A Joint-Parametric Realistic Traffic Model for Wireless Internet using Hidden Markov Model

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Abstract—**With the increasing usage of mobile devices to ubiquitously access heterogeneous applications in wireless Internet, the measurement, analysis and modeling of Internet traffic has become a key research area. Solving performance related issues of networks and ensuring better Quality of Service (QoS) for end-users calls for simple, tractable and realistic traffic models. The model should not only be able to predict the traffic in the network but also should evolve with the current and future networks. In this paper, we propose a Hidden Markov Model (HMM) based wireless Internet traffic model considering the source traffic at packet level. Mathematical details of the model are included for the CBR and the VBR traffic types, jointly analyzing Packet Delay (PD), IP Packet Delay Variation (IPDV) and Packet Size (PS). Modeling results are presented for the non-cooperative measurements carried over UDP in GPRS, UMTS and Wi-Fi networks using Vodafone-India and BSNL-India networks. The specific contributions in this work are: (a) a traffic measurement tool for mobile devices is designed and its architecture is presented, (b) measurements are carried out for GPRS, UMTS and Wi-Fi networks to collect the traces and (c) an analytical model for wireless Internet traffic is proposed and validated by real-time traffic.**

Keywords- Wireless Interne; Traffic modeling; Hidden Markov Model; Packet Delay; IP Packet Delay Variation; Packet Size

I. Introduction

The ability to accurately measure and characterize the network traffic associated with different applications is fundamental to numerous network related activities like network performance management, security monitoring, traffic modeling, network planning and Quality of Service provisioning. Although the collection and analysis of traffic traces from various networks has become simple with the advent of fast and accurate sniffers, wireless Internet still poses some of the challenges in measurement like mobility, limited device capability, heterogeneity etc. The lack of real-time traces to model traffic gives a solution applicable to certain scenarios only. With the advancement of technology, the model is required to evolve so as to meet the demands, not only of the present networks, but also of the Next Generation Networks (NGN).

Indeed, there exist a rich literature on traffic characterization and modeling [1, 3, 4, 5], most of these focus on fitting marginal distribution of Quality of Service (QoS) parameters, sometimes by arbitrary splitting the time series or finding out the time dependency of the parameters which work well in a simulation framework but, lacks accuracy in real networks. Traffic measurements can be carried out at various levels like byte, packet, flow, or session level. Source traffic at packet-level has the following benefits as compared to the other higher level methods: (a) most of the network problems (loss, delay, jitter etc.) occur at the packet level; (b) packet-level approach is independent of protocols being used; (c) traffic at the packet-level remains observable even after encryption made by different protocols.

Recently, the use of Hidden Markov Model (HMM) for learning and prediction has increased in many fields including traffic engineering, speech processing, finance etc. [2, 6, 7, 8, 12]. In this paper, we propose a packet level, simple yet accurate, single source based traffic model for fixed as well as variable packet size. The measurement and modeling done in this paper has the following salient features: (a) non-cooperative measurements are carried out over wireless networks like BSNL and Vodafone, and are benchmarked by an existing Wi-Fi network in laboratory; (b) measurements are carried in the mobile device (essentially a mobile phone) using test-tool developed in J2ME, specifically for the purpose. It deserves to be mentioned that Wireshark or any other similar measurement tool cannot be deployed in the mobile due to its limited capabilities; (c) India-specific networks are employed which gives scope for better traffic management for 3G networks which are soon to be deployed in India; (d) the proposed HMM based wireless Internet traffic model is shown to perform better with initial short term predictions. The model contributions are as follows: (a) it allows delay-IPDV (Inter-Packet Delay Variation) and delay-IPDV-PS (Packet Size) joint description for a network. It is worthwhile to note that IPDV is a very important metric for some real time Internet applications (b) it allows for synthetic generation of traffic consisting of all the three metrics described above (c) the model is designed using the real test traces taken from the live networks (d) the model is scalable, flexible and can be easily incorporated into any practical system. Since the proposed model is based a packet level source traffic model, it is valid for TCP as well as UDP protocols. Measurements are carried over UDP as an example to illustrate the validity of the proposed model.

The paper is organized as follows. Section II introduces the measurement framework and trace collection procedure.

Section III provides the detailed description of the proposed model. In Section IV we present and discuss the numerical results. Finally, Section V concludes the paper with a brief discussion over results.

