Traffic Characterisation for Telecommunication Networks

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1. Introduction

One of the most important research issue of the evolving B-ISDN (Broadband Integrated Services Digital Network) is the characterisation of the traffic. The efficiency and feasibility of the designed ATM (Asynchronous Transfer Mode [1]) based worldwide high speed networks strongly depends on the nature of the traffic thereby there is an urgent need to find appropriate traffic models which are able to capture the profiles of the new traffic types appeared in B-ISDN but on the other hand they can also be applied efficiently in practical network designing and dimensioning tasks [2][3].

At present there are only a few measurements from real ATM networks and these are mostly from some experimental ATM pilots working with restricted services and users. Moreover it is quite a challenge to predict the nature of the traffic in future services. In spite of these difficulties of traffic modelling numerous models have been developed in the last decade. In this paper we give a brief overview of the most important traffic models and two successful modelling directions are presented in more detail.

2. Overview of Traffic Modelling

In the traffic source characterisation the following fundamental parameters are used which are also recommended by ITU [4]:

- *Peak cell arrival rate* which is defined as the reciprocal of the minimum interarrival time between two consecutive cells belonging to the same connection.
- *Average cell arrival rate* which can be characterised by the True Average Cell Rate (the number of cells generated during a connection divided by its duration) or the Estimated Average Cell Rate (the number of cells generated during a long time interval divided by the length of the interval).
- *Burstiness* which can be defined as the ratio of the peak and average cell rate but several other burstiness measure are also exist (see Chapter 4.3).
- *Average duration of active state*

There are various different parameters which are not mentioned here like burst length, average interarrival time between two consecutive bursts, etc. but these are mostly equivalent parameters of the presented list.

A simple model of a data source is the *Bernoulli model.* In this model a cell is generated in a slot with a fixed probability p, independently of the past history. This provides a simple renewal process with geometrically distributed interarrival times. For exponential interarrival time we get the well-known *Poisson process* while allowing any distributions we have the whole set of *renewal processes* for traffic characterisation. In data traffic modelling the so called *ON-OFF models* are also widely used where the cells are generated only in active periods. In order to capture the correlation structure of the traffic the *Markov modulated processes* are frequently applied.

In voice traffic modelling an important group of services is the CBR (Constant Bit Rate) services where cells are generated at a constant rate. However, another group of applications which utilises that almost 65% of the speech conversation involves no talk can yield to VBR (Variable Bit Rate) services where both the talk and idle periods are approximated by capturing the talkspurt statistics. The *IPP* (Interrupted Poisson Process) is a simple model for VBR speech communication.

In video communications most of the services are VBR services and the one of the most important characteristics to be captured is the autocorrelation function of the traffic. *ARMA* (Autoregressive Moving Average) processes, *Markov models* or are intensively used for modelling video sources.

In the following two promising modelling approach are presented. The first one is the *phase type model* which can successfully be used in modelling different source types providing the facility that any interarrival time distribution can be captured by phase type models. The second approach uses *fractal models* and it is intended to cope with the nature of some data communications where self-similarity is detected.

3. Phase Type Traffic Models

3.1 The phase type distribution

The *phase type (PH) distribution* [5][6][7] represents the first passage time distribution of a Markov chain. The essence of the Markovian property is that the process is memoryless. It means that each state of the process depends only on the previous one, therefore the process can be described simply by its intensity matrix. In practice, traffic

models are based on Markov processes which have discrete state space. The phase representation of a typical Markov chain is depicted on Fig 3.1.

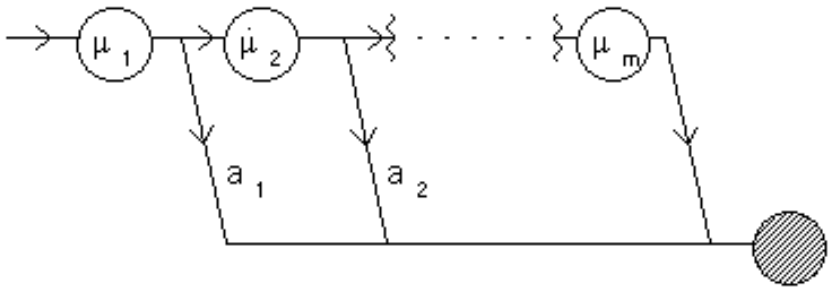

Fig 3.1: Phase representation of an m+1 state Markov chain with an absorbing state

As the main advantage of the phase type distribution, it must be emphasised that, in theory, this sort of distributions can be used for approximating any types of distributions with arbitrary accuracy and it is also computationally tractable if the number of the phases is not too large.

On the basis of the PH distribution one can define the so-called *PH renewal process* [5, 6, 7] in a way that after an arrival at the absorbing state the process is restarted according to an initial probability vector ($\underline{\pi}$). Each element of this vector provides the probability of returning to a certain state of the process. A simple example (phase representation) of the PH renewal process is shown on the figure below.

