Offered Load Estimation in a Multimedia Cable Network System*

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ABSTRACT: *In this paper, the problem of traffic load estimation in a shared-medium contention-based network is investigated and applied to a hybrid fiber coaxial (HFC) cable network. In particular, an estimator that utilizes channel feedback to estimate network traffic load is presented. The performance of this estimator is investigated and is enhanced by introducing modifications which provide for a better reaction to load variations.*

1: INTRODUCTION

Contention-based media access control (MAC) protocols for shared-medium networks have been studied extensively in the past and have been deployed in a variety of wireless and wire-line networking environments [2]. An integral part of such protocols is a collision resolution algorithm (CRA), which specifies the behavior of the distributed network users based on feedback information that is available to them via the common channel. The users can detect the state of the common channel, or a centralized network entity can communicate that state to them. Depending on the type of channel states (or channel feedback) that is available, different CRAs may be employed to resolve collisions.

While the problem of designing effective CRAs has received considerable attention in the past two decades, little effort has been directed towards dynamic estimation of the load of network traffic, which can be valuable to the efficient operation of a CRA and overall management of networking resources. Although the distributed users do not communicate their traffic load individually, some information regarding the cumulative traffic of the users can be obtained by processing the shared channel state (or feedback). Since the channel state is shaped by the network traffic load, an estimate of the load could be obtained by processing the channel feedback. A common type of feedback is ternary feedback, indicating whether a (fixed-size) slot is involved in a collision, a successful transmission or is idle.

The problem of traffic load estimation in a multiple access environment has been considered in [3] and [4]. In [3], a method is proposed to estimate the offered load in slotted dynamic frame length ALOHA, where data – as opposed to requests – is directly used for contention. The expected number of users contending in a slot with a collision is computed, given that the throughput is (1/e), which is the maximum throughput slotted ALOHA. An estimated value of the load is then derived from this number. In [4], an approach is proposed to estimate the number of backlogged stations. It uses ternary feedback and Bayes' rule for the estimation. Each backlogged station transmits its packet with a probability based on this estimate.

A hybrid fiber-coaxial (HFC) cable network has a tree and branch topology [5], where the root is the cable television (CATV) headend and the leaves represent the cable modems (CMs). The transmission medium consists of a downstream broadcast channel and an upstream multi-access channel that utilizes a MAC protocol to coordinate channel access. Both channels are controlled by the headend. In [6], a control strategy is proposed for a CATV network in which upstream channel access utilizes a distributed ALOHA protocol, and the headend uses a separate contention-free channel for sending acknowledgment of correctly received packets and other dynamic control parameters. In the strategy, data offered load is estimated as a negated natural logarithm of the measured fraction of time during which the upstream channel is idle. This estimate is used for dynamically adjusting the maximum waiting time for retransmission of a collided packet. With the emerging two-way CATV standards, where upstream bandwidth allocation is centrally controlled by the headend, the above strategy is no longer applicable.

As the fraction of users that are simultaneously busy on an HFC cable network is typically small, contention-based reservation protocols are particularly suitable for upstream channel allocation. Each backlogged user, which has not already made a reservation for upstream bandwidth, waits for contention opportunities provided by the headend. In a generic contention-based reservation protocol for HFC cable networks, each contention opportunity allows a group of users to contend for upstream bandwidth reservation at a specific time with request packets. Following each contention opportunity, the headend monitors for contention and determines its outcome, specifically whether no user, one user or more than one users transmitted. Due to the tree topology and other physical constraints, the users cannot detect contention outcome directly. The headend must inform

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them of the contention outcome, so that it can be utilized by them to execute a CRA.

The headend schedules future contention opportunities and data transmission opportunities based on, among other elements, the result of the contention-based reservation. If a successful reservation was made by a user, the headend allocates bandwidth to the user based on its quality of service (QoS) requirements, so that it can transmit user information upstream contention-free over the shared upstream channel. If multiple users responded, the headend attempts to resolve the collision by providing additional contention opportunities.

