected App curve shows more details, making perceptible the influence of the different contributions for the global traffic; the expected Dev curve shows a more uniform behaviour for the hours of highest traffic usage, which arises from the fact that the majority of the General models, that characterise each device, are TS models. Regarding the App collection, the expected global traffic curves guarantee a $\sqrt{\overline{\varepsilon^2}} < 12\%$ and a $R^2 > 84\%$; and, regarding the Dev collection, the expected global traffic curves guarantee a $\sqrt{\overline{\varepsilon^2}} < 11\%$ and a $R^2 > 86\%$. The Global Traffic Model, based on the regression models obtained, returns reliable predictions, regardless of the time of the year and origin of the data set.

For two distinct times of the year, in which one of the periods shows the length of day increasing throughout the days, and the other shows the length of day decreasing, for WD, people follow a more structured schedule, so there are no noteworthy differences; for WE, as for the first case there is sunlight until later in the day, people stay active until later hours of the night, while, for the second case, people start the day slightly earlier to seize the natural light and end up being less active during the later hours of the night.

For the Prediction Global Traffic curves, different scale factors, lead to different behaviours and curve shapes, emphasising the more influential cases.

Regarding the App collection, VoIP, InMe and P2P reveal symmetric traffic usage, with nearly the same usage of DL and UL; and, E-mail, FiTr, Games, M2M, Streaming and WebAp reveal higher usage of DL than UL. Some applications are more sensitive to daily life. Lunch time varies depending on if it is WD or WE; starting earlier on WD, around 13:00, from the hours of 12 to 14; and, on WE, around 15:00, from the hours of 13 to 16. Dinner time is the same, for both WD and WE, from 20 to 22, with a minimum around 21. For both WD and WE, the bulk of activity decreases after 22, with a faster reduction after midnight. During the WE, entertainment, leisure and personal purpose applications, either maintain the same overall traffic usage or show an increase in activity.

Smartphone and Tablet, during commute times, due to mobility and their compact size, allow the user, to check their e-mail, news, SNS, or read a book, in a quick and simple manner. These types of terminals gather all conveniences in one equipment, and are gradually replacing the paper format. Android or iOS operating systems are mostly used in smartphones; during the lower activity period, due to background signalling, and keep-alive messages, Android maintains higher UL traffic. The overall traffic usage of these operating systems remains nearly the same for the entire week, which emphasises the uniform and permanent, every day, utilisation of smartphones. Devices and operating systems must be developed with the easiness of use in mind.

The global busy hours, for WD, are between 10:00 and 24:00; WE present a delayed and slower start to the days' activities. The daytime can influence peoples' activity levels and dispositions, which can

alter slightly the busy hours. Knowing the busy hour traffic usage allows to define the maximum traffic capacity the network should guarantee to satisfy all active users. After midnight, up until the early hours of the morning, there is a low activity period, that represent less than 10% of the average daily traffic usage, and so, the available resources and, network managing structures, may be reduced, while still maintaining QoS.

For different periods of the day, with different requirements, different network configurations may be deployed to maintain communications, and increase efficient resource usage. A better management of infrastructures and resources, based on the model prediction of the behaviour of data, reduces the operators' costs.

The regression models can be used to guide and establish target resource values and help define the allocation of data rates; or predict traffic usage by scaling the curves to the maximum expected values; or, by combining different models, obtain a global traffic prediction. Understanding and being able to model data behaviours and traffic usage is crucial to the design and optimisation of networks.

The regression models, either Best or General, can be tested against new data from a live cellular network, for different regions, with different locality granularity, for different times of the year, or even different countries, to assess if their applicability still prevails.

# Annex A

## Regression Models with Training Data

This Annex contains the goodness of fit statistics' results, the Best and General regression models for traffic usage for applications, devices, and operating systems, for both weekdays and weekends.

Table A.1 – APP_GROUP Best Models: Ranking.

| | | (1) E-Mail | (2) FiTr | (3) Games | (4) InMe | (5) M2M | (6) Other | (7) P2P | (8) Streaming | (9) VoIP | (10) WebAp |
|---|---|---|---|---|---|---|---|---|---|---|---|
| WD DL | 1º | TG | TG | TG | TG | TG | TG | TS | TG | TG | TS |
| | 2º | TS | TS | DG | TS | TS | T | TG | TS | TS | TG |
| WD UL | 1º | DG | TG | TG | TG | TG | TG | DG | TS | TG | TG |
| | 2º | TG | DG | TS | DG | DG | DG | TS | T | DG | TS |
| WE DL | 1º | TG | TG | T | TG | TG | TS | DG | TS | TS | TG |
| | 2º | DG | TS | TS | TS | TS | TG | TS | TG | TG | TS |
| WE UL | 1º | TG | TG | TG | TG | TG | TG | T | TS | TS | TG |
| | 2º | DG | DG | DG | DG | DG | TS | TG | T | TR | TS |

Table A.2 – APP_GROUP General Model.

| | (1) E-Mail | (2) FiTr | (3) Games | (4) InMe | (5) M2M | (6) Other | (7) P2P | (8) Streaming | (9) VoIP | (10) WebAp |
|---|---|---|---|---|---|---|---|---|---|---|
| WD DL | DG | TG | TS | TG | TG | TG | TS | TS | TS | TS |
| WD UL | DG | TG | TS | TG | TG | TG | TS | TS | TS | TS |
| WE DL | TG | TG | P | TG | TS | TS | TS | TS | TS | TS |
| WE UL | TG | TG | TS | TG | TS | TS | TR | TS | TR | TS |

Table A.3 – Weekdays Download APP_GROUP E-Mail General Model.

| $\bar{\sigma}_{[\%]} = 7.371$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Double Gaussian | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06; 14] | $f_{gauss}$ | $v_1$ | 0.055 | 0.011 | 0.100 | $\sqrt{\overline{\varepsilon^2}}$ | 11.1 |
| | | | $u_1$ | 0.225 | 0.196 | 0.254 | $R^2$ | 92.1 |
| | | | $\mu_1$ | 0.507 | 0.500 | 0.514 | $R^2_{adj}$ | 92.0 |
| | | | $\sigma_1$ | 0.092 | 0.083 | 0.101 | | |
| 2 | [14; 06] | $f_{gauss}$ | $v_2$ | 0.070 | 0.051 | 0.089 | $\sqrt{\overline{\varepsilon^2}}$ | 8.6 |
| | | | $u_2$ | 0.383 | 0.359 | 0.407 | $R^2$ | 93.7 |
| | | | $\mu_2$ | 0.680 | 0.673 | 0.688 | $R^2_{adj}$ | 93.7 |
| | | | $\sigma_2$ | 0.176 | 0.166 | 0.185 | | |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 4.4 |
| | | | | | | | $R^2$ | 98.4 |
| | | | | | | | $R^2_{adj}$ | 97.8 |