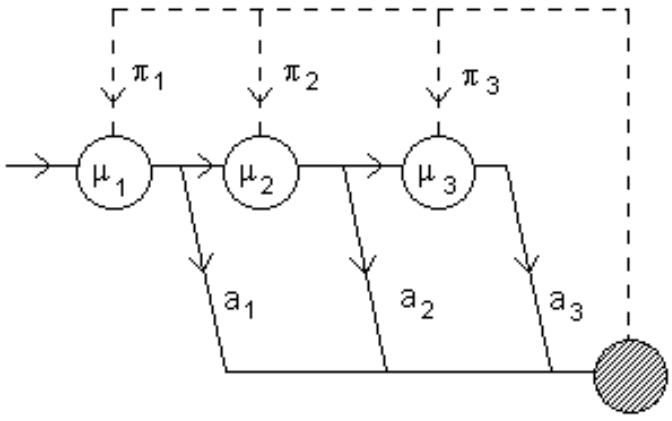

Fig 3.2: Phase representation of the PH renewal process

It can be seen from the phase representation diagram that the PH distribution can be considered as a kind of generalisation of the Erlang type exponential distribution since more than two states are involved in this model connected by branching probabilities.

3.2 Phase type queueing models

In case of *PH/PH/N queueing models*, both the arrival and the service process is described by PH distribution and *N* means the number of servers. In the course of setting up the model, first we consider the arrival and the service process independently, than we construct the complex model [6].

Fig 3.3: Method of the construction

The arrival process of the *PH/M/N queueing system* is considered as a PH renewal process, while the service process is of exponential type. Three kinds of transitions can be distinguished in the system:

- an arrival occurs (i.e. the PH renewal process reaches the absorbing state),
- the number of customers is not changed in the system (only an internal transition takes place),
- one customer leaves the system.

According to the three types of transitions we can define three matrices describing these cases (which are *UP-A*, *SAME-A*, *DOWN-A*, respectively).

The *M/PH/N queueing system* is constructed in a way that the arrival process is Poissonian and the service process is modelled by identical PH distributions. Although these distributions can also have different sizes or different parameters (inhomogenous servers) it would make the computations much more difficult. Just like in case of the PH/M/N queueing system three different types of transitions can be observed:

- if there were any idle servers before the transition then one more server becomes idle as a consequence of the service,
- if there were more customers in the system than the number of servers then after the transition all of the servers remain busy (since this case means only an internal event),
- the number of customers can also increase according to the Poissonian arrival process.

On the basis of the events mentioned above one can construct three types of matrices (which are *DOWN-S*, *SAME-S*, *UP-S*, respectively).

Any state of the PH/PH/N queueing system can be described by the following triplet:

- the number of customers in the system,
- the state of the arrival PH process,
- a quantity describing the overall state of the servers.

After the composition of the transition matrices of the PH/M/N and the M/PH/N models we can use them for the analysis of the PH/PH/N system. From these matrices we can derive the intensity matrix which enables us to solve the linear equation system and we can obtain the steady state probabilities of the queueing system. Applying the solution of this equation system we can determine numerous performance measures, some of them are listed below:

- *Time Congestion* (the probability of having no idle server),
- *Call Rejection* (the probability that a customer is not being served at all),
- *Calls Queueing* (the probability that a customer joins the queue before being served).

3.3 A program package for analyzing phase type queueing models

The algorithm presented above has been implemented in a software package [8]. The main concern of our analysis program is to facilitate the computation of the performance measures of the PH/PH/N queueing system. It is also important that this program makes it possible to easily keep track of the parameters' effect on these measures.

The main steps of specifying the queueing system are the following:

- first of all we have to specify the quantities which determine the sizes of the PH/PH/N queueing system (these are the number of phases in the arrival and the service process, the number of servers and the buffer size), since these are the parameters upon which all the additional parameters to be defined depend. In case of a PH/PH/N system a PH renewal process describes the arrival traffic. The operation of the identical servers can be characterised by a PH process. These quantities can be set up in a dialog box of the program.
- when the number of phases of the processes have already been specified, the program can select the proper phase diagram scheme. As a second step, hence, we can define the arrival and the service process by typing in the values of the intensities connected

to each phase and the branching probabilities. The three-phase scheme is shown on Fig 3.4:

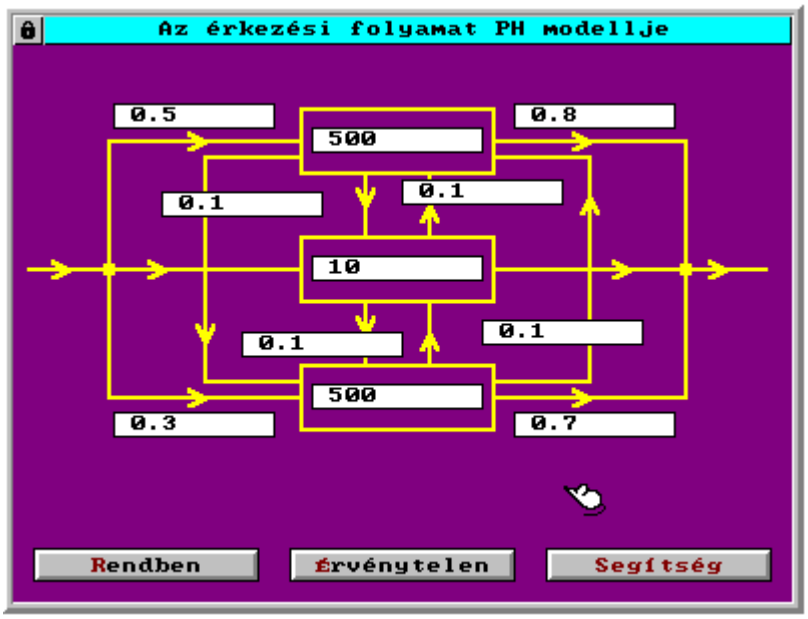

Fig 3.4: Set up dialog box

The elements of the initial probability vector can also be set in this dialog box. The group of parameters mentioned so far are sufficient to characterise the whole PH/PH/N queueing system.

- having set all of the parameters of the system, finally we can have the performance measures computed by the program. The results of the computations can be visualized after the program has solved the equation system and computed the steady state probabilities.

4. Traffic Characterization Based on Fractals and Chaos

4.1 Fractals and chaos

The fractal geometry and the chaos theory have been developed dinamically in the last decades. They belong fundamental to mathematics, but they can not be delimited from some areas of the physics and chemics. One of the applications of these theories is the traffic modelling of telecommunication networks. The fractal geometry and the chaos theory have created a new approach. By means of this challenging approach some phenomena of teletraffic can be characterized which cannot be easely treated by classical

models. We will discuss the basic notions of fractals and chaos theory and examine the possibilities of mathematical modelling of fractals and chaos.

Fractals, Self-Similarity and Chaotic Systems

Fractals have many properies, that differ from the properties of conventional euclidean objects. The conventional mathemetical apparatus could not describe these different features, therefore new notions had to be created. The word *fractal* was constructed by B. B. Mandelbrot [10].

Self-similarity is the fundamental property of fractals. By definition, a set is self-similar if it consists of pieces that are similar to the whole. This property is very important for us in the examination of packet traffic. The topic is discussed in detail in Chapter 4.4.

There are several ways to characterise fractals. The *dimension* is the most important for us. There are several dimensions in matematics, for example the topological dimension, box dimension, Hausdorff dimension, capacity dimension, etc. [9]. In some cases there is a connection among these dimensions, but in certain cases they have different values. The fractal (or Hausdorff) dimension can characterize fractals [9]. This is a general notion of dimension, that has an integer value for the conventional Euclidean object, and has a fractional dimension for fractals. The *correlation dimension* is in relationship with the fractal dimension and it can characterize the packet traffic, so this dimension is very important for us in practice. We will see and discuss it in Chapter 4.3.

There are dynamical systems with unpredictable behaviour, although the laws of the system is deterministic. The fundamental property of these systems is *the sensitive dependence on the initial conditions* (SIC). It means, that the distance between two states grows rapidly, although the two initial states were close together. The connection between these chaotic systems and fractals is that the chaotic systems are usable to generate fractal structures, i. e. the attractor of a chaotic system is a fractal.

4.2 The fractal nature of packet traffic

Recent measurement studies have demonstrated that the traffic of some packet-switched networks is different from the traffic of circuit-switch networks. Examinations of several packet traffic show the following features which are not captured by conventional stochastic models [11] [12] [13].

1. *Self Similarity*: A process is called "bursty" if the number of arrivals in successive time intervals exhibit substantial random variability. In such processes packet arrivals mostly occur during specific time intervals called "burst" periods. Self similarity refers to the "burst within burst" structure observed over a wide range of time scales (10 ms through hours).

2. *Heavy Tailed Interarrival Densities*: A basic feature of the examined traffic is the distribution of the packet interarrival times. In most existing theoretical models, this distribution decays exponentially. In contrast, interarrival densities of actual traffic processes decay much more slowly, as power laws.

3. *Infinite Moments*: A consequence of the power law decay in interarrival times is that moments above a certain order may not exist, i. e. they are infinite. (In some cases even the mean does not exist.)

4. *Long Range Dependence*: The autocovariance function of conventional traffic processes decays exponentially, and correlations are assumed to exist for only short time scales. In contrast, correlations in packet traffic processes can span many time scales.

5. *1/f Noise*: This is a frequency domain manifestation of long range dependence. The power spectra of real traffic processes diverge at low frequencies, in contrast to widely used theoretical models that are flat (nearly zero value) at low frequencies.

6. *Fractal Dimension*: Conventional traffic processes are characterised by a dimension of 1, according to several commonly used measures. Over time scales of engineering interest actual traffic is observed to have fractal dimension ($D<1$). (See Chapter 4.3. in more detail.)

