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A Fuzzy Based Equivalent Capacity Estimation Method for Bandwidth Allocation in High-speed Networks

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The dynamic nature of high-speed networks poses difficult traffic control problems when trying to achieve efficient use of network resources. One such problem is the issue of bandwidth management allocation. Because of the statistical multiplexing of all connections and the variation of connections bit rates, it is important to evaluate the equivalent capacity of all connections. The purpose of the equivalent capacity is to provide a metric to represent the effective bandwidth used by connections and the corresponding effective load on network links. In order 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, fluid flow approximation, stationary approximation and equivalent capacity method has been proposed. But, they 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 simulations shows that proposed fuzzy equivalent capacity estimator has a good equivalent capacity estimation compared with fluid flow and stationary approximations. Furthermore, the combination of fuzzy equivalent capacity estimator and stationary approximation give a better estimation compared with Guérin's method.

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.

The equivalent capacity estimation is a very important function for Call Admission Control (CAC). To estimate the equivalent capacity, flow fluid and stationary approximations[1] are proposed. But, they make many approximations, which result in an overestimate of equivalent capacity. In order to deal with the problems of flow fluid and stationary approximations, Guérin, et al.[1] proposed a method which calculates the equivalent capacity as combination of fluid flow model and the approximation of the stationary bit rate distribution. But, also the Guérin's method still overestimates the actual bandwidth requirements. Also, these methods 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 high-speed networks. In addition, another major challenge is to provide the equivalent capacity estimation in real-time, upon the arrival of a connection request. This procedure must be computationally simple enough so the overall complexity is consistent with real time requirements.

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

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networks must be adaptive, flexible, and intelligent for efficient network management. 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)~6)]. In Refs. 2), 3), the FL is used to build fuzzy Policing Mechanisms (PM), whose performance is better than conventional PMs and very close to ideal behavior. In Ref. 4), a fuzzy controller for adaptive traffic in telephone networks is proposed. A simplified inference method is derived which attempts to represent gradual inference rules using fuzzy control. The inference method is based on heuristic rules derived from expert knowledge and human experience. It is proved that FL is an effective way to control the complex systems such as telecommunication networks. Some NN applications for traffic control in ATM networks are proposed in Ref. 5). 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. 6). The proposed routing algorithm has a fast decision and shows an adaptive behavior based on GA.

In this paper, we propose a Fuzzy Equivalent Capacity Estimator (FECE) for bandwidth allocation in high-speed networks[7)]. The equivalent capacity computation focuses on the bandwidth requirement of the bit rate generated by sources, and not on the different interactions that take place within the network. Such interactions are often too complex to even be accurately described. Focusing directly on the bit rate requirement of a source is reasonable in the context of a high-speed network attempting to provide a transparent service to sources. Our proposed FECE can provide an equivalent capacity estimation close to the exact value and the Fuzzy Rule Base (FRB) is simple (only 18 rules), which is practical for real-time network traffic control applications.

The proposed fuzzy estimator is part of a CAC scheme[8)] which is the subject of another paper. Performance evaluation via simulations shows that the FECE has a good equivalent capacity estimation compared with fluid flow and stationary approximations. Furthermore, the combination of FECE and stationary approximation give a better estimation compared with Guérin's method.

The organization of this paper is as follows. In the next Section, we will introduce the previous work. The proposed FECE is presented in Section 3. The simulation results are discussed in Section 4. Some implementation issues are treated in Section 5. Finally, our conclusions are given in Section 6.

