A Complex System Characterization of Modern Telecommunication Services

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A modern telecommunication service is portrayed as a complex system and is characterized by its stochastical attributes and fuzzy performance considerations. Asynchronous transfer mode (ATM) telecommunication is studied as an example of such a complex system. A call admission control (CAC) procedure is developed using a fuzzy inference method applied to the complex connection patterns of ATM service. Such an inference alleviates the potentially over-conservative nature of resource allocation. A complex system parameter is defined and used as a fuzzy variable in the inference strategies pursued. Some practical considerations and merits of the present study are indicated and discussed.

1. Introduction

Modern telecommunication systems are aptly qualified to be described as *complex systems*. The associated vastness of inherent technology, variety in service considerations, and the plethora of application profiles have posed an inevitable attribute of interaction between the constituent subsystems of modern telecommunication engineering. Such an attribute describes, in general, how the resources of one subsystem are expended in interacting with other subsystems in a complex manner.

The quality of service (QOS) parameters associated with a telecommunication system depicts the metric of complexity. This metric assays the global performance of telecommunication service offered *versus* the cost involved. Estimating QOS parameters, or prescribing such parameters while negotiating with a service provider to access a specific class of connection across the network, warrants a meaningful modeling of complexity associated with the telecommunication system. The relevant modeling should include spatial stochasticity of interacting resources as well as the temporal dynamics of information flow between the end entities of a telecommunication channel.

Studies [1, 2] indicate that such spatiotemporal considerations in the modern telecommunication environment are often fuzzy. That is, the activity of information transfer across the network refers to the *non-*

specificity of the values and *sharplessness* of the boundaries of activity variables involved. Hence, it can be expected that the telecommunication QOS parameters would map onto a fuzzy domain. Correspondingly, the performance attributes as well as any inferences made thereof could be more realistically specified in fuzzy domains. Further, any control endeavor on the system can be accomplished *via* a fuzzy inference engine. In other words, the complex system parameters depicting the system performance can be used as fuzzy variables to arrive at a control decision criterion as required.

In the context of modern telecommunication systems the relevance of stochastical considerations, fuzzy attributes, and complexity (in both spatial and temporal characterizations) arise mainly due to the following.

1. Heterogeneity of traffic types (voice, video, and data transmissions).
2. Variety in the physical media of transmission (copper wires, optical fibers, and wireless means).
3. Different versions of switching which interconnect the lines with varying buffer sizes.
4. Temporal fluctuation of traffic demands (peak and slack hour traffics).
5. Temporal variations in bits per second emitted by the source (variable bit-rate traffics).
6. Time-dependent bandwidth demands (multimedia transmissions).
7. Synchronous and asynchronous transmissions of packetized information.
8. Types of packetization of bits (either as variable size packets or as fixed size cells).
9. Protocol specifics such as call admission control (CAC), congestion control, and service priority scheduling.
10. Statistical multiplexing of packets with traffic priorities on contention.
11. Signal-to-noise ratio (SNR) and bit-error rate considerations (bit-error detection and correction methods implemented).
12. Statistical aspects of the amount of information emitted by different sources (loading factor considerations as a function of time).
13. Mobility of end entities (wireless communication systems).
14. Types and modes of implementing signaling for connection setup and release.
15. Connection-oriented and connectionless configurations of the network.

16. Geographical outlays: wide-area network, local-area network, metropolitan-area network, and global-area network considerations.

17. Network security (encryption and decryption requirements).

The gross features of the network (in terms of its connectivity size and extent of traffic handled) plus the stochastical nature of network performance (as a function of time) render the telecommunication system realistically complex.

In order to capture fully the intuitive concept of the complexity of telecommunication systems, it is necessary to portray the associated complexity in a multidimensional framework. This multidimensionality should include the gamut of measures, each addressing a specific aspect of service category, QOS objectives, and traffic descriptors along one dimension. Further, inasmuch as many of these measures could be correlated, the modeling should facilitate the corresponding enhancement in the complexity being assessed due to the interactiveness of the measures involved.

The metric of QOS objectives in crisp form denotes primitive measures. They do not, *per se*, reflect the gross and correlatory attributes between the parameters. Neither do they depict the fuzziness of the variables. At most, they are represented in probabilistic norms signifying only the stochastical attributes.

In order to include cohesively the stochastical considerations and fuzzy characteristics, as well as the gross complexity of the system, an integration of the following is needed. (i) The spatiotemporal dynamics of the system specified in the entropy or information-theoretic plane [3–5]; and (ii) rendering fuzzy of the variables involved in the dynamics [6].

The purpose of this paper is to indicate how the complexity of a telecommunication system can be analytically modeled *via* considerations of information-theoretics (IT) and fuzzy properties. Specifically, an asynchronous transfer mode (ATM) switching stage is considered. Modeling is performed in respect to the following two QOS parameters. (i) Variations in the delay of cell-transfers. Such cell-delay variations (CDVs) or *jitter* lead to dropping those cells which are delayed beyond a permissible upper bound on CDV. This is of concern especially in a congested traffic ambient. (ii) Additional loss in the number of cells (packetized segment of bits, which carry the information) due to bit errors caused by the noisy channel.

The performance of a telecommunication network *vis-à-vis* a given set of QOS objectives can be deduced in terms of a complexity profile posed by stochastical considerations and fuzzy attributes of the relevant network technology. It is shown in this paper how to reduce the multidimensionality of primitive measures concerning network performance to a single complexity parameter (with fuzzy properties) which can decide an upper bound on the performance. The relevant strategy involves, as stated earlier, a blend of IT and fuzzy logic considerations.

Using the complexity parameter deduced, it is shown how a fuzzy inference engine can be constructed using the complexity parameter as a fuzzy variable. This inference engine is adopted to formulate an algorithm that enables CAC in ATM networks. That is, a fuzzy inference engine, which assesses the complex connection patterns of the network and prescribes fuzzy norms on resource utilization, is developed. This approach alleviates the risk of over-conservative resource allocations in the CAC implementation. The efficacy of this algorithm is demonstrated *via* simulated results pertinent to a typical ATM environment.

Thus, the content of this paper is presented in two parts. In Part I a time-dependent complexity metric $s(t)$ is deduced *via* an IT approach for ATM telecommunication systems. The statistical bounds on the per-connection guarantee (i.e., QOS parameters) solicited from the network operator are obtained in terms of the complexity measure proposed.

The modeling strategy adopted is based on the following. (i) The flow of information-bearing ATM cell streams is regarded as a queueing system. Unlike the conventional queueing model wherein the temporal statistics of cell arrival and cell waiting are used in the analysis, the present study considers the flow of entropy (or information content in Shannon's sense) borne by the queue [4–6]. A relevant metric of complexity $s(t)$ is defined thereof, and deduced in terms of the Shannon information content. (ii) The temporal dynamics of $s(t)$ are then formulated in terms of stochastical differential calculus. Further, (iii) fuzzy attributes to $s(t)$ are introduced *via* Zadeh's extensive principle and a fuzzy Fokker–Planck equation [7] describing the dynamics of $s(t)$ is obtained.

The considerations of an IT strategy allow a direct evaluation of the impairment to information flow (or information loss) posed by the statistics of cell loss. That is, the effects of cell loss impairing the information transmitted are introduced appropriately in terms of the complexity parameter adopted. The cell losses considered include both those lost as a result of buffer-overflows or queueing at the ATM switch (or multiplexer) and those dropped due to uncorrectable bit errors stemming from a finite SNR (which depicts the finite extent of noise in the system).

In Part II, using the strategy developed in Part I, a CAC algorithm is deduced and its efficacy is demonstrated with simulated data.

2. Asynchronous transfer mode telecommunication

2.1 A brief review

ATM is a platform recommended to support broadband integrated systems of digital networks (B-ISDNs). It is a technique that has been de-

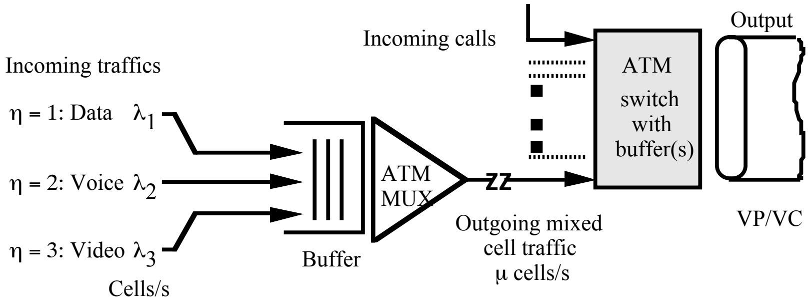

Figure 1. ATM multiplexing and switching. $\eta = 1, 2, 3$ are incoming cells from different types of sources at the call-origination end.

veloped to handle cohesively the telecommunication of heterogeneous streams of messages emanating from different sources such as data, voice, and video on a given network [8].

The characteristics of mixed ATM traffic are as follows. (i) A vast difference in the speeds of individual traffic (in terms of bits per second). (ii) Delay sensitiveness of isochronous traffic such as video and voice (relative to data traffic). (iii) Cell losses incurred while in transit across the network. (iv) Virtual connectivity offered to the cells (fixed-size packets, each with 53 bytes) for transmission across the network.

When the delay experienced by a cell becomes too excessive, the ATM protocol would let the cell be dropped from the transmission. The fraction of such cells dropped is designated by a QOS parameter, known as the cell loss ratio (CLR). Inasmuch as the causative mechanisms and the deciding factors of these delays are largely statistical, the delay parameter fluctuates randomly with respect to time. This statistically varying cell delay, as stated before, refers to a parameter designated as cell delay variation (CDV). It represents one of the QOS parameters. A typical multiplexing of cells from different sources and switching of ATM calls is illustrated in Figure 1.

Apart from excessive cell transfer delay (CTD) variation (scaling beyond an upper bound) causing cell losses, bit errors in the cell-header which are detected but cannot be corrected would also lead to dropping cells. The first type arises as a result of the randomness of the traffic. The second type is due to a change in the bit pattern in the cell-header due to a finite extent of noise (specified by a finite SNR prevailing in the transmission path). A bound on CLR depicts the limit on the number of cells lost in the transmission path which can be tolerated without any significant impairment to the semantic transparency of the information transferred. It is proposed in the present work that the CDV-based cell losses and noise-induced cell losses can be combined and represented by a single parameter in the IT plane. The corresponding upper bound on the resultant variation in the CTD can be decided by the tail-end probability α in the resultant probability distribution of the CDV. Suppose the CLR corresponding to jittered CDV is CLR1 and that due to noise-induced bit-error is CLR2. The net CLR bound should then be the result of the joint influences of CLR1 and CLR2. The problem of linking CDV *versus* CLR1 and SNR *versus* CLR2 can be done *via* IT considerations. Part I is devoted to relevant efforts.

Part II of this paper refers to using the complexity metric (deduced in Part I) to develop a call admission algorithm under fuzzy operational conditions. When a call request comes, an ATM switch has to decide whether the connection would enable or not a required QOS if the call is accepted. If the ATM switch judges that the required QOS can be facilitated, then the call will be accepted. Otherwise, the call will be rejected. This is the strategy known as CAC. Basically, it refers to a set of rules or algorithms to decide whether a new call should be accepted or not [9].

There is a set of essential QOS parameters that characterize source traffic and are required to address CAC issues. Based on these QOS parameters declared by the user, the CAC could determine the type of service required. For example, a connection can be facilitated on the basis of available-bit-rate service provided by the network. In this case, the connection is assigned whatever the bit rate is available at that particular time.

A broadband call, for example, can be a multimedia call having a number of components such as still-picture, video, voice, and text. Each component generally requires a separate *connection*. Facilitating connectivity (meeting a set of specified QOS objectives) to a call refers to assigning virtual channel identification to that category of cells belonging to the call. Transport of these cells takes place on the assigned virtual channels. A bundle of virtual channels constitutes a virtual path which is identified by a virtual path identifier. Each virtual connection has a *transfer capacity* (a bandwidth) assigned to it according to the user's request. This is usually done during the connection setup procedure using CAC. This connection process also determines such parameters as maximum CTD/CDV and/or CLR that a connection will be allowed depending on user needs.

The decision on whether a call be permitted or not is made based on the traffic characteristics of the call and availability of required network resources to handle the additional traffic without affecting the resource requirements of the existing calls. In other words, the additional traffic demand on the resources to be generated by the new call should not have any effect on the traffic performance aspects of existing calls.

