Abstract: - The rapid growth of the Internet, the massive amount of data traffic it carries and increased demand to use the Internet for time-sensitive voice and video applications necessitates the design and utilization of effective congestion control algorithms. Existing TCP/IP protocol suite has been designed for best effort (delay tolerant) services and cannot effectively support time sensitive applications. We will use the Integrated Dynamic Congestion Control (IDCC) scheme. The problem that comes up is the lack of an effective way of dealing with congestion. On the other hand, the IDCC scheme controls the traffic using information on the status of each queue in the network. It is based on a non-linear model of the network that is generated using fluid flow considerations. The aim of this paper is to design a robust active queue management system to secure high utilization, bounded delay and loss, while the network complies with the demands each traffic class sets. To this end, we will use the $H_\infty$ control theory. Simulation results of the proposed control action demonstrate the effectiveness of the controller in providing robust queue management system.

Key-Words: - Differentiated services networks, network management, robust control theory.

1 Introduction

- The events in the area of computer networks The rapid growth of the Internet and increased demand to use the Internet for time-sensitive voice and video applications necessitate the design and utilization of new Internet architectures to include more effective congestion control algorithms in addition to the TCP based congestion control. As a result, the Differentiated Services (Diff-Serv) architecture was proposed [1] to deliver (aggregated) Quality of Service (QoS) in IP networks. It should also be mentioned that, even for the present Internet architecture, network congestion control remains a critical and high priority issue, and is unlikely to disappear in the near future. Furthermore, if we consider the current utilization trends, congestion in the Internet maybe come unmanageable unless effective, robust, and efficient methods for congestion control are developed. For example, the existing congestion control solutions for TCP transported traffic [2] are increasingly becoming ineffective, and it is generally accepted that these solutions cannot easily scale up even with various proposed “fixes” [3,4], new approaches [5], and architectures [6]. The congestion control schemes employed by the TCP/IP protocol have been widely studied. The Internet protocol architecture is based on a connectionless, best-effort, end-to-end packet service using the IP protocol. TCP is an end-to-end transport protocol that provides reliable, in-order service over the IP packet service.

As demand for multimedia (streaming) applications increases, it becomes increasing important to ensure that these applications can co-exist with current TCP applications. It is becoming widely accepted that streaming media should be subjected to similar rate controls, as TCP traffic, and recently a number of researchers advocate that they should also exhibit TCP-friendly behavior [9,10]. This makes the control of the congestion in the Internet considerably more difficult. Furthermore, the congestion control problem in the Internet is exacerbated, as the Internet is increasingly transformed into a multi-services high-speed network. Asynchronous Transfer Mode (ATM) also witnessed a similar approach, with the performance of various congestion control schemes proposed for solution of Available Bit Rate (ABR) problem not proven analytically. Most proposed schemes are developed using intuition and simple nonlinear control designs. These have been demonstrated to be robust in a variety of scenarios that have been simulated [11]. Since these schemes are designed with significant nonlinearities (e.g. two-phase—slow start and congestion avoidance—dynamic windows, binary feedback, additive-increase multiplicative-decrease flow control etc), the analysis of the closed loop
behavior is difficult if at all possible, even for single control loop networks. The interaction of additional nonlinear feedback loops can produce unexpected and erratic behavior [12]. Despite the successful application of control theory to other complex systems, the development of network congestion control based on control theoretic concepts is quite unexplored. Most of the current congestion control methods are based on intuition and ad hoc control techniques together with extensive simulations to demonstrate their performance. The problem with this approach is that very little is known why these methods work and very little explanation can be given when they fail. Recently several attempts have been made to develop congestion controllers [13-15], mostly using linear control theory. Despite these efforts the design of congestion controllers whose performance can be analytically established and demonstrated in practice is still a challenging unresolved problem.

In [16-18] a very useful model is developed to this problem, which divides traffic into three basic types of service (in the same spirit as those adopted for the Internet by the IETF Diff-Serv working group, i.e. Premium, Ordinary, and Best Effort). We will apply a robust control strategy based on $H_\infty$ control theory [19-22] to such system. The proposed control strategy is shown via simulations to be robust with respect to traffic modeling uncertainties and system non-linearities, yet provide tight control (and as a result offer good service).

2 Dynamic network model

In this section, a state space equation for M/M/1 queue is presented. The model has been extended to consider traffic delays and includes modeling uncertainties then three classes of traffic services are introduced in a Diff-Serv network.

3.1. Fluid flow model

A diagram of a sample queue is depicted in Fig.1. Let $x(t)$ be a state variable denoting the ensemble average number in the system at an arbitrary queuing model at time $t$. Furthermore, let $f_{in}(t)$ and $f_{out}(t)$ be ensemble averages of the flow entering and exiting the system, respectively.

\[ x(t) = \frac{dx(t)}{dt} \]

The above equation has been used in the literature, and is commonly referred to as fluid flow equation [17,18]. To use this equation in a queuing system, $C$ and $\lambda$ have been defined as the queue server capacity and average arrival rate, respectively. Assuming that the queue capacity is unlimited, $f_{in}(t)$ is just the arrival rate $\lambda$. The flow going out of the system, $f_{out}(t)$, can be related to the ensemble average utilization of the queue, $\rho(t)$, by $f_{out}(t) = \rho(t)C$. It is assumed that the utilization of the link, $\rho$, can be approximated by the function $G(x(t))$, which represents the ensemble average utilization of the link at time $t$ as a function of the state variable. Hence, queue model can be represented by the following nonlinear differential equation:

\[ \dot{x}(t) = -CG(x(t)) + \lambda \]

Utilization function, $G(x(t))$, depends on the queuing in the under study system. If statistical data is available, this function can be empirically formulated. This, however, is not the general case and $G(x(t))$ is normally determined by matching the results of steady state queuing theory with (2). M/M/1 has been adopted in many communication network traffics. In this model, input and service rates both have Poisson distribution function. For M/M/1 the state space equation is:

\[ \dot{x}(t) = -C \frac{x(t)}{1 + x(t)} + \lambda \]

The validity of this model has been verified by a number of researchers [17,18]. It is noticeable that (3) fits the real model, however there exists some mismatch. In order to include the uncertainties, (3) can be modified as:

\[ \dot{x}(t) = -\rho C \mu \left( \frac{x(t)}{1 + x(t)} + \Delta \right) C + \lambda \]

where $\Delta$ denotes model uncertainties and

\[ \|\Delta\| \leq \Delta_{\text{max}} \]

3.2. Differentiated services architecture

In the Diff-Serv networks, Traffic is classified into several classes. Theoretically 64, but commonly 3 or 4 classes of traffic may exist in a Diff-Serv communication network. Two standard classes of traffic exist in Diff-Serv networks, and each can be sub-classified to smaller groups: Expedited Forwarding Per Hop Behavior (EFPHB), which is used for low-loss, low-delay, high priority traffic.
and Assured Forwarding Per-Hop Behavior (AF-PHB), which itself can be divided into 4 subclasses: Class 1 has the highest priority among others. AF-PHB does not guarantee real-time delivery of packets and thus has low priority compared to EF-PHB. In this paper, three classes of traffic is considered: Premium, Ordinary and Best-effort. The premium belongs to EF-PHB in Diff-Serv and is used for traffics of low-delay and high Quality of Service in applications like Video on Demand (VoD), audio and etc. The ordinary class belongs to the first class of AF-PHB and is used for non-real-time applications flexible to delay changes such as E-mail, FTP. Best-effort traffic, which has the lowest priority, just uses the bandwidth remained by other classes and is no-controlled.

3 System structure
Consider a router of \( K \) input and \( L \) output ports handling three differentiated traffic classes mentioned above. At each output port, a controller is employed to handle different classes of traffic flows entering to that port. An example case of the controller is illustrated in Fig. 2. The incoming traffic to the input node includes different classes of traffic. The input node separates each class according to their class identifier tags and forwards the packets to the proper queue. The output port can transmit packets at maximum rate of \( C_{\text{server}} \) to destination where

\[
C_{\text{server}} = C_p + C_r + C_b \tag{6}
\]

allocated by controller to be sent from ordinary sources

\[
\dot{x}_r(t) = -C_p(t) \frac{x_p(t)}{1 + x_p(t)} + \lambda_p(t) \tag{7}
\]

Here, the control goal is to determine \( C_p(t) \) at any time and for any arrival rate, \( \lambda_p(t) \), in which the queue length, \( x_p(t) \), is kept close to a reference value, \( x_{\text{ref}}^P(t) \), which is determined by the operator or designer. So in \( (7) \), \( x_p(t) \) is the state to be tracked, \( C_p(t) \) is the control signal determined by the congestion controller and \( \lambda_p(t) \) is the disturbance.

The objective is to allocate minimum possible capacity for the premium traffic to save extra capacity for other classes of traffic as well as providing a good QoS for premium flows. Note that we are confined to control signals as

\[
0 < C_p(t) < C_{\text{server}} \tag{8}
\]

In other words, the assigned premium capacity must always be less than the maximum server capacity \( C_{\text{server}} \). This constraint can make the controller design more difficult.

4.2. Ordinary control strategy
In the case of ordinary traffic flow, there is no limitation on delay and we assume that the sources sending ordinary packets over the network are capable to adjust their rates to the value specified by the bottleneck controller. The queue dynamic model is as follows:

\[
\dot{x}_r(t) = -C_r(t) \frac{x_r(t)}{1 + x_r(t)} + \Delta + \lambda_r(t - \tau) + \lambda_b(t) \tag{9}
\]

The control goal here is to determine \( \lambda_r(t) \) at any time and for any allocated capacity \( C_r(t) \) so that \( x_r(t) \) be close to a reference value \( x_{\text{ref}}^R(t) \) given by the operator or designer. Some points here must be taken into consideration:

a) Total arrival rate is

\[
\lambda(t) = \lambda_r(t-\tau) + \lambda_b(t)
\]

where \( \lambda_r(t-\tau) \) is the rate specified by the controller and sent from sources to the bottleneck router, \( \tau \) denotes the round-trip delay from bottleneck router to ordinary sources and back to the router and \( \lambda_b(t) \) is the arrival rate of the background traffic, which is any extra traffic passing the ordinary queue and should be considered as a disturbance in the controller design. We assume that

\[
\lambda_b(t) <_\lambda \lambda_r(t-\tau).
\]

b) \( \Delta \) as like in the premium case, denotes modeling uncertainty in which \( |\Delta| \leq \Delta_{\text{max}} \).
c) $C_r(t)$ is the remaining capacity, $C_r(t) = C_{server} - C_p(t)$ and should be considered as disturbance, which could be measured from the premium queue. In our controller scheme we will try to decouple the affect of $C_r(t)$ on the state variable $x_r(t)$.

d) Another constraint that makes controller design more challenging is that $\lambda_r$ is limited to a maximum value, $\lambda_{max}$, and no-negative $\lambda_r$ is allowed, i.e.,

$$0 \leq \lambda_r(t) \leq \lambda_{max} \leq \lambda_{max}$$

4.3. Best-effort traffic

As mentioned in the previous section, best effort traffic has the lowest priority and therefore can only use the left capacity not used by Premium and Ordinary traffic flows. So, this class of service is no-controlled.

4 Controller design

In this section, we present the design of the proposed control action based on $H_\infty$ control theory for congestion control in Diff-Serv networks discussed in the previous sections. We have made the following assumptions for controller design throughout this paper:

$C_{max} = 300000$ Packets Per Second

$\lambda_{max} = 280000$ Packets Per Second

$\tau = 0.2$ msec

For the case of Premium traffic controller design, consider the controller $K_p$ as follows:

$$K_p = \hat{K}_p * P(x)$$

where

$$P(x) = \begin{cases} (\beta_p + 1)/x_p, & x_p \geq 0.2 \\ 0, & x_p < 0.2 \end{cases}$$

This can greatly simplify our design procedure and reduce the model to a linear one as shown in Fig. 3.

Fig. 3. The linear model for Premium traffic controller design.

It is noticeable that $\lambda$ should be a band-limited signal (i.e. $B.W.(\lambda)= f_\lambda$), so we use a first order low-pass filter $W_d(s)$ for $\lambda$ in the LFT model. For the control signal $C_p(t)$ in the LFT model, we use a high-pass filter $W_u(s)$ in which $C_p(t)$ can satisfy the constraint (8) and $\|\hat{K}_p W_u\|_\infty \ll 1$, where $S_o$ is the output sensitivity.

Using trial-and-error to modify filters $W_d(s)$ and $W_u(s)$ in the LFT model and solving sub-optimal solution for $C_p$ using Glover’s and Doyle’s $H_\infty$ algorithm [19,20] after 25 iterations, the following results are attained:

$$W_d = \frac{1}{0.01s + 1}, \quad W_u = \frac{0.03s}{0.08s + 1}, \quad \gamma = 1.02,$$

$$\hat{K}_p(s) = -\frac{6.4 \times 10^6}{s + 1864}(s + 12.5)$$

where $\gamma$ is the performance bound.

The controller block diagram for Ordinary traffic control action along with the controller $K$ is shown in Fig. 4, where

$$K = K_e * \hat{K}_c$$

Choosing $\hat{K}_c = x/(x + 1)$, the model can be reduced, where the reduced model is depicted in Fig. 5.

Fig. 4. The block diagram of Ordinary traffic control.

Fig. 5. The block diagram of reduced Ordinary traffic control.

In order to consider the delay, the block $K_e(s)$ is modified as $K_e(s)\times \frac{1 - (\tau / 2)s}{1 + (\tau / 2)s}$, where $\tau$ is the round trip delay. Choosing $\tau = 0.2$ msec, and using trial-and-error after 21 iterations, the following results have been attained (We have used no filter for $\lambda_o$ so that not to increases controller order):

$$W_d = \frac{1}{0.01s + 1}, \quad W_u = \frac{0.03s}{0.08s + 1}, \quad \gamma = 0.71,$$

$$\hat{K}_c(s) = -\frac{1.64 \times 10^6(s + 10^3)(s + 1380)(s + 20)}{(s^2 + 9.95s + 500)(s^2 + 1.21 \times 10^6 s + 3.95 \times 10^6)}$$
Simulation results of the proposed robust control action are depicted in Figs. 6 and 7. Fig. 6 shows the Premium traffic for a pulse signal as a desired state value, \( x^{ref}(t) \). The disturbance, \( \lambda(t) \), is assumed as a pulse signal as shown in the figure. As it can be seen, the performance of the closed-loop system with the proposed control action is satisfactory and the system has robust performance in response to \( \lambda(t) \). The Ordinary traffic response with \( A=0.15\sin(2\pi*1000t) \) is shown in Fig. 7, which demonstrates a satisfactory robust performance. For all simulations the behavior of the network remains very well controlled, without any unacceptable degradation. This demonstrates the robustness of the proposed congestion controller. Given also that there was no change in the selected design constants the proposed scheme has demonstrated its universality and suitability to operate effectively and efficiently under diverse network conditions in both LAN and WAN configurations.

5 Conclusion

This paper proposes a robust scheme for congestion control based on \( H_{\infty} \) control theory, which uses an integrated dynamic congestion control approach (IDCC). A specific problem formulation for handling multiple differentiated classes of traffic, operating at each output port of a switch is illustrated. IDCC is derived from non-linear control theory using a fluid flow model. The fluid flow model depicts the dynamical system behavior, using packet flow conservation considerations and by matching the queue behavior at equilibrium. In this way, analytical performance bounds can be derived, for provable controlled network behavior. We divide traffic into three basic types of service (in the same spirit as those adopted for the Internet by the IETF Diff-Serv working group, i.e. Premium, Ordinary, and Best Effort). The proposed control algorithm possesses a number of important attributes such as provable stable and robust behavior, provable high utilization with bounded delay and loss performance (can be set by reference values), good steady state and transient behavior. It uses minimal information to control the system and avoids additional measurements and noisy estimates. That is, it uses only one primary measure, namely the queue length, it does not require per connection state information, queuing, or servicing at the switch, or any state information about the set of connections bottlenecked elsewhere in the network (not even a count of these connections). The controller works in an integrated way with different services and has simple implementation and low computational overhead, as well as featuring a very small set of design constants that can be easily set (tuned) from simple understanding of the system behavior. These attributes make the proposed control algorithm appealing for implementation in real, large-scale heterogeneous networks.

References:


