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Teletraffic Models for Mobile Network Connectivity

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Abstract

We are in an era marked by tremendous global growth in mobile traffic and subscribers due to change in the mobile communication technology from second generation to third and fourth generations. Especially usage of packet-data applications has recorded remarkable growth. The need for mobile communication networks capable of providing an ever increasing spectrum of services calls for efficient techniques for the analysis, monitoring and design of networks. To meet the ever increasing demands of the user and to ensure on reliability and affordability, system models that can capture the characteristics of actual network load and yield acceptable precise predictions of performance in a reasonable amount of time must be developed. This can be achieved using teletraffic models as they capture the behaviour of system through interpret-able functions and parameters. Past years have seen extremely numerous teletraffic models for different purposes. Nevertheless there is no model that provides a proper frame work to analyse the mobile networks. This report attempts to provide a frame work to analyse the mobile traffic and based on the analysis we design teletraffic models that represent the realistic mobile networks and calculate the buffer under-flow probability.

Keywords: Buffer under flow probability, Delay, Maximum likelihood estimation, ON-OFF phase.

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Acronyms

ASRP Alternating State Renewal Process

BTH Blekinge Tekniska Högskola

CCDF Complimentary Cumulative Distribution Function

CPU Central Processing Unit

DES Discrete Event Simulation

EMC Embedded Markov Chain

EoF End of File

GPS Global Positioning System

IAT Inter Arrival Time

IID Independent and Identical Distribution

IP Internet Protocol

IPD Inter Packet Duration

IPP Interrupted Poisson Process

MC Markov Chain

MMFM Markov Modulated Fluid Models

MMPP Markov Modulated Poisson Process

MMRP Markov Modulated Rate Process

MLE Maximum-Likelihood Estimation

MOS Mean Opinion Score

QoD Quality of Delivery

QoE Quality of Experience

QoS Quality of Service

STDEV Standard Deviation

TCP Transfer Control Protocol

UDP User Datagram Protocol

Chapter 1

Introduction

The rapid adoption of cell phones and, especially the spread of internet-connected smart phones are changing people's communications with others and their relationships with information. User's ability to access data immediately through applications and web browsers is creating a new culture of real-time information seekers and problem solvers. Recently the number of mobile users equipped with wireless devices capable of video streaming on the go has increased immensely. The trend follows the ever expanding choice of multi-access wireless technologies to which they connect and the growing popularity of mobile video applications. Increasingly more users use mobile devices to watch videos streamed over mobile wireless networks and they demand more content at better quality. Delivering digital video content with enhanced Quality of Experience QoE to the end user over wireless networks has become a challenging issue for mobile service providers. It is important to know whether the user is satisfied with mobile streaming service and there is a need to assess the QoE. QoE depends on Quality of Delivery QoD of packets, i.e., QoE links user reactions to delivery problems [1].

The performance of these networks is highly varying due to their availability and coverage issues. Network problems will have immediate impact on the videos and interactive applications. Particularly outages in network i.e. temporary disruptions and competition for resources lead to gaps in the network, which causes different network based problems such as freezes, packet loss, longer download times, timeouts, delay etc. can impair the perceived video quality in transmission over wireless network. Reference [2] presents the characteristics of mobile wireless networks and extends these characteristics to the requirements of video transmission. The method used in this can be efficiently used for evaluation of video sequences in both congested and error prone environments. Apart from this they have established guidelines for the transmission of video based on the limits of mobile and wireless networks.

To address network based problems, measurements, analysis and modeling of mobile traffic has become an important issue and the increase in usage of mobile devices for streaming services made it a key research area. Accurate teletraffic models play a crucial role in mobile network planning and design. Teletraffic models are mathematical representation of telecommunication systems, which capture the behavior of system through functions and parameters. In particular, ON-OFF models capture the essential phases of user communication.

Reference [3] presents a passive monitoring and analysis method devised to assist in the identification of traffic gaps that may result in degradation of QoE. Analytical model proposed in paper [4] provides a simple, general, unified and versatile frame work for the teletraffic analysis of mobile cellular networks.

In papers [5–8], the teletraffic models for different purposes such as estimation and characterization of the expected teletraffic, performance evaluation of mobile wireless communication networks, simple mobile traffic model and indoor network traffic analysis were presented. Modeling of real traffic considering network outages should be taken into account. Current research on mobile networks emphasizes on designing generalized teletraffic models. Our research focuses especially on video streaming in mobile networks, as the consequences of network problems are immediately shown as buffering and freezes leading to uninteresting sessions. In [1], a simple ON-OFF model is proposed for buffer over-or underflow probability using Gilbert-Elliott model for mobile streaming. Our work is extension of reference [1] in which we are going to design teletraffic models that are approximation of realistic mobile connections. Analysis of network using these models can help to improve the performance of mobile networks.

1.1 Motivation

Today we are in an era marked by tremendous global growth in mobile traffic and subscribers. Infonetics Research forecasts that mobile data subscribers will grow to 1.8 billion in 2014. Mobile broadband networks must support multiple applications of voice, video and data on a single IP-based infrastructure. Rapid evolution of mobile networks from second generation to third and fourth generations made packet data applications such as live streaming and interactive applications (like video conferencing) available even at remote places. Streaming media is multimedia that is constantly received by and presented to an end user while being delivered by a provider. Impact of network performance is clearly shown on live streaming, as any sort of disturbance is shown in the form of freeze. Freezes for certain time are bearable but when it is for typically longer time it results in an uninteresting and boring session. This lead to interest in analysing network performance and we focus on longer time delays as they are responsible for uninteresting sessions.

1.2 Research Questions

The following research questions are formed based on the motivation described.

1 How is a teletraffic model (for mobile networks) designed based on the traffic characteristics of real mobile networks?

2 How is parameter estimation done?

3 How can mobile network performance and QoE be analysed and potentially improved using teletraffic models for mobile networks?

1.3 Research Methodology

Our research follows on empirical path. The intention is to present teletraffic models for mobile network connectivity. For that purpose we analyzed the performance of non-existing network through mathematical analysis. The way we carried out our research is as follows:

1 Collection of mobile network traces under controlled environment.

2 Analysis of traces: Before analysing the traces it is essential to know the nature of data. Calculation of inter packet duration helps to know which type of data it is i.e. either smooth or disturbed. We analyse disturbed data to find the network problems.

3 ON-OFF behaviour: Gaps for greater than one second are considered as OFF times. Capturing the ON-OFF behaviour of data packets accurately.

4 Matching: visualizing ON-OFF phases graphically using CCDF and matching with different curves such as exponential, linear, logarithmic, power series and polynomial. The extent to which the matching takes place is measured by correlation.

5 Parameter estimation: Estimating the values of expected ON time and expected OFF time using Maximum Likelihood Estimation.

6 Finally modeling the buffer under-flow probability using estimated values.

1.4 Organization Of Thesis

Introduction to thesis work is described in chapter 1. In chapter 2, related work for our thesis work and extraction of mobile network traces are described. Chapter 3 describes the experimentation part and analysis. Results are presented in chapter 4. The conclusion part and future work are presented in chapter 5 and chapter 6 respectively.

