A Fuzzy Equivalent Capacity Estimator for Bandwidth Allocation in High-Speed Networks

Leonard Barolli†, Akio Koyama‡, Takako Yamada†, Shoichi Yokoyama††, Norio Shiratori‡‡

†Department of Public Policy and Social Studies, Yamagata University
1-4-12 Kojirakawa-machi, Yamagata 990-8560
{barolli, takako}@human.kj.yamagata-u.ac.jp

‡Department of Computer Software, The University of Aizu
Tsuruga, Ikki-machi, Aizu-Wakamatsu 965-8580, Fukushima
koyama@u-aizu.ac.jp

††Department of Electrical and Information Engineering, Yamagata University
4-3-16 Jonan, Yonezawa 992-8510, Yamagata
yokoyama@eie.yz.yamagata-u.ac.jp

‡‡Research Institute of Electrical Communication (RIEC), Tohoku University
2-1-1 Katahira, Aoba-ku, Sendai 980-8577
norio@shiratori.riec.tohoku.ac.jp

Abstract

The dynamic nature of high-speed networks poses difficult traffic control problems when trying to achieve efficient use of network resources. To cope with rapidly changing network conditions, traffic control methods for high-speed networks must be adaptive, flexible, and intelligent for efficient network management. Use of intelligent methods based on fuzzy logic, neural networks and genetic algorithms can prove to be efficient for traffic control in high-speed networks. The equivalent capacity estimation is a very important function for call admission control. To estimate the equivalent capacity, flow and stationary methods make many approximations, which result in an overestimate of equivalent capacity. In this paper, we propose a fuzzy equivalent capacity estimator for bandwidth allocation in high-speed networks. Performance evaluation via simulation shows that proposed fuzzy estimator has a good equivalent capacity estimation compared with flow and stationary approximations.

1. Introduction

In high-speed networks such as ATM networks, several classes of traffic streams with widely varying traffic characteristics are statistically multiplexed and share common switching and transmission resources. Because all connections are statistically multiplexed at the physical layer and the bit rate of connections varies, a challenging problem is to estimate the effective bandwidth requirement as a function of Quality of Service (QoS). The basic objective of a bandwidth management control strategy is to allow for high utilization network resources, while sustaining an acceptable QoS for all connections.

In ref.[1], the equivalent capacity is computed from the combination of two different approaches, one based on a fluid flow model and the other one on an approximation of the stationary bit rate distribution. These two approaches are used because they complement each other, capturing different aspects of the behavior of multiplexing connections. For a given QoS, the equivalent capacity of a single connection and the aggregate capacity of multiplexed connection are calculated. But, these methods makes many approximations, which result in an overestimate of equivalent capacity. Also, they suffer from some fundamental limitations. Generally, it is difficult for a network to acquire complete statistics of input traffic. As a result, it is not easy to accurately determine the effective bounds or equivalent capacity in a various bursty traffic flow conditions of ATM networks.

Use of intelligent methods based on Fuzzy Logic (FL), Neural Networks (NN) and Genetic Algorithms (GA) can prove to be efficient for traffic control in high speed networks [2, 3, 4]. In ref.[2], the FL is used to build a fuzzy Policing Mechanisms (PM), which performance is better than conventional PMs and very close to ideal behavior. Some NN applications for traffic control in ATM networks are proposed in ref.[3]. The NN are well suited to applications in the control of communications networks due to their adaptability and high speed. They can achieve an efficient adaptive control through the use of adaptive learning capabilities. A GA based routing method is proposed in ref.[4]. The proposed routing algorithm has a fast decision and shows an adaptive behavior based on GA.

The equivalent capacity estimation is a very important function for Call Admission Control (CAC). To estimate the equivalent capacity, flow and stationary methods make many approximations, which result in an overestimate of equivalent capacity. In this paper, we propose a fuzzy equivalent capacity estimator for bandwidth allocation in high-speed networks. The proposed fuzzy estimator is part of a CAC scheme. Performance evaluation via simulation shows that fuzzy estimator has a good equivalent capacity estimation compared with flow and stationary approximations.

