NNGT Int. J. of Information Systems , Vol. 1, July 2014

Markovian Model for Packet Loss in MPLS Networks

Islam Amro
Faculty of Information Technology
Al-Quds Open University
Ramallah, Palestine
iamro@qou.edu

***Abstract*—In this Paper, we worked on the modeling of packet loss within MPLS environment. The research exploited real data from a real network running MPLS as its core switching. The data were obtained from 6 nodes, each node participated with 6 hours of traffic segments used as data set, all nodes formed 36 hours as testing data. Each dataset was divided into one-hour segment, each segment loss and no-loss was represented as a binary series. From the 36 segments; 26 segments were found stationary. For Stationary segments;9 segments were modeled using Bernoulli model, 16 segments were modeled using 2-state Markov chain and 9 segments showed k-th order Markov chain tendencies with orders higher than 2. these segments were excluded from modeling due to the uniqueness of their conditions. 4 other segments were found non-stationary thus couldn't be modeled. Each segment stationarity was checked using average filter conditions with threshold of 0.05 and with confidence of 0.95 for lags selection. After modeling each segment independently; an average loss model for each node was estimated using its modeled segments. confidence of these models were 95%. The Model error was tested and the error was around 0.001 for a segment.**

Keywords-component; Temporal Packet Loss, Packt Loss, Networks Performance,Binary time series, Markov chains, Bernoulli modeL, MPLS.

I. INTRODUCTION

Multi-Protocol Label Switching (MPLS) depends on labeling to perform a very fast packet switching over networks, this is done to bind switching techniques of fast layer two with IP routing technique that governs the source and destination purposes, this enables us to achieve higher stability for connectivity due to multiple possible paths, along with and higher agility since it exploits several layer two protocols. MPLS technology works between the second and the third layer. Although it is developed for IP specially, it still can integrate with switching capability of second layer, this enables IP networks to have essential properties found in high speed Switching such as, Flow Control, QoS. Therefore, MPLS is adapted as a core network switching technology.[1] MPLS Packet is depends on working environments, varying environments and applications leads to different modeling methods, most of the modeling approaches focused on the circumstances at which packet lost. For high speed networks as in [14], researchers focused on managing the buffer sizes dynamically to meet the Quality of service conditions, in [4] a well detailed combination with QoS requirements was introduced in term of packet loss. Researchers investigated the process of packet loss in QoS environment without going into the modeling process, another approach for calculating the loss is by using probabilistic function as in[5]. Another domain to analyze packet loss is hybrid wireless networks with wired networks, and commonly using Gilbert approach (based on Markovian), and the proposed model is shown to be very accurate and very representative to the IEEE 802.11g loss scenarios [6]. Research [7] discussed losses in hybrid wireless networks as well; and how such networks exhibit both a high latency and a high packet loss with combinations of stresses TCP's congestion avoidance algorithms. Heavy Traffic combination of wireless and multimedia was investigated in [8].Fault recovery mechanism for MPLS were discussed in [10], packet loss is seen as on of the critical faults in MPLS networks, the research discusses the recovery mechanism rather than discussing the modeling process itself, the research considering managing the packet loss with QoS using general loss prevention approaches caused by Latency, delay and Jitter. VoIP is the most critical application utilizes MPLS, it may encounters several loss effects; reference [9] discusses how Packet loss degrades the perceived quality of voice over IP (VoIP) in several connectivity schemas including MPLS. In [11]; the losses in streaming environment were investigated within MPLS Environemnt. Packet loss can be detrimental to compressed video with interdependent frames because errors potentially propagate across many frames. While latency requirements do not permit retransmission of all lost data, a mechanism was suggested for recovering this data using post processing techniques on reception. The research develop an analytical model to explain these effects.[12]. Paper [14] discusses the temporal packet loss modeling for Internet, it is useful for design and analysis of delay-sensitive multimedia applications. This paper presents the analysis of and end-to-end unicast packet loss measurement over MPLS Network, it considers the packet loss dependency as a modeling reference, it exploits the autocorrelation function of the original loss data (represented in binary time series) to measure dependencies between predefined lag ranges. The research usefulness is its representation of packet loss over MPLS network regardless to application types The Network used for this purpose a real network running heavy duty

DOI : 01.IJIS.2014.1.4

application, it is the network of Al-Quds Open University in Palestine, we selected 6 locations (called regions) inside Palestine, each has a campus serves not less than 2000 students, connected with high speed MPLS links reached up to 12 Mbps. In this paper; Section II discusses the experiment design and conditions, the following section describes data representation and modeling conditions and guidelines. Section IV discusses the modeling approach itself. then we represent results in Section V for the plain model and exhibited the results and afterwards we carry out an error testing for a sample segment . then we conclude the work in section VII. The Main Purpose of this study to find a representative models for average packet loss in real environments based on real data, this model aims at finding the loss model for MPLS Network. These models can be exploited in future works for estimating memory required to avoid this loss, or it can be used to represent the financial efficiency for theses links, this can be a key issue for Service Level Agreements between clients and providers.

II. EXPERIMENT DESIGN

In this paper we worked on an end-to-end packet loss analysis over 36 hours (Gaza, Hebron, Bethlehem, Tulkarem, Nublus and Jerusalem) -each has 6 hours length- from Ramallah Head Quarter, The probe packets sent were with regular intervals of 20, and 160 milliseconds. This was used to construct a binary time series to represent data losses, the binary series fields expressed the loss with 1 and no-loss with 0, each series was segmented into 1 hour segments to check its Stationarity. For stationary segments; we analyzed the temporal dependence in data loss between segment's lags, we depended on the correlation time scale at which packet loss happened, this is used to measure the mutual dependence between losses within each segment, and how far is the dependence, the acceptance or rejection of lags dependency within each segment was approved against a certain threshold, this threshold is defined by a confidence bound for segment's autocorrelation function. the information obtained about each segment lag is used for modeling. For all segments with lags below threshold and correlation close to zero; no interdependent loss were found and modeled as Bernoulli model. For higher dependency orders; Morkov Chain with the same dependency order is used for modeling

III. DATA MODELING

Table 1 represents a sample for packet loss over links for a given interval of time.

TABLE 1: PACKET LOSS OVER REGIONS LINKS

	Destination	Duration	Packet Loss
1.	Gaza	6h	9. 2%
2.	Hebron	6h	8. 45%
3.	Bethlehem	6h	6.13%
4.	Jerusalem	6h	5.17%
5.	Tulkarem	6h	4.78%
6.	Nablus	6h	4.62%

For the mentioned durations in table 1; packet loss is being considered as binary time series $\{x_i\}_i^n = 1$ where x_i value is 0 when i^{th} probed packet is received and 1 if it was lost, the propping interval τ refers to the interval used in probing packets, the time series models is represented as the set $x = \{0,1\}$. The (no losses) subset consists of consecutive 0s, the Loss set consists of consecutive 1s. this results in two interleaving sequences observations: $\{g_i\}_{i^e=1}$ and $\{l_i\}_{i^e=1}$, where g_i is the i^{th} no loss sequence and length l_i is the i^{th} loss sequence. This leads to a long binary time series where each consecutive similar sequences indicates the occurrence of loss, and the groups of g and l indicates the position of each loss, i and l represent length of each sequence. these lengths and positions of each sequence within the series enables us to identify stationarity and inter dependency among sequences. Stationarity was achieved by segmenting the time series into one hour segments, it was verified by checking whether the average loss rate varies for a given trace segment, this is achieved by using finite moving average filter with window size of 2000 packet, reference [12] used 0.05 change in average as threshold as we did in this research. The result of stationarity test for given segments are found in table 2, in the field of average filter value. All the 20 segments were sampled at 160ms were stationary according to the mentioned threshold as in table 2, and for interval of 20 ms we had 8 non-stationary segments out of 16 segment. we have chosen to represent our research by the values of 160 ms samples. After the stationarity of segments is being specified; we can investigate the autocorrolation fucntion for each segement, in order to realize its interdependace and destribution, this is required to find the IID sequences over segments. For samples over $[-n,n]$; the autocorrolation function for each segmenat sample defined as the ratio between sample's autocovariance function over arbitaray lag h and the sample's autocoveraince function at lag $h = 0$. It also can be expressed in term of time, let d be the lag interm of time, then $d = h\tau$, this leads to define the corrolation time scale c that expresses the minimum lag in term of time, the uncorrolated lags are found at $d \geq c$. Using this condition; the autocorrolation function is set to zero for lag d against c, then alag is considered independant. In previous steps; we explained how lag independance can be investigated, now we work on investigating if samples are identically destributed. For large n; the sample autocorrolation of an IID sequence with finite veriance are approximately IID with normal destribution $N(0,1/n)$ (mean of 0, veriance of $1/n$), then approximately 95% of samples autocorrolation should fall between confidance bounds $\pm 1.96/\sqrt{n}$. this can

DOI : 01.IJIS.2014.1.4

be investigated through the sample's autocoroaltion function S at lag h using $S = \hat{\rho}(\mathrm{h}) / \sqrt{n}$, where $\hat{\rho}(h)$ is lag h autocorrolation function.

Figure 1 represents a stationary segment for a segment from that chosen dataset; with 50 lags and τ 160 ms, it shows that the autocorrelation function did not exceed the confidence bound of value $\pm 1.96/\sqrt{n}$ at any lag represented by the dotted line, this means that there is entirely no dependency between segment's lags, for this graph the minimum value were 0.005 and the highest value were 0.046 and the average were 0.011, this was the highest independent loss sample among the whole segments and was identical for Bernoulli modeling.

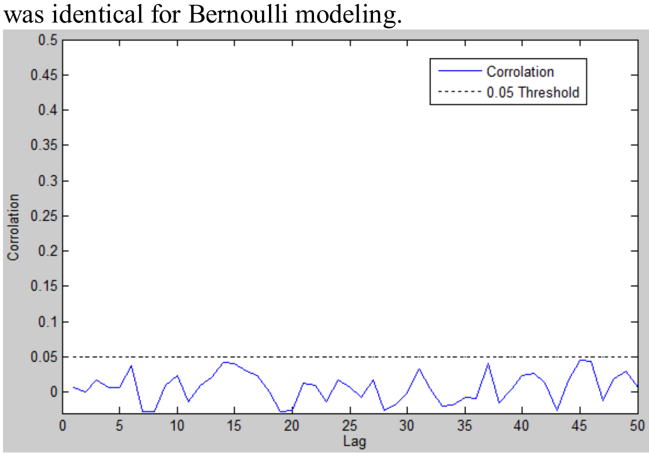

Figure 1: Stationary Segment with no dependancy

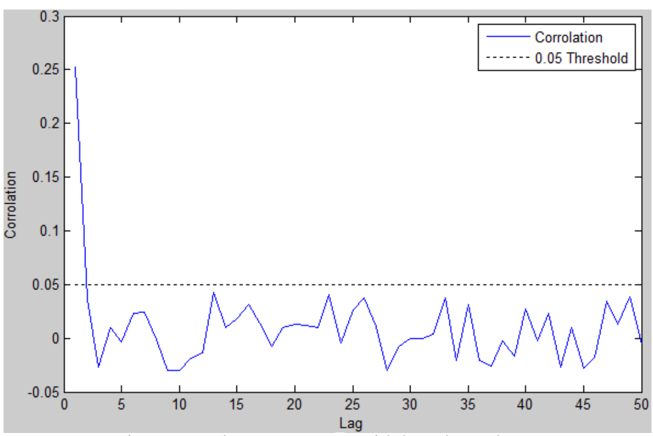

Figure 2:stationary segment with low dependency

Figure 2 shows a segment that shows correlation value close to 0.235on its first lag, it is clear that from lag 2 and onward the correlation function becomes insignificant and small, this means that data depends up to lag 2 and the correlation timescale for this segment take $2 \times \tau$, for the previous figure $\tau = 160$, the correlation time scale for this segment is 320 ms. for figure 3, a segment of 50 lags and τ 20 ms we see that the autocorrelation function is insignificant for most samples and blow the dotted bound line of $\pm 1.96/\sqrt{n}$. For the values excceds the thershold of 0.05, this means the the order of the system is equevelenat to the number of the lag at wich the reashold line is crossed.

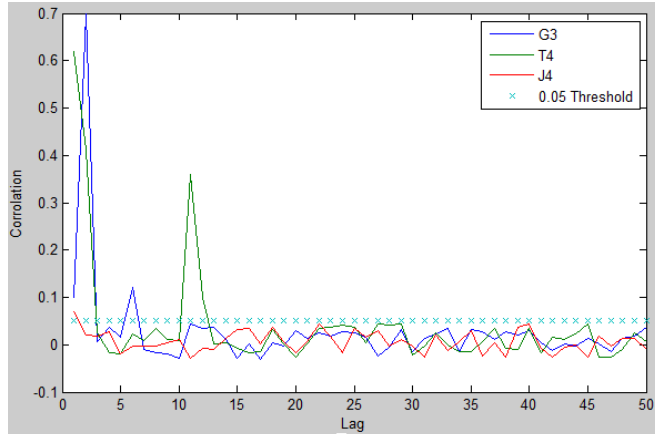

Figure 3:Stationary segment with high dependency

In Figure 4 we see three segments probed with interval of 160 ms. H2, T3 and J2, all of these segment crossed the correlation threshold at lag 1 and went steady over all lags below the threshold, these segments are modeled with two states Markov chains.

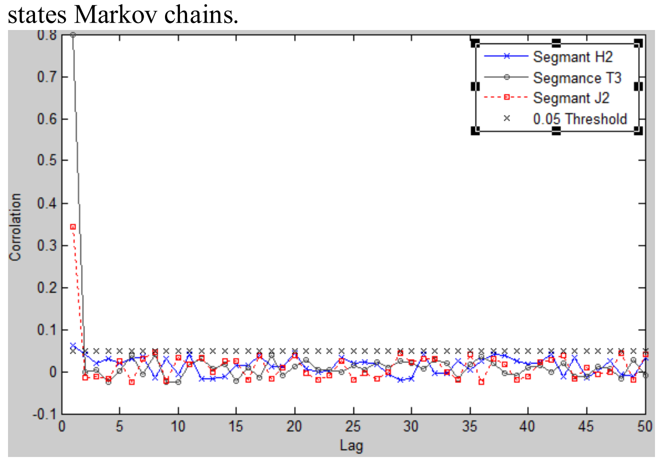

Figure 4: highly dependent stationary segment

IV. Packet Loss Modeling with Markov Chains

The modeling for packet loss considers increasing complexity, the complexity levels are Bernoulli Model, 2-state Markov Model and Markov Chain Model of K-th order. Bernoulli loss model is used to model IID random variables with probability X_i (being either 0 or 1) is independent from all other values over the series. This Model is characterized by a single parameter r which is the probability of X_i being 0 or 1. and estimated from the trace sample as $\hat{r} = n_1/n$ where n_1 is the number of times 1(occurrence of loss) occurs in the time series $\{x_i\}_i^n = 1$ and n is the number of samples in the time series. Note that $\hat{r}$ represents the average loss rate, the trace with no-loss distribution for this model is $f(j) = \hat{r}(1-\hat{r})^{j-1}$ for $j = 1,2,..,\infty$ and the trace with loss distribution is $f(i) = \hat{r}(1-\hat{r})^{i-1}$ for

DOI : 01.IJIS.2014.1.4

$i = 1,2,..,\infty$. for segments applies with Bernoulli conditions; the model is found by calculating $\hat{r}$. For the Two State Markov Chain Model, the loss process is modeled as Markov chain with two states, the current state X_i depends only on the pervious state X_{i-1} , this leads to the presence of transition probability between the two state $p = n_{01}/n_0$ (n_{01} represents the number of 1s followed by 0) and $q = n_{10}/n_1$ (n_{10} represents the number of 0s followed by 1), n_0 is the number of 0s and n_1 is the number of 1s. the model for data with no loss is expressed as $f(j) = \hat{p}(1-\hat{p})^{j-1}$ for $j = 1,2,..,\infty$ and for the loss distribution is $f(i) = \hat{q}(1-\hat{q})^{i-1}$ for $i = 1,2,..,\infty$. the modeling in this case is based on finding p and q . In case of having the process depending on several states before for the time series, the k-th order Markov chain model is used, this process is characterized by its order k , and by a $k \times 2$ conditional probability matrix P_k , the rows of P_k are the probability mass function on $\chi(\chi = \{0,1\})$; according to which the next random variable X_i is generated when the process changes between states and modeled as follows, let $\underline{b} = (b_1,...,b_k)$ be a given state of a machine, let $n_{\underline{b}a}$ be the number of times state $\underline{b}$ is followed by value a , let $n_{\underline{b}}$ be the number of times state $\underline{b}$ is seen. Let $P^k_{\underline{b};a}$ be the estimate probability that $x_i = a$, given that $(x_{i-k},...,x_{i-1}) = \underline{b}$, then $P^k_{\underline{b};a}$ estimates the state transition probability from state $\underline{b}$ to state $(\underline{b},...,b_{k-1},a)$. The maximum likely hood of the state transition probabilities of the k-th order Markov chain are $n_{\underline{b}a} / n_{\underline{b}}$ if $n_{\underline{b}}$ >0 and 0 other wise. According to previous modeling parameters, and the stationarity conditions, we can specify the model that each segment follows by finding the modeling parameters for each model. the order of Markov chain process is estimated by finding the minimum lag beyond which the loss becomes independent, if all of the correlation values were below threshold $\pm 1.96/\sqrt{n}$, then there is no lag dependancy within segment, meaning that all of the loss value are independant, this means that the loss can be modeled as as Bernoulli loss model, and modeling process can be modeled by finding $\hat{r}$. If the lag value for a segment is 1, then then it can be modeled as 2-state Markov processm, the model can be estimated by finding $\hat{p}$ and $(1-\hat{q})$. For higher number of lags over $\pm 1.96/\sqrt{n}$; Markov chain model of order k is required.

V. RSEARCH FINDINGS

The research considered 36 segment, with 1 hours length each, 32 segments were found to be stationary. For Stationary segments; 9 segments were modeled using Bernoulli model, 16 segments were modeled using 2-state Markov chain, we have segments showed k-th order Markov chain tendencies with orders higher than 1. The research results are exhibited in tables 2. For table 2; the segments of each country is exhibited with its corresponding number, and table 2 represents results for $\tau = 160$, the first filed in both tables gives the segment's number of 1 hour width, the filter average field indicated Stationarity information, we can see for stationary segments table; the average values for stationary segments doesn't exceed 0.05. For stationary segment the lags field in tables expresses at which lag within segment; there is exists a considerable correlation higher than $\pm 1.96/\sqrt{n}$, which is the lag depedancy information, and a foundation for calculating Bernoulli parameters-the adjacent field to lag infromation- if lag was zero and 2-state Markov in case of lag=1. For lags higher than one; we suggeted the k order of Markov chain which is equal to lag value, we neglected its effect on the avarege loss over the 6 hours period. we didnot include the analysis of samloing interval on 40 ms for space resons.

TABLE 2: MODELING RESULTS FOR 160 MS SEGMENTS

Data Set	**Filter Average**	**Lags**	$\hat{r}$	$\hat{p}$	$1-\hat{q}$
Gaza G1	0.043927	1	0	0.0466	0 .041
Gaza G2	0.041059	0	0.032	0	0
Gaza G3	0.037629	3	0	0	0
Gaza G4	0.044281	0	0.0627	0	0
Hebron H1	0.043196	0	0.209	0	0
Hebron H2	0.013919	0	0.0149	0	0
Hebron H3	0.036172	1	0	0.017	0.091
Hebron H4	0.016379	18	0	0	0
Bethlehem B1	0.048903	1	0	0.0814	0.065
Bethlehem B2	0.038524	1	0	0.0361	0.0637
Bethlehem B3	0.031758	3	0	0	0
Bethlehem B4	0.018319	1	0	0.0635	0.0718
Jerusalem J1	0.049296	0	0.0582	0	0
Jerusalem J2	0.040174	1	0	0.0187	0.0284
Jerusalem J3	0.043851	2	0	0	0
Jerusalem J4	0.011072	3	0	0	0
Tulkarem T1	0.04137	1	0	0.0491	0.0536
Tulkarem T2	0.04129	6	0	0	0
Tulkarem T3	0.02748	1	0	0.0308	0.0637
Tulkarem T4	0.04816	12	0	0	0
Nablus N1	0.003816	0	0.06022	0	0
Nablus N2	0.04034	0	0.0125	0	0
Nablus N3	0.016373	2	0	0	0
Nablus N4	0.04552	1	0	0.0792	0.0122

TABLE3:AVAREGE MODELS VALUES FOR 160 MS

DOI : 01.IJIS.2014.1.4

	$\hat{r}$	$\hat{p}$	$1-\hat{q}$
Gaza	0.04735	0.0466	0.041
Hebron	0.0179	0.04595	0.0675
Bethlehem		0.060333	0.0668333
Jerusalem	0.0582	0.0187	0.0284
Tulkarem		0.03995	0.05865
Nablus	0.04261	0.0792	0.0122

Table 3 repesents the varege model values for each country, all equevelent models for each region were avareged to represent and avarege value that loss follows for that region.

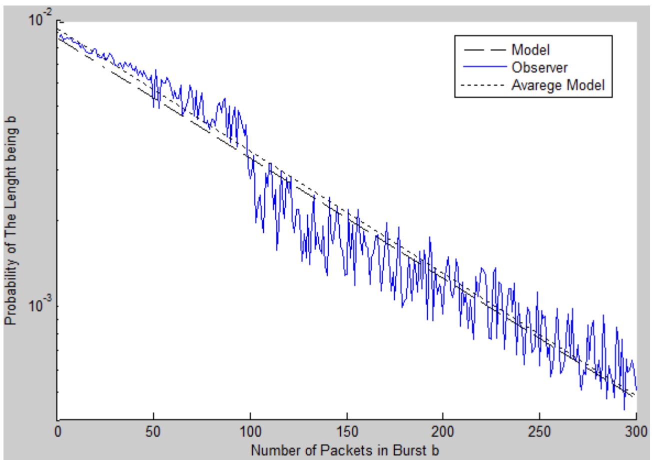

Figure 6: Evaluation for Modeling

Figure 6 represents a logarithmic scale distribution for no-loss situation for a packet burst of 300 packets for the given segment H2 in table 3, Bernoulli values were estimated by $f(j)=\hat{r}(1-\hat{r})^{j-1}$ as mentioned before at $\hat{r}$ equals 0.0149 for the segment value itself, for the actual values of H2 (called Observed in figure 6 legend) and the average value for the Bernoulli Model for Hebron (Average model Value in figure) is taken by the averaging process represented in table 4, the avarege value for the whole segments of Hebron are equals to 0.0179, we can see that the segment modeling shows a very close value for the whole segment model using averaging, it has a variation around 0.005, the model value itself that calculated using direct way on matlab with one hour, it is seen segment is below the average model value in figure, which leads to variations of 0.0051 in average, the maximum value for error in modeling for the segment was less than 0.001, and the maximum value for error for the whole region (Hebron Value) was less than 0.005. so we were able to model the whole region segments that follows Bernoulli under and accepted confidence interval condition.

VI. CONCLUSION AND FUTURE WORK

we were able to introduce a model for packet loss for networks that runs MPLS connectivity. For 36 hours samples, each of 1 hour length, 20 segments were sampled using an interval of 160 ms and the rest with an interval of 40 ms, all of the segments samples with 160 ms were found stationary, 10 segments from the 36 had an only first lag correlation, hence were modeled using second order Markov. 7 segments had no leg dependency so they were modeled using Bernoulli. The average loss model for each region(node) was introduced. We were able to model the whole region segments that follows Bernoulli under and accepted confidence interval condition, also We were able to model the whole region segments that follows two second order Morkov under and accepted confidence interval condition. we were able to compare the model to the actual data as in figure 6, and the errors of modeling were tolerable. The data loss modeling information can give estimation about other performance parameters such is the memory sizes required to avoid loss, the financial cost of loss and give better connectivity scenarios to avoid these losses.

REFERENCES

[1] Qui et el,"A Research of MPLS-based Network Fault Recovery", 3rd IEEE International Conference on Intelligent Networks and Intelligent Systems (ICINIS), China, 2010.

[2] Nahur Fonseca and Mark Crovella,"Bayesian Packet Loss Detection for TCP", IEEE Communications Society, INFOCOM, 2005.

[3] Sakshi Kausha, R.K Sharma, "Modeling and Analysis of Adaptive Buffer Sharing Scheme for Consecutive Packet Loss Reduction in Broadband Networks ", International Journal Of Computer Systems Science And Engineering Volume 1 Number 1, 2007.

[4] H. Sanneck and G. Carle ,"A Framework Model for Packet Loss Metrics Based on Loss Run lengths ", Proceedings of the SPIE/ACM SIGMM Multimedia Computing and Networking Conference 2000 ,San Jose, CA, January 2000.

[5] Cuyt et el ,"Computing packet loss probabilities in multiplexer models using rational approximation", IEEE Transactions on Computers Volume 52, Issue 5, May 200.

[6] Carvalho et el, "new packet loss model of the IEEE 802.11g wireless network for multimedia communications", IEEE Transactions on Consumer Electronics, Volume: 51, Issue: 3, Aug 2005.

[7] Barsocchi et el, "Packet Loss In TCP Hybrid Wireless Networks", Institute of the National Research Council, Italy January 31, 2006.

[8] Carvalho et el, "new packet loss model of the IEEE 802.11g wireless network for multimedia communications ", IEEE Transactions on Consumer Electronics, Volume: 51, Issue: 3 Aug. 2005.

[9] Schulzrinne et el, "Comparison and optimization of packet loss repair methods on VoIP perceived quality under bursty loss",International Workshop on Network and Operating System Support for Digital Audio and Video,Proceedings of the 12th international workshop on Network and operating systems support for digital audio and video, ACM, 2002.

[10] Jia et el.," Multiple mode protection switching failure recovery mechanism under MPLS network", IEEE Second International Conference on Modeling, Simulation and Visualization Methods (WMSVM), China, 2010.

[11] Feamster et el, "Packet Loss Recovery for Streaming Video", M.I.T. Laboratory for Computer Science Cambridge, MA, 2005.

[12] Velibor Markovski, Fei Xue, and Ljiljana ,"Simulation and analysis of packet loss in video transfer using User Datagram Protocol",School of Engineering Science, Simon Fraser University, Vancouver, British Columbia, 2001.

[13] Mase, K.; Toyama, Y.; Bilhaj, A.A.; Suda, Y.,"QoS management

DOI : 01.IJIS.2014.1.4

for VoIP networks with edge-to-edge admissioncontrol",Global Telecommunications Conference, 2001. GLOBECOM apos;01. IEEE Volume 4, Issue, 2001.

[14] Yajnik et el,"Measurement and Modelling of the Temporal Dependence in Packet Loss", Computer Science Dpt. University of Massachusetts Amherst, MA, 2005.

DOI : 01.IJIS.2014.1.4