Chapter 2

Background

2.1 Need for teletraffic models

Due to ever-increasing user demands, the design of robust and reliable mobile network services is becoming highly difficult in today's world. The only way to achieve this is to optimize the networks function in an effort to maximize capacity, minimize latency and offer high reliability regardless of bandwidth available and occurrence of failures. Network performance management consists of tasks like measuring, modeling, planning and optimizing networks to ensure that they carry traffic with the speed, capacity and reliability that is expected by the applications using the network or required in a particular scenario.
Networks are categorized into different types and based on several factors. However, the factors that affect the performance of the different networks are more or less the same. These involve parameters like latency, packet loss and throughput. In order to design high performance networks or guarantee performance of any type of network detailed analysis of the above factors is a crucial step. Often the foremost step in such an analysis is the study of the traffic on the network. As a consequence the type of traffic model used to understand the flow of traffic in the network, and how closely the model depicts the real-time characteristics of the network, become vital parameters. If the underlying traffic models does not efficiently capture the characteristics of the actual traffic, the result may be an under-estimation or over-estimation of the performance of the network. This would totally impair the design of the network. Traffic models are hence a core component of any the performance evaluation of networks and they need to be very accurate. Depending upon the type of network and the characteristics of the traffic on the network, a traffic model can be chosen for modeling the traffic.

2.2 Quality of service (QoS)

The term Quality of Service, in the field of networking, refers to control procedures that can provide a guaranteed level of performance to data flows in accordance to requests from an application user using the network. There are several factors that might affect such QoS guarantees. Hence, to design a network to support QoS is not an easy task. The primary step is to once again have a clear understanding of the traffic in the network. Without a clear understanding of the traffic and the applications that might be using the network, QoS guarantees cannot be provided. Therefore, modeling of traffic becomes a crucial and necessary step in accessing QoS.

2.3 Related Work

Today we are in an era marked by tremendous global growth in mobile traffic and subscribers. Recent survey of CISCO shows that mobile data traffic in 2012 was nearly 12 times the amount of entire global internet traffic in 2000 and the mobile video traffic constitutes 51% of the entire mobile traffic [9]. If this traffic goes on increasing, network based problems such as delay, packet loss, time-outs etc may occur. The user gets distracted for the longer delay times, there are some researches which indicate that longer delays lead to consumer frustration and a negative attitude toward the product or service displayed [10–12]. The ability to transmit video and support real-time multimedia applications is considered important in mobile networks [12]. Much literature work has been done to determine accurate jitter models for longer delays [13]. In order to provide service with high capacity and good quality performance analysis of mobile networks comes into account.

Reference [3] presents a passive monitoring and analysis method devised to assist in the identification of traffic gaps that may result in degradation of QoE. To address network based problems, measurements, analysis and modeling of mobile traffic has become an important issue and the increase in usage of mobile devices for streaming services made it a key research area. Accurate teletraffic models play a crucial role in mobile network planning and design [14]. Teletraffic models are mathematical representation of telecommunication systems, which capture the behavior of system through functions and parameters. There exist many researches on teletraffic models [15].

The fluid flow model is considered as a key model capturing important factors for performance evaluation in a network [16]. An approach of presenting teletraffic models for mobile network connectivity is provided. An experimental test bed is developed to collect the mobile traffic traces from the network for which the modeling is done. The teletraffic modeling plays an important role in network design and analysis. Reference [17] addresses the combination of mobility and teletraffic models based on next event time advance approach.

In particular, ON-OFF models capture the essential phases of user communication with web servers. In paper [18], the author illustrated the user web session characterization with an ON-OFF model. The experiment was carried in two different places in Sweden and Germany on Wi-Fi networks. Due to the inactivity of the user and the behavior of the application there forms gaps in the traffic which leads to ON-OFF models. The OFF phase in the network reflects the gaps. These gaps in the network lead to the deterioration of QoE. There is no packet seen in the network link level during the OFF time. There are many researches on ON-OFF times modelling [19]. Analyzing the ON-OFF models we can estimate the parameters and find the behavior of distribution by using Maximum likelihood estimation and can check the fitness [1].Author says that, for a live mobile video streaming in a moving car to avoid these tail behaviors that indicate long off times we need to model a buffer over or underflow probability [1].

In paper [20], the authors have described about analysis and modeling of computer network traffic. They have performed the heavy tail modeling for the network traffic traces. They have proposed behavioural and structural models for heavy tails and long range dependence of network traffic. The behavioural models tend to mimic the trend seen in measured data without considering the network traffic nature. The structural behavioral models tend to explain the data seen by the knowledge of the traffic. We can extract large amount of information from traces used for designing structural models.

In paper [13], traffic shaping is applied at the edge of the networks. By making traffic patterns more useful, the leaky bucket algorithm aims at improving of the utilization of the network. The author states that the feedback from the network controls the shaper which is modeled as a buffer with variable capacity.

In [21, 22], the author introduced the fluid flow models, buffer modeling, coefficient of buffer and over-flow probability of buffer threshold which are important for teletraffic modeling. The buffer modeling is defined as a bucket with hole showing the outgoing link led by one or more packets. The fluid flow modeling approach is the tool to study the sensitivity of the loss probabilities and the effects for buffer dimensioning.

In [23], the author investigated the possibility for modeling of Ethernet traffic, which is used for fluid flow analysis and in scaling the behavior of traffic. The author considered there the usage of Markov Modulated Poisson

Process (MMPP) for traffic modeling and Markov Modulated Rate Process (MMRP) for analysis. The bit-rate estimation and fitness assessment for modeling are also explained.

A detailed background study from the above references was done in our thesis and we found gap in this area in context of live video streaming in mobile networks and to model the buffer under flow probability. We develop a frame-work to analyze the mobile networks. For this purpose, we first analyze the network traces for longer time delays, capture ON-OFF phases and estimate the parameters using maximum likelihood estimation. Using the estimated parameters we design a set of teletraffic models.

2.4 Teletraffic Models

Analysis of the traffic provides information like the average load, the bandwidth requirements for different applications, and numerous other details. Traffic models enable network designers to make assumptions about the networks being designed based on past experience and also enables to predict the performance for future requirements. Traffic models are used in two fundamental ways:

- As part of an analytical model or
- To drive a Discrete Event Simulation (DES).

Simple traffic comprises of single arrivals of discrete entities, viz., packets. This kind of traffic can be expressed mathematically as a Point Process. Point Process: A point process consists of a sequence of arrival instants $T_1, T_2, T_3 ... T_n$ (by convention, $T_0 = 0$). Point processes can be described as a Counting Process or Inter-Arrival Time (IAT) Process.

Counting process: A counting process $N(t)$ is a continuous time, non-negative, integer-valued stochastic process, where

$$N(t) = \ max \{n : T_n \leq t\}$$

denotes the number of arrivals in the time interval (0, t] [24].

Inter-arrival process: An inter-arrival process is a non-negative random sequence $\{A_n\}$, where

$$A_n = T_n - T_{n-1}$$

is the length of the time interval separating the n^{th} arrival from the previous one [24].

Discrete-time traffic: Discrete-time traffic processes are characterized by slotted time intervals. In other words, the random variable A_n can assume only integer values.