In this paper, the problem of traffic load estimation is considered for an HFC cable network employing a MAC protocol as described in the Data-Over-Cable Interface Specifications (DOCSIS) [7], an overview of which is provided in section 2. A simple traffic load estimation method is derived in section 3.1 by using channel feedback statistics collected over one CRA activity cycle. Channel feedback statistics collected over multiple CRA activity cycles are employed in section 3.2 where a potentially more accurate estimate is derived by properly processing a larger collection of statistics.

2: THE DOCSIS MAC PROTOCOL

The DOCSIS MAC protocol is specified by a consortium of cable operators, known as the Multimedia Cable Network System (MCNS) [7]. The upstream channel is modeled as a stream of mini-slots. The headend, referred to as a cable modem termination system (CMTS), allocates upstream bandwidth to a group of CMs by transmitting downstream a control message containing an information element known as a MAP. Each MAP specifies the allocation of transmission opportunities in a group of contiguous mini-slots in the upstream channel within a given transmission frame. Specifically, a MAP specifies various transmission intervals for maintenance, request, and data packets respectively (see Fig. 1). Additionally, each MAP contains other control information that is necessary for the operation of the system.

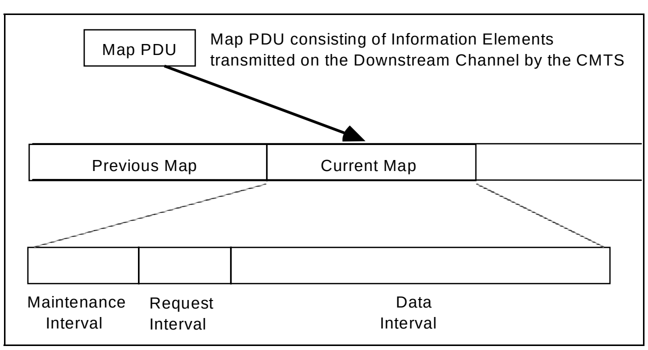

Fig. 1: Allocation MAP mechanism in MCNS

Contention resolution is based on a truncated binary exponential backoff strategy, characterized by a starting backoff window and an ending backoff window. The CMTS conveys the sizes of these backoff windows to the CMs via MAPs. In this paper, we assume that the starting backoff window size is set to the quasi-static (see Section 3) number of available contention opportunities in the MAP, and the size of the ending backoff window is set to twice the size of the starting backoff window. When a CM wants to transmit a request packet for the first time, it sets its backoff window to the starting backoff window, and randomly selects a transmission opportunity within this window to transmit its request packet. The CM then waits for feedback from the CMTS, in the form of either a data grant or an acknowledgment in the next MAP. If either is received, the transmission is considered successful, and the contention resolution procedure is complete. Otherwise, the transmission is considered unsuccessful, and the CM doubles its backoff window as long as it is less than the ending backoff window. The CM subsequently repeats the same procedure. Note that although ternary feedback may be available, each CM only makes use of binary feedback (i.e., success versus failure) for collision resolution.

Fig. 2 shows a realization of request arrivals occurring over a given time horizon and how MAP frames (k-1) and k are used to allocate this time horizon to contention intervals (M_{k-1} and M_k), maintenance intervals (F_{k-1} and F_k) and data intervals (W_{k-1} and W_k), all in mini-slots. T_k denotes the size of MAP frame k in mini-slots. The DOCSIS MAC protocol provides CMs with gated access to the upstream channel, wherein, only requests which arrived prior to a contention interval are eligible for transmission in the contention interval.

