

Traffic-Flow Analysis for Fast Performance Estimation of Communication Systems

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The traffic-flow analysis (TFA) is a promising method for the performance estimation of communication systems. TFA produces approximate results with much less computation (that is, much faster) than discrete-event simulation of the system.

In the first step, TFA distributes the traffic in units of properly chosen size using the actual routing algorithm of the network. In the second step, TFA adjusts the time distribution of the traffic according to the finite capacities of the network.

It was found that the results of TFA approximate the results of the analytical method well.

Keywords: communication networks, performance analysis, traffic modelling, discrete-event simulation, importance sampling

1. Introduction

Simulation is a widely used method for the performance analysis (Jain, 1991) of communication systems. There is a large number of various methods used to describe the behaviour of complex systems. (Banks et al., 1996; Bratley et al., 1986; Jávör, 1985; Jávör, 1993) The simulation of large and complex systems requires a large amount of memory and computing power that is often available only on a supercomputer. Efforts are made to use multiprocessor systems or clusters of workstations. The conventional synchronisation methods for parallel simulation (e.g., conservative, optimistic) (Fujimoto, 1990) use event-by-event synchronisation and they are unfortunately not applicable to all cases, or do not provide the desirable speedup. The conservative method is efficient only if certain strict conditions are met. The

most popular optimistic method “Time Warp” (Jefferson et al., 1987) often produces excessive rollbacks and inter-processor communication. The Statistical Synchronisation Method proposed by Pongor (Pongor, 1992) does not exchange individual messages between the segments but rather the statistical characteristics of the message flow. The method can produce excellent speed-up (Lencse, 1998a) but has a limited area of application (Lencse, 1999).

In this paper we propose a simulation-like method for the fast performance analysis of communication systems. Let us consider the typical conditions of the simulation of communication systems. During the simulation we imitate the operation of the network. Traffic sources produce traffic with the same time- and packet length distributions as in the modelled network. We also model the routing algorithm, as well as the line and switching capacities of the network. During the execution of the simulation we collect statistics to determine the characteristics of the system we need. The accuracy of the results depends on both the accuracy of our model and the statistics collection method we use. To collect the required number of observations, we must execute the simulation in a virtual time interval of appropriate length. In the case of a large and complex system, the execution requires a huge number of computation cycles, and sometimes it takes hours or days to produce the required results. This is not acceptable in the early stage of the design of a network, when one would like to check one’s concepts, or wants to have a quick look at the results of the changes

made. The **traffic-flow analysis** (TFA) can fulfil this need. TFA is a combination of simulation and analytical and/or numerical methods. Unlike detailed simulation, TFA does not distribute the traffic in the network packet by packet but in larger units of carefully chosen size. TFA determines the time distribution of the traffic separate from the spatial distribution. The computational cost of the whole procedure — and in this way the execution time too — may be much less than that of the detailed simulation of the system.

This paper is organized as follows: first, a general description of TFA is given, then the selected traffic model is depicted including its operations, next some critical questions are discussed, afterwards an implementation of the method is shown, finally a case study is given: TFA is compared with the pure analytical method.

This topic was identified as being of importance in the fast performance analysis of large communication systems.

2. General Description of the Method

2.1. The Networking Model of the Traffic-Flow Analysis

The traffic-flow analysis assumes that the model of the network is built up by **nodes** (routers, switches, etc.) and transmission **lines**. The traffic of the network is generated by **application models** connected to the nodes. The intensity and the time distribution of the traffic are described by a mathematical model (typically statistics).

TFA is a general method which can work with various traffic models and routing algorithms. The requirements for the traffic model will be given after the basic description of the operation of TFA.

2.2. The Operation of the Method

A program which does traffic-flow analysis on the model of a network produces results in two phases.

Phase 1. — Determining the spatial distribution of the traffic

In the first phase, the applications in the model send the generated traffic to their destinations in **routing units** of parametrised size. (Routing units are the basic portions of the traffic that are handled together.) The nodes forward the routing units according to the routing algorithm of the modelled network while the lines and the nodes record the characteristics of the traffic flowing through them. The nodes may use the line capacity values for the routing decisions, but the time distribution of the traffic is not influenced by the finite capacities of the lines and nodes in this phase. The time distributions of the traffic transferred on various elements of the network are stored at the elements and will be summed up in the second phase according to the method described there.

Phase 2. — Determining the time distribution of the traffic

In the second phase, we must sum up the transferred traffic for the lines and nodes. The addition uses the addition operation of the traffic model. The operands are summed up first and the finite capacity is only taken into consideration at the end. This method will be detailed when discussing the selected traffic model.

2.3. Requirements for the Traffic Model

The traffic model must fulfil the following requirements:

- It is possible to describe the intensity and time distribution of the traffic by a mathematical model called the **traffic model**.
- The traffic model is closed for the operation of addition: that is, the summed up traffic will be characterised with the same methods as its components.
- It is possible to calculate the effect of the finite capacities of the nodes and lines to the time distribution of the traffic. (The traffic model is not necessarily closed for this calculation.)
- For all the source and destination node pairs, the traffic of all the application models of the same class (e.g. file transfer, VoIP, video

conference, web, etc.) can be handled together or even in units of arbitrary size, as aggregated traffic model.

