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A Direct Adaptive Controller for ATM ABR Congestion Control

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Abstract

One of the more challenging and yet unresolved issues which is paramount to the success of ATM networks is that of congestion control for Available Bit Rate (ABR) traffic. Unlike other ATM service categories, ABR provides a feedback mechanism, allowing interior nodes to dictate source rates. Previous work has demonstrated how linear control theory can be utilized to create a stable and efficient control system for the purposes of ATM ABR congestion control. This paper extends our previous contribution that assumed a minimum-phase plant, an assumption that is likely violated in practice. Presented here is a direct adaptive controller that uses a finite impulse response (FIR) filter to approximately invert the FIR plant. This controller is well suited for the ATM ABR non-minimum-phase plant. Other control architectures, which motivate the final proposed controller, are also discussed.

1 Introduction

In 1984, the Consultative Committee on International Telecommunications and Telegraph (CCITT), a United Nations organization responsible for telecommunications standards, selected Asynchronous Transfer Mode (ATM) as the paradigm for broadband integrated service digital networks (B-ISDN) [3]. ATM networks provide 6 service categories. Each category of service is customized for a particular type of traffic. Of these 5 categories, only one, Available Bit Rate (ABR), uses a feedback mechanism to create a closed-loop congestion control. The creation of a control mechanism for a switch that can work with the closed-loop congestion control mechanism specified by the ATM Forum [2] is the focus of the present study.

The complete congestion control mechanism is described in [1] and [3]. This paper limits its consideration to explicit rate congestion control. The plant description of Section 2 is an approximation to the mechanisms specified in [1].

The present challenge is to devise a controller that resides at the output queue of an ATM switch and produces a single Explicit Rate $u(n)$ to be sent to all ABR sources passing through the queue. The Explicit Rate $u(n)$ must be chosen such that the incoming ABR bandwidth y matches the available ABR bandwidth y^* in some appropriate sense. Specifying a single Explicit Rate at time n for all sources ensures fairness. Matching y to y^* attains efficiency.

Previous contributions to the problem of ATM ABR congestion control include [3]-[10]. In addition, there has been significant contributions made in the ATM Forum [2]. Our recent contribution [7] examined the UT algorithm [9] (and, due to its similarity, [6]), in the context of adaptive control theory. A congestion control algorithm was proposed based on estimating the number of ABR sources responsive to rate changes as a function of discrete time. Representing this estimation as a polynomial $B(z^{-1})$ in the delay variable z^{-1}, then a requirement for proper operation of the controller in [7] is that $B(z^{-1})$ be minimum phase. However, this assumption is not rooted in the underlying plant process and would be violated in many normal situations.

Thus effort was focussed on applying controllers for Non-Minimum Phase (NMP) plants. In doing so, an extension was made to the indirect-form Approximate Inverse Controller proposed by [11], producing approximately a direct formulation.

The remainder of this paper is organized as follows: Section 2 presents the ATM ABR congestion plant used for analysis. Sections 3-5 consider four control mechanisms. The first, described in Section 3, is a previously published controller that motivates the remaining three. The next two, discussed in Section 4, are both fatally flawed, but provide intuition to the proposed controller, which is presented in Section 5. Conclusions and future work are outlined in Section 6.

2 Plant Definition

Since each switch implements its own, independent controller, one may consider the plant from the perspective of a single switch *SW*. A discrete-time model is used, where sample intervals correspond to control intervals, i.e. a new control action $u(n)$ is calculated for each n. Port j of switch *SW* carries N simultaneous Available Bit Rate (ABR) sessions, and serves as output port for data cells and input port for Backward Resource Management Cells. All session sources are assumed greedy, i.e. will send cells continuously at the maximum Allowed Cell Rate (ACR) dictated by the switch output ports through which they pass. To be fair to all connections, port j generates a single desired rate $u(n)$ for all connections. This $u(n)$ is copied into the Explicit Rate (ER) Field of each Resource Management (RM) cell for which port j is an output port if $u(n)$ is smaller than the current value of the Explicit Rate field. The RM cell transports this ER to each ABR Source. It is assumed that at least one RM cell from each of the N ABR sources passes j during each sample interval. Rates $u(n)$, $y(n)$, and $y^*(n)$ are in units of cells/second.