Table A.4 – Weekdays Download APP_GROUP FiTr Best/General Model.

| $\bar{\sigma}_{[\%]} = 14.323$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Triple Gaussian | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06;13] | $f_{gauss}$ | $v_1$ | 0.089 | 0.021 | 0.157 | $\sqrt{\overline{\varepsilon^2}}$ | 18.3 |
| | | | $u_1$ | 0.194 | 0.162 | 0.227 | $R^2$ | 79.5 |
| | | | $\mu_1$ | 0.484 | 0.477 | 0.491 | $R^2_{adj}$ | 79.2 |
| | | | $\sigma_1$ | 0.081 | 0.071 | 0.092 | | |
| 2 | [13;21] | $f_{gauss}$ | $v_2$ | 0.500 | -3.301 | 4.301 | $\sqrt{\overline{\varepsilon^2}}$ | 18.5 |
| | | | $u_2$ | 0.163 | -2.159 | 2.484 | $R^2$ | 6.6 |
| | | | $\mu_2$ | 0.696 | 0.671 | 0.721 | $R^2_{adj}$ | 5.0 |
| | | | $\sigma_2$ | 0.153 | -0.670 | 0.976 | | |
| 3 | [21;06] | $f_{gauss}$ | $v_3$ | 0.098 | 0.062 | 0.134 | $\sqrt{\overline{\varepsilon^2}}$ | 11.8 |
| | | | $u_3$ | 0.189 | 0.161 | 0.217 | $R^2$ | 83.9 |
| | | | $\mu_3$ | 0.923 | 0.913 | 0.933 | $R^2_{adj}$ | 83.7 |
| | | | $\sigma_3$ | 0.107 | 0.094 | 0.119 | | |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 3.2 |
| | | | | | | | $R^2$ | 98.9 |
| | | | | | | | $R^2_{adj}$ | 98.1 |

Table A.5 – Weekdays Download APP_GROUP Games General Model.

| $\bar{\sigma}_{[\%]} = 28.164$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [07;19] | $f_{exp}$ | $c_1$ | 0.000 | -0.220 | 0.220 | $\sqrt{\overline{\varepsilon^2}}$ | 25.1 |
| | | | $k_1$ | 0.284 | 0.141 | 0.427 | $R^2$ | 47.4 |
| | | | $t_1$ | 0.812 | 0.761 | 0.863 | $R^2_{adj}$ | 47.1 |
| 2 | [19;24] | $f_{linear}$ | $b_2$ | 1.674 | 0.208 | 3.139 | $\sqrt{\overline{\varepsilon^2}}$ | 39.1 |
| | | | $m_2$ | -0.864 | -2.498 | 0.770 | $R^2$ | 1.1 |
| | | | | | | | $R^2_{adj}$ | 0.1 |
| 3 | [24;07] | $f_{exp}$ | $c_3$ | 0.059 | -0.233 | 0.352 | $\sqrt{\overline{\varepsilon^2}}$ | 32.5 |
| | | | $k_3$ | -0.152 | -0.297 | -0.007 | $R^2$ | 28.1 |
| | | | $t_3$ | 0.943 | 0.907 | 0.979 | $R^2_{adj}$ | 27.4 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 4.2 |
| | | | | | | | $R^2$ | 97.6 |
| | | | | | | | $R^2_{adj}$ | 96.7 |

Table A.6 – Weekdays Download APP_GROUP InMe Best/General Model.

| $\bar{\sigma}_{[\%]} = 9.526$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Triple Gaussian | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06; 13] | $f_{gauss}$ | $v_1$ | 0.009 | -0.054 | 0.072 | $\sqrt{\overline{\varepsilon^2}}$ | 8.5 |
| | | | $u_1$ | 0.255 | 0.195 | 0.315 | $R^2$ | 92.4 |
| | | | $\mu_1$ | 0.532 | 0.515 | 0.548 | $R^2_{adj}$ | 92.3 |
| | | | $\sigma_1$ | 0.123 | 0.104 | 0.143 | | |
| 2 | [13; 22] | $f_{gauss}$ | $v_2$ | 0.500 | -5.693 | 6.693 | $\sqrt{\overline{\varepsilon^2}}$ | 18.6 |
| | | | $u_2$ | 0.255 | -4.619 | 5.129 | $R^2$ | -1.9 |
| | | | $\mu_2$ | 0.740 | 0.713 | 0.767 | $R^2_{adj}$ | -3.4 |
| | | | $\sigma_2$ | 0.200 | -1.200 | 1.600 | | |
| 3 | [22; 06] | $f_{gauss}$ | $v_3$ | 0.069 | 0.051 | 0.087 | $\sqrt{\overline{\varepsilon^2}}$ | 7.4 |
| | | | $u_3$ | 0.174 | 0.155 | 0.193 | $R^2$ | 94.9 |
| | | | $\mu_3$ | 0.927 | 0.919 | 0.936 | $R^2_{adj}$ | 94.8 |
| | | | $\sigma_3$ | 0.085 | 0.078 | 0.093 | | |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 3.0 |
| | | | | | | | $R^2$ | 99.3 |
| | | | | | | | $R^2_{adj}$ | 98.7 |

Table A.7 – Weekdays Download APP_GROUP M2M Best/General Model.

| $\bar{\sigma}_{[\%]} = 9.999$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Triple Gaussian | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06; 13] | $f_{gauss}$ | $v_1$ | 0.088 | 0.028 | 0.147 | $\sqrt{\overline{\varepsilon^2}}$ | 10.8 |
| | | | $u_1$ | 0.234 | 0.195 | 0.273 | $R^2$ | 90.4 |
| | | | $\mu_1$ | 0.501 | 0.493 | 0.509 | $R^2_{adj}$ | 90.3 |
| | | | $\sigma_1$ | 0.103 | 0.091 | 0.115 | | |
| 2 | [13; 21] | $f_{gauss}$ | $v_2$ | 0.400 | -1.931 | 2.732 | $\sqrt{\overline{\varepsilon^2}}$ | 11.8 |
| | | | $u_2$ | 0.305 | -1.547 | 2.157 | $R^2$ | 22.6 |
| | | | $\mu_2$ | 0.698 | 0.682 | 0.715 | $R^2_{adj}$ | 21.4 |
| | | | $\sigma_2$ | 0.200 | -0.254 | 0.654 | | |
| 3 | [21; 06] | $f_{gauss}$ | $v_3$ | 0.120 | 0.085 | 0.156 | $\sqrt{\overline{\varepsilon^2}}$ | 9.4 |
| | | | $u_3$ | 0.197 | 0.164 | 0.230 | $R^2$ | 89.2 |
| | | | $\mu_3$ | 0.942 | 0.929 | 0.954 | $R^2_{adj}$ | 89.1 |
| | | | $\sigma_3$ | 0.109 | 0.095 | 0.123 | | |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 1.9 |
| | | | | | | | $R^2$ | 99.6 |
| | | | | | | | $R^2_{adj}$ | 99.3 |