2. Previous Work

2.1 Fluid Flow Approximation

In the fluid flow approximation model, the bit rate generated by a number of multiplexed connections is represented as a continuous flow of bits with intensity varying according to the state of an underline continuous-time Markov chain. This Markov chain is obtained from the superposition of sources associated with each connection. In order to determine the equivalent capacity, it is necessary to obtain an expression giving the distribution of the buffer contents and a function of the connections characteristics and the service rate. This expression must then be inverted to determine the value of the service rate, which ensures an overflow probability smaller than a given value ϵ for the available buffer size. This value is the equivalent capacity that should be allocated to the connections. Although this method provides the necessary information to determine the equivalent capacity, the associated computational complexity is often not compatible with the real-time requirements. This is because, even when the buffer content distribution can be easily derived, the resulting expression can not be easily inverted to yield the equivalent capacity as a function of other known parameters. Iterative numerical procedures must then be used to determine the value of the equivalent capacity.

2.2 Stationary Approximation

When the effect of statistical multiplexing is the dominant factor, a base for an approximation can be obtained by studying the impact of the assumption $\beta \approx 1$. The parameter β value depends on the mean burst period and the number of connections. The parameter β is significantly different from 1 when a number of connections with equivalent capacity much larger than their mean bit rate are multiplexed. This is essentially the case for connections with long burst periods and relatively low utilization. It should be noted that in the case of long burst periods, the relation between buffer overflows and packet losses may be inaccurate. Also, the asymptotic (large buffer) approximation itself is likely to be inaccurate as well in the case of large burst periods. This points to the limitation of the fluid flow model and the assumption $\beta \approx 1$, in the case of many connections with long burst periods.

When a number of connections with relatively long burst periods are multiplexed, a reasonably accurate estimate of the required bandwidth can be obtained from stationary bit rate distribution. The value of equivalent capacity can be selected to ensure that the aggregate stationary bit rate exceeds the equivalent capacity only with a probability smaller than the value ϵ of desired buffer overflow probability. This ensures a buffer overflow probability below ϵ, but if often a substantial overestimate of the actual bandwidth required as it ignores the "smoothing" effect of the buffer, i.e., the buffer allows the input rate to exceed the output rate for a short period.

In most of the cases where the effect of statistical multiplexing is of significance, the distribution of the stationary bit rate can be approximated by Gaussian distribution. The Gaussian distribution allows the use of standard approximations to estimate the tail of the bit rate distribution. However, it should be noted that some care must be exercised to avoid situations where the Gaussian assumption does not hold. This typically happens with small numbers of very bursty connections with high peak rate, low utilization, and long burst periods. In such cases, the stationary approximation can yield a lower capacity than actually required.

2.3 Equivalent Capacity

In order to deal with problems of fluid flow and stationary approximations, Guérin, et al. proposed the equivalent capacity method which is a combination of fluid flow and stationary approximations. This method calculates the equivalent capacity as the minimum of fluid flow approximation and stationary approximation. The fluid flow and stationary approximations are used because they complement each other, capturing different aspects of the behavior of multiplexing connections. As both fluid flow and stationary approximations overestimate the actual value of the equivalent capacity and are inaccurate for different ranges of connections characteristics, the Guérin's equivalent capacity method also overestimates the actual bandwidth requirements.

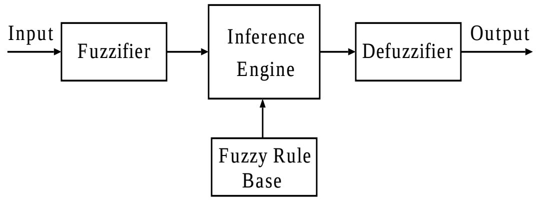

Fig. 1 FLC structure.

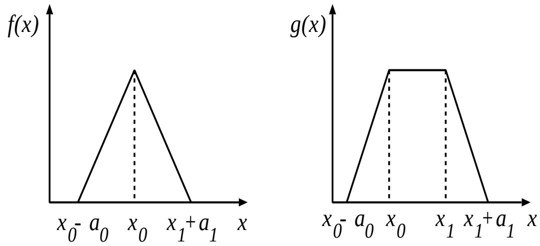

Fig. 2 Triangular and trapezoidal membership functions.

