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A Robust Adaptive Congestion Control Strategy for Large Scale Networks with Differentiated Services Traffic

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Abstract—In this paper, a robust *decentralized* congestion control strategy is developed for a large scale network with Differentiated Services (Diff-Serv) traffic. The network is modeled by a nonlinear fluid flow model corresponding to two classes of traffic, namely the premium traffic and the ordinary traffic. The proposed congestion controller does take into account the associated physical network resource limitations and is shown to be robust to the *unknown* and *time-varying* delays. Our proposed decentralized congestion control strategy is developed on the basis of Diff-Serv architecture by utilizing a robust adaptive technique. A Linear Matrix Inequality (LMI) condition is obtained to guarantee the ultimate boundedness of the closed-loop system. Numerical simulation implementations are presented by utilizing the QualNet and Matlab software tools to illustrate the effectiveness and capabilities of our proposed decentralized congestion control strategy.

Keywords—Congestion control, Large scale networks, Decentralized control, Differentiated services traffic, Time-delay systems.

I. Introduction

The congestion control problem is of paramount importance in communication networks specially given the growing need for speed (bandwidth), size, load, and connectivity of the increasingly integrated services. This fact has necessitated the design and utilization of new network architectures by including more effective congestion control algorithms in addition to the standard TCP based congestion control schemes. Specifically, the Internet Engineering Task Force (IETF) has proposed the Differentiated Services (Diff-Serv) architecture [1] to deliver aggregated quality of service (QoS) in IP networks. In the Diff-Serv architecture the traffic is aggregated into different classes of flows and the bandwidth allocation and the packet dropping rules are applied to the traffic classes according to their QoS requirements and specifications.

For the TCP/IP networks, a number of congestion control design techniques have been proposed in the literature [2]- [4], which have shown excellent performance and were demonstrated to be robust in a variety of scenarios. However, the current TCP based congestion control mechanisms cannot adequately address simultaneously the congestion problem and achieve fairness among traffic aggregates within the Diff-Serv networks [2], [3]. It has been recognized that generally scaling up the existing congestion control approaches that use *ad hoc* techniques and intuitive methods are not formal in nature and are indeed problematic even with a number of proposed tuning solutions. Furthermore, by simply relying on the TCP congestion control algorithms, the service QoS requirements that are expected from the differentiated services traffic cannot be fully realized [4]. This problem is more challenging for large scale networks that need to operate under constraints such as bandwidth limitations, real-time requirements, latency management, unknown and time-varying delays, and specially when the resources are not effectively controlled. Therefore, development of new congestion control schemes for large scale Diff-Serv networks is critically needed.

The control systems community has shown a growing interest in addressing the challenges in the area of congestion control. Since the congestion control concept that was introduced in [5], several attempts at control theoretic-based schemes have been made in the literature by using approaches such as optimal control [6]; linear control [7]; fuzzy and neural control [8]; predictive adaptive control [9]; and nonlinear control techniques [10], [11]. Despite these efforts, formal, quantitative, and analytical investigation of performance of large scale networks with Diff-Serv traffics have not been fully addressed and resolved.

Several new congestion control schemes for Diff-Serv networks whose performance can be analytically established have been presented in the literature by using sliding mode control [12] and robust adaptive control [13] techniques. The results developed in these works are quite interesting. However, the above solutions have also serious drawbacks. First, the nature of discontinuities of the sliding mode controller may result and introduce unavoidable and undesirable oscillations in the closed-loop system [14], and therefore reduce the effectiveness of the developed congestion control solutions. On the other hand, the approach in [13] is designed for *only* a *cascade network* of switches and considered the bottleneck switch as a single node. Consequently, the presence of unknown and time-varying delays and latencies are *not* considered in the design of the congestion control scheme. The lack of explicit consideration of the delays will yield a critical challenge and even an instability when the approach is applied to a large scale network consisting of many nodes structured in *arbitrary configurations* containing feedback [15], [16], [17], [18].

The main objective of this paper is to extend the robust congestion control strategy that was proposed in [13] corresponding to a cascade network of nodes with differentiated services traffic to a large scale network of fully connected

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nodes in arbitrary configurations. Our proposed congestion control strategy is designed based on nonlinear and adaptive control methodologies. A fluid flow model is developed where the controller is designed in a *decentralized* manner. This will ensure that the proposed congestion control solutions are feasible to be implemented and scaled up to large scale networks. The justifications and rationale for selecting the fluid flow model and the extension of it to a large scale Diff-Serv network is given in the next section.

