THE FUZZY INFERENCE APPROACH TO THE ESTIMATION OF UPPER BOUND OF CELL LOSS RATIO FOR CONNECTION ADMISSION CONTROL IN ATM NETWORKS

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ABSTRACT

This paper proposes a connection admission control (CAC) method for ATM networks based on the estimation cell loss ratio accordance with fuzzy logic theory. The cell loss ratio is estimated in a fuzzy inference scheme by using observed data of cell loss ratio. This method makes possible secure CAC, thereby guaranteeing the allowed cell loss ratio. In this paper, a fuzzy inference method is studied, based on a weighted average of fuzzy sets, in order to estimate possibility distribution of cell loss ratio. In contrast to conventional methods, the studied method can avoid estimating excessively large values of cell loss ratio and it can guarantee the allowed cell loss ratio in the CAC and attains higher multiplexing gain as much as possible.

I. INTRODUCTION

Asynchronous transfer mode (ATM) is a key technology for integrating broadband multimedia services (B-ISDN) in heterogenous networks, where multimedia application consisting of data, video and voice sources transmit information. ATM provides services to these sources with different traffic characteristics by statisticaly multiplexing cells of fixed length packets of 53 bytes. In ATM networks, transmission data from source terminals are divided into 48 byte length units and a header including destination address is added to each unit. Each transmission unit with its header, called a cell, can be sent at the allowed rate. The cells from the terminals are multiplexed asynchronously in the networks. Thus, ATM networks can support a wide variety of transmission rates and provide high transmission efficiency by asynchronous multiplexing.

Although ATM networks have the advantages mentioned above, cells might be lost in ATM switches if cells are excessively fed into the networks. Due to the of broadband traffic pattern uncertainties and unpredictable statistical fluctuations of traffic flows can cause congestion in the network switches and transmission links [1]. In order to avoid this situation, the terminals are required to specify their transmission rates as traffic parameter, e.g., peak cell rate and average cell rate, in advances of transmission. According to these declarations of transmission rates, ATM switches judge whether the required quality of services (QoS), evaluated by the cell loss ratio (CLR) in this paper, can be achieved or not. Although it must be guaranteed that the QoS objectives are satisfied under the specified cell delay variation (CDV), this paper assumes for simplicity as a step that the traffic parameters are transformed by taking account of CDV or that CDV is removed or reduced by shaper [2].

The transmission rates are often classified into a number of classes on the basis of the transmission rates such as peak cell rate and average cell rate. Namely, terminals select one of the transmission rate classes in advance of transmission. When a call request comes from the terminals, ATM switches have to predict whether the required quality in CLR can be achieved or not if the call accepted. If ATM switches judge the required quality can be achieved, they accept the call. Otherwise, they reject the call. This process is called connection admission control (CAC). Therefore, CAC requires the estimation of CLR from the number of connections in each transmission rate class.

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 architectures [3]. The cell generation process, however, has a wide variety of patterns and ATM switches have become complex in order to attain higher performance. It makes the construction of the analytical models difficult. Moreover, the analysis requires approximation with excessive estimation of CLR.

In order to solve the problems, fuzzy inference systems have been applied to the estimation of CLR. The conventional observation based methods, however, cannot always perform CAC guaranteeing the allowed CLR. This study considers the CAC based on fuzzy inference which can guarantee the allowed CLR [4].

In this paper, a fuzzy inference method is proposed in order to effectively estimate the upper bound of CLR from its observed data. This method is based on a weighted average of fuzzy sets.

II. FUZZY INFERENCE APPROACH TO CELL LOSS RATIO

Bandwidth allocation deals with determining the amount of bandwidth required by a connection for the network to provide the required QoS. There are two alternative approaches for bandwidth allocation: deterministic multiplexing and statistical multiplexing [5].

In deterministic multiplexing, each connection is allocated its peak bandwidth. Doing so couses large amounts of bandwidth to be wasted for bursty connections, particularly for those with large peak to average bit rate ratios. Deterministic multiplexing goes against the philosophy of ATM since it doesn't take advantage of the multiplexin capability of ATM and restricts the utilizatiob of network resources.

An alternative method is statistical multiplexing. In this sheme, the amount of bandwidth allocated in the network to a variable bit rate (VBR) source (statistical bandwidth of a connection) is less than its peak, but necessarily greater than its average bit rate [5]. Then, the sum of peak rates of connections multiplexed onto a link can be greater than the link bandwidth as long as the sum of their statistical bandwidths is less than or equal to the link bandwidth.

The bandwidth efficiency due to statistical multiplexing increases as the statistical bandwidths of connections get closer to their average bit rates and decreases as they approach their peak bit rates. In general, statistical multiplexing allows more connections to be multiplexed in the network than deterministic multiplexing, thereby allowing better utilization of network resources [4].

The relation between CLR and the number of connections is often nonlinear. Thus, in the observation based CAC, fuzzy inference method must be applied to the estimation of upper bound of CLR. The CAC must guarantee the allowed CLR satisfying the traffic parameters of the transmission class. Even if the maximum value of observed CLR at each number of connections is used, it cannot guarantee the allowed CLR. From this point view, the estimation of the possibility distribution of CLR is needed in order to guarantee the allowed CLR in CAC. That is, if possibility distribution can be obtained, its upper bound can make possible the CAC guaranteeing the allowed CLR.

The nonparametric approach also has been studied [1] for estimating the upper bound of CLR because the cell arrival process in practise is not specified. Altough this approach is effective to guarantee the allowed CLR, it tends to estimate excessively high CLR and results in lower multiplexing gain in a practical environment. Even in constructing the analytical models without use of the nonparametric approach, approximations have been often performed so as to guaratee the allowed CLR and make the multiplexing gain lower in practice.

From the discussion above, the fuzzy inference approach is feasable. This is because the then-part of each fuzzy rule can give the possibility ditribution of CLR for the number of connections covered with the if-part in the fuzzy rule. Therefore, the inference consequence provides the estimated upper bound of CLR for the input of the number of connections. The conventional methods tend to estimated CLR's having excessively large values. In this paper, we propose a fuzzy inference method in order to solve these problems this inference method is based on a weighted average of fuzzy sets. It provides the useful proporties in its application to CAC [7].

In fuzzy inference for CLR estimation, if-parts define the fuzzy number connections x_i in transmission rate class C_i, whereas then-parts define the estimated CLR under the condition given by the if-parts. The following shows the examples of fuzzy rules [6].

Rule 1) If x_1 is 250 then CLR is 10^{-5}

Rule 2) If x_1 is 260 then CLR is 10^{-4}

Rule 3) If x_1 is 280 then CLR is 10^{-3}

Rule 4) If x_1 is 300 then CLR is 10^{-2}

The if-then fuzzy rules adopted in this paper will be explained simply hereinbelow:

Rule 1) If x is *mf*1 then *CLR* is *mf*1

Rule 2) If x is *mf*2 then *CLR* is *mf*2

Rule 3) If x is *mf*3 then *CLR* is *mf*3

Rule 4) If x is *mf*4 then *CLR* is *mf*4

Equation (1) gives the average of fuzzy sets y_i (i=1,2,...), weighted by membership degree w_i, where Σ denotes al algebraic sum. The weighted average method is formed by weighting each membership function in the output by its respective maximum membership value.

$$CLR = \frac{\sum_{i=1}^{4} w_i y_i}{\sum_{i=1}^{4} w_i} \quad (1)$$

A fuzzy inference method based on a weighted average of fuzzy sets is proposed. Its inference process consists of the following steps [6], [7].

1) Calculate the adaptabilities (w_i) of the fuzzy rules
2) Calculate the inferred results (y_i) of the fuzzy rules on the basis of the adaptabilities (w_i) and the membership functions of the consequent
3) Obtain the overall inferred result (CLR) as weighted mean by y_i (CLR_i) and w_i.

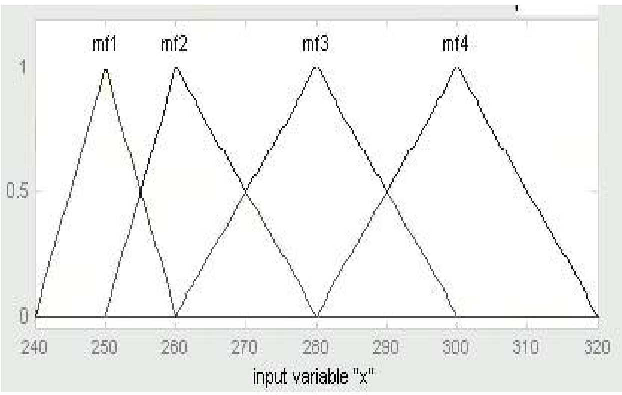
The following Tables 1 and 2 show the traffic characteristics of source and the specification of the experiments for sources.

Table 1. Traffic chacteristics of On-off sources

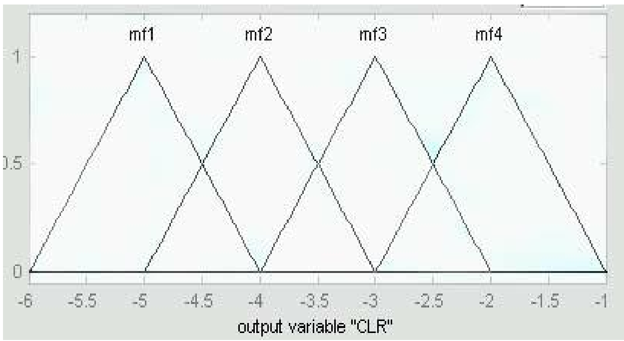
Traffic class	Peak rate (Mbps)	Mean rate (Mbps)	Burst length (cells)
Voice	0.064	0.022	58
Data	10	1	339
Image	2	0.087	2604

Table 2. Specification of the experiments for sources

Application	Traffic types	The number of connections	Load	Link capacity (Mbps)	Peak/Link capacity	Figures
A1	Voice	250-300	0.8-0.95	7	0.00914	Fig. 3
A2	Voice	15-25	0.05-0.08	0.7	0.0914	Fig. 4
A3	Data	160-300	0.5-0.85	350	0.28	Fig. 5
A4	Data	8-26	0.15-0.5	52	0.192	Fig. 6
A5	Image	4-20	0.05-0.25	30	0.133	Fig. 7
A6	Image	80-220	0.25-0.65	7	0.285	Fig. 8



(a)



(b)

Figure 1. Examples of the input variable (x) and output variable (CLR) membership functions (determined in Matlab Program).

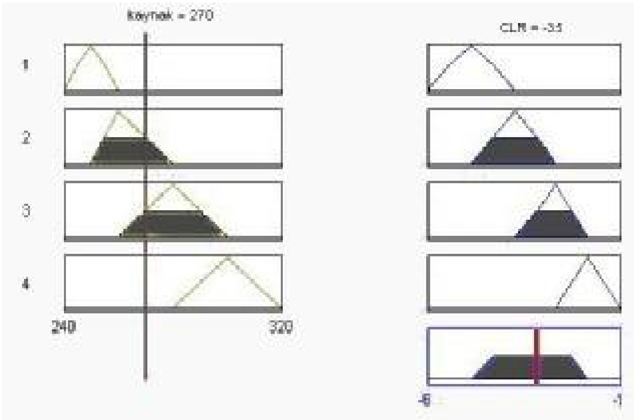


Figure 2. Example of the estimated value of CLR ($CLR=10^{-3.5}$) based on fuzzy inference system.

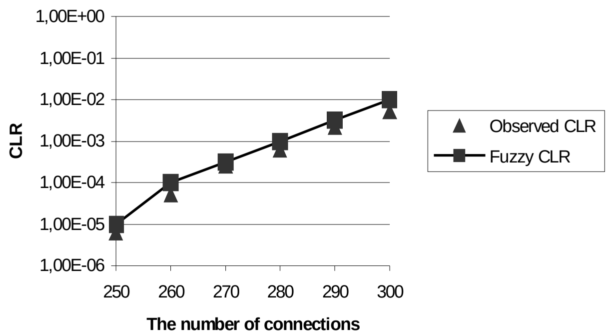


Figure 3. Simulation A1 (Voice sources, C=7 Mbps).

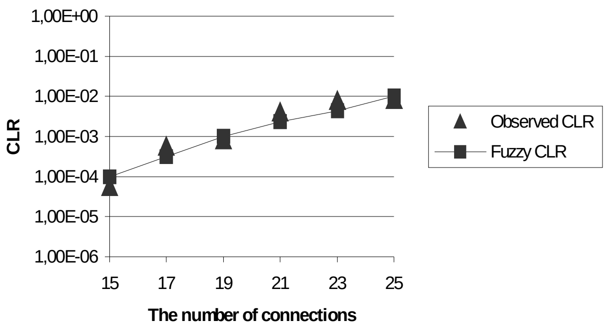


Figure 4. Simulation A2 (C=0.7 Mbps).

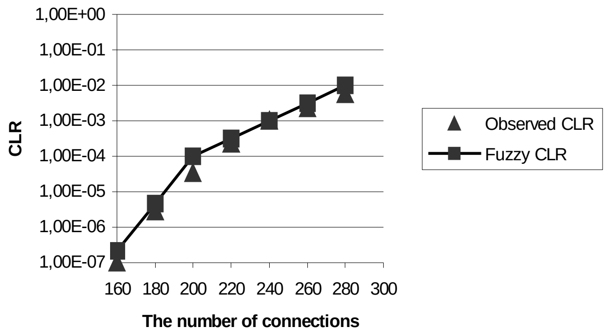


Figure 5. Simulation A3 (Data sources C=350 Mbps).

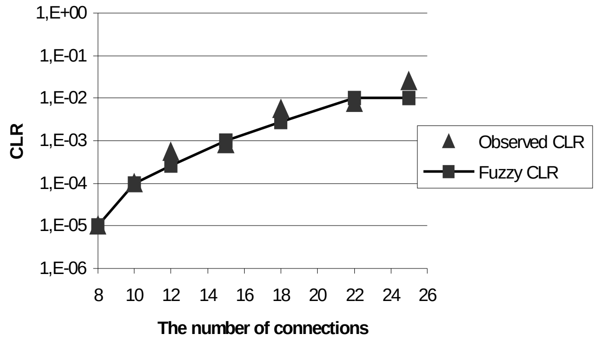


Figure 6. Simulation A4 (Data sources C=52 Mbps).

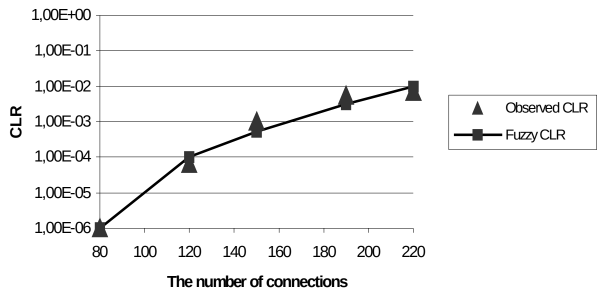


Figure 7. Simulation A5 (Image sources C=30 Mbps).

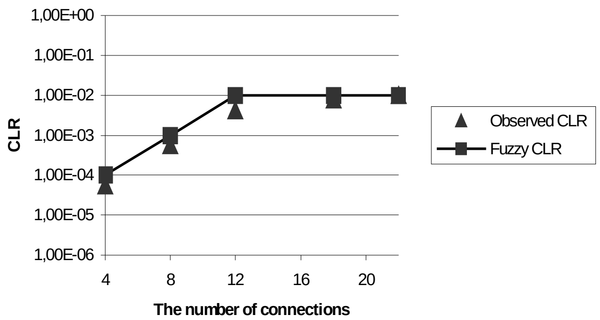


Figure 8. Simulation A6 (Image sources C=0.7 Mbps).

The figures 3, 4, 5, 6, 7, 8 show the estimation of upper bound of CLR belonging to the different sources. Therefore, fuzzy infence approach to estimating the possibility distribution of CLR can be applied all kind of traffic sources.

The experiments described in this paper refer to a single ATM link and the QOS is expressed in terms of cell loss at the output buffer of an ATM switch. The traffic sources are VBR sources, modelled as On-Off sources described by the peak and mean bit rates and mean burst length.

A basic challenge associated with CAC based on a heuristic method is knowledge elicitation, i.e. the transfer of knowledge from some source into a fuzzy rule base, of the relationship between traffic offered to an ATM switch and obtained network performance, e.g. cell losses. This is because all the knowledge that can be obtained on ATM traffic is expressed in terms of input/output data pairs (examples) collected from measurements. The Fuzzy inference approach to cell loss ratio presented, uses an automatic design of the associated fuzzy system based on a method of learning from examples.

The results obtained by fuzzy inference method were compared with measured CLR values versus the number of connextions and used as the training set for the fuzzy tool. The results obtained using this method are plotted in figures Figure 3 to Figure 8. The number of sources and the link capacity values were chosen in order to obtain a range of cell loss values between 10^{-2} and 10^{-8}.

III. CONCLUSION

This paper has proposed a method for connection admission control based on fuzzy inference. In order to estimate the upper bound of CLR from observed data, a fuzzy inference method was proposed on the basis of a weighted average of fuzzy sets. Some proporties of the proposed inference method are presented, which are useful in estimating the upper bound of CLR. In contrast to conventional methods, the proposed method can control the width of its final inference consequence by adjusting the width of fuzzy sets in then-parts. Moreover, the inference consequences can represent the possibility distribution of CLR in convex forms. These properties have an important role in the proposed CAC method.

By applying the CLR estimation method proposed, the CAC method has been considered. Although the CAC method proposed here has been discussed mainly in the case of one transmission rate class for simlicity, it can be extended for a number of transmission rate classes.

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