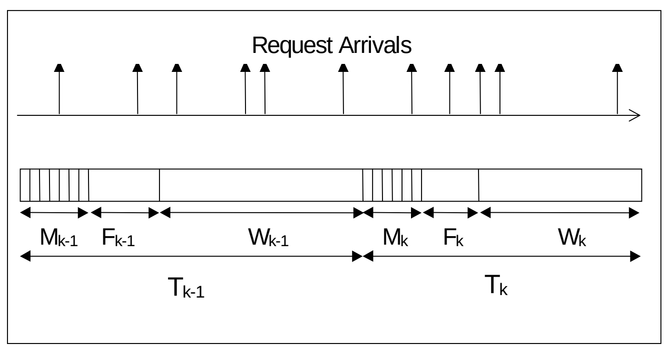

Fig. 2: MAP parameters on the upstream channel time axis

The inter-arrival time of requests for upstream bandwidth reservation is assumed to follow a general distribution with a positive and finite mean. The multiplicative inverse of this mean defines the offered load, which is the average number of request arrivals per upstream mini-slot. Note that this offered load accounts for first attempt arrivals as well as retransmissions due to previously collided requests. In practice, the variation of the offered load during a MAP frame is quasi-static, i.e., very small and negligible. Various functions for upstream bandwidth management require the knowledge of the system offered load for dynamic operations. Since such information is typically not provided to the CMTS, it could be estimated dynamically based on available real-time information, such as contention outcome.

3: OFFERED LOAD ESTIMATION SCHEMES

Let R represent the number of mini-slots needed to transmit a request packet. Let $N_k = M_k/R$. N_k be the number of contention opportunities available in MAP frame k. Although N_k is practically selected to be an integer, it is considered here to be a real number for simplicity. Since the service mechanism is gated, all the new requests that arrive during MAP frame (k-1) will be transmitted during the contention interval of MAP frame k. It is assumed in our model that ternary feedback is available.

3.1: Derivation of an offered load estimate based on a single MAP frame

Let g_k denote the offered load associated with MAP frame k. Let G_k denote the effective offered load during the contention interval of MAP frame k, defined to be the average number of requests pending transmission in frame k, divided by the number of contention opportunities available in the contention interval of frame k. Assuming that the number of retransmitted requests competing for contention opportunities available in a MAP frame is negligibly small compared to the number of new requests competing for the same contention opportunities, G_k can be viewed as the average number of request arrivals per contention opportunity in MAP frame k. Since the average number of request arrivals during MAP frame (k-1) is $g_{k-1} \times T_{k-1}$, we obtain

$$G_k = \frac{g_{k-1} \times T_{k-1}}{M_k / R} = \frac{g_{k-1} \times T_{k-1} \times R}{M_k} \qquad (1)$$

Let Y_k be a random variable denoting the number of request arrivals in a contention opportunity of MAP frame k. Since Y_k is generated by randomizing the accumulated requests over an interval of length N_k, its distribution will converge to a Poisson distribution for sufficiently large N_k. Thus,

$$P[Y_k = i] = \frac{G_k{}^i \times \exp\{-G_k\}}{i!} \qquad (2)$$

and consequently,

$$\begin{aligned} P[Y_k = 0] &= \exp(-G_k) = P[Idle] \equiv p_k^I \\ P[Y_k = 1] &= G_k \times \exp(-G_k) = P[Success] \equiv p_k^S \qquad (3) \\ P[Y_k > 1] &= 1 - G_k \times \exp(-G_k) - \exp(-G_k) = P[Coll] \equiv p_k^C \end{aligned}$$

Let E_k^I, E_k^S and E_k^C, denote respectively the expected number of contention opportunities resulting in idles, successes, and collisions in MAP frame k. Clearly,

$$E_k^I = N_k \times p_k^I \;,\; E_k^S = N_k \times p_k^S \;,\; E_k^C = N_k \times p_k^C \qquad (4)$$

Let I_k^1, S_k^1 and C_k^1, denote respectively the measured number of contention opportunities, in MAP frame k, which resulted in idles, successes, and collisions. I_k^1, S_k^1 and C_k^1, may be viewed as the 'time averages' of the quantities whose expected values are given by E_k^I, E_k^S and E_k^C, respectively.

Proposition 1:

For sufficiently large N_k, the offered load g_{k-1} can be estimated from $\hat{g}_{k-1}^1$, where,

$$\hat{g}_{k-1}^1 \equiv \frac{M_k}{R \times T_{k-1}} \times \ln\left[\frac{M_k}{R \times I_k^1}\right] = \frac{N_k}{T_{k-1}} \times \ln\left[\frac{N_k}{I_k^1}\right] \qquad (5)$$

Proof:

Assuming ergodicity conditions, and for sufficiently long time averaging (that is, sufficiently large value of N_k), ensemble averages may be accurately estimated by time averages. Thus,

$$E_k^I \cong I_k^1 \Leftrightarrow p_k^I \times N_k \cong I_k^1 \Leftrightarrow \exp(-G_k) \times N_k \cong I_k^1 \qquad (6)$$

By substituting for G_k from (1), and solving for $\hat{g}_{k-1}^1$, we obtain (5), which is a reasonable estimate for $\hat{g}_{k-1}$.