2.4.1 Pareto Distribution Process

The Pareto distribution process produces independent and identically distributed (IID) inter-arrival times [25]. In general if X is a random variable with a Pareto distribution, then the probability that X is greater than some number x is given by

$$P\left(X > x\right) = \left(\frac{x}{x_m}\right)^{-k} \text{Forall } x \geq x_m$$

Where k is a positive parameter and x_m is the minimum possible value of X_i

The probability distribution and the density functions are represented as:

$$F\left(t\right) = 1 - \left(\frac{\alpha}{t}\right)^{\beta}$$

where $\alpha, \beta \geq 0$ and $t \geq \alpha$

$$f\left(t\right) = \beta\alpha^{\beta}t^{-\beta-1}$$

The parameters β and α are the shape and location parameters, respectively. The Pareto distribution is applied to model self-similar arrival in packet traffic. It is also referred to as double exponential, power law distribution. Other important characteristics of the model are that the Pareto distribution has infinite variance, when $\beta \geq 2$ and achieves infinite mean, when $\beta \leq 1$.

2.4.2 Poisson Distribution Model

One of the most widely used and oldest traffic models is the Poisson Model. The memory-less Poisson distribution is the predominant model used for analyzing traffic in traditional telephony networks [24]. The Poisson process is characterized as a renewal process. In a Poisson process the inter-arrival times are exponentially distributed with a rate parameter λ:

$$P\left\{A_n \leq t\right\} = 1 - e^{-\lambda t}$$

The Poisson distribution is appropriate if the arrivals are from a large number of independent sources, referred to as Poisson sources. The distribution has a mean and variance equal to the parameter λ. The Poisson distribution can be visualized as a limiting form of the binomial distribution, and is also used widely in queuing models. Poisson processes are common in traffic applications scenarios that comprise of a large number of independent traffic streams. The reason behind the usage stems from Palm's Theorem which states that under suitable conditions, such large number of independent multiplexed streams approach a Poisson process as the number of processes grows, but the individual rates decrease in order to keep the aggregate rate constant. Nevertheless, it is to be noted that traffic aggregation need not always result in a Poisson process. The two primary assumptions that the Poisson model makes are:

- Infinite number of sources.
- Traffic arrival pattern is random.

The probability distribution function and density function of the model are given as:

$$F\left(t\right) = 1 - e^{-\lambda t}$$

$$f\left(t\right) = \lambda e^{-\lambda t}$$

2.4.3 Weibull Distribution Process

The Weibull distributed process is heavy-tailed and can model the fixed rate in ON period and ON/OFF period lengths, when producing self-similar traffic by multiplexing ON/OFF sources. The distribution function in this case is given by:

$$F\left\{t\right\} = 1 - e^{-\left(\frac{t}{\beta}\right)^{\alpha}} t > 0$$

and the density function of the weibull distribution is given as:

$$f\left(t\right) = \alpha\beta^{-\alpha}t^{\alpha-1}e^{-\left(\frac{t}{\beta}\right)^{\alpha}} t > 0$$

where parameters $\beta \geq 0$ and $\alpha > 0$ are the scale and location parameters respectively.
The Weibull distribution is close to a normal distribution. For $\beta \leq 1$ the density function of the distribution is L shaped and for values of $\beta > 1$, it is bell shaped [24]. This distribution gives a failure rate increasing with time. For $\beta > 1$, the failure rate decreases with time. At, $\beta = 1$, the failure rate is constant and the lifetimes are exponentially distributed.

2.4.4 Markov and Embedded Markov Models:

Markov models attempt to model the activities of a traffic source on a network, by a finite number of states. The accuracy of the model increases linearly with the number of states used in the model. However, the complexity of the model also increases proportionally with increasing number of states. An important aspect of the Markov model is that the probability of the next state depends only on the current state. Assuming a sequence of independent and identically distributed input signals, if the machine is in state X_n at time n, then the probability that it moves to X_{n+1} at time $n+1$ depends only on current state i.e., X_n.
The set of random variables referring to different states $\{X_n\}$ is referred to as a Discrete Markov Chain. If the state transitions of the system under study happen only at integral values $0, 1, 2, 3...n$, then the Markov chain (MC) is discrete time and the random variable X follows a geometric distribution; otherwise, it is continuous time, with the random variable taking an exponential distribution. In a simple Markov Traffic model, each of the state transition represents a new arrival process on the network. For modeling a continuous time system, the inter-arrival times are assumed to be exponentially distributed.

ON-OFF model:

The design and development of an ON-OFF model relies on an accurate description of traffic entities from link level to application level. The model is generally used, when it is necessary to capture the scaling behaviors of network traffic. For instance, analysis of the structure of IP traffic is performed predominantly using ON-OFF models. The ON-OFF model uses only two states, namely ON and OFF. The time spent between the ON and OFF states, commonly referred to as the transition time, is typically expected to follow an exponential distribution [24]. The subsequent queuing analysis of multiplexed ON-OFF sources would detail the development of the model.

The Interrupted Poisson Process (IPP):

IPP is yet another two state process. The network channel is one of the two states, ON or OFF. In a discrete time IPP or Interrupted Bernoulli Process, a packet arrives in each of the time slots of the ON state, following a Bernoulli distribution. Though the IPP model is similar to the ON-OFF model, there is a slight variation that differentiates the two models. The difference is that in case of the IPP model, there is no traffic or in other words, no packets arrive during the OFF state.

Alternating State Renewal Process (ASRP):

Conventional Markov models, though mathematically tractable, may fail to fit actual traffic of high speed networks. In high-speed networks the packets are transmitted in a packet train fashion; once such a packet train is triggered, the probability that another packet will follow is very large. Further, the length of the packets exhibits a heavy-tail distribution. This observation led to the well-known ASRP [26]. ASRP is another two-state process used to model network traffic. Though there are only two states, $S1$ and $S2$, similar to the previous two-state models discussed, there is no self-transition in this model. The amplitude of the traffic in state $S1$ is 0 and 1 in the state $S2$. The mean time taken for transition between the two states is denoted by t_1 and t_2 respectively. The ASRP model can be visualized as an Embedded Markov Chain (EMC) varying between the two states of the model. The probabilities for being in the individual states can be calculated using the simple formula,

$$P_{S1} = \frac{t_1}{(t_1 + t_2)}$$

and

$$P_{S2} = \frac{t_2}{(t_1 + t_2)}$$

Markov Modulated Fluid Models (MMFM):

Fluid flow models are conceptually simple. For instance, event simulation for an ATM multiplexer has several advantages, when fluid flow models are used for the simulation. Models other than the fluid flow models, which distinguish between the cells and consider the arrival of each cell as a separate event, typically consume huge amounts of memory and CPU time for the simulation. On the contrary, a fluid flow model that characterizes the incoming cells by a finite flow rate, require comparatively less resources [25]. This is because in a fluid flow model, an event is generated only when the flow rate changes; and changes in flow rates are less frequent compared to the arrivals of cells. A fluid flow model as a consequence, utilizes lesser computing power and memory resources, compared to simulation using other models.

The basic feature of a fluid model is to characterize the traffic on a network as a continuous stream of input with a finite flow/stream rate. In other words, the incoming traffic rate is represented as a stream with a finite rate. By capturing the rate changes at the input, the models analyze the different events that occur in the network. Due to simple method of characterization of traffic, the fluid modes are analytically tractable and easier to simulate. Like any other Markov modulated process the MMFM, uses an underlying

MC that determines the rate of the sources. At any instant, the current state of the underlying MC determines the flow rate of the inputs.