- The traffic of all the source and destination node pairs can be handled in arbitrary order.

2.4. What are the Capabilities of the Traffic-Flow Analysis?

TFA is able to determine some classic statistical characteristics of the traffic on the nodes and lines of the network such as throughput, delay, etc.

TFA tells us the steady state behaviour of the network.

The application models handle together the traffic of several applications, that even alone may consist of large number of sent/received packets. As TFA takes statistics through the network, they do not need to be collected on the basis of a large number of observations. This way, *the execution time* of the TFA of a system *may be a fraction* of the execution time of the detailed simulation of the same system. Of course, the choice of the size of the routing unit (see 4.2.) and the characteristics of the traffic model are compromises between the speed and the accuracy.

As we have mentioned, TFA takes into consideration the effect of the finite capacities of the nodes and lines to the time distribution only after the spatial distribution. What are the consequences? Let us consider an end-to-end path that contains a bottleneck: a relatively low capacity line. This low capacity line changes the time distribution of the traffic for the remainder of the path in the real system, but not in the TFA model. For this reason, TFA does not give us an exact picture of the traffic conditions of the network. However, it is still *able to show if there is a bottleneck in the network, and if there is one, TFA shows where it is*. The effective solution of this important problem justifies the Traffic-Flow Analysis.

3. The Selected Traffic Model

For the description of the intensity and time distribution of the traffic, we could use any mathematical or statistical characterisation form that

complies with the requirements above, however, now we will use the PDF of **throughput** and the PDF of **delay**. They can be interpreted as follows: if the value of the probability density function of the throughput distribution is $p(x)$ at the position of x , it means that the throughput takes the value x by the probability of $p(x)$. Similarly, the probability density function of the delay shows the probability of the various values of the delay.

The traffic model should be able to describe the traffic adequately both in the nodes and on the lines. We apply the bit-throughput and packet-throughput distributions for these purposes. Only the PDF's of the traffic generated by the application models are considered for the throughput analysis of the network. The delay distributions are determined only after summing up the traffic on these elements, when taking into consideration the finite line and node capacities.

3.1. The Derivation of the Throughput

Under throughput we mean the number of bits or packets arrived in a time interval of T length. The value of the T parameter drastically influences the obtained throughput distribution. We use the example of the bit-throughput distribution of the lines for our considerations. A line can have only two states: either it carries traffic or not. (Multiplexed channels are treated as separate lines.) In this way, if $T \rightarrow 0$ then the PDF of the bit-throughput of the line consists of two impulses, one of them can be found at 0 throughput and the other one is located at the line capacity. Their height gives the probability of the empty or busy state of the line. If $T \rightarrow \infty$, then the PDF of the bit-throughput of the line is a single impulse that can only be found at the expected value of the traffic. Both cases produce useless results for us.

We should choose the value of T so that the resulted PDF of the bit-throughput characterises the traffic of the application model best (that is, the PDF of the bit-throughput carries the most information of the application we model). Of course, it is not easy to measure that. For the determination of parameter T , we start from the purpose of the traffic-flow analysis. A key question can be: with what resolution do we want

to get the delay distribution of the traffic on the line? The answer depends on the purpose of TFA. Let us see two examples:

- If we want to check whether the size of the buffer for the line is large enough, an important quantity is the time it takes to fill the buffer up:

$$T_f = \frac{\text{BufferSize}}{\text{LineCapacity}}$$

In this case, T can be determined as a certain portion of T_f , for example $T = T_f/10$.

- If we want to check whether the end-to-end delay is less than a certain value, then T can be determined as a certain portion of T_d , the allowed delay value for the given line.

3.2. Addition

We must sum up the throughput distributions at various points of the network. First, we sum up all the throughput distributions without any concern of the finite capacity of the line or node and finally apply the correction according to the finite capacity of the element.

Let us have look at how to add two throughput distributions. Let $p(x)$ and $q(x)$ denote the probability density functions of the two throughput distributions to add. In the result, the $r(y)$ probability of the y throughput is being contributed by all the cases when the throughput of the first source is x , and the throughput of the second source is $(y - x)$, considered the sources independent, probabilities should be multiplied, so:

$$r(y) = \int_{x=0}^y p(x)q(y-x)dx$$

That means that the probability density functions of the throughput distributions can be added by convolution.

In practice, we approximate the theoretically absolutely continuous probability density functions of the throughput distributions by histograms. A cell of the histogram shows the probability that the throughput is between the

lower and upper limit of the cell. Now the convolution is:

$$r[l] = \sum_{k=0}^l p[k]q[l-k]$$

The histograms used for the traffic model are often produced by measurements on an existing network. Adaptive on-line density estimation methods like P^2 (Jain and Clamtaç, 1985) and k -split (Varga and Babak, 1997) are particularly useful for this purpose, although it is naturally also possible to collect and store all data during measurement and process them later off-line. For the purposes of TFA, k -split is more useful than P^2 , because it is possible to convert a k -split density estimate into an equi-distant histogram without loss of information. (In k -split, cell sizes are a multiple of the smallest cell size; P^2 does not have this property.) More information about the properties of some statistics collection methods can be found in (Lencse, 1998b)

3.3. Correction for the Finite Capacity

The traffic that exceeds the line or node capacity is delayed and its service means an additional load that contributes to the load of the traffic arrived later. Let us discuss the problem in the case of a node and packet-throughput. However, we should take care so that our results may be used for the lines too.