II. MEASUREMENT FRAMEWORK AND TRACE COLLECTION

A. Client-Server architecture

The wireless IP QoS testbed is set-up in the CAD/CAM laboratory of Department of Mechanical Engineering, Indian Institute of Technology Kharagpur, India. It consists of a few Access Points (APs), such as 802.11b/g access points, and a number of wireless and wired devices (e.g. mobiles, laptops, PCs), which are able to access the Internet through Wi-Fi, GPRS, UMTS, or a LAN. Wi-Fi is accessed using AP while all other networks are accessed using base stations. The packet goes through operator's typical network, over which we have no control. The last mile i.e. from Access Point (AP) or Base Station (BS; for GPRS or UMTS) to mobile devices is Wireless. The mobile, [10], device supports Wi-Fi, GPRS and UMTS.

The simplified client-server architecture used for testbed used for measurements is shown in Fig. 1. Base station depicts the GPRS or UMTS network. Server is set-up in the campus and can be accessed using Internet with one of the four networks i.e. Vodafone GPRS, BSNL GPRS, BSNL UMTS or Wi-Fi. All measurements and experiments are done using IPv4. Internal IP (local IP) is used while accessing the server through Wi-Fi as it is an in-campus network. For all other networks, global IP is used. Java and J2ME based test applications are run on the server and the client side respectively to collect the traces.

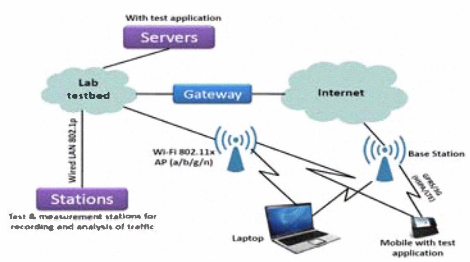

Fig. 1: Client-Server architecture for traffic measurement

B. Measurement lifecycle

Making the available data useful for the characterization and modeling is difficult due to issues like understanding the traces and the network topology. Fig. 2 shows the life cycle of the data analysis for modeling. The trace obtained is made useful by filtering and sanitizing.

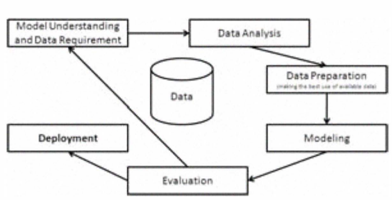

Fig. 2: Life Cycle of Data Analysis

C. Measurement tool and its architecture

To accurately measure the send and receive time of packets, we have developed Java based test tools, the architecture of which is shown in Fig. 3. The main function of the tools is to time-stamp the packets at both the client and server sides, store it in the database and retrieve the trace file after completing experiment.

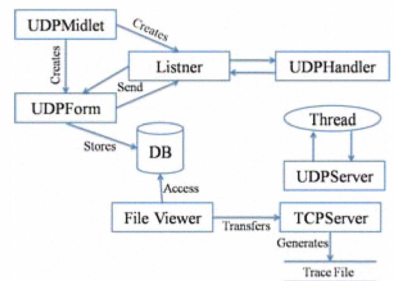

Fig. 3: Traffic measurement tool architecture

The functions of various components of the tool are as follows:

UDPMIDlet: It runs in mobile client to provide the user interface.

UDPForm: This application is developed to store the actual trace file into the phone database (using Record Management Store).

UDPEchoServer: This is the server application based on UDP to send the Echo reply to the client.

UDPHandler: The actual UDP mechanism is developed in this module.

FileViewerMidlet: It retrieves the trace file from the database and transfers it to the TCPServerFile (described below) using socket mechanism.

TCPServerFile: It runs in the server to collect the trace file.