2.5 Mobile Network Traces

The authors in paper [27] opted passive traffic measurement and analysis scheme to make the experiment cost effective and to observe all network phenomena. They generated the traces we have worked on using a special experimental set-up in a controlled environment. In this set up TCP and UDP packets are generated by modifying the existing TCP and UDP generators to facilitate random pay-load sizes and random IPD governed by distribution. This generated traffic is transmitted to the receiver via Gateway vololink VA126, a wireless link connected to the sender. A special wiring scheme is used to ensure that the packets are time stamped by the same clock. These packets are transmitted along RAN or BTH network using GW or 10 Mbps Ethernet and then through mobile operators core network or Swedish university network and again through BTH or RAN to the receiver. Measuring points are equipped with Endace network monitoring DAG 3.5E cards, synchronized with GPS via an Endace TDS 2 yielding time stamp accuracy of 60 ns in DAG cards. Link level packet traces collected by measuring points are stored locally in binary format of capture files (.cap). These cap files are not human readable. To make them so they are converted into text files using software that uses libcap library utilities for conversion. We used these text files for our thesis.

Chapter 3

Experimentation And Analysis

3.1 Analysis of Traces

A well designed and optimally performing network is required to maintain user satisfaction. Network performance is evaluated through measurements and analysis. Analysis of traces plays a crucial role in understanding and analyzing the network behavior. But to perform any functionality or calculations, basically the trace files should be user friendly and easily understandable. To make them so, initially we imported raw text files into excel sheet using colon as delimiter. This trace file constitutes sender and receiver time stamp values, sequence numbers and IP addresses. To analyze the network behavior, we concentrate on the traces at receiver side as sender has nothing to do with network problems.
For this purpose receiver values are filtered and saved to another sheet for further use. One thing to be considered is all the receiver time stamp values are in POSIX standard and hence there will not arise any confusion while calculating and comparing results. For accurate results sequence numbers in the file should follow particular order, any abnormal values (i.e., the values which break the sequence or the values from unknown sender) occurring in between them are filtered using IP address. Now except receiver time stamps all the other columns are deleted as they are no way required. Last step to make sure whether the trace file is required or not is to find inter packet difference (IPD) and to check if the values are greater than one second.

Inter-Arrival Time (IAT) and Inter Packet Duration (IPD)

IPD is the length of time interval separating the nth arrival from the previous one. It helps to identify the gaps in the traffic. Analysis of IPD helps to differentiate between smooth and disturbed traffic flow. So we have concentrated on this step to observe if there are any disturbances in the network. If T_{R_n}, $T_{R_{n+1}}$ represents receiver time stamps of n^{th} and $(n+1)^{th}$ arrival, then IPD is given by

$$IPD = T_{R_{n+1}} - T_{R_n}$$

Files with IPD values greater than one second are retained and remaining files are discarded.This is because we have decided to focus on considering delay of atleast one second as off time. To make it simple, instead of doing it manually we developed a Perl program to perform both the tasks i.e. to calculate IPD and to check if there are IPD values greater than one second. Flow chart for the Perl program is shown below in the Figure 3.1.1. This program takes trace files in the (.txt) as input and checks if the End of File (EoF) flag is set. If the condition fails, it calculates IPD of successive arrivals and stores the result into an array. It is an iterative loop, the loop runs until the condition fails (i.e., as long as EoF doesn't apply). Once it is EoF the control directly goes to check the condition if at least one value of IPD (i.e., at least one value in the array) is greater than one second. If the condition fails the program exits there itself, else the entire array is saved into a new file.

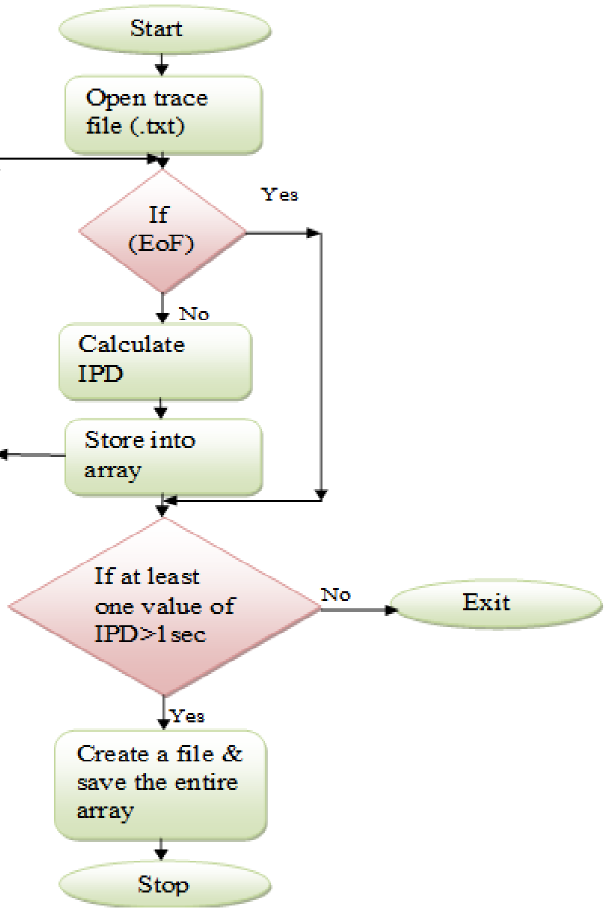

Figure 3.1.1: Flow chart of the perl program to calculate IPD and to retain required trace files.

After separating required trace files from the bunch of files, analysis is carried out in different ways searching in each and every direction.

As IPD helps only to identify the gaps i.e., OFF phases in the traffic, analysis of it is not sufficient provide information for questions like, when does the reception of packets at the receiver (ON time) begins? How long it stays? When the state transition takes place from ON to OFF and vice versa? etc. Comparatively time scaling phenomenon gives a better shape to all these questions.

3.2 Multiple time scaling:

Multiple time scaling helps to monitor number of packets arriving at the receiver per unit time in different time scales. ON-OFF models are necessary to capture the scaling behaviors of network traffic. There by, scaling visualizes the ON and OFF phases easily and provides a broad view of traffic flow. The smaller the time unit, the larger is the possibility to capture the ON and OFF times accurately. We have scaled packets for three time units 1 sec, 0.1 sec and 0.01 sec, of them 0.01 sec gives broad view of traffic flow. It gives the packets received in each unit time and number of packets received for unit time (i.e. if it is for 1 second scale, unit time equals to one sec) is obtained using COUNTIF function.