There are several CAC algorithms described in the literature [1, 2, 8, 9]. CAC is a software function in a switch that is invoked at the call setup time, when a virtual channel or a virtual path is established. It accepts the request only if the QOS for all existing connections will still be met if accepted.

3. Part I: Quality of service specification a system complexity metric

In the present study, the QOS specification of the telecommunication system (such as an ATM network) is presented as a single parameter by taking into considerations of the associated stochastical and fuzzy attributes of the system parameters.

In the relevant modeling, the end-to-end delay, or CTD, of the *i*th cell is assumed to be governed by a random factor arising out of queueing and buffering (multiplexing) within the network, as well as by the extent of noise (in terms of SNR) involved. As stated before, it is assumed that the SNR attribute of the network leads to a bit-error based, finite CLR, CLR2; and the buffer induced CDV in the cells which eventually leads to dropping of cells to an extent that is specified by CLR1. Thus, there are two phenomena which ultimately lead to an effective CLR in the system. Normally, the CDV-based cell dropping is decided by the extent of buffering used while the SNR-based cell dropping is largely decided by the physical media. For example, if the physical medium corresponds to a wireless transmission, the bit errors are relatively larger than in the telecommunication facilitated *via* fiber optic lines.

Presently, a complexity metric is proposed that is deduced *via* maximum entropy considerations [10] plus the fuzzy attributes associated with the stochastical characteristics of cell losses. Such cell losses include cohesively, the SNR considerations and CDV performance. In terms of the metric so derived, it is possible to bifurcate the network end-to-end transmission as "simple" or "complex" in a fuzzy domain. The dividing line sets a limit on the acceptance level of CLR and imposes an upper bound on the CAC implemented. Pertinent analyses are elaborated in the following section using a heuristic approach of the aforesaid problem.

3.1 A complexity metric for the acceptable threshold of cell loss ratio

Suppose $0 \le p(i) \le 1$ denotes the probability of occurrence of the *i*th cell in an ATM transmission. Let $i = 1, 2, \ldots, M$ represent the cells for which the end-to-end performance is assessed in an ATM link. Then, the axiomatic probability requirement is that $\sum_{i=1}^{M} p(i) = 1$ and the mean value $\sum_{i=1}^{M} ip(i) \le \beta_0$. Here $\beta_0 > 0$ depicts the constraining value on the ensemble mean as decided by the limit of acceptable traffic performance. Given a set of parameters attributed to a virtual channel traffic, the entropy (Shannon information) parameter of the epochs of cell occurrence is given by:

$$H(p) = -\sum_{i=1}^{M} p(i) \ln[p(i)] \text{ nats.} \quad (1)$$

Following the procedure presented by one of the authors elsewhere [6], the entropy associated with the M participating cells can be written in terms of a complexity parameter s as follows:

$$H(s, M) = \ln\left[\frac{1 - s^{M+1}}{1 - s}\right] - \left[\frac{s}{1 - s} - \frac{(M + 1)s^{M+1}}{1 - s^{M+1}}\right] \ln(s), \quad \text{for } s < 1 \quad (2a)$$

$$= \left[\frac{1 - \rho^{M+1}}{1 - \rho}\left(\frac{1}{\rho^{M}}\right)\right] - \left[\frac{\rho}{1 - \rho}\left(\frac{1}{\rho}\right) + \frac{(M + 1)\rho^{M+1}}{1 - \rho^{M+1}}\rho\left(\frac{1}{\rho^{M+1}}\right)\right] \ln(\rho), \quad \text{for } \rho \leq 1 \quad (2b)$$

where s is the complexity parameter [10].

The given relations refer to the maximized entropy functional that is based on the probability of having i disorderly (performance-wise) subsets in the cell space of total size M. That is, $p(i)$ depicts the probability distribution which maximizes the entropy $H(p)$ of disorderliness associated with epochal occurrence of cell events and implicitly refers to the statistics of associated performance impairment such as jitter and/or bit-errors. Explicitly, the entity s in equation (2) is specified by $\exp(-b)$ where b is a lagrangian parameter used in maximizing the entropy functional [10].

The entropy of disordered subsets is a positive function increasing monotonically with respect to M for all values of $s \geq 0$. It also increases monotonically with s for $s < 1$ but decreases monotonically with s for $s > 1$.

The coefficient s can be regarded as a *measure of complexity* associated with the ATM transmission experiencing cell losses as a result of cell delay jitter and SNR-dependent bit errors in an end-to-end connection. Suppose the mean value β_0 (specified as a constraint on the statistics of M) is specified in terms of s as $\beta_0 = E[s, M]$. For a given stretch of cells, s represents the extent of CLR expected. As such, when $s = 0$, the cells flowing between an end-to-end connection constitute a "simple" subsystem with an expected value of $E[0, M]$ equal to zero. The other extreme situation refers to $s \to \infty$, in which case the system is totally complex with $E[\infty, M] = M$ meaning that the associated loss of information is excessively large inasmuch as the cell loss includes all of the M cells involved.

That is, when the number of disordered subsets of cell loss in a cell population $M \to \infty$, the complexity associated refers to the entire universe of the jittered cells and/or bit errors. The corresponding expected value $E[s, \infty]$ can be deduced using the following relations [10].

In the limit $M \to \infty$, the functions associated with (M, s) become nonanalytic at $s = 1$. Explicitly, this implies that

$$E[s, M]|_{M\to\infty} = \begin{cases} \frac{s}{1-s} & s < 1 \\ \frac{M}{2} & s = 1 \\ \frac{\rho}{1-\rho} & s = \frac{1}{\rho} \geq 1 \end{cases} \tag{3a}$$

and

$$E[s, \infty] = E[s, M] \text{ for small } s \text{ and moderately large } M. \tag{3b}$$

Correspondingly,

$$H[\langle s, M\rangle]_{M\to\infty} = -\ln(1-s) - \frac{s\ln(s)}{1-s} \qquad 0 \leq s < 1 \tag{4a}$$

$$= -\ln(1-\rho) - \frac{\rho\ln(\rho)}{1-\rho} \qquad s = \frac{1}{\rho} \geq 1 \tag{4b}$$

and $H(s, M) \simeq H(s, \infty)$ for small s. Relevant inferences pertinent to these algorithmic derivations follow.

(a) For very small extents of CLR with $s \ll 1$, the expected extent of cell loss is almost independent of the number M of cells involved.

(b) For very large extents of CLR with $s \gg 1$, the expected extent of cell loss is characterized by the number of participating cells M.

(c) The characteristic value of $s = 1$ bifurcates the system as simple or complex in respect to the extent of information loss perceived due to dropping cells caused by CDV and/or bit-errors.

The simple, or small extents of CLR, when grown to a larger level would make the overall system performance be designated as complex. That is, small values of cell losses can be considered as quasi-autonomous (simple) subsets, but when grown to a large extent would render the system complex in terms of its performance assessed *via* CDV and/or SNR parameters. To model this consideration, the complexity coefficient s can be written as a function of M. Specifically, around $s = 1$, let $s = (1 - \Omega)$ where $\Omega = (A/M) \to 0$ as $M \to \infty$ and the constant A remains invariant. Using Taylor's expansion, on equation (3a) at $s = 1$, one has:

$$E[s, M] \approx \frac{M}{2}\left(1 - \frac{A}{3}\right) \Big/ \left(1 - \frac{A}{2} + \frac{A^2}{6} + \cdots\right) \tag{5}$$

and the corresponding entropy deduced from equation (2) is,

$$H(s, M) \approx \ln(M + 1). \tag{6}$$

This result leads to defining a coefficient of cell loss complexity in a functional form of the type:

$$s = \exp\left(-\frac{A}{M}\right) \tag{7}$$

with $s < 1$ and $A > 0$, (i.e., when the system is considered simple). With the exponential form of s given by equation (7), the following results can be deduced with $A > 0$:

$$s(e^{-A/M}) = \frac{M}{A}[1 - e^{-A}] + \frac{1}{2}[1 - e^{-A}] + \vartheta\left(\frac{A}{M}\right) \tag{8}$$

$$E[e^{-A/M}, M] = MF(A) - G(A) + \vartheta\left(\frac{A}{M}\right) \tag{9}$$

$$H[e^{-A/M}, M] = \ln M - U(A) + \vartheta\left(\frac{A}{M}\right) \tag{10}$$

where

$$F(A) = \frac{1}{A} - \frac{1}{(e^A - 1)},$$

$$G(A) = \frac{1}{2} + \frac{1}{(e^A - 1) - \frac{Ae^A}{(e^A-1)^2}},$$

$$U(A) = AF(A) + \ln\frac{1}{A}(1 - e^{-A}).$$

Further, $\vartheta(\cdot)$ represents the "order of $(\cdot)$."

At the critical point of $s = 1$ and in its neighborhood, the mean value of system performance denotes the extensive property in respect to the possible number of impaired cells (M) and the propensity of impairment is directly proportional to $\ln(M)$, namely, the message content of M cells.

When $s \geq 1$, the exponential law can be modified as $s = \exp(A/M)$ in which case,

$$E[e^{A/M}, M] = \{1 - F(A)\}M - G(A) + \vartheta\left(\frac{A}{M}\right) \tag{11}$$

$$H[e^{A/M}, M] = \ln M + U(A) + \vartheta\left(\frac{A}{M}\right). \tag{12}$$

These algorithmic considerations can be adopted appropriately to use the complexity parameter s as a cohesive measure of the extent of a QOS parameter (such as cell losses) in an end-to-end ATM connection. Relevant details follow.

3.2 Entropy of cell losses: Information-theoretic considerations

Suppose the statistics of CDV (δ_η) of a traffic (identified as the traffic from source η) is assumed to be gaussian. Then the probability density function of δ_η, namely, $p(\delta_\eta)$ can be written as:

$$p(\delta_\eta) = \frac{1}{\sqrt{2\pi\sigma_{\delta\eta}}} \exp\left[-\frac{(\delta_\eta - \mu_{\delta_\eta})^2}{2\sigma_{\delta\eta}^2}\right] \tag{13}$$

where $\sigma_{\delta\eta}$ and $\mu_{\delta\eta}$ denote the mean and standard deviations of δ_η respectively. The maximum entropy *vis-à-vis* the gaussian statistics is given by:

$$(H_{\max})\eta = \frac{1}{2} \ln[2\pi e(\sigma_{\delta\eta}^*)^2] \tag{14}$$

where $\sigma_{\delta\eta}^*$ is $\sigma_{\delta\eta}$ normalized with respect to a time parameter, such as the total time of transmission of M cells, T seconds.

As detailed earlier, a critical transition from a simple to a complex state mediated by M cells arriving at a rate λ_η cells/second occurs when the complex parameter $s \to 1$. Using equation (6), the corresponding maximum entropy associated with M cells flowing at a rate λ_η is given by

$$(H_{\max})_\eta = \ln\left[\frac{M+1}{\lambda_\eta T}\right]. \tag{15}$$

Hence, combining equations (14) and (15), it follows that $\ln[(M + 1)/\lambda_\eta T] = \ln[2\pi e(\sigma_{\delta\eta}^*)_{\max}^2]^{1/2}$. Or, $(M+1)/\lambda_\eta = \sqrt{2\pi e}(\sigma_{\delta\eta})_{\max}$.

In other words, for a set of M cells for which end-to-end delay is assessed, the maximum entropy associated with the delay δ_η has a standard deviation given by:

$$\sigma_{\delta\eta} = \frac{M+1}{\sqrt{2\pi e}\lambda_\eta} \text{ second.} \tag{16}$$

The corresponding variance parameter then decides the upper limit on the permissible cell delay jitter beyond which the network is led to discard the cells as indicated earlier.

3.3 Net cell loss ratio due to cell delay variation and signal-to-noise ratio influences

Considering the two possible reasons that lead to the dropping of cells, the tail-end probability α, which can be deduced from equation (13), places an upper bound on net CLR; and, α can be bifurcated into α_1 and α_2 corresponding to CLR1 and CLR2 respectively. That is, the functional relations to be ascertained are:

$$\alpha_1 \leftrightarrow \text{CLR1} \Rightarrow \text{CTD1} \tag{17a}$$

$$\alpha_2 \leftrightarrow \text{CLR2} \Rightarrow \text{CTD2} \tag{17b}$$

where CTD1 and CTD2 are parameters which decide jointly to specify a net upper bound on CTD and lead to a corresponding (net) upper bound on CLR.