II. Fluid Flow Model of a Large Scale Diff-Serv Network

An "ideal" congestion control mechanism should be able to simultaneously satisfy the QoS specifications of the aggregate traffics in addition to congestion avoidance. The main QoS specifications of the aggregate flows and the performance metrics of any congestion control scheme should include both the node throughput as well as the delay and the packet loss rates [19], [20]. Given the trade-offs among the performance metrics it is clearly important to consider them all together. The trade-offs are most clearly expressed and represented in terms of the queue management mechanism [19]. Therefore, an analytical and a quantitative model which has the queueing length as a state and network resources, such as the bandwidth, as control inputs would be the most appropriate model for our desired congestion control design. The remainder of this section is focused on the selection and development of such analytical models for large scale networks operating under differentiated services traffic. We first illustrate the modeling and the approximation of the traffic flow dynamics for a single node, and then extend and generalize this model to a large scale network with specific considerations given to the Diff-Serv traffic flows.

A. Fluid Flow Model of a Single Node

Among a number of formal models that may be used for describing a queueing system in a traffic network, the following conservation law was first introduced in [21]

$$\dot{x}(t) = -f_{out}(t) + f_{in}(t) \tag{1}$$

where $x(t)$ denotes the length of the queue. The above equation is quite general and can be used to model a wide range of queueing and contention systems [22], [21] and is often known as the *fluid flow model*.

Assuming that the queue storage capacity is unlimited and the traffic arrives at the queue with the rate of $\lambda(t)$, then $f_{in}(t)$ is simply the offered load rate $\lambda(t)$. The flow out of the node, $f_{out}(t)$, can be related to the ensemble average utilization of the link by $f_{out}(t) = C(t)\rho(t)$, where $C(t)$ is the link capacity. Note that $\rho(t)$ is the probability that the number of packets in the queue is nonzero (i.e. $\rho(t) = P(N(t)) > 0$, where $N(t)$ is the number of packets in the queue). Therefore, equation (1) can be written as

$$\dot{x}(t) = -C(t)\rho(t) + \lambda(t) \tag{2}$$

In general, determining an exact expression for $\rho(t)$ is quite difficult even for the simplest queues [23]. Hence, an approximate method is generally applied. We assume that $\rho(t)$ can be approximated by a function of the state $G(x(t))$. Thus, the dynamics of the queue can be represented by the following nonlinear differential equation

$$\dot{x}(t) = -C(t)G(x(t)) + \lambda(t) \tag{3}$$

with the initial condition $x(0) = x_0$. The expression for $G(x(t))$ which will accurately model the system is dependent on the type of the queue that one chooses for study.

In this paper, we represent the dynamics of a queue as an M/M/1 queue by matching the steady state of the queueing length $x(t) = \lambda/(\mu C - \lambda)$ to the steady state of the fluid flow model (3), the dynamics of a single node can consequently be expressed as

$$\dot{x}(t) = -\mu \frac{x(t)}{1 + x(t)} C(t) + \lambda(t) \tag{4}$$

where $C(t)$ is the link capacity, $\lambda(t)$ is the average rate of incoming traffic, and $1/\mu$ is the average length of the packets being transmitted in the network. This model has already been validated and utilized in previous work [13], [22]- [23].

B. Fluid Flow Model of Large Scale Diff-Serv Networks

Consider next a general network with N nodes. Using the representation (4), the fluid flow model corresponding to each node is governed by

$$\dot{x}_i(t) = -\mu \frac{x_i(t)}{1 + x_i(t)} C_i(t) + \lambda_i(t) + \sum_{j \in \wp_i} \lambda_j(t - \tau_{ji}(t)) g_{ji}(t) \tag{5}$$

$$\lambda_j(t - \tau_{ji}(t)) = \mu \frac{x_j(t - \tau_{ji}(t))}{1 + x_j(t - \tau_{ji}(t))} C_j(t - \tau_{ji}(t)) \tag{6}$$

where $\wp_i$ is the set of the nearest neighboring nodes associated with the node i and $g_{ji}(t)$ represent the time-varying gains that are to be selected by the designer. In a large scale network the input traffic $f_{in}(t)$ can consist of two parts, namely: (1) the external traffic $\lambda_i(t)$ which in principle could represent the traffic that is being sent from nodes of other clusters (defined as groups of nodes not belonging to $\wp_i$) as well as disturbances or environmental stimuli; and (2) the internal traffic $\lambda_j(t - \tau_{ji}(t))$ which is the delayed input traffic from all the neighboring nodes within a given cluster.

Compared to the fluid flow model (4) that is expressed for a single node, inclusion of the extra gains, namely $g_{ji}(t)$ in (5) does represent a possible traffic compression rate that is now acting on node j to node i. The inclusion of this feature is motivated by the fact that in large scale Diff-Serv networks allowing traffic compression is quite essential due to the sheer size and amount of the aggregated traffic. Determination of an optimal or minimum feasible compression rates that can simultaneously ensure (a) reduction of the queued and transmitted traffic, and (b) avoidance of the overall network congestion are quite crucial. Consequently, introducing traffic compression rates represents an important novel aspect of our proposed network model and congestion control design.

The delays $\tau_{ji}(t)$ in (5)-(6) are modeled as *time-varying and unknown* signals which satisfy the conditions

$$0 \leq \tau_{ij}(t) \leq h, \quad \text{and} \quad \tau_{ij}(t) = \tau_{ji}(t) \tag{7}$$

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where (a) the delays are assumed to be upper bounded by h which is a *known* maximum upper bound in the overall network, (b) the delays are heterogeneous implying that between any node i and node j they can have *different* values, and (c) without loss of generality the bidirectional delays between any two pair of nodes are assumed to be the same.

C. Network Physical Constraints

The large scale network that is considered in our work may be composed of various types of nodes each with its unique properties and characteristics that could affect the controller design and analysis. Therefore, before describing the control strategy, certain *network physical constraints* should be formally identified and specified. Each node is embedded with buffer and output link capacity limitations, which imply that the queues and capacities should satisfy the following constraints

$$0 \le x_i(t) \le x_{buffer,i} \quad , \quad 0 \le C_i(t) \le C_{server,i} \tag{8}$$

On the other hand, each node has a transmitter which can support a maximum transmission rate of $\lambda_{max} = \hat{k}$. Therefore, the instantaneous traffic transmission rate and its rate of change at each node should satisfy

$$\lambda_i(t) \le \hat{k}_i \le C_{server,i} \quad , \quad \dot{\lambda}_i(t) < \infty \tag{9}$$

D. Differentiated Services (Diff-Serv) Traffic

In this paper, we consider three kinds of traffic, namely, the *premium*, *ordinary*, and the *best-effort*. Their definitions and properties are available from the Internet Engineering Task Force (IETF) report [1]. It should be noted that the queueing state space representation and model (5)-(6) are valid for all the three classes of services. However, their control objectives are different. Since the transmission rate of the premium traffic is unmeasurable, the control objective here is to regulate and to allocate an appropriate bandwidth to this service to meet the desired performance specifications. Therefore, the premium traffic will be allocated sufficient capacity for transmission whenever needed. Consequently, the QoS requirements such as delay and packet loss are guaranteed, which in turn decrease the possibility of congestion.

III. Preliminary Result

Before formally presenting our congestion control strategies a preliminary that is needed for our subsequent discussions are briefly introduced below. The preliminary result concerns the derivation of stability conditions of switched time-delay systems. As shown in the next section, the closed-loop congestion controlled system belongs to this class of systems, and therefore its stability properties are crucial for our investigations. The results derived in this section will be applied directly in Section 4.

Consider the following linear switched system with *unknown* and *time-varying* delays τ_l, that is

$$\dot{x}(t) = A_i x(t) + \sum_{l=1}^{n} B_l x(t - \tau_l(t)) + \sum_{l=1}^{n} C_l v_l(t) \tag{10}$$

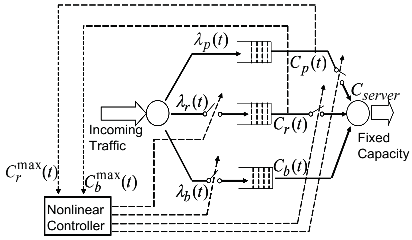

Fig. 1. An adaptive congestion control strategy for a differentiated services traffic for a single node [13].

where $0 \le \tau_l(t) \le h, i \in \wp, \quad \wp = 1, 2,\ x(t) \in \Re^n$ is the state vector, $v_l(t) \in \Re^m$ is the external disturbance signal, and the matrices A_i, B_l, and C_l are time-invariant. Majority of approaches in the literature consider stability of a nominal system, therefore these results cannot be directly applied to our large scale network that is subject to external disturbances. In other words, ultimate bounded stability conditions of switched time-delay systems that are subject to disturbances have not been addressed before explicitly in the literature. Our main result in this subsection is given by the following theorem.

Theorem 1: The switched time-delay system (10) is uniformly ultimately bounded if there exist symmetric positive definite matrices Y_{1i}, Y_2, Y_3, $\bar{R}_i$, $\bar{S}$, $i = 1, 2$; positive definite matrices $\bar{M}_i$, $\bar{N}_i$, $i = 1, 2$; and matrices U_i, $\bar{U}_i$, T_{li}, $\bar{T}_{li}$, $\bar{Q}_{li}$ of appropriate dimensions, $i = 1, 2$ and $l = 1, ..., n$, such that the LMI conditions (11) are satisfied

$$\Omega_i = \begin{bmatrix} 2(U_i + \sum_{l=1}^{n} T_{li}) + \bar{M}_i & Y_{1i}^T - Y_2 + \bar{U}_i & -h \sum_{l=1}^{n} \bar{T}_{li} \\ * & -\bar{R}_i - \bar{R}_i^T + \bar{S} + \bar{N}_i & -h \sum_{l=1}^{n} \bar{Q}_{li} \\ * & * & -Y_3 \end{bmatrix} < 0 \tag{11}$$

Under these conditions, in steady state the ultimate bound of the system states has a radius of $r = max(r_1,\ r_2)$ with $r_i = \frac{\lambda_{max}(\Psi_i)}{\lambda_{min}(-\Omega_i)} \|v(t)\|^2,\ i = 1, 2$, where $v(t) = [v_1(t) \ ... \ v_n(t)]^T$, $\lambda_{max}(.)$ and $\lambda_{min}(.)$ are the maximum and the minimum eigenvalues of the corresponding matrix, respectively and

$$\begin{aligned} \Psi_i &= diag\{\Phi_{1i} \ ... \Phi_{ni}\} \\ \Phi_{li} &= C_l^T(\bar{M}_i^{-1} + (Y_2^{-1})^T \bar{R}_i \bar{N}_i^{-1} \bar{R}_i^T Y_2^{-1}) C_l \end{aligned} \tag{12}$$

Proof: Omitted due to space limitations.

IV. Proposed Decentralized Robust Congestion Control Strategy

Consider a large scale network with N nodes. Suppose each node has three queues corresponding to the premium, the ordinary and the best-effort traffics. The congestion controller is implemented at the output port of each node, as shown in Figure 1. The control strategy adopts the Diff-Serv framework that was originally introduced in [1]. The control objective pursued for the premium traffic is to allocate the output capacity, that is denoted by $C_{p,i}(t)$, by incorporating an adaptive estimator to cope with the incoming traffic uncertainties. The ordinary traffic controller needs to simultaneously regulate the incoming flow rate, that is denoted by $\lambda_{r,i}(t)$, and allocate its capacity $C_{r,i}(t)$ by also using an adaptive controller. Finally, for the best-effort traffic, no explicit active control is designed in this paper since this traffic does not have any QoS requirements.

A. Premium Traffic Control Strategy

Let us rewrite the state space model (5)-(6) corresponding to the premium traffic as follows (the subscript "p" denotes the "premium" traffic)

$$\begin{aligned}\dot{x}_{pi}(t) &= -\mu\frac{x_{pi}(t)}{1+x_{pi}(t)}C_{pi}(t)+\lambda_i(t)\\ &+ \sum_{j\in\wp_i}\lambda_{pj}(t-\tau_{ji}(t))g_{ji}(t), i=1,...,N \quad (13)\end{aligned}$$

with

$$\lambda_{pj}(t-\tau_{ji}(t))=\mu\frac{x_{pj}(t-\tau_{ji}(t))}{1+x_{pj}(t-\tau_{ji}(t))}C_{pi}(t-\tau_{ji}(t)) \quad (14)$$

Similar to the approach in [13], the ***link capacity controller*** is first selected for the premium traffic as follows

$$\begin{aligned}&C_{pi}(t)=\max\{0,\min[C_{server,i},m_{pi}(t)]\}\\ &m_{pi}(t)=\rho_{pi}(t)\frac{1+x_{pi}(t)}{x_{pi}(t)}\left[\alpha_{pi}\bar{x}_{pi}(t)+k_{pi}(t)\right] \quad (15)\end{aligned}$$

where $\bar{x}_{pi}(t)=x_{pi}(t)-x_{pi}^{ref}$, and x_{pi}^{ref} denotes the desired queueing length specified by the network manager. In the controller (15), α_{pi} is a design parameter that affects the queueing state tracking convergence rate and performance, and $k_{pi}(t)$ is a parameter that will be used subsequently to estimate the incoming traffic $\lambda_{pi}(t)$.

The time-varying parameter $\rho_{pi}(t)$ is used to avoid division by extremely small values of $x_{pi}(t)$ in (15). This is due to the fact that $\lim_{x_{pi}(t)\to 0} m_{pi}(t)=\infty$, which results in $C_{pi}(t)=C_{server,i}$. This implies that the full capacity is allocated when there is almost no packets that are stored in the queue and need to be transmitted. To overcome this drawback, $\rho_{pi}(t)$ is selected as follows

$$\rho_{pi}(t)=\begin{cases}0 & \text{if } x_{pi}(t)\le 0.01\\ 1.01x_{pi}(t)-0.01 & \text{if } 0.01<x_{pi}(t)<1\\ 1 & \text{if } x_{pi}(t)\ge 1\end{cases} \quad (16)$$

where the continuity of $x_{pi}(t)$ in the interval $[0.01\ \ 1]$ guarantees the existence and uniqueness of a solution for the associated differential equation in (13).

According to the *switching* control law (15)-(16), the controller $C_{pi}(t)$ of each node can take on three different values, namely, 0, $m_{pi}(t)$, or $C_{server,i}$ depending on the changes in $x_{pi}(t)$. Specifically, we have

(i) when $x_{pi}(t)$ is sufficiently large, then $m_{pi}(t)\ge C_{server,i}$, which leads to $C_{pi}(t)=C_{server,i}$, or

(ii) when $x_{pi}(t)$ is sufficiently small, then $m_{pi}(t)\le 0$, which leads to $C_{pi}(t)=0$, or

(iii) when $0<m_{pi}(t)<C_{server,i}$, then $C_{pi}(t)=m_{pi}(t)$.

Cases (i) and (ii) are referred to as the *edge state* and case (iii) is denoted as the *normal control state*. Therefore, the queueing system (13) will experience different operational modes depending on the changes in the queueing state over time. We expect that the system remains within case (iii) at all times so that the congestion controller $m_{pi}(t)$ can take on its most control effect. Our proposed strategy is therefore to force the two edge state situations to behave similar to the normal control state (iii) by tuning or adjusting the traffic compression gains $g_{ji}(t)$ as follows

$$g_{ji}(t)=\begin{cases}\bar{g}_{ji}(t), & \text{if } C_{pi}(t)=C_{server,i}\\ & \text{and } C_{server,i}-\hat{k}_i\le\sum_{j\in\wp_i}\hat{k}_j\\ g_{ji}(t), & \text{otherwise}\end{cases} \quad (17)$$

where $\bar{g}_{ji}(t)$ is chosen according to

$$0\le\bar{g}_{ji}(t)<\frac{C_{server,i}-\hat{k}_i}{\sum_{j\in\wp_i}\hat{k}_j} \quad (18)$$

The analysis corresponding to the above three operational modes are omitted due to space limitations.

We now need to check the incoming traffic from each neighboring node $j\in\wp_i$. Certain nodes controllers may be given by $C_{pj}(t-\tau_{ji}(t))=C_{server,j}$ for $j\in\wp_{i1}$; others may be given by $C_{pk}(t-\tau_{ki}(t))=m_{pk}(t-\tau_{ki}(t))$ for $k\in\wp_{i2}$; and yet others may be given by $C_{li}(t-\tau_{li}(t))=0$ for $l\in\wp_{i3}$, where $\wp=\wp_{i1}\bigcup\wp_{i2}\bigcup\wp_{i3}$. Therefore, the state equation (13) may be approximated as follows

$$\begin{aligned}\dot{x}_{pi}(t) &= -[\alpha_{pi}\bar{x}_{pi}(t)+k_{pi}(t)]+\lambda_{pi}(t)+\sum_{k\in\wp_2}C_{server,k}g_{ki}(t)\\ &+ \sum_{j\in\wp_1}[\alpha_{pj}\bar{x}_{pj}(t-\tau_{ji}(t))+k_{pj}(t-\tau_{ji}(t))]g_{ji}(t) \quad (19)\end{aligned}$$

Let us define $\bar{x}_{pi}(t)=x_{pi}(t)-x_{pi}^{ref}$, $\bar{x}_p(t)=vec\{\bar{x}_{pi}(t)\}$, $k_p(t)=vec\{k_{pi}(t)\}$, $\lambda_p(t)=vec\{\lambda_{pi}(t)\}$, and $C_{server}=vec\{C_{server,i}\}$. The queueing state of the entire network after applying the controller (15) is now given by

$$\begin{aligned}\dot{\bar{x}}_p(t) &= A_0\bar{x}_p(t)-k_p(t)+\lambda_p(t)+B_cC_{server}\\ &+ \sum_{l=1}^{M}A_l\bar{x}_p(t-\tau_l(t))+\sum_{l=1}^{M}B_lk_p(t-\tau_l(t)) \quad (20)\end{aligned}$$

where $\tau_l(t)$ denotes the time-varying delay, $l=1,...,M$; M is the number of time-varying delays in the network; A_0, A_l, B_l, and B_c are the system matrices that are defined as follows

$$\begin{aligned}&A_0=diag[-\alpha_l]\\ &\sum_{l=1}^{M}A_l[i][j]=\begin{cases}\alpha_jg_{ji}, & \text{if nodes } i \text{ and } j \text{ are connected}\\ 0, & \text{otherwise}\end{cases}\\ &\sum_{l=1}^{M}B_l[i][j]=\begin{cases}-g_{ji}, & \text{if nodes } i \text{ and } j \text{ are connected}\\ 0, & \text{otherwise}\end{cases}\\ &B_c[i][j]=\begin{cases}g_{ji}, & \text{if nodes } i \text{ and } j \text{ are connected}\\ 0, & \text{otherwise}\end{cases} \quad (21)\end{aligned}$$

Motivated from the robust adaptive control techniques in [24], the time-varying gain $k_{pi}(t)$ is now designed according to the ***modified parameter projection method*** and is applied to system (20) to estimate the unknown but bounded incoming traffic $\lambda_{pi}(t)$ as follows

$$\dot{k}_{pi}(t)=\begin{cases}\delta_i^p\bar{x}_{pi}(t)-\beta_i^pk_{pi}(t), & \text{if } 0\le k_{pi}(t)\le\hat{k}_{pi} \text{ or}\\ & k_{pi}(t)=0,\ \bar{x}_{pi}(t)\ge 0 \text{ or}\\ & k_{pi}(t)=\hat{k}_{pi},\ \bar{x}_{pi}(t)\le 0\\ -\beta_i^pk_{pi}(t), & \text{otherwise}\end{cases} \quad (22)$$

where δ_i and β_i are constant design parameters. It should be noted that the Integrated Dynamic Congestion Control (IDCC) scheme update law in [13] is a special case of (22) when $\beta_i = 0$.

For the purpose of stability analysis, let us introduce a new state $\bar{k}_{pi}(t) = k_{pi}(t) - \lambda_{pi}(t)$, and define the states of the closed-loop system as $z_p(t) = [\bar{x}_p^T(t) \;\; \bar{k}_p^T(t)]^T$. Due to the switching conditions on $k_{pi}(t)$, the closed-loop system will switch between the following two subsystems depending on the changes in the state values, namely

Subsystem 1: If either $-\hat{k}_{pi} \leq \bar{k}_{pi}(t) \leq \hat{k}_{pi}$; or $-\hat{k}_{pi} \leq k_{pi}(t) \leq 0$ but $\bar{x}_{pi}(t) \geq 0$; or $0 \leq \bar{k}_{pi}(t) \leq \hat{k}_{pi}$ but $\bar{x}_{pi}(t) \leq 0$, for $i = 1, ..., N$, then the following subsystem will be active

$$\dot{z}_p(t) = D_1 z_p(t) + \sum_{l=1}^{M} F_l z_p(t - \tau_l(t)) + \sum_{l=1}^{M} H_l v_l(t) \quad (23)$$

Subsystem 2: Otherwise, the following subsystem will be active

$$\dot{z}_p(t) = D_2 z_p(t) + \sum_{l=1}^{M} F_l z_p(t - \tau_l(t)) + \sum_{l=1}^{M} H_l v_l(t) \quad (24)$$

The system matrices in the above subsystems are defined as $D_1 = \begin{bmatrix} A_0 & -I \\ \Delta & -\Pi \end{bmatrix}$, $D_2 = \begin{bmatrix} A_0 & -I \\ 0 & -\Pi \end{bmatrix}$, $F_l = \begin{bmatrix} A_l & B_l \\ 0 & 0 \end{bmatrix}$, and $H_l = \begin{bmatrix} 0 & 0 & B_l & B_c \\ -\Pi & -I & 0 & 0 \end{bmatrix}$, where $\Delta = diag\{\delta_{pi}\}$ and $\Pi = diag\{\beta_{pi}\}$. The input signal is given by $v_l(t) = \begin{bmatrix} \lambda_p^T(t) & \dot{\lambda}_p^T(t) & \lambda_p^T(t - \tau_l(t)) & C_{server}^T \end{bmatrix}^T$. Comparing equations (23)-(24) with the switching system (10), one can conclude that by applying Theorem 1 in Section 3, the stability conditions of the closed-loop system (23)-(24) can be derived. This is discussed next.

Note that the transmission gains g_{ij} and the control parameters α_i, β_i, δ_i are present in the system matrices D_i and $\sum_{l=1}^{M} F_l$, $i = 1, 2$. In order to select these parameters, one can apply the LMI condition (11) and first check the feasibility of $\Omega_1 < 0$ to obtain the control parameters from $D_1 = U_1 Y_{11}^{-1}$ and $F_l = T_{l1} Y_{11}^{-1}$. We then substitute the system parameters into $\Omega_2 < 0$ and check its feasibility corresponding to the maximum bound of the delay h. The above results are now summarized in the following lemma.

Lemma 1: Considering that the dynamical model of the premium traffic is governed by (13)-(14), the application of the congestion controller (15)-(16) with the traffic compression gains satisfying (17)-(18) and the estimated traffic gains updated according to (22) and the congestion controller other parameters are selected to satisfy the LMI conditions in Theorem 1, will consequently result in a closed-loop system with states that are uniformly ultimately bounded.

Proof: Follows closely along the lines of the proof of Theorem 1, but omitted due to space limitations. ∎

B. Ordinary Traffic Control Strategy

Let us rewrite the queueing model (5)-(6) for the ordinary traffic as (the subscript "r" refers to the "ordinary" traffic)

$$\begin{aligned} \dot{x}_{ri}(t) &= -\mu \frac{x_{ri}(t)}{1 + x_{ri}(t)} C_{ri}(t) + \lambda_{ri}(t) \\ &+ \sum_{j \in \wp_i} \lambda_{rj}(t - \tau_{ji}(t)) g_{ji}(t) \\ \lambda_{rj}(t - \tau_{ji}(t)) &= \mu \frac{x_{rj}(t - \tau_{ji}(t))}{1 + x_{rj}(t - \tau_{ji}(t))} C_{rj}(t - \tau_{ji}(t)) \end{aligned} \quad (25)$$

The maximum available capacity that may be used for the ordinary traffic is given by

$$C_{ri}^{max}(t) = \max[0, \;\; C_{server,i} - C_{pi}(t)] \quad (26)$$

In the next two subsections, we will address the *flow rate control* and the *bandwidth allocation control* problems for the ordinary traffic as governed by (25)-(26).

1) Flow Rate Regulation: At the beginning of each measurement cycle, we calculate the maximum allowable capacity $C_{ri}^{max}(t)$ from (26) and compare it with the ordinary incoming traffic $\lambda_{ri}(t)$. If the incoming traffic $\lambda_{ri}(t)$ is greater than the available capacity, that is $\lambda_{ri}(t) > C_{ri}^{max}(t)$, then the traffic needs to be regulated first and the *flow rate control* is adopted as follows

$$\lambda_{ri}(t) = \min[C_{ri}^{max}(t), \;\; \lambda_{ri}(t)] \quad (27)$$

Once the above regulator is invoked, the ordinary incoming traffic $\lambda_{ri}(t)$ is guaranteed to be bounded by $0 \leq \lambda_{ri}(t) \leq C_{ri}^{max}(t)$.

2) Bandwidth Allocation: Provided that $0 \leq \lambda_{ri}(t) \leq C_{ri}^{max}(t)$, the ordinary traffic capacity controller $C_{ri}(t)$ is selected as

$$\begin{aligned} C_{ri}(t) &= \max\{0, \min[C_{ri}^{max}(t), b_i(t)]\} \\ b_i(t) &= \rho_{ri}(t) \frac{1 + x_{ri}(t)}{x_{ri}(t)} [\alpha_{ri} \bar{x}_{ri}(t) + k_{ri}(t)] \end{aligned} \quad (28)$$

where $\bar{x}_{ri}(t) = x_{ri}(t) - x_{ri}^{ref}$, α_{ri} is a constant design parameter, and x_{ri}^{ref} denotes the desired reference ordinary queueing length that is specified by the network manager. The time-varying parameter $\rho_{ri}(t)$ is defined similar to $\rho_{pi}(t)$ in equation (16) with $x_{pi}(t)$ replaced by $x_{ri}(t)$. From equation (28), the controller $C_{ri}(t)$ can take on three different values, that is, 0, $b_i(t)$, and $C_{ri}^{max}(t)$ depending on the changes in the queueing state $x_{ri}(t)$ and the premium controller $C_{pi}(t)$.

V. Performance Evaluations and Simulation Results

In order to evaluate and quantify the performance of our proposed control strategies, a number of simulations are performed and comparative results are provided in this section. We use a network that consists of a number of randomly distributed nodes with more than one bottleneck link.

Our simulation model is shown in Figure 2. This network consists of 3 clusters where each cluster has 5 nodes. The three edge nodes 1, 2 and 3 can communicate with each other to share the information among the three clusters. This network

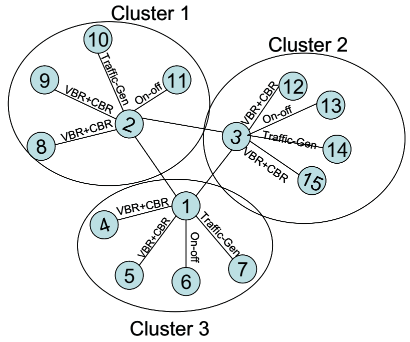

Fig. 2. The schematic of the large scale traffic network consisting of three clusters and 15 nodes that is used in simulation studies.

configuration is quite general and can be found in many applications such as sensor/actuator networks, cooperative team of unmanned vehicles [15], [16], [17], [18], and high speed Ethernet networks. For our simulation studies we implement the network behavior by an event-based simulator tool known as QualNet [25] software environment.