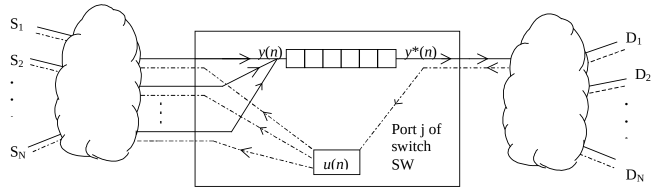

Figure 1 – Plant from perspective of Switch Output Port

Output port j will observe changes to its input rate $y(n)$ as various sources (S_i) react to previously specified Explicit Rates $u(n-m)$. The *reaction delay, m*, for source S_i, as viewed by j, is the time between j adjusting $u(n-m)$ and the time j measures $u(n)$ as its input rate from S_i. These reaction delays will vary for different sources. Assume that there are b_0 sources that respond with reaction delay d, b_1 sources that respond with delay $d+1$, and b_{dB} with delay $d+dB$, where dB is a known upper bound on *SW*'s reaction delay. In addition, one or more of the N flows may be unresponsive to $u(n)$. There are at least two reasons for this possibility. First, a source may be controlled or bottlenecked by another switch along its path. Second, a source may have been guaranteed a Minimum Cell Rate (MCR) greater than the rate assigned by *SW*. The part of $y(n)$ comprised of non-responsive flows is C cells/second. It is assumed that C, b_0, b_1,…, b_{dB} remain constant for periods of time long enough for adaptive identification to occur. Faster convergence speed of the adaptive algorithm results in better tracking of these time-varying parameters.

The plant is therefore given by

$$y(n) = b_0 u(n-d) + \cdots + b_{dB} u(n-d-dB) + C \qquad (1)$$

$$y(n) = B(z^{-1}) u(n-d) + C \qquad (2)$$

Note that for convenience, filters in z^{-1} and time sequences in n will be mixed in expressions such as (2); (2) is equivalent to (1).

Since the minimum delay in the plant is d, adjustments in $u(n)$ will not be observed until $n+d$. Therefore to generate $u(n)$, we must decided at time n the desired value of $y(n+d)$, which is notated as $y^*(n+d|n)$. $y^*(n+d|n)$ may reflect both bandwidth and buffer measurements made up to time n and may be generated by a prediction filter as in [5]. By extension, in many cases, we shall assume that the input of the algorithm is $y^*(n+d+V|n)$ (for some non-negative V), i.e. the desired value of $y(n+d+V)$ known at time n.

The goal of the congestion control mechanism of *SW* is to choose $u(n)$ so as to minimize $E[(y(n+d+V) - y^*(n+d+V|n))^2]$.

3 Approximate Inverse Indirect Control

In this section, we briefly outline a previously published control strategy. This controller motivates the control strategies presented in Section 5. In Section 5.3, a special DC tap is introduced for the purposes of matching DC offsets. Until then, it is convenient to set $C = 0$ in (2), thus the plant becomes

$$y(n) = B(z^{-1}) u(n-d) \qquad (3)$$

The plant (3) is an FIR filter $B(z^{-1})$ and is thus BIBO stable. The controller proposed in [7] cancels the dynamics of the plant by placing controller poles where plant zeros are located (all plant poles are at the origin). The assumptions needed for stability included that the zeros of $B(z^{-1})$ lie within the unit disk, i.e. that the plant $B(z^{-1})$ is minimum-phase. However the underlying physical plant does not suggest that this assumption is appropriate. A non-minimum phase plant is not only possible, but quite likely. Thus a controller capable of controlling a non-minimum phase (NMP) plant is needed.

Yahagi and Lu proposed an intuitive controller for NMP plants in 1993 [11]. In their approach, plant zeros are not directly cancelled by the closed-loop poles. Instead, the controller consists of a time-varying, FIR filter $\hat{Q}(z^{-1})$ (note that this notation drops the implicit dependence on time n), which when placed in series with the $B(z^{-1})$, approximately produces a delayed unit pulse, i.e.

$$B(z^{-1})\hat{Q}(z^{-1}) \approx z^{-V} \qquad (4)$$

V is an operator-chosen delay which is non-negative, introduced to improve the approximation made in (4). More comments on V will be made in Section 5.1.