The organization of this paper is as follows. In the next Section, we will introduce the proposed fuzzy estimator. The simulation results will be discussed in Section 3. Finally, conclusions will be given in Section 4.

2. Proposed Fuzzy Estimator

In ref.[1], in order to get the Equivalent capacity (Ec) of N identical On-Off traffic sources parameter β was approximated by one. But, the assumption of $\beta \approx 1$ ignores the effect of statistical multiplexing. In in order to gain from statistical multiplexing of bursty connections and make a more accurate estimation of equivalent capacity, we propose a Fuzzy Equivalent Capacity Estimator (FECE). The Fuzzy Logic Controller (FLC) is the main part of the FECE and its basic elements are shown in Fig.1. They are the fuzzifier, inference engine, Fuzzy Rule Base (FRB) and defuzzifier. As membership functions, we use triangular and trapezoidal functions, because they are suitable for real-time operation [5]. As shown in Fig.2, the triangular and trapezoidal functions are given as:

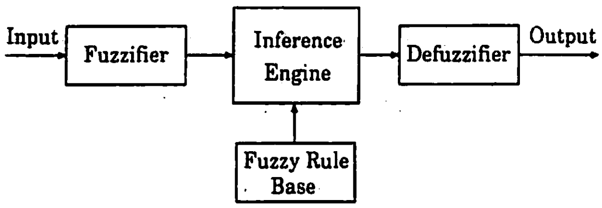

Figure 1: FLC structure.

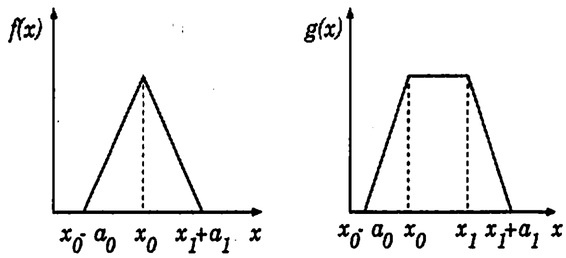

Figure 2: Triangular and trapezoidal membership functions.

$$f(x; x_0, a_0, a_1) = \begin{cases} \frac{x-x_0}{a_0}+1 & \text{for } x_0 - a_0 < x \leq x_0 \\ \frac{x_0-x}{a_1}+1 & \text{for } x_0 < x \leq x_0 + a_1 \\ 0 & \text{otherwise} \end{cases}$$

$$g(x; x_0, x_1, a_0, a_1) = \begin{cases} \frac{x-x_0}{a_0}+1 & \text{for } x_0 - a_0 < x \leq x_0 \\ 1 & \text{for } x_0 < x \leq x_1 \\ \frac{x_1-x}{a_1}+1 & \text{for } x_1 < x \leq x_1 + a_1 \\ 0 & \text{otherwise} \end{cases}$$

where x_0 in $f(.)$ is the center of triangular function; $x_0(x_1)$ in $g(.)$ is the left (right) edge of trapezoidal function; and $a_0(a_1)$ is the left (right) width of the triangular or trapezoidal function.

The FECE predicts the Ec required for a new connection based on the traffic parameters Peak rate (Pr), Source utilization (Su), and Peak bitrate duration (Pbd). The term sets of Pr, Su, and Pbd are defined respectively as:

$$\begin{aligned} T(Pr) &= \{Small, Medium, Large\} = \{S, M, L\}; \\ T(Su) &= \{Low, High\} = \{Lo, Hi\}; \\ T(Pbd) &= \{Short, Medium, Long\} = \{Sh, Me, Lg\}. \end{aligned}$$

The set of the membership functions associated with terms in the term set of Pr, $T(Pr) = \{S, M, L\}$, are denoted by $M(Pr) = \{\mu_S, \mu_M, \mu_L\}$, where μ_S, μ_M, μ_L are the membership functions for S, M, L, respectively. They are given by:

$$\begin{aligned}
\mu_S(Pr) &= g(log(Pr); Pr, min, S_c, 0, S_w); \\
\mu_M(Pr) &= f(log(Pr); M_c, M_{w0}, M_{w1}); \\
\mu_L(Pr) &= g(log(Pr); L_c, Pr, max, L_w, 0).
\end{aligned}$$

The small letters c, $w0$ and $w1$ mean center, right width and left width, respectively.