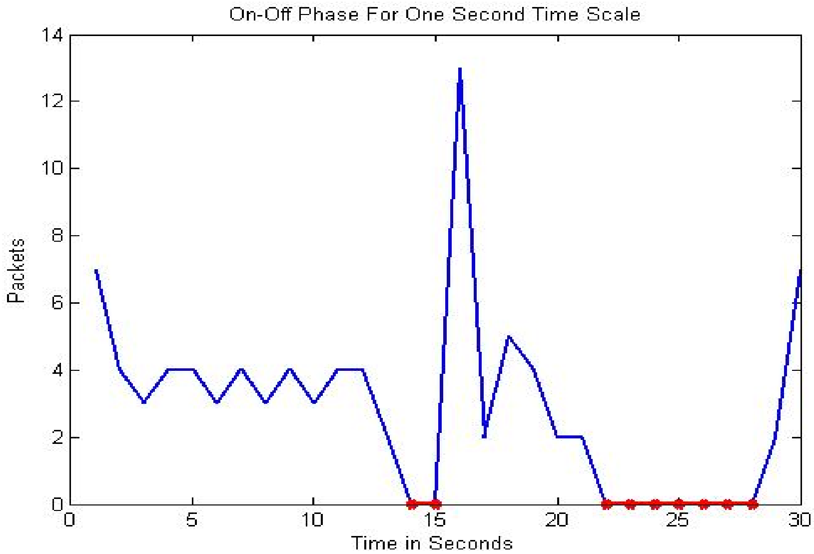

Figure 3.2.1: ON-OFF phase for one second time scale, where red represents OFF phase

Figure 3.2.1 shows the number of packets arrived in each time interval. Apart from this it also visualizes the gaps in red color on the desired unit scale. As only longer time delays are of our interest, we considered the gaps which are greater than one second only. Gaps which are red in color in the above figure were considered as OFF phases.

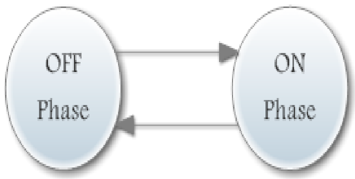

Figure 3.2.2: Illustration of ON-OFF phase

Based on the existence of packets and gaps in unit time, we have classified the time intervals into ON and OFF phases respectively. During the ON time packet flow takes place but it is completely opposite in case of OFF time i.e. no packet is seen in the network link level during OFF time. We calculated the period for which ON time and OFF time stays and tabulated the values for each trace file separately. These values of OFF phase and ON phase are visualized as CCDF graphs.

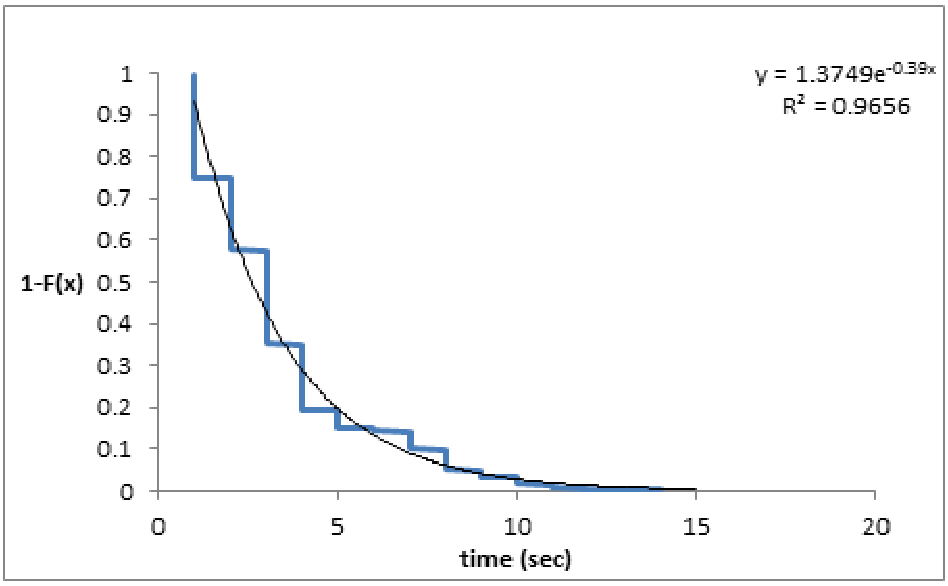

Figure 3.2.3: CCDF graph for OFF time using scaled time intervals

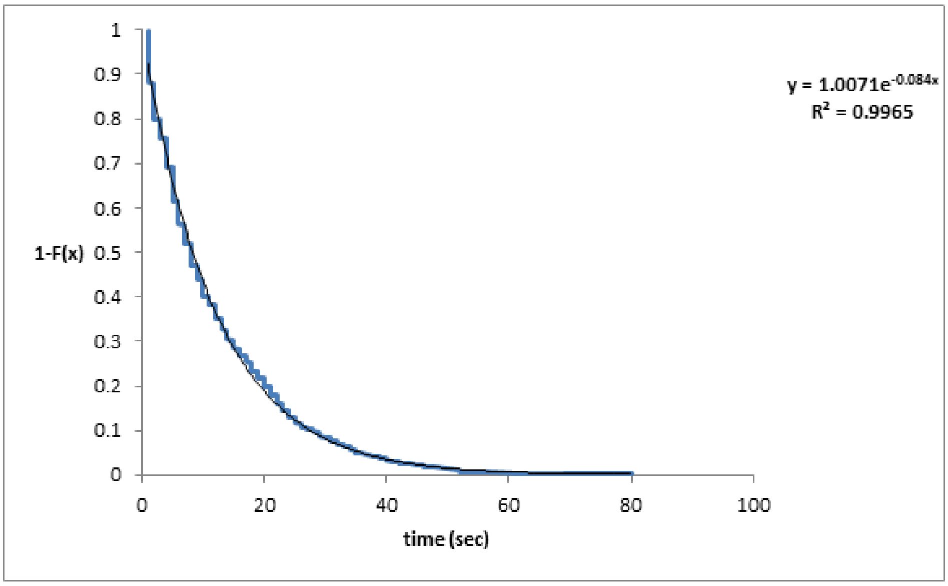

Figure 3.2.4: CCDF for ON time using scaled time intervals

Figures 3.2.3, 3.2.4 represent CCDF graphs for OFF and ON times which are plotted using scaled time intervals. Observations shows that the CCDF graphs obtained exhibit granularity effects. To avoid granularity effects, time intervals ON-OFF times are calculated using receiver time stamps instead of scaled time intervals. This is because when scaling is done each time unit has uniform length and when ON-OFF times are calculated, the time periods we get will be multiples of those units but not the actual length. Using time stamps even fraction of seconds is captured, which gives accurate results and avoids granularity.

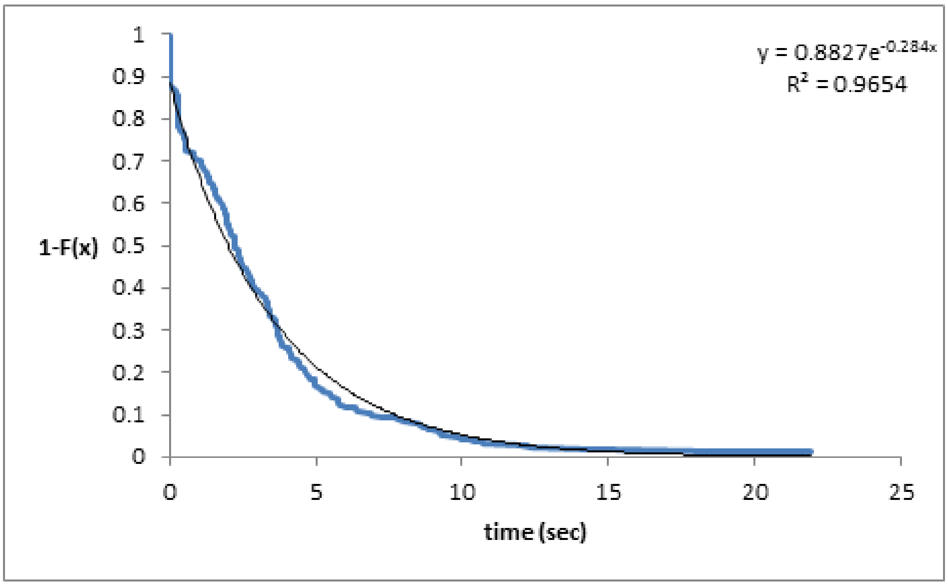

Figure 3.2.5: CCDF for ON time using receiver time stamps.