Let $p_T[k]$ denote the probability that k packets arrive to the node in T time. In the beginning all the queues of the system are empty, so in the 1st T long time slice no waiting packets contribute to the actual packet arrival. The node can route K packets in T time. For the analytical simplicity, let us accept that if $k > K$ packets arrive, then K out of the k packets are serviced and $(k - K)$ will wait and will be added to those that will arrive in the next interval of length T , and if $k \leq K$ packets arrive then, all the k packets are serviced. (This is not necessarily true, it depends on the time distribution of the packet arrival within the T interval, but now we simplify the problem.) The probability that no packets will be queued for the next time slot is:

$$p_0 = \sum_{k=0}^K p_T[k]$$

The probability that a certain number of packets will remain in the queue is: $p_1 = 1 - p_0$. For this case, let us determine the number of packets that require service in the 2nd time slot. The tail of the distribution beginning from the value that gives the probability of the arrival of $(K + 1)$ packets should be added to the PDF that describes the arrival of the packets in the next T long time slot. The addition can be done by convolution:

$$p_T^x[k] = \sum_{l=0}^k p_T[l + K]p_T[k - l].$$

The summation variable l expresses how many waiting packets contribute to those that will arrive in the next time slot.

The new PDF ($p_T[k]^2$, which describes the situation if the 2nd time slot) will be the weighted sum of $p_T[k]$ (the PDF that describes the arrival in case of an empty queue) and $p_T^x[k]$ (the PDF that we got as a result of the convolution and describes the sum of the queuing and the newly arrived packets).

$$p_T[k]^2 = p_0 p_T[k] + p_T^x[k].$$

Remark: $p_T^x[k]$ already contains the p_1 weighting factor because the PDF of the tail was not normalised.

For this new PDF in the 2nd time slot, we can calculate the probabilities of the events if there will be no waiting packet or there will be some waiting packets that will be in the queue at the beginning of the 3rd time slot. Using these values we can derive $p_T[k]^3$ and afterwards $p_T[k]^4$, etc. Finally the system will reach its steady state, this is described by $p_T[k]^*$ that shows the probability that exactly k **packets require service in a T long time interval**. (The word “require” is to cover the difference between a packet that arrived in the T long time interval or a packet that was in the queue before.)

Let $P_T[k]$ denote the PDF that shows the probability that exactly k **packets are serviced in a T long time interval**. This function can be derived from $p_T[k]^*$ by adding its tail from the $(K + 1)$ -th cell to its K -th cell. (The addition is the standard mathematical “+”.)

$$P_T[k] = \begin{cases} p_T[k]^*, & k < K \\ \sum_{l=K}^{\infty} p_T[l]^*, & k = K \\ 0, & k > K \end{cases}$$

The traffic that is described by the tail from the $(K + 1)$ -th cell of $p_T[k]^*$ is delayed. Let us calculate the distribution of the delay caused by the finite capacity. Let $D_T[i]$ denote the probability that the **packets are delayed by i number of T long time intervals**.

$$D_T[i] = \begin{cases} \sum_{k=0}^K p_T[k]^*, & i = 0 \\ \sum_{k=iK+1}^{(i+1)K} p_T[k]^*, & i \geq 1 \end{cases}$$

Now, let us see an example. We have chosen the parameters so that the effect of the capacity thresholding is quite visible.

Fig. 1 and Fig. 2 show the original PDF and the result of the repeated convolutions, respectively. It can be observed that the expected value of the PDF was slightly moved to the right. Fig. 3 shows the result of the capacity thresholding.

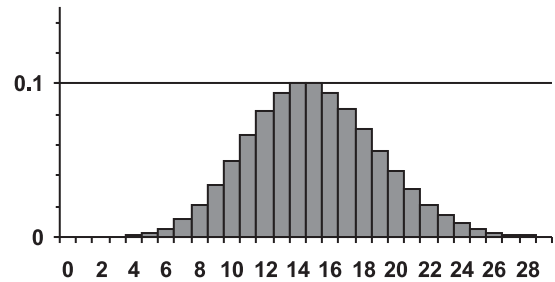


Fig. 1. $p_T[k]$ — the original PDF.

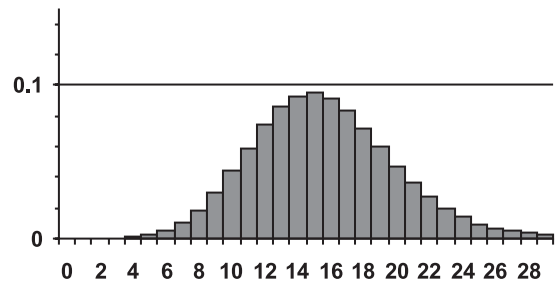


Fig. 2. $p_T[k]^*$ — result of convolutions.