Table A.8 – Weekdays Download APP_GROUP Other Best/General Model.

| $\bar{\sigma}_{[\%]} = 25.996$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Triple Gaussian | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [07;14] | $f_{gauss}$ | $v_1$ | 0.037 | -0.209 | 0.284 | $\sqrt{\overline{\varepsilon^2}}$ | 27.9 |
| | | | $u_1$ | 0.213 | 0.027 | 0.399 | $R^2$ | 39.9 |
| | | | $\mu_1$ | 0.551 | 0.508 | 0.593 | $R^2_{adj}$ | 39.0 |
| | | | $\sigma_1$ | 0.122 | 0.053 | 0.192 | | |
| 2 | [14;21] | $f_{gauss}$ | $v_2$ | 0.429 | -3.593 | 4.450 | $\sqrt{\overline{\varepsilon^2}}$ | 95.6 |
| | | | $u_2$ | 0.100 | -1.936 | 2.136 | $R^2$ | 1.8 |
| | | | $\mu_2$ | 0.677 | 0.486 | 0.868 | $R^2_{adj}$ | -0.1 |
| | | | $\sigma_2$ | 0.115 | -0.960 | 1.189 | | |
| 3 | [21;07] | $f_{gauss}$ | $v_3$ | 0.110 | 0.088 | 0.133 | $\sqrt{\overline{\varepsilon^2}}$ | 9.5 |
| | | | $u_3$ | 0.115 | 0.094 | 0.136 | $R^2$ | 73.4 |
| | | | $\mu_3$ | 0.916 | 0.901 | 0.932 | $R^2_{adj}$ | 73.2 |
| | | | $\sigma_3$ | 0.108 | 0.091 | 0.124 | | |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 8.4 |
| | | | | | | | $R^2$ | 89.2 |
| | | | | | | | $R^2_{adj}$ | 80.9 |

Table A.9 – Weekdays Download APP_GROUP P2P Best/General Model.

| $\bar{\sigma}_{[\%]} = 23.651$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [09;12] | $f_{exp}$ | $c_1$ | 0.196 | -0.563 | 0.955 | $\sqrt{\overline{\varepsilon^2}}$ | 18.6 |
| | | | $k_1$ | 0.083 | -0.220 | 0.387 | $R^2$ | 19.8 |
| | | | $t_1$ | 0.550 | 0.394 | 0.706 | $R^2_{adj}$ | 17.7 |
| 2 | [12;00] | $f_{linear}$ | $b_2$ | 0.472 | 0.320 | 0.624 | $\sqrt{\overline{\varepsilon^2}}$ | 28.9 |
| | | | $m_2$ | 0.490 | 0.292 | 0.688 | $R^2$ | 6.6 |
| | | | | | | | $R^2_{adj}$ | 6.3 |
| 3 | [00;09] | $f_{exp}$ | $c_3$ | 0.312 | 0.258 | 0.365 | $\sqrt{\overline{\varepsilon^2}}$ | 19.4 |
| | | | $k_3$ | -0.079 | -0.116 | -0.043 | $R^2$ | 34.2 |
| | | | $t_3$ | 0.977 | 0.946 | 1.009 | $R^2_{adj}$ | 33.6 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 4.3 |
| | | | | | | | $R^2$ | 96.4 |
| | | | | | | | $R^2_{adj}$ | 95.1 |

Table A.10 – Weekdays Download APP_GROUP Streaming General Model.

| $\bar{\sigma}_{[\%]} = 5.763$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06;10] | $f_{exp}$ | $c_1$ | 0.035 | -0.029 | 0.098 | $\sqrt{\overline{\varepsilon^2}}$ | 4.4 |
| | | | $k_1$ | 0.104 | 0.075 | 0.133 | $R^2$ | 90.8 |
| | | | $t_1$ | 0.498 | 0.486 | 0.511 | $R^2_{adj}$ | 90.7 |
| 2 | [10;24] | $f_{linear}$ | $b_2$ | 0.162 | 0.126 | 0.198 | $\sqrt{\overline{\varepsilon^2}}$ | 7.2 |
| | | | $m_2$ | 0.879 | 0.830 | 0.929 | $R^2$ | 78.4 |
| | | | | | | | $R^2_{adj}$ | 78.3 |
| 3 | [24;06] | $f_{exp}$ | $c_3$ | 0.000 | -0.062 | 0.062 | $\sqrt{\overline{\varepsilon^2}}$ | 7.1 |
| | | | $k_3$ | -0.125 | -0.144 | -0.106 | $R^2$ | 93.8 |
| | | | $t_3$ | 0.993 | 0.986 | 0.999 | $R^2_{adj}$ | 93.7 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 2.5 |
| | | | | | | | $R^2$ | 99.2 |
| | | | | | | | $R^2_{adj}$ | 98.9 |

Table A.11 – Weekdays Download APP_GROUP VoIP General Model.

| $\bar{\sigma}_{[\%]} = 8.366$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06;10] | $f_{exp}$ | $c_1$ | 0.044 | 0.009 | 0.079 | $\sqrt{\overline{\varepsilon^2}}$ | 4.5 |
| | | | $k_1$ | 0.072 | 0.052 | 0.092 | $R^2$ | 84.4 |
| | | | $t_1$ | 0.499 | 0.481 | 0.517 | $R^2_{adj}$ | 84.1 |
| 2 | [10;23] | $f_{linear}$ | $b_2$ | -0.095 | -0.153 | -0.037 | $\sqrt{\overline{\varepsilon^2}}$ | 11.7 |
| | | | $m_2$ | 1.126 | 1.046 | 1.206 | $R^2$ | 69.6 |
| | | | | | | | $R^2_{adj}$ | 69.5 |
| 3 | [23;06] | $f_{exp}$ | $c_3$ | 0.027 | -0.012 | 0.067 | $\sqrt{\overline{\varepsilon^2}}$ | 7.5 |
| | | | $k_3$ | -0.092 | -0.106 | -0.078 | $R^2$ | 90.5 |
| | | | $t_3$ | 0.971 | 0.967 | 0.976 | $R^2_{adj}$ | 90.4 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 2.8 |
| | | | | | | | $R^2$ | 99.1 |
| | | | | | | | $R^2_{adj}$ | 98.7 |

