CHAPTER II

ESTIMATION OF CELL LOSS RATIO -
A FUZZY APPROACH

In this chapter, fuzzy based estimation of CLR for different traffic models is analyzed and a modified approach for improvement is also presented. The fuzzy based approach to estimate the possibility distribution of CLR from the observed data using a fuzzy inference scheme (FIS) is presented in the first part. This FIS scheme is analyzed for the on-off source model. The main problem in the design of FIS is that the observed data is required for all types of traffic classes and the number of connections for each class. If the incoming traffic does not fit into the predefined traffic class and if the observed data is not available for a certain number of connections (this may happen due to an expansion of the network or a failure of nodes), then this method cannot be applied.

A Set Right Algorithm (SRA) that operates as a defense mechanism against rare or irregular abnormalities is also proposed here. In the second part of the chapter, a more versatile fuzzy adaptive algorithm to overcome the drawbacks in FIS is presented. This adaptive fuzzy algorithm (Bensaou et al. 1997) predicts the CLR for large sized systems based on a small amount of information from small sized systems obtained either experimentally or analytically using the mathematical models. From the analysis of the adaptive fuzzy system, for Markov and Geom/Geom/1/k models, it is observed that there exists a big difference between the estimated and the theoretical values,
especially, at buffers of large sizes. Hence, to obtain improved results, an improved method of loss calculation for Markov and a modified fuzzy logic system with appropriate correction factor for Geom/Geom/k/1 models are implemented.

2.1 IMPORTANCE OF REAL TIME CLR ESTIMATION

Through statistical multiplexing, the network efficiently shares the transmission resources by taking advantage of the statistical behavior of the sources with different traffic characteristics. Since ATM is a connection-oriented circuit, a contract on connection request should first be established between the source and the network. The source first declares a set of parameters to describe the traffic and agrees to generate its traffic according to the declared parameters. Once the call is accepted, the network agrees to guarantee the required QoS by maintaining the CLR. Obviously, estimation of CLR in real time for achieving satisfactory call admission control is an important problem.

![Figure 2.1 Model of an ATM multiplexer](image-url)
Figure 2.1 shows the model of an ATM multiplexer with a finite buffer of size B (cells) and link capacity of \( \mu \) cells. In an ATM multiplexer, cell loss occurs when a new set of cells arrives at the multiplexer at a rate greater than the link rate (\( \mu \) cells/sec) or the transmission capacity, while the buffer is still full with B number of cells. To allow the network to decide whether to accept or reject the new connection, given the transmission resources, an accurate estimation of CLR is the basic requirement.

2.2 CLR ESTIMATION METHODS

There are many statistical methods in the available literature for the estimation of CLR, in which the actual arrival process of the cells to the buffer is approximated to some of the mathematically tractable models, for example a fluid flow (FF) model. In this approximation, to represent the fluctuation of the cell arrival rate, the arrival of information is assumed to be continuous rather than discrete as it is in reality. When the rate of fluctuation occurs on a much larger time scale than the intervals between periods of cell arrival, the effects on the CLR due to the discrete nature of the actual arrival process become negligible. Under such circumstances, solving a set of differential equations with certain assumptions leads to a closed form solution (Anick et al 1982) or under more general assumptions to a numerical solution that results only in the approximate estimation of CLR. The CLR can also be estimated at the expense of complex and time consuming numerical algorithms (Sykas et al 1994). In the Markov Modulated Deterministic Process (MMDP), the cells arrive according to a deterministic renewal process and their arrival rate is controlled by the Markov process (Yang and Tsang 1995). Here, the CLR values can be estimated accurately by solving a set of linear equations using the Gauss-Siedal algorithm. But, the Markov modulated Poisson process (MMPP) is not
appealing due to its analytical and numerical complexity. Though, these approaches are good in predicting the CLR in ATM multiplexer, they lead to computational complexity and memory problems when the system size becomes large.

To avoid the shortcomings of the above said methods, many other approximate approaches have also been proposed in the literature for the estimation of CLR in an ATM multiplexer. For example, the approximations have been derived for the queue length distribution of a fluid multiplexer fed by a superposition of homogeneous on-off sources. This approach uses the large deviation estimates of the queue length distribution when the link capacity and the multiplexer buffer size diverge with the number of sources sharing the multiplexer (Simonian 1995). The same approach is used for heterogeneous arrival processes such as superposition of Gaussian process, Ornstein-Uhlenbeck processes, etc. Although, these large deviation approaches give very good approximations of CLR even under more practical assumptions, while avoiding the complexity of FF, MMPP and MMDP models, they still depend on the knowledge of the arrival process, which for most practical ATM sources, is yet to be determined. For example, even though MPEG video sequences are known to exhibit self-similar behavior, it is shown that there is no typical video source behavior since $H$, the Hurst parameter that characterizes the self-similarity, changes from one type of video source to another. (Heyman and Lakshman1996).

In the Global rational approximation (GRA) algorithm (Yang 1995) the CLR is assumed to be a function of buffer size or the number of users is approximated by a relational function, $R(x) = P_m(x)/Q_n(x)$, where $P_m(x)$ and $Q_n(x)$ are polynomial functions of degree $m$ and $n$. Though, the GRA approach
is efficient and accurate, it still has some major problems like long computational time and singularity in solution finding. Moreover, the known values of CLR do not fit into a smooth curve, which is the case when the values of CLR are obtained from measurements that normally contain some amount of error.

In conventional methods, the estimation of CLR is often performed on the basis of analytical models of the cell generation process in terminals and ATM switch architecture, (Murase et al 1991). The cell generation process, however, has a wide variety of patterns and ATM switches have become increasingly complex in order to attain higher performance. It makes the construction of the analytical models difficult and often requires approximations, which result in an excessive estimation of CLR. The learning systems observe the CLRs in ATM switches, and extract the relation between the CLR and the number of connections in each transmission class. Based on the declared traffic parameters, the ATM switch judges whether the CLR values can be achieved or not. This is done by a fuzzy inference method by estimating the possibility distribution based on the observed CLR value (Uehara and Hiroto1997). Even though, the traffic parameters may be the same for many sources of traffic, they may actually be dissimilar in other respects. It is, therefore, obvious that these parameters are insufficient for traffic characterization and hence this method is not suitable for real time estimation of CLR. Moreover, in the fuzzy inference method, connection requests are classified into a sets of call classes, each of which are pre-calculated using traffic parameters specified by the user and stored in some lookup table. The disadvantages of this method are difficulty in managing the lookup table, classifying the wide range of traffic characteristics of the ATM network into a
reasonable number of class groups and verifying the suitability of the existing model to other arrival processes.

Hence, in order to overcome the shortcomings in the above-mentioned approaches, an adaptive fuzzy system to predict the CLR efficiently in large-sized systems based on a little information from small sized systems is proposed by Bensaou et al (1997). In this system, Gaussian membership functions are considered for the input fuzzy set and a center average defuzzifier is considered for the output. The block diagram of the fuzzy system is shown in Figure 2.2. When this fuzzy system is applied for Geom/Geom/1/k model, it is observed that CLR values are inaccurate, especially for lower load factors. Hence, in the present work, a modified fuzzy logic system (MFLS) is proposed with an appropriate membership function and correction factor (CF) to get a better estimate of the real time CLR for Geom/Geom/1/k model. The fuzzy system is applied to Markov models, namely MMPP and MMF models with improved cell loss calculations in an ATM multiplexer. To design the fuzzy logic system, theoretical CLR values are obtained using analytical expressions.

![Block diagram of a fuzzy system](image-url)
The following sections describe the FIS used to determine the possibility distribution of CLR from the observed data.

### 2.3 FUZZY INFERENCE APPROACH TO ESTIMATE CLR

In order to simplify the CAC procedure and to overcome the difficulties posed by analytical models, learning systems are applied for the estimation of CLR. In these methods, the CLRs are observed in ATM switches, and the relation between the CLR and the number of connections in each transmission rate class is arrived at by the learning systems. These observation-based methods are quite effective because analytical models need not be constructed and the switches can be equipped with adaptive mechanisms to cope with dynamic situations. However, these conventional methods cannot always perform CAC guaranteeing the allowed CLR. Hence, FIS is chosen to effectively estimate the possibility distribution of CLR (PDCLR) from the observed data. The FIS is based on the weighted average of the fuzzy set.

Often there is a non-linear relation between the CLR and the number of connections and therefore Artificial Neural Networks (ANNs) are adopted in the observation based CAC. But, the ANNs learn only the average of the observed CLR data, which has a large dispersion even in a particular transmission rate class due to a wide variety of generation patterns. For any cell arrival process satisfying the traffic parameters of the transmission class, the CAC must guarantee the allowed CLR. This means that learning the average process may not guarantee the allowed CLR in CAC. Even if the maximum value of the observed CLR for each set of connections of a certain number is used, it cannot guarantee the allowed CLR. This is because, the maximum values are also dispersed and this average learning provides the average of these
dispersed maximum values. Hence, the estimation of the possibility distribution of CLR is needed in order to guarantee the allowed CLR in CAC. That is, if the possibility distribution can be obtained, its upper bound can make possible the CAC guaranteeing the allowed CLR. Figure 2.3 compares the average estimation and the upper-bound estimation.

![Figure 2.3 Average estimation and upper bound estimation](image)

The nonparametric approach has also been used for estimating the upper bound CLR since the arrival process is not specified in practice. Although this approach is effective in guaranteeing the allowed CLR, it tends to estimate excessively high CLR and results in lower multiplex gain (Uehara and Hiroto 1997). Even in constructing the analytical models without using the nonparametric approach, approximations are used so as to guarantee the allowed CLR, which reduces the multiplex gain.

Because of the drawbacks mentioned above, the fuzzy inference approach is applied. In this approach the **then part** of each fuzzy rule can give the possibility distribution of CLR for the number of connections covered with
the if-part in the fuzzy rule. The inference consequence, therefore, provides the estimated possibility distribution of CLR for the given number of input connections. The fuzzy rule based inference system is explained in the following section.

2.4 FUZZY RULE-BASED SYSTEMS

Fuzzy systems are precisely defined with a strong mathematical basis. What is "fuzzy" in a fuzzy system is the information it deals with. The fuzzy sets theory describes incomplete or vague concepts, which might be difficult to formulate mathematically. Fuzzy systems are knowledge-based systems (also called rule-based systems). The heart of the fuzzy system is a knowledge base, which consists of a set of IF - THEN rules. The rules are statements in which some words are characterized by continuous membership functions. For example, IF the link is close to congestion THEN reduce the input rate, the words "close to congestion" are characterized by a membership function as shown in Figure 2.4, where congestion occurs when the link utilization is above 0.8. The word "reduce" can also be characterized by another membership function.

![Figure 2.4 Membership function of the linguistic variable "close to congestion"](image)
A fuzzy system is basically made of a fuzzifier, a defuzzifier, an inference engine and a rule base as shown in Figure 2.2. The role of the fuzzifier is to map the crisp input data values into fuzzy sets defined by their membership functions depending on the degree of “possibility” of the input data. Among the many types of fuzzifiers available, the most commonly considered in practical applications is the singleton fuzzifier, which maps the crisp input into a singleton fuzzy set. Intuitively this means that the degree of possibility of the input data is equal to one. When the degree of possibility of the input data can be known only in a certain range, other fuzzifiers, such as Gaussian or triangular or trapezoidal, are also available. The goal of the defuzzifier is to map the output fuzzy sets into a crisp output value. It combines the different fuzzy sets with different degrees of possibility to produce a single numerical value.

The most commonly used defuzzifier is the centre-average defuzzifier, which calculates a weighted average of the centers of the output fuzzy sets to produce the crisp output. This defuzzifier is chosen to implement the fuzzy systems here. The fuzzy inference engine defines the method that is adopted by the system to infer through the rules in the rule base to determine the output fuzzy sets. The FIS to estimate the upper-bound CLR (UBCLR)) from the possibility distribution of CLR (PDCLR) is explained below.

2.5 FUZZY INFERENCE SCHEME (FIS)

The block diagram of FIS is given in Figure 2.5. When a request comes from a user it is classified according to the traffic bit rate using the traffic classifier. Then, it is fed to the CLR database wherein the number of connections and their possibility distributed CLR values are verified. After this,
the fuzzy rules are adjusted by learning and the upper bound CLR is estimated. Suppose, for a certain number of connections, the CLR data is not available in the database, then, the new rules are generated by the extrapolator. These rules are used to determine the upper bound CLR. The new upper bound CLR so estimated is fed to the Call Admission Controller (CAC), where it is decided whether to accept or reject the request for connection. When a sudden change in CLR value is observed in the channel link, then a new upper bound CLR is set using the Set Right Algorithm (SRA). The following section describes the functioning of FIS.

Figure 2.5 Block diagram of fuzzy inference scheme
The fuzzy inference scheme is based on a weighted average of fuzzy sets. The **then-part** of each fuzzy rule can give the possibility distribution of CLR for the number of connections covered by the **if-part** in the fuzzy rule. The inference consequence, therefore, provides the estimated possibility distribution of CLR for the number of input connections (Uehara and Hiroto 1997). The fuzzy rules are given by:

\[
\text{If } x \text{ is } P_1 \text{ then } y \text{ is } Q_1 \\
\text{If } x \text{ is } P_2 \text{ then } y \text{ is } Q_2 \\
\text{If } x \text{ is } P_3 \text{ then } y \text{ is } Q_3 \\
\vdots \\
\text{If } x \text{ is } P_n \text{ then } y \text{ is } Q_n
\]

If the given fact \( x \) is \( P^- \) then the consequence \( y \) is \( Q^- \), where \( P, Q, P^- \) and \( Q^- \) are fuzzy sets. These sets are defined with the membership functions as,

\[
P_j = \int_X \mu_{P_j} (x) / X, \quad Q_j = \int_Y \mu_{Q_j} (y) / Y, \quad (2.1)
\]

\[
P^- = \int_X \mu_{P^-} (x) / X, \quad Q^- = \int_Y \mu_{Q^-} (y) / Y. \quad (2.2)
\]

Here, a fuzzy inference method based on the weighted average of fuzzy sets is analyzed. The inference process consists of the following steps:

1. Calculate the compatibility degree, \( p_j^- \) between \( P^- \) and \( P_j \) (\( j = 1, 2, 3 \ldots n \)) which is given by,

\[
p_j^- = \sup \left[ \mu_{P^-} (x) \land \mu_{P_j} (x) \right] \quad (2.3)
\]

where \( \land \) denotes the minimum operation. When \( P^- \) is a singleton at a numerical value \( x^- \), then Equation (2.3) becomes,
\[ p_j = \mu_{P_j}(x^-) \]  

(2.4)

2. Compute the inference consequence \( Q^- \) as,

\[
Q^- = \sum_j \tilde{p}_j Q_j / \sum_j \tilde{p}_j \tag{2.5}
\]

Equation (2.5) gives the average of fuzzy sets \( Q_j \), weighted by \( p_j^- \) where \( j=1,2,3...n \). Let \( Q_{\alpha} \) and \( Q_{\alpha}^- \) denote the \( \alpha \) - level sets of \( Q_j \) and \( Q^- \) respectively. When \( Q_j \) and \( Q^- \) are both convex (Dubois, D.1980) and normal fuzzy sets, each of their \( \alpha \) - level sets can be represented by a single interval as,

\[
Q_{\alpha} = [y_l Q_{\alpha}^- , y_u Q_{\alpha}^- ] \quad Q_{\alpha}^- = [y_l Q_{\alpha}^- , y_u Q_{\alpha}^- ] \tag{2.6}
\]

where \( y_l Q_{\alpha}^- \) and \( y_u Q_{\alpha}^- \) are the lower and upper limits of the set \( Q_j \) and \( y_l Q_{\alpha}^- \) and \( y_u Q_{\alpha}^- \) are defined as,

\[
y_{Q^- \alpha}^{-} = \frac{\sum_j \tilde{p}_j y_{Q_{\alpha}^-}}{\sum_j \tilde{p}_j} \tag{2.7}
\]

\[
y_{Q \alpha}^{-} = \frac{\sum_j \tilde{p}_j y_{Q_{\alpha}}} {\sum_j \tilde{p}_j} \tag{2.8}
\]

The upper bound CLR can be effectively estimated using the fuzzy inference method. In the FIS, if-parts define the number of connections \( x_i \) in transmission rate class \( K_i \), whereas, then-parts define the possibility distribution of CLR under the condition given by the if-parts.
In the fuzzy inference method, the fact $P^\gamma$, is the number of connections in a transmission rate class, is the input to the inference engine. Thus, $P^\gamma$ is given by a singleton. The inference consequence $Q^\gamma$, namely the output of the inference engine, gives the possibility distribution of CLR, reflecting the effect of the proposed inference method. The learning algorithm described in the following section.

### 2.5.1 Learning algorithm

The FIS can control the width of its final inference consequence by adjusting the membership functions in the THEN parts. The learning algorithm is applied to adjust the width of the membership functions, together with their positions, by tuning their parameters of the membership functions. Thereby, the possibility distribution of the CLR is obtained. In the learning algorithm, the energy function is used for the estimation of the possibility distribution. The centre of the distribution is the average of the observed CLR data. From the possible values of the CLR, a value $y^0$ for which the energy function $E$ is minimum is obtained. The resultant energy function is given by,

$$E_0 = \frac{1}{2} \Sigma (y^0 - y^s)^2 \quad (2.9)$$

where $y^s$ (s=1,2,..., S) denote the observed CLR values, which represent the target data. In the learning process, the parameters of the fuzzy sets in each fuzzy rule are tuned with this energy function. To adjust the width of the membership functions in the THEN-parts, an energy function $E_w$ is applied as follows:

$$E_w = \frac{1}{2} \Sigma (\mu_Q^\gamma (y^s) - \alpha')^2 \quad (2.10)$$

where $\alpha' = \begin{cases} 1, & (\mu_Q^\gamma (y^s)) \leq \alpha \\ 0, & (\mu_Q^\gamma (y^s)) > \alpha \end{cases} \quad (2.11)$
and α is the threshold for obtaining the upper bound of CLR. In the energy function given by Equation (2.10), the target data α' is dynamically changed. If \((μ_Q(y^-)\) is smaller than or equal to α, then the target data α' is set to one. Thus, the membership function of the inference consequence is forced to assume the highest value of the membership grade. As a result, it makes the width of inference consequence larger because its height of the inference consequence is fixed to one. On the other hand, if \((μ_Q(y^-)\) is larger than α, the target data α' is set to zero. Thus, the membership function of inference consequence is forced to assume the lowest value of membership grade. As a result, the width of the inference consequence reduces. Figure 2.6 illustrates these processes mentioned above. If α is small, then the width of μ̂_Q(y) is also small. Conversely, if α is large then, the width is also large. The dynamics in Equation (2.10) controls the value of α' so that the observed data are included in the interval given by the inference consequence at a threshold α. This interval I_{CLR} is the α-level set of Q^- at the level of α and is given by,

\[
I_{CLR} = \{ y | μ_̂_Q(y) \geq α \} = Q^-_α
\]  

(2.12)
Figure 2.7 shows the interval $I_{CLR}$ from $\alpha$ and a final inference consequence. The $\alpha$-level set of $Q^-$ is given by only one closed interval as

$$I_{CLR} = [y^-, y^+]$$  \hspace{1cm} (2.13)
2.5.2 Fuzzifier and defuzzifier

The fuzzy inference operations can be simplified by using unimodal functions for the membership. The fuzzy membership functions are defined as:

\[ \mu_P(x) = \begin{cases} \frac{2}{\eta} (x - x^0) + 1, & x < x^0 \\ \frac{-2}{\eta} (x - x^0) + 1, & x > x^0 \end{cases} \] (2.16)

\[ \mu_Q(y) = \exp\left[- \frac{(y - y^0)^2}{2\eta^2}\right] \] (2.17)

where \( x^0 \) and \( y^0 \) represent central positions of membership functions and \( \eta \) is the parameter for their width. Each of the membership functions is represented by these two parameters only. It reduces the computational complexity in both the inference mode and the learning mode. The inference consequence \( Q^- \) is given by,

\[ y_{Q^-}^0 = \frac{\sum_j p_j y_{Q_j}^0}{\sum_j p_j} \] (2.18)

\[ \eta_{Q^-} = \frac{\sum_j p_j \eta_{Q_j}}{\sum_j p_j} \] (2.19)

By using these membership functions in the fuzzy inference method, effective CLR is obtained. The fuzzy rules are formed from the already existing data. The CLR values for a certain number of connections are obtained using (Yang and Tsang 1995) and these are kept as observed CLR values for designing the fuzzifier and the defuzzifier. For a single service class, the
number of connections is assumed to be 1000. The triangular membership functions are assumed and, for various combinations, with respect to their width and centre, are tested and the results are analyzed.

In case-I, four triangular membership functions with equal width (width =200) are chosen and are analyzed. Figure 2.8 shows the membership functions and the corresponding results. Here, it is observed that the upper bound CLR is inaccurate when the connections are between 450-500 and 850-950. This is because of the fact that the number of membership functions assumed is inadequate. To correct this, the fuzzifier width is reduced to 50, and so the number of fuzzy sets is increased to 18. In case-II, it is observed that it takes longer time to predict the CLR. Even though, the error is less. Figure 2.9 gives the membership functions and the output for caseII fuzzifier. So, in order to reduce the delay, non-linear membership functions are applied in case III between 450-550 and 900-950. In this case, the number of fuzzy membership functions used is 13 and it is observed that the delay is less, but at the higher end the results are still not accurate as shown in Figure 2.10. In order to overcome these difficulties a compromise has been made. Non-linear membership functions are assumed only at the beginning (case IV). An optimum value of nine fuzzy sets is chosen leading to less tuning time and negligible error. Figure 2.11 shows the membership functions and the corresponding output for case IV fuzzifier. For the defuzzifier, three types of membership functions are analyzed and Figures 2.12, 2.13 and 2.14 show the type of membership functions along with the centres and widths and the corresponding results. In Table 2.1 the three types of defuzzifier’s membership functions along with their shapes are given. Out of the three defuzzifiers case-II and case-III defuzzifiers estimate the CLR without much error. The behavior patterns of the three types of defuzzifiers are compared in Figure 2.15.
Case I: Fuzzifier
No. fuzzy Sets = 4
Properties: Linear
Centre = [550 650 750 850]
Width = [200 200 200 200 ]

Figure.2.8 Case I. Fuzzifier Membership Function and the Output.
Case II: Fuzzifier

No. fuzzy Sets = 19

Properties: Linear

Centre = [475 500 525 ... 875 900 925]

Width = [50 50 50 ... 50 50 50 ]

Figure 2.9 Case II. Fuzzifier Membership Function and the Output.
Case III: Fuzzifier

No. fuzzy Sets = 13

Properties: Non-Linear

Centre = [460 470 475 500-550 650 750 850 900 925 930 940]

Width = [20 40 50 100 200 200 200 200 100 50 40 20 ]

Figure 2.10 Case III. Fuzzifier Membership Function and the Output.
Case IV: Fuzzifier

No. fuzzy Sets = 9

Properties: Non-Linear

Centre = [460 470 475 500 550 650 750 850 950 ]

Width = [20 40 50 100 200 200 200 200 200 ]

![Membership Function](image)

![Graph](image)

Figure 2.11 Case IV. Fuzzifier Membership Function and the Output.
Case I: Gaussian Defuzzifier

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Figure 2.12 Case I. Defuzzifier Membership Function and the Output.
**CASE II: PARABOLIC DEFUZZIFIER**

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**Figure 2.13** Case II. Defuzzifier Membership Function and the Output.
**CASE III: MODULUS DEFUZZIFIER**

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**Figure 2.14 Case III. Defuzzifier Membership Function and the Output.**
Figure 2.15 Comparison of Defuzzifier Output.
2.5.3 Extrapolation

Extrapolation addresses the problem of the estimation of CLR in the region where there is no observed CLR data. Such areas exist because of the absence of experience in connections, with the lack of observed CLR data. To solve this problem, fuzzy rules are automatically generated by using the existing fuzzy rules, which are already tuned by using the existing fuzzy rules covering the area where the observed data exists. These newly generated fuzzy rules together with the existing ones are applied for the estimation of CLR in the area where there is no observed CLR data. Now, new CLR data can be observed in this area. These observed data are used for tuning all fuzzy rules including the newly generated fuzzy rules. In this way, fuzzy rules are successively generated. The extrapolation algorithm is verified by simulation.

For the purpose of simulation the non-observed region is assumed to be in the range of 950-1050. It is found that the algorithm works well if the width of the extrapolated region is half the width of the fuzzifier. The centre of the defuzzifier in the region of no observed CLR is calculated based on the assumption that the centers of the defuzzifier almost follow a geometric progression with a slight deviation. To compensate for this deviation, a correction factor is introduced. The defuzzifier used for extrapolation is the one with the Gaussian membership function and the fuzzifier is that of case IV as they are found to be most suitable for the estimation of CLR with less error. It is assumed that the UBCLR follows an exponential pattern and that the centres increase in geometric progression. The general formulae used for finding the centre and the width are as follows:
It is observed that as the number of connections increases, the upper bound CLR value increases. When the extrapolation formulae are applied, it is noted that, in the areas where there is no observed CLR data there is a decreasing tendency for UBCLR. But, this is not correct. Hence, in order to correct this, a slight change in the formulae is incorporated. The corrected formulae are as follows:

\[
\text{Centre (n)} = \frac{[\text{Centre (n-1)}]^2}{[\text{Centre (n-2)}]} \times 1.1 \quad (2.20)
\]

\[
\text{Width (n)} = \frac{[\text{width (n-1)}]^2}{[\text{width (n-2)}]} \quad (2.21)
\]

A comparison of the extrapolated results with and without the correction formulae for deterministically and randomly distributed observed CLRs are shown in Figures 2.16 and 2.17 respectively. From these figures, it is observed that the corrected formulae give better UBCLR values when compared to the general formulae.
Figure 2.16 Output of the Extrapolation for deterministically distributed CLR data with and without CF.
Figure 2.17 Output of the Extrapolation for randomly distributed CLR data with and without CF.
2.5.4 Set right algorithm (SRA)

Network behaviour and traffic patterns are highly random in nature. Whether this random nature is to be viewed as exceptions and neglected or is to be included in the network features under the assumption that such exceptions are the nature of the network is a subjective matter. In the operation of ATM switches, it is conceivable that the observed CLR, after accepting a call, unexpectedly exceeds the estimated CLR in the CAC stage. This situation requires immediate compensation for this CLR estimation error. The Set Right Algorithm (SRA) proposed here compensates for the estimation errors in real time with a simple mechanism as illustrated in Figure 2.18. A fuzzy scheme is implemented in such a way that, based on the observation of the network over a period of time, the abnormalities are set right without human intervention. The threshold for the decision is to be fed as an input to this scheme. The threshold, $th_n$, is determined by analyzing the variation of the observed CLR data for the number of connections. The quantity $th_n = |CLR(i+1) − CLR(i)/CLR(i)|$ which is the normalized difference between the consecutive observed CLRs is compared with $th_n$. If $th_n$ is greater than the input threshold value $th_{in}$, then the hike is decided in favour of network abnormality and the higher value CLR is replaced by the predecessor CLR value before proceeding. Further, the assumption here is that, the network abnormality does not occur consecutively.

If the threshold is set to be very low, then the small variation in the CLR could be eliminated, which affects the QoS. On the other hand, if the threshold is very large, then the estimated UBCLR would be very high, which may decrease utilization. Hence, an optimum value of the threshold should be chosen from the observed data. The sudden change in CLR value is added with the observed CLR data for verifying the SRA. The performance of the proposed
SRA is studied for the deterministically and randomly distributed CLR values. When the SRA is applied for the rare event i.e. a sudden change in the CLR value, the output CLR value with and without the SRA is shown in Figures 2.19 and 2.20 for the deterministically and randomly distributed CLR values respectively. These figures shows the snapshot at a particular instant when there is a network abnormality when the number of connection is 500. The graphs shown above in Figures 2.19 and 2.20 is the estimated upper bound without SRA.

\[ th_m = \frac{CLR(i+1) - CLR(i)}{CLR(i)} \]

\[ th_m > th_{in} \]

\[ CLR(i+1) = CLR(i) \]

**Figure 2.18 Flow chart for Set Right Algorithm**
Figure 2.19 SRA performance for deterministically distributed CLR
Figure 2.20 SRA performance for randomly distributed CLR.
2.6 ADAPTIVE FUZZY LOGIC SYSTEM

The FIS explained above has the following inherent limitations. (i) it can be applied only if a large amount of observed CLR data is available, (ii) it cannot estimate accurate CLR values when there is an expansion in the network or failure of some nodes, (iii) if the incoming traffic does not fit into the already defined classes then it is not suitable and (iv) the FIS is slightly complicated.

In order to overcome these drawbacks, an adaptive fuzzy logic system is chosen. This is a simple algorithmic approach to estimate the CLR in large systems, relying only on information from small systems and some qualitative information on the CLR function. Depending on the problem under consideration, the system size can be the multiplexer buffer size, the number of connected users or the link capacity. This approach takes advantage of the qualitative and quantitative information provided by analytical models or real-time measurements, without suffering from the commonly made simplifying assumptions in analytical modeling or prohibitively long stretches of measurement time. The fuzzy rule based system has already been explained in section 2.4 and the fuzzy system block diagram has been shown in Figure 2.2. Here, a singleton fuzzifier and a centre average defuzzifier are used. The adaptive fuzzy logic system is applied for Markov, and Geom/Geom/1/k, models. The sample values of CLR for these models are obtained analytically. The following section explains the analytical CLR estimation for the above-mentioned models.
2.6.1 Estimation of CLR for Markov’s models

Markov modulated arrival processes find many applications in computer and communication systems. Special cases of this model are used to model voice, data and video traffic sources. For this arrival process, a solution for the loss probability is computationally intensive and impractical, when the aggregate arrival process is large. This is usually the case in high-speed ATM networks, since many different types of sources are served by an ATM multiplexer. A quasi-stationary approximation, called the histogram model, was found to be valid because the probability of loss did not significantly decrease when the buffer size was increased beyond a certain range called the cell region. This model predicts the loss behaviour well for small buffers, however, for large buffers it is not accurate. Most reports in the literature have focused on using the tail probability in an infinite-buffer system to approximate the loss in a finite system, which results in a significant over estimation of the cell loss probability. To overcome this difficulty, quasi-stationary analysis and large buffer theories are combined to form a simple model called the hybrid model (Shroff and Schwartz 1998). Using the hybrid model, the cell loss probability at a finite buffer ATM multiplexer can be efficiently and accurately determined.

The Markov modulated Poisson process (MMPP) and the Markov – modulated fluid (MMF) are used to model many different types of traffic sources. The ATM multiplexer considered here is shown in Figure 2.1. It is well known that for Markov modulated arrival processes and deterministic servers there are typically two main regions in which increasing the buffer size reduces the cell loss - the “cell region” and the burst region as shown in Figure 2.21. In the cell region, the main reason for the loss rate is the cell variability within the modulated process. As the buffer size is increased, this variability gets absorbed
and the loss rapidly decreases. In the burst region, the loss due to cell variability is negligible and it is caused mainly due to the fact that the rate in one or more of the states is greater than the link capacity $\mu$.

$$\text{Cell region} \quad \text{Burst region}$$

Figure 2.21 Cell and burst regions. Y-axis log scale and x-axis linear scale

The probability of cell loss in the cell region for buffer size $B$ is given by, (Shroff and Schwartz 1998)

$$P_{\text{cell}}(B) = \frac{1}{E(\lambda)} \sum_{i=1}^{N} P_{i} \lambda_{i}$$  \hspace{1cm} (2.22)

where $P_{i}$ (B) is the probability of loss on the condition of the arrival being in state $i$. The probability of loss $P_{\text{cell}}(B)$ is leveled off with increasing $B$ for any general Markov modulated source, as long as the peak rate of this source is greater than the capacity i.e., as long as $\max \lambda_{i} > \mu$.

It is assumed that the arrival rate in state ‘i’ of the aggregate source is $\lambda_{i}$ the probability of being in state $i$ is $P_{i}$ and the total number of states is $N$. The MMF model can be thought of as approximating a Markov- modulated deterministic process (MMDP) where the cells corresponding to a given state
arrive equispaced. Hence, $P_{li}(B)$ is the loss probability in a D/D/1/B system with arrival rates $\lambda_i$ and service rate $\mu$ and is given by,

$$P_{li}(B) = \begin{cases} 1 - \frac{\mu}{\lambda_i}, & \text{if } \frac{\lambda_i}{\mu} > 1 \\ 0, & \text{otherwise} \end{cases} \quad (2.23)$$

Substituting $P_{li}(B)$ of Equation (2.23) into Equation (2.22), it is shown that

$$P_{Lcell}(B) = \frac{1}{E(\lambda)} \sum_{i=1}^{N} \lambda_i P_i (1 - 1/\rho_i) \quad (2.24)$$

where $\rho_i = \lambda_i / \mu_i$. Also, since the fluid source assumes a constant arrival rate, the cell region is only a point on the y-axis, and the cut-off point is given by the buffer size $B_0 = 0$, at which the transition from the cell region to the burst region takes place. Hence, the loss in the burst region, which is the overall cell loss, is given by

$$P_L = P_{Lburst}(B) = \frac{1}{E(\lambda)} \sum_{i=1}^{N} \lambda_i P_i (1 - 1/\rho_i) e^{-\delta B} \quad (2.25)$$

where $\delta$ is the asymptotic slope of the burst region, which is simply the negative of the asymptotic decay rate.

In the case of MMPP, the arrival process corresponding to each state of the aggregate histogram is Poisson. Hence, $P_{li}(B)$ can be determined by a solution for the loss in an M/D/1/N system with arrival rate $\lambda_i$ and service rate $\mu$ and is given by,
Using the Equations (2.25) and (2.26) the theoretical cell loss probability is determined for Markov models by varying the buffer size and these values are used as input values for the adaptive fuzzy logic system.

For the Geom/Geom/1/k model, the cell loss probability is given by, (Zu Frost et al 1996)

\[
CLR = \frac{(1-\rho) \rho^k (1-s)}{(1 - \rho^{k+1} - (1-\rho)^s)}
\]  

(2.27)

where \( \rho = \frac{[p(1-s)/(s(1-p))]}{P} = \) arrival probability of a cell during a time slot; 
\( S = \) departure probability of a cell during a time slot.

Using the Equations (2.25) and (2.26) for Markov models, Equation. (2.27) for Geom/Geom/1/k model the theoretical CLR values are determined by varying the buffer size and these values are used as samples for the adaptive fuzzy logic system (Bensaou et al 1997). Here, it is observed that for Markov models with improved loss calculation, the predicted values are exactly equal to the theoretical CLR values, whereas for Geom/Geom/1/k model there is a big difference between the fuzzy estimated values of CLR and the theoretical CLR values. Hence, a modified fuzzy logic system is proposed for Geom/Geom/1/k model and it is explained in the following section.
2.7 MODIFIED FUZZY LOGIC SYSTEMS (MFLS)

An ATM multiplexer queue whose performance depends on the input traffic, which in turn is unpredictable, is very difficult to represent accurately by analytical models. If $N$ sets of input-output pairs $(X_j^i; y_j^i)$ are known, $X_j^i = (x_{0j}^i, ..., x_{nj}^i)^T \in \mathbb{R}^n$, $j=1,2,3,...,N$, where $N$ is a small number then the adaptive fuzzy algorithm can be applied. In Fuzzy systems with a singleton fuzzifier, the product inference engine and the centre-average defuzzifier are given by, (Wang 1997)

$$f(X) = \frac{\sum_{j=1}^{N} y_0^j \prod_{i=1}^{n} \mu^i_j(x_i)}{\sum_{j=1}^{N} \prod_{i=1}^{n} \mu^i_j(x_i)}$$

(2.28)

where $X=(x_1, ..., x_n)^T \in \mathbb{R}^n$ is the crisp input to the fuzzy system, $f(X) \in \mathbb{R}$ is the output of the fuzzy system, and $\mu^i_j$ are the membership functions of the input fuzzy sets. The CLR is viewed as an unknown function of the real variable; the multiplexer's buffer size. The fuzzy logic system to predict the CLR does not assume anything about the traffic parameters but requires only the following information:

1. CLR values of the multiplexer when the system size is small. The large CLR values can be estimated theoretically.
2. Asymptotic behaviour of the CLR when the system size is very large. Let $x_k, k=1,2,...$ denotes the cell loss ratio when the system is of size $S_k$. 


The (M-2) sets of input-output pairs of CLRs are formed from the analytically computed M-numbers of CLRs as,

\[
\begin{align*}
( x_{k-j-1}, x_{k-j} ) & ; (x_{k-j+1} - x_{k-j}) \\
. & \\
. & \\
( x_{k-M+1}, x_{k-M+2} ) & ; (x_{k-M+3} - x_{k-M+2}) \\
\end{align*}
\]

where \(( x_{k-j-i}, x_{k-j} )\) are the input vectors and \((x_{k-j+1}, x_{k-j})\) are the output vectors for \(j=1,2,\ldots,M-2\), and \(k\) represents the current state.

The fuzzy system is constructed from a few (M-2) input-output pairs by taking advantage of the monotony of the parameterized curve, which represents the CLR as a function of the buffer size. The inputs are represented by the CLR values from the previous and the current states. The output is the difference between the current and the following CLR values.

The membership functions for the input fuzzy sets are given by,

\[
\begin{align*}
\mu^1_j (x_{k-j}) &= \exp\{\Delta^2_{k,j} / (\sigma^1_j)^2 \} \\
\mu^2_j (x_{k}) &= \exp\{\Delta^2_{k+1,j} / (\sigma^2_j)^2 \}
\end{align*}
\]

where \(\Delta_{k,j} = x_{k-1} - x_{k-j}\)

\[
\sigma^1_j = \frac{\max(x_{k-j}) - \min(x_{k-j})}{M-2} \\
\sigma^2_j = \frac{\max(x_{k-j}) - \min(x_{k-j})}{M-2}
\]
with \( j \in 1, 2, \ldots, M-2 \).

The membership functions define the degree of influence of the first component of the input vector \( j \) on the output value. \( \sigma_1^j \) and \( \sigma_2^j \), \( j = 1, 2, \ldots, M-2 \) are free parameters which determine the accuracy of the approximations. \( \sigma_1^j \) and \( \sigma_2^j \) are so chosen that the membership functions uniformly cover the range of the input vectors, i.e., the influence of the previous values of the CLR on the next predicted value is uniform.

### 2.7.1 Correction factor

It is observed that when Equation (2.27) is applied to predict the CLRs for Geom/Geom/1/k model the predicted values are not accurate. Hence, an appropriate correction factor is introduced to predict the CLRs accurately. The correction factors have been arrived at by trial and error, and they have been computed using the following expressions:

\[
CF = \begin{cases} 
(1-\alpha)^{B/25} & \text{for } \beta > 0.05\alpha \\
[ (1-\beta)\alpha ]^2 & \text{for } \beta \leq 0.05\alpha 
\end{cases} \tag{2.35}
\]

where \( B \) is the buffer size, \( \alpha \) the mean of the differences of adjacent \((M-1)\) input CLR samples and \( \beta \) is the difference between adjacent \( \alpha s \). The fuzzy system with the correction factor is given by,

\[
F(X) = \frac{\sum_{j=1}^{N} y_0 \prod_{i=1}^{n} \mu_{ij}(x_i)}{\sum_{j=1}^{N} \prod_{i=1}^{n} \mu_{ij}(x_i)} * CF \tag{2.36}
\]
2.7.2 Working of the modified fuzzy logic system.

In the fuzzy system of Equation (2.36) \( N \) is taken as \( (M-2) \), and \( n=2 \), where \( M \) represents the number of input CLR sample values obtained from a small sized system analytically. Figure 2.22 illustrates the implementation of the proposed modified fuzzy logic system (MFLS). Initially five computed CLRs are taken as inputs, i.e., \( j=1,2,3,4 \) and \( 5 \), and the fifth state is considered as the current state. The \( (M-2) \) input-output pairs are then formed and substituted in the Equation (2.36). The output from the fuzzy system represents the difference in the values of the current and the following CLRs, i.e., the CLR at the \( (M+1) \) state is given as CLR at the \( M^{th} \) state \( \pm f(X) \). To predict the CLR at \( (M+2) \) state, the input-output pairs are formed by deleting the CLR at state one and adding the CLR at \( (M+1) \) state to the set and the procedure is repeated.

![Figure 2.22 Block diagram of modified fuzzy logic system](image_url)
2.8 RESULTS AND DISCUSSIONS

Figures 2.23 and 2.24 show the comparison of the CLR values estimated theoretically and predicted using the fuzzy system as a function of the buffer size for MMF and MMPP models. It is observed that the predicted values coincide exactly with the theoretical values for both the models. Figures 2.25 and 2.26 show the CLR as a function of the buffer for various load factors for Geom/Geom/1/k model. Figure 2.27 shows the comparison of CLR values estimated theoretically and using the adaptive fuzzy against the buffer for various load factors for Geom/Geom/1/k model. Figures 2.28 and 2.29 show the comparison of theoretical and MFLS CLR values with and without the correction factor for Geom/Geom/1/k model. It is observed that the predicted CLR values by MFLS with the correction factor coincide exactly with the theoretical values. The CLR values estimated theoretically, using fuzzy system and the modified fuzzy system are compared by taking the input samples as five (5) and ten (10) and the result is given in Table 2.1. From this table it is observed that MFLS with correction factor estimates the CLR accurately for Geom/Geom/1/k model.
Figure 2.23 Comparison of theoretical and fuzzy predicted CLR values for MMF model

Figure 2.24 Comparison of theoretical and fuzzy predicted CLR values for MMPP model
Figure 2.25 Theoretical CLR versus buffer for Geom\Geom\l\k model

Figure 2.26 Comparison of theoretical and fuzzy predicted CLR values for Geom\Geom\l\k model
Figure 2.27  Comparison of theoretical and modified fuzzy predicted CLR values without correction factor for Geom\Geom\lk model

Figure 2.28  Comparison of theoretical and modified fuzzy predicted CLR values with correction factor for Geom\Geom\lk model
### Table 2.1 Types of defuzzifiers and the membership functions

<table>
<thead>
<tr>
<th>Type of defuzzifier</th>
<th>Membership function used</th>
<th>Shape of the membership function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case I. Gaussian</td>
<td>( \exp {-\frac{1}{2} \left( \frac{x - \mu}{\sigma} \right)^2 } )</td>
<td><img src="image-url" alt="Gaussian function" /></td>
</tr>
<tr>
<td>Case II</td>
<td>(- \exp {-\sigma</td>
<td>x - \mu</td>
</tr>
<tr>
<td>Case III</td>
<td>( \frac{1}{1+\sigma^2 (x-\mu)^2} )</td>
<td><img src="image-url" alt="Triangular function" /></td>
</tr>
</tbody>
</table>

where, \( \mu \) is the center of the defuzzifier, \( \sigma \) is the width of the defuzzifier and \( x \) is the observed CLR values.

### Table 2.2 Comparison of CLR Values by theoretical, fuzzy and modified fuzzy with \( \lambda = 0.8 \) and Buffer size = 200 for Geom/Geom/1/k Model

<table>
<thead>
<tr>
<th>Traffic Model</th>
<th>Values of CLR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Theoretical</td>
</tr>
<tr>
<td>Geom/Geom/1/k</td>
<td>Number of input samples</td>
</tr>
<tr>
<td>5</td>
<td>-5.918</td>
</tr>
<tr>
<td>10</td>
<td>-6.8879</td>
</tr>
<tr>
<td>7.8570</td>
<td>-7.8570</td>
</tr>
<tr>
<td>10.7643</td>
<td>-10.7643</td>
</tr>
</tbody>
</table>