The distribution was limited to 20 cells numbered from 0 to 19. In more than 23% of the cases the utilisation is 100%. The original value of cell 19 in Fig. 2 was 0.059, and 0.177 was added to it due to the tail was cut off. Fig. 4 shows the PDF of the delay distribution. The probability of the $1 * T$ delay is about 17.7%.

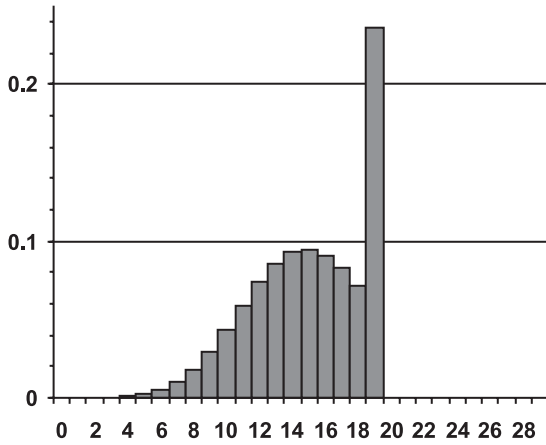


Fig. 3. $P_T[k]$ — result of capacity thresholding.

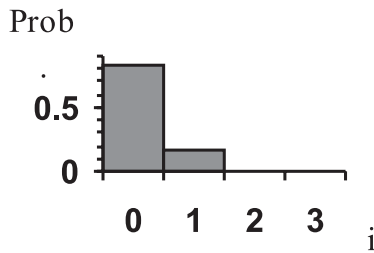


Fig. 4. $D_T[i]$ — delay distribution.

In the procedure above, we used histograms, with a cell size of 1. In the case of the bit-throughput histograms, and sometimes also in the case of the packet-throughput histograms, the size of the cells must be greater than one for efficiency. Then we need to consider the effect of the larger cell size and use the modified convolution algorithm we will describe in the next chapter.

4. Discussion of Important Details

4.1. The Effect of the Finite Cell Size

If the size of the cells of the histogram is negligible, the convolution is trivial (Fig. 5 and Fig. 6).

If the size of the cells of the histogram is not negligible, the convolution behaves like Fig. 7 and Fig. 8 show. The explanation is the following: Let w denote the size of the cells. We number the cells from 0. The position of the i -th cell is: $[iw, (i + 1)w]$, the position of the j -th one is: $[jw, (j + 1)w]$, the position of the

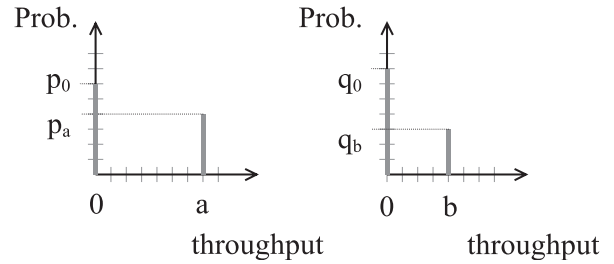


Fig. 5. Density functions to add — ideal case.

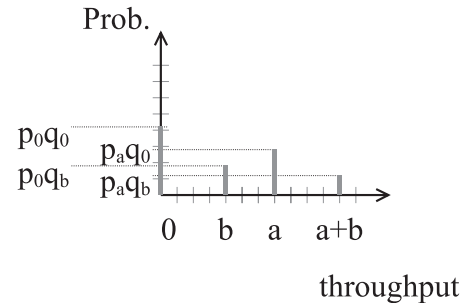


Fig. 6. The result of the convolution — ideal case.

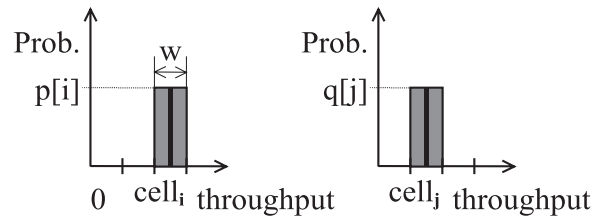


Fig. 7. Density functions to add — the cell size is not negligible.

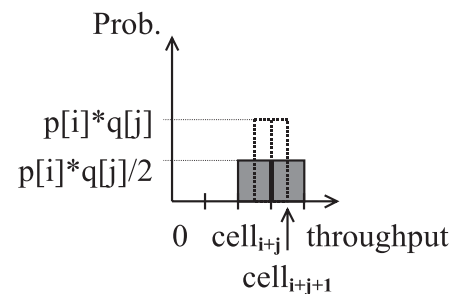


Fig. 8. The result of the convolution — the cell size is not negligible.

middle points of the cells are: $(i + 0.5)w$ and $(j + 0.5)w$. The position of the resulting cell is then: $[(i + j)w, (i + j + 2)w]$, that is exactly the place of the $(i + j)$ -th plus the $(i + j + 1)$ -th cells. As the width of the resulting cell is $2w$ the height of the cell must be divided by 2, so the result of the convolution remains a normalised probability density function.