Table A.12 – Weekdays Download APP_GROUP WebAp Best/General Model.

| $\bar{\sigma}_{[\%]} = 4.992$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06;10] | $f_{exp}$ | $c_1$ | 0.000 | -0.057 | 0.057 | $\sqrt{\overline{\varepsilon^2}}$ | 6.4 |
| | | | $k_1$ | 0.079 | 0.066 | 0.093 | $R^2$ | 94.0 |
| | | | $t_1$ | 0.436 | 0.432 | 0.439 | $R^2_{adj}$ | 93.9 |
| 2 | [10;24] | $f_{linear}$ | $b_2$ | 0.849 | 0.811 | 0.887 | $\sqrt{\overline{\varepsilon^2}}$ | 7.6 |
| | | | $m_2$ | 0.128 | 0.076 | 0.180 | $R^2$ | 6.4 |
| | | | | | | | $R^2_{adj}$ | 6.2 |
| 3 | [24;06] | $f_{exp}$ | $c_3$ | 0.045 | 0.013 | 0.076 | $\sqrt{\overline{\varepsilon^2}}$ | 6.1 |
| | | | $k_3$ | -0.090 | -0.099 | -0.080 | $R^2$ | 95.2 |
| | | | $t_3$ | 0.983 | 0.980 | 0.987 | $R^2_{adj}$ | 95.2 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 4.4 |
| | | | | | | | $R^2$ | 98.3 |
| | | | | | | | $R^2_{adj}$ | 97.7 |

Table A.13 – DEV_TYPE Best Models: Ranking.

| | | (1) Hotspots | (2) Others | (3) Pens | (4) Routers | (5) Smartphone | (6) Tablet |
|---|---|---|---|---|---|---|---|
| WD DL | 1º | TG | TG | TG | TS | TS | TS |
| | 2º | TS | TS | TS | DG | T | TG |
| WD UL | 1º | TG | TG | TG | TG | TG | TG |
| | 2º | TS | DG | DG | TS | TS | TS |
| WE DL | 1º | TS | TG | TG | TS | TG | TS |
| | 2º | TG | DG | TS | T | T | TG |
| WE UL | 1º | TS | TS | TG | TG | TG | TG |
| | 2º | TG | TG | DG | DG | DG | DG |

Table A.14 – DEV_TYPE General Model.

| | (1) Hotspots | (2) Others | (3) Pens | (4) Routers | (5) Smartphone | (6) Tablet |
|---|---|---|---|---|---|---|
| WD DL | TS | TG | TS | TS | TS | TS |
| WD UL | TS | TG | TS | TS | TS | TS |
| WE DL | TS | TS | TS | TS | TS | TS |
| WE UL | TS | TS | TS | TS | TS | TS |

Table A.15 – Weekdays Download DEV_TYPE Hotspots General Model.

| $\bar{\sigma}_{[\%]} = 7.045$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [07;10] | $f_{exp}$ | $c_1$ | 0.015 | -0.107 | 0.137 | $\sqrt{\overline{\varepsilon^2}}$ | 3.4 |
| | | | $k_1$ | 0.123 | 0.056 | 0.191 | $R^2$ | 85.8 |
| | | | $t_1$ | 0.545 | 0.513 | 0.577 | $R^2_{adj}$ | 85.5 |
| 2 | [10;00] | $f_{linear}$ | $b_2$ | -0.022 | -0.071 | 0.027 | $\sqrt{\overline{\varepsilon^2}}$ | 10.7 |
| | | | $m_2$ | 0.964 | 0.899 | 1.029 | $R^2$ | 69.9 |
| | | | | | | | $R^2_{adj}$ | 69.8 |
| 3 | [00;07] | $f_{exp}$ | $c_3$ | 0.103 | 0.076 | 0.130 | $\sqrt{\overline{\varepsilon^2}}$ | 5.3 |
| | | | $k_3$ | -0.090 | -0.100 | -0.079 | $R^2$ | 94.0 |
| | | | $t_3$ | 1.004 | 1.000 | 1.008 | $R^2_{adj}$ | 94.0 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 3.9 |
| | | | | | | | $R$ | 97.5 |
| | | | | | | | $R^2_{adj}$ | 96.7 |

Table A.16 – Weekdays Download DEV_TYPE Others Best/General Model.

| $\bar{\sigma}_{[\%]} = 26.976$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Triple Gaussian | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06;14] | $f_{gauss}$ | $v_1$ | 0.075 | -0.031 | 0.181 | $\sqrt{\overline{\varepsilon^2}}$ | 25.0 |
| | | | $u_1$ | 0.166 | 0.086 | 0.246 | $R^2$ | 52.2 |
| | | | $\mu_1$ | 0.515 | 0.486 | 0.545 | $R^2_{adj}$ | 51.5 |
| | | | $\sigma_1$ | 0.097 | 0.061 | 0.133 | | |
| 2 | [14;21] | $f_{gauss}$ | $v_2$ | 0.428 | -0.368 | 1.223 | $\sqrt{\overline{\varepsilon^2}}$ | 60.0 |
| | | | $u_2$ | 0.100 | -0.192 | 0.392 | $R^2$ | 5.2 |
| | | | $\mu_2$ | 0.688 | 0.657 | 0.719 | $R^2_{adj}$ | 3.6 |
| | | | $\sigma_2$ | 0.080 | -0.042 | 0.201 | | |
| 3 | [21;06] | $f_{gauss}$ | $v_3$ | 0.082 | 0.017 | 0.147 | $\sqrt{\overline{\varepsilon^2}}$ | 19.5 |
| | | | $u_3$ | 0.154 | 0.113 | 0.195 | $R^2$ | 55.4 |
| | | | $\mu_3$ | 0.948 | 0.933 | 0.962 | $R^2_{adj}$ | 54.8 |
| | | | $\sigma_3$ | 0.104 | 0.083 | 0.126 | | |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 3.5 |
| | | | | | | | $R^2$ | 98.1 |
| | | | | | | | $R^2_{adj}$ | 96.7 |