The Approximate Inverse Indirect Controller for the current scenario is given as [11]:

$$u(n) = \hat{\mathbf{Q}}(n)^T \mathbf{y}_n^*(n+d+V|n), \qquad (5)$$

$$\hat{\mathbf{Q}}(n) \equiv [\hat{q}_0(n),..., \hat{q}_{dQ}(n)]^T \qquad (6)$$

$$\mathbf{y}^*(n+d+V|n) \equiv [y^*(n+d+V|n),..., y^*(n+d+V-dQ|n-dQ)]^T \qquad (7)$$

Using the polynomial notation $\hat{Q}(z^{-1})$ and vector notation $\hat{\mathbf{Q}}(n)$ interchangeably, the plant (3) and controller (5) give the closed loop response $y(n) = \hat{Q}(z^{-1})B(z^{-1})y^*(n+V|n-d)$. If the approximation of (4) is assumed to be exact, then $y(n)= y^*(n|n-V-d)$.

The least squares fit to the estimated $1/\hat{\mathbf{B}}(n)$ is $\hat{\mathbf{Q}}(n)$ that is defined as:

$$\hat{\mathbf{Q}}(n) = \arg_{\mathbf{Q}}(\hat{\mathbf{B}}(n)^T\mathbf{Q} - \mathbf{e}_v)^T(\hat{\mathbf{B}}(n)^T\mathbf{Q} - \mathbf{e}_v), \quad (8)$$

$$\mathbf{B} \equiv \begin{bmatrix} b_0 & b_1 & \cdots & & b_{dB} & 0 & 0 & 0 \\ 0 & b_0 & b_1 & \cdots & & b_{dB} & 0 & 0 \\ \vdots & & & & & & & \vdots \\ 0 & 0 & 0 & \cdots & b_0 & b_1 & \cdots & b_{dB} \end{bmatrix}, \quad (9)$$

with estimate $\hat{\mathbf{B}}(n)$ similarly defined, and also define $\hat{\mathbf{Q}} \equiv [\hat{q}_0, \hat{q}_1, ..., \hat{q}_{dQ}]^T$, $\mathbf{e}_v \equiv [0,0,...,0,1,0,...0]^T$, with the ($V$+1)th element of $\mathbf{e}_v$ equal to 1. The solution of (8) is given by the Wiener solution [12]

$$\hat{\mathbf{Q}}(n) = (\hat{\mathbf{B}}(n)\hat{\mathbf{B}}(n)^T)^{-1}\hat{\mathbf{B}}(n)\,\mathbf{e}_v \quad (10)$$

The computational cost of evaluating (10) can be reduced by using a Levinson algorithm, but is still $O(dQ^2)$.

Operation of the Approximate Inverse Indirect Controller Algorithm consist of the following steps at each time *n*. First, update estimate $\hat{\mathbf{B}}(n)$ using an appropriate identification algorithm, e.g. Normalized Least Mean Squares. Second, calculate $\hat{\mathbf{Q}}(n)$ from (10), using the latest estimate of $\hat{\mathbf{B}}(n)$. Finally, calculate $u(n)$ from (5). A computationally less expensive alternative is presented next.

4 Rejected Direct Controllers

In this section, two adaptive controllers are presented. Both are fatally flawed, as will be discussed. However, their inclusion here motivates the controller of Section 5.

The controllers of Sections 4 and 5 are direct adaptive controllers. The term *direct* means that controller parameters are directly identified using an adaptive identification method. In contrast, the *indirect* controller of Section 3 first identifies the plant parameters and then derives controller parameters from the estimates of the plant parameters. The controller in this section was developed in our attempt to find a direct formulation of the indirect controller discussed in Section 3 and presented in [11]. The motivation for finding a direct formulation is to reduce computational cost by eliminating the calculation of (10).