4.2. Routing Units

When determining the **size of the routing unit** (S_{RU}) we must consider the following issues:

The larger S_{RU} we choose, the fewer messages are to be routed in the first phase and the less traffic model addition is to be performed in the second phase of TFA. However, if S_{RU} is too large, the spatial distribution of the traffic may considerably differ from the one that is formed in the detailed simulation (and in the real system). If S_{RU} is small, the spatial distribution of the traffic may be quite precise, but the larger amount of messages to be routed and traffic models to be added slow down analysis. ***The choice of S_{RU} must be a reasonable compromise that is made in the knowledge of the whole system modelled.***

The author would like to highlight another important feature of TFA now. The facts that S_{RU} can be chosen for the applications of different types independently, and $S_{RU} < 1$ is possible assure the following advantage: if there is an application A whose traffic is just a small portion of the traffic of another application B, but for some reason it is very important for us to know its spatial distribution, TFA has an additional comparative advantage over the detailed simulation. In this case, one has to continue the detailed simulation until he can collect enough samples from the traffic of application A. Meanwhile the detailed simulation transfers much more from the traffic of the application B than it would be necessary for the statistics collection. If we use TFA and choose the value of S_{RU} for all the application types well, not much more has to be transferred from the traffic of any type of applications than it is necessary. This way TFA may serve the **importance sampling**.

5. Application of TFA - an Example

Let us use a commercial network as an illustration of the application of the method. A number of different types of applications may use the network such as POS (Point Of Sale), ATM (Automatic Teller Machine), file transfer, alarm systems, etc. For TFA, all these applications will be modelled by the **General Application Model** (GAM). The most important parameter of the GAM is the **type** of the applications it represents. The traffic generated by the GAM is determined by a number of parameters that are defined for all the different types of applications.

As it was mentioned before, we use aggregated traffic model, so the GAM is able to represent the traffic of all the applications of its type (that are connected to the given node). If the routing algorithm for the propagation of packets is symmetrical i.e. the same from A to B as from B to A, then the traffic between A and B can be handled together and the combined traffic is propagated from A to B. For example: a “client” generates the traffic model that describes its traffic towards one or more “servers” that receive the traffic model but generate no reply because the traffic model sent by the client represents the traffic of both directions (sent and received by the client).

5.1. The Parameters of the GAM

We estimate the number of the different types of applications in the network, as well as their spatial distribution, and the time distribution of their activity during the day. In addition to that, for TFA, we have to determine what size of traffic can be handled together. Hence, the parameters of the GAM are:

- $N_{App}(\mathbf{type})$ Number of Applications — the number of all the applications of the given type
- $N_{AppPN}(\mathbf{type, node})$ Number of Applications Per Node — the number of all the applications of the given type connected to the given node
- $P_{Ac}(\mathbf{type, day, time})$ Probability of Activity — the probability that an application of the given type is active at the given time of the given day of week

- $S_{RU}(\mathit{type})$ Size of Routing Unit — the maximum size of the unit of the traffic (that can be handled together) for the given type of application

The reader may have noticed that for the description of the users' behaviour we consider the time of day and distinguish the days of the week too. The latter is justified, for example, by the different behaviour of the users on working days and on holidays. Of course, it is possible that for some applications the users' behaviour depends on the position of the day within the month or in the season, but because this would give no theoretical novelty, we avoid the usage of unnecessarily many parameters.

The GAM generates traffic according to the number of the active applications:

$$N_{App}(\mathit{type}, \mathit{node}, \mathit{day}, \mathit{time}) = \frac{N_{App}(\mathit{type}, \mathit{node})P_{Act\mathit{type}}, \mathit{day}, \mathit{time}}{N_{App}(\mathit{type})}$$

and issues the traffic (model) in at most $S_{RU}(\mathit{type})$ size of units, where N_{App} and S_{RU} are not necessarily integers.

The traffic of the GAM can be categorized into a given number of **transaction types** (abbreviated as tt). The transactions are the basic units of the traffic in our model of the considered commercial network.

5.2. Elimination of the Time Change within The Transactions

In our model, we suppose that the time change of the intensity of the transaction generation is relatively slow compared to both the T size of the throughput collection interval and the duration of the transactions. So we consider that the starting time of the transactions in a T interval has a uniform distribution. Moreover, distribution of the starting time of the transactions was very similar just before the beginning of that T interval. In this way, we may say that in a well chosen T interval we take into consideration the **whole traffic** of the transactions beginning in that T time interval.

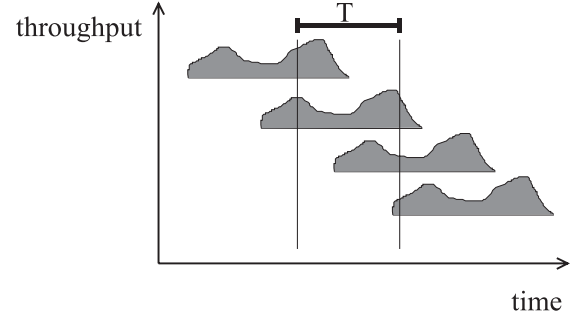


Fig. 9. The elimination of the time change within the transactions — illustration.