Table A.17 – Weekdays Download DEV_TYPE Pens General Model.

| $\bar{\sigma}_{[\%]} = 9.363$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06;10] | $f_{exp}$ | $c_1$ | 0.092 | 0.065 | 0.119 | $\sqrt{\overline{\varepsilon^2}}$ | 5.9 |
| | | | $k_1$ | 0.049 | 0.041 | 0.056 | $R^2$ | 91.9 |
| | | | $t_1$ | 0.445 | 0.441 | 0.449 | $R^2_{adj}$ | 91.7 |
| 2 | [10;24] | $f_{linear}$ | $b_2$ | 0.928 | 0.857 | 1.000 | $\sqrt{\overline{\varepsilon^2}}$ | 14.3 |
| | | | $m_2$ | -0.030 | -0.128 | 0.068 | $R^2$ | 0.1 |
| | | | | | | | $R^2_{adj}$ | -0.2 |
| 3 | [24;06] | $f_{exp}$ | $c_3$ | 0.030 | -0.020 | 0.080 | $\sqrt{\overline{\varepsilon^2}}$ | 7.1 |
| | | | $k_3$ | -0.109 | -0.127 | -0.092 | $R^2$ | 92.0 |
| | | | $t_3$ | 0.974 | 0.969 | 0.979 | $R^2_{adj}$ | 91.9 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 5.1 |
| | | | | | | | $R^2$ | 97.4 |
| | | | | | | | $R^2_{adj}$ | 96.5 |

Table A.18 – Weekdays Download DEV_TYPE Routers Best/General Model.

| $\bar{\sigma}_{[\%]} = 7.594$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [07;10] | $f_{exp}$ | $c_1$ | 0.000 | -0.051 | 0.051 | $\sqrt{\overline{\varepsilon^2}}$ | 6.2 |
| | | | $k_1$ | 0.054 | 0.043 | 0.065 | $R^2$ | 92.1 |
| | | | $t_1$ | 0.440 | 0.437 | 0.444 | $R^2_{adj}$ | 91.9 |
| 2 | [10;23] | $f_{linear}$ | $b_2$ | 1.012 | 0.950 | 1.073 | $\sqrt{\overline{\varepsilon^2}}$ | 12.4 |
| | | | $m_2$ | -0.185 | -0.270 | -0.100 | $R^2$ | 5.2 |
| | | | | | | | $R^2_{adj}$ | 4.9 |
| 3 | [23;07] | $f_{exp}$ | $c_3$ | 0.000 | -0.043 | 0.043 | $\sqrt{\overline{\varepsilon^2}}$ | 6.7 |
| | | | $k_3$ | -0.124 | -0.144 | -0.103 | $R^2$ | 89.9 |
| | | | $t_3$ | 0.949 | 0.942 | 0.955 | $R^2_{adj}$ | 89.8 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 6.0 |
| | | | | | | | $R^2$ | 96.7 |
| | | | | | | | $R^2_{adj}$ | 95.5 |

Table A.19 – Weekdays Download DEV_TYPE Smartphone Best/General Model.

| $\bar{\sigma}_{[\%]} = 5.585$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06;09] | $f_{exp}$ | $c_1$ | 0.000 | -0.051 | 0.052 | $\sqrt{\varepsilon^2}$ | 5.5 |
| | | | $k_1$ | 0.058 | 0.047 | 0.070 | $R^2$ | 94.0 |
| | | | $t_1$ | 0.402 | 0.398 | 0.405 | $R^2_{adj}$ | 93.9 |
| 2 | [09;24] | $f_{linear}$ | $b_2$ | 0.681 | 0.640 | 0.722 | $\sqrt{\varepsilon^2}$ | 9.5 |
| | | | $m_2$ | 0.289 | 0.231 | 0.347 | $R^2$ | 20.9 |
| | | | | | | | $R^2_{adj}$ | 20.7 |
| 3 | [24;06] | $f_{exp}$ | $c_3$ | 0.000 | -0.036 | 0.036 | $\sqrt{\varepsilon^2}$ | 5.6 |
| | | | $k_3$ | -0.105 | -0.117 | -0.093 | $R^2$ | 95.3 |
| | | | $t_3$ | 0.978 | 0.975 | 0.982 | $R^2_{adj}$ | 95.2 |
| Model vs. Average | | | | | | | $\sqrt{\varepsilon^2}$ | 5.2 |
| | | | | | | | $R^2$ | 97.2 |
| | | | | | | | $R^2_{adj}$ | 96.2 |

Table A.20 – Weekdays Download DEV_TYPE Tablet Best/General Model.

| $\bar{\sigma}_{[\%]} = 9.814$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06;09] | $f_{exp}$ | $c_1$ | 0.000 | -0.064 | 0.064 | $\sqrt{\varepsilon^2}$ | 5.6 |
| | | | $k_1$ | 0.066 | 0.044 | 0.087 | $R^2$ | 84.8 |
| | | | $t_1$ | 0.430 | 0.419 | 0.442 | $R^2_{adj}$ | 84.5 |
| 2 | [09;00] | $f_{linear}$ | $b_2$ | 0.189 | 0.136 | 0.243 | $\sqrt{\varepsilon^2}$ | 13.3 |
| | | | $m_2$ | 0.778 | 0.704 | 0.851 | $R^2$ | 52.8 |
| | | | | | | | $R^2_{adj}$ | 52.7 |
| 3 | [00;06] | $f_{exp}$ | $c_3$ | 0.000 | -0.049 | 0.049 | $\sqrt{\varepsilon^2}$ | 7.2 |
| | | | $k_3$ | -0.087 | -0.102 | -0.071 | $R^2$ | 90.9 |
| | | | $t_3$ | 1.012 | 1.007 | 1.016 | $R^2_{adj}$ | 90.8 |
| Model vs. Average | | | | | | | $\sqrt{\varepsilon^2}$ | 3.7 |
| | | | | | | | $R^2$ | 98.2 |
| | | | | | | | $R^2_{adj}$ | 97.6 |

Table A.21 – OP_SYS Best Models: Ranking.

| | | (1) Android | (2) Others | (3) Windows | (4) iOS |
|---|---|---|---|---|---|
| WD DL | 1º | TG | TG | TS | TS |
| | 2º | TS | TS | T | T |
| WD UL | 1º | TG | TG | TG | TG |
| | 2º | DG | TS | T | T |
| WE DL | 1º | TG | TS | TG | TG |
| | 2º | TS | TG | TS | TS |
| WE UL | 1º | TG | TG | TG | TG |
| | 2º | DG | TS | T | T |