The problem of linking α_1 and CLR1 is the same as correlating the variance of δ, namely, $(\sigma_\delta)^2$ and the CLR1. That is, the variance of the CDV (under the worst case condition) that corresponds to the CTD1 exceeding a maximum value equal to fixed delay (F) plus (σ_δ) with a probability no greater than α_1. It specifies the maximum limit on CTD, CTD1. Similarly, assuming that the cell losses due to SNR-based bit errors (represented by CLR2) correspond to an equivalent delay CTD2, a relation between the bounding parameters α_2 (of CTD2) and CLR2 has to be established. The relevant exercise is indicated in [5] and summarized as the resultant cell loss parameter that can be ascertained from CLR1 and CLR2 that eventually specifies a bound, which can then be utilized to establish a CAC criterion.

3.4 CLR1 versus $P_{x\eta}$ and α_1

Relevant to a source η, suppose a cell loss probability $P_{x\eta}$ is specified as the impairment parameter of end-to-end traffic performance due to asynchronous multiplexing and/or congestion induced CDV and $P_{E\eta}$ denotes the bit-error probability leading to relevant cell erasures caused by finite SNR. The strategy to implement the required interrelations specified in equation (17) is based on the following heuristics.

The CLR1 parameter concerning cell losses (arising from CDV caused by multiplexing/congestion in ATM links) can be specified by a corresponding cell erasure probability $P_{x\eta}$ that leads to a loss of average information content per unit bandwidth associated with M cells constituting the ATM traffic. The nonzero value of $P_{x\eta}$ can be regarded as an "equivalent probability of error" induced by a "corruption factor" $C_{x\eta}$. That is, the cell loss due to excessive CDV resulting from the multiplexing/congestion mechanism can be dubbed equivalently, as if such a cell loss is a result of some corrupting entity (analogous to noise) being present in the traffic flow. Therefore, from the considerations of digital communication theory as applied to binary digit errors introduced due to noise, $P_{x\eta}$ in reference to an ηth source ($\eta = 1, 2, \ldots, N$), can be specified by an exponent relation, namely, $P_{x\eta} = k_m \exp(-C_{x\eta})$ where k_m is a constant dependent on the modulation scheme. (For example, $k_m = 1/2$ in frequency shift keying.) In this relation, the corruption factor $C_{x\eta}$ is represented as an erasure exponent that sets a limit on CDV exceeding an upper bound. This exponent is analogous to the SNR parameter.

The multiplexer of ATM cells (MUX) is a multi-access shared processor where cells from different sources compete for the processor time to get accessed on the trunk line (Figure 1). The more sources active at a given time, the less rate of service each receives, since there is more contention. The total service rate rendered by the MUX depends on the state of the queue through the number of cells competing for multiplexing service. Following the IT model of a multi-access system discussed in [4] and using the underlying concepts of equation (6), it can be shown that the average information loss $H_\eta(L_\eta)$ of the ηth source resolved per unit time at the multiplexer can be specified as:

$$H_\eta(L_\eta) = \ln[M_T L_\eta(m_\eta) + 1] \text{ nats per bandwidth} \tag{18}$$

where $L_\eta(\cdot)$ denotes the expected number of cells dropped at the multiplexer due to the delay suffered as a result of queueing and contentions, and M_T is the total number of cells from all the N active sources resolved per unit time. Further, m_η refers to the cells in the ηth source traffic stream.

The mean delay time $\Delta_{1\eta}$ equivalence (representing the cell loss) can be obtained from the well known Little's formula. That is, when $M_T L_\eta(m_\eta) \gg 1$,

$$\Delta_{1\eta} \approx \frac{M_T L_\eta(m_\eta)}{\lambda_\eta} \text{ second} \tag{19}$$

where the subscript 1 corresponds to traffic impairment specified by CLR1.

The expected loss of information caused by the cell drops pertinent to the ηth source as given by equation (18), is identically equal to the entropy associated with the CDV. Hence,

$$\ln\left[\frac{M_T L_\eta(m_\eta)}{\lambda_\eta}\right] \equiv \ln[2\pi e \sigma_{1\eta}^2]^{1/2} \tag{20a}$$

or,

$$\sigma_{1\eta} = \frac{\Delta_{1\eta}}{(2\pi e)^{1/2}} \tag{20b}$$

which represents the standard deviation of the statistics describing the CDV equivalence of the cell loss pertinent to the ηth source. It should be noted that both the mean value ($\Delta_{1\eta}$) and the standard derivation ($\sigma_{1\eta}$) are specified per unit bandwidth of trunk transmission and resolved per unit time.

3.5 CLR2 versus $P_{E\eta}$ and α_2

Additional delay $\Delta_{2\eta}$ is induced as a result of cell drops due to uncorrectable bit-errors caused by a finite SNR_η value prevailing in the ηth ATM source-to-MUX link. It can be specified explicitly in terms of the error probability as: $P_{E\eta} = k_m \exp(-\mathrm{SNR}_\eta)$. That is, given $P_{E\eta}$ or its exponent SNR_η, the pertinent CLR, namely, CLR2 when linked to CTD will give rise to a corresponding average delay $\Delta_{2\eta}$ with a variance $\sigma_{2\eta}$. The parameters $\Delta_{2\eta}$ and $\sigma_{2\eta}$ can be determined by a similar procedure indicated in section 3.4 replacing $P_{x\eta}$ by $P_{E\eta}$ and $C_{x\eta}$ by SNR. Again, the subscript 2 in Δ and σ refers to the conditions dictated by CLR2.

Summarizing, the net CTD specification pertinent to an ATM system can be deduced in reference to an ηth source in terms of the following.

1. Fixed-delay (F) due to propagation, delay induced by switching system and/or processes and due to fixed components.
2. Random delay introduced by asynchronous transfer involving buffering performed on incoming cells from different sources (of different bandwidths and bit rates). This has the worst case or maximum value decided by $\Delta_{1\eta}$ and $\sigma_{1\eta}$.
3. Random delay introduced by cell drops due to uncorrectable bit-errors caused by a finite SNR value prevailing in the ATM link. This has the worst case or maximum value decided by $\Delta_{2\eta}$ and $\sigma_{2\eta}$.

The combined effects of multiplexing/congestion and nonerasable bit-errors can be specified by a single gaussian statistic of CDV with a mean value of $\Delta_\eta = (\Delta_{1\eta} + \Delta_{2\eta})$ and a standard deviation of $(\sigma_\eta) = [(\sigma_{1\eta})^2 + (\sigma_{2\eta})^2]^{1/2}$. Hence, a corresponding effective CLR bound can be stipulated. The probability α is decided by an upper bound set by the quartile value equal to $2/3\sigma_\eta$.

Thus, for a given set of specifications on the expected number of 1s dropped $(L_{X\eta}, L_{E\eta})$, probability of error values $(P_{X\eta}, P_{E\eta})$, rate of transmission (λ_η), and m_η of the ηth traffic, a gaussian probability density function curve can be constructed for δ_η when a total of M_T cells (from all the sources) are impressed on the input to the MUX. It is given by:

$$p(\delta_\eta) = \frac{1}{\sqrt{2\pi\rho_\eta}} \exp\left\{-\left[\frac{(\delta_\eta - \Delta_\eta)^2}{2\rho_\eta^2}\right]\right\}. \tag{21}$$

4. Fuzzy attributes of cell loss characteristics

Referring to earlier discussion, in the region of $s \leq 1$ in which the ATM system is assumed to be simple (in terms of the net CLR experienced being lower than a certain upper bound), the complexity metric *versus* entropy is given by equation (6), it follows that

$$\Phi(s) = \exp[H(s)] = \left[1 - \frac{A}{\ln(s)}\right] \qquad s = 1 \tag{22}$$

with $A > 0$. Further, in terms of $\Phi(s)$, equations (6), (10), and (12) can be written respectively as:

$$H(s) = \ln(M+1) = \ln[\Phi(s)] \qquad s = 1 \tag{23a}$$

$$= \ln(M) + U(A) \approx \ln[\Phi(s)] + U(A) \qquad s < 1 \tag{23b}$$

$$= \ln(M) + U(A) \approx \ln[\Phi(s)] + U(A) \qquad s > 1 \tag{23c}$$

with the approximations indicated when $M \gg 1$.

For the three cases given by equation (23), the following differential equation can be validly specified:

$$\frac{d^2H(s)}{ds^2} + \left[\frac{dH(s)}{ds}\right]^2 = \frac{\Phi''(s)}{\Phi'(s)}. \tag{24}$$

This equation depicts the calculus of entropy (or Shannon information) associated with the complexity parameter s. It describes the calculus of $H(s)$ *versus* s in the crisp domain. Presently, it is attempted to fuse fuzzy concepts using interval-value calculus into the above nonlinear differential equation. Further, the so-called "extensive principle" due to Zadeh [11] is adopted notionally to infuse the fuzzy attributes to the telecommunication system, the cell loss performance of which is described by the complexity parameter s.

For this purpose, a general (algebraic) description of the nonlinear differential equation (equation (24)) relating the sets $\{\mathbf{H}_i(s)\}$ and $\{\mathbf{s}_i\}$ which bear crisp values is first considered. Suppose $\{\mathbf{x}\}$ and $\{\mathbf{y}\}$ are crisp sets, which identically represent the independent variable set $\{\mathbf{s}_i\}$ and the dependent variable set $\mathbf{H}_i(s)$ respectively. These sets are crisp in the sense that certain definitive values can be assigned to each element of the respective universal set (so as to discriminate between members and nonmembers of the crisp set). The uncertainty features of real world problems (such as in telecommunication systems), however, warrant the following considerations.

The values so assigned (to the elements of the universal sets) should fall rather within a specified range and qualify the associated uncertainty by a "membership grade" given to each of the elements in these sets in question. That is, the sets $\{\mathbf{x}\}$ and $\{\mathbf{y}\}$ should be regarded as fuzzy sets with linguistic gradation and having corresponding membership functions. Denoting the corresponding fuzzy variables as x^f and y^f (with the superscript f denoting explicitly the fuzzy considerations), the membership gradation should allow the representation of the range concepts attributed to the variables involved to be expressed in natural language within the scope of the context pertinent to $\{\mathbf{x}^f, \mathbf{y}^f\}$.

Rewriting equation (24) in terms of x and y, suppose the set of input values of $\{\mathbf{x}_i\}$ are nonspecific or fuzzy. Extending Taylor's formula to intervals, the output $y_i(x_i)$ has a fuzzy value $y_i^f(x_i)$ for a generic set $\{\mathbf{x}_i\}$. That is, $\{y_i^f\}$ refers to the fuzzy transmission of the crisp set $\{\mathbf{y}_i\}$ whose generic elements are $\{\mathbf{x}_i\}$. The ith component of $\{\mathbf{y}_i^f\}$ can, therefore, be written in respect to the uncertain (fuzzy) boundary value of all vectors $y_i^f(x_i)$ in the interval $x \in [x_L, x_H]$ as, [7]:

$$y_i^f(x_i) = y_i^f(x_L) + \sum_{j=1}^{k-1} [{}^f\psi^{(j-1)} y_i^f(x_L)] x^{j/j!} \tag{25}$$

where ${}^f\psi(\cdot)$ denotes the corresponding function $\psi(\cdot)$ defined in respect to the fuzzy set $\{y_i^f\}$.

Equation (25) is an algebraic sum of addenda, each one of which takes an interval value. The summation computed *via* interval arithmetic leads to a "width of results" resulting from superposition of the addenda. In this interval arithmetic, any interval-value of y_i^f will become wider with increasing values of x_i^f. Conversely, the interval value of y_i^f will become narrower with decreasing values of x_i^f.

Considering equation (24), it can be written in the fuzzy domain in a vector form where the variables and parameter values can be expressed as intervals with k being the number of interval-valued parameters and n is the order of the system. That is,

$$\frac{d^2\mathbf{Y}^f(\mathbf{x}, I)}{dx^2} + \left(\frac{d\mathbf{Y}(\mathbf{x}, I)}{dx}\right)^2 = g(\mathbf{x}) \tag{26}$$

where the vector boundary of y_i^f is specified by $Y^f(X_{L,H}) = Y_{L,H}^f$. Further, $\{\mathbf{I}\}$ represents the vector set of parameters whose value is an interval and $I = [I_1, I_2, \ldots, I_k]$. Since equation (24) is a second order (nonlinear) equation, its order n is equal to 2. The explicit solution of this fuzzy differential equation (equation (26)), namely, $y^f(x) = {}^fF(x)$ is indicated in section 6.

