



Measurement and Forecasting of Next Generation Wireless Internet Traffic

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Measurement and Forecasting of Next Generation Wireless Internet Traffic

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Abstract— Next Generation Wireless Internet will comprise heterogeneous networks connected to seamlessly access multitude of applications and services; managing traffic will become very crucial to successfully run those networks. In this paper, we report a framework to measure end-to-end traffic between Server and Client located in India and USA. The measured traffic is used to design Hidden Markov Model based forecasting algorithm and is validated for different packet size.

Keywords—Hidden Markov Model; traffic measurement; traffic forecasting; LTE; Next Generation Wireless Internet

I. INTRODUCTION

Recent trends indicate that the Internet is being rapidly flooded by multiple traffic flows (e.g. traffic from YouTube, Skype, IPTV etc.) consuming a considerable amount of bandwidth from the network. Such traffic requires a good management of the network and not only just providing of additional bandwidth by a service provider, but also QoS management and control techniques. Several traffic models for wired and wireless networks have been proposed in the literature. However, only few modelling results are derived from real measurement data and rarely do they provide a complete and consistent view of the entire wireless network scenario. Also, the much-needed application specific traffic modelling for wireless is in its infancy which gives researchers a direction to proceed.

There exists a rich literature on traffic modelling and forecasting. The self-similar nature of Internet traffic [1, 2] allows researchers to measure and analyze characteristics of both flow level and packet level traffic which give a key to synthetically generate and use similar traffic for various applications; a time-consuming process otherwise. Lee et al. present a campus wide measurement set-up for Internet traffic in [3] and show that the flow inter-arrival times are long-range dependent and exhibit multifractal scaling. In [4], Estan et al. present the directions for traffic measurement. Traffic measurement approaches presented in [5] are classified as active, passive, offline, online etc. and also various traffic trace resources are documented. In [6], Mobile Internet users are modeled by an ON/OFF source using a fluid flow model. The fluid flow model is also used in [7] to measure and model Internet gaming traffic. In [8], Web Traffic is modelled using Markov Modulated Poisson Process. In [9], differentiated QoS based model for multimedia is presented whereas [10] proposes

discrete-time Markov models for live and stored-media streaming using TCP. The source is characterized by a stream of fixed size packets with ON and OFF time to model VoIP in [11].

The emerging new heterogeneous wireless networks bring in considerable challenges to traffic modelling. For example, in IP-based internetworking, traffic can hardly be modelled in a generic format. Recently, the use of Hidden Markov Model (HMM) [12] for learning and prediction has increased in many fields including traffic engineering, speech processing, finance etc. due to its simple learning mechanism. Performance improvement of networks and to ensure better QoS for end-users, simple, tractable and realistic traffic models are to be designed.

Conventional traffic models are not well suited for the NGWI networks because of their limitations with respect to outdated data traces used to design the models. The study of performance and optimal use of network can be carried out over the existing technologies in a laboratory environment considering the transition from available technologies to next generation technologies as shown in Fig. 1. The trace collected by such measurements can further be used to model the traffic, which in turn can be utilized for traffic prediction, network performance management, security monitoring, network planning and QoS provisioning.