These properties are associated with fractals and self similar processes [10] rather than conventional stochastic models, therefore we call these fractal properties.

4.3 Fractal measures of traffic burstiness

Numerous measures of burstiness have been proposed over the last two decades, such as peak to mean ratio (PMR), the average burst length, the squared coefficient of variation (CSQ), the peakedness and so on. [12] In this paper we will use the PMR and CSQ to compare with the correlation dimension.

The peak to mean ratios are - as the name implies - calculated by taking the ratio of peak rate to an average rate over a predefined rate measurement interval. PMR are widely used as a measure of burstiness but, however, somewhat arbitrary because the peak rate sensitively depends on the time interval over which the measure is made and the overall length of the observation interval. The squared coefficient of variation is defined as the ratio of the variance and the square of the mean of the interarrival times: $CSQ=\sigma^2/\tau^2$. CSQ is widely used as a measure of burstiness too. But the estimation of CSQ requires measurement of the interarrival times, and CSQ is typically not included on on-line network measurements. The CSQ of Poisson traffic is 1, and higher CSQ corresponds to increasing burstiness.

The impact of the fractal properties of packet traffic is that measures such as CSQ, variance and even the mean may not exist for the interarrival process (See Chapter 4.2). The practical consequence of this that these measures may increase unboundedly as the observation interval increases, rather than converge to some value. Thus CSQ can often be arbitrary, sensitively depending on the length of the observation interval.

To summarise, many of the existing models consider packet traffic as alternating active and silent periods with well defined statistics. This can be described in mathematical terms easily, but it is not an accurate representation of actual packet traffic. Informally, there is no natural burst length, and bursts occur over a wide range of time scales, at every time scale closer examination of that shows that an apparent busy period resolves into smaller busy periods separated by idle intervals. Such “bursts within bursts” (or self similar) structure is a fundamental property of packet traffic. Conventional models cannot quantify this self similar structure, (or at least without considerable complexity, i.e. many parameters) but fractal models do so. In theory any of the fractal properties listed in Chapter 4.2 is adequate but possibly the fractal dimension is the most descriptive and easy to calculate. [12]

The Dimension and the Correlation Dimension

A measure can be used to give a number or size of a set. A dimension is an indication of the extent to which a set or an object, by some measure, fills the space in which it is embedded.

The notion of a dimension can be applied for a traffic arrival process by considering the set of arrival time instants, and seeing to what extent the arrivals “fill” the time line. Smooth traffic processes such as Poisson arrivals, are spread out over the time line, whereas packet traffic processes occur in bursts interspersed with long idle periods.

Intuitively, bursty processes "fill" the time line to a smaller extent than smooth processes, and can be expected to have a lower dimension than smooth processes. It is the intuition that is quantified by a calculation of the fractal dimension of the traffic processes. Depending on the measure used, one can in fact define several fractal dimensions. We use the notion of correlation measure, and the associated correlation dimension, which is widely used in practice [12].

The correlation measure $C(t)$ of a point set is defined as the fraction of the numbers of pairs of points that are less than a distance t apart. $C(t)$ can be calculated from the following equation:

$$C(t) = \sum_{i=1}^{M} \sum_{j=1}^{M} \frac{1}{M^2} \times C_{ij}$$

where: M is the number of points in the set, and C_{ij}=1, if the time between arrivals i. and j. is smaller than t, otherwise 0.

$C(t)$ can be interpreted as the probability that a pair of arrivals occur within a time interval t. The correlation dimension [14]:

$$D_c = \lim_{t \to 0} \frac{\log C(t)}{\log t}$$

In practice, *C(t)* is calculated for a range of t values, and it is seen if *C(t)* follows a scaling relation of the type for some range of t [12]:

$$C(t) = \lambda t^{D_C}$$

This scaling relation is indicated if the log$C(t)$ vs. log$t$ plot is linear for a range spanning several orders of magnitude of t. The slope of the best linear fit to the log$C(t)$ vs. log$t$ plot is then taken to be estimate of D_c. Computation of the correlation dimension converges fairly rapidly, and good estimates are possible with data sets as few as 10^3 points.

4.4 Traffic modelling by chaotic maps

There are two ways to describe self-similarity. The first possibility is using stochastic models. Several stochastic processes exist which possess the self similar feature (i.e. fractional Gaussian noise, fractional *ARIMA (Autoregressive Integrated Moving Average*) processes) The second way to model self-similar packet traffic is based on the

application of deterministic chaotic maps [15]. We can illustrate the main idea behind this approach by using a nonlinear *f(.)* function, which describes the evolution of the state variable $x_n \in (0,1)$ in discrete time. The $x_{n+1}=f(x_n)$ expression gives the next value of the state variable at the next time instant. We can now model a packet generation process by stipulating that the source generates a packet or a silent interval at time *n* depending on whether x_n is above or below a threshold. (see Figure 4.3). If *f* is a chaotic map, the sequence of packet generations can mimic complex stochastic processes. Erramilli and Singh (1992) show that a simple, two parameter nonlinear map referred to as the *intermittency map* [15] can capture the fractal properties of packet traffic.

