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A Fuzzy Admission Control Scheme and Its Performance Evaluation

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In high-speed networks, the traffic control design becomes an important challenge, because of the diverse services support and the need for an efficient network resource engineering. To cope with rapidly changing network conditions and bursty traffic, the traffic control methods 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. In this paper, we propose an intelligent call admission control scheme based on fuzzy logic. Performance evaluation via simulation shows that proposed scheme has a good equivalent capacity estimation compared with conventional methods. Furthermore, the proposed method shows better admission regions than equivalent capacity method.

1. Introduction

In high-speed networks, the traffic control design becomes an important challenge, because of the diverse services support and the need for an efficient network resource engineering.

One area of very importance in high-speed networks is congestion control. The primary role of a network congestion control procedure is to protect the network and the user in order to achieve network performance objectives and optimize the usage of network resources. Congestion control procedures can be classified into preventive and reactive control. Preventive congestion control involves Call Admission Control (CAC) and Policing Mechanisms (PMs). The CAC deals with acceptance or rejection of new connections. The decision is done based on how the new connection affects the Quality of Service (QoS) of the existing connections and network resources. After a call is accepted by CAC procedure, the call may exceed the parameters declared in call-setup phase. Therefore, a PM is needed to act on each source before all the traffic is multiplexed, in order to guarantee the negotiated QoS.

Traditional CAC schemes can be classified in equivalent capacity, heavy traffic approximation, upper bounds of the cell loss probability, fast buffer/bandwidth allocation, and time windows. Among proposed CAC schemes, the equivalent capacity gives better results [1)]. But, the equivalent capacity scheme makes many approximations, which result in an overestimate of equivalent capacity. Using conventional CAC scheme, it is not easy to accurately determine the effective bounds or equivalent capacity in various bursty traffic flow conditions of high-speed networks. Thus, to cope with rapidly changing network conditions and bursty traffic, the 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 (FL), Neural Networks (NN) and Genetic Algorithms (GA) can prove to be efficient for traffic control in high speed networks [2)~4)]. In Ref. 2), the FL is used to build a fuzzy PM, which performance is better than conventional PMs and very close to ideal behavior. Some NN applications for traffic control in high-speed 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.

In this paper, we propose a Fuzzy Admission Control (FAC) scheme. The proposed scheme can achieve a better estimation of the required equivalent capacity compared with con-

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ventional methods. Furthermore, the proposed method shows better admission regions than equivalent capacity method.

The organization of this paper is as follows. In the next Section, we will introduce the previous work. The proposed FAC scheme and its components will be introduced in Section 3. The simulation results will be discussed in Section 4. Finally, conclusions will be given in Section 5.

2. Previous Work

The CAC deals with the question of whether or not a node can accept a new connection. The decision to accept or reject a new connection is based on the following questions: does the new connection affect the QoS of the connections currently being carried by the network? can the network provide the QoS requested by the new connection?

A variety of different CAC schemes have been proposed. They are classified into the following groups: equivalent capacity; heavy traffic approximation; upper bounds of the cell loss probability; fast buffer/bandwidth allocation; and time windows [1)].

The equivalent capacity is a popular scheme for CAC. 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 [5)]. These two approaches are used because they complement each other, capturing different aspects of the behavior of multiplexing connections.

Sohraby [6)] proposed an approximation for bandwidth allocation based on the asymptotic behavior of the tail of the queue length distribution. Saito [7)] proposed a CAC scheme by inferring the upper bound of cell loss probability from the traffic parameters specified by user.

The fast buffer/bandwidth allocation scheme was devised for the transmission of bursty sources. In this scheme, when a virtual circuit is established, the path through the network is set up and the routing tables are appropriately updated, but no resources are allocated to the virtual circuit. When a source is ready to transmit a burst, at that moment the network attempts to allocate necessary resources for the burst duration [8)].

In time window scheme, a source is only allowed to transmit up to a maximum number of bits within a fixed period of time which is known as time window. Golestani [9)] proposed a mechanism where for each connection the number of cells transmitted on any link in the network is bounded. Thus, a smooth traffic flow is maintained throughout the network. This is achieved using the notion of a frame which is equal to a fixed period of time. For each connection, the number of cells per frame transmitted on an outgoing link cannot exceed its upper bound.

The above mentioned CAC schemes 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. Among proposed CAC schemes, the equivalent capacity gives better results [1)]. However, 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 equivalent capacity method also overestimates the actual bandwidth requirements.