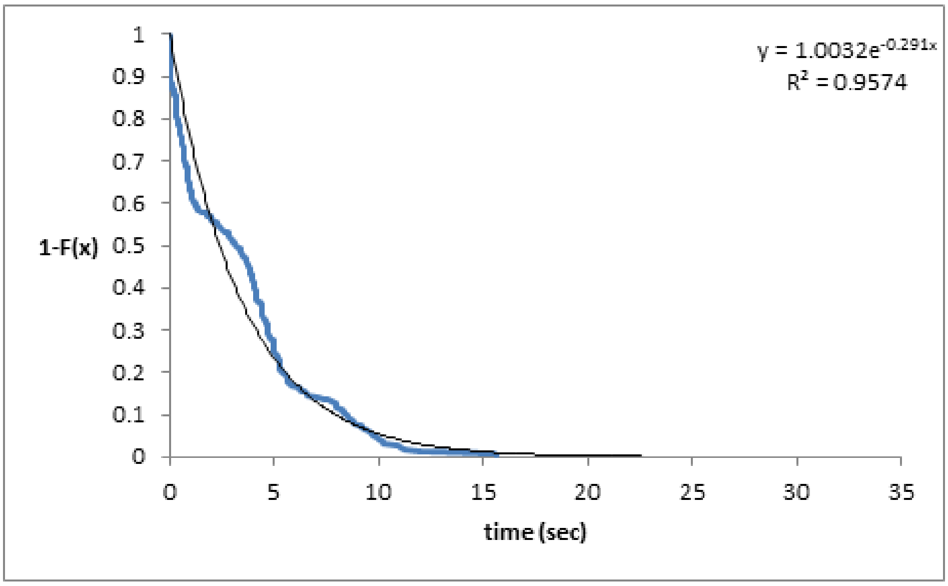

Figure 3.2.6: CCDF for OFF time using receiver time stamps.

Figures 3.2.5 and 3.2.6 represent the CCDF graphs for ON-OFF times calculated using receiver time stamps. Comparing Figures 3.2.4 and 3.2.3 with Figure 3.2.5 and 3.2.6 we can clearly see that there is lot of difference between these two sets of graphs though they they represent the same trace file. Figures 3.2.3 and 3.2.4 are exhibiting granularity, while in Figures 3.2.5 and 3.2.6 granularity is avoided .

3.3 Matching with curves:

Obtained CCDF graphs are matched with different curves such as exponential, linear, logarithmic, polynomial and power to check for the curve it fits the most. All the CCDF curves matched with exponential the most, with an R^2 value greater than 0.90 for both ON and OFF phases respectively. R^2 value represents the extent to which the CCDF curve fits with the matched curve. The closer the value of R^2 to one, the higher is the ability of the values to match with the curve. R^2 values and the equations of the curves are tabulated and shown in the third and fifth columns of Table 3.3.1.

File	State	R^2 Value	Correlation	Equation
3275-2757-121	ON	0.95	0.98	$Y = 0.6925e^{-0.272x}$
3275-2757-121	OFF	0.99	0.99	$Y = 1.5802e^{-0.526x}$
3250-3008-121	ON	0.95	0.97	$Y = 0.6946e^{-0.496x}$
3250-3008-121	OFF	0.97	0.98	$Y = 1.1928e^{-0.307x}$
3250-3007-121	ON	0.96	0.98	$Y = 0.7209e^{-0.395x}$
3250-3007-121	OFF	0.98	0.99	$Y = 1.3586e^{-0.385x}$
350-507-121	ON	0.87	0.94	$Y = 0.689e^{-0.583x}$
350-507-121	OFF	0.98	0.99	$Y = 0.892e^{-0.179x}$
3275-2758-121	ON	0.95	0.99	$Y = 0.8615e^{-0.274x}$
3275-2758-121	OFF	0.96	0.98	$Y = 1.0032e^{-0.291x}$
3500-5007-121	ON	0.96	0.99	$Y = 0.747e^{-0.099x}$
3500-5007-121	OFF	0.98	0.99	$Y = 1.3924e^{-0.275x}$
3500-5002-121	ON	0.96	0.96	$Y = 0.8067e^{-0.002x}$
3500-5002-121	OFF	0.76	0.88	$Y = 7.5638e^{-1.935x}$

Table 3.3.1: Table showing correlation values and equations of the curves.

Observation show that the equations of curves in fifth column of the table are in the same form. General equation representing the curves in the table 3.3.1 is

$$Y = ae^{-bx}$$

In all the equations pre-factor value a is either greater than or less than one. For a complementary distribution, the a value should be one. Depending on the value of a it is classified into two cases:

1. Damped case $(a < 1)$**:**
If $a < 1$, we assume a delta peak of height $(1 - a)$ at $x = 0$, i.e. there is a chance of $(1 - a)$ that the corresponding on or off period has a length of zero. The corresponding density is thus

$$f(x) = (1 - a)\,\delta(x) + abe^{-bx}$$

where $\delta(x)$ denotes the Dirac pulse

2. Shifted case $(a > 1)$**:**
If $a > 1$, then one needs to maximize the value of the CCDF to 1, which means that for values $x < x^*$ for which $Y(x^*) = 1$, there will not be any density. In other words, there are no values smaller than x^*. We can calculate x^* from

$$1 = abe^{-bx}$$

$$=> x^* = \frac{\ln\left(\frac{1}{ab}\right)}{-b}$$

$$= \frac{\ln(ab)}{b}$$

The corresponding density is

$$f(x) = 0 \text{ For } x < x^*, or$$
$$f(x) = be^{(-b(x-x^*))} \text{ For } x \geq x^*$$

In other words, a "regular" exponential density is shifted by x^*.

Both cases can be formulated into

$$CCDF(x) = \min\{Y(x), 1\}$$

The good correlation values from Table 1 motivate us to try a standard, non-damped and non-shifted version of the exponential CCDF:

$$CCDF(x) = e^{-bx}$$

The corresponding MLE is solely determined by taking average over X. Then, the formula is

$$CCDF(x) = e^{-bx}$$

For such a matching, the MLE is given by

$$b = \frac{1}{E(X)}$$

i.e. b represents the reciprocal on / off time, respectively.

Chapter 4

Results

In the sequel, we are using the MLE approach described at the end of Chapter 3 to calculate the two parameters expected ON time $E[T_{on}]$ and expected OFF time $E[T_{off}]$. Obtained values are tabulated and shown in the Table 4.0.1

File	$E[T_{on}]$	$E[T_{off}]$
3275-2757-121	3.11	2.43
3250-3008-121	1.69	3.58
3250-3007-121	2.13	3.06
350-507-121	1.21	5.55
3275-2758-121	3.508	3.44
3500-5007-121	8.695	4.34

Table 4.0.1: Table showing MLE estimated ON, OFF time values .