Chaotic systems differ from the conventional dynamical systems because they are unpredictable despite that the laws which describe the system are deterministic. The main feature of chaos is the sensitivity on initial conditions (SIC) which means that starting the system from two arbitrarily near states the states diverge exponentially from each other.

The chaotic map can be written as follows and introduce the so called indicator variable y_n:

$$x_{n+1} = \begin{cases} f_1(x_n), & 0 < x_n \le d \\ f_2(x_n), & d < x_n < 1 \end{cases}, \qquad y_n = \begin{cases} 0, & 0 < x_n \le d \\ 1, & d < x_n < 1 \end{cases}$$

For the map to be chaotic, $f_1(.)$ and $f_2(.)$ must satisfy the SIC condition. (The formula is deterministic, that is an initial condition determines the process unambiguously.)

The source is in active or passive state at the time instant *n* depending on whether y_n is 0 or 1. The choice is arbitrary. We could choose a limit value for y_n different from *d* or even the dynamical system could generate inter-arrival times directly.

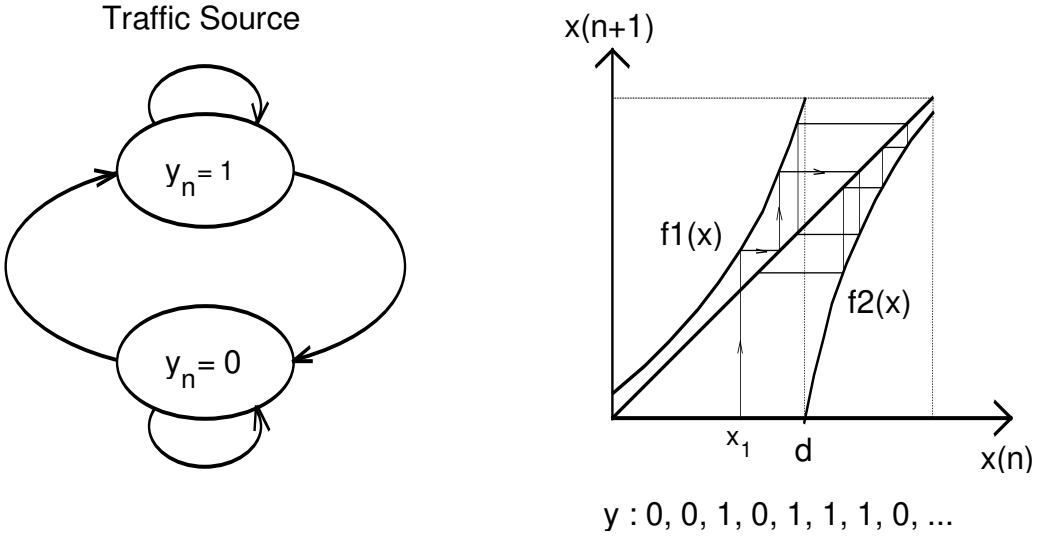

Figure 4.3: Chaotic maps as traffic source models.

In practice y_n can be observed but x_n is a hidden variable of the system. The real challenge is to find the appropriate $f_1(.)$ and $f_2(.)$ functions to adjust the model to the observed traffic. (i.e. *Bernoulli Shift*, *Liebovitch Map*, *Intermittency Map*, etc.) [15]. Using piecewise linear maps (i.e. $f_1(.)$ and $f_2(.)$ are linear) the model can be fitted to the existing traffic models [15]. The real power of the chaotic map approach lies using nonlinear segments. Using a simple quadratic function for $f_1(.)$, referred to as the intermittency map can capture the fractal properties of packet traffic (i.e. fractal dimension) [11].

The advantage of chaotic maps is that that they can capture various features observed with actual packet traffic data, with a relatively small number of parameters. The chaotic map approach may be well suited to study the performance implications of fractal arrival processes ("*fractal queuing*").

4.5 Analysis of traffic measurements

During our work we analysed two data sets. We have made some measurement on an Ethernet LAN [16] and analysed those data. In addition, we obtained some public data, which data contained the results of a four-year-long measurement at the Bellcoce Morristown Research and Engineering Centre [12]. In this chapter we describe the methodology of the analysis in more details.

DTT-TUB Data

Network Environment: The measurements were made in the High Speed Network Laboratory of the Department of Telecommunications and Telematics at Technical

University of Budapest. We measured the traffic of a backbone-network consisting of three LANs of three departments. The environment is typical of a research or software development environment where workstations are the primary machines on people's desk.

The majority of machines are Novel servers and IBM PCs but there are several RISC-6000s connected to the network. There is also a Token Ring LAN in one of the laboratories connected to the backbone, too. All the one and a half hundred terminals and workstations are connected to 8 or 10 servers generating considerable traffic on local segments. The servers connected to the backbone are routers simultaneously, so only those traffic flows through over the backbone where the source and destination are not on the same segment. The backbone itself is a thick Ethernet segment which is connected to the FDDI ring via a multiport bridge, which ring is connected to the InterNet.