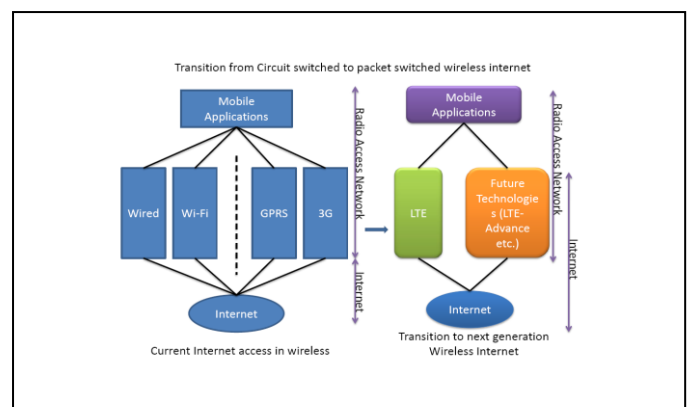


Figure 1. Transition to the Next Generation Wireless Internet

II. MEASUREMENT SET-UP

The next generation Wireless Internet is envisioned to have heterogeneous networks comprising of multiple technologies like Wi-Fi, LTE, LTE-A, WiMAX. A set-up is established at Houston, USA, accessible from High Performance Computing and Networking laboratory at the Department of Mechanical Engineering, Indian Institute of Technology Kharagpur, to take traces using Internet over LTE. The set-up is an enhancement to the already existing IP QoS testbed for wired networks [14–16]. The complete set-up is shown in Fig. 2. The client access Wi-Fi using Novatel 4510L, 4G (LTE) MiFi which in turn runs on the Verizon LTE network. The server is in the wired domain in IIT Kharagpur, India.

We use simple *Ping* command to collect RTT traces at the client side. A windows batch file is developed and deployed at the client. It sends automated ping requests to the server continuously for a fixed packet size. Traces like round-trip-time (RTT), packet loss and IPDV (Inter Packet Delay Variation) are collected for the packet size of 10 bytes to 1400 bytes with a difference of 50 bytes each. Fig. 3 shows the RTT of a sequence of 1024 byte packets sent from client to server using the LTE set-up and Fig. 4 shows the average RTT for different packet size. For each packet size, thousand packets are considered for averaging.

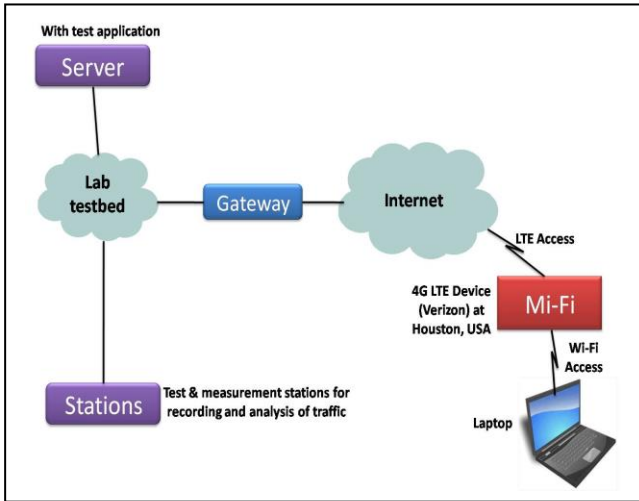


Fig. 2. LTE-WiFi Set-up for Data Collection

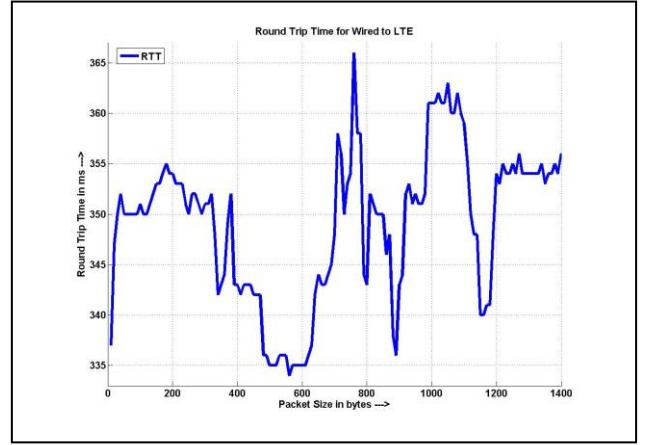


Figure 3. Average RTT for wired-to-LTE for different packet size

III. JOINT PARAMETRIC FORECASTING MODEL

We propose to use an HMM [13] for packet-level network traffic for (a) fixed packet size and (b) variable packet size. The model is designed using the real test traces as described in the previous section. The model is scalable, flexible and can be easily incorporated into any practical system. In general, the HMM consists of two variables:

- The hidden variable whose temporal evolution follows a Markov chain.
- The observable variable (the observed output) that stochastically depends on the hidden state.

A Hidden Markov Model consists of two sets of states and three sets of probabilities:

- hidden states: the states of a system that may be described by a Markov process
- observable states: the states of the process that are visible
- Initial probabilities for hidden states
- Transition probabilities for hidden states
- Emission probabilities from hidden states to observable states

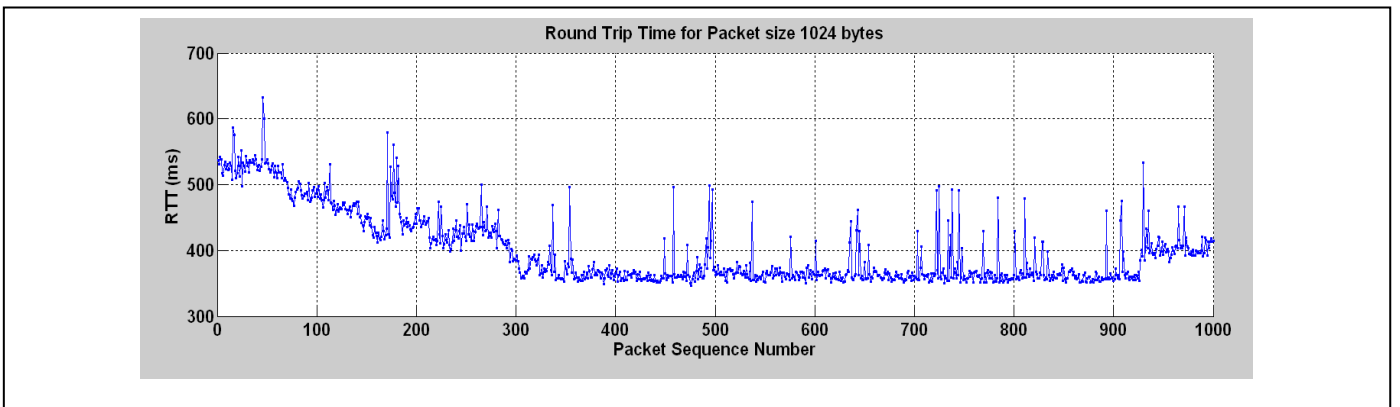


Figure 4. RTT for packet size 1024 bytes using LTE set-up

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 the 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 probabilities 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 [17]. Fig. 5 shows a sample Viterbi path for 100 packets for a four-state HMM while training is in progress. Each observed packet can come from one of the four hidden states. For example, packet number 10 has come from the fourth state while packet number 30 has come from state number one.

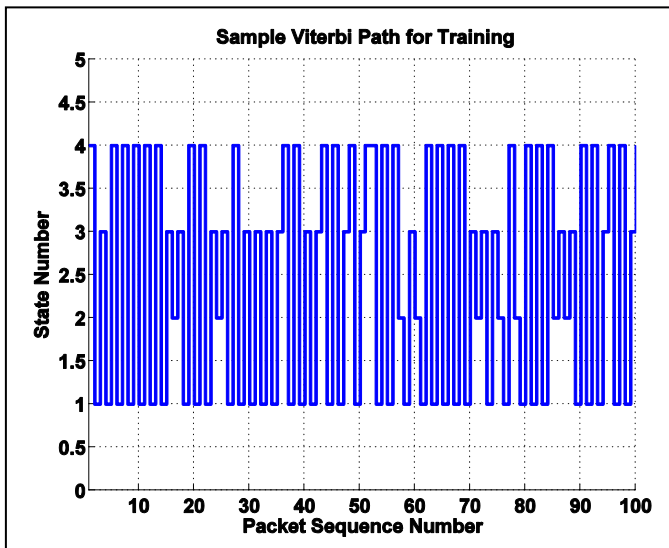


Figure 5. Sample Viterbi Path for 100 Packets

Some of the assumptions considered while modelling are as follows:

- client and server are synchronized in μs level of accuracy,
- packet and its acknowledgement travel the end-to-end path in equal time,
- each packet can come from any of the four traffic classes namely, conversation, streaming, interactive and background,
- each training data sample is of equal importance in the estimation of the new parameters,
- model is unaware of the network being used for measurement, and
- all the states are of equal importance.

For prediction, we have used a one-step prediction recursively to obtain the subsequent values. The data set used as the training part to model the traffic is obtained from the testbed set-up discussed in Section II. From the same sequence, ten percentage data is kept aside as the test set. In our prediction methodology, we set our forecast step to one.

Based on the parameters estimated from the time series using the HMM model and, on the information, obtained from the last time instant of the time series data, we proceed to forecast the traffic for the next time instant. We update the traffic data each time the actual traffic is available to us; and this process is recursively performed. The prediction methodology used is also simple to be performed in real time.

The prediction process is carried out in the training phase. The parameters of the HMM are updated and the Viterbi algorithm is executed to find the most reliable mixtures associated with the most probable state. The weighted average of the mean of the Gaussian mixture is taken as the prediction for next sample.

The training set can be of any size, however as most Internet based applications run for a session, a set equivalent of a session is desirable. There is a balance between the size of the training set and the complexity of the model. The bigger the training set, the more accurate the model in terms of finding long term prediction values; but at the same time, the algorithm complexity increases significantly.

In a real scenario where an adaptive mechanism has to be considered, the model parameters have to be relearned periodically as the network environment can change dramatically. It is evident that reducing the length of the training sequence reduces the complexity of the training algorithm, but it also results in a stationarity (practically no prediction) which means that the training step has to be executed more frequently. In this work, we used a training set of 1000 samples and prediction of 10 percent sample is done. Since we already have the actual data set (collected using testbed set-up), we use it for comparison with our predicted values.

IV. RESULTS AND DISCUSSION

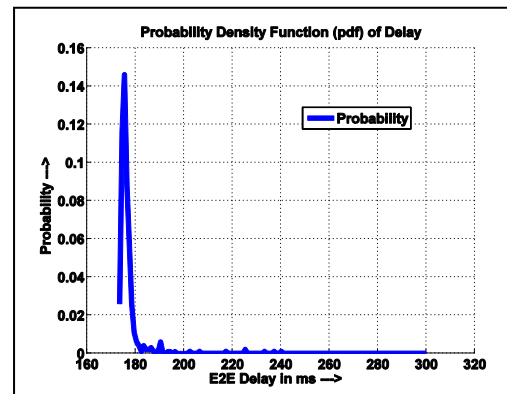


Figure 6. Probability Density Function of E2ED

The trace collected by the measurement set-up as discussed in the Section II are used to forecast the QoS parameters like, End-to-end delay (E2ED) and Inter-Packet Delay Variance (IPDV). 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 a measurement point Measurement Point 1 (MP1) to another measurement point MP2 [18]. We have illustrated all the results using the packet

size of 1200 bytes. Fig. 6 and 7 show the probability density function of E2ED and IPDV respectively.

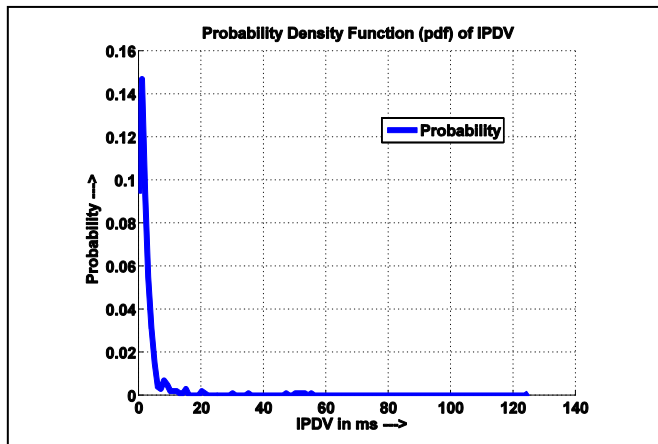


Figure 7. Probability Density Function of IPDV

Given a real stochastic process $X(t)$, the auto-covariance is the covariance of the variable with itself, i.e. the variance of the variable against a time-shifted version of itself. If the process has the mean $E[X_t] = \mu_t$, then the auto-covariance is given by equation (1) as follows:

$$C_{XX}(t, s) = E[(X_t - \mu_t)(X_s - \mu_s)] = E(X_t X_s) - \mu_t \mu_s \quad (1)$$

where, E is the expectation operator.

The term cross-covariance is used to refer to the covariance $cov(X, Y)$ between two random vectors X and Y and is given by equation (2) as follows:

$$cov(X, Y) = E[(X - \mu_X)(Y - \mu_Y)^T] \quad (2)$$

The cross-covariance function of two jointly stationary processes $\{X_t\}$ and $\{Y_t\}$ is given by equation (3) as follows:

$$\gamma_{xy}(h) = E[(X_{t+h} - \mu_x)(Y_t - \mu_y)] \quad (3)$$

where, μ_x and μ_y are means of the stationary processes and h is the lag between the processes.

We have calculated the auto- and cross-covariances up to the lag of ten to see the correlations between the actual and predicted data sets. Fig. 9 and 10 shows the auto-covariance of E2ED and IPDV respectively up to a lag of ten. Fig. 11 shows the cross-covariance of E2ED and IPDV for a lag up to ten.

We define tolerance as the percentage of error a predicted value can have with respect to the actual value. Range is defined as the difference between the maximum and the minimum values a data set can take (equations 4–6).

Range is given by:

$$\text{Range} = (\text{maximum value in actual data set} - \text{minimum value in actual data set}) \quad (4)$$

Tolerance is given by:

$$\text{Tolerance} = (\text{actual value} - \text{predicted value} / \text{Range}) \quad (5)$$

Percentage tolerance is given by:

$$\text{Percentage tolerance} = \text{Tolerance} * 100 \quad (6)$$

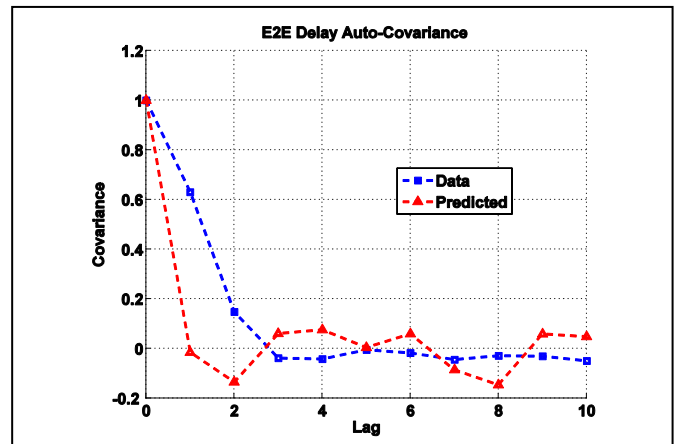


Figure 8. E2ED auto-covariance

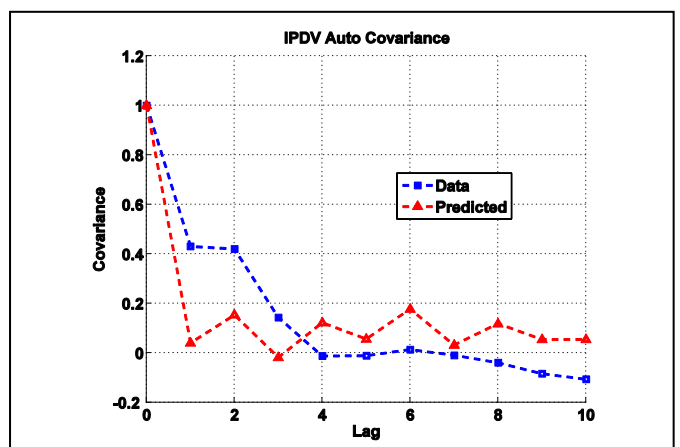


Figure 9. IPDV auto-covariance

Fig. 8 shows the percentage tolerance with percentage prediction for the packet size of 1200 bytes. It can be seen that for a tolerance limit of 5%, E2ED prediction is around 84% and IPDV prediction 82%.

V. CONCLUSION

Traffic measurement, analysis, and modeling play a vital role in determining network performance. The lack of a real-time measurement set-up leads to an unrealistic traffic model. 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 modelling, network planning and QoS 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 to meet the

demands, not only of the present networks, but also of the Next Generation Networks (NGN) which include wired as well as wireless Networks. Traffic forecasting is one major research interest for many network engineers. To accurately forecast the traffic, a good model that can represent the inherent traffic characteristics is required. With a good traffic model and an accurate forecast technique, better traffic management system can be designed. Based on the traffic forecast methodology, network engineers can envision traffic engineering tools which can adapt to any future conditions. A forecast algorithm can play a very important role in this.

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REFERENCES

- [1] M. E. Crovella and A. Bestavros, "Self-similarity in World Wide Web traffic: evidence and possible causes" in Proc. 1996 ACM SIGMETRICS Int. Conf. Meas. Model. Comput. Syst., May 1996.
- [2] K. Park and W. Willinger, "Self-Similar Network Traffic and Performance Evaluation", Wiley Interscience, 2000.
- [3] I. W.C. Lee, A. O. Fajolu, "Analysis and modelling of a campus wireless network TCP/IP traffic" in Computer Networks: The International Journal of Computer and Telecommunications Networking, Volume 53, Issue 15, October 2009, pp. 2674-2687.
- [4] Cristian Estan and George Varghese, "New Directions in Traffic Measurement and Accounting: Focusing on the Elephants, Ignoring the Mice", ACM Transactions on Computer Systems, Vol. 21, No. 3, August 2003, Pages 270-313.
- [5] C. Williamson, "Internet Traffic Measurement", *IEEE Internet Computing* 5, November 2001, pp. 70-74.
- [6] Tim Irnich, Peter Stuckmann, "Fluid-flow modelling of Internet traffic in GSM/GPRS networks", in Computer Communications 26 (2003) 1756-1763.
- [7] J Lakkakorpi, A Heiner, J Ruutu, "Measurement and characterization of Internet gaming traffic," Research Seminar on Networking, Helsinki University of Technology, Networking Laboratory, Espoo, Finland, Feb. 2002.
- [8] Steven L. Scott and Padhraic Smyth, "The Markov Modulated Poisson Process and Markov Poisson Cascade with Applications to Web Traffic Modelling", Oxford University Press, 2003.
- [9] M. Al-Akaidi and O. Alani, "Analytical model for multimedia traffic in 3G wireless systems", Fifth IEE International Conference on 3G Mobile Communication Technologies (3G 2004).
- [10] Bing Wang et al., "Multimedia Streaming via TCP: An Analytic Performance Study", ACM Transactions on Multimedia Computing, Communications and Applications, Vol. 4, No. 2, Article 16, May 2008.
- [11] H. Hassam, J.M. Garcia, and C. Bockstal, "Aggregate Traffic Models for VoIP Applications", in Proc. International conference on Digital Telecommunications.
- [12] A Dainotti, A Pescap' e, PS Rossi, F Palmieri, and G Ventre, "Internet traffic modelling by means of hidden markov models", Computer Networks, 52(14), pp. 2645-2662, 2008.
- [13] Sumit Maheshwari, Vasu K., Sudipta Mahapatra and C. S. Kumar, "A Joint-Parametric Realistic Traffic Model for Wireless Internet using Hidden Markov Model", in CSQRWC, vol. 1, pp. 806-811, July 2011.
- [14] Sumit Maheshwari, Vasu K., C. S. Kumar and Sudipta Mahapatra, "Measurement and Comparative Analysis of UDP Traffic over Wireless Networks", in ICWN, pp. 258-262, Las Vegas, USA, July 2011.
- [15] Maheshwari, Sumit, et al. "Measurement and Analysis of UDP Traffic over Wi-Fi and GPRS." arXiv preprint arXiv:1707.08539 (2017). In ICCCD, IIT Kharagpur, India, December 2010.
- [16] Sruti Gan Chaudhuri, C.S. Kumar and R.V. Raja Kumar, "Design and Implementation of a Differentiated Service Based QoS Model for Real-Time Interactive Traffic on Constrained Bandwidth IP Networks", M.S. thesis, IIT Kharagpur, Feb. 2010.
- [17] J. Bilmes, "A gentle tutorial on the EM algorithm and its application to parameter estimation for Gaussian mixture and hidden markov models", Technical Report ICSI-TR-97-02, University of Berkeley, 1997.
- [18] <http://www.ietf.org/rfc/rfc3393.txt>; Last accessed in Mar. 2012.

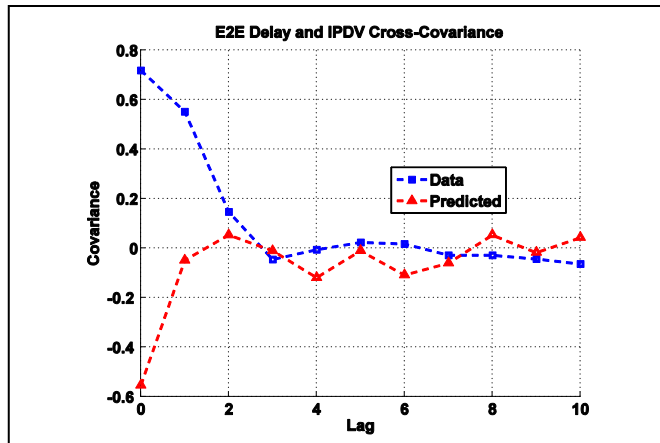


Figure 10. E2ED and IPDV auto-covariance

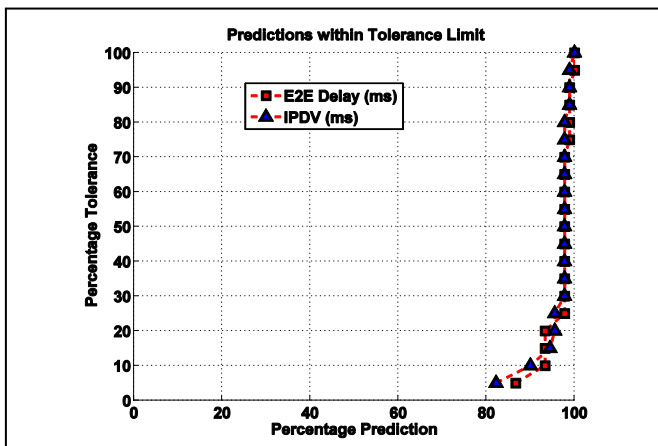


Figure 11. Sample Viterbi Path for 100 Packets

In this paper, we report our measurements carried out over LTE using a remote access at Verizon 4G network. A simple ping batch file is developed and deployed at the remote client to collect the parameters such as RTT, packet loss and packet size. Also, it is proposed to use HMM based traffic forecasting algorithm for joint E2ED and IPDV predictions. Results are shown to be within a tolerance limit of 5% while prediction around 82% of QoS parameters for incoming packets.