Adaptive Modelling of IP Packet Aggregation

Abbas Makki

Department of Electronic & Electrical Engineering, University College London
abbas.makki@ee.ucl.ac.uk

Abstract: DiffServ is characterised as an aggregation of flows where packets are classified into behaviour aggregates identified by the DS field in the IP header. Packets are then queued and forwarded based on their source and destination addresses and the DS field value. Modelling this aggregation adaptively would enable guaranteeing the QoS for the class of traffic the aggregation carries. A single flow is modelled by an ON-OFF source model [1,2,3]. An analytical solution has been developed in [4] for flows that are homogeneous and Markovian, where "N" flows are collapsed into a single equivalent ON-OFF source model. However, in real IP traffic, flows are heterogeneous and non Markovian. In this paper, a solution is presented to the problem by sampling the aggregation at such a rate to track the traffic variation (Burst ness). This is simulated by the ns-2 simulator. This rate of sampling proved to be so extensive and thus computationally expensive. To resolve the problem artificial neural network (ANN) is deployed, where during training the traffic is sampled at the most extensive rate to learn the characteristics or the pattern of the traffic, but in the normal estimating phase only limited number of snapshots are needed for the same end results. The integrating probabilistic RAM "ipRAM" ANN is employed for this purpose.

1- Introduction

Queuing behaviour arises at an output port of an IP router as multiple streams of packets from various input ports are multiplexed over the port. It can be safely assumed that the flows are independent as they are human triggered, but packet arrivals of individual streams and thus the aggregation at the output port, are proved to be highly correlated of Self-Similar nature [5, 6].

It is quite tedious and computationally expensive to analyse the aggregation at the flow level. So, it behoves us to model the aggregation at the aggregation level to economise on computation and in an adaptive manner to track the dynamic nature of the flows. Should this objective be met, it results in an accelerated method to simulate the flows and to optimise the use of network resources.

2. Mathematical Modelling of Heterogeneous Flows

In [4, Chapter 15], "N" number of such sources is collapsed to a single ON-OFF source model. The parameterisation in the ON and OFF states in the equivalent model is the mean of the incident traffic rates and times, and surely these can be measured should these times be known. Sampling the aggregate traffic at these times and measuring would prove to be an alternative method to obtaining the equivalent model. The number of samples and consequently number of measurements that need be taken proves to be massive. This in a way defeats the objective of not analysing at the flow level. However, it is only the means of these measurements that count, and quite a number of these samples may be skipped if the remaining number results in the same mean. This is a typical application of the use of artificial neural network (ANN). In the training phase the ANN trains on the most extensive number of samples, but in the estimation phase or normal operation, a limited number of snapshots are enough for the same end results within a small acceptable error. Having set the sampling rate for the homogenous set, a heterogeneous set of the same average rate value may be sampled by the same sampling rate. The rates that results in the two states (Ron and Roff) and there respective times (Ton and Toff) reflect the heterogeneous degree there is in the aggregation. So, for any heterogeneous set we can argue that there exist an equivalent homogeneous set of the same average source rate. The same argument applies when the sources are non-Markovian.

3- Accelerated Simulation by NS-2 [14]

3.1 The Homogeneous case (Case study)

Assume that there are N = 100 packet voice sources. Each source produces packets at a rate of h = 167 packets/s, when active. The sources feed a buffer of size = 100 packets at a service capacity C = 7302.5 packets/s. For each source the mean time when active is Ton = 0.35 second and when inactive is Toff = 0.65 second. Thus each source has, on average, one active period every T = Ton + Toff = 1 second.

3.2. Solution by the analytical method

The rate at which these active periods arrive is $F = N / (Ton + Toff) = 100\ s^{-1}$

The overall mean load Ap = F. Ton. h = 100 X 0.35 X 167 = 5845 packets/s

The offered traffic is: A = F.Ton = 100 X 0.35 = 35 erlangs

The maximum number of sources is; $N_0 = ?C / h? = 43$

The Erlang's loss probability $B = \{A^{No} / N_0!\} / {}^{No}\Sigma_{r=0} \{A^r / r!\} = 0.02814$

From which the conditional delay probability $D = \{N_0.B\} / \{N_0 - A + A.B\} = 0.13466$

$R_{on} = C + h\ A/\{N_0 - A\} = C + h\ .A_p/\{C - A_p\} = 7972.22$ pps & $R_{off} = (A_p - D.R_{on}) / (1\text{-}D) = 5513.98$ pps

$T_{(on)} = \{t_\omega /D\} = T_{on} /\{N_0 - A\} = h_e.T_{on} /\{C - A_p\} = 0.0401$ S & $T_{(off)} = T_{(on)}\ \{(1\text{-}D)/D\} = 0.25771$ second

From which $a = 1 - 1 / \{ T_{(ON)}\ (R_{on} - C)\} = 0.96277$ and $s = 1 - 1 / \{T_{(Off)}\ (C - R_{off})\} = 0.99783$

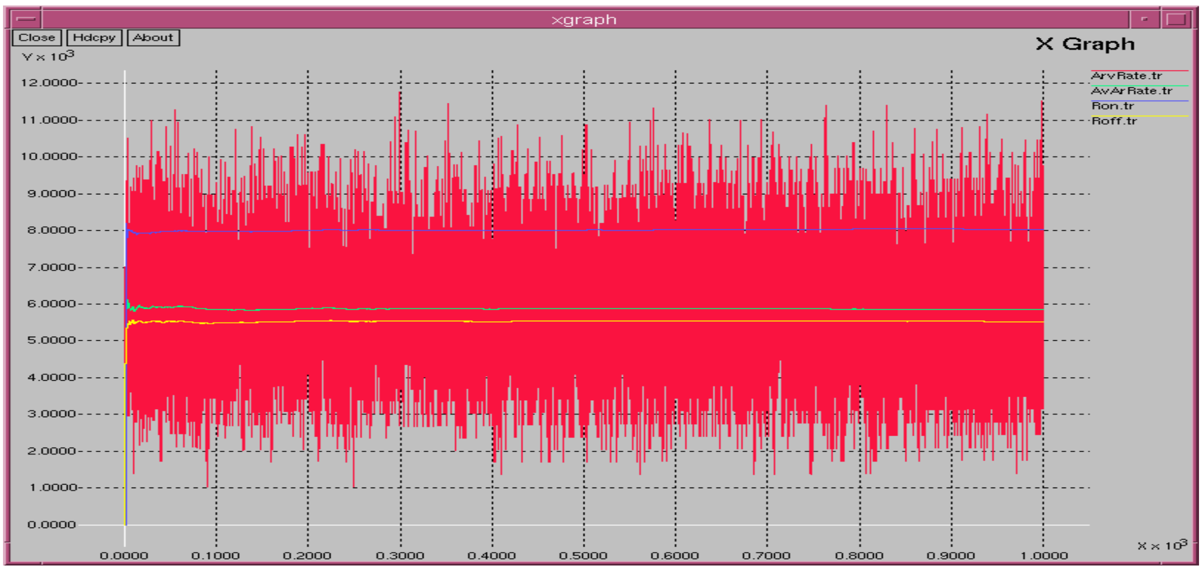
The decay rate = (a/s) = 0.96486

The probability that a packet is in excess rate arrival: P_r[packet is excess-rate arrival] = $h\ .D /\{C - A_p\}$ = 0.01543

And the packet loss probability: $Q(x) = \{\ (h.\ D) / (C\text{-}A_p)\}\{\ a/s\}^{x+1} = 4.16135 \times 10^{-4}$

3.3 Simulating the above example by ns -2

The ns-2 [22] is an object oriented simulator, written in C++, with an OTCL interpreter as a front end. A front end simulation program in the Tool Command Language "TCL" was written for the example above. The simulation in 1000 seconds of simulation time show good results, shown in figure 3.1, with an average sampling window converging to 0.00296 second from a priory based on the Nyquist rate of the sending source = (1/2h) = 0.002994 seconds.



- **Red : Sampled Packet Arrivals Green : mean Rate Ap Packets/S**
- **Blue : mean Ron Packets/S Yellow : mean Roff Packets/S**

Steady State Parameters

he = 167, Ap = 5844.6 pps, Ron = 7978.42pps
Ton = 0.04 S, Roff = 5491.8 pps Toff 0.25 S, NS = 43

Fig. 3.1 Simulation results by ns-2

4 The Integrated Probabilistic RAM based Artificial Neural Network

The Ron and Roff at the respective sampling times may be learnt by an ANN at the training phase. However, most samples need be skipped at the estimating phase. So, the ANN is arranged to train on sample difference in a predictive set up as shown in fig. 5.1.

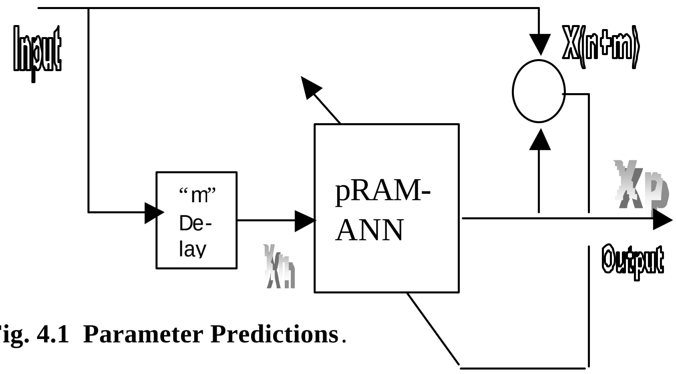


Fig. 4.1 Parameter Predictions.

4.1 **Reported Results**:

The trace file Sampled Arrival Rate "ArvRate.tr" is given to the program as input with number of samples per source period = (1/ step size) = (1/0.00296) = 338 samples. The output is stored in files Train.tr and Estimate.tr. In the training phase the Train.tr shows each sample trained the network to an error of 0.1 % and gives the Ron and Roff values almost exact.

In the estimate phase with the same ArvRate.tr file skipping 10 samples between readings, the estimated results Ron and Roff were almost exact to the calculated values.

For example, on running a small portion of the Arrival rate file "ArvRate.tr" for one second, the table below outlines the results.

File Name	Ron	Roff	Size of File
TrainRate.tr	8031.5	5831.3	400
EstRate.tr	8036.7	5823.6	40
Percentage error	-0.065	0.13	

It is clear that the file is reduced to one tenth for a worst error of 0.13 %. Roff is most affected because it is of the largest number of samples and consequently variations.

5. Conclusions

In this paper it has been shown that a DiffServ aggregation may be modelled as an aggregate by collapsing "N" ON-OFF source models into a single effective ON-OFF source model. It has been shown that the effective model may be arrived at by measurement through sampling the arrived traffic to a FIFO queue. The amount of sampling, 400 samples per second, proved to be extensive to track the variations of the arrived traffic assumed in this paper as homogeneous and Markovian. The massive number of samples is proved to be reduced by a factor of at least ten, 40 samples per second, by the use of artificial neural network "ANN" based on the integrating probabilistic RAM "ipRAM".

This research would find applications in accelerated simulation of DiffServ traffic as it models the aggregation as a set with an effective source rate "h". Since, it is measurement based not tracking the flows, the model is expected to be accurate and effective whether the flows are homogeneous or heterogeneous Markovian or non Markovian. Further, the Model is adaptive by the use of the ANN, and therefore provides optimal match between offered traffic and network available resources.

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