5. Bifurcation of the fuzzy domain and membership attribution to fuzzy sets

In reference to earlier discussions, the set $\{\mathbf{y}_i\}$ in response to a set $\{\mathbf{x}_i\}$ in the fuzzy domain is indicated by a fuzzy differential equation given by equation (26). Now, the question is how the membership attributes can be incorporated into the fuzzy set. The specifications of membership functions as discussed earlier are $\mu_A(\cdot) = [0, 1]$ and its rth interval I_r is given by $(\lambda_{r1}, \lambda_r)$.

The fuzzy function under discussion corresponds to the solution of equation (26). The variables x and Y^f are bounded by $x \in (x_{\min} \to 0, x_{\max} \to +\infty)$ and $Y = \{\ln[\Phi(s)], \ln[\Phi(s)] + U(A)\}$, respectively.

Now, consider the function $B(s) = H(s)/H(\sigma)|_{\sigma\to 1}$. Explicitly, it is written as follows:

$$B(s) = \left.\frac{H(s)}{H(\sigma)}\right|_{\sigma\to 1} = \left.\frac{\ln[\Phi(s)]}{\ln[\Phi(\sigma)]}\right|_{\sigma\to 1} = \left.\frac{\ln\left[1 - \frac{A}{\ln(s)}\right]}{\ln\left[1 - \frac{A}{\ln(\sigma)}\right]}\right|_{\sigma\to 1}. \tag{27}$$

The graphical representation of equation (27) is presented later in Figure 4.

Equation (27) decides the transcritical regimes of simple and complex while considering s as a fuzzy variable. Further, this heuristically derived bifurcation function $B(s)$ includes the overlapping, linguistic attributes of the variable s in each of the bifurcated regimes as will be indicated later.

6. Part II: Fuzzy attributes of cell loss ratio and their implications on call admission control

In general, the values of bounds on CLR required for CAC cannot be ascertained to a deterministic extent. This is due to the inherent fuzzy attributes and stochastic nature of the complex telecommunication transmission involved as discussed earlier.

The nonspecificity of CLR bounds therefore, warrants enforcing a fuzzy inference scheme which an ATM switch can use to facilitate a call admission so that the connection enabled would offer a guaranteed CLR on the limit of not falling out of its upper bound.

In the efforts due to Uehara and Hirota [1], fuzzy CAC for ATM networks have been indicated in which the guarantee is restricted to the CLR value; and, as far as CDV is concerned, the associated implications are taken care of *via* traffic smoothing.

In the present study, as mentioned before, the traffic impairment attributes of CLR are represented by a single complexity parameter s. This single parameter cohesively accounts for the influences of CDV and SNR (or bit errors) in deciding the resultant cell losses in the ATM transmission. Further, s can be regarded as a fuzzy parameter.

Considering the complexity specified by end-to-end performance of an ATM link (in terms of s), we now describe a CAC scheme which guarantees respect of the bounding limits on s. This CAC is based on fuzzy inference and guarantees a limited CLR. The inference engine proposed uses the complexity algorithm deduced *via* IT considerations. That is, from the considerations presented earlier, it can be observed that the complexity parameter s inherently has entropy details (or Shannon information) concerning information loss experienced by the ATM cells due to CLR. Hence, by using the parameter s, a fuzzy inference method to implement the CAC is developed. Two analytical methods are suggested. The first one refers to constructing an if-then rule-based look-up table portraying the implicative output for a set of if-considerations. This table represents a fuzzified, overlapping implication set. For example, given a set of traffic descriptors and resource profiles, the relevant call is implicated to a membership class specified by the complexity metric s.

Thus, in reference to an ith call, the look-up table offers an implicative inference on s_i (usually in a linguistic format) which overlaps with adjoining (neighborhood) inferences. A (defuzzification) procedure can now be adopted to extract a defuzzified value of s_i from its fuzzified map. CAC is then specified on the basis of this extracted value of s_i.

The second step deduces a possible distribution of s_i in the fuzzy domain. Using the relevant algorithm, the upper bound on s is ascertained. That is, the upper bound on s allows establishing a CAC (when a number of connection requests prevail at a switch) and an admitted call guarantees a limit on CLR (as well as the associated CDV). The following sections elaborate the procedure involved and present simulation studies performed to evaluate the efficacy of the proposed strategy.

6.1 Fuzzy complexity based call admission control

The CLR *versus* number of connections (or traffic load) is invariably a nonlinear relation. This is due to extensive variations in the cell generation patterns of participating sources of an ATM transmission. Such patterns are usually characterized by constant bit rate and/or variable bit rate transmissions and in each class, the rate may vary significantly.

A typical CLR database *versus* the number of connections realized in repeated measurements would exhibit a significant dispersion due to the statistics of cell emission characteristics of the sources. Therefore, in order to facilitate a meaningful CAC, a correct choice for the upper bound on CLR should be made despite the fact that the observed data is dispersed.

Deciding on the upper bound of CLR can be done with artificial neural networks (ANNs) by training them with a measured set of CLR data [12–14]. However, since the learning in ANN follows the average trend in the learned data, the prediction phase of ANN also yields only an average prediction on CLR; and such an average prediction is crispy and does not portray the fuzzy profile of the CLR values. As a result, the connection facilitated would not guarantee the actual trends in CLR for any cell arrival process so as to satisfy the traffic parameters of the transmission class without overburdening the available resource allocation schedules.

Another approach adopted in the literature [8] to ascertain the CLR bound refers to a flow approximation model in which a variable bit rate source is assumed to pose alternate active and silent periods of cell emission characterized solely by its peak and average bit rates. No assumptions on the statistical distributions of the two periods are made. The resulting algorithm depicting the Chernoff bound on CLR is then used to make the CAC. However, there are two drawbacks of this technique. First, this method does not consider the buffer size in decision-making. This means that the decision does not account for any statistical multiplexing gain involved. Second, the procedure does not distinguish cell loss requirements of individual connections. That is, any connection in the transmission is assumed to have the same CLR characteristics as the other connections.

A nonparametric approach has also been studied [15, 16] wherein the peak and average cell rates of the connections are alone considered without the statistical distribution of the arrival process being specified. This approach, however, overestimates the CLR bound, making CAC less efficient; that is, it results in lower multiplexer gain.

Therefore, fuzzy traffic control and fuzzy CAC have been addressed in the literature as alternative strategies [1, 2] and relevant simulation studies have indicated promising results. But as mentioned before, the CAC in these efforts [1, 2] is based on an established bound on the CLR alone. And, a traffic smoothing is presumed so as to ignore the influence of CDV on CAC.

The present study presents a parallel approach, but the fuzzy inference made here refers to the complexity parameter s. This parameter also cohesively includes both influences of congestion and buffer overflow-based CDV as well as SNR-based bit errors on the resulting CLR attributes. The "then" part of the if-then rules adopted in the fuzzy inference approach presented here lead to ascertaining the membership class of s, namely, $\mu(s)$ governing the connections (to which the if-then rule is applied). Based on this decided value of s, CAC is performed.

In general, CAC algorithms should be able to cope with normal and heavy traffic situations. Further, they must facilitate negotiation between the user and the connection service on QOS requirements. Typically, CAC may permit a certain amount of resource overbooking in order to increase the statistical multiplex gain. Other factors, such as the slack, are implied by the compliant connection definition. CDV tolerance parameter, buffer size available for a certain cell loss, delay in QOS objective, and so forth, may also allow for a certain laxity in the admission threshold of the CAC algorithm. All these considerations contribute to the fuzziness of the inference strategies pursued towards CAC.

6.2 Linguistic description of fuzzy rules

The linguistic descriptions of if-then rules towards estimating the complexity aspects of ATM connectivity can be specified as follows. Let a traffic (such as from a multimedia user) constituting an end-to-end call connectivity be identified by an index i. Suppose X_i and Z_i are two functional attributes that belong to a relevant transmission rate class C_i. The entity X_i, for example, may denote the variety attributes of the sources involved. That is, X_i depicts the number and variety of the bit rates emitted by the source constituting the ith traffic. It is a collective representation, for example, of data, voice, and video signals from a multimedia source.

Likewise, Z_i may represent the distribution and availability of resources handling the ith traffic. Hence, pertinent to the ith traffic, there exists a performance index s_i, which depicts the complexity profile posed by X_i and Z_i. That is, $s_i \in (X_i, Z_i)$. The set of variables, namely $\{\mathbf{X}_i, \mathbf{Z}_i, \mathbf{s}_i\}$ constitutes, in general, a fuzzy set for which the following linguistic norms of descriptions can be prescribed explicitly.

Set $\{\mathbf{X}_i\}$ $\mathbf{X}_i$: Source type	Linguistic identification
Extremely varying constituent bit rates and burstiness:	EX
Largely varying constituent bit rates and burstiness:	LX
Moderately varying constituent bit rates and burstiness:	MX
Constant constituent bit rates:	CX

Set $\{\mathbf{Z}_i\}$ $\mathbf{Z}_i$: Profile of the resources	Linquistic identification
Large extent of buffers and traffic smoothing plus high SNR physical medium:	RA
Moderate extent of buffers and traffic smoothing plus high SNR physical medium:	RB
Large extent of buffers and traffic smoothing, but low SNR physical medium:	RC
Moderate extent of buffers and traffic smoothing, but low SNR physical medium:	RD
Low extent of buffers and traffic smoothing plus high SNR physical medium:	RE
Low extent of buffers and traffic smoothing plus low SNR physical medium:	RF

Set $\{\mathbf{s}_i\}$ $\mathbf{s}_i$: Type of system complexity	Linguistic identification
Extremely simple system:	ES
Highly simple system:	HS
Somewhat simple system:	SS
Somewhat complex system:	SC
Highly complex system:	HC
Extremely complex system:	EC

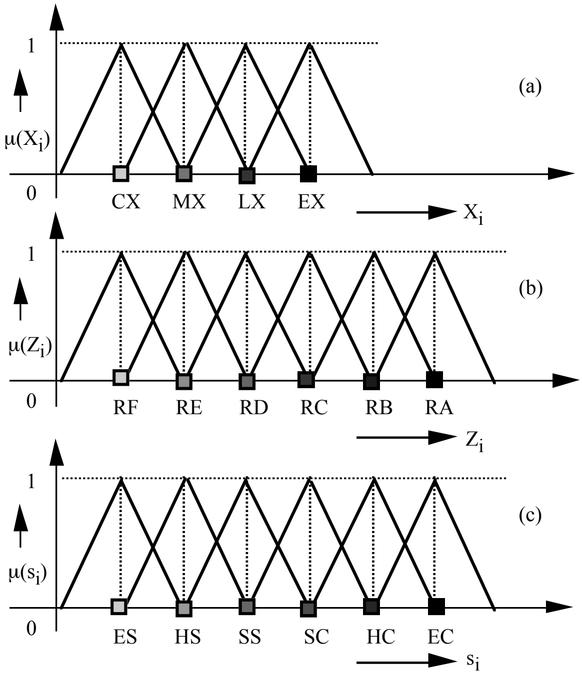

Figure 2. Graphical representation of membership class and overlapping elements of the set $\{\mathbf{X}_i, \mathbf{Z}_i, \mathbf{s}_i\}$.

Each fuzzy variable of the set $\{\mathbf{X}_i, \mathbf{Z}_i, \mathbf{s}_i\}$ identified by these linguistic descriptions can be assigned a membership class using a membership function $\mu(\cdot) \in [0, 1]$, as illustrated in Figure 2. The choice of membership function $\mu(\cdot)$ is rather arbitrary. In Figure 2, a triangle function is used for illustration. A host of other functions have been adopted in the literature [17] to represent $\mu(\cdot)$.

In terms of the linguistic descriptions of $\{\mathbf{X}_i, \mathbf{Z}_i\}$ as identified previously, the extent of the complexity $\{\mathbf{s}_i\}$ should be evaluated, despite the ambiguous overlapping features of the linguistic norms depicted in Figure 2. For this purpose, a set of if-then rules should, therefore, be first established with crisp variables. Here is an example.