D. Measurement Approach

The client generates constant size packets when we input the first sample packet, and variable traffic by using a random function that sends packets of variable size to the server using GPRS, UMTS or Wi-Fi network. The network is selected at the beginning of each experiment. The packet size varies from 0 to 300 bytes. The maximum packet size limit is imposed by the limited capability of the mobile device. The send time for each packet is logged into the mobile (client). The server upon receiving packets keeps a copy and sends back the original packets to the mobile using the same network as used by the client. Thus, using UDP, which otherwise doesn't give acknowledgement, we are able to calculate round trip time of a packet. This method of calculating the round trip time is used in many applications like probing etc. [11]. To avoid synchronization and other practical issues, it is assumed that the one way trip time i.e. end-to-end delay (d) is half of the round trip time (RTT). This is reasonable as the experiment is conducted several times to obtain a series of traces. The client logs the receive time for each packet and keeps the trace file in its memory. The procedure is repeated several times and then the complete trace file is transferred to a system for analysis using HMM, described in the next section. The number of consecutive repetitions of the experiment is limited by the fixed buffer size of the mobile devices. The impact of introducing Inter-Packet Transmission Delay (IPTD) between the sent packets is discussed at the end of the paper. The Java based test tool deployed in the mobile has the capability to introduce finite amount of delay between packets as shown in Fig. 4 and Fig. 5.

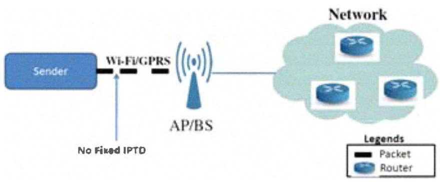

Fig. 4: No fixed Inter Packet Transmission Delay

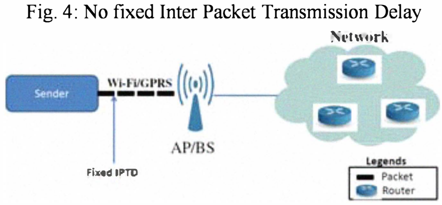

Fig. 5: Fixed Inter Packet Transmission Delay

Table I gives details of the traces collected using different networks. The Inter Packet Delay Variation (IPDV) of a pair of packets within a stream of packets is defined for a selected pair of packets in the stream going from measurement point MP1 to measurement point MP2 [9].

TABLE I: Trace Description

S.No.	Network	Transport Protocol	IPTD in ms	QoS Parameters	Packet Size (bytes)
1.	Vodafone GPRS	UDP	0 & 25	Delay & IPDV	constant/ variable
2.	BSNL GPRS	UDP	0 & 25	Delay & IPDV	constant/ variable
3.	BSNL UMTS	UDP	0 & 25	Delay & IPDV	constant/ variable
4.	Wi-Fi	UDP	0 & 25	Delay & IPDV	constant/ variable

RTT and IPRT give bestfit for Normal and Weibull distributions as shown in Fig. 6. IPTD, RTT and IPRT values are in milliseconds (ms).

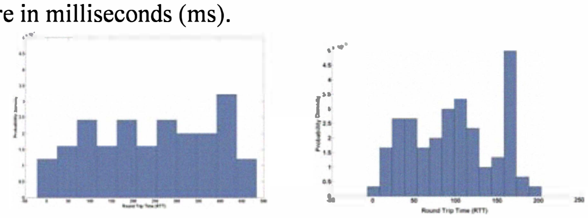

Fig. 6: PDF plot for (a) Vodafone Network for variable packet size; IPTD=0ms (b) BSNL Network for fixed packet size; IPTD=25ms; RTT is in ms.

The traces collected are fitted for all the networks of Table I and are found to follow Weibull and Normal Distributions closely. The bin size for the histogram is chosen using Surge's formula for the simplicity of the approach. The parameters of various distributions for RTT and Inter Packet Receive Time (IPRT) are presented in Table II and Table III, where the symbols have their usual meanings.

TABLE II
PARAMETERS FOR RTT

N/W	Round Trip Time (RTT)		
	Distribution	IPTD=0	IPTD=25
Vodaf-one GPRS	Normal	μ=246.66 σ^2=139.26	μ=174.15 σ^2=32.21
	Weibull	λ=273.96 k=1.71	λ=182.46 k=9.19
BSNL GPRS	Normal	μ=149.09 σ^2=81.40	μ=192.16 σ^2=39.20
	Weibull	λ=166.09 k=1.82	λ=203.44 k=7.17
BSNL UMTS	Normal	μ=240.61 σ^2=138.67	μ=158.37 σ^2=31.11
	Weibull	λ=267.05 k=1.68	λ=167.98 k=7.21
Wi-Fi	Normal	μ=76.97 σ^2=68.92	μ=11.16 σ^2=2.46
	Weibull	λ=77.45 k=1.01	λ=11.91 k=7.27