Observations show that there are only two states ON, OFF and there is no self-transition in this model. The expected mean time taken for transition between the two states is denoted by $E[T_{on}]$ and $E[T_{off}]$ respectively. The ASRP model can be visualized as an EMC varying between the two states of the model. The probabilities for being in the individual states can be calculated using the simple formulae,

$$P_{off} = \frac{E[T_{off}]}{E[T_{on}] + E[T_{off}]} \text{ and}$$

$$P_{on} = \frac{E[T_{on}]}{E[T_{on}] + E[T_{off}]}$$

i.e., P_{off} and P_{off} will give the probabilities that the channel stays in OFF and ON states respectively.

Channel off probability is calculated for all the cases and the values are tabulated.

File	$E[T_{on}]$	$E[T_{off}]$	P_{off}
3275-2757-121	3.11	2.43	0.44
3250-3008-121	1.69	3.58	0.67
3250-3007-121	2.13	3.06	0.59
350-507-121	1.21	5.55	0.82
3275-2758-121	3.50	3.44	0.49
3500-5007-121	8.69	4.34	0.33

Table 4.0.2: Table showing MLE estimated ON, OFF time values and also the probability that the channel is OFF.

From Table 4.0.2 it is observed that P_{off} value is very high when $E[T_{off}]$ value is greater than $E[T_{on}]$ value.

Based on these values, we arrive at the CCDFs of the state duration that are shown in Table 4.0.3 together with the corresponding correlation values.

File	State	Correlation	Equation
3275-2757-121	ON	0.98	$Y = e^{-0.321x}$
3275-2757-121	OFF	0.99	$Y = e^{-0.411x}$
3250-3008-121	ON	0.97	$Y = e^{-0.59x}$
3250-3008-121	OFF	0.98	$Y = e^{-0.279x}$
3250-3007-121	ON	0.98	$Y = e^{-0.469x}$
3250-3007-121	OFF	0.99	$Y = e^{-0.326x}$
350-507-121	ON	0.93	$Y = e^{-0.82x}$
350-507-121	OFF	0.99	$Y = e^{-0.18x}$
3275-2758-121	ON	0.99	$Y = e^{-0.304x}$
3275-2758-121	OFF	0.98	$Y = e^{-0.29x}$
3500-5007-121	ON	0.99	$Y = e^{-0.115x}$
3500-5007-121	OFF	0.98	$Y = e^{-0.23x}$

Table 4.0.3: Correlation values and equations of distributions.

Table 4.0.3 shows the correlation values and the equations of the standard, non-damped and non-shifted version of the CCDF. Figure 4.0.1 and 4.0.2 represents the OFF time and ON time distributions of the equations in above table. The validity of the matching is verified through correlation values and the graphs. Almost in all the cases correlation values in the table are greater than 0.90, which implies that there is a good agreement between the matching.

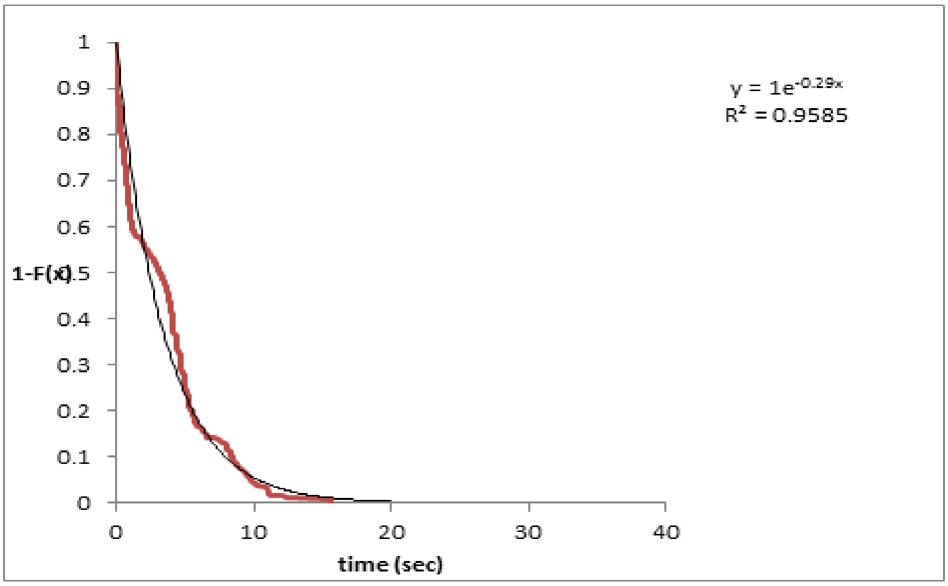

Figure 4.0.1: OFF time distribution.

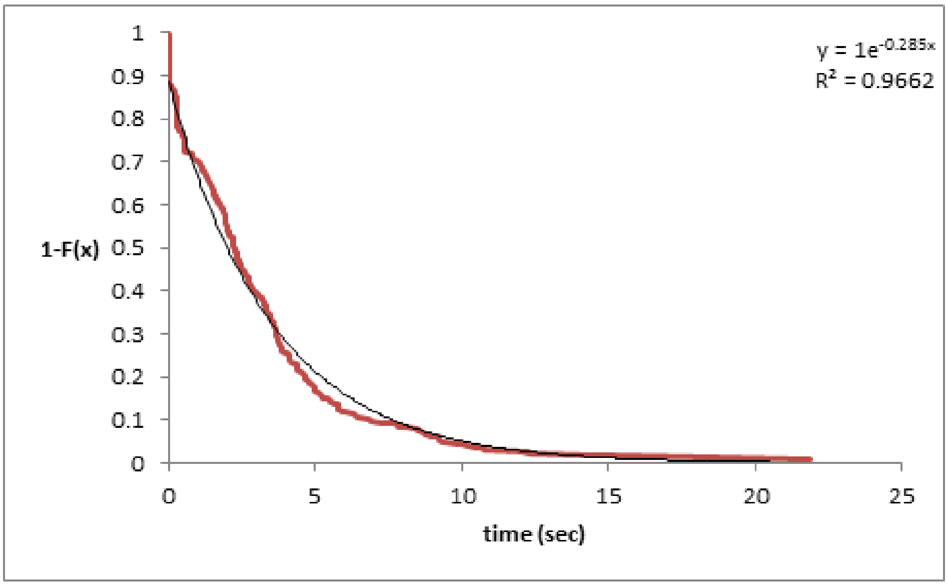

Figure 4.0.2: OFF time distribution.

Table 4.0.1 gives the calculations of the expected ON times $E\left[T_{on}\right]$ and OFF times $E\left[T_{off}\right]$ respectively. $E\left[T_{off}\right]$ is the reciprocal value of the factor in the argument of the exponential function for the OFF times. Similarly

$E[T_{on}]$ is the reciprocal value of the factor in the argument of the exponential function for the ON times. Using these parameters buffer underflow probability is modelled as:

The probability that buffer of time t under flows is approximated by

$$P^t = P_{off} \cdot e^{\left(\frac{-t^\star}{E[T_{off}]}\right)}$$

Where $E[T_{off}]$ is the expected off time value and P_{off} is the estimated probability that the channel is off. As already given P_{off} is:

$$P_{off} = \frac{E[T_{off}]}{(E[T_{on}] + E[T_{off}])}$$

Using the expected parameters, P^t is found for all the OFF times we have. Obtained values are plotted in a single graph for analysis and comparison.