- Rule 1: If the source is of type EX and the resource profile is RF, then the complexity is EC.
- Rule 2: If the source is of type CX and the resource profile is RA, then the complexity is ES.
- Rule 3: If the source is of type MX and the resource profile is RD, then the complexity is SS.

and so on.

$\mathbf{X}_i$ \ $\mathbf{Z}_i$	RA	RB	RC	RD	RE	RF
EX	SC	HC	HC	EC	HC	EC
LX	HS	SS	SS	SC	SC	HC
MX	HS	SS	SS	SS	SC	HC
CX	ES	ES	HS	SS	HC	HC

Table 1. Decision table on $\{\mathbf{s}_i\}$ given $\{\mathbf{X}_i, \mathbf{Z}_i\}$: crisp domain representation. The double thick line boundary specifies a symmetric dichotomy of simple and complex entities; for the upper set $s_i < 1$ and for the bottom set $s_i \geq 1$.

Rules 1 through 3 are largely intuitive but have the expert's reasoning behind them. For example, Rule 1 represents the extremities in regards to the source characteristics and resource restrictions. Under these conditions, achieving a performance of end-to-end connectivity meeting a given set of QOS requirements on CDV/CLR is rather constrained extensively. As such, the associated complexity is declared of extreme value.

The collection of all if-then rules pertinent to the crisp set $\{\mathbf{X}_i, \mathbf{Z}_i, \mathbf{s}_i\}$ can be concisely stated in the form of a look-up table as shown in Table 1. Approximately, the linguistic descriptions presented in Table 1 can be split into a crisp dichotomoy of classes, namely, simple and complex by a symmetrically dividing boundary shown (by a double thick line) across Table 1. The top set of this boundary is complex (with $s_i > 1$) and the bottom set is simple (with $s_i < 1$). That is, for the linguistic elements of the upper set, the s_i values are specified as those of equation (4a) with $s_i < 1$; and, for the bottom set, the s_i values refer to those of equation (4b) with $s_i \geq 0$.

Now, a decision table relevant to fuzzy considerations can be studied. That is, a procedure to construct a decision table by taking into account the overlapping attributes of each of the sets $\{\mathbf{X}_i\}$, $\{\mathbf{Z}_i\}$, and $\{\mathbf{s}_i\}$ can be evolved. Corresponding to the map of Table 1, a fuzzy decision table can be constructed as shown in Table 2. The procedure used in constructing Table 2 is as follows. Write the linguistic identifications of $\{\mathbf{X}_i\}$ and $\{\mathbf{Z}_i\}$ in their overlapping formats (consistent with their membership profiles indicated in Figure 2), then for each intersection of X_i and Z_i, the corresponding linguistic identification of system complexity is borrowed from Table 1 and indicated. For corners and edges having only one side neighbor, the missing side neighbor is indicated as a null using asterisks.

The linguistic representation of if-then relations between the variables $\{\mathbf{X}_i^{(f)}, \mathbf{Z}_i^{(f)}\}$ *versus* $\{\mathbf{s}_i^{(f)}\}$, as specified in Table 2, depicts the overlapping attribute of the implication $\{\mathbf{s}_i^{(f)}\}$. That is, by pairing $X_i^{(f)}$ and $Z_i^{(f)}$, a multiple set of overlapping implications are triggered.

$\mathbf{X}_i^{(f)}$ \ $\mathbf{Z}_i^{(f)}$	∗-RA-RB	RA-RB-RC	RB-RC-RD	RC-RD-RE	RD-RE-RF	RE-RF-∗
∗ EX LX	∗ / ∗ ■ HC / HS	∗ / SC ■ HC / SS	∗ / HC ■ EC / SS	∗ / HC ■ HC / SC	∗ / EC ■ EC / SC	∗ / HC ■ ∗ / HC
EX LX MX	SC / ∗ ■ SS / HS	HC / HS ■ SS / SS	HC / SS ■ SC / SS	EC / SS ■ SC / SS	HC / SC ■ HC / SC	EC / SC ■ ∗ / HC
LX MX CX	HS / ∗ ■ SS / ES	SS / HS ■ SS / ES	SS / SS ■ SS / HS	SC / SS ■ SC / SS	SC / SS ■ HC / HC	HC / SC ■ ∗ / HC
MX CS ∗	HS / ∗ ■ ES / ∗	SS / ES ■ HS / ∗	SS / ES ■ SS / ∗	SS / HS ■ HC / ∗	SC / SS ■ HC / ∗	HC / HC ■ ∗ / ∗

Table 2. Fuzzy decision table on $\{\mathbf{s}_i^{(f)}\}$ given $\{\mathbf{X}_i^{(f)}, \mathbf{Z}_i^{(f)}\}$. ■ Is the defuzzified value to be determined.

Suppose the set $\{\mathbf{X}_i^{(f)}, \mathbf{Z}_i^{(f)}\}$ denoting a specific traffic, seeks call admission at a switch. Likewise, there are other traffics, each having a universe of discourse, $\{\mathbf{X}_i^{(f)}, \mathbf{Z}_i^{(f)}\}_{j,k,l\cdots}$ which also request a connection at the same switch. Whether a given call be admitted or not is then decided by ascertaining the implication vector $\{\mathbf{s}_i^{(f)}\}_{j,k,l\cdots}$ pertinent to that call.

In Table 2, this implication vector $\{\mathbf{s}_i^{(f)}\}$ of the *i*th traffic (or call) resides in the neighborhood as a set of four fuzzy variables represented *via* linguistic identifications. From the overlapping attributes of $\{\mathbf{s}_i^{(f)}\}$ in Table 2, a meaningful metric should, therefore, be assessed in order to depict the actual complexity of the *i*th call, so that this metric can be used to decide the CAC criterion under the fuzzy discourses.

6.3 Concept of possibility distribution and construction of fuzzy look-up table

Using the if-then based fuzzy logic scheme discussed in section 6.2, a set of s_i values and their membership function $\mu(s_i)$ for a given incoming *i*th call (constituted by an heterogeneous mixture of cells) can be specified as follows.

From the IT considerations on CLR1 and CLR2 described earlier, the mean delay Δ_i and the standard deviation σ_i corresponding to an *i*th call constituted by a set of service categories (voice, video, and data) can be evaluated. This refers to a set cell population M that loads the line connected to the input of the ATM switch (Figure 1). Corresponding to this set $\{\Delta_i, \sigma_i\}$, the entropy function $H(\Delta_i, \sigma_i)$ can be determined

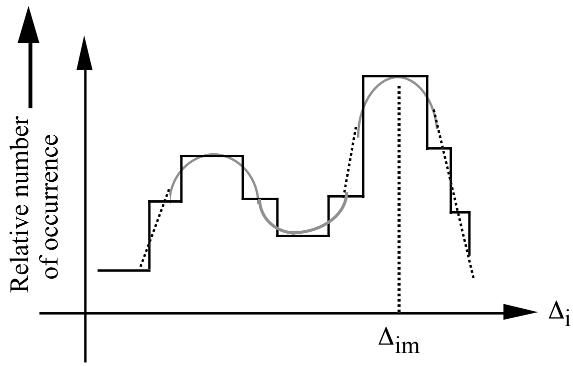

Figure 3. Histogram of Δ_i (Δ_{im} is the modal value).

via equation (14). Hence, the associated complexity metric s_i can be extracted from $H(s_i, M) \equiv H(\Delta_i, \sigma_i)$ given by equation (4).

The population M is then increased in steps, together with random changes (within specified bounds) of the values of the parameters pertinent to the service categories constituting the ith call. For each step of the increased population with the randomly perturbed parameters, the mean delay Δ_i is ascertained. Hence an histogram depicting the mean delay values Δ_i *versus* their relative occurrence can be drawn as illustrated in Figure 3.

Using the histogram of Figure 3, for any Δ_i, the corresponding s_i and the bifurcation domain values $B(s_i)$ in the simple and complex regimes are plotted as depicted in Figure 4. In Figure 4(a), the set of points $[\cdot\cdot\cdot]$ represent the aggregation of data on s_i collected *via* linguistic attributes of fuzzy sets of antecedents (premises). Further, the X_i denote the characteristics of service categories of the ith call and the Z_i represent the resource profiles handling the ith call on their respective universe of discourse which decide the delay statistics or possibility distribution of Δ_i presented in Figure 3.

For each population sample depicting a set of linguistic descriptions of input vectors $\{\mathbf{X}_i, \mathbf{Z}_i\}$ having appropriate statistical attributes, the corresponding s_i (deduced *via* Δ_i as the consequent) falls under a linguistic characterization (such as "extremely simple" or "somewhat complex"). Hence, in the bifurcation diagram of Figure 4(a), the overlapping membership class pertinent to the linguistic descriptions of the s_i values is depicted by means of a chosen membership function (such as the triangular function). Thus, the set of s_i values deduced from the histogram of Figure 3 and presented on the bifurcation diagram of Figure 4(a), maps on the linguistic overlapping descriptions of s_i as shown in Figure 4(b).

Now, the task is to decide a single or specific linguistic description of s_i from the fuzzy, overlapping map of Figure 4. This effort calls

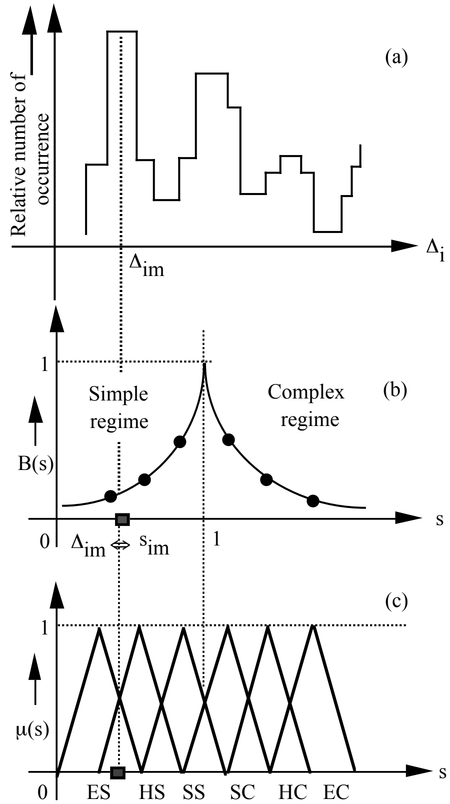

Figure 4. Bifurcation and membership functions. (a) Histogram depicting the population of cell delays (Δ_{im} = modal value). (b) Bifurcation function $B(s_i)$ obtained from the values of s_i extracted from the histogram of Δ_i in Figure 3. (c) Projection of $\{\mathbf{s}_i\}$ onto the overlapping membership set of linguistic descriptions, {ES, ..., EC}.

for a defuzzification procedure and the following two approaches are pursued in the present study.

- *Approach 1*. This approach uses the so-called centroid method [17]. In this procedure, the defuzzified value is evaluated by considering a surface such that all the neighborhood values fall onto this surface. Following this procedure, the defuzzified value of s_i is determined from the neighborhood information in respect to the fuzzy look-up table constructed.

- *Approach 2*. From the possibility distribution of Figure 3, the modal value of Δ_i, namely, Δ_{im} is ascertained and the corresponding s_{im} is marked on the bifurcation diagram of Figure 4(a). By projecting s_{im} further on the $\mu(s_i)$ map, the membership class of s_{im} to the appropriate (defuzzified) linguistic description is determined.

Thus, the extent of complexity in terms of the defuzzified complexity-metric value s_i and its linguistic description are made available with respect to the ith call by either one of the two approaches indicated. Based on this value, CAC will be implemented as discussed later.

6.4 Call admission boundary: Crisp and fuzzy considerations

As indicated earlier, in practical CAC mechanisms, the ATM switch converts the connection of service request signaled across the user–network interface into an appropriate service categorization, traffic description, and QOS objective.

The service categorization is declared in terms of a peak-to-average bit ratio parameter associated with different types of services (such as voice, video, or data) being handled. Each of these categorized services can be labeled as distinct call types with specified traffic requirements or descriptors (such as peak cell rate) and/or QOS objectives like CLR, CTD, and CDV.