4.1 A Potentially Unstable Controller

Consider a direct controller where $\hat{\mathbf{Q}}$ is directly estimated from plant input and output signals, shown in Figure 2. Using NLMS [12], adaptively estimate $\hat{\mathbf{Q}}_{y^*}$ to obtain the ideal $\hat{\mathbf{Q}}_{y^*,0}$ that minimizes the least squares criterion $\hat{\mathbf{Q}}_{y^*,0} = \arg\min_{\hat{\mathbf{Q}}_{y^*}} E[e^2(n)]$.

A careful study of Figure 2 shows that convergence cannot be assured. Briefly stated, the update error $e(n)$ is not the required inner product of the parameter error vector $\hat{\mathbf{Q}}_{y^*}(n) - \hat{\mathbf{Q}}_{y^*,0}$ and input vector $\mathbf{y}^*(n+V\,|\,n-d)$, but instead this inner product filtered by the FIR filter $B(z^{-1})$. Since $B(z^{-1})$ is not strictly positive real (SPR), except for the case of $dB = 0$ ($B(z^{-1})=b_0$), convergence cannot be assured. Therefore, the controller of Figure 2 is disqualified as viable ABR congestion controller.

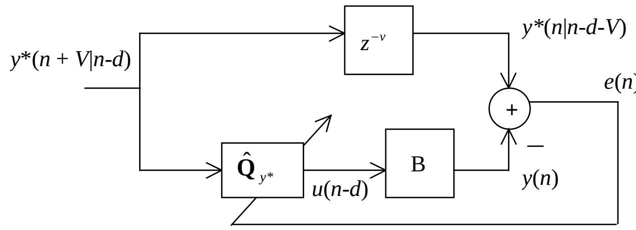

Figure 2 – A Direct Adaptive Controller System for Controlling MA Plant That MAY NOT CONVERGE

4.2 An Unrealizable Controller

Consider a second control method by inverting the order of $\hat{\mathbf{Q}}$ and $\mathbf{B}$ in Figure 2, as in Figure 3. The auxiliary signal $t(n)$ is introduced. The issue of filtering the coefficient error vector is overcome.

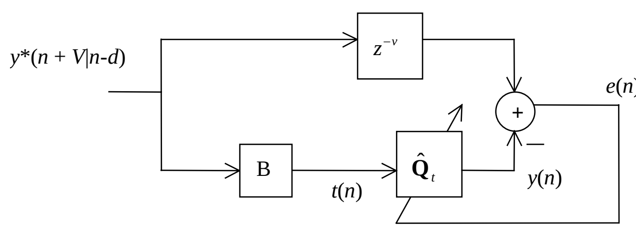

Figure 3 – Inverting Plant and Controller, AN UNREALIZABLE CONTROLLER ($t(n)$ is not available).

Comparing Figure 3 with Figure 2, clearly $\hat{\mathbf{Q}}_{t,0} = \hat{\mathbf{Q}}_{y^*,0} = \arg\min_{\hat{\mathbf{Q}}_t} E[e^2(n)]$. Then the Wiener solution, as given by [12], is

$$\hat{\mathbf{Q}}_{t,0} = \hat{\mathbf{Q}}_{y^*,0} = (\mathbf{B}\mathbf{R}_{y^*}\mathbf{B}^T)^{-1}\mathbf{B}\,\mathbf{R}_{y^*}\mathbf{e}_V \quad (11)$$

where $\mathbf{R}_{y^*} \equiv E[\mathbf{y}^*(n+d+V\,|\,n)\mathbf{y}^*(n+d+V\,|\,n)^T]$ is a dB+dQ+1 by dB+dQ+1 autocorrelation matrix assumed to be full rank, i.e. there is sufficient excitation. Note that if $\{y^*\}$ is white noise with $\mathbf{R}_{y^*} = \sigma^2\mathbf{I}$, then (11) is equivalent to (10).

However, there is a problem. Since $B(z^{-1})$ is unknown, $t(n)$ cannot be created. The formulation of Figure 3 is useful for insight and intuition, but cannot be implemented.

5 Direct Adaptive Inverse Control

In this section, we present a control strategy which was developed expressly for an ATM ABR congestion controller. It is based in part on the identification scheme shown in Figure 3.