3. Proposed Fuzzy Equivalent Capacity Estimator

3.1 Fuzzy Membership Functions Design

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 order to gain from statistical multiplexing of bursty connections and make a more accurate estimation of equivalent capacity, we propose a 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, FRB and defuzzifier. As membership functions, we use triangular and trapezoidal functions, because they are suitable for real-time operation[9]. As shown in **Fig. 2**, the triangular and trapezoidal functions are given as:

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

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

where x_0 in $f(.)$ is the center of triangular function; $x_0(x_1)$ in $g(.)$ is the left (right) edge

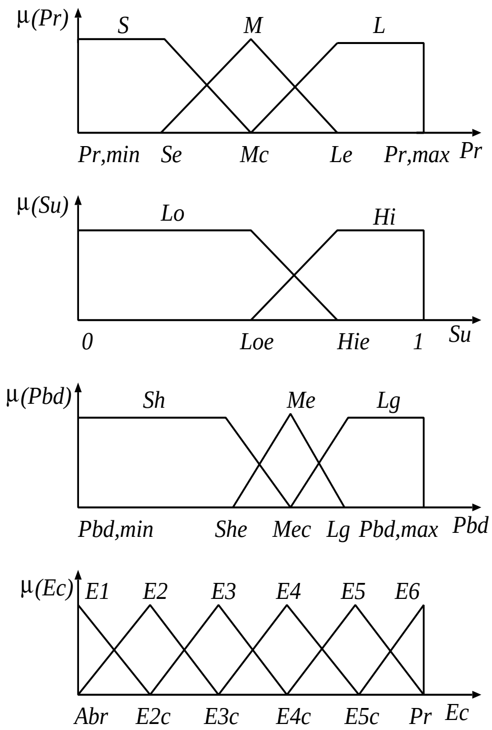

Fig. 3 FECE membership functions.

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 bit-rate duration (*Pbd*). The membership functions for FECE are shown in **Fig. 3**. The term sets of *Pr*, *Su*, and *Pbd* are defined respectively as:

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

Based on many simulations, we decided that three membership functions are enough for *Pr* linguistic parameter, two membership functions are enough for *Su* linguistic parameter, and three membership functions are enough for *Pbd* linguistic parameter.

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:

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

The small letters *e*, *c*, w0 and w1 mean edge, center, left width and right 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:

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

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:

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

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:

$$\begin{aligned} \mu_{E1}(Ec) &= f(\log(Ec); E1_c, 0, E1_{w1}); \\ \mu_{E2}(Ec) &= f(\log(Ec); E2_c, E2_{w0}, E2_{w1}); \\ \mu_{E3}(Ec) &= f(\log(Ec); E3_c, E3_{w0}, E3_{w1}); \\ \mu_{E4}(Ec) &= f(\log(Ec); E4_c, E4_{w0}, E4_{w1}); \\ \mu_{E5}(Ec) &= f(\log(Ec); E5_c, E5_{w0}, E5_{w1}); \\ \mu_{E6}(Ec) &= f(\log(Ec); E6_c, E6_{w0}, 0). \end{aligned}$$

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

3.2 Fuzzy Rule Base and Its Tuning

The 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".

Because there are three input linguistic pa-

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

rameters the maximal and minimal number of the membership functions fired at a moment of time is 6 and 3, respectively. To decide an appropriate output membership function, the strength of each rule must be considered. Also, a trade-off between the evaluation accuracy and the FRB complexity is needed. For this reason, we selected three input linguistic parameters and the parameter values of output membership functions are assigned as follows. The value of $E1_c$ is set equal to Abr and the value of $E6_c$ is set equal to Pr. The other values are calculated based on the following equation:

$$Ei_c = E(i-1)_c + (Pr - Abr)/5 \qquad (1)$$

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

Our policy for FRB tuning is to get an Ec estimation close to the exact value. The value of Ec is proportional with Pr, Pbd, and $(1-Su)$. Let us see the meaning of rules in the FRB. By way of illustration, Rule 0 in Table 1 has to be read as: If (Pr is small) and (Su is low) and (Pbd is short) then (Ec is E1). In Rules 0, 1, and 2, the Pr is small and Su is low, but the Pbd changes as short, medium, and long. By increasing the Pbd parameter the Ec is increased. For this reason, the Ec for these rules is E1, E2, and E3, respectively. In Rules 3, 4, and 5, the Su becomes high. The Ec is proportional with $(1-Su)$. Therefore, the Ec increases fast when Su is low, but increases slowly when Su is high. This is why the Rules 3, 4, and 5 are weaker compared with Rules 0, 1, and 2. The tuning of the following rules is the same, but in Rules 6, 7, 8, 9, 10, and 11, the Pr becomes medium, therefore these rules are stronger than rules when the Pr was small. When the Pr becomes large (Rules 12, 13, 14, 15, 16, and 17), the strength of output membership functions is increased more compared with membership functions when Pr was medium.

4. Simulation Results

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

$$\epsilon = \beta \cdot \exp\left(-\frac{B(Ec - Su \cdot Pr)}{Pbd(1-Su)(Pr-Ec)Ec}\right) \qquad (2)$$

where,

$$\beta = \frac{(Ec - Su \cdot Pr) + \epsilon \cdot Su(Pr - Ec)}{(1-Su)Ec}. \qquad (3)$$

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

$$\hat{Ec} \approx \frac{\alpha \cdot Pbd(1-Su)Pr - B}{2\alpha \cdot Pbd(1-Su)} + \frac{\sqrt{[\alpha \cdot Pbd(1-Su)Pr - B]^2}}{2\alpha \cdot Pbd(1-Su)} + \frac{\sqrt{4B\alpha \cdot Pbd \cdot (1-Su)Pr}}{2\alpha \cdot Pbd(1-Su)} \qquad (4)$$

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:

$$F(B) = \sum_{i=1}^{N} a_i \Phi_i e^{Z_i B} \qquad (5)$$

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 Eqs. (3) and (5). But, this calculation, although exact, is complicated and is not compatible with a dynamic and real-time environ-

Table 2 Assignment of values for input and output linguistic parameters.

	Pr	
$S_e = -3$	$S_{w0} = 0$	$S_{w1} = 1$
$M_c = -2$	$M_{w0} = 1$	$M_{w1} = 1$
$L_e = -1$	$L_{w0} = 1$	$L_{w1} = 0$
	Su	
$Lo_e = 0.6$	$Lo_{w0} = 0$	$Lo_{w1} = 1$
$Hi_e = 0.75$	$Hi_{w0} = 0.15$	$Hi_{w1} = 0$
	Pbd	
$Sh_e = -3$	$Sh_{w0} = 0$	$Sh_{w1} = 1$
$Me_c = -2$	$Me_{w0} = 1$	$Me_{w1} = 1$
$Lg_e = -1$	$Lg_{w0} = 1$	$Lg_{w1} = 0$
	Ec	
$E1_c = -2$	$E1_{w0} = 0$	$E1_{w1} = 0.4$
$E2_c = -1.6$	$E2_{w0} = 0.4$	$E2_{w1} = 0.4$
$E3_c = -1.2$	$E3_{w0} = 0.4$	$E3_{w1} = 0.4$
$E4_c = -0.8$	$E4_{w0} = 0.4$	$E4_{w1} = 0.4$
$E5_c = -0.4$	$E5_{w0} = 0.4$	$E5_{w1} = 0.4$
$E6_c = 0$	$E6_{w0} = 0.4$	$E6_{w1} = 0$

ment.

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

$$\hat{E}c_{(F)} = \sum_{i=1}^{N} \hat{E}c_i \tag{6}$$

where $\hat{E}c_i$ are determined from Eq. (4).

In fluid 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.

