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# Modeling Upper Layer Reaction to QoS Degradation as a Congestion Avoidance Mechanism

**Shigeaki HARADA**[†a)], ***Member***, **Keisuke ISHIBASHI**[††], ***Senior Member***, ***and*** **Ryoichi KAWAHARA**[†††], ***Member***

**SUMMARY** On the Internet, end hosts and network nodes interdependently work to smoothly transfer traffic. Observed traffic dynamics are the result of those interactions among those entities. To manage Internet traffic to provide satisfactory quality services, such dynamics need to be well understood to predict traffic patterns. In particular, some nodes have a function that sends back-pressure signals to backward nodes to reduce their sending rate and mitigate congestion. Transmission Control Protocol (TCP) congestion control in end-hosts also mitigates traffic deviation to eliminate temporary congestion by reducing the TCP sending rate. How these congestion controls mitigate congestion has been extensively investigated. However, these controls only throttle their sending rate but do not reduce traffic volume. Such congestion control fails if congestion is persistent, e.g., for hours, because unsent traffic demand will infinitely accumulate. However, on the actual Internet, even with persistent congestion, such accumulation does not seem to occur. During congestion, users and/or applications tend to reduce their traffic demand in reaction to quality of service (QoS) degradation to avoid negative service experience. We previously estimated that 2% packet loss results in 23% traffic reduction because of this upper-layer reaction [1]. We view this reduction as an upper-layer congestion-avoidance mechanism and construct a closed-loop model of this mechanism, which we call the Upper-Layer Closed-Loop (ULCL) model. We also show that by using ULCL, we can predict the degree of QoS degradation and traffic reduction as an equilibrium of the feedback loop. We applied our model to traffic and packet-loss ratio time series data gathered in an actual network and demonstrate that it effectively estimates actual traffic and packet-loss ratio.

***key words:*** *closed loop, congestion avoidance, latent traffic demand*

## 1. Introduction

The volume and variation in Internet traffic have been increasing [2], [3]. Such traffic is generated by many heterogeneous players, such as content providers and social network services (SNS) providers, and received by end-users, whose usage patterns are dynamically changing. Between these players, network providers store and forward the traffic with various traffic-control mechanisms. Therefore, traffic patterns actualized in a network are determined through interaction mechanisms among many players.

Because of the increase in traffic volume, networks sometime become congested [4]–[7]. Congestion is defined as "a state or condition that occurs when network resources are overloaded, resulting in impairments for network users as objectively measured by the probability of loss and/or delay" [8]. Senders, receivers, and transmitters try to mitigate this state by using congestion avoidance mechanisms [9]. For example, network nodes store temporary traffic overloads in their buffers. When the buffers are full, the nodes simply drop incoming packets or some nodes have a back-pressure mechanism that informs backward nodes to pause to send packets [10]. When congestion lasts longer and cannot be absorbed by node buffers, Transmission Control Protocol (TCP) congestion control equipped in end-hosts can mitigate the congestion by reducing the TCP sending rate.

To provide a satisfactory Internet service, network operators need to understand those interaction mechanisms and predict traffic patterns. There is a large amount of literature on analyzing congestion controls and modeling their behavior to clarify the equilibrium that the control achieves in various environments and with TCP parameters [11]–[13]. There have also been analyses in which TCP connection stochastically occurs to bring a certain amount of data. In these analyses, the normalized average load is assumed to be smaller than one (traffic load is smaller than the link capacity). If the load is larger than one, unsent traffic will infinitely accumulate and transfer time may significantly increase (this phenomenon is called 'congestion collapse'). In an actual Internet service, however, even in a persistent overload state, this phenomenon does not seem to occur [7]. Therefore, there are assumed to be other mechanisms to reduce traffic during persistent congestion.

Along with such transport or under layer mechanisms, the dynamics of user-communication behaviors, such as abandoning watching video streaming in reaction to quality of service (QoS) degradation, have recently been investigated as user engagement with Internet services. Various application-level controls dynamically also change content size (video streaming bit-rate) depending on the degree of QoS degradation. Though these reactions are not intended to reduce network traffic load, they reduce it as a result and mitigate congestion. We previously introduced the possibility that with these upper-layer reactions, traffic demand may be latent when congestion occurs and QoS is degraded [1]. We also proposed a method of inferring the latent traffic demand by developing a model for the degree of traffic reduction as a function of QoS degradation, which is called the Common Trend and Regression with Independent Loss (CTRIL) model.

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[†] The author is with NTT Network Technology Laboratories, NTT Corporation, Musashino-shi, 180-8585 Japan.

[††] The author is with Division of Arts and Sciences, College of Liberal Arts, International Christian University, Mitaka-shi, 181-8585 Japan.

[†††] The author is with Faculty of Information Networking for Innovation and Design, Toyo University, Tokyo, 115-0053 Japan.

a) E-mail: shigeaki.harada.fy@hco.ntt.co.jp

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For this paper, we view the upper-layer reaction to QoS degradation as a congestion-avoidance mechanism. With this idea, we can understand why, even in a persistent congested network, the above phenomenon (i.e., congestion collapse) has been avoided. Then, if this upper-layer reaction avoids congestion collapse, a question naturally arises: in what situation does this upper-layer reaction work and how? To answer this question, borrowing the idea of Low et al. [11], we constructed a closed-loop model, named Upper-Layer Closed-Loop (ULCL), that describes this mechanism. The ULCL model provides the degree of QoS degradation and actualized traffic as an equilibrium state with given latent traffic demand and link capacity. To the best of our knowledge, this paper is the first attempt to view this upper-layer reaction as a congestion-avoidance mechanism and model this mechanism.

The main objective of the study is to understand and model the upper-layer reaction to QoS degradation as a closed-loop congestion-avoidance mechanism. In addition, we also discuss some applications and implications of the model. For example, network designers can estimate the impact of congestion due to a possible network failure by predicting the degree of QoS degradation with given latent traffic demand and capacity of rerouted links. Network researchers can also asses the requirement of additional congestion controls when user/application reaction changes by changing the sensitivity parameters of the ULCL model that express how upper layers reduce their traffic volumes in reaction to QoS degradation. We discuss these applications in Sect. 6.

The rest of the paper is organized as follows. In Sect. 2, we briefly survey current congestion-avoidance mechanisms and their modeling. Then in Sect. 3, we discuss the possibility of traffic reduction as an upper-layer reaction to QoS degradation and a method of inferring latent traffic demand, which was shown in our previous paper [1]. In Sect. 4, we introduce an idea that the above reaction can be considered as a congestion-avoidance mechanism and a construct a ULCL model to infer the equilibrium state of the mechanism. We also discuss an experimental analysis of this model in Sect. 5 and applications and implications of this model in Sect. 6. We finally summarize our results and implications in Sect. 7.

## 2. Congestion-Avoidance Mechanisms

In this section, we first briefly review the transport- and lower-layer congestion-avoidance mechanisms and their modeling. Then, we discuss the possibility of traffic-volume reduction by users and/or applications as a reaction to QoS degradation (Fig. 1).

### 2.1 Transport- and Lower-Layer Congestion Controls

Congestion avoidance mechanisms or controls prevent or mitigate congestion [9]. They are categorized 1) node-based control that corresponds to link-layer or network-layer control and 2) host-based control that corresponds to transport-layer control. We briefly review these two types of congestion controls and their modeling below.

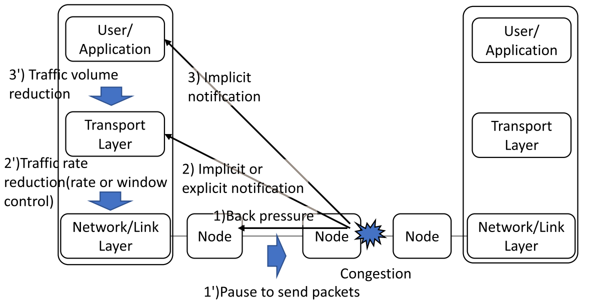

**Fig. 1** Congestion-avoidance mechanisms implemented in various layers. Link- and transport-layer mechanisms, 1') and 2'), respectively, as lower-layer controls. We argue the possibility of upper-layer mechanism 3').

A node stores temporal overloaded traffic in its buffer. If the node has a back-pressure-type congestion control, it detects the congestion state by the increase in its queue length in the buffer. It then notifies the nodes located between the sender-host and the congested nodes and requests them to reduce their sending rates [10]. This type of control is implemented in link-layer technology. For example, IEEE802.3 has a "pause" control to indicate connected nodes to suppress sending packets [14]. In addition, Frame-Relay has functions called backward explicit congestion notification (BECN) and forward explicit congestion notification (FECN) that indicate the sender-side digital service unit (DSU) to reduce the data-transfer rate. Back-pressure-type congestion control is modeled and analyzed in which the control is stabilized (i.e., converges to an equilibrium state) in terms of the arrival rate, control delay, and control parameters (gain) [10], [15]–[17].

In addition, there have also been proposals to combine back-pressure-type control with network-layer control, such as traffic engineering (routing), as back-pressure routing [18], [19].

However, these node-based controls absorb overloaded traffic at the buffers of those nodes; thus, they can only absorb congestion whose duration is the buffer time scale (buffer size (bits) divided by link speed (bps)), which is at most sub seconds for most network nodes.

A transport-layer function, such as Transmission Control Protocol (TCP), adjusts its sending rate as host-basis congestion control. It can absorb congestion longer than the node buffer time scale because unsent traffic can be stored inside sending hosts. In this congestion control, the congestion state is notified to the sender implicitly or explicitly. In the implicit control, the sender recognizes the congestion state from packet loss or delay increase. There are many variants of TCP to achieve heterogeneity, scalability, and fairness [8]. A TCP variant was recently developed that uses the estimated available bandwidth to adjust its sending rate [20], and this control is adopted not only to TCP but also to User Datagram Protocol (UDP) [21].

The explicit control detects congestion through messages sent by intermediate nodes marked in forward or backward packets (explicit congestion notification) [22]. The random early detection (RED) can also be considered as in this line [23]. A method has recently been proposed that reports not only the existence of congestion but also an increase in queuing delay for data-center networks [24].

There is a large amount of literature on analyzing such congestion control as a closed loop to seek the condition under which the control is stable, or equilibrium state achieved by TCP in various environments and TCP parameters [11]–[13]. Low et al. modeled the behaviors of various TCP versions as an optimization problem [11]. Specifically, by considering the degree of congestion as a price, a congestion control system is modeled for finding the optimum sending rate to maximize the utility of sending traffic minus cost determined by the price. Because the price (degree of congestion) will increase as the traffic rate increases, there are equilibrium points. They also proposed a TCP-control algorithm based on a control-theoretic framework. Takagaki et al. also took the control theoretic approach to investigate the stability and equilibrium on a TCP closed control loop [13]. These studies focused on network links that are shared by TCP connections that always have data to send.

There have also been studies that focused on which TCP connections statistically arrive at a network with a finite size of data to send [25]–[27]. In these studies, connections were assumed to share link capacities fairly and the processor-sharing model was applied to evaluate the performance of TCP connections. These studies focused on elastic traffic, which does not require a specific sending rate but dynamically adapts to the available bandwidth by TCP control. Berger and Kogen [28] proposed a method of provisioning link bandwidth in existing TCP control loops for elastic data traffic. Kawahara et al. also proposed a method of bandwidth dimensioning using TCP flow statistics [29]. These methods can infer required bandwidth for a specified performance objective for a given traffic load.

Although these studies focused on temporal overload, they assumed that traffic load, which is arrival rate multiplied by the average size of each connection, is smaller than capacity in terms of the long-run average value. Thus, these models cannot be applied to persistent congestion, e.g., longer than that of most connections (sub-hours). This is because current congestion-avoidance mechanisms, whether link/network layer or transport layer, only control the sending rate not traffic volume. On the sender side and above the transport layer, however, applications or users that generate traffic to be sent might respond to congestion and decrease traffic volume. Fredj et al. [25] proposed a model on traffic reduction in an overload case due to user impatience. That is, users terminate flows when flow duration exceeds a threshold depending on flow size. The model was simulated but not verified by using actual data.

### 2.2 Upper-Layer QoS Degradation Reaction

User behaviors as reactions to QoS degradation have been investigated as user engagement with Internet services. The objective is to optimize user retention of or engagement with services under various QoS and quality of experience (QoE) circumstances [30], [31]. For example, Krishnan and Sitaraman showed that video-starting delay of more than 2 s results in a 5.8% increase in abandonment rate [30]. Dobrian et al. evaluated the relationship between user engagement with a video streaming service (video play time) and application-level performance such as stalling length of video replay [31]. Along the same lines, Koto et al. investigated the relationship between web-browsing behavior and network performance (download throughput) [32].

In addition to such user reactions, application-level control that dynamically adjusts contents size (video bitrate) in accordance with the available network QoS has recently been proposed and implemented [33]. This control aims to maintain moderate QoE even with degraded QoS by avoiding streaming stalling with low-grade video. With this control, traffic demand will decrease when QoS is degraded. Optimizing video bitrate in accordance with QoE with predicted QoS (available bandwidth) has recently gained much attention [34]–[38].

From the viewpoint of network operators, such user/application-level reactions can be considered as feedback control that mitigates congestion in the network. To the best of our knowledge, there have been no studies on the above relationship, which we modeled and verified in this study.

## 3. Estimating Latent Traffic Demand

We now briefly summarize our previously proposed model (the CTRIL model), which enables the inference of latent traffic demand. In the next section, we introduce a negative feedback model by using the CTRIL model. We summarize the notations introduced in Sects. 3, 4 in Table 1.

To infer the volume of latent traffic, which is not actualized and cannot be measured, we assume that diurnal patterns of link-traffic time series are almost the same when the links are used for the same service and homogeneous users [39]. We then prepare traffic time series of an uncongested link, whose traffic might not be changed from latent traffic demand, and that of a congested link, whose traffic volume might decrease due to QoS degradation. Based on the assumption that latent traffic of both links shares a diurnal pattern, the difference in actualized traffic patterns between both links is caused by QoS degradation.

We adopted a state space model to represent the above assumption [1]. Figure 2 shows the overall structure of the model, which is described hereafter. We use packet-loss ratio as the degree of QoS degradation. To model this structure, we begin with two actualized traffic-demand time series measured at congested and uncongested links and de-

**Table 1** Notations. The subscript of link type $l$ is omitted in Sect. 4.

| | |
|---|---|
| $N$ | Number of time slots |
| $\Delta$ | Duration of time slot [s] |
| $\mathbf{T}_l = \{T_{l,t}\}_{t=1}^{N}$ | Actualized traffic time series of link type $l$ ($l = u$ indicates uncongested link and $l = c$ denotes congested link) |
| $\mathbf{L}_l = \{L_{l,t}\}_{t=1}^{N}$ | Packet-loss ratio time series of link type $l$ |
| $\{Y_t\}_{t=1}^{N}$ | Latent traffic demand pattern time series |
| $\alpha_l$ | Scale parameter of link type $l$ |
| $\gamma$ | QoS degradation effect parameter |
| $D_{c,t} := \alpha_c Y_t$ | Latent traffic demand time series at congested link |
| $v(t)$ | White noise of observation |
| $w(t)$ | White noise of latent state renewal |
| $T$ | Random variable representing actualized traffic deviation at congested link in time slot, the average of which is $T_{c,t}$ |
| $P(T)$ | Probability density function of $T$ |
| $\delta$ | Parameter that determines the variance of $T$ as $\delta T_t$ |
| $C$ | Capacity of congested link |

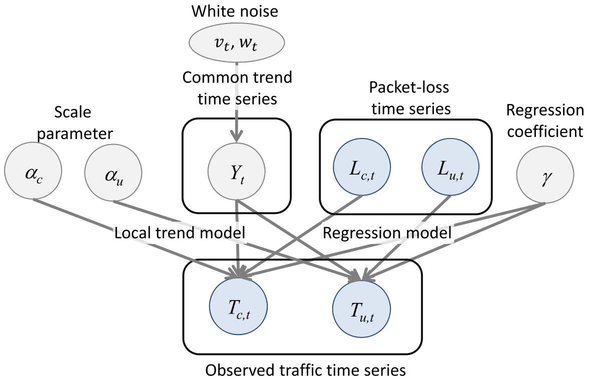

**Fig. 2** Common Trend and Regression with Independent Loss (CTRIL) model. Time series variables are grouped in rectangles. Blue circles are observed variables, and grey circles are unobserved variables and to be estimated.

noted as $\mathbf{T}_c = (T_{c,1}, \ldots, T_{c,N})$ and $\mathbf{T}_u = (T_{u,1}, \ldots, T_{u,N})$, respectively ($N$ is the number of measurement periods). Specifically, both $T_{u,t}$ and $T_{c,t}$ are traffic rates averaged during a measurement time bin $\Delta$ [s]. Thus, the total measurement duration is $N\Delta$ [s]. In the same manner, we denote the packet-loss-ratio time series on both congested and uncongested links as $L_{c,t}$ and $L_{u,t}$, respectively. We use $L_{c,t}$ and $L_{u,t}$ as exogenous time series in this section. As described above, the latent traffic demand for both $T_{c,t}$ and $T_{u,t}$ share a common diurnal pattern. Let $Y_t$ be the time series that represents the common diurnal pattern. We also introduce scale parameters $\alpha_c$ and $\alpha_u$ to express the difference between the diurnal pattern and actual traffic volumes for the congested and uncongested links, respectively. The scale parameters correspond to the number of users for the respective links. We then assume that the packet-loss ratio exponentially decreases actualized traffic from the latent traffic as follows:

$$T_{c,t} = \alpha_c Y_t \exp(-\gamma L_{c,t}) + v(t) \tag{1}$$

$$T_{u,t} = \alpha_u Y_t \exp(-\gamma L_{u,t}) + v(t), \tag{2}$$

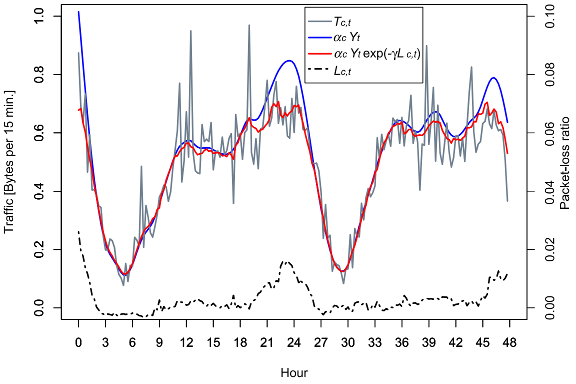

**Fig. 3** Modeling with CTRIL for overloaded and underloaded link traffic.

where $v(t)$ is white noise the average of which is zero, and $\gamma$ is a regression parameter and called the "QoS degradation effect parameter." This means $\gamma$ describes how much users or applications reduce actualized demand from latent traffic demand with a given degree of QoS degradation ($L_t$).

We define $D_{c,t} := \alpha_c Y_t$ as the latent traffic demand for a congested link, which coincides with the average $T_{c,t}$ if $L_{c,t}$ equals zero. To obtain the diurnal pattern, we adopt a local trend model for $Y_t$ that can be represented as follows [40]:

$$Y_t - Y_{t-1} = Y_{t-1} - Y_{t-2} + w(t), \tag{3}$$

where $w(t)$ is another type of white noise the average of which is zero. Then, by adopting a Bayesian inference method, such as the Markov chain Monte Carlo (MCMC) method, we can infer $Y_t$ as well as other parameters such as $\gamma$, $\alpha_{c,t}$, $\alpha_{u,t}$, and the variances of $v(t)$ and $w(t)$.

We now discuss our previous experimental results [1]. We used 48-hour-long data measured from August 2nd to 3rd, 2013 at congested and uncongested links. A link was defined as congested if its actualized traffic reached its capacity and showed a plateau during at least one hour. On the other hand, a link was defined as uncongested if its actualized traffic averaged in each time bin (15 minutes) did not reach its capacity. We selected such links and monitored their traffic. One time bin lasted 15 min; thus, the time series had 192 time bins. The physical bandwidths of the links were both 1 Gbps. Both links were aggregation links of Internet access in the same area. Their traffic was dominated by HTTP traffic, which consisted of 60 ∼ 70% of the total traffic depending on the time periods. A packet loss was detected as a re-order event of a TCP sequence number. Thus, we measured packet losses that occurred not only at the monitored links but at some points in the end-end path. To focus on packet losses occurring at the monitored link, we subtracted the mean value of packet losses at the uncongested link. We also extracted apparent outliers in the time series that did not seem to occur at the monitored links.

Figure 3 shows the results for the CTRIL model. The maximum likelihood estimate (MLE) of the regression coefficient ($\gamma$ in Eq. (2)) was 13.2. Thus, when packet-loss ratio is 1%, the CTRIL model predicted that traffic demand would decrease by 12.3% (= $1 - \exp(-0.01 \times 13.2) \times 100$).

## 4. Modeling Upper-Layer Congestion-Avoidance Mechanisms

In the previous section, we discussed the possibility that actualized traffic decreases due to QoS degradation and constructed the CTRIL model, which quantitatively relates QoS degradation and actualized traffic decrease. On the other hand, QoS degradation is mainly caused by actualized traffic increase. If we combine the two relationships, we can obtain a closed loop where actualized traffic increase causes QoS degradation, which in turn decreases actualized traffic. This closed loop can be considered as a congestion-avoidance mechanism that maintains QoS degradation to some extent, even though latent traffic increases. In this section, we first discuss the construction of a model for QoS degradation due to traffic increase and then its combination with the CTRIL model to construct a closed-loop model named ULCL, borrowing the idea of Low et al. [11], which involves modeling a TCP closed-loop control. We also show that we can predict the degree of QoS degradation and actualized traffic as an equilibrium given latent traffic demand.

Note that, because the CTRIL model infers latent traffic demand with observed actualized traffic volume and the degree of QoS degradation, by inversely adopting the CTRIL model, we can also infer the degree of QoS degradation with given latent traffic demand and actualized volume. In contrast, the ULCL model infers the degree of QoS degradation with given latent traffic demand and **link capacity**, not the actualized traffic volume, which is obtained as the equilibrium of the close-loop mechanism.

### 4.1 QoS-Degradation Model

There are many models for QoS degradation as a function of link load. These models have been studied in queuing theory. Specifically, the packet-loss ratio and delay are expressed by stochastically modeling the traffic-arrival process. However, these models mainly cover an average link load of under 100% and are difficult to apply to a congested link where the average link load is over 100%. We adopted the simple zero buffer approximation (ZBA) [41], which does not require an arrival process of actualized traffic and simply estimates the packet-loss ratio even with a congested link.

Hereafter, we use the packet-loss ratio and traffic of only the congested link and omit subscript $c$ from the variables. As described in Sect. 3, $T_t$ is the average traffic rate during $\Delta$ [s], and traffic rate $T$ deviates around $T_t$. Let $P(T)$ be the probability distribution function of $T$, which deviates around $T_t$. ZBA approximates $L_t$, the average packet-loss ratio during $\Delta$, as the probability that $T$ exceeds the link capacity $C$ [bps] as follows:

$$L_t = \int \max\left(\frac{T - C}{T}, 0\right) P(T)dT$$

$$= \int_C^\infty \left(1 - \frac{C}{T}\right) P(T)dT. \tag{4}$$

Because ZBA ignores the buffering effect, it overestimates packet-loss probability even if $P(T)$ is correct. On the other hand, if $P(T)$ underestimates the tail probability, it results in underestimation of the packet-loss probability. Because of the above two effects, the packet-loss ratio is not accurately estimated, as discussed in the next section. Constructing a more complex time-series model for the arrival process of traffic and finite buffer effect is for future work.

Because the marginal distribution of backbone traffic tends to obey a Gaussian distribution [42], which is parameterized with mean and variance, we adopted the Gaussian distribution $P(T)$. However, other probabilistic distributions can also be applied.

The average of $P(T)$ is provided as $T_t$ obtained through the CTRIL model. However, the variance is not provided with the CTRIL model and should be separately estimated. If the traffic-generation processes of flows comprising link traffic are independent, then the variation in link traffic is proportional to the average link traffic [43] and we can approximate the variation as $\sigma^2 = \delta T_t$ and adopt this approximation equation[†].

### 4.2 Derivation of Packet-Loss Ratio and Actualized Traffic as Equilibrium

Summarizing the previous subsection, we can approximate packet-loss ratio $L_t$ with ZBA and Gaussian distribution, whose mean and variance are denoted as $T_t$ and $\delta T_t$. At the same time, the CTRIL model provides the $T_t$ of Eq. (6). Thus, we have the following simultaneous equations on $L_t$ and $T_t$:

$$\begin{cases} L_t(T_t) = \\ \displaystyle\int_C^\infty \left(1 - \frac{C}{T}\right) \frac{1}{\sqrt{2\pi\delta T_t}} \exp\left(-\frac{(T - T_t)^2}{2\delta T_t}\right) dT & (5) \\ T_t(D_t, L_t) = D_t \exp(-\gamma L_t) & (6) \end{cases}$$

where $D_t := \alpha Y_t$ is the latent traffic demand at time $t$. Here, the Eq. (6) explicitly expresses $T_t$ as the function of $D_t$ and $L_t$ compared with Eq. (2).

We now discuss the existence and uniqueness of the solution for the above equations. First, if we set $L_t$ to two extremes, i.e., $L_t = 0$ and $L_t = 1$, in Eq. (6), then we have $T_t(D_t, 0) = D_t$ and $T_t(D_t, 1) = D_t \exp(-\gamma)$, respectively. On the other hand, for arbitrary $T_t$ including $D_t$ and $D_t \exp(-\gamma)$, $0 \leq L_t(T_t) \leq 1$ in Eq. (5) because $L_t(T_t)$ is the probability calculated as an integral of the normal distribution density function. Thus, from the intermediate value theorem, at least one solution exists for the equations for $T_t$ in the

[†] In fact, the traffic-generation process of flows might not be independent due to TCP congestion control, as noted in Sect. 2, TCP congestion control smooths actualized traffic, and variation would decrease compared with the average link traffic. Including the TCP congestion control effect on the variation of link traffic, such as [44], is for future work.

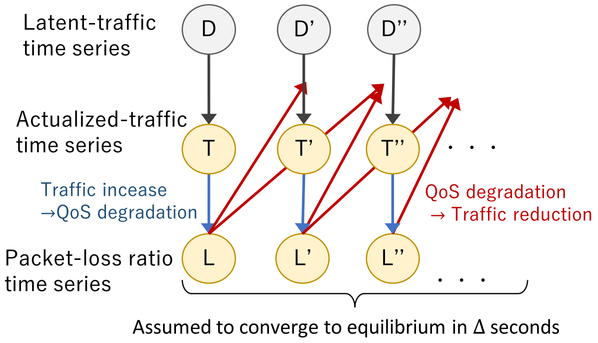
Latent-traffic time series
D
D'
D''
Actualized-traffic time series
T
T'
T''
. . .
Traffic incease →QoS degradation
QoS degradation → Traffic reduction
Packet-loss ratio time series
L
L'
L''
. . .
Assumed to converge to equilibrium in Δ seconds

**Fig. 4** Negative feedback between actualized traffic and QoS given latent traffic demand. Actualized traffic increase causes QoS degradation, and QoS degradation reduces actualized traffic from latent traffic demand.

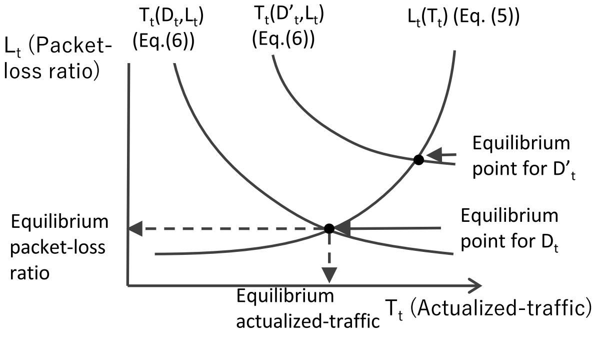
L_t (Packet-loss ratio)
T_t(D_t,L_t) (Eq.(6))
T_t(D'_t,L_t) (Eq.(6))
L_t(T_t) (Eq. (5))
Equilibrium point for D'_t
Equilibrium point for D_t
Equilibrium packet-loss ratio
Equilibrium actualized-traffic
T_t (Actualized-traffic)

**Fig. 5** Conceptual diagram of equilibrium of packet-loss ratio and actualized traffic given latent traffic demand.

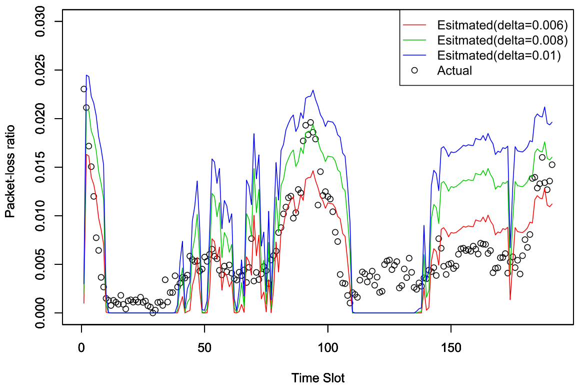

**Fig. 6** Estimation of packet-loss ratio with zero buffer approximation.

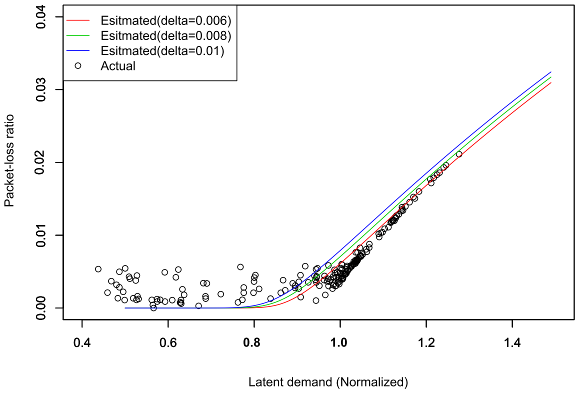

**Fig. 7** Packet-loss-ratio estimation as equilibrium of packet-loss ratio.

range $[D\exp(-\gamma), D]$ and for $L_t$ in the range $[0, 1]$. Because $T_t(D_t, L_t)$ is a non-increasing function on $L_t$ and $L_t(D_t)$ is a non-decreasing function on $D_t$, the solution is unique.

By solving Eqs. (5) and (6), we can obtain the solution of $L_t$ and actualized traffic $T_t$ given $D_t$. This solution is actualized as an equilibrium of the closed-loop of traffic increase → QoS degradation → traffic reduction. Whereas the effect of traffic increase → QoS degradation is actualized with the buffering time scale (buffer size divided by $C$), the effect of QoS degradation → traffic reduction is actualized with the time scale of user/application behavior. If we observe the loop with a larger time scale of both effects, then we can observe the equilibrium state of $L_t$ and $T_t$ (Fig. 4). Figure 5 shows the idea of the equilibrium of the negative feedback loop given $D_t$. The equilibrium varies over the curve $L_t(T_t)$ with varying $D_t$.

## 5. Experimental Analysis

We calculated the equilibrium of the ULCL model by using the data in Sect. 4. Because the variance in actualized traffic deviated 0.006 ~ 0.01 times the average actualized traffic rate, we approximated the variance with $\delta = 0.006 \sim 0.01$.

First, we evaluated the packet-loss-ratio estimation with ZBA. Figure 6 compares the actual packet-loss ratio of the congested link and estimated packet-loss ratio obtained from Eq. (5). Although we observed some discrepancies between the actual and estimated packet-loss ratios during slots 100 to 180, in other time slots, both packet-loss ratios agreed. Thus, we used Eq. (5) for estimating the packet-loss ratio.

Next we calculated the equilibrium-loss ratio by varying $D_t$. The $\gamma$ was set to 13.2, which was estimated in Sect. 3. Because Eqs. (5) and (6) of the ULCL model cannot be analytically solved, we solved them numerically with the semi-Newton method. As a comparison, we also plotted the actual packet-loss ratio with the estimated $D_t$. The $D_t$ was normalized with $C$. Figure 7 shows the results. We can see that when the normalized $D_t$ was under 1.0, there was a discrepancy, but when it is over 1.0, the actual and estimated packet-loss ratios agreed. This indicates that the observed packet-loss ratio can be obtained through the converged status of the closed-loop.

### 5.1 Equilibrium for Various QoS Degradation Effect Parameter Values

We analyzed simultaneous Eqs. (5) and (6) to derive the equilibrium-loss ratio and actualized traffic by varying $\gamma$ as well as when different $\gamma$ values are mixed. We used $\delta = 0.006$ to calculate actualized traffic variance[†].

[†] In this evaluation, we determined $\delta$ by using actual packet-loss data. Determining the parameter without such data remains as

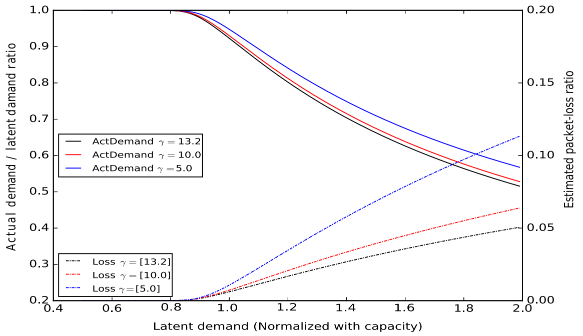

**Fig. 8** Actualized traffic and packet-loss ratio by varying QoS degradation effect parameter $\gamma$.

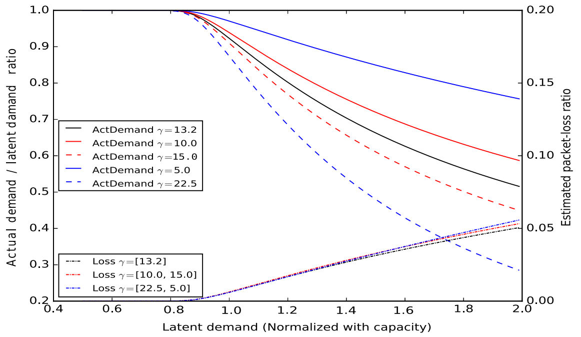

**Fig. 9** Equilibrium for heterogeneous QoS degradation effect.

Figure 8 shows the estimated packet-loss ratio when changing $\gamma$ to 10.0 and 5.0; other than 13.2. Latent traffic was changed from 0.4 to 2.0 times $C$. We also calculated the ratio of actualized traffic to $D_t$. When $D_t$ increased to twice of $C$, actualized traffic halves from $D_t$ as the packet-loss ratio increased to 0.05 ~ 0.11 with various $\gamma$ values. This is the closed-loop mechanism that reduces actualized traffic with the QoS degradation. As $\gamma$ decreases, which means that the QoS effect decreases, a higher packet-loss ratio is needed to decrease actualized traffic to $C$.

The $\gamma$ was estimated as 13.2 in Sect. 3, where dominant traffic is expected as video streaming, the application of which has various upper-layer closed-loop such as video bitrate control by server-side applications or user abandonment of video watching. However, if the dominant application is different and generates its traffic independently to the degree of QoS degradation, $\gamma$ becomes small and the actualized packet-loss ratio might increase, as shown in Fig. 8. We call such traffic QoS insensitive traffic. For example, machine generated traffic such as software updates or transferring sensing data is an example of QoS insensitive traffic, because even though the application-level QoS degrades depending on the (network-level) QoS degradation, the traffic generation patterns are relatively independent of QoS degradation. We analyze the effect of such traffic in the next subsection.

## 5.2 Equilibrium for Heterogeneous Traffic

Thus far, we have assumed that link traffic is homogeneous and $\gamma$ is the same for all traffic in the link traffic. However, users/applications in link traffic are heterogeneous, and parameter $\gamma$ might differ. We now derive the closed-loop and equilibrium for heterogeneous traffic. Assume that there are $n$ types of traffic, whose QoS degradation effect parameters are $\gamma_i, (i = 1 \dots n)$, and their latent traffic demands are $D_{i,t}, (i = 1 \dots n)$. Packet-loss ratio can be assumed to be the same for all traffic types (e.g., $L_{i,t} = L_t$ for all $i$) if two conditions are met: 1) The congested link does not adopt a queuing control that differently processes packets depending on their traffic type (e.g., the queue is a simple FIFO), and 2) there is no dominant traffic type whose connections generate their traffic in a synchronized manner and cause congestion at the same time (traffic time series and packet loss time series are independent) [46]. Those assumptions are expected to be met at a backbone link that handles a relatively large number of connections. In that case, actualized traffic for traffic type $i$ can be expressed as follows:

$$T_{i,t}(L_t, D_{i,t}) = D_{i,t}(1 - \exp(-\gamma L_t)). \tag{7}$$

Thus, the probability distribution of the traffic sum can be identified as the distribution whose mean and variance of Eq. (5) are replaced with $\sum_{i=1}^{n} T_{i,t}(L_t, D_i)$ and $\delta \sum_{i=1}^{n} T_{i,t}(L_t, D_i)$, respectively. Thus, the equilibrium can also be calculated.

We now discuss the results of the numerical evaluation for the heterogeneous-traffic case. Let there be two types of traffic whose mix ratios are 50%. We considered three cases: those in which the QoS degradation effects are (13.2, 13.2), (10.0, 15.0), and (5.0, 22.5). We calculated the equilibrium packet-loss ratio and actualized traffic ratio $T_{i,t}/D_t$, where $D_t$ varied from 0.4 to 2.0. The results are shown in Fig. 9. Whereas the equilibrium packet-loss ratios were almost the same for all cases, the actualized traffic ratios significantly differed. That is, when the difference between $\gamma$s was large, then actualized traffic ratios was also large.

Therefore, as previously described, if machine-generated traffic increases, then QoS-sensitive traffic ratio severely decreases due to QoS degradation. For congestion avoidance mechanisms, fairness among traffic types is a key index to be achieved [8]. In terms of the congestion avoidance mechanism modeled in this paper, which reduces traffic volume during congestion, one possible definition of fairness is the difference among the ratios of actualized traffic to latent traffic (i.e., if all traffic types reduce their traffic with the same ratio, then the mechanism is fair). With simultaneous Eqs. (5) and (6) mentioned in Sect. 4.2, we can quantitatively calculate the above ratios for all traffic types and calculate the difference among the traffic types. By using the calculated fairness index, we can evaluate the necessity of a congestion-control mechanism other than the end-end user/application-level feedback mechanism.

future work, but as shown in Fig. 7, the equilibrium state is rather insensitive to $\delta$ and we might use a larger values of $\delta$ for safe-side evaluation.

## 6. Applications and Implications

For network operators, the ULCL model can predict the degree of QoS degradation and the actualized traffic with the given volume of latent traffic demand and link capacity even if the volume is persistently larger than the capacity. Although it should be avoided, traffic is occasionally routed to a link whose capacity is below the volume of the traffic. Our ULCL model can be used to predict the users' or applications' impact on the basis of the degree of QoS degradation and traffic reduction from the latent traffic.

Our model can be used by network researchers to assess the necessity of transport or lower-layer congestion control. Specifically, current congestion controls are evaluated in terms of their stability, efficiency, and fairness. However, our model derives a new aspect of fairness: not only actualized flow rate (throughput) but also how much the flow decreases the volume of traffic from the latent demand. Our model has a sensitivity parameter to determine how the upper layer reduces traffic volume in reaction to QoS degradation. If users or applications have different sensitivity parameters, then we might have to evaluate the fairness among flows during congestion with the given parameters as presented in Sect. 5.2.

In addition, the above fairness should be predicted in advance for the case when the application mix changes, e.g., machine generated traffic such as IoT traffic will increase. Although there are debates on which state is fair [47], to assess fairness, this upper-layer mechanism should be taken into account because even when fairness at the transport layer is achieved and the state is achieved by sacrificing some users/applications to reduce traffic as a reaction to QoS degradation, it cannot be considered as fair from the user/application point of view.

## 7. Conclusion

We discussed the possibility of viewing upper-layer reaction to quality of service (QoS) degradation as a congestion-avoidance mechanism and constructed a closed-loop model, named Upper-Layer Closed-Loop (ULCL), that links traffic volume to the degree of QoS degradation and vice versa. By using our model, we can predict the packet-loss ratio and actualized traffic given latent traffic demand by considering the actualized traffic ratio as service impact due to QoS degradation of user/application.

This paper is just a preliminary study, and just one series of data was evaluated. Thus, the universality and applicability of our model and its parameters should be evaluated with various types of data. Specifically, though $\gamma$ is estimated as 13.2 with the measured data, the value depends on the data. To apply our ULCL model to other data whose application mix is different, we need to have $\gamma$s for every application and take their weighted sum. To do this, we need do have traffic data that can be separated for each application such as Deep Packet Inspection (DPI) data. In addition, an effort should be made to estimate $\gamma$ from user engagement models that describe how much user communication behavior will change depending on the degree of QoS [30]–[32].

Our model also has much room for improvement, as in estimating the degree QoS degradation as a function of input traffic. A more sophisticated time series model should be applied to ULCL.

In modeling the upper-layer reaction, we assume that the time scale differs from those of other congestion-avoidance mechanisms. However, in reality, there should be overlapping among time scales and behaviors should be interdependent; thus, those mechanism should be integrated [45]. We believe that by combining upper-layer congestion-avoidance mechanisms with current congestion control such as the Transmission Control Protocol (TCP), we will provide a comprehensive view of Internet traffic congestion-avoidance mechanisms that explains why congestion collapse is avoided even in persistent congestion links.

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**Shigeaki Harada** received his B.S., M.S., and Ph.D. in information science from Tohoku University in 2001, 2003, and 2006. Since joining NTT Network Technology Laboratories (formerly NTT Service Integration Laboratories) in 2006, he has been engaged in research on traffic analysis and traffic control in IP networks. He is a member of IEICE.

**Keisuke Ishibashi** received his B.S. and M.S. in mathematics from Tohoku University in 1993 and 1995 and his Ph.D. in information science and technology from the University of Tokyo in 2005. From 1995 to 2018, he worked at NTT Laboratories, where he was involved in research on the measurement and analysis of Internet traffic and performance. He is currently an associate professor of information science at the International Christian University. He is a member of IEICE, IEEE, and the Japan Society for Software Science and Technology. He received Best Paper Awards from IEICE in 2019.

**Ryoichi Kawahara** received his M.E. in automatic control and his Ph.D. in telecommunication engineering from Waseda University, Tokyo, Japan, in 1992 and 2001. He joined NTT Laboratories in 1992, and was engaged in research on traffic control for telecommunication networks, traffic measurement and analysis for IP networks, and network management, for 26 years. He is currently a professor at the Department of Information Networking for Innovation and Design, Faculty of Information Networking for Innovation and Design, Toyo University. He is a member of IEICE, IEEE, and ORSJ. He received Telecom System Technology Award from The Telecommunications Advancement Foundation in 2010 and Best Paper Awards from IEICE in 2003 and 2009.