$M(Su) = \{\mu_{Lo}, \mu_{Hi}\}$ are the membership functions for term set of Su. The membership functions μ_{Lo}, μ_{Hi} are given by:

$$\begin{aligned}
\mu_{Lo}(Su) &= g(Su; 0, Lo_c, 0, Lo_w); \\
\mu_{Hi}(Su) &= g(Su; Hi_c, 1, Hi_w, 0).
\end{aligned}$$

The membership functions for term set Pbd are $M(Pbd) = \{\mu_{Sh}, \mu_{Me}, \mu_{Lg}\}$, and μ_{Sh}, μ_{Me}, μ_{Lg} are given by:

$$\begin{aligned}
\mu_{Sh}(Pbd) &= g(log(Pbd); Pbd, min, Sh_c, 0, Sh_w); \\
\mu_{Me}(Pbd) &= f(log(Pbd); Me_c, Me_{w0}, Me_{w1}); \\
\mu_{Lg}(Pbd) &= g(log(Pbd); Lg_c, Pbd, max, Lg_w, 0).
\end{aligned}$$

The Ec for a connection should fall between its Pr and Average bit rate (Abr). Based on the number of input membership functions, we divide the Ec range in six membership functions. The term of Ec is defined as $T(Ec) = \{E1, E2, E3, E4, E5, E6\}$.

The term set of the output membership functions, are denoted by $M(Ec)$. They are written as $\{\mu_{E1}, \mu_{E2}, \mu_{E3}, \mu_{E4}, \mu_{E5}, \mu_{E6}\}$, and are given by:

$$\begin{aligned}
\mu_{E1}(Ec) &= f(log(Ec); E1c, 0, E1_{w1}); \\
\mu_{E2}(Ec) &= f(log(Ec); E2c, E2_{w0}, E2_{w1}); \\
\mu_{E3}(Ec) &= f(log(Ec); E3c, E3_{w0}, E3_{w1}); \\
\mu_{E4}(Ec) &= f(log(Ec); E4c, E4_{w0}, E4_{w1}); \\
\mu_{E5}(Ec) &= f(log(Ec); E5c, E5_{w0}, E5_{w1}); \\
\mu_{E6}(Ec) &= f(log(Ec); E6c, E6_{w0}, 0).
\end{aligned}$$

The membership functions for FECE are shown in Fig.3 and its FRB is shown in Table 1.

The FRB forms a fuzzy set of dimensions $|T(Pr)| \times |T(Su)| \times |T(Pbd)|$, where $|T(x)|$ is the number of terms on $T(x)$. Therefore, the FRB has 18 rules. The control rules have the following form: IF "conditions" THEN "control action". Statements on conditions go like "Pr is small" or "Su is long". Likewise, statements on control action might be "Ec is E1".

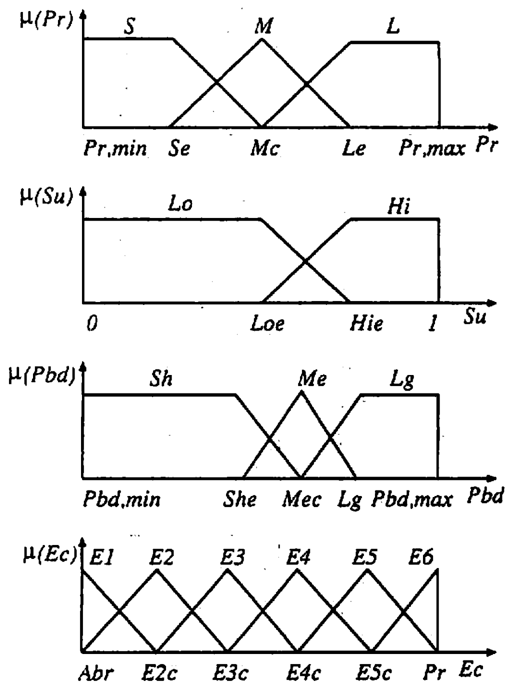

Figure 3: FECE membership functions.

In order to accommodate a wide variety of different traffic sources, we use for some membership functions a logarithmic function.