Shown in Figure 5(a) is a crisp call admission boundary in respect to calls identified by the index $i = 1, 2, 3, \ldots K$. For each call, the CLR is regarded as the QOS parameter to control. Suppose each call bears three distinct services designated by η_1, η_2, and η_3. A call is a multiplex of these services. Further, the cell loss rate of an ith traffic with a specific combination of η_1, η_2, and η_3 is denoted by $\mathrm{CLR}(\ell)_i = (\ell_1\eta_1, \ell_2\eta_2, \ell_3\eta_3)_i$ where (ℓ_1, ℓ_2, ℓ_3) are relative proportions of the traffics belonging to the participating service categories. Let the required CLR objective be an upper bound CLR_0. Then one can divide the $(\ell_1\eta_1, \ell_2\eta_2, \ell_3\eta_3)_i$ map into two regions: $\mathrm{CLR}(\ell)_i > \mathrm{CLR}_{0i}$ and $\mathrm{CLR}(\ell)_i < \mathrm{CLR}_{0i}$. The corresponding surface boundary between these two regions is a crisp call admission boundary. When the combination of the numbers of connected categorized calls lies above this boundary surface, the ATM switching node will reject the call setup requests.

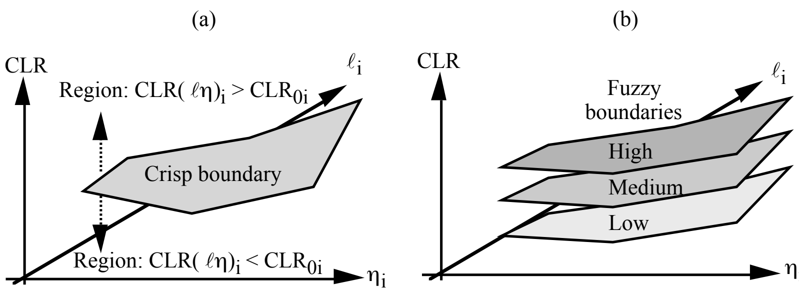

Figure 5. The call admission boundary surface of an ith call. (a) Crisp boundary. (b) Overlapping fuzzy boundaries.

For the reasons stated earlier, if the call admission inference is decided on the basis of the crisp boundary as described, the decision rule is rigid and more often would lead to a conservative approach in the allocation of available resources. That is, the resource utilization would become inefficient and not cost-effective.

Further, based on earlier discussions, it is rather prudent to consider the call admission boundary to be fuzzy with linguistic attributes of high, low, or medium in respect to the decision on call admission with a desired CLR_{0i}. In other words, Figure 5(a) can be redrawn to indicate the fuzziness of accept/reject regimes as illustrated in Figure 5(b).

Thus, a given combination of $\ell_1\eta_1$, $\ell_2\eta_2$, and $\ell_3\eta_3$ constituting the *i*th call has an associated fuzzy cell loss ratio, ${}^{(f)}\text{CLR}(\ell)_i = {}^{(f)}(\ell_1\eta_1, \ell_2\eta_2, \ell_3\eta_3)_i$ where the superscript (f) explicitly denotes the fuzzy attribute. The membership class of ${}^{(f)}\text{CLR}(\ell)i$ to high, medium, or low regimes is stipulated by the membership function, $\mu\{{}^{(f)}\text{CLR}(\ell)_i\} = [1, 0]$.

In the present study, the call admission criterion is set by a similar fuzzy procedure but with a modification. The call admission boundary is constructed in terms of the complexity parameter s_i (instead of CLR or any other objective parameters such as CTD or CDV). The reason (as indicated earlier) is that the complexity parameter s_i is derived from IT considerations and cohesively includes the information loss suffered by a particular set $\{\ell_1\eta_1, \ell_2\eta_2, \ell_3\eta_3\}$ as a result of the global traffic impairments caused by cell losses due to CDV and/or SNR. Thus, Figure 5(b) illustrating the fuzzy call admission boundaries can be modified to denote overlapping boundaries of the system complexity, namely simple through complex and specified *via* linguistic identification ES through EC indicated before. Hence, relevant fuzzy inference would lead to a decision on call admission devoid of over- or under-utilization of available resources. Therefore, the information loss impairment due to CDV and/or SNR is addressed through the complexity parameter s.

6.5 Fuzzy call admission control procedure

Suppose a CAC scheme is designed assuming that the 24 different calls (described in Table 1) are presented to an ATM switch. The call admission criterion for the *i*th traffic, for example, is set by the value of s_i obtained *via* one of the defuzzification procedures (Approach 1 or 2) described in section 6.4. The relevant parameters required are indicated in Table 3.

For simulation purposes two sets of data with source descriptions $\{\mathbf{X}_i\}$ and profiles of the resources $\{\mathbf{Z}_i\}$ of the *i*th call are presumed as given in Tables 4 and 5.

Service categories	Parameters
η_1: Data traffic (CBR: Interrupted Bernoulli process)	High bit rate = λ_{1h} Low bit rate = $\lambda_{1\ell}$ Transition probability from high-to-low rate = $P_{\rm HL}$ low-to-high rate = $P_{\rm LH}$ Loading factor: ℓ_1^*
η_2: Voice traffic (CBR: On-off Bernoulli process)	On-time bit rate = λ_2 On-state probability = $P_{\rm on}$ Off-state probability = $P_{\rm off}$ Loading factor: ℓ_2^*
η_3: Video traffic (VBR: Markov-modulated Bernoulli process)	Nonbursty bit rate = λ_3 Burstiness ratio = BP Transition probability from bursty-to-nonbursty state = $P_{\rm BN}$ Transition probability from nonbursty-to-bursty state = $P_{\rm NB}$ Loading factor: ℓ_3^*

Table 3. Source descriptions ($\ell_1^* + \ell_2^* + \ell_3^* = 1$).

	Service category	Priority, if any
EX	Video: λ_3 = 10 Mbps (MPEG2); BP = 3; ℓ_3^* = 0.35; $P_{\rm NB}$ = 0.35; $P_{\rm BN}$ = 0.55 Voice: λ_2 = 32 Kbps (compressed voice); $P_{\rm on}$ = 0.50; $P_{\rm off}$ = 0.20; ℓ_2^* = 0.40 Data: λ_{1h} = 2 Mbps (data file transfer); λ_{2h} = 64 Kbps; $P_{\rm LH}$ = 0.50; $P_{\rm HL}$ = 0.90; ℓ_1^* = 0.30	I: Video II: Voice III: Data
LX	Video: λ_3 = 10 Mbps (broadband video retrieval); BP = 5; ℓ_3^* = 0.30; $P_{\rm NB}$ = 0.50; $P_{\rm BN}$ = 0.50 Voice: λ_2 = 64 Kbps (telephony); $P_{\rm on}$ = 0.80; $P_{\rm off}$ = 0.10; ℓ_2^* = 0.30 Data: λ_{1h} = 64 Kbps (narrowband document retrieval); $\lambda_{1\ell}$ = 64 Kbps; $P_{\rm LH}$ = 0.50; $P_{\rm HL}$ = 0.50; ℓ_1^* = 0.40	I: Video II: Voice III: Data
MX	Video: λ_3 = 2 Mbps (video phone); BP = 1; ℓ_3^* = 0.80; Voice: λ_2 = 64 Kbps (telephony); $P_{\rm on}$ = 0.60; $P_{\rm off}$ = 0.40; ℓ_2^* = 0.20	I: Video II: Voice
CX	Voice: λ_2 = 32 Kbps (compressed voice); $P_{\rm on}$ = 0.50; $P_{\rm off}$ = 0.50; ℓ_2^* = 0.40 Data: 64 Kbps = λ_{1h} = $\lambda_{1\ell}$ (data on demand); $P_{\rm LH}$ = $P_{\rm HL}$ = 0.50; ℓ_1^* = 0.60	I: Voice II: Data

Table 4(a). Data set I: Traffic (source) types, $\{\mathbf{X}_i\}$.

Type	Description	Nominal parameters (typical)
RA: (intense traffic-handling and medium BER)	Large buffers Medium SNR	Buffer size: 30 SNR: 3.5 dB $\mu/\lambda_3 = 15$ $\mu/\lambda_{1h} = 75$
RB: (moderate traffic-handling and high BER)	Medium buffers Low SNR	Buffer size: 10 SNR: 2 dB $\mu/\lambda_3 = 1.5$ $\mu/\lambda_{1h} \approx 30$
RC: (intense traffic-handling and high BER)	Large buffers Low SNR	Buffer size: 30 SNR: 2.5 dB $\mu/\lambda_3 = 5$ $\mu/\lambda_{1h} \approx 20$
RD: (low traffic-handling and medium BER)	Low buffers Medium SNR	Buffer size: 5 SNR: 3 dB $\mu/\lambda_3 = 2$ $\mu/\lambda_{1h} = 5$
RE: (low traffic-handling and low BER)	Low buffers High SNR	Buffer size: 3 SNR: 10 dB $\mu/\lambda_3 = 5$ $\mu/\lambda_{1h} = 10$
RF: (low traffic-handling and high BER)	Low buffers Low SNR	Buffer size: 2 SNR: 1.5 dB $\mu/\lambda_3 = 3$ $\mu/\lambda_{1h} = 10$

Table 4(b). Data Set I: Profile of the resources, $\{\mathbf{Z}_i\}$.

	Service category	Priority, if any
EX	Multimedia Video/MPEG: $\lambda_3 = 90$ Mbps; $BP = 4$; $P_{\text{BN}} = 0.20$; $P_{\text{NB}} = 0.50$; $\lambda_3^* = 0.35$ Voice: $\lambda_2 = 64$ Kbps; $P_{\text{off}} = 0.40$; $P_{\text{on}} = 0.60$; $\ell_2^* = 0.55$ Data: $\lambda_{1h} = 10$ Mbps; $\lambda_{1\ell} = 6$ Mbps; $P_{\text{LH}} = 0.20$; $P_{\text{HL}} = 0.85$; $\ell_1^* = 0.10$	I: Video II: Voice III: Data
LX	Multimedia Video: $\lambda_3 = 30$ Mbps; $BP = 3$; $P_{\text{BN}} = 0.13$; $P_{\text{NB}} = 0.75$; $\ell_3^* = 0.30$ Voice: $\lambda_2 = 64$ Kbps; $P_{\text{off}} = 0.24$; $P_{\text{on}} = 0.76$; $\ell_2^* = 0.40$ Data: $\lambda_{1h} = 6.3$ Mbps; $\lambda_{1\ell} = 2.33$ Mbps; $P_{\text{LH}} = 0.30$; $P_{\text{HL}} = 0.90$; $\ell_1^* = 0.30$	I: Video II: Voice III: Data
MX	Voice: $\lambda_2 = 32$ Kbps (compressed); $P_{\text{off}} = 0.30$; $P_{\text{on}} = 0.70$; $\ell_2^* = 0.50$ Data: $\lambda_{1h} = 10$ Mbps; $\lambda_{1\ell} = 3$ Mbps; $P_{\text{LH}} = 0.20$; $P_{\text{HL}} = 0.80$; $\ell_1^* = 0.50$	I: Voice II: Data
CX	Voice: $\lambda_2 = 64$ Kbps; $P_{\text{off}} = 0.15$; $P_{\text{on}} = 0.85$; $\ell_2^* = 0.65$ Data: $\lambda_{1h} = 3$ Mbps; $\lambda_{1\ell} = 500$ Kbps; $P_{\text{LH}} = 0.30$; $P_{\text{HL}} = 0.80$; $\ell_1^* = 0.35$	I: Voice II: Data

Table 5(a). Data set II: Traffic (source) types, $\{\mathbf{X}_i\}$.

Type	Description	Nominal parameters (typical)
RA: (intense traffic-handling and low BER)	Large number of buffers Traffic-smoothing present Large SNR	Buffer size: 20 SNR: 15 dB Traffic-intensities: $\mu/\lambda_3 = 4$; $\mu/\lambda_{1b} = 30$
RB: (moderate traffic-handling and medium BER)	Medium number of buffers Traffic-smoothing present Medium SNR	Buffer size: 15 SNR: 10 dB Traffic-intensities: $\mu/\lambda_3 = 3$; $\mu/\lambda_{1b} = 15$
RC: (intense traffic-handling and high BER)	Large number of buffers Traffic-smoothing present Low SNR	Buffer size: 20 SNR: 3 dB Traffic-intensities: $\mu/\lambda_3 = 4$; $\mu/\lambda_{1b} = 30$
RD: (moderate traffic-handling and high BER)	Medium number of buffers Traffic-smoothing present Low SNR	Buffer size: 10 SNR: 2 dB Traffic-intensities: $\mu/\lambda_3 = 2$; $\mu/\lambda_{1b} = 10$
RE: (low traffic-handling and medium BER)	Low number of buffers Traffic-smoothing present Medium SNR	Buffer size: 5 SNR: 7.5 dB Traffic-intensities: $\mu/\lambda_3 = 3$; $\mu/\lambda_{1b} = 5$
RF: (low traffic-handling and high BER)	Low number of buffers Traffic-smoothing: present Low SNR	Buffer size: 5 SNR: 2 dB Traffic-intensities: $\mu/\lambda_3 = 3$; $\mu/\lambda_{1b} = 5$

Table 5(b). Data set II: Profile of the resources, $\{\mathbf{Z}_i\}$.

7. Simulations and results

Relevant to fuzzy heuristics concerning the complexity attributes of an ATM transmission as discussed, a call admission strategy is considered in the simulation experiments. It involves the assignment of an outgoing virtual channel/virtual path in response to an incoming call request at an ATM switch. The admission of a call meets the negotiated QOS objectives in a heterogeneous system of incoming calls. As indicated before, the QOS objectives are conglomerated into a single complexity parameter s. Further, the traffics associated with each incoming call are characterized by certain stochastic attributes and the related performance inferences are regarded as fuzzy.

Suppose the incoming call at an ATM switch corresponds to a given set of categories *vis-à-vis* source characteristics and resource profiles presented in section 6. Referring to Figure 1, it is presumed that the cell streams offered by each source are multiplexed at the entry node of a high-speed line with a rate of μ cells per second.

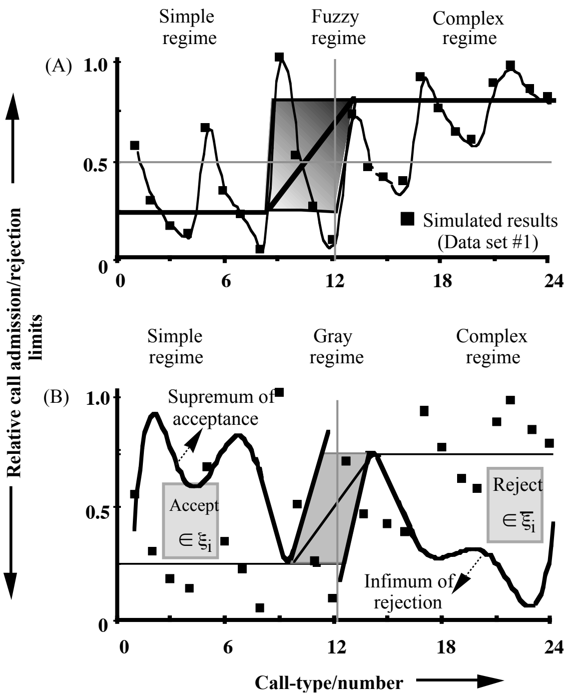

Figure 6(a). Simulated results pertinent to data set I, Approach 1. The asterisk denotes normalization with respect to the peak value and $(s_i^*)_{\rm df}$ is the defuzzified value obtained from $s_i^{(f)}$. (A) $(s_i^*)_{\rm df}$ values *versus* the call-type/number mapped to depict the single, fuzzy, and complex regimes. (B) Supremum limit on call-accept decision $\{\boldsymbol{\xi}_i\}$ and infimum limit on call-reject decision $\{\overline{\boldsymbol{\xi}}_i\}$ with a gray transition across ξ_i and $\overline{\xi}_i$.

Now, the CAC function with respect to the multiplexed cells of each incoming ith call can be interpreted as a mapping of the state vector $\{\mathbf{s}_i\}$ into the acceptance decision vector $\{\boldsymbol{\xi}_i\}$. This functional mapping divides the state-space crisply into two regions, namely, the acceptance region and rejection region (as indicated in Figure 5(a)), if the input variable s_i and the decision considerations $\{\boldsymbol{\xi}_i\}$ are studied in crisp formats. However, due to the reason indicated earlier, the input $\{\mathbf{X}_i, \mathbf{Z}_i\}$ would cause fuzzy, overlapping decision regions while implementing the acceptance or rejection of a connection request.

Hence, using the fuzzy set $\{\mathbf{s}_i\} \in \{\mathbf{X}_i, \mathbf{Z}_i\}$ pertinent to the ith call, the defuzzification procedure (Approach 1 or 2) would lead to a defuzzified value $(s_i)^f$, say, (s_i). In Approach 1, it corresponds to the centroidal value and in Approach 2, it refers to the modal value s_{im}.

Using the defuzzification approaches, the defuzzified values (s_i) are obtained for the 24 calls ($i = 1, 2, \ldots, 24$) pertinent to the data sets I and II.

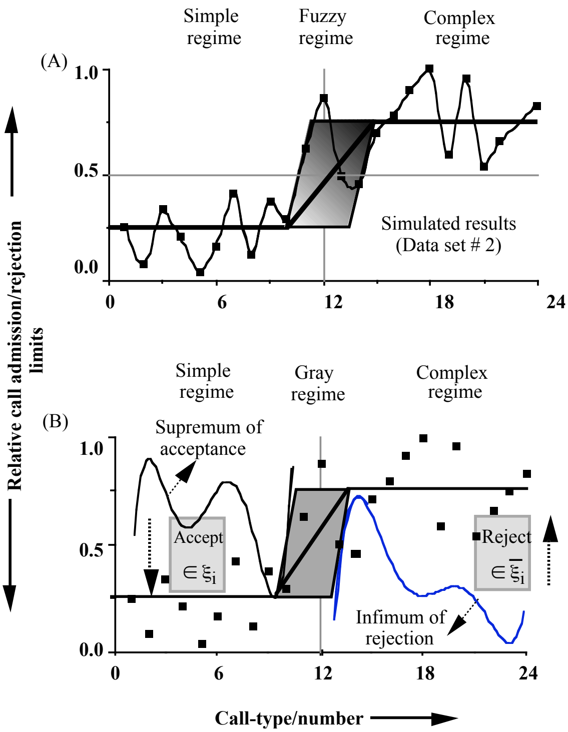

Figure 6(b). Simulated results pertinent to data set I, Approach 2. The subscripts $1m$ and $2m$ on (s_i^*) represent the dichotomous solution obtained *via* equation (4) corresponding to the modal value $\Delta_{im} \Rightarrow s_{im}$. (A) $(s_i^*)_{1m}$ and $(s_i^*)_{2m}$ *versus* the call-type/number mapped to depict the single, fuzzy, and complex regimes. (B) Supremum limit on call-accept decision $\{\xi_i\}$ and infimum limit on call-reject decision $\{\xi_i\}$ with a gray transition across ξ_i and $\bar{\xi}_i$.

Since the call admission corresponds to the condition that (s_i) of any ith call maps onto a preset acceptance decision vector $\{\xi_i\}$, the call is allowed, if $(s_i) \in \{\xi_i\}$. In Figures 6(a) and 6(b), the defuzzified results for data set I are presented. The simulated results for data set II are shown in Figures 7(a) and 7(b). The simulations indicated can be performed for any given set of calls submitted to the ATM switch for call admission; and, the admission priority schedule can be specified accordingly.

Consider the graphical results of data set I presented in Figures 6(a) and 6(b) corresponding to Approaches 1 and 2 respectively. In Figure 6(a)/A, the defuzzified and normalized values of s_i, namely $(s_i^*)_{\mathrm{df}}$ *versus* each call type (number) are indicated. These values show two distinct clusters in the extreme regions marked as simple and complex. In the middle, the set of values presented show transitional characteristics. That is, their membership in the simple or complex category is rather fuzzy or nonspecific.

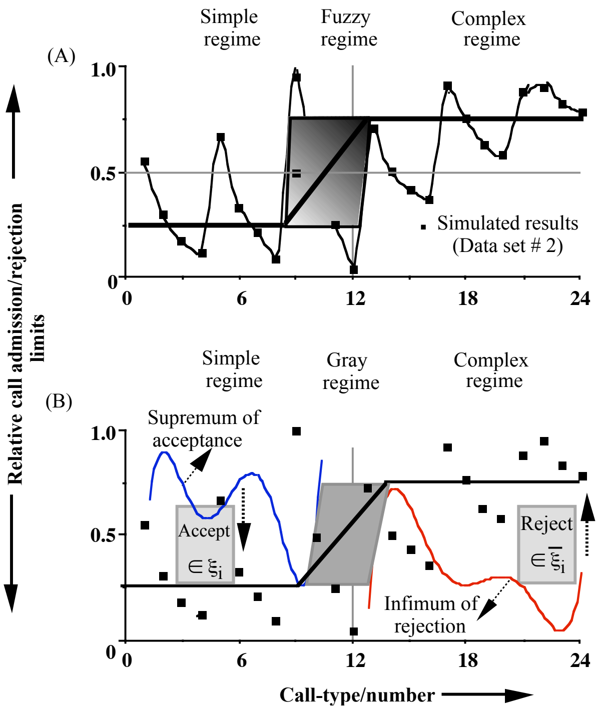

Figure 7(a). Simulated results pertinent to data set II, Approach 1. (A) $(s_i^*)_{\mathrm{df}}$ values *versus* the call-type/number mapped to depict the single, fuzzy, and complex regimes. (B) Supremum limit on call-accept decision $\{\xi_i\}$ and infimum limit on call-reject decision $\{\overline{\xi}_i\}$ with a gray transition across ξ_i and $\overline{\xi}_i$.

The task now is to decide a boundary across this fuzzy regime. This is done as shown in Figure 6(a)/B. First, a supremum bound is fitted for the simple (or accept regime $\in \xi_i$) and for the complex (or reject regime $\overline{\xi}_i$) an infimum bound is fitted. These boundaries are obtained by considering the dichotomous values of s_i (obtained *via* equation (4)) for the linguistic attributes of Table 1. If a value of $(s_i^*)_{\mathrm{df}}$ shown in Table 6(a) (and plotted in Figure 6(a)/A) is set by neighborhood values $(s_i^*)_{1,2}$, the corresponding supremum or infimum value is set by the neighborhood values $(s_i^*)_{2,1}$ or *vice versa*.

Similarly, using Approach 2, simulations with data set I (as illustrated in Figure 6(b)), the bounding limits can be specified by $(s_i^*)_{2m}$ and $(s_i^*)_{1m}$ and *vice versa*.

In both approaches the bounds of call accept/reject domains indicate a transitional gray regime as shown in Figures 6 and 7. A line constructed across this gray region of discontinuity in either case can be regarded as the boundary of separation between ξ_i and $\overline{\xi}_i$ (in this gray regime).

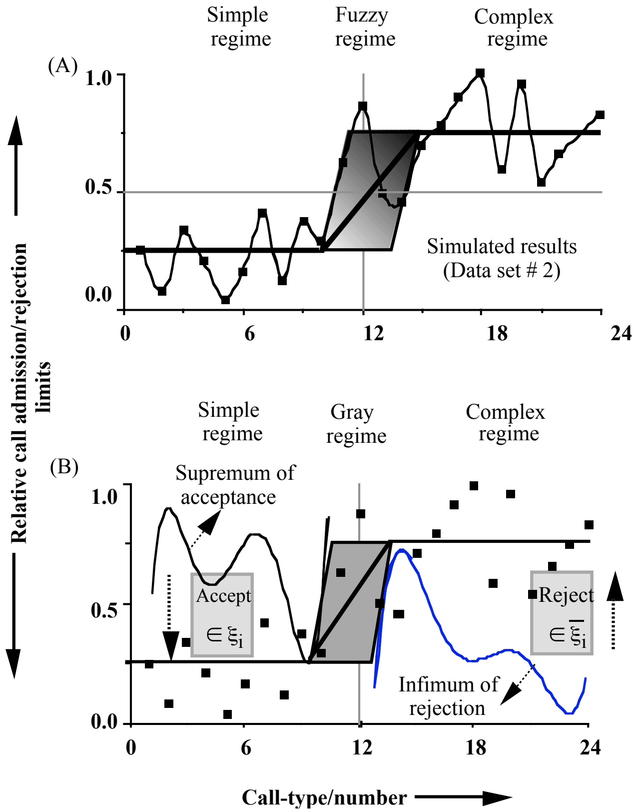

Figure 7(b). Simulated results pertinent to data set I, Approach 2. (A) $(s_i^*)_{1m}$ and $(s_i^*)_{2m}$ *versus* the call-type/number mapped to depict the single, fuzzy, and complex regimes. (B) Supremum limit on call-accept decision $\{\xi_i\}$ and infimum limit on call-reject decision $\{\overline{\xi}_i\}$ with a gray transition across ξ_i and $\overline{\xi}_i$.