Table A.22 – OP_SYS General Model.

| | (1)<br>Android | (2)<br>Others | (3)<br>Windows | (4)<br>iOS |
|---|---|---|---|---|
| WD DL | TS | TS | TS | TS |
| WD UL | TS | TS | TS | TS |
| WE DL | TS | TS | TS | TS |
| WE UL | TS | TS | TS | TS |

Table A.23 – Weekdays Download OP_SYS Android General Model.

| $\bar{\sigma}_{[\%]} = 5.439$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06;10] | $f_{exp}$ | $c_1$ | 0.000 | -0.057 | 0.057 | $\sqrt{\overline{\varepsilon^2}}$ | 5.7 |
| | | | $k_1$ | 0.085 | 0.070 | 0.100 | $R^2$ | 94.1 |
| | | | $t_1$ | 0.445 | 0.441 | 0.448 | $R^2_{adj}$ | 94.0 |
| 2 | [10;24] | $f_{linear}$ | $b_2$ | 0.770 | 0.730 | 0.809 | $\sqrt{\overline{\varepsilon^2}}$ | 7.9 |
| | | | $m_2$ | 0.188 | 0.133 | 0.242 | $R^2$ | 12.0 |
| | | | | | | | $R^2_{adj}$ | 11.8 |
| 3 | [24;06] | $f_{exp}$ | $c_3$ | 0.045 | 0.011 | 0.079 | $\sqrt{\overline{\varepsilon^2}}$ | 5.8 |
| | | | $k_3$ | -0.097 | -0.109 | -0.085 | $R^2$ | 94.3 |
| | | | $t_3$ | 0.971 | 0.967 | 0.975 | $R^2_{adj}$ | 94.2 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 4.0 |
| | | | | | | | $R^2$ | 98.4 |
| | | | | | | | $R^2_{adj}$ | 97.8 |

Table A.24 – Weekdays Download OP_SYS Others General Model.

| $\bar{\sigma}_{[\%]} = 7.315$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [07;10] | $f_{exp}$ | $c_1$ | 0.067 | 0.021 | 0.113 | $\sqrt{\overline{\varepsilon^2}}$ | 3.9 |
| | | | $k_1$ | 0.067 | 0.052 | 0.082 | $R^2$ | 93.1 |
| | | | $t_1$ | 0.471 | 0.463 | 0.478 | $R^2_{adj}$ | 93.0 |
| 2 | [10;00] | $f_{linear}$ | $b_2$ | 0.454 | 0.404 | 0.504 | $\sqrt{\overline{\varepsilon^2}}$ | 10.9 |
| | | | $m_2$ | 0.485 | 0.419 | 0.552 | $R^2$ | 36.1 |
| | | | | | | | $R^2_{adj}$ | 36.0 |
| 3 | [00;07] | $f_{exp}$ | $c_3$ | 0.106 | 0.086 | 0.126 | $\sqrt{\overline{\varepsilon^2}}$ | 4.4 |
| | | | $k_3$ | -0.083 | -0.091 | -0.075 | $R^2$ | 95.4 |
| | | | $t_3$ | 1.001 | 0.997 | 1.005 | $R^2_{adj}$ | 95.3 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 3.4 |
| | | | | | | | $R^2$ | 98.5 |
| | | | | | | | $R^2_{adj}$ | 97.9 |

Table A.25 – Weekdays Download OP_SYS Windows Best/General Model.

| $\bar{\sigma}_{[\%]} = 11.633$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06;09] | $f_{exp}$ | $c_1$ | 0.000 | -0.065 | 0.065 | $\sqrt{\overline{\varepsilon^2}}$ | 6.9 |
| | | | $k_1$ | 0.058 | 0.045 | 0.072 | $R^2$ | 91.4 |
| | | | $t_1$ | 0.398 | 0.395 | 0.402 | $R^2_{adj}$ | 91.3 |
| 2 | [09;24] | $f_{linear}$ | $b_2$ | 0.604 | 0.535 | 0.673 | $\sqrt{\overline{\varepsilon^2}}$ | 15.9 |
| | | | $m_2$ | 0.350 | 0.252 | 0.447 | $R^2$ | 12.0 |
| | | | | | | | $R^2_{adj}$ | 11.8 |
| 3 | [24;06] | $f_{exp}$ | $c_3$ | 0.000 | -0.080 | 0.080 | $\sqrt{\overline{\varepsilon^2}}$ | 12.2 |
| | | | $k_3$ | -0.105 | -0.131 | -0.080 | $R^2$ | 82.4 |
| | | | $t_3$ | 0.983 | 0.975 | 0.990 | $R^2_{adj}$ | 82.2 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 5.5 |
| | | | | | | | $^2$ | 96.6 |
| | | | | | | | $R^2_{adj}$ | 95.5 |

Table A.26 – Weekdays Download OP_SYS iOS Best/General Model.

| $\bar{\sigma}_{[\%]} = 5.577$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Model** Tree Stump | | | | | | | | |
| Section$_K$ | $[X_i; X_f]_{[h]}$ | Eq. | **Coefficients** | | **95% confidence bounds** | | **GOF** [%] | |
| 1 | [06;09] | $f_{exp}$ | $c_1$ | 0.016 | -0.029 | 0.062 | $\sqrt{\overline{\varepsilon^2}}$ | 5.7 |
| | | | $k_1$ | 0.052 | 0.042 | 0.062 | $R^2$ | 93.9 |
| | | | $t_1$ | 0.400 | 0.397 | 0.403 | $R^2_{adj}$ | 93.7 |
| 2 | [09;24] | $f_{linear}$ | $b_2$ | 0.664 | 0.625 | 0.702 | $\sqrt{\overline{\varepsilon^2}}$ | 8.8 |
| | | | $m_2$ | 0.320 | 0.266 | 0.374 | $R^2$ | 27.2 |
| | | | | | | | $R^2_{adj}$ | 27.0 |
| 3 | [24;06] | $f_{exp}$ | $c_3$ | 0.000 | -0.038 | 0.038 | $\sqrt{\overline{\varepsilon^2}}$ | 6.1 |
| | | | $k_3$ | -0.102 | -0.114 | -0.090 | $R^2$ | 95.0 |
| | | | $t_3$ | 0.983 | 0.980 | 0.987 | $R^2_{adj}$ | 94.9 |
| Model vs. Average | | | | | | | $\sqrt{\overline{\varepsilon^2}}$ | 4.8 |
| | | | | | | | $R^2$ | 97.7 |
| | | | | | | | $R^2_{adj}$ | 96.9 |

# References


[1] 3GPP, Radio Access Milestones, http://www.3gpp.org/about-3gpp, Jan. 2016.

