An Adaptive Fuzzy approach for Connection Admission Control in ATM Networks

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Abstract

This paper proposes an adaptive fuzzy logic based approach for Connection Admission Control (CAC) in ATM broad-band communications networks. CAC is a traffic control function which decides whether or not to accept a new connection into the network, subject to ensuring the required quality of service of all the connections. In the method introduced in this paper, CLR parameter is estimated using a worst case formula and then a fuzzy inference scheme is used for connection admission decision. This method makes possible secure CAC, thereby guaranteeing the allowed CLR. In contrast to the other fuzzy CAC methods, the proposed method avoids estimating CLR using fuzzy inference which is a very complex and time consuming process. Simplicity of computations and very good rate of convergence are the most important advantages of the method.

Keywords: ATM networks, cell loss ratio, connection admission control, fuzzy logic, quality of service.

1. Introduction

The Asynchronous Transfer Mode (ATM) has been widely recognized to be a promising technique for implementing an integrated access in high speed transport networks that are shared by end users holding multi-rate service calls. The fact that ATM involves statistical multiplexing scheme means that network congestion can easily cause queuing delay, delay variation and cell loss. Traffic control is, thus, necessary to avoid congestion. Connection Admission Control (CAC) can be used to prevent congestion since it decides whether or not to accept a new connection into an ATM network, while preserving the QoS requirements for the existing connections and the new connection. In other words, CAC is a sophisticated control mechanism whose specific goal is to maintain a fine balance between two contradictory objectives of maximizing network utilization and delivery of QoS guarantees to connections in progress. CAC is the first control step in the provisioning of network resources to connections.

Over the past years, significant progress has been made in theory and practice of ATM CAC. However, there still some issues remain to be resolved. Full understanding of traffic characteristics and properties which is essential in exploiting statistical multiplexing in order to maximizing the utilization of the ATM networks is to be done. Most of the present day CACs are based on the complex queueing models and are known to have large processing demand. Alternative adaptive methods derived from Artificial Intelligence (AI) can play an important role towards the development of fast intelligent CAC. These methods should be able to learn from the actual traffic behavior to which they are subjected to and thus relieve the model-based dependency which otherwise affects queuing or stochastic theoretic solutions.

The fuzzy logic is one of the most attractive AI systems to solve the control problems in ATM network [6]. The most complex part of developing fuzzy algorithms for CAC problems is generating the fuzzy rule base.

Recently, a number of researches have been done in fuzzy CAC methods. Uehara and Hirota (1997) introduced a fuzzy CAC method based on possibility distribution of cell loss ratio. Chen et al. (1999) proposed an adaptive method for generating a fuzzy rule base for estimating the admission probability of new connections. Ren and Ramamurthy (2000) introduced a CAC method based on traffic modeling, measurement, and Fuzzy Logic Control.

In this paper we present a new fuzzy CAC approach for generating the acceptance probability of the new connections. This method is based on the estimation of cell loss ratio parameter using traffic descriptors declared by the traffic sources (see [4] and [5] for ATM CAC methods).

The remaining parts of the paper have been organized as follows. The general structure of fuzzy CAC methods is described in section 2. Our proposed adaptive fuzzy
The algorithm for CAC problem is presented in section 3. Defuzzification and adaptation are described in section 4. In section 5, simulation results and discussions are presented. Finally, concluding remarks are given in section 6.

2. Fuzzy CAC systems structure

The fuzzy CAC systems have two main stages: the learning stage and the inference stage [2], [3]. Figure 1 shows a simple diagram of these two stages. As is shown, the learning stage occurs at a pre-specified time, namely when a given number of samples are collected from ATM traffic. The knowledge base is then updated with the set of rules selected during the learning process.

The inference stage occurs independent of the learning stage. Each time a new source is accepted in the network, the inference process infers the bandwidth value to be allocated to this new connection and then computes the available bandwidth value to be allocated to the new sources.

![Figure 1. Diagram of the main components of fuzzy CAC systems](image)

2.1 The learning stage

The learning stage is the core of decision support system as it is the one that makes a synthesis after analyzing the collected data samples from the system under study. The learning process is, therefore, a learning from examples process with the peculiarity that the example data (crisp set) is matched with fuzzy data (fuzzy systems) of the domain of system fuzzy variables. The fuzzy variables express uncertain data related with a specific connection type such as effective bandwidth, burstiness, and cell loss probability. The learning stage updates the knowledge base with a new set of selected rules given a set of examples.

2.2 The inference stage

The inference stage occurs each time a new source is accepted into the network and it produces as output the bandwidth value to be allocated to the new source in order to fulfill the negotiated cell loss requirements. As shown in figure 2, the inference process consults the knowledge base to infer this bandwidth result.

The output from inference process is given to the low level CAC module and it works as a support decision element, in the sense that it gives a more accurate value for the bandwidth that a specific connection needs to meet its cell loss requirements.

The input to the inference process is composed of the new source traffic characteristics as well as the existing connections and the cell loss requirements for the new connection.

![Figure 2. Interconnection between the different system modules](image)

3. The adaptive fuzzy algorithm

We will now present our proposed method for implementation of the fuzzy system for connection admission control in ATM networks. The block diagram of the adaptive fuzzy CAC algorithm is shown in figure 3. As shown in figure 3, the CLR is estimated using a worst case formula. The inputs of this formula are the peak cell rate and the network current load. The estimated CLR and its acceptable value declared by the traffic source, compose the inputs of the fuzzifier. At the end of the process, the fuzzy CAC rule base results the acceptance probability (AP) of the new connection.
The worst case formula for estimation of the CLR parameter is as follows:

\[
CLR = \frac{(current\ load - PCR)s}{(number\ of\ cells)}
\]  

where \( s \) is the time in seconds. Equation (1) can be explained in the following sense. The worst case CLR happens when a traffic flow with peak cell rate of PCR arrives into the network while the network is out of any available resource to allocate. This will cause the network to allocate this amount of PCR from other existing apriori allocated resources, and hence disrupts their normal operation and undermines the QoS agreed between the parties. In fact, this new connection is the only one who is serviced with the correct PCR.

In this work, a fuzzy PD rule base, based on the nominal behavior of a stable second order system has been considered and the network configuration has been included in it to modify the operation of the algorithm. The structure of fuzzy rule base is as follows:

If \( k_1 \Delta CLR \) is \( A \) and \( k_2 \Delta CLR \) is \( B \)

Then \( k_3 AP \) is \( C \)  

where, \( \Delta CLR \) is the difference between the estimated CLR (obtained by the worst case formula) and the acceptable CLR declared traffic source. The input and output membership functions of the fuzzy rule base are shown in figure 4.

**Figure 4. Input and output membership functions**

As shown in figure 4, there are seven triangular functions, as the fuzzy membership functions of the algorithm. Scale factors \( k_1, k_2 \) and \( k_3 \) determine the slope of these triangular functions. The scale factors are updated via an adaptive strategy.

4. Defuzzification and adaptation

In the defuzzification step, the commonly used center of area (C. O. A) formula is applied to defuzzify the outputs of the fuzzy system. By employing center of area formula, we obtain the following closed forms for the fuzzy system [7].

\[
AP(k) = \frac{\sum_{j} c_j \mu(c_j)}{\sum_{j} \mu(c_j)}
\]  

where \( c_j \) is the j th member of the output reference set and \( k \) is the iteration number.

Next step is to update the input and output scale factors via an adaptive updating law. To do this, we introduce the following cost function:

\[
J = \frac{1}{2} \|E\|^2
\]  

where

\[
E = [k_1 E_1 \quad k_2 E_2]^T
\]

\[
E_1 = B W - (PCR + current\ load)
\]

\[
E_2 = \dot{E}_1
\]

To update the scale factors \( k_1, k_2 \) and \( k_3 \) we use the gradient descent method as follows:
\[
\frac{d k_i}{dt} = -\gamma \frac{\partial f}{\partial k_i}
\]  
(8)

where \(0 \leq \gamma \leq 1\) is the adaptation rate. The algorithm is run until the output \(AP\) is converged. If the converged output is larger than a specified threshold, the connection is accepted, otherwise it is rejected.

5. Simulation results and discussion

In order to evaluate the performance of the proposed method, a case study is developed in the following. This case has been previously studied in [1] and the performance of the fuzzy upper bound CLR estimation has been evaluated. Here, we apply our adaptive fuzzy algorithm for connection admission control and compare our results with that obtained from the algorithm proposed in [1]. It must be noted that the upper bound CLR is estimated very accurately in the method proposed in [1] and so it is a very good reference for evaluating the performance of our method.

In the simulation, only one transmission-rate class characterized by PCR and SCR was considered for simplicity. The transmission rate class is set for SCR at 98 kb/s and PCR at 6.3 Mb/s. The traffic source can select this class as long as their traffic rate is shaped in this rate pattern, which means a wide variety of traffic patterns could be multiplexed in one transmission rate class. Two different types of traffic sources are intentionally multiplexed in the transmission rate class. One of the traffic sources is on-off traffic in which the rate in on-period is 6.3 Mb/s, the average length of on-period is 1.433 cell time, and its average rate is 98 kb/s. The other traffic source is CBR at the rate of 98 kb/s. As long as the declared traffic parameters are satisfied, such a wide variety of traffic could arrive in practice and their characteristics other than declared parameters cannot be known in advance.

For background traffic, two different types of traffic sources are also multiplexed in the same way as the foreground traffic. One of the traffic sources is on-off traffic in which the rate in on-period is 51.84 Mb/s, the average length of on-period is 1.433 cell time, and its average rate is 810 kb/s. The other traffic source is CBR at the rate of 810 kb/s. The ATM switch was assumed to have a single buffer with 32-cell length and output rate was 155.52 Mb/s. The cells arriving from the traffic sources mentioned above were multiplexed into this buffer.

![Figure 5. Upper bound of observed CLR](image5.png)

Figure 5 shows the upper bound of observed CLR that has been estimated in [1]. The solid line shows the upper bound of CLR which is obtained by learning from the observed CLR data shown by +. From this figure, it can be found that the upper bound of CLR has been well extracted in [1] and no observed CLR data exceed this estimated upper bound.

![Figure 6. Maximum observed CLR in Fuzzy CAC method](image6.png)

Figure 6. Maximum observed CLR in Fuzzy CAC method

![Figure 7. Fuzzy CAC methods performance](image7.png)

Figure 7. Fuzzy CAC methods performance
Figure 6 shows the Maximum observed CLR obtained by applying our fuzzy CAC method and figure 7 shows the performance of our method compared with the method introduced in [1]. As shown in figure 7, the performance of our method is very close to the method used in [1]. In these simulations, the acceptable CLR is $10^{-4}$ and the value of adaptation rate in our method is $\gamma = 0.01$.

6. Conclusions

This paper has proposed a method for connection admission control based on an adaptive fuzzy algorithm. In contrast to conventional fuzzy inference methods, in the proposed method, the CLR or its upper bound values are not estimated using the fuzzy rule base. In order to estimate the CLR, a worst case formula was introduced and the fuzzy rule base that is updated via an adaptive law was used to compute the acceptance probability of the new connections. High accuracy, simplicity of computations and very good rate of convergence are the most important advantages of the proposed method.

7. References