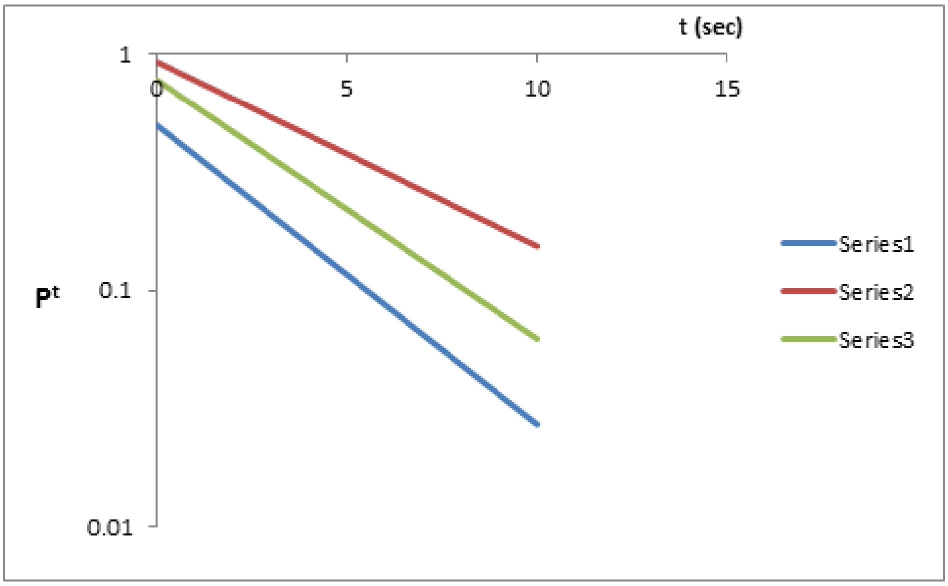

Figure 4.0.3: Comparison of buffer under flow probability for different traces.

In the above graph 4.0.3 Series 1 represents buffer underflow probability of trace $3275 - 2758 - 121$, Series 2 represents $350 - 507 - 121$ and Series 3 represents $3250 - 3007 - 121$. In all the cases as the buffer time t increases the probability that it under flows is decreasing. But when a particular case is considered underflow probability depends on the channel off probability P_{off}. From the table 4.0.2 the P_{off} values for three series are $0.49, 0.82$ and 0.59 respectively. It implies that P_{off} value of Series 1 is less than that of Series 3 and the value of Series 2 is greater than the values of Series 1 and 3.

At $t = 0$ when we observe the positions of the three series, they are sorted according to their P_{off} values. The position of Series 2, who's P_{off} value is 0.82 occupies the top most position near to one, whereas Series 1 whose P_{off} value is 0.49 occupies the bottom position and the Series 3 whose P_{off} value lies in between the values of Series 1 and 2 is positioned in-between the two series. Higher P_{off} implies higher curves and bigger risk for under-flow of a buffer of a given size.

$$P^t = P_{off} \cdot e^{\left(\frac{-t^\star}{E\left[T_{off}\right]}\right)}$$

Substituting $P^t = 0.01$ in the above equation

$$0.01 = P_{off} \cdot e^{\left(\frac{-t^\star}{E\left[T_{off}\right]}\right)}$$

Where $t^\star$ is buffer size (in seconds)

$$=> \ln\left(\frac{0.01}{P_{off}}\right) = \left(\frac{-t^\star}{E\left[T_{off}\right]}\right)$$

$$=> \ln\left(\frac{P_{off}}{0.01}\right) \cdot E\left[T_{off}\right] = t^\star$$

$$=> t^\star = \ln\left(\frac{P_{off}}{0.01}\right) \cdot E\left[T_{off}\right]$$

Based on above formula, the buffer can be dimensioned such that a certain under flow probability is not surpassed.

File	$t^\star(0.1)$	$t^\star(0.01)$	$t^\star(0.001)$
3275-2757-121	3.6	9.2	14.8
3250-3008-121	6.8	15.1	23.3
3250-3007-121	5.4	15.5	19.5
350-507-121	11.7	12.5	37.2
3275-2758-121	5.5	13.4	21.3
3500-5007-121	5.2	15.2	25.2

Table 4.0.4: Buffer size for different P^t values

Table 4.0.4 shows the buffer sizes of different traces for different buffer under-flow probability values. Row-wise observations imply that as the P^t value decreases from 0.1 to 0.001 buffer time is increasing noticeably. Consider the trace file $3275 - 2757 - 121$ in which buffer time increased from 3.6 to 14.8 seconds as the P^t decreased from 0.1 to 0.001. Values of trace $350 - 507 - 121$ are quite odd when compared to others which is because the corresponding P_{off} value is very high (0.82). The higher $E\left[T_{off}\right]$ with respect to $E\left[T_{on}\right]$, the higher P_{off}, and the flatter the curves. This implies larger risk for buffer under-flow, which entails QoE issues and large buffer sizes in order to limit the risk of perceiving freezes

Chapter 5

CONCLUSION

5.1 Answers To Research Questions

RQ 1: How is a teletraffic model (for mobile networks) designed based on the traffic characteristics of real mobile networks?

Answer: This question covers our entire thesis. Analysis of traces plays a crucial role in understanding the nature of traffic and the disturbances present in it. Traces are analysed for longer time delays and ON-OFF phases are captured. These phases are visualized as CCDF graphs and matched with the curves. The validity of the matching is verified through graphs and correlations. Parameters required for modeling are estimated using MLE and finally the model for buffer underflow probability is designed using estimated parameters.

RQ 2: How is parameter estimation done?
Answer: The two essential parameters for modeling buffer overflow probability are

- Expected ON time $E\left[T_{on}\right]$
- Expected OFF time $E\left[T_{off}\right]$

These are estimated using maximum likelihood estimation. $E\left[T_{off}\right]$ is the reciprocal value of the factor in the argument of the exponential function for the OFF times. Similarly $E\left[T_{on}\right]$ is the reciprocal value of the factor in the argument of the exponential function for the ON times.

RQ 3: How can mobile network performance and QoE be analyzed and potentially improved using teletraffic models for mobile networks?

Answer: The higher $E\left[T_{off}\right]$ with respect to $E\left[T_{on}\right]$, the higher P_{off}, and the flatter the curves. This implies larger risk for buffer underflow, which entails QoE issues. Reducing expected OFF time $E\left[T_{off}\right]$ gives better queuing performance, i.e. a smaller risk of buffer underflow. If possible, reducing

$E\left[T_{off}\right]$ as compared to $E\left[T_{on}\right]$ helps to improve the network performance potentially.

Chapter 6

Future Work

Our current work aims in designing buffer under-flow probability for mobile networks in 3G environment. This work can be extended by searching for possibilities to reduce the OFF times and taking MOS from user QoE point of view. Apart from reducing the OFF times it can also be extended by designing teletraffic models for Wi-Fi and 4G environments.

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