[2] Ericsson, *Ericsson Mobility Report*, Ericsson, Stockholm, Sweden, Nov. 2016 (https://www.ericsson.com/assets/local/mobility-report/documents/2016/ericsson-mobility-report-november-2016.pdf).

[3] Y. Ouyang, M.H. Fallah, S. Hu, Y. Yong Ren, Y. Hu, Z. Lai, M. Guan, and W.D. Lu, "A novel methodology of data analytics and modeling to evaluate LTE network performance", in *Proc. of WTS'14 - 13th IEEE Wireless Telecommunications Symposium*, Washington, D.C., USA, Apr. 2014 (http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6835006).

[4] S.K. Baghel, K. Keshav, and V.R. Manepalli, "An investigation into traffic analysis for diverse data applications on smartphones", in *Proc. of NCC'12 - 2012 IEEE National Conference on Communications*, Kharagpur, India, Feb. 2012 (http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6176903).

[5] Ericsson, *Ericsson Mobility Report*, Ericsson, Stockholm, Sweden, Jun. 2015 (http://www.ericsson.com/res/docs/2015/ericsson-mobility-report-june-2015.pdf).

[6] 3GPP, *UTRAN Overall Description (Release 14)*, Report TS 25.401 V14.0.0, Technical Specification Group Radio Access Network, 3GPP, Valbonne, France, Mar. 2017 (http://www.3gpp.org/ftp//Specs/archive/25_series/25.401/).

[7] H. Holma and A. Toskala, *WCDMA for UMTS (5th Edition)*, John Wiley & Sons, Chichester, UK, 2010.

[8] A.F. Molisch, *Wireless Communications*, John Wiley & Sons, Chichester, UK, 2011.

[9] L.M. Correia, *Mobile Communication Systems*, Lecture Notes, Instituto Superior Tecnico, Technical University of Lisbon, Lisbon, Portugal, 2015 (http://fenix.tecnico.ulisboa.pt/disciplinas/SCM364511/2014-2015/2-semestre).

[10] H. Holma and A. Toskala, *LTE for UMTS: Evolution to LTE Advanced (2nd Edition)*, John Wiley & Sons, Chichester, UK, 2011.

[11] S. Sesia, I. Toufik, and I. Baker, *LTE - The UMTS Long Term Evolution: From Theory to Practice (2nd Edition)*, John Wiley & Sons, Chichester, UK, 2011.

[12] M. Sá, *Performance Analysis of Software Defined Networks in LTE-A*, M.Sc. Thesis, Instituto Superior Tecnico, Technical University of Lisbon, Lisbon, Portugal, 2015 (http://grow.inov.pt/wp-content/uploads/2015/08/Thesis_MiguelSa_FinalVersion.pdf).

[13] ANACOM, *Final Report Auction (in Portuguese)*, ANACOM, Lisbon, Portugal, Jan. 2012 (https://www.anacom.pt/render.jsp?contentId=1112758).

[14] E. Dahlman, S. Parkvall, and J. Sköld, *4G LTE/LTE-Advanced for Mobile Broadband*, Academic

Press, Oxford, UK, 2011.

[15] Z. Zhang, Z. Zhao, H. Guan, D. Laselva, D.I. Park, K.M. Hwang, D.H. Kim, and Z. Tan, “A novel traffic generation framework for LTE network evolution study”, in *Proc. of PIMRC’14 - 25th IEEE Annual International Symposium on Personal, Indoor, and Mobile Radio Communication*, Washington, D.C., USA, Sep. 2014 (http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7136372).

[16] 3GPP, *Policy and charging control architecture (Release 14)*, Report TS 23.203 V14.3.0, Technical Specification Group Services and System Aspects, 3GPP, Valbonne, France, Mar. 2017 (http://www.3gpp.org/ftp//Specs/archive/23_series/23.203/).

[17] K. Sina, *Radio Resource Management Strategies in Virtual Networks*, Ph.D. Thesis, Instituto Superior Tecnico, Technical University of Lisbon, Lisbon, Portugal, 2016 (http://grow.tecnico.ulisboa.pt/user/skhatibi/).

[18] Huawei Technologies, *Smartphone Solutions*, White Paper, Prepared by Smartphone ecosystem R&D support team, Issue 2.0, Huawei Technologies, Shenzhen, China, Jul. 2012 (www.huawei.com/ilink/en/download/HW_193034).

[19] P. Pastor, F. Fradella, A. Ravagnolo, and P. Valenza, *Conceptual approach for a mobile BU-LRIC model*, Report for ICP-ANACOM, Public Version, Reference 2002126-153, Analysys Mason Limited, London, UK, Apr. 2015 (http://www.anacom.pt/streaming/anexo3_MTRmodelconceptpaper.pdf?contentId=1354319&field=ATTACHED_FILE).

[20] ANACOM, Network Dimensioning - Geographic Characterisation, http://www.anacom.pt/render.jsp?categoryId=381856&cat=381862, in Portuguese, Mar. 2016.

[21] P. Pastor, F. Fradella, A. Ravagnolo, and P. Valenza, *Bottom-up mobile cost model update*, Report for ICP-ANACOM, Public Version, Reference 2002126-153, Model documentation, Analysys Mason Limited, London, UK, Apr. 2015 (http://www.anacom.pt/streaming/anexo2_MTRmodeldocumentation.pdf?contentId=1354318&field=ATTACHED_FILE).

[22] P. Pastor, F. Fradella, A. Ravagnolo, and P. Valenza, *Update of the mobile LRIC model: change report*, Report for ICP-ANACOM, Public Version, Reference 2002126-153, Analysys Mason Limited, London, UK, Apr. 2015 (http://www.anacom.pt/streaming/anexo4_MTRmodelupdate.pdf?contentId=1354320&field=ATTACHED_FILE).

[23] M. Afanasyev, T. Chen, G.M. Voelker, and A.C. Snoeren, “Usage Patterns in an Urban WiFi Network”, *IEEE/ACM Transactions on Networking*, Vol. 18, No. 5, Oct. 2010, pp. 1359–1372 (http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5401061).