Traffic Monitor: For monitoring the traffic we used a Siemens K1102 Protocol Tester. The K1102 unit consists of a hardware part, which hardware can be inserted into an IBM PC, and a related software part. With the help of this equipment we were able to register the time stamps, the length and the first 32 bytes of all the frames occurring over the network. The time stamp accuracy is 10μs. The limit for the measurement time was the finite capacity of the PCs hard disk. We chose 60 minutes long measurement periods for further analysis.

Bellcore Data

Network Environment at Bellcore: During the measurement there were about 140 hosts and routers connected to the intra-laboratory network, of which 121 spoke up during the 27 hour monitoring period. The network consisted of two cable segments connected together with a bridge, implying that not all the traffic on the network as a whole was visible from the monitoring point. During the period the data was collected, among the 25 most active hosts were two DEC™ 3100 fileservers, one Sun-4™ fileserver, six Sun-3™ fileservers, two VAX™ 8650 minicomputers, and one CCI Power 6™ minicomputer. [12]

Traffic Monitor: Earlier Ethernet studies used time measurements with low resolution and (relatively) high loss rates (1% to 5%). Between 1989 and 1992, Leland and Wilson were able to collect very high quality, high time-resolution LAN traffic data at Bellcore using a custom-built Ethernet monitor. They were able to record hundreds of millions of Ethernet packets without loss, and with recorded time-stamps accurate to within 100μs.

Leland and Wilson (1991) present a preliminary statistical analysis and comment in detail on the presence of "burstiness" across a wide range of time scales.

Statistical Characteristics of Ethernet Traffic

Packet-length Distribution and Interarrival Time Distribution

The packet length distribution diagram (see Figure 4.4) was calculated from a segment of the EST02 (25. Oct. '94, 18:30-19:30) data set, which data was collected from the network at DTT-TUB. The whole set consists more than 1 million time stamps and the total time of the measurement was 1 hour. The distribution is typical for Ethernet traffic.

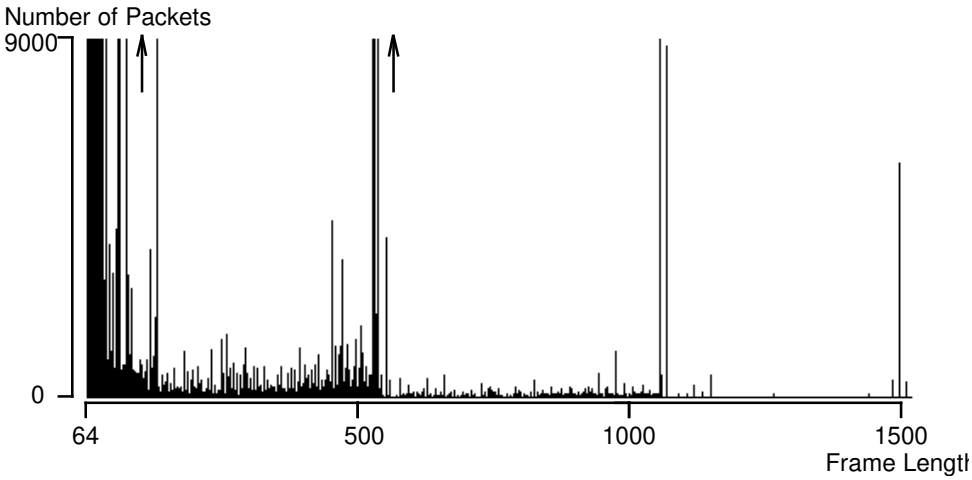

Figure 4.4: Ethernet packet length distribution

Analysing the distribution, one can find that certain packet lengths occur more frequently. The reason for this behaviour is that there are different protocols using different packet sizes over the data communication. The short (64 byte long) packets are related to the interactive communications, the middle size packets are used by the NFS (Network File System) protocols and the maximal size (1540 byte) packets are mostly used by file transfers.