The link capacities of the three edge nodes are set to $C_{server,1} = 20$ Mb, $C_{server,2} = 10$ Mb, and $C_{server,3} = 5$ Mb, while the capacities of other nodes are set to $C_{server} =$ 100 Mb. Using the above specifications, we assume that each node has three separate logical buffers that are collecting the premium, ordinary and the best-effort traffics. The buffer size for each traffic is set to 5 Mb. As shown in Figure 2, the premium and the ordinary traffics in each cluster are generated by the source nodes dynamically. In the simulation results presented below all the source traffics are simulated by the applications that are defined in QualNet. In each cluster, there are two premium traffic source nodes that simultaneously generate a variable bit rate traffic (VBR) and a constant bit rate traffic (CBR) (i.e. VBR+CBR). As defined according to the IETF Diff-Serv architecture [1], the premium traffic is used mainly for voice, video and other real-time constrained services that need to be strictly controlled. Based on the network model specifications that are defined above, we first implement the integrated dynamic congestion controller (IDCC) scheme [13] and use the results obtained as a benchmark for comparative analysis with our proposed control strategies. For the sake of making an unbiased and fair evaluation and comparison, we actually do apply the same setting for the parameters as well as the same maximum delays in the IDCC algorithm as those that are selected for our proposed scheme. We evaluate the performance of our proposed controllers under both stationary and dynamic conditions, and compare the performance of the three bottleneck links and nodes.

Simulations that are conducted (graphs are not shown due to space limitations) illustrate that the resulting queueing lengths (bits) by utilizing the IDCC method [13] are *unstable*; that is the buffers for both the premium and the ordinary traffics *do not* converge to their desired set point values but instead have overflown and reached their upper bound buffer sizes. One explanation for this undesired behavior is due to the presence of the time-varying *heterogeneous* delays that are not explicitly taken into account by the IDCC controller. On the other hand, by applying our proposed congestion controllers with the parameters that are derived from the LMI conditions, the queueing lengths do indeed converge to their desired set points and the overall performance of the network is greatly improved as compared to that of the IDCC method.

TABLE I
AVERAGE PACKET LOSS RATE (PLR) (%)

Premium Traffic	IDCC [13] Scheme	Our Proposed Scheme
Node 1	92.96	0
Node 2	93.86	0
Node 3	93.27	0
Ordinary Traffic	IDCC [13] Scheme	Our Proposed Scheme
Node1	87.93	5.66
Node 2	96.08	4.65
Node 3	96.13	2.34

TABLE II
AVERAGE QUEUEING DELAY

Premium Traffic	IDCC [13] Scheme	Our Proposed Scheme
Node 1	∞	48.8ms
Node 2	∞	44.9ms
Node 3	∞	22.5ms
Ordinary Traffic	IDCC [13] Scheme	Our Proposed Scheme
Node 1	∞	67.8ms
Node 2	∞	138.1ms
Node 3	∞	178.5ms

A quantitative comparison related to the packet loss rate (PLR) metric is now provided and summarized in Table I. As can be seen from Table I, by utilizing the IDCC method a large number of the premium and the ordinary packets to the three nodes are lost. This is due to the fact that the buffer size of the nodes are overflown and all the incoming packets have to be discarded. However, by utilizing our proposed congestion control approach the performance of the average packet loss rate is significantly improved when compared to that of the IDCC approach. By utilizing our proposed method the premium traffic has no packet losses and the ordinary traffic's loss rate is *less than* 6%. Table II provides the comparative results corresponding to the average queueing delays. As can be seen from Table II by utilizing the IDCC method the queueing delays are *infinite* due to the buffer overflow and packet losses. However, by utilizing our proposed congestion control the performance is significantly improved. The queueing delays remain bounded to less than 50 ms for the premium and 200 ms for the ordinary traffics.

VI. CONCLUSIONS

In this paper, a decentralized robust adaptive congestion control strategy for differentiated services (Diff-Serv) traffic in large scale network is proposed. The LMI conditions that facilitate design of the controller parameters as well as the network traffic compression/transmission gains are derived. Simulation results presented demonstrate that the resulting steady-state and the transient behavior of our proposed closed-loop controlled system are greatly improved when compared to that of the IDCC approach [13], which was selected as a benchmark approach in this study. Numerical results demonstrate that the network packet loss rates and its corresponding stability conditions are significantly improved by utilizing our proposed control strategies when compared to the other available method in the literature.

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