Hence, with the limiting bounds on call acceptance or rejection established, the two approaches can be compared. Listed in Table 6 are the counts on accepted type calls (A) and reject type calls (R) enumerated within the bounds indicated in Figures 6(a) and 6(b). There are certain calls which are close to the boundaries and are marked as A/BL or R/BL (where BL denotes the borderline cases). Table 7 is similar, using the results of Figures 7(a) and 7(b) obtained from the simulations relevant to data set II with Approaches 1 and 2.

8. Discussions on the results

Referring to the results presented in Figures 6 and 7 and in Tables 6 and 7, a summary of details on call admission and/or rejection can be made as shown in Table 8.

Call Number	Type	Approach 1 (Figure 6(a))			Approach 2 (Figure 6(b))		
		Accept (A)	Reject (R)	Regime/ Counts	Accept (A)	Reject (R)	Regime/ Counts
1	EX-RA	A/BL		Simple	A		Simple
2	LX-RA	A			A		
3	MX-RA	A		6-A	A		
4	CX-RA	A		2-A/BL	A		
5	EX-RB	A/BL		1-R	A		9-A
6	LX-RB	A			A		
7	MX-RB	A			A		
8	CX-RB	A			A		
9	EX-RC		R		A		
10	LX-RC	A/BL		Fuzzy	A/BL		Gray
11	MX-RC	A				R	2-A
12	CX-RC	A		4-A		R/BL	2-R
13	EX-RD		A/BL	1-A/BL	A		1-A/BL
14	LX-RD	A		1-R/BL	A		1-R/BL
15	MX-RD	A				R	
16	CX-RD	A		Complex		R	Complex
17	EX-RE		R			R	
18	LX-RE		R			R	
19	MX-RE		R	1-A		R	
20	CX-RE		R	8-R		R	9-R
21	EX-RF		R			R	
22	LX-RF		R			R	
23	MX-RF		R			R	
24	CX-RF		R			R	

Table 6. Call accept/reject decisions (data set I, Approaches 1 and 2).

From Table 8, it can be observed that Approach 1 leads to decisions more diffused and indicates the existence of certain borderline decision cases. On the other hand, Approach 2 specifies distinct accept/reject division of calls even in the fuzzy regime. Nevertheless, both approaches in majority agree on common decisions.

The above observations are quite justifiable. Approach 1 is based on the centriod of fuzzy opinion gathered from the neighborhood; whereas, Approach 2 relies on a dichotomous opinion centered around a modal value. Hence, a diffused transition across simple-to-complex regimes and abrupt transitions across these regimes can be expected in Approaches 1 and 2 respectively.

Relatively, the diffused decisions obtained *via* Approach 1 are robust inasmuch as they also indicate the borderline cases (decisions which can be made only subject to system tolerance or *via* predefined criterion). Approach 2 on the other hand, has a tendency towards crisp decisions and therefore may lead to over- or under-specified decisions.

Relevant to these observations, the following inferences can be enumerated.

Call Number	Type	Approach 1 (Figure 7(a))			Approach 2 (Figure 7(b))		
		Accept (A)	Reject (R)	Regime/ Counts	Accept (A)	Reject (R)	Regime/ Counts
1	EX-RA	A		Simple	A		Simple
2	LX-RA	A			A		
3	MX-RA	A			A		
4	CX-RA	A		7-A	A		8-A
5	EX-RB	A/BL		1-A/BL	A		1-A/BL
6	LX-RB	A		1-R/BL	A		
7	MX-RB	A			A		
8	CX-RB	A			A		
9	EX-RC		R/BL		A/BL		
10	LX-RC	A/BL		Fuzzy	A/BL		Gray
11	MX-RC	A				R	1-A
12	CX-RC	A		4-A		R	1-A/BL
13	EX-RD		R/BL	1-A/BL		R/BL	2-R
14	LX-RD	A		1-R/BL		A	2-R/BL
15	MX-RD	A				R/BL	
16	CX-RD	A		Complex		R	Complex
17	EX-RE		R			R	
18	LX-RE		R			R	
19	MX-RE		R	1-A		R	
20	CX-RE		R	8-R		R	9-R
21	EX-RF		R			R	
22	LX-RF		R			R	
23	MX-RF		R			R	
24	CX-RF		R			R	

Table 7. Call accept/reject decisions (data set II, Approaches 1 and 2).

Data set	Regime	Decision	Approach 1 % of calls	Approach 2 % of calls
I	Simple	Accept	34*	38
		Reject	4	—
	Gray	Accept	18*	12
		Reject	6*	12
	Complex	Accept	4	—
		Reject	34	38
II	Simple	Accept	34*	37*
		Reject	5*	—
	Gray	Accept	17*	8*
		Reject	5*	17*
	Complex	Accept	5	—
		Reject	34	38

Table 8. Summary of accept/reject decisions. (*Includes borderline decisions.)

- The linguistic classification of calls distinctly fall into three categories, namely, "simple type," "complex type," and "fuzzy type" in regards to their admissibility across the ATM switch.
- Approaches 1 and 2 presented here classify these calls and cluster them into two specific domains namely, simple/accept regime ($\in \xi_i$) and complex/reject regime ($\in \overline{\xi}_i$). Also, a nonspecific (fuzzy) domain is indicated (between the accept/reject regimes) in which a partial set of calls appear.
- A procedure is indicated to obtain the limiting bounds (a supremum on accept decisions and an infimum on reject decisions) in the accept (ξ_i) and reject ($\overline{\xi}_i$) domains.
- Across the fuzzy domain, a transitional boundary (which can brute-force the decision either as accept or reject) is drawn by smoothing the asymptotic discontinuities of supremum and infimum bounds.
- With the limiting bounds constructed as above, the decisions made *via* the two approaches proposed in respect to data sets I and II can be enumerated as summarized in Table 8.

Another interesting inference that can be made from Figures 6 and 7 refers to the nonlinear transition from simple/accept regime to complex/reject regime across the fuzzy regime that lies in between.

The nonlinearity of this type arises from the interaction between various subsystems/parameters, which decide the performance (depicting simple or complex considerations), in reference to the call admissibility profile of the traffic. The interaction and the associated uncertainty leads to a fuzzy nonlinearity which is governed by the fuzzy nonlinear equation (equation (26)) as discussed by one of the authors elsewhere [7].

Typically, the simple-to-complex transitional nonlinearity is dictated by the order-to-disorder (or *vice versa*) changes in an interactive system. The nonlinear curve is sigmoidal and can be functionally specified by the Langevin–Bernoulli function, namely $L_Q(x)$ with Q depicting the extent of order/disorder of the system. Its slope at the origin $x = 0$ is $\alpha_0 = (1 + Q)/3$. Shown in Figures 6 and 7 are linear approximations of the sigmoidal nonlinearity depicting the transitional states. In Figure 8, the call accept/reject boundary is illustrated in terms of $L_Q(x)$ where x denotes a call characterization parameter.

9. Concluding remarks

The present study offers a robust design methodology to construct a fuzzy inference engine, which can manage CAC in ATM transmissions. It uses the concept of complexity in depicting the expert knowledge on overlapping attributes of traffic parameters. The fuzzy complexity metric adopted merges cohesively the delay considerations resulting from buffer flow and SNR-induced cell losses. Further, two approaches of

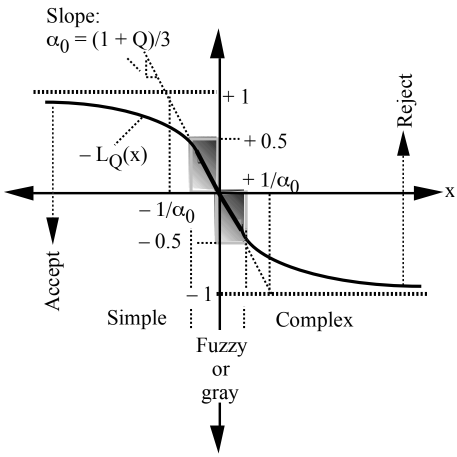

Figure 8. Normalized sigmoidal nonlinearity depicting the bounding limit on call acceptance/rejection criterion.

defuzzification are indicated. The efficacy and implementation of this CAC technique are presented *via* simulated results on a set of calls having characteristics of practical significance. The CAC proposed here would match any traffics with varying mean rates and mixed applications as normally encountered in ATM telecommunication. The major feature of the CAC strategy indicated here is its simplicity and straightforwardness.

References

[1] K. Uehara and H. Hirota, "Fuzzy Connection Admission Control for ATM Networks Based on Possibility Distribution of Cell Loss Ratio," *IEEE Journal on Selected Areas in Communications*, **15** (1997) 197–190.

[2] R. Cheng, "Design of a Fuzzy Traffic Controller for ATM Networks," *IEEE/ACM Transactions on Networking*, **4** (1996) 460–469.

[3] N. G. Duffield, J. T. Lewis, N. O'Connell, R. Russell, and F. Toomey, "Entropy of ATM Traffic Streams: A Tool for Estimating QOS Parameters," *IEEE Journal on Selected Areas in Communications*, **13** (1995) 981–990.

[4] I. E. Telatar and R. G. Gallager, "Combining Queueing Theory with Information Theory for Multiaccess," *IEEE Journal on Selected Areas in Communications*, **13** (1995) 963–969.

[5] S. Hsu, P. S. Neelakanta, and S. Abeygunawardana, "Maximum Cell-transfer Delay versus Cell-loss Ratio in ATM Transmission," *Proceedings of ATM'96 Workshop* (San Francisco, CA, Aug. 25–27, 1996, Paper #4, Session TP2).

[6] P. S. Neelaknata and W. Deecharoenkul, "Fuzzy Aspects of Queueing Dynamics of ATM Cell Streams in Information-theoretic Domain," *Proceedings of the Thirty-third Annual Conference on Information Sciences and Systems* (Baltimore, MD, March 17-19, 1999).

[7] P. S. Neelakanta (editor), *Information Theoretic Aspects of Neural Networks* (CRC Press, Boca Raton, FL, 1999).

[8] R. J. Gibbens, F. P. Kelly, and P. B. Key, "A Decision-theoretic Approach to Call Admission Control in ATM Networks," *IEEE Journal on Selected Areas in Communications*, **13** (1995) 1101–1113.

[9] J. Libenherr, D. E. Wrege, and D. Ferrari, "Exact Admission Control for Networks with a Bounded Delay Service," *IEEE/ACM Transactions on Networking*, **4** (1996) 885–901.

[10] A. E. Ferdinand, "A Theory of System Complexity," *International Journal of General Systems*, **1** (1994) 19–23.

[11] L. A. Zadeh, "Fuzzy Sets," *Information and Control*, **8** (1965) 338–354.

[12] I. Herrero, A. Diaz-Estrella, and F. Sandoval, "Neural Call Admission Control through Virtual Link Estimates," *Proceedings of ATM'97 Workshop* (May 25–28, 1997, Lisboa, Portugal).

[13] C. Douligeris and G. Develckos, "Neuro-fuzzy Control in ATM Networks," *IEEE Communication Magazine*, (May 1997) 154–162.

[14] J. E. Neves, M. J. Leitao, and L. B. Almeida, "Neural Networks in B-ISDN Flow Control: ATM Traffic Prediction or Network Modeling," *IEEE Communication Magazine*, (October 1995) 50–56.

[15] H. Saito, *Teletraffic Technologies in ATM Networks* (Artech House, Boston, MA, 1994).

[16] H. Saito, "Toward a Future Dimensioning Method: Nonparametric Approach," *Institute of Electronics Information and Communications Transactions*, **J.76-B-I** (3) (1993) 1373–1379.

[17] B. Kosko, *Fuzzy Engineering* (Prentice Hall, Upper Saddle River, NJ, 1997).