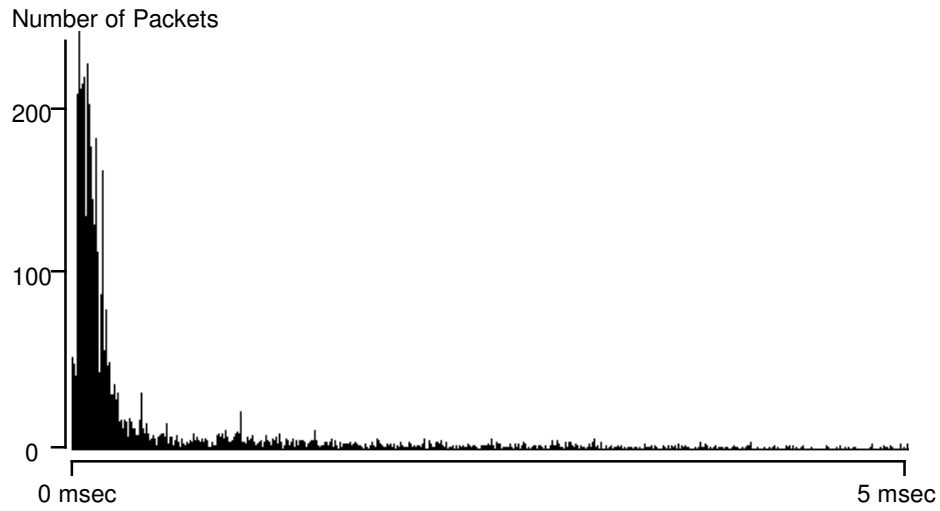

Figure 4.5: Interarrival time distribution

At first glance and without any numerical analysis one can only state that in contrast to the first fast decaying of the distribution the 'tail' of the histogram decays slowly, or in other words, relatively long silent periods occur with positive possibility. Further analysis of this behaviour could reveal more information about the fractal behaviour of Ethernet traffic (see Chapter 4.2, second fractal property).

Examining Self Similarity

In the following, we would like to reveal the fractal properties of packet traffic by analysing the measured data. At first, some qualitative statements are presented, and after that we verify the qualitative results ourselves by quantitative statements with the help of calculating the correlation dimension.

For the qualitative study we chose the 'p.Aug.tl' data set from the Bellcore data [18]. By looking at the network load as the function of time, we could find an interesting behaviour. Figure 4.6 *(a)-(d)* depicts a sequence of simple plots of the packet counts for four different choices of time units. Starting with a time interval of 30 minutes *(a)*, each subsequent plot is obtained from the previous one by increasing the time resolution by a factor of 10 and by concentrating on a randomly chosen subinterval (indicated by a lighter shade).

Surprisingly, all four plots are intuitively very "similar" to one another in a distributional sense (apart from the irritating quantization effect associated with the finest resolution level, plot *(d)*). If we cover the scale of the co-ordinates, the plots are indistingvisable from each other.

According to the definition of self similarity (see Chapter 4.1), a set is said to be self similar when it can be assembled from a finite number of part similar to the whole set. In the sense of this statement, Ethernet traffic is self similar and this self similarity is present at many time scales, (four in this example). This scale-invariant feature of Ethernet traffic is drastically different from stochastic models for packet traffic currently considered in the literature. The conventional models typically produce plots of packet counts which are indistingvisable from white noise after aggregating over a few hundred milliseconds, as illustrated in Figure 4.6. *(e)-(f)*.

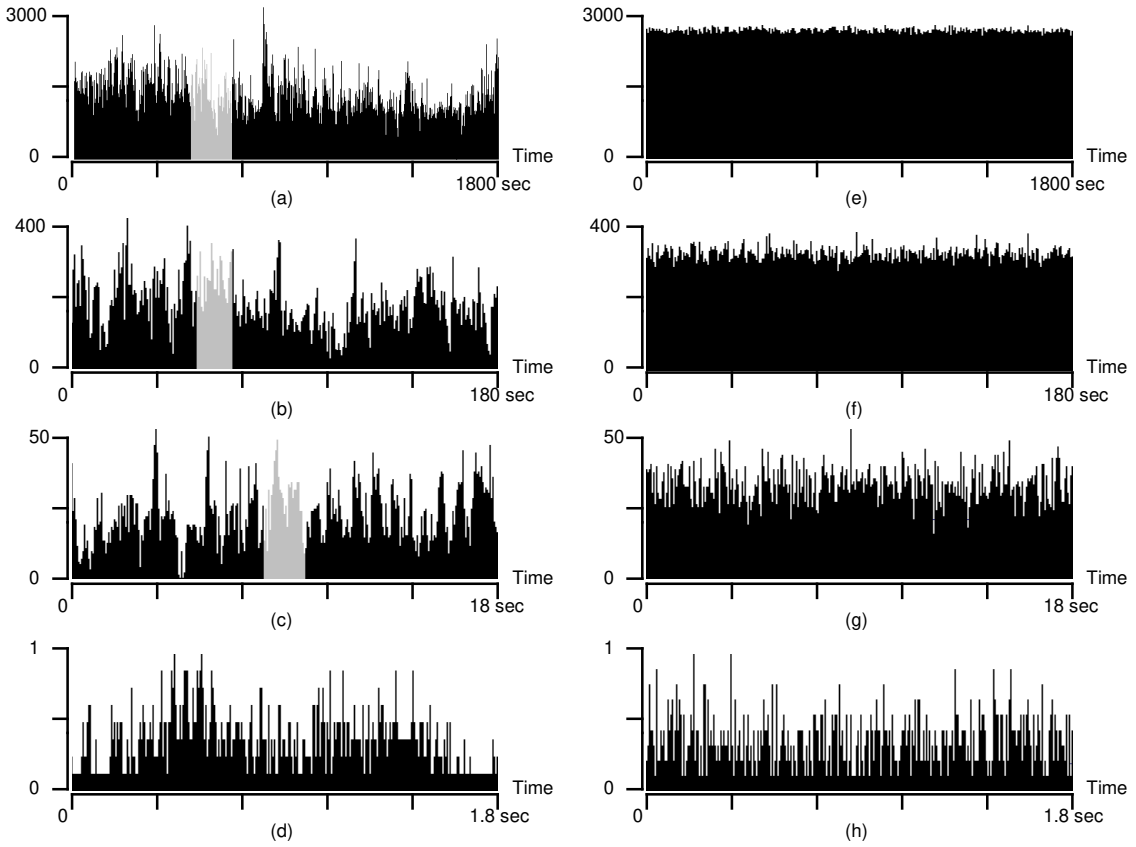

Figure 4.6: Analysis of Ethernet (a-d) and Poisson (e-h) traffic.

The sequence of plots *(e)-(f)* was obtained in the same way as the sequence *(a)-(d)* except that it depicts 'artificial' traffic generated from a Poisson process. The time interval and the expected value of this Poisson process was set to be identical to the real measured traffic and we used the same steps creating the plots. If we compare the two columns of Figure 4.6, the difference is clear between the measured Ethernet data and traffic generated by a Poisson process: in contrast to the measured data the Poisson traffic begin to 'smooth out' while the time resolution decreases. (It can be mentioned that even more complicated Markovian arrival processes would produce plots indistinguishable from *(e)-(h)*.) [18]

In the following section we quantify our statements using the notion of the correlation dimension (see Chapter 4.3). For further analysis we chose the 'pAug.tl' data set from the Bellcore data and a regression line was fitted to the points of log*C(t)*-log*t* graph (see Chapter 4.3).

As a result, we found that the correlation dimension calculated from the measured Ethernet data is about 0.9, and that is in contrast to the correlation dimension of the traffic generated by conventional models (i.e. Poisson process) which is equal to 1. To present the results, the most descriptive way to do this is to present it graphically. Figure 4.7. shows the plot of the correlation measure (*C(t)*) as a function of time for both - the measured Ethernet and the Poisson - data sets. It can be seen that the slopes of the linear segments differ from each other.

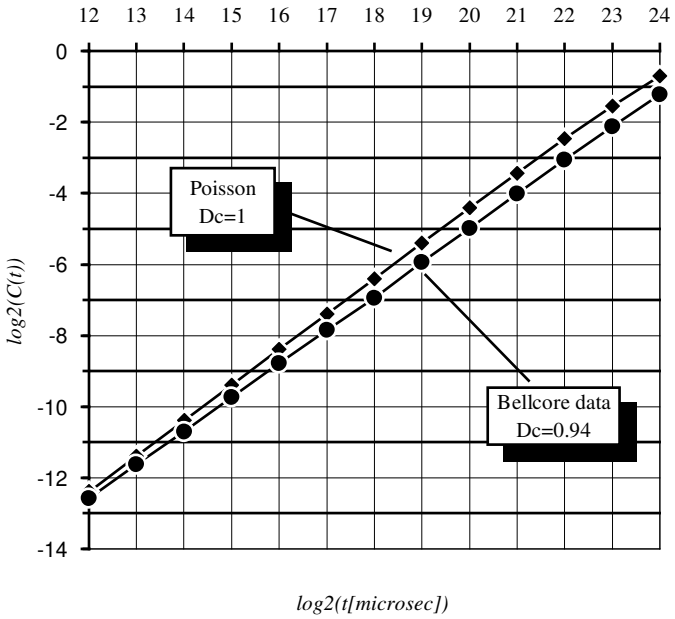

Figure 4.7: The Correlation Measure and the Correlation Dimension.

The difference between the slopes of the to fitted line means that the correlation dimensions for the data sets are different, too. This difference can be the evidence for the presence of self similarity in packet traffic.

As a summary, we could say that some signs of self similarity show up in Ethernet traffic. The self similar property can likely be detected in high speed, broadband networks (i.e. B-ISDN) more strikingly. It is among our aims to extend the measurements to experimental ATM networks and to analyse another fractal properties.

5. Conclusions

The modelling of traffic sources of B-ISDN is a significant research area of the developing of future high speed telecommunication networks. In this paper we overviewed the most important traffic models of data, voice and video communications and two promising modelling approach are presented in detail. The application area of the presented phase type models is the characterisation of traffic sources where the accurate modelling of the cell interarrival time is the most important factor. By using the phase type models we have the great advantage that any distributions can be approximated by phase type distributions with arbitrary accuracy. The application area of the fractal models is the data traffic modelling where the traffic has long-term correlations. The main advantage of this approach that such rather complex data traffic with self-similarity can be efficiently characterised by only a few parameters in contrast to classical models where a similar modelling accuracy requires numerous model parameters.

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