However, further investigation revealed that the control methodology presented in this section is nearly identical to Adaptive Inverse Control, a methodology previously proposed by Widrow and Walach [14]. One distinction between their and our approach is our use of the Normalized Least Mean Square (NLMS) adaptation scheme, where Widrow uses Least Mean Square (LMS). Our use of NLMS allows setting the adaptive gain to its optimal value (=1), resulting in the fastest possible stable convergence. Use of NLMS required a new proof of convergence that can be found in [10].

5.1 *Comments on Parameter 'V'*

Before preceding to our controller, a few comments are made to motivate the use of positive V. This particular explanation does not appear in [11] or [14].

Generally, $B(z^{-1})$ is an FIR filter with roots inside and outside the unit circle. Consider the ideal inverting IIR filter $1/B(z^{-1})$. Consider a region of convergence for $1/B(z^{-1})$ be $|p_{+,\max}| < z < |p_{-,\min}|$, where $p_{+,\max}$ is the location of the largest magnitude pole of $1/B(z^{-1})$ inside the unit circle, and $p_{-,\min}$ is the location of the smallest magnitude pole outside the unit circle. With this stated region of convergence, the impulse response $b(n)^{-1} \equiv Z^{-1}[(B(z))^{-1}]$ is two-sided, i.e. non-zero for both positive and negative n, with its largest magnitude terms surrounding $n = 0$ [13].

Let $\hat{Q}(z)$ be a causal, FIR filter that attempts to invert $B(z)$. If $b(n-V)^{-1} \approx 0$ for $n < 0$ and $n > L$, then an L tap FIR filter with impulse response $\hat{q}(n)$ could potentially well approximate $b(n-V)^{-1}$, whereas $b(n)^{-1}$ could only be poorly approximated by a causal FIR filter $\hat{q}(n)$.

5.2 *A Stable, Realizable Control Strategy*

The inspiration for the controller presented here is Figure 3. We need to find an FIR filter which, when placed in series with **B**, well approximates a delayed impulse. Further, we need the adaptation error not to be filtered by a non-SPR filter (e.g. by **B**, as it was in Figure 2). Figure 3 achieves this. Unfortunately $t(n)$ is not available. However, if in Figure 3, the signals $y^*(n+V|n)$, $t(n)$, and $y(n)$ are replaced respectively with $u(n-d)$, $y(n)$, and $\hat{u}(n-V-d)$, as in Figure 4, all necessary signals are available.

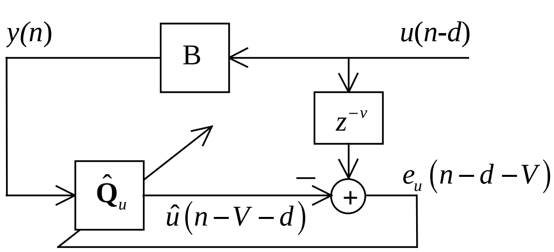

Figure 4 – Direct Inverse Plant modeling

Figure 4 specifies the structure for controller identification used in our ATM ABR controller. It will be shown that $\hat{\mathbf{Q}}_{u,0} \approx \hat{\mathbf{Q}}_{t,0}$, and that $\hat{\mathbf{Q}}_u$ can be found using a NLMS estimation process.

Defining $\hat{\mathbf{Q}}_{u,0} \equiv \arg\min_{\mathbf{Q}_u} E[e_u(n)^2]$ and the $dB+dQ+1$ by $dB+dQ+1$ autocorrelation matrix $\mathbf{R}_u \equiv E[\mathbf{u}(n)\mathbf{u}(n)^T]$, (assumed to be full rank). Then the Wiener solution gives

$$\hat{\mathbf{Q}}_{u,0} = (\mathbf{B}\,\mathbf{R}_u\,\mathbf{B}^T)^{-1}\,\mathbf{B}\,\mathbf{R}_u\,\mathbf{e}_V \qquad (12)$$

Although (12) and (11) are not equal, except for the case of $B(z^{-1})=b_0$, both provide an approximate inverse of **B**. To better compare $\hat{\mathbf{Q}}_{y^*,0}$ and $\hat{\mathbf{Q}}_{u,0}$, consider the formulation of Figure 5.