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:

$$\hat{E}c_{(S)} \approx Abr + \hat{\alpha}\sigma \tag{7}$$

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

Considering the values of $Pr, \min = 10^{-6}$, $Pr, \max = 1$, $Pbd, \min = 10^{-9}$, $Pbd, \max = 100\,\mathrm{s}$, and $Abr = 10^{-2}$, their logarithmic values will be $Pr, \min = -6$, $Pr, \max = 0$, $Pbd, \min = -9$, $Pbd, \max = 2$, and $Abr = -2$, respectively. Based on these values, the values for input and output linguistic parameters are assigned as shown in **Table 2**.

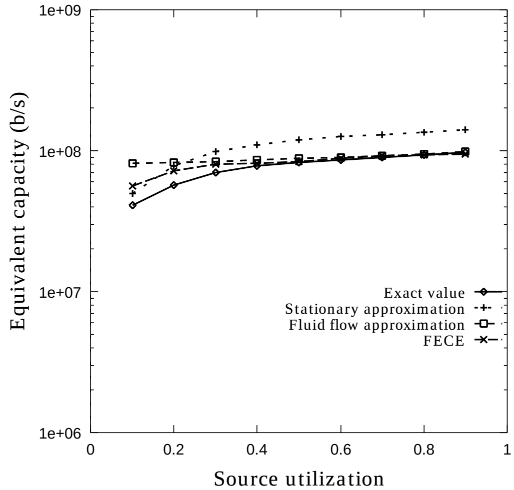

Fig. 4 Ec versus Su ($N = 5$).

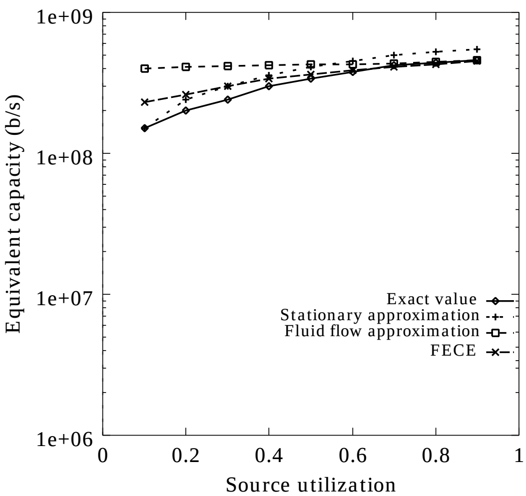

Fig. 5 Ec versus Su ($N = 50$).

By using the same parameters for four methods: the normalized value of $Pr = 6.6 \times 10^{-3}$, $Pbd = 2 \times 10^2$, and the probability of overflow 10^{-5}, the characteristic of the required Ec versus Su for three different number of connections $N = 5$, $N = 50$ and $N = 90$ are shown in **Figs. 4**, **5**, and **6** 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 does not have a good Ec accuracy. But, for traffic sources with high source utilization, the flow approximation does have a good Ec estimation. On the other hand, the stationary approximation has a good Ec accuracy for low source uti-

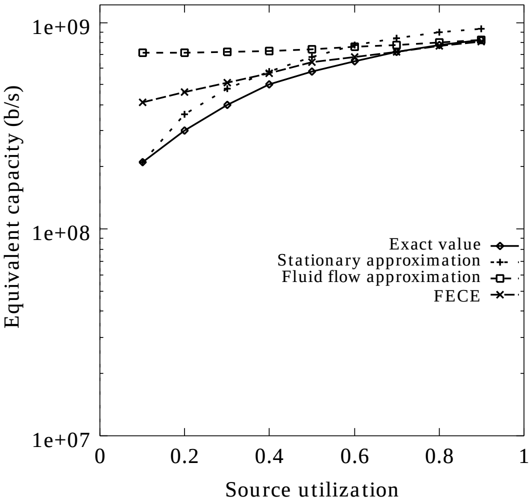

Fig. 6 Ec versus Su ($N = 90$).

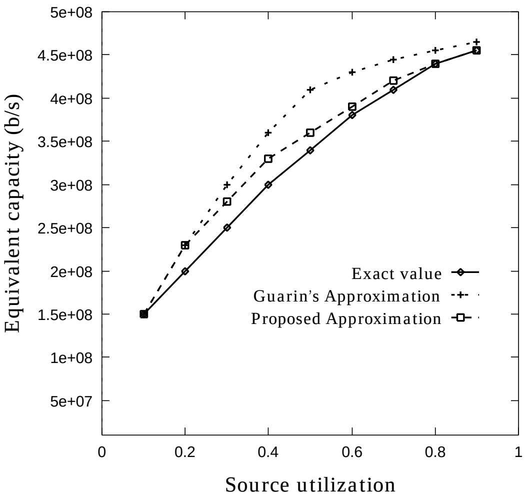

Fig. 7 Performance comparison between Guérin's method and proposed method.

lization and a poor estimation for high source utilization. The characteristic of FECE is more close to the exact value compared with both flow and stationary estimations. However, for sources with very low utilization, the stationary approximation gives a better accuracy than FECE.

In order to get a better estimation of Ec, Guérin calculated the Ec as the minimum value of fluid flow approximation and stationary approximation. We also get a good Ec estimation by calculating the Ec value as the minimum value of FECE and stationary approximation. The performance comparison between Guérin's method and our proposed method for $N = 50$ is shown in **Fig. 7**. At the beginning, both methods have the same behavior, because they use the stationary approximation, but as the source utilization increases, our method makes a better estimation than Guérin's method. For $Su = 0.5$, our method and the exact value are very close. Otherwise, Guérin's method has a difference of about one order of magnitude compared with the exact value. For high source utilization, Guérin's method uses the flow approximation and the characteristic is approaching the exact value. However, our method shows a better performance even for high source utilization.

5. Implementation Issues

Many ultra-low cost fuzzy chips exist and are recently proposed. We consider as a fuzzy chip for implementation, the parallel architecture proposed in Ref. 10). This processor has the following characteristics: the hardware implementation of the processor comprises 4 Fuzzy Processing Units (FPUs); the clock frequency at which each processor operates is 60 MHz; the speed of this fuzzy chip is about 77000 Fuzzy Logic Inference Operations Per Second (FLIOPS), if one FPU is operating.

In order to use the FECE for Ec estimation in real-time, we should consider the time constraint which the incoming connections shoud be processed. Let us consider two time constraints t_c of about 12 ms and 2.7 μs. The t_c is the maximum time limit by which the FECE has to infer the output. If we denote the processing time of the FECE with t_f, the value of t_f should be smaller than t_c. Let express the time constraint in terms of FLIOPS. The FECE has to give a minimum performance of $1/t_c$, so the performance required is 84 FLIOPS and 370 FLIOPS for 12 ms and 2.7 μs, respectively. The fuzzy processor has a speed of 77000 FLIOPS, thus, the FECE is capable of calculating the Ec of thousand and few hundred of connections for 12 ms and 2.7 μs, respectively. This results in an improvement of the exploitation of hardware when the fuzzy processor is used to estimate the Ec of many connections in time sharing.

6. Conclusions

In this paper, we proposed a FECE for bandwidth allocation in high-speed networks. The behavior of FECE was investigated by simulations. From the simulations results, we conclude:

- the fluid flow approximation has a good

Ec estimation for traffic sources with high source utilization, but a poor estimation for bursty traffic sources when the sources have a low utilization;
- 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 fluid flow and stationary estimations;
- for sources with very low utilization, the stationary approximation give a good accuracy than FECE;
- combination of FECE and stationary approximation gives a more accurate estimation of Ec than Guérin's method;
- the FECE can be used for real time estimation of Ec and an improvement of the exploitation of hardware can be achieved when the fuzzy processor is used to estimate the Ec of many connections in time sharing.

The authors are working toward a CAC scheme which is based on FL and will use the proposed FECE as a cooperative agent to evaluate the Ec.

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