3. Simulation Results

Considering a two-state Markov source the expressions of Ec for exact value, flow approximation and stationary approximation are given in ref.[1]. Assuming a finite Buffer (B) size, the equation satisfied by the Ec for an overflow probability of ϵ is given by:

$$\epsilon = \beta \cdot exp(-\frac{B(Ec - Su \cdot Pr)}{Pbd(1 - Su)(Pr - Ec)Ec} \tag{1}$$

where,

$$\beta = \frac{(Ec - Su \cdot Pr) + \epsilon \cdot Su(Pr - Ec)}{(1 - Su)Ec}. \tag{2}$$

If the parameter β is approximated by 1, the Ec for a single connection is given by:

$$\begin{aligned}
\hat{Ec} &\approx \frac{\alpha \cdot Pbd(1 - Su)Pr - B}{2\alpha \cdot Pbd(1 - Su)} \\
&+ \frac{\sqrt{[\alpha \cdot Pbd(1 - Su)Pr - B]^2 + 4B\alpha \cdot Pbd \cdot (1 - Su)Pr}}{2\alpha \cdot Pbd(1 - Su)}
\end{aligned} \tag{3}$$

Table 1: FRB.

Rule	Pr	Su	Pbd	Ec
0	S	Lo	Sh	E1
1	S	Lo	Me	E2
2	S	Lo	Lg	E5
3	S	Hi	Sh	E1
4	S	Hi	Me	E1
5	S	Hi	Lg	E4
6	M	Lo	Sh	E1
7	M	Lo	Me	E3
8	M	Lo	Lg	E6
9	M	Hi	Sh	E1
10	M	Hi	Me	E2
11	M	Hi	Lg	E5
12	L	Lo	Sh	E4
13	L	Lo	Me	E6
14	L	Lo	Lg	E6
15	L	Hi	Sh	E3
16	L	Hi	Me	E5
17	L	Hi	Lg	E6

where $\alpha = ln(1/\epsilon)$.

For multiple connections, when the input bit rate is characterized by a N-state Markov chain, the distribution of the buffer contents is of the following form:

$$F(B) = \sum_{i=1}^{N} a_i \Phi_i e^{Z_i B} \qquad (4)$$

where Z_i and Φ_i are, respectively, generalized eigenvalues and eigenvectors associated with the solution of the differential equation satisfied by the stationary probabilities of the system, and a_i are coefficients determined from boundary conditions.

The exact value of the Ec for single and multiple connections are calculated by iteratively solving equations (2) and (4). But, this calculation, although exact, is complicated and is not compatible with a dynamic and real-time environment [1].

The Ec for multiple connections using flow approximation is calculated by:

$$\hat{E}c_{(F)} = \sum_{i=1}^{N} \hat{E}c_i \qquad (5)$$

where $\hat{E}c_i$ are determined from equation (3).

In flow approximation, the parameter β is considered 1. This approximation can do a good evaluation in the case when either Number (N) of connections is small of the actual total Ec is close to overall Abr. In other cases, this approximation results in an overestimate of Ec.

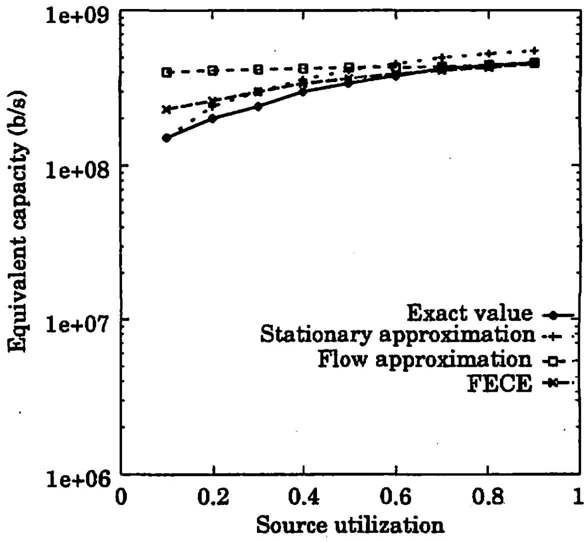

Figure 4: Ec versus Su (N=50).

When N connections with relatively long burst periods are multiplexed, a reasonably accurate estimate of the required Ec can be obtained from the stationary approximation. The value of the Ec can be expressed as:

$$\hat{E}c_{(S)} \approx Abr + \hat{\alpha}\sigma \qquad (6)$$

where Abr is the average aggregate bit rate ($Abr = \sum_{i=1}^{N} Abr_i$); $\hat{\alpha}$ is $\sqrt{-2ln(\epsilon) - ln(2\pi)}$, and σ is the standard deviation of the aggregate bit rate ($\sigma^2 = \sum_{i=1}^{N} \sigma_i^2$).

The stationary approximation gives a substantial overestimate of the Ec because it ignores the effect of the buffer.

The parameter values of input membership functions for FECE are assigned as follows. For Pr, S_e=-3, S_w=1, M_c=-2, M_{w0}=M_{w1}=1, L_e=-1, L_w=1, Pr,min=10^{-4}, Pr,max=1; for Su, Lo_e=0.6, Lo_w=0.15, Hi_e=0.75, Hi_w=0.15; for Pbd, Sh_e=-3, Sh_w=1, Me_c=-2, Me_{w0} = Me_{w1} =1, Lg_e=-1, Lg_w=1, Pbd,min=10^{-9}, Pbd,max=100s.

The parameter values of output membership functions for FECE are assigned as follows. The value of Ec_1 is set equal to Abr and the value of Ec_6 is set equal to Pr. The other values are calculated based on the following equation:

$$C_i c = C_{i-1} c + (Pr - Abr)/5 \qquad (7)$$

where i = 2, 3, 4, 5, 6.

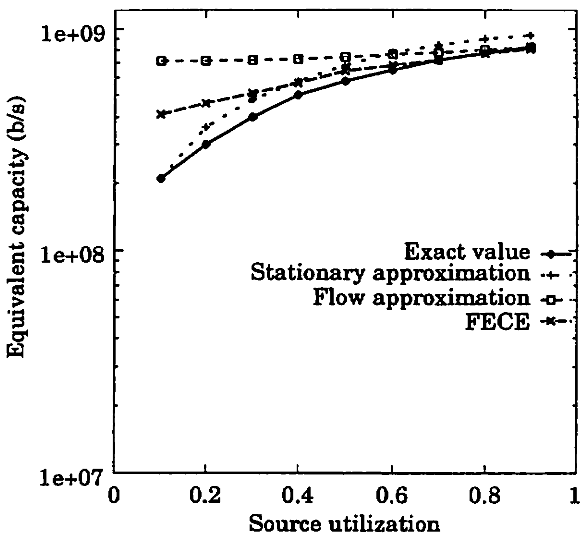

Figure 5: Ec versus Su (N=90).

Considering the same parameters for four methods: $Pr = 10$ Mb/s, $Pbd = 0.02$s, the probability of overflow 10^{-5}, the characteristic of the required Ec versus Su for two different number of connections $N = 50$ and $N = 90$ are shown in Fig.4 and Fig.5, respectively. As shown in these figures, the required Ec calculated by FECE is very close to the exact value. For bursty traffic sources when the sources have a low utilization, the flow approximation hasn't a good Ec accuracy. But, for traffic sources with high source utilization, the flow approximation has a good Ec estimation. On the other hand, the stationary approximation has a good Ec accuracy for low source utilization and a poor estimation for high source utilization. The characteristic of FECE is more close to exact value compared with both flow and stationary estimations. But, for sources with very low utilization, the stationary approximation give good accuracy than FECE. Therefore, it is possible to get a better estimation of Ec if we calculate the value of Ec as the minimum value of FECE and stationary approximation.

4. Conclusions

In this paper, we proposed a FECE for bandwidth allocation in high-speed networks. First, we gave a brief introduction of the previous work. Next, we treated the proposed FECE. Finally, the simulation results were discussed. The behavior of FECE was investigated by simulations. From the simulations results, we conclude:

- the FECE has a good Ec estimation compared with conventional methods;
- combination of FECE and stationary approximation will result in a more accurate estimation of Ec.

In the future, the authors will use the FECE in a CAC scheme for ATM networks.

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