[24] L. Korowajczuk, *How to Dimension User Traffic in 4G Networks*, CelPlan Technologies, Reston, VA, USA, Jun. 2014 (http://www.celplan.com/webinars/How to Dimension User Traffic in 4G Networks rev13.pdf).

[25] R.A. Kalden, *Mobile Internet Traffic Measurement and Modeling Based on Data From Commercial GPRS Networks*, Ph.D. Thesis, University of Twente, Twente, Netherlands, 2004 (http://doc.utwente.nl/48238/1/thesis_kalden.pdf).

[26] S. Almeida and J. Queijo, *Spatial and Temporal Traffic Distributions Models for GSM (in Portuguese)*, Diploma Thesis, Instituto Superior Tecnico, Technical University of Lisbon, Lisbon, Portugal, 1998 (http://grow.inov.pt/wp-content/uploads/2014/01/SandraJose_Lic_1998.pdf).

[27] D. Silva, *Energy efficient solutions in GSM/UMTS based on traffic profiling models*, M.Sc. Thesis, Instituto Superior Tecnico, Technical University of Lisbon, Lisbon, Portugal, 2012 (http://grow.inov.pt/wp-content/uploads/2014/01/DiogoSilva_MSc_2012final.pdf).

[28] H. Motulsky and A. Christopoulos, *Fitting Models to Biological Data Using Linear and Nonlinear Regression: A Practical Guide to Curve Fitting*, Oxford University Press, Oxford, UK, 2004.

[29] L. Guan, X. Zhang, Z. Liu, Y. Huang, R. Lan, and W. Wang, "Spatial modeling and analysis of traffic distribution based on real data from current mobile cellular networks", in *Proc. of ICCP'13 - 2013 IEEE International Conference on Computational Problem-Solving*, Jiuzhai, China, Oct. 2013 (http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6893524).

[30] S. Park and J. Kim, "Effect of LTE service adoption on mobile data traffic in Korea", in *Proc. of ICCCT'12 - 7th IEEE International Conference on Computing and Convergence Technology*, Seoul, South Korea, Dec. 2012 (http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6530518).

[31] H. Khedher, F. Valois, and S. Tabbane, "Traffic characterisation for mobile networks", in *Proc. of VTC'02-Fall - 56th IEEE Vehicular Technology Conference*, Vancouver, Canada, Sep. 2002 (http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=1040463).

[32] EARTH, *Energy efficiency analysis of the reference systems, areas of improvements and target breakdown*, INFSO-ICT-247733 EARTH, Deliverable D2.3, EARTH, Jan. 2012 (https://www.ict-earth.eu/publications/deliverables/deliverables.html).

[33] G. Micallef, "Methods for Reducing the Energy Consumption of Mobile Broadband Networks", *Telektronikk*, No. 1, 2010, pp. 121–128.

[34] Z. Zhu, G. Cao, R. Keralapura, and A. Nucci, "Characterising Data Services in a 3G Network: Usage, Mobility and Access Issues", in *Proc. of ICC'11 - 2011 IEEE International Conference on Communications*, Kyoto, Japan, Jun. 2011 (http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5962985).

[35] UMTS Forum, *Mobile traffic forecasts 2010-2020 report*, UMTS Forum Report 44, UMTS Forum, London, UK, Jan. 2011 (http://www.umts-forum.org/component/option,com_docman/task,cat_view/gid,485/Itemid,213/).

[36] Q. Xu, J. Erman, A. Gerber, Z. Mao, J. Pang, and S. Venkataraman, "Identifying Diverse Usage Behaviors of Smartphone Apps", in *Proc. of IMC'11 - 2011 ACM/SIGCOMM Internet Measurement Conference*, Berlin, Germany, Nov. 2011

(https://web.eecs.umich.edu/~zmao/Papers/imc11_xu.pdf).

[37] M. Boulmalf, J. Abrache, T. Aouam, and H. Harroud, "Traffic analysis for GSM networks", in *Proc. of AICCSA'09 - 2009 IEEE/ACS International Conference on Computer Systems and Applications*, Rabat, Morocco, May 2009 (http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5069370).

[38] Vodafone Portugal, Vodafone Hotspot 4G, https://loja.vodafone.pt/tablets-pens-hotspots/vodafone/hotspot-4g-r216-cartao-gratuito-branco, Mar. 2017.

[39] Vodafone Portugal, Vodafone Pen 4G, https://loja.vodafone.pt/tablets-pens-hotspots/vodafone/pen-4g-k5160-cartao-gratuito-branco, Mar. 2017.

[40] Vodafone Portugal, Vodafone Router 4G, https://negocios.vodafone.pt/loja/tablets-pens-hotspots/vodafone/router-4g-b4000-branco, Mar. 2017.

[41] D.C. Montgomery and G.C. Runger, *Applied Statistics and Probability for Engineers, 6th Edition*, John Wiley & Sons, Inc., Hoboken, NJ, USA, 2014.

[42] S. McKillup, *Statistics Explained: An Introductory Guide for Life Scientists, 2nd Edition*, Cambridge University Press, Cambridge, UK, 2011.

[43] MathWorks, Lilliefors test, https://www.mathworks.com/help/stats/lillietest.html, MATLAB R2016a Documentation, Apr. 2016.

[44] J. Sá, *Applied Statistics Using SPSS, STATISTICA, MATLAB and R*, Springer Berlin Heidelberg, Berlin, Germany, 2007.

[45] M. Lovric, *International Encyclopedia of Statistical Science*, Springer Berlin Heidelberg, Berlin, Heidelberg, 2011.

[46] MathWorks, Evaluating Goodness of Fit, https://www.mathworks.com/help/curvefit/evaluating-goodness-of-fit.html, MATLAB R2016a Documentation, Apr. 2016.

[47] S.M. Ross, *Introduction to probability and statistics for engineers and scientists, 4th Edition*, Elsevier/Academic Press, Burlington, MA, USA, 2009.

[48] M.C. Morais, *Probability and Statistics*, Lecture Notes, Instituto Superior Tecnico, Technical University of Lisbon, Lisbon, Portugal, 2010.

[49] M. Holický, *Introduction to Probability and Statistics for Engineers*, Springer Berlin Heidelberg, Berlin, Germany, 2013.

[50] MathWorks, Interp1, https://www.mathworks.com/help/matlab/ref/interp1.html, MATLAB R2016a Documentation, Apr. 2016.

[51] MathWorks, Fit, https://www.mathworks.com/help/curvefit/fit.html, MATLAB R2016a Documentation, Apr. 2016.