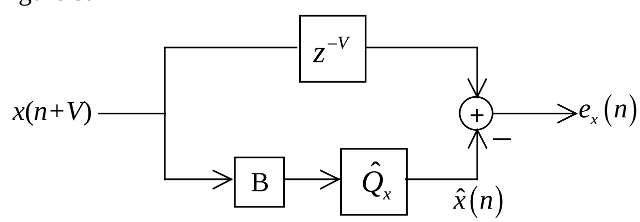

Figure 5 – $\hat{\mathbf{Q}}_{x,0}$ is a function of {x}

$E[e_x(n)^2]$ is to be minimized as a function of $\hat{\mathbf{Q}}_x$. Clearly $\hat{\mathbf{Q}}_x$ must approximately invert **B**, but the specific $\hat{\mathbf{Q}}_{x,0} = (\mathbf{B}\,\mathbf{R}_x\,\mathbf{B}^T)^{-1}\,\mathbf{B}\,\mathbf{R}_x\,\mathbf{e}_V$ is a function of the spectral content of excitation signal $\{x\}$. If $\{x\}$ is primarily a low-frequency signal, then $\hat{\mathbf{Q}}_x$ can only hope to match the inverse of **B** at these low frequencies; $\hat{\mathbf{Q}}_x$ may not be a good match for the inverse of **B** at higher frequencies not represented by $\{x\}$.

For $\hat{\mathbf{Q}}_{y^*,0}$, the driving signal is $\{y^*\}$, while the driving signal of $\hat{\mathbf{Q}}_{u,0}$ is $\{u\}$. When $\{y^*\}$ and $\{u\}$ have similar spectral characteristics, then by (11) and (12), $\hat{\mathbf{Q}}_{y^*,0} \approx \hat{\mathbf{Q}}_{u,0}$. Further, if both $\hat{\mathbf{Q}}_{y^*,0}$ and $\hat{\mathbf{Q}}_{u,0}$ have enough taps to well match the inverse of **B** at all frequencies, assuming sufficient excitation, then $\hat{\mathbf{Q}}_{y^*,0} \approx \mathbf{B}^{-1} \approx \hat{\mathbf{Q}}_{u,0}$.

5.3 *DC tap*

For Sections 3 - 5.2, we have simplified the analysis by assuming the plant parameter C=0. To extend these results to the non-zero C case, we add a DC tap to our estimator and controller. This simply requires increasing $\hat{\mathbf{Q}}_u(n)$ by one tap and appending a constant to the vectors **y** and **y***, i.e. $\breve{\mathbf{y}}(n) = [y(n), y(n-1), ..., y(n-dQ), y_{DC}]^T$ and

$$\breve{\mathbf{y}}^*(n+d+V\,|\,n) \equiv [y^*(n+d+V\,|\,n), ..., y^*(n+d+V-dQ\,|\,n-dQ), y_{DC}]^T.$$

The final tap of $\hat{\mathbf{Q}}_u(n)$ is called the DC tap, and once converged, ensures that

$E[u(n-V-d)] = E[\hat{u}(n-V-d)]$. The DC tap is further discussed in [10].

5.4 Normalized Least Mean Square Adaptive Mechanism

Unlike $\hat{\mathbf{Q}}_{y*,0}$, $\hat{\mathbf{Q}}_{u,0}$ can be estimated using the Normalize Least Mean Square algorithm [12]. At time *n*, calculate

$$u(n) = \hat{\mathbf{Q}}_u(n)^T \breve{\mathbf{y}}^*(n+V+d \mid n) \tag{13}$$

$$\hat{u}(n-V-d) = \hat{\mathbf{Q}}_u(n)^T \breve{\mathbf{y}}(n) \tag{14}$$

$$e_u(n-V-d) = u(n-V-d) - \hat{u}(n-V-d) \tag{15}$$

$$\hat{\mathbf{Q}}(n+1) = \hat{\mathbf{Q}}(n) + \frac{\mu \breve{\mathbf{y}}(n)}{\breve{\mathbf{y}}(n)^T \breve{\mathbf{y}}(n)} e_u(n-V-d) \tag{16}$$

Defining $\tilde{\mