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Performance of Gaussian and Non-Gaussian Synthetic Traffic on Networks-on-Chip

Amit Chaurasia, Jaypee University of Information Technology, Department of Computer Science and Engineering, Waknaghat, India

Vivek Kumar Sehgal, Jaypee University of Information Technology, Department of Computer Science and Engineering, Waknaghat, India

ABSTRACT

In this paper, we have worked on the bursty synthetic traffic for Gaussian and Non-Gaussian traffic traces on the NoC architecture. This is the first study on the performance of Gaussian and Non-Gaussian application traffic on the multicore architectures. The real-time traffic having the marginal distribution are Non-Gaussian in nature, so any analytical studies or simulations will not be accurate, and does not capture the true characteristics of application traffic. Simulation is performed on synthetic generated traces for Gaussian and Non-Gaussian traffic for different traffic patterns. The performance of the two traffics is validated by simulating the parameters of packet loss-probability, average link-utilization & average end-to-end latency shows that the Non-Gaussian traffic captures the burstiness more effectively as compared to the Gaussian traffic for the desired application.

KEYWORDS

Gaussian, Hermite Process, Loss-Probability, Non-Gaussian, Self-Similarity

INTRODUCTION

Today the NoC with increasing number of cores becoming universal solution in solving the problem of all kinds of communication ranging from the computer data of binary patterns or the simple communication, consisting of voice and video data in multicore architecture. The characteristics of traffic helps in elucidating the performance and optimization of the communication resources such as buffer-size etc. which helps the designer to choose optimal resources during the early design process of the architecture. Recent study shows the performance of self-similar traffic on the NoC where the distribution of the traffic is Gaussian in nature, whereas study shows that the real-time applications have the Non-Gaussian marginal distribution. The initial study of traffic model shows the self-similar application traffic with Long Range Dependency (LRD) variability for the multimedia application. It has been found the real-time internet traffic consist of Non-Gaussian nature of marginal distribution (Mori, Kawahara, & Naito, 2002) and most of the traffic whose skewness are evaluated

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are positive i.e. most traffic concentrated in the left direction of the mean and its right side is having a tailed distribution. The first study where the performance of the marginal distribution and the network performed on the fluid traffic model (Grossglauser & Bolot, 1999) having the Long Range Dependency (LRD) traffic. Ribeiro et al. (Ribeiro, Riedi, Crouse, & Baraniuk, 1999) generated the Non-Gaussian LRD traffic using the principle of multifractal wavelet model demonstrates the performance of generated traffic on queueing packets.

We have found the traffic generated from the Norros method (Norros, 1995) generating the fractional brownian motion, Varatkar et al. (Varatkar & Marculescu, 2004) generating the self-similar traffic for multimedia applications and Taqqu et al. (Willinger, Taqqu, Sherman, & Wilson, 1997) generating ON/OFF period traffic with heavy-tailed distribution, all are having its marginal distribution Gaussian in nature. Internet traffic and its anomalies in order distinguish between DDoS attacks and flash crowds, the Non-Gaussian traffic model is generated having the LRD properties studied in (Scherrer, Larrieu, Owezarski, Borgnat, & Abry, 2007), here the statistical network traffic is generated having the first and second-order statistics. But all the studies for Non-Gaussian traffic is found for the internet traffic, no studies have been done in order to calculate the performance of On-Chip networks under Gaussian and Non-Gaussian traffic.

GAUSSIAN AND NON-GAUSSIAN

To distinguish between the Gaussian and Non-Gaussian traffic we have taken two parameters one is Skewness & Kurtosis. Skewness represented in Equation 1 measures the orientation or the asymmetry the bell-shaped distribution about its mean, if it's value is positive, then most the distribution are longer and flatter on the right of the mean as compared to its left, otherwise for the negative value the distribution is are longer and flatter on the left of the mean as compared to its left. Kurtosis is another parameter similar to Skewness which measures the peakedness of the distribution represented in Equation 2:

$$s = \mu^3 \,/\, \sigma^3 = E\left[W-\mu\right]^3 \,/\left[E\left[W-\mu\right]^2\right]^{3/2} \tag{1}$$

$$k = \mu^4 \,/\, \sigma^4 = E\left[W-\mu\right]^4 \,/\left[E\left[W-\mu\right]^2\right]^{2} \tag{2}$$

where μ, σ and W are the mean, standard deviation and the distribution respectively.

The value of these two parameters decides the nature of traffic if the value of Skewness is equal to 0 and of Kurtosis is 3 then the distribution of the traffic is Gaussian otherwise it is Non-Gaussian. As from the Table 2 we have taken four traces of each for Gaussian and Non-Gaussian traffic, the Skewness values of all four traces for Gaussian traffic is almost 0 and its Kurtosis is almost 3 i.e. the traces are not purely Gaussian but very near to be called Gaussian, whereas, for the Non-Gaussian traces the values Skewness is not near to 0 and same with the values of Kurtosis is not near to 3.

In Mandelbrot et al. (Mandelbrot & Wallis, 1969) is the first studied about the self-similarity which is the principle in which certain objects, for example- a time series data is preserved with respect to scaling in time or space i.e the nature of the data is same if there is change in time or scale. When the self-similar sub objects are magnified then they resemble the shape of the whole object from which it is originated. An example is taken from (Park & Willinger, 2000) from Chapter 1 to understand the notion of self-similarity in which the iterated function used to generate self-similar fractals. The zoomed part of each of the sub objects fractal from the figure shows the resemblance from the full-figured image coin or justify the term of self-similarity. Using the principle of self-similar sub objects