5.3. Parameters of the GAM

Transactions of the GAM are also described by parameters. The parameters express what load the transactions of a given type cause for the lines and nodes, how many of them occur a day, and what their time distribution within the day is. The parameters of the transactions are:

- $N_b^{\{s|r\}}(\mathit{tt})$ Number of Bits Sent | Received — the number of bits sent or received by the application during a transaction of the given type
- $N_p^{\{s|r\}}(\mathit{tt})$ Number of Packets Sent | Received — the number of packets sent or received by the application during a transaction of the given type
- $N_c(\mathit{tt})$ Number of Connection Set-ups — the number of connections set-ups performed by the application during a transaction of the given type, typically 0 or 1, if this is possible at all (for connection oriented protocols only)
- $N_{TrPD}(\mathit{tt}, \mathit{day})$ Number of Transactions Per Day — the number of transactions performed by an application of the given transaction type on a given day of the week
- $I_{Tr}(\mathit{tt}, \mathit{day}, \mathit{time})$ Intensity of Transaction generation — the value of the PDF at the given time that PDF describes the time distribution of the transactions of the given type on the given day of week.

Remarks:

1. In the case of connection-oriented networking protocols, the connection set-ups may

cause significant load for the nodes (switches). E.g. the load caused by a connection set-up may equal the load of the switching of 10 packets. This is the reason for introducing the parameter N_c .

2. I_{Tr} is defined for all the days of the week when there are transactions of the given type. Being a probability density function:

$$\int_{time=0}^{24 \times 3600} I_{Tr}(tt, day, time) = 1$$

(the time is measured in seconds).

5.4. Transaction Generation with Poissonian Distribution

In our model, the active applications generate transactions according to a Poissonian process with parameter λ , that means the inter-arrival time has an exponential distribution with parameter λ . Thus, the probability that k transactions are generated in T time is:

$$p_T[k] = \frac{(\lambda T)^k}{k!} e^{-\lambda T}.$$

The intensity of the transaction generation is:

$$\begin{aligned} & \lambda(tt, node, day, t) \\ &= \frac{N_{AppPN}(type, node) \cdot N_{TrPD}(tt, day)}{N_{App}(type)} \\ & \cdot I_{Tr}(tt, day, time) \end{aligned}$$

Remark: as the transaction type (tt) determines the application type ($type$), $type$ can be omitted if tt is included.

Therefore the traffic model is built up by the transaction type-wise λ , N_b^s , N_b^r , N_p^s , N_p^r , N_c parameters.

5.5. Addition

Let us exploit the possibilities for simplification. Considering that the sum of two Poissonian distribution variables has also Poissonian distribution we can numerically add the λ values of the same transaction type. (Either they came from different sources or from the same

one, but were carried by a separate routing unit.) Consequently, the network elements may collect the statistics of the transmitted traffic into a single scalar intensity variable for each transaction type. This is an important result, because thus we use scalar addition operations only (and not convolutions) during the spatial distribution phase.

While intensity values can be simply added up in the case of transactions of the same type, this cannot be done with transactions of different types as their N_b^s , N_b^r , N_p^s , N_p^r , N_c parameters may differ. Let us consider the sent bit-throughput as an example. We get the sent bit-throughput histogram from the histogram of the Poissonian distribution with parameter $\lambda(tt)$ by multiplying the cell width and dividing the cell height by $N_b^s(tt)$. These sent bit-throughput histograms are then added up by convolution for all the transaction types.

The calculation is still not finished. To get the traffic of a line in one direction, we must add up the cumulated sent bit-throughput histogram of the given direction and the cumulated received bit-throughput histogram of the other direction.

The capacity thresholding should be done the same way as described in 3.3.

5.6. Questions of the Efficient Implementation

To speed up the execution of TFA, we applied sometimes ε values (given as parameters) to express the accuracy expected by the user. These are as follows:

- ε_P **Epsilon of Poissonian Tail** — It is used when calculating the histogram of the Poissonian distribution from the transaction type-wise cumulated λ value. If $p_T[k] < \varepsilon_P$ for a given k , then the tail of the distribution is omitted from k .
- ε_A **Epsilon of Addition** — It is used to bound the result of the convolution in the above-mentioned manner. Without this, the number of the small probability cells could grow beyond measure so as the computation requirement of the further convolutions.
- ε_C **Epsilon of Change** — When doing the capacity thresholding, we calculate the

difference of $p_T[k]^2$ and the original $p_T[k]$: *firstChange*. After each step we calculate the difference of $p_T[k]^i$ and $p_T[k]^{(i-1)}$: *actualChange*. We may stop when:

$$actualChange < \varepsilon_C^* firstChange.$$

As for efficiency, another important issue is the quantity of the human work used for the analysis. To be economical with this, we have prepared an object-oriented library. Various objects e.g. traffic generator, line, node, traffic sink, etc. are C++ classes with pure virtual functions that are defined when implementing the layer 3 protocol of the analysed network. This solution requires less amount of work from the person who implements the model than using only a predefined library of functions.

At present we do not apply it, but in the future the convolutions may be eliminated by using FFT and FFT⁻¹ transformations. It returns especially when the resolution of the histograms and/or the number of convolutions are high.

As a module of the Iminet network expert system, a TFA implementation applicable for the fast analysis of commercial networks was prepared for the Elassy Consulting Ltd.

6. Comparison of TFA and the Pure Analytical Method

We use a simple network with 6 nodes for the comparison of the two methods. The nodes are connected by 64kbps lines according to the topology shown in Fig. 10. A server is connected to one of the nodes and is used by the terminals connected to the 5 other nodes. There are 150 terminals per node, and they are active with the probability of 60%. When they are active, they perform about 2 transactions per minute. One transaction of the terminals contains 5 sent and 4 received packets. The length distribution of the packets is uniform in the [140 byte, 180 byte] interval.

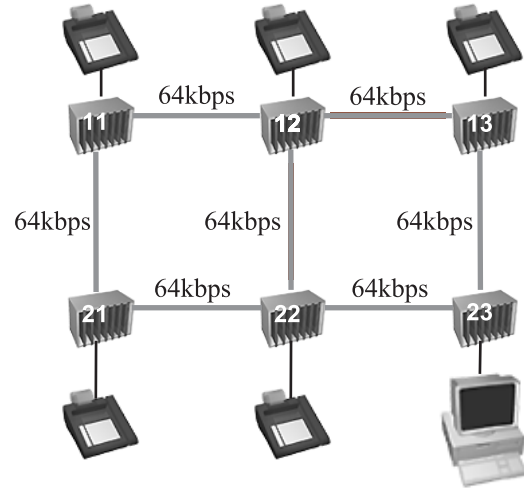


Fig. 10. Topology of the network (Iminet graphics).

The nodes of the network are X.25 switches that use no fixed routing table rather adaptive algorithm. They find the minimal cost route for every new connection according to the following conditions: there is a fixed switching cost (C_{Sw}) for every switch the path contains, and the cost for the contained lines is in direct proportion to the number of already existing connections on the line. The factor is C_{pC} (cost per connection).

Let us determine the parameters of the TFA model. There is a single application type with one transaction type only, thus the *type* and *tt* parameters will be omitted. The number of applications in the system is: $N_{App} = 5 \times 150 = 750$. The 5 nodes each have $N_{AppPN} = 150$ number of terminals that are active with the probability of $P_{Ac} = 0.6$. During a single transaction the application sends $N_b^s = 6400$ and receives $N_b^r = 5120$ bits. The number of packets sent is: $N_p^s = 5$, the number of packets received is: $N_p^r = 4$, the number of connection set-ups is: $N_c = 1$, and the number of all the transactions per day is:

$$N_{TrPD} = N_{App} \times P_{Ac} \times (2/60) \times 24 \times 3600,$$

that is

$$N_{TrPD} = 15 \times 86400$$

As the text above states nothing about the time distribution of the transactions during the day, let us suppose uniform distribution when the

value of the density function is constant all over the day:

$$I_{Tr} \equiv 1/86400$$

The size of the routing unit (S_{RU}) is an important parameter of the analysis, we executed TFA using different values for it.

Table 1, Table 2, and Table 3 show the results for the utilisation of the lines. We calculated the analytical values of the average utilisation of the lines and we give them in the first column for comparison. (Naturally, they are identical in all the 3 tables.) To save space, only the

line	anal.	average	s. dev.	min.	max.
11 → 12	15360	15337	66.5	15104	15488
12 → 13	23040	23009	108.8	22699	23232
21 → 22	23040	23063	127.5	22912	23296
22 → 23	53760	53792	153.9	53568	54101
11 → 21	3840	3863	167.6	3712	4096
12 → 22	11520	11528	178.3	11328	11626
13 → 23	42240	42209	198.0	41899	42432

Table 1. Line utilisation values — $S_{RU} = 0.1$.

line	anal.	average	s. dev.	min.	max.
11 → 12	15360	15181	378.4	14080	15787
12 → 13	23040	22859	533.1	21333	23680
21 → 22	23040	23219	653.7	22613	24320
22 → 23	53760	53941	753.9	53120	55467
11 → 21	3840	4019	843.5	3413	5120
12 → 22	11520	11522	881.1	10453	12160
13 → 23	42240	42059	957.8	40533	42880

Table 2. Line utilisation values — $S_{RU} = 1$.

line	anal.	average	s. dev.	min.	max.
11 → 12	15360	14229	1096	10667	17067
12 → 13	23040	22101	1834	19200	23467
21 → 22	23040	24171	2136	21333	27733
22 → 23	53760	54699	2593	53333	57600
11 → 21	3840	4971	2815	2133	8533
12 → 22	11520	11328	3000	8533	12800
13 → 23	42240	41301	3341	38400	42667

Table 3. Line utilisation values — $S_{RU} = 10$.

sent bit-throughput is presented, the received bit-throughput carries no further information concerning the spatial distribution of the traffic. As the application models wait for a random delay between the sending of the constive routing units, the result of TFA depends on the actual representation of these random numbers. We performed TFA a great number of times, averaged the results, computed the standard deviation, determined the minimum and the maximum values. As we will not have “analytical values” when applying TFA for a real life problem, we used the formula of the empirical deviation:

$$\sigma = \sqrt{\frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N - 1}}$$

Examining the results, we can point out that in the case of $S_{RU} = 0.1$, the deviation is always less than 5 with higher load it is less than 1%, or even 0.5%. The difference between the minimal and maximal values is little, thus in this case a single experiment gives good approximation with high probability.

In the case of $S_{RU} = 10$ the average values are still good approximations of the analytical values (except for the 11 → 21 line) but the minimal and maximal values differ much, thus in this case really a great number of experiments are needed. Let us examine what causes the significant difference from the analytical value for the 11 → 21 line. The analytical method has shown that this line carries only 18 transactions (in expected value). Naturally, this value cannot be approximated well in the case $U = 10$. The problem can be handled by decreasing S_{RU} and/or increasing the number of experiments, but it is not always necessary. In this particular case if we do not intend to decrease the line capacity below 64kbps just wish to decide whether 64kbps is enough for all the lines, the exact bit rate values of a lines are not important for us if we know they are much less than the line capacity.

Besides the average, let us examine the bit-throughput distributions and delay distributions of the lines. Let us select two interesting lines. The first one is line 22 → 23. The analytical throughput value of this line is 53 760 bps which

is higher than the 80% of the 64kbps that is considered to be safe according to the well-known rule of thumb.

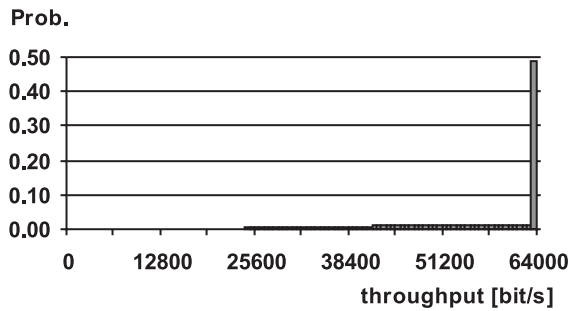


Fig. 11. The bit-throughput distribution of line 22 \rightarrow 23.

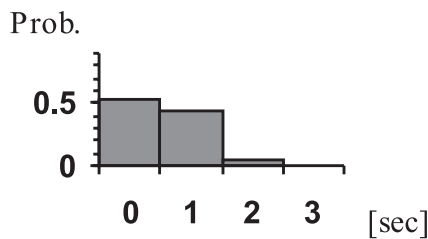


Fig. 12. The delay distribution of line 22 \rightarrow 23.

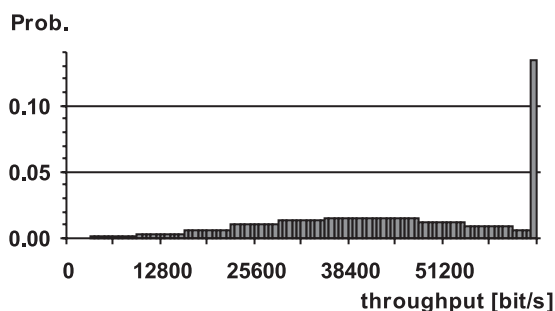


Fig. 13. The bit-throughput distribution of line 13 \rightarrow 23.

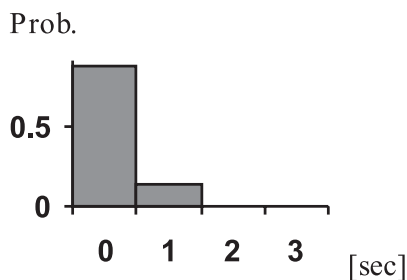


Fig. 14. The delay distribution of line 13 \rightarrow 23.

A Fig. 11 shows the bit-throughput distribution of line 22 \rightarrow 23. It is conspicuous, that the line is fully utilised with nearly 50% probability. It results in the delay distribution is displayed in Fig. 12. The application of a 128k line is worth considering here.

Fig. 13 shows the bit-throughput distribution of line 13 \rightarrow 23. Here, the probability of 100% utilisation is less than 14%. The delay distribution (Fig. 14) can be considered as acceptable.

In the case of the other lines, full utilisation has no significant probability thus the analysis of their traffic is of no interest for us.

This example demonstrated how TFA could be used for revealing bottlenecks in a network.

7. Conclusions

The reader was introduced to the traffic-flow analysis describing its networking model, general operation and capabilities enlarging upon the selected traffic model and its operations. After the discussion of some critical details an actual implementation of TFA was presented. Finally, a case study was given comparing the results of TFA to those of the pure analytical method. We have found that the results of TFA approximate well the results of the pure analytical method.

We conclude that TFA can be an efficient method for the fast approximate performance analysis of large communication systems.

The direction of the future research may be the comparison of TFA and the detailed simulation applying them for the analysis of more complex networks (that cannot easily be studied in the analytical way) concerning both the accuracy of the results and the execution time.

8. Acknowledgements

The results recited in this paper arose from the R&D project of Elassy Consulting Ltd that deals with information technology and simulation of communication systems.

The author would like to express his thanks to László Dobosy and András Varga for the valuable discussions during the research.

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Received: May, 2000

Accepted: September, 2000

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