TABLE III
PARAMETERS FOR IPRT

N/W	Inter Packet Receive Time (IPRT)		
	Distribution	IPTD=0	IPTD=25
Vodaf-one GPRS	Normal	μ=9.13 σ^2=0.12	μ=9.13 σ^2=0.08
	Weibull	λ=9.21 k=34.89	λ=9.19 k=46.99
BSNL GPRS	Normal	μ=9.16 σ^2=0.09	μ=9.15 σ^2=0.08
	Weibull	λ=9.22 k=51.65	λ=9.21 k=45.00
BSNL UMTS	Normal	μ=9.15 σ^2=0.05	μ=9.14 σ^2=0.07
	Weibull	λ=9.18 k=104.21	λ=9.19 k=50.62
Wi-Fi	Normal	μ=4.62 σ^2=0.03	μ=4.63 σ^2=0.02
	Weibull	λ=4.63 k=77.97	λ=4.65 k=150.53

III. PROPOSED FRAMEWORK

A. *Hidden Markov Model*

In this work we propose to use an HMM for packet-level network traffic for (a) fixed packet size and (b) variable packet size. In general, the HMM consists of two variables:

(a) The hidden variable whose temporal evolution follows a Markov chain.

(b) The observable variable (the observed output) that stochastically depends on the hidden state.

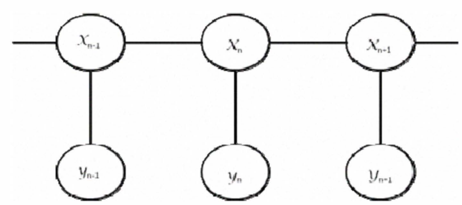

Fig. 7: HMM Topology

HMM consists of three phases evaluation, reconstruction, and learning. The main challenges in using an HMM are: (a) computation of probability of a particular measured output data sequence from the trace and the probabilities of hidden states, (b) finding most likely sequence of hidden states that could have generated a given output sequence and (c) finding the most likely sequence of state transition and output probability when an output sequence or a set of such sequences is given. The challenges are addressed by the forward-backward algorithm, Viterbi algorithm and Baum-Welch algorithm respectively.

The topology considered for HMM is shown in Fig. 7. In this figure,

$$x_n = \{s_1, s_2, s_3, \ldots, s_N\}$$

and

$$y_n = \{o_1, o_2, o_3, \ldots, o_M\}$$

represent the state and the observable at discrete time n respectively, N and M being number of states and number of observables, respectively. Let us say we denote HMM by $\Lambda = \{\boldsymbol{u}, \boldsymbol{A}, \boldsymbol{B}\}$ with the symbols defined as follows:

- $\boldsymbol{u}$: initial state distribution, where $u_i = \Pr(x_1 = s_i)$
- $\boldsymbol{A}$: NxN state transition matrix, where $A_{i,j} = \Pr(x_n = s_j / x_{n-1} = s_{j-1})$
- $\boldsymbol{B}$: NxM observable generation matrix, where $B_{i,j} = \Pr(y_n = o_j / x_n = s_i)$

B. QoS based Packet level Source traffic model

As shown in section II*(D)*, end-to-end delay (*d*) and IPDV for various wireless networks follow the Weibull or the Normal distribution. We choose Weibull distribution to model HMM due to following reasons: (a) It shows bestfit for both the quantities (b) It holds only for positive values which is quite applicable for packet size *(PS)*, delay *(d)* and *IPDV* as negative values for *PS*, *d* and *IPDV* are meaningless. (c) By varying the shape parameter, k, of Weibull distribution, we can achieve exponential (k=1) as well as Rayleigh (k=2) distributions as shown in Fig. 8.