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Note that the expression for $\hat{g}_{k-1}^1$ has been derived in terms of I_k^1 but not S_k^1 and C_k^1, in which cases numerical computation would have been necessary.

3.2: Offered load estimation based on a window of MAP frames

As the number of contention opportunities in a MAP frame is typically not large enough to provide for an accurate estimate of g_{k-1}, a more accurate estimate could be obtained by increasing the time averaging interval to include a number n of contention intervals associated with n consecutive MAP frames. This set (or window) of consecutive MAP frames will be referred to henceforth as a sample window.

3.2.1: Derivation of an offered load estimate based on a window of *n* MAP frames

Let l denote the index of the l^{th} MAP frame in the sample window of size n. Let I_l^1, S_l^1, C_l^1, denote the measured number of contention opportunities in MAP frame l, with idles, successes, and collisions respectively. Let I^n, S^n, C^n denote the measured number of contention opportunities in the size n sample window, with idles, successes and collisions respectively. Then,

$$I^n = \sum_{l=1}^{n} I_l^1 \ , \quad S^n = \sum_{l=1}^{n} S_l^1 \ , \quad C^n = \sum_{l=1}^{n} C_l^1 \qquad (7)$$

As the offered load is quasi-static, we simply assume that, over the sample window of size n, $g = g_0 = g_1 = \ldots = g_{n-1}$.

Proposition 2:

The offered load g can be estimated as follows, from $\hat{g}^n$ in terms of the measured quantity I^n and known system parameters, from the following functional relation:

$$I^n = \sum_{l=1}^{n} (M_l / R) \times \exp\left[-\frac{\hat{g}^n \times T_{l-1} \times R}{M_l}\right] \qquad (8)$$

or $\quad g \cong \hat{g}^n \equiv f(I^n), \qquad I^n > 0$

where $f(.)$ represents the solution of equation (8).

Proof:

Assuming ergodicity conditions, and for sufficiently large time averaging (that is value of $\sum_{l=1}^{n}(M_l / R)$), ensemble averages may be accurately approximated by time averages.

Thus, $\quad \sum_{l=1}^{n} E_l^I \cong \sum_{l=1}^{n} I_l^1 = I^n$

or, $\quad I^n \cong \sum_{l=1}^{n} p_l^I \times \frac{M_l}{R} = \sum_{l=1}^{n} \exp(-G_l) \times \frac{M_l}{R}$

Substituting G_l in terms of g_l, the following is obtained.

$$I^n \cong \sum_{l=1}^{n} (M_l / R) \times \exp\left[-\frac{g_{l-1} \times T_{l-1} \times R}{M_l}\right] \qquad (9)$$

Since $g = g_0 = g_1 = \ldots = g_{n-1}$, the right hand side of (9) results in an estimate for g, denoted by $\hat{g}^n$, by solving the functional relation of (8).

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In a typical HFC cable network, the offered load over a sample window of approximately 16 MAP frames (equivalent to a time interval of 80 milliseconds), can be considered as practically constant.

It is computationally involved to obtain an expression for the function $f(.)$. We thus resort to the following alternate expression for the function $f(.)$ in terms of I^n, M_{eff} and T_{eff} , where M_{eff} and T_{eff} are defined as the effective values of the request contention interval size and the MAP size respectively, satisfying the following relationship.

$$\sum_{l=1}^{n} (M_l / R) \times \exp\left[-\frac{\hat{g}^n \times T_{l-1} \times R}{M_l}\right] = n \times (M_{eff} / R) \times \exp\left[-\frac{\hat{g}^n \times T_{eff} \times R}{M_{eff}}\right] \qquad (10)$$

It follows that

$$\hat{g}^n = \frac{M_{eff}}{T_{eff} \times R} \times \ln\left[\frac{n \times M_{eff}}{R \times I^n}\right] = f(I^n, M_{eff}, T_{eff}) \qquad (11)$$

Note that solving for $\hat{g}^n$ requires an exact value of a pair (M_{eff}, T_{eff}) satisfing equation (10) be known. As the determination of such a pair is computationally involved, we resort to an approximation. Since the variation of g is small over the sample window, the variations in M_k and T_k can be assumed to be small. Thus, it is reasonable to use, as approximate values for M_{eff} and T_{eff}, simple average values M_{avg} and T_{avg} of M_k and T_k, respectively, over the sample window. M_{avg} and T_{avg} may be defined as the measured mean values of the associated quantities over the sample window. As explained in the next section, a different type of average capturing the relative importance of the various past samples may also be used. By employing the approximations $T_{eff} \cong T_{avg}$ and $M_{eff} \cong M_{avg}$, and substituting M_{avg} and T_{avg} into equation (11), we obtain

$$\hat{g}^n = \frac{M_{avg}}{T_{avg} \times R} \times \ln\left[\frac{n \times M_{avg}}{R \times I^n}\right] = f(I^n, M_{avg}, T_{avg}) \cong \hat{g}'^n \qquad (12)$$

3.2.1: Discussion on the estimation mechanism

In addition to the size of the sample window considered, another factor impacting on the accuracy of the estimate is that of the sampling mechanism itself. The sampling mechanism specifies the frequency of the estimation process as well as the set of the n samples considered each time. One possible sampling mechanism generates an estimate every n MAPs based on the n most recent MAPs (equally weighted). Another sampling mechanism generates an estimate every MAP based on the n most recent MAPs (equally weighted) through a sliding window averaging process.

The first mechanism considers consecutive disjoint sample windows each of size n, and updates the estimation at the end of each window. This approach is ineffective, and can lead to oscillations of the estimate around the actual offered load. To understand the reason for this, consider the following scenario. Assume that at the end of some sample window j, the offered load is under-estimated. This would eventually result in the CMTS setting the size of all the contention intervals in the next sample window (j+1) to a value smaller than it should be. It would lead to collisions in MAP frame 1 of window (j+1), and due to retransmissions, it would consequently lead to increased collisions in the entire window (j+1). A big jump in the estimated value will be created, leading to an over-estimation. Similarly, this over-estimation yields contention interval sizes in sample window (j+2) larger than they should be, leading to an under-estimation. As the cycle continues, the estimated offered load fluctuates around the actual offered load. The first plot in each of Figs. 3 and 4 illustrates the above discussion. It can be seen that the magnitude of the peak-to-peak oscillations is significant, causing a maximum estimation error as high as 250% and an average error of 40%.

The effect of oscillations can be reduced by employing a sliding window averaging mechanism. Instead of updating the estimation at the end of each sample window, the sample window is slid and the estimate is updated each time a new MAP is generated. Simulation results (see plot 2 in each of Figs. 3 and 4) confirm that this mechanism outperforms the previous one. The average estimation error is reduced from 40% to 20%. Unfortunately, the oscillations remain significant for the following reason. If at the end of MAP frame *k*, the offered load is under-estimated, the size of the contention interval in MAP frame (*k*+1) will be smaller than it should be, leading to more collisions. Since the size of the sample window can be as large as 16, the effect of the higher probability of collision in MAP frame (*k*+1) can be minimal, leading to a very minimal increase in the estimated value, which remains an under-estimation. This under-estimation will cause more collisions in MAP frame (*k*+2). During this process, the actual offered load is, due to retransmissions, increasing faster than the estimated value. After several MAP frames, the sample window will start including more and more of those MAP frames with a very large number of collisions, until the estimated offered load exceeds the actual offered load. It will take much time for the estimated value to subside, for the same reason as above. As the cycle continues, varying from over-estimation to under-estimation, there could be more oscillations.

The problem seems to originate from a slow estimator response. Had the sample window size been smaller, this problem wouldn't have existed. However, reducing the size of the sample window implies a smaller number of samples, and hence degrading the accuracy of the estimator. The bottom line is that enough samples are needed while a fast estimator response is desirable. A remedy to this problem is to assign a larger weight to the most recent samples of the sample window and a smaller weight to earlier samples. This scheme is discussed in the next section.

3.2.3: Derivation of an offered load estimate based on a window of weighted MAP frames

Let *l* denote the index of the l^{th} MAP frame in a sample window of size *n*; *l*=1 corresponds to the earliest MAP. Let a generic integral function $\omega(l)$ represent the weight associated with the l^{th} MAP frame. $\omega(l)$ is defined to be a non-decreasing function of *l*. In Section 3.2.1, a constant uniform weight (equal to 1) has been used for all the MAPs in the sample window, that is, $\omega(l) = 1,\ 1 \le l \le n$. Extending equations (7), (8) and (11) to reflect the MAPs weighting mechanism, the following equations are obtained.

$$I_\omega^n = \sum_{l=1}^{n} \omega(l) \times I_l^1 ,$$

$$I_\omega^n = \sum_{l=1}^{n} \omega(l) \times (M_l / R) \times \exp\left[-\frac{\hat{g}^n \times T_{l-1} \times R}{M_l} \right]$$

$$I_\omega^n = \sum_{l=1}^{n} \omega(l) \times (M_{eff} / R) \times \exp\left[-\frac{\hat{g}^n \times T_{eff} \times R}{M_{eff}} \right] \qquad (13)$$

Then, the function $f_\omega(.)$ that determines the estimated offered load $\hat{g}_w^n$ in terms of the known quantities I_ω^n, M_{eff}, T_{eff} and the weighting function $\omega(l)$, can be expressed as follows.

$$\hat{g}_w^n = f_\omega(I_\omega^n, M_{eff}, T_{eff}) = \frac{M_{eff}}{T_{eff} \times R} \times \ln\left[\frac{\sum_{l=1}^{n} \omega(l) \times M_{eff}}{R \times I_\omega^n} \right] ,$$

$$I_\omega^n > 0 \qquad (14)$$

Since the determination of a pair (M_{eff}, T_{eff}) satisfying equation (14) is computationally involved, it is desirable to find approximate values for M_{eff} and T_{eff}. By following similar thinking as before, they can be respectively approximated by M_{wavg} and T_{wavg} , which are based on the same averaging operator as that of the samples themselves. Thus, let M_{wavg} be the weighted average number of contention opportunities per MAP frame over a sample window of size *n*. That is,

$$M_{wavg} = \left(\sum_{l=1}^{n} \omega(I) \times M_l \right) \left(\sum_{l=1}^{n} \omega(I) \right)^{-1} \qquad (15)$$

and T_{avg} be the average MAP frame size over a sample window of size *n*. That is,

$$T_{wavg} = \left(\sum_{l=1}^{n} \omega(I) \times T_{l-1} \right) \left(\sum_{l=1}^{n} \omega(I) \right)^{-1} \qquad (16)$$

Making the approximations $T_{eff} \cong T_{wavg}$, $M_{eff} \cong M_{wavg}$, and substituting M_{wavg} and T_{wavg} into equation (14), the following expression for $\hat{g}'^n$ is obtained, where $\hat{g}'^n_w$ is a simple approximation of $\hat{g}_w^n$.

$$\hat{g}_w^n \cong \hat{g}'^n_w = f(I_\omega^n, M_{wavg}, T_{wavg})$$

$$= \frac{M_{wavg}}{T_{wavg} \times R} \times \ln\left[\frac{\sum_{l=1}^{n} \omega(l) \times M_{wavg}}{R \times I_\omega^n} \right] \qquad (17)$$

Note that any weighting function $\omega(l)$ may be considered as long as it is a non-decreasing function of l. The following function has been verified empirically to work well.

$$\omega(l) = \begin{cases} \beta, & \text{for } 1 \le l \le n\text{-}x\text{-}2 \\ \alpha, & \text{for } n\text{-}x+1 \le l \le n \end{cases} \qquad (?)$$

where $\alpha > \beta$ and $x \geq 1$. This weighting function assigns a certain weight α to the last x sample MAP frames: (n-x), (n-x+1) , ... , (n), and a weight β to earlier samples, with $\alpha > \beta$. Simulation results showed that this function can potentially provide effectively faster response in the estimator, given appropriate values of α, β and x, and it helps to reduce oscillations while keeping the number of samples large enough to guarantee accurate estimation.

For a given value of x, if α/β is too small, then the slow response problem may arise. If α/β is too large, then the inaccuracy problem may arise, because it is as if only the last x sample MAP frames are considered. As to the choice of x, a large value would again yield a bad performance in terms of fast response because the x samples still carry considerable memory from the past. Simulation results (see plot 3 in each of Figs. 3 and 4) show that the best estimation performance is achieved by choosing x to be around 3 or 4, and setting α and β, such that the weight assigned to the last 3 or 4 samples constitutes about 40% of the total weight of the MAPs sample window. As β can be arbitrarily set to 1, it follows that

$$\frac{x \times \alpha}{x \times \alpha + (n-x) \times \beta} = \frac{x \times \alpha}{x \times \alpha + (n-x)} \cong 0.4 \ .$$

This can be intuitively explained as follows. Recall that the starting backoff window size is not to exceed N_k and the ending backoff window size is not to exceed ($2 \times N_k$). Therefore, the retransmissions of collided requests in MAP frame (n-2) will all show, with a high probability, in MAP frames (n-1) and n. For the same reason, the effect of collisions in MAP frames prior to (n-2) is minimal in MAP frame n. To put it in a nutshell, when estimating the offered load at the beginning of MAP frame (n+1), it is desirable to give a larger weight to the x previous MAP frames which affect MAP frame (n+1) most. Due to the selected backoff window sizes, as described before, this value of x is approximately 3.

4: CONCLUSION

In this paper, a mechanism has been developed for estimating the offered load in an HFC cable network utilizing the DOCSIS MAC protocol with contention-based reservation. An offered load estimate is derived based on contention feedback over a time interval corresponding to a single MAP frame. Since the length of a single MAP frame may not be large enough to allow for the derivation of a good estimate, an offered load estimate based on observations over multiple consecutive MAP frames is then derived. While a large number of observations (samples) can potentially result in a more accurate estimation, this may not be the case when observations are spread over a large time horizon and the estimated quantity is time-varying. In such cases, more recent observations may reflect the current value of the estimated quantity more accurately. A more accurate estimate may be derived by assigning different weights to different samples. The performance of the offered load estimation techniques presented in this paper has been verified through extensive simulation studies using the Common Simulation Framework (CSF) Opnet models[i].

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[i] Opnet is a trademark of MIL3 Inc. CSF has been developed by CableLabs and MIL3 Inc.

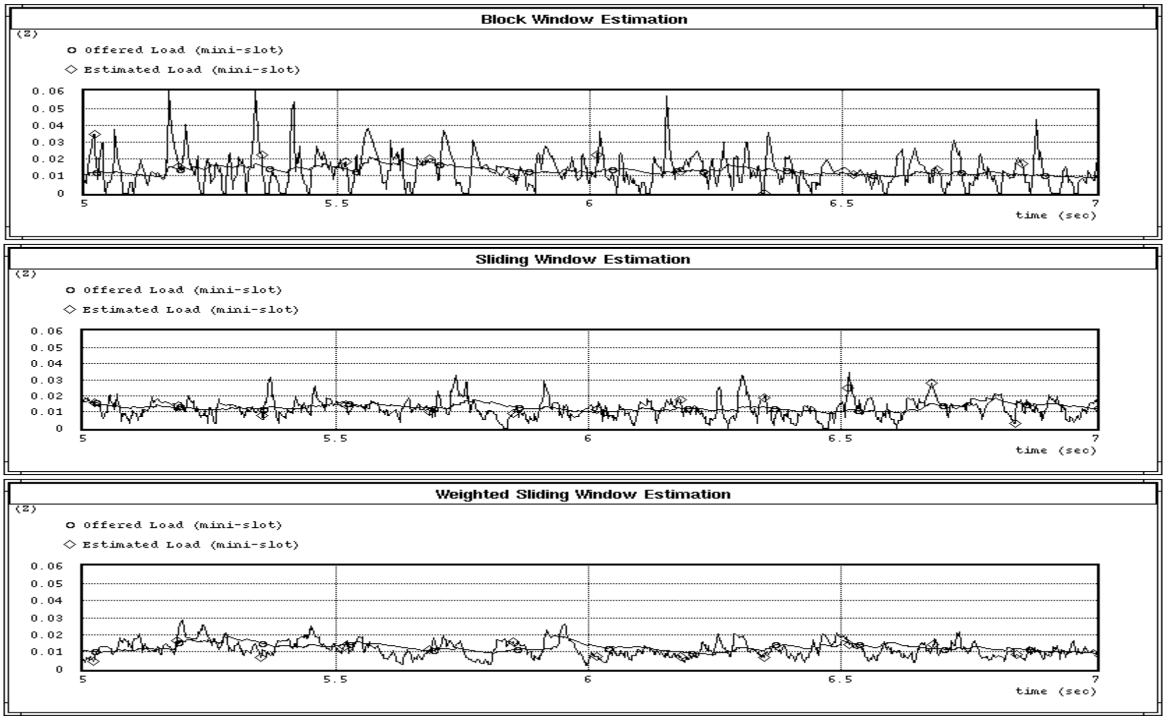

Fig. 3: Estimators comparison for the different estimation mechanisms

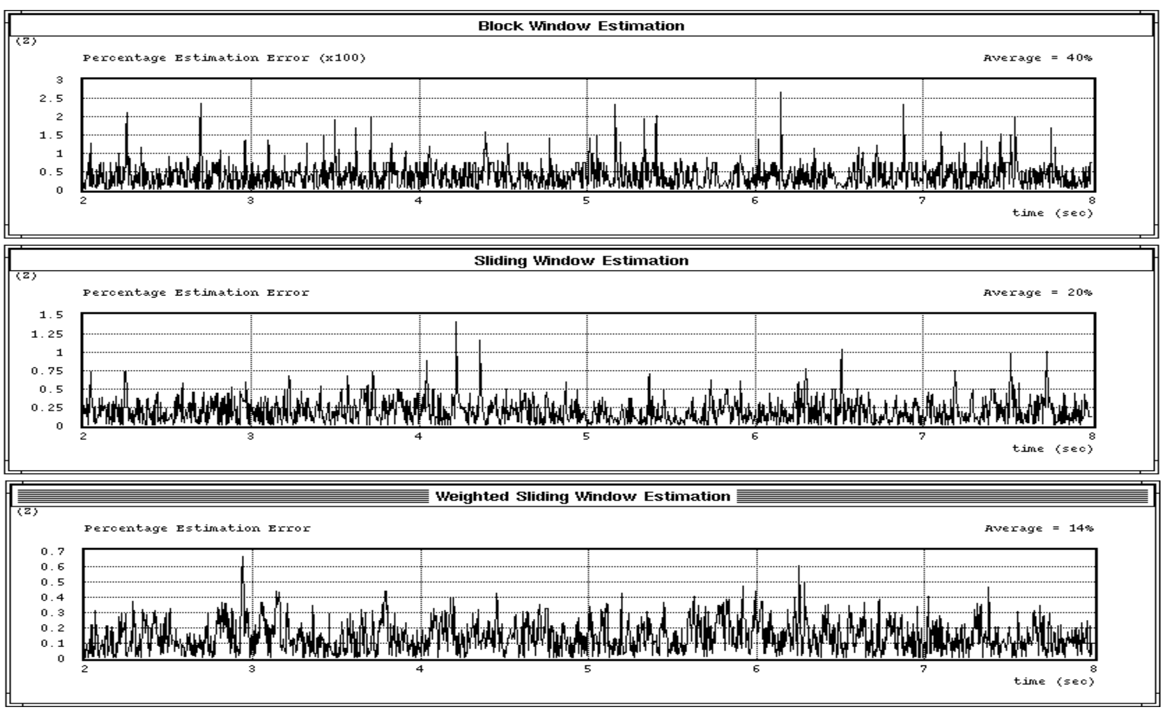

Fig. 4: Estimation error comparison for the different estimation mechanisms