3. Proposed Fuzzy Admission Control Scheme

In order to make a more accurate decision for connection acceptance, we propose a fuzzy based CAC scheme, called FAC scheme. The Fuzzy Logic Controller (FLC) is the main part of the FAC 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 membership functions because they are suitable for real-time operation [10)]. They are shown in **Fig. 2** and 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 of trapezoidal function; and $a_0(a_1)$ is the left (right) width of the triangular or trapezoidal function.

In difference from the equivalent capacity ad-

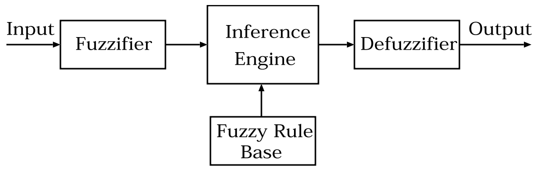

Fig. 1 FLC structure.

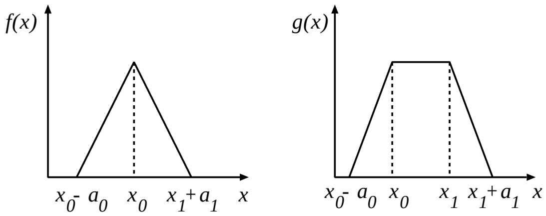

Fig. 2 Triangular and trapezoidal membership functions.

mission control method[5)], which uses only the available capacity as the only variable for the call admission decision, our FAC scheme considers four parameters: Quality of service (Qs), Network congestion parameter (Nc), Available capacity (Ac), and user requirement parameter which is expressed by Equivalent capacity (Ec). We decided the number of membership functions for each linguistic parameters based on many simulations. We found that two membership functions are enough for Qs, Nc, Ac linguistic parameters, and three membership functions are enough for Ec linguistic parameter. The output linguistic parameter is the Acceptance decision (Ad). In order to have a soft admission decision, not only "accept" and "reject" but also "weak accept", "weak reject", and "not accept not reject" are used to describe the accept/reject decision. The membership functions for input and output linguistic parameters are shown in **Fig. 3**. The small letters *e*, *c*, *w0* and *w1* mean edge, center, right width and left width, respectively. In the case of trapezoidal membership functions which have only one width, we write the width simply as *w*. While, in the case of triangular functions, the widths are written as *w0* and *w1*.

The term sets of Qs, Nc, Ac, and Ec are defined respectively as:

$$T(Qs) = \{Satisfied, NotSatisfied\} = \{S, NS\};$$
$$T(Nc) = \{Negative, Positive\} = \{N, P\};$$
$$T(Ac) = \{NotEnough, Enough\} = \{NE, E\};$$
$$T(Ec) = \{small, medium, big\} = \{sm, me, bi\}.$$

The membership functions for input parameters of FAC are defined as follows.

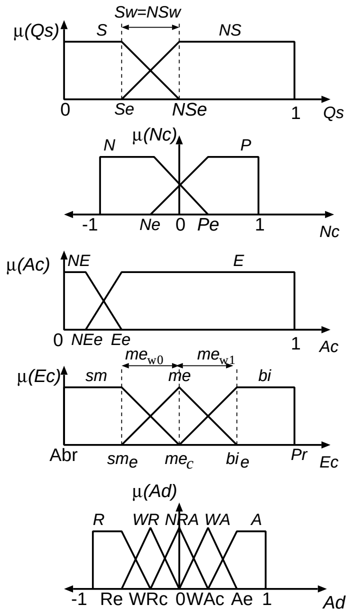

Fig. 3 FAC membership functions.

$$\mu_S(Qs) = g(\log(Qs); 0, S_e, 0, S_w);$$
$$\mu_{NS}(Qs) = g(\log(Qs); Ns_e, 1, Ns_w, 0);$$
$$\mu_N(Nc) = g(Nc; -1, N_e, 0, N_w);$$
$$\mu_P(Nc) = g(Nc; P_e, 1, P_w, 0);$$
$$\mu_{NE}(Ac) = g(\log(Ac); 0, NE_e, 0, NE_w);$$
$$\mu_E(Ac) = g(\log(Ac); E_e, 1, E_w, 0);$$
$$\mu_{sm}(Ec) = g(\log(Ec); Abr, sm_e, 0, sm_w);$$
$$\mu_{me}(Ec) = f(\log(Ec); me_c, me_{w0}, me_{w1});$$
$$\mu_{bi}(Ec) = g(\log(Ec); bi_e, Pr, bi_w, 0).$$

The term set of the output linguistic parameter $T(Ad)$ is defined as {Reject, Weak Reject, Not Reject Not Accept, Weak Accept, Accept}. We write for short as {R, WR, NRA, WA, A}. The membership functions for the output parameter Ad are defined as follows.

$$\mu_R(Ad) = g(Ad; -1, R_e, 0, R_w);$$
$$\mu_{WR}(Ad) = f(Ad; WRc, WR_{w0}, WR_{w1});$$
$$\mu_{NRA}(Ad) = f(Ad; NRAc, NRA_{w0}, NRA_{w1});$$
$$\mu_{WA}(Ad) = f(Ad; WAc, WA_{w0}, WA_{w1});$$
$$\mu_A(Ad) = g(Ad; A_e, 1, A_w, 0).$$

The FRB forms a fuzzy set of dimensions $|T(Qs)| \times |T(Nc)| \times |T(Ac)| \times |T(Ec)|$, where $|T(x)|$ is the number of terms on $T(x)$. The FRB1 shown in **Table 1** has 24 rules. The control rules have the following form: IF "conditions" THEN "control action". Statements on conditions go like "the Qs is satisfied" or "the Nc is congested". Likewise, statements on control action might be "reject" or "accept".

Table 1 FRB1.

Rule	Qs	Nc	Ac	Ec	Ad
0	S	N	NE	sm	NRA
1	S	N	NE	me	WR
2	S	N	NE	bi	WR
3	S	N	E	sm	WA
4	S	N	E	me	NRA
5	S	N	E	bi	WR
6	S	P	NE	sm	WA
7	S	P	NE	me	NRA
8	S	P	NE	bi	WR
9	S	P	E	sm	A
10	S	P	E	me	A
11	S	P	E	bi	A
12	NS	N	NE	sm	R
13	NS	N	NE	me	R
14	NS	N	NE	bi	R
15	NS	N	E	sm	NRA
16	NS	N	E	me	NRA
17	NS	N	E	bi	R
18	NS	P	NE	sm	WR
19	NS	P	NE	me	R
20	NS	P	NE	bi	R
21	NS	P	E	sm	NRA
22	NS	P	E	me	NRA
23	NS	P	E	bi	WR

The FRB1 is tuned based on the following policy. The calls will be accepted when the Qs is satisfied, the network is congestion-free ($Nc = P$), and the Ac (available capacity) is enough. In these cases, the number of accepted calls will depend on Ec value. In order to increase the network utilization, calls will be weakly accepted in the cases when: the Qs is satisfied, the network is congested, Ac is enough, and Ec is small; the Qs is satisfied, the network is congestion-free, the Ac is not enough, and Ec is small. The acceptance decision will be NRA in the cases when: the Qs is satisfied, the network is congested ($Nc = N$), the Ac is not enough, and the Ec is small; the Qs is satisfied, the network is congested, Ac is enough, and Ec is medium; the Qs is satisfied, the network is congestion-free, the Ac is not enough, and Ec is medium; the Qs is not satisfied, the network is congested, the Ac is enough, and Ec is small or medium; and the Qs is not satisfied, the network is not congested, the Ac is enough, and Ec is small or medium. The calls will be weakly rejected in the cases when: the Qs is satisfied, the network is congested, the Ac is not enough, and Ec is medium or big; the Qs is satisfied, the network is congested, the Ac is enough, and Ec is big; the Qs is satisfied, the network is congestion-free; the Ac is not enough, and Ec is big; the Qs is not satisfied, the network is not congested, the Ac is not enough, and Ec is small; and the Qs is not satisfied, the network is congestion-free, the Ac is enough, and Ec is big. In the other cases the calls will be rejected.

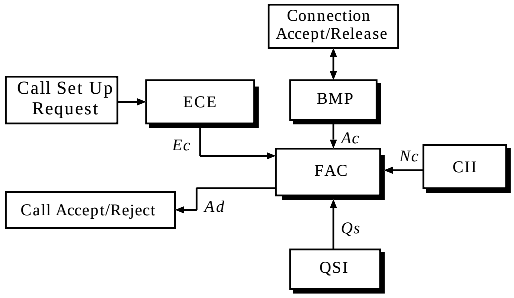

Fig. 4 FAC scheme.

In order to have a simple FRB and a good admission decision, we selected 4 input linguistic parameters and one output linguistic parameter. To have a soft admission decision, not only A and R, but also WA, NRA, and WR are used as output membership functions. Because there are 4 input linguistic parameters, the maximal and minimal number of the membership functions fired at a moment of time is 8 and 4, respectively. To decide an appropriate output membership function, the strength of each rule must be considered. For this reason, the output membership function is a complicated function and we use as a defuzzification method the center of area method, which get the center point of the fuzzy output membership function. This value is used for admission control. As a result, the connections will be accepted if the output value is more than zero and will be rejected if the output value will be less than zero.

The FAC scheme is shown in **Fig. 4**. The information for FAC are given by Bandwidth Management Predictor (BMP); Congestion Information Indicator (CII); QoS Indicator (QSI); and Equivalent Capacity Estimator (ECE). The BMP works in this way: if a connection is accepted, the connection bandwidth is subtracted from the available capacity of the network, otherwise, if a connection is released, the connection bandwidth is added to the available capacity of the network. The CII decides whether the network is or isn't congested. The QSI determines whether allowing a new connection violates or not the QoS guarantee of the existing connections.

In order to get a better estimation of Ec, we propose a Fuzzy ECE (FECE) scheme. The FECE predicts the Ec required for a new connection based on the traffic parameters Peak rate (Pr), Source utilization (Su), and Peak bit-

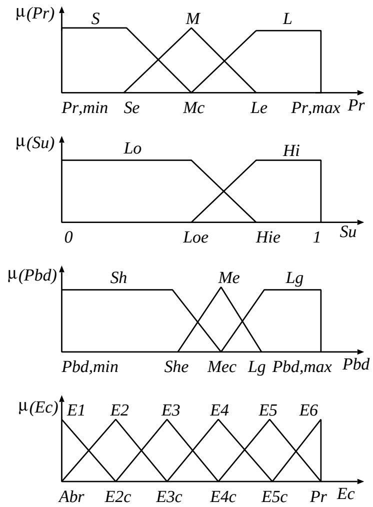

Fig. 5 FECE membership functions.

rate duration (*Pbd*). The membership functions for FECE are shown in **Fig. 5**. The term sets of *Pr*, *Su*, and *Pbd* are defined respectively as:

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

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:

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

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

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

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:

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

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:

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

Table 2 FRB2.

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

The FRB2 is shown in **Table 2** and has 18 rules. Because there are three input linguistic parameters 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 tuning of FECE FRB 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 2 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.

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

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:

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

where,

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

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

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

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:

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

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 environment.

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

$$\hat{Ec}_{(F)} = \sum_{i=1}^{N} \hat{Ec}_i \quad (6)$$

where $\hat{Ec}_i$ 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:

$$\hat{Ec}_{(S)} \approx Abr + \hat{\alpha}\sigma \quad (7)$$

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.

Considering the values of $Pr,\min = 10^{-6}$, $Pr,\max = 1$, $Pbd,\min = 10^{-9}$, $Pbd,\max =$ 100s, and $Abr = 10^{-2}$, the values for input and output linguistic parameters for FECE are assigned as follows. The parameter values of input membership functions are assigned as: for Pr, $S_e = -3$, $S_w = 1$, $M_c = -2$, $M_{w0} = M_{w1} = 1$, $L_e = -1$, $L_w = 1$; for Su, $Lo_e = 0.6$, $Lo_w = 0.15$, $Hi_e = 0.75$, $Hi_w = 0.15$; for Pbd, $Sh_e = -3$, $Sh_w = 1$, $Me_c = -2$, $Me_{w0} = Me_{w1} = 1$, $Lg_e = -1$, $Lg_w = 1$. While, the values for output membership functions are assigned based on Eq. (1).

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 over-

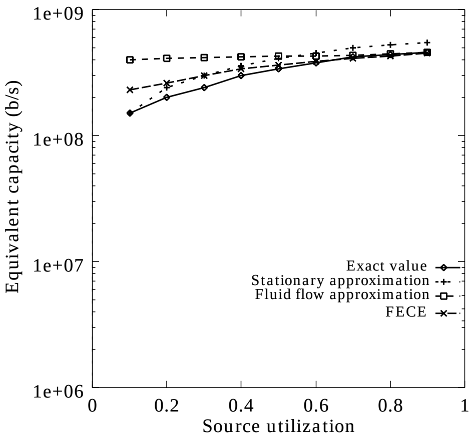

Fig. 6 Ec versus Su (N=50).

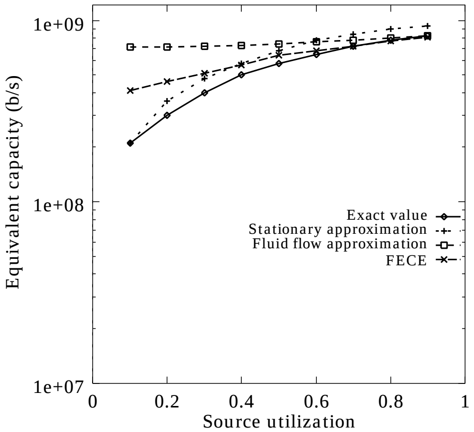

Fig. 7 Ec versus Su (N=90).

flow 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. 6** and **Fig. 7**, 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.

In order to get a better estimation of Ec, Guérin calculated the Ec as the minimum value

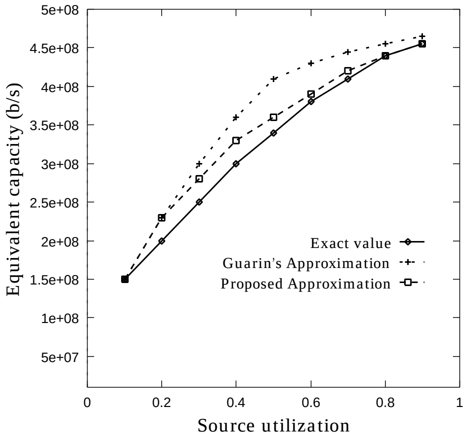

Fig. 8 Performance comparison between Guérin's method and proposed method.

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. 8**. 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.

In order to compare the statistical multiplexing gain of FAC scheme and equivalent capacity method, we consider a multiplexer which can process two classes of connections: class 1 and class 2. We consider that all connections in a class have the same traffic parameters $Pr = 4$ Mb/s, $Su = 0.4$, $Pbd = 0.106$ s, and $Pr = 10$ Mb/s, $Su = 0.4$, $Pbd = 0.021$ s, for class 1 and class 2, respectively.

The parameter values of input FAC membership functions are assigned as: for Qs, $S_e = 5\times 10^{-6}$, $NS_e = 1\times 10^{-5}$, $S_w = NS_w = 5\times 10^{-6}$; for Nc, $N_e = -0.2$, $P_e = +0.2$, $N_w = P_w = 0.4$; for Ac, $NE_e = 0.05$, $E_e = 0.1$, $NE_w = E_w = 0.05$; for Ec, $sm_e = 0.2(Pr - Abr)$, $me_c = 0.5(Pr - Abr)$, $bi_e = 0.7(Pr - Abr)$, $sm_w =$

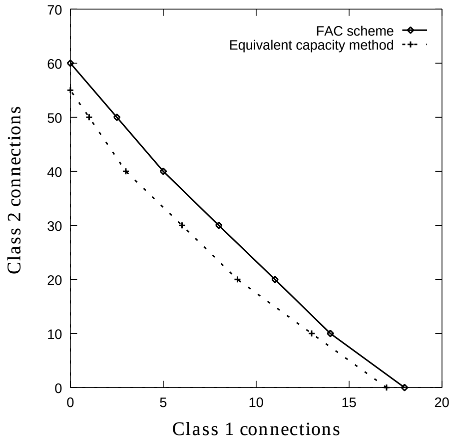

Fig. 9 Admission regions: case 1.

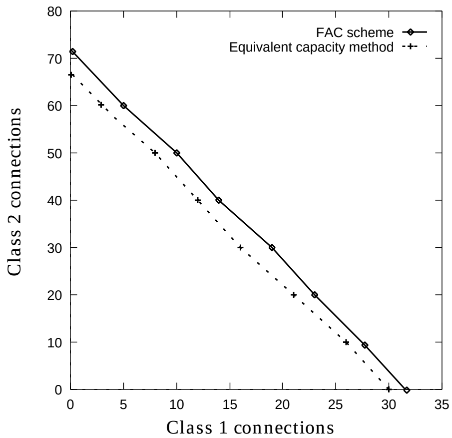

Fig. 10 Admission regions: case 2.

$me_{w0} = me_{w1} = bi_w = 0.3(Pr - Abr)$.

The parameter values of output FAC membership functions are assigned as follows: $R_e = -0.6$, $WR_c = -0.3$, $NRA_c = 0$, $WA_c = 0.3$, $A_e = 0.6$.

Using the FAC scheme and equivalent capacity method, the admission regions for two buffer size cases: case 1 (1 000 cells) and case 2 (10 000 cells) are shown in **Fig. 9** and **Fig. 10**, respectively. As the buffer size increases, the number of connections admitted into the network is increased. The FAC scheme can admit more connections than equivalent capacity method, thus increasing the network utilization.

5. Conclusions

In this paper, we proposed a FAC scheme for high-speed networks. First, we introduced the previous works. Next, we treated the proposed FAC scheme with its components. Finally, the simulation results were discussed. The behavior of FECE and FAC scheme were 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 give a more accurate estimation of Ec;
- FAC scheme has a better admission region than the equivalent capacity method.

The authors are planing to use this scheme in an integrated CAC and routing mechanism for high-speed networks.

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