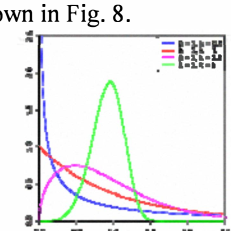

Fig. 8: Weibull plot for various shape and scale parameters

i) Fixed Packet Case:

Referring to the single source of traffic, we consider an HMM with the discrete state variable x_n and the observable variable as a continuous bi-dimensional vector, $\mathbf{y}_n = [d_n, j_n]^T$. The first parameter of $\mathbf{y}_n$ represents end-to-end delay and the second parameter represent inter-packet delay variation, for nth packet in dBm, which is defined as $10\log_{10}(d/1ms)$. It is assumed that d and j are statistically independent for a given state. Also, we assume that u=q and that the steady-state distribution is given by A^Tq=q . Thus $\Lambda = \{\boldsymbol{A}, \boldsymbol{g}^{(t)}, \boldsymbol{w}^{(t)}, \boldsymbol{g}^{(l)}, \boldsymbol{w}^{(l)}\}$ defines the complete set of parameters for the model -

- $A_{i,j} = \Pr(x_n = s_j / x_{n-1} = s_{j-1})$ denotes the state transition matrix
- $d_n \mid x_n = s_i \sim W(g_i^{(t)}, w_i^{(t)})$ denotes the conditional *delay* distribution vector and
- $j_n \mid x_n = s_i \sim W(g_i^{(l)}, w_i^{(l)})$ denotes the conditional IPDV distribution vector.

The conditional pdfs for *d* and IPDV are gives by:

$$f_i^{(t)}(d) = \frac{g_i^{(t)}(d/w_i^{(t)})^{g_i^{(t)}-1} e^{-(d/w_i^{(t)})^{g_i^{(t)}}}}{w_i^{(t)}} (d > 0)$$

$$f_i^{(l)}(j) = \frac{g_i^{(l)}(j/w_i^{(l)})^{g_i^{(l)}-1} e^{-(j/w_i^{(l)})^{g_i^{(l)}}}}{w_i^{(l)}} (j > 0)$$

Thus we have an HMM, which jointly describes IPT and IPDV, and is given by:

$$f_i(\mathrm{y}_n) = f_i^{(t)}(d) f_i^{(l)}(j)$$

Model Statistics:

d and IPDV conditional means and standard deviations are given by:

$$\mu_i^{(t)} = w_i^{(t)}\Gamma(1 + (1/g_i^{(t)}))$$

$$\mu_i^{(l)} = w_i^{(l)}\Gamma(1 + (1/g_i^{(l)}))$$

$$\sigma_i^{(t)} = [w_i^{(t)}]^2[\Gamma(1 + (2/g_i^{(t)}) - \Gamma^2(1 + (2/g_i^{(t)})]$$

$$\sigma_i^{(l)} = [w_i^{(l)}]^2[\Gamma(1 + (2/g_i^{(l)}) - \Gamma^2(1 + (2/g_i^{(l)})]$$

The conditional duration in a state is given by:

$$\phi_i = \frac{1}{1 - A_{i,i}}$$

Estimated Parameters using the Model:

The Expectation-Maximization (EM) algorithm [13] is an optimization procedure that allows learning of a new set of parameters for a stochastic model according to improvements of the likelihood of a given sequence of observable variables. For structures like HMMs this optimization technique reduces to the Baum-Welch algorithm, studied for discrete and continuous observable variables with a broad class of allowed conditional pdfs. The Baum-Welch algorithm is an iterative procedure looking for a local maximum of the likelihood function that typically depends upon the initial settings given to the model. Multiple trainings with different initial conditions provide the global maximum. The Baum-Welch algorithm of the proposed model is driven by the following equations:

$$estA_{i,j} = \frac{\sum_{i=1}^{L_k - 1} \alpha_n^{(k)} A_{i,j} f_i(\mathrm{y}_{n+1}^{(k)}) \beta_{n+1}^{(k)}(j)}{\sum_{i=1}^{L_k - 1} \alpha_n^{(k)} \beta_n^{(k)}(i)}$$

$$est(g_i^{(t)} w_i^{(t)}) = \frac{\sum_{i=1}^{L_k} \alpha_n^{(k)}(i) \beta_n^{(k)}(i) d_n^{(k)}}{\sum_{i=1}^{L_k - 1} \alpha_n^{(k)}(i) \beta_n^{(k)}(i)}$$

$$est(g_i^{(l)} w_i^{(l)}) = \frac{\sum_{i=1}^{L_k} \alpha_n^{(k)}(i) \beta_n^{(k)}(i) j_n^{(k)}}{\sum_{i=1}^{L_k - 1} \alpha_n^{(k)}(i) \beta_n^{(k)}(i)}$$

$$est(g_i^{(t)}(w_i^{(t)})^2) = \frac{\sum_{i=1}^{L_k} \alpha_n^{(k)}(i)\beta_{\mathrm{n}}^{(\mathrm{k})}(i)(d_n^{(k)} - \mu_i^{(t)})^2}{\sum_{i=1}^{L_k - 1} \alpha_n^{(k)}(i)\beta_{\mathrm{n}}^{(\mathrm{k})}(i)}$$

$$est(g_i^{(l)}(w_i^{(l)})^2) = \frac{\sum_{i=1}^{L_k} \alpha_n^{(k)}(i)\beta_{\mathrm{n}}^{(\mathrm{k})}(i)(j_n^{(k)} - \mu_i^{(l)})^2}{\sum_{i=1}^{L_k - 1} \alpha_n^{(k)}(i)\beta_{\mathrm{n}}^{(\mathrm{k})}(i)}$$

The likelihood for the k[th] sequence is given by:

$$\pounds^{(\mathrm{k})} = \Pr(Y^{(k)} \mid \Lambda) = \sum_{i=1}^{N} \alpha_n^{(k)}(i)\beta_{\mathrm{n}}^{(\mathrm{k})}(i)$$

and the forward and backward variables are computed using the following recursions:

$$\alpha_n^{(k)}(j) = \begin{cases} \sum_{i=1}^{N-1} \alpha_{n-1}^{(k)}(i) A_{i,j} f_j(\mathrm{y}_{\mathrm{n}}^{(k)}) \\ \delta_{i,j} \end{cases}$$

$$\beta_n^{(k)}(i) = \begin{cases} \sum_{j=0}^{N-1} f_j(\mathrm{y}_{\mathrm{n+1}}^{(k)}) A_{i,j} \beta_{n+1}^{(k)}(j) \\ 1 \end{cases}$$

ii) Variable Packet Case:

In this case we consider *d*, IPDV and PS (Packet Size) as the model parameters. The joint model is given by:

$$f_i(\mathrm{y}_n) = f_i^{(t)}(d) f_i^{(l)}(j) f_i^{(p)}(b)$$

where,

$$f_i^{(p)}(b) = \frac{g_i^{(p)}(b/w_i^{(p)})^{g_i^{(p)}-1} e^{-(b/w_i^{(p)})^{g_i^{(p)}}}}{w_i^{(p)}} (b > 0)$$

is the conditional pdf for PS (packet size). The model is scaled to three parameters for a variable packet size.

IV. RESULTS

The EM (Expectation Maximization) algorithm searches for the local maxima implying model learning. In case for fixed packet sizes, Fig. 8 and Fig. 9 show that learning is complete in two to three iterations. It is to be noticed that the global maxima is obtained by repeatedly training the model with different sets of starting parameters.

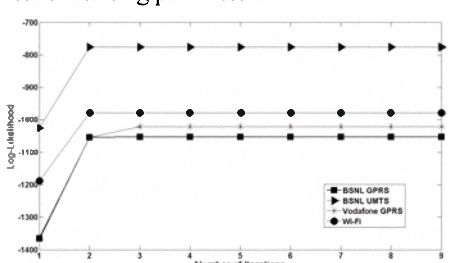

Fig. 8: Log-likelihood vs Number of iterations for various wireless networks with IPTD=0 ms.

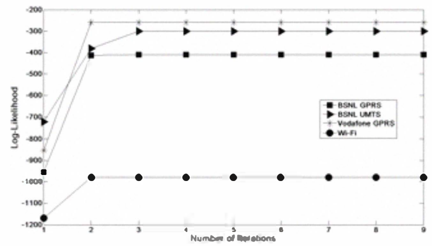

Fig. 9: Log-likelihood vs Number of iterations for various wireless networks with IPTD=25 ms.

Above figures depict that the Wi-Fi network is more suitable for applications involving no delay between packets as it has higher available bandwidth and gets trained faster even for high data rate applications. BSNL UMTS showed much better performance for both the cases, though introduction of 25ms delay improves performance of all the four networks. The model is trained and the model parameters are obtained to generate the synthetic traffic. For some of the networks, we assumed the presence of four states while for others, two states suffice to characterize the source behavior. The model parameters are presented in table IV, V, VI and VII for all the four networks. The states represent the various behavior exhibited by the source. For example in table VI, the life time in state 1 is higher and the mean is lower, which implies that more users are downloading small sized packets and less number of users are downloading packets of a larger size. In particular, we observed that the *delay* for most of the networks, except Wi-Fi was in the range of 80 to 200ms, but the average comes much higher due to the fact that either the packets or their acknowledgements get lost and the *mean delay* increases.

TABLE IV. UDP conditional statistics: steady-state probability, conditional mean and mean time in a state (ms) for BSNL GPRS with IPTD=0ms (left; four states) and IPTD=25ms (right; two states)

s_i	q_i	Mean	ϕ_i
s_1	0.2678	4.639	1.41
s_2	0.2282	4.661	1.35
s_3	0.2504	4.682	1.33
s_4	0.2536	4.703	1.33

s_i	q_i	Mean	ϕ_i
s_1	0.49	4.721	2.127
s_2	0.51	4.248	2.040

TABLE V. UDP conditional statistics: steady-state probability, conditional mean and mean time in a state (ms) for BSNL UMTS with IPTD=0ms (left; two states) and IPTD=25ms (right; four states)

s_i	q_i	Mean	ϕ_i
s_1	0.576	4.23	2.56
s_2	0.424	4.01	1.89

s_i	q_i	Mean	ϕ_i
s_1	0.249	0.693	1.40
s_2	0.251	0.694	1.34
s_3	0.25	0.695	1.33
s_4	0.25	0.745	1.36

TABLE VI. UDP conditional statistics: steady-state probability, conditional mean and mean time in a state (ms) for Vodafone GPRS with IPTD=0ms (left; four states) and IPTD=25ms (right; two states)

s_i	q_i	Mean	ϕ_i
s_1	0.250	3.691	1.41
s_2	0.251	3.697	1.33
s_3	0.249	4.250	1.34
s_4	0.250	4.967	1.34

s_i	q_i	Mean	ϕ_i
s_1	0.431	0.183	1.748
s_2	0.569	0.199	2.311

TABLE VII. UDP conditional statistics: steady-state probability, conditional mean and mean time in a state (ms) for Wi-Fi (802.11g) with IPTD=0ms (left; four states) and IPTD=25ms (right; two states)

s_i	q_i	Mean	ϕ_i
s_1	0.23	0.107	1.38
s_2	0.25	0.107	1.32
s_3	0.21	0.106	1.34
s_4	0.31	0.111	1.34

s_i	q_i	Mean	ϕ_i
s_1	0.5	0.102	1.31
s_2	0.5	0.105	1.29

V. Discussion and Conclusion

The data collected over all the networks, i.e., GPRS, UMTS and Wi-Fi are statistically correlated. For different values of IPTD, the distribution of end-to-end delay (*d*), Inter Packet Delay Variation (*ipdv*) and Packet Size are greatly influenced. It is observed that *d* and *ipdv* are higher for larger packet size for IPTD=0, as compared to IPTD=25 for all the four networks. The Vodafone GPRS and BSNL GPRS networks show almost the same performance for fixed packet sizes when no IPTD is introduced. Delay keeps on increasing for more packets entering into the network, which may be due to buffering in the SGSN/GGSN. The traces collected by our test tool are verified with the Wireshark traces collected at the desired port in server and client sides.

For constant packet size with IPTD=25ms, there are more fluctuations in BSNL network as compared to Vodafone GPRS network but the overall delay is less in case of Vodafone. The introduction of 25ms IPTD avoids the buffering at the network and thus delay seems to be constant after some time. Wi-Fi shows better performance due to its inherent advantage of having a larger available bandwidth. Variable packet size case is similar to the fixed one when no IPTD is introduced between packets except that the packet loss is more when variable size packets are sent, partly due to the fact that the network is unaware of the next incoming packet that results in inefficient resource allocation. The use of traffic monitoring and modeling will be advantageous there. BSNL network shows better performance as compared to Vodafone GPRS in the variable packet with no IPTD case. The situation for variable packets case with increasing delay is controlled by introducing an IPTD of 25ms between packets. The performance of both, the BSNL and the Vodafone GPRS networks seem to improve in this case.

In conclusion, the proposed model takes into account the *delay*, IPDV and PS metrics, jointly. Along with this, the influence of IPTD on various networks is analyzed so as to direct the networks to optimize the available resources. The model is validated with real-time traffic and is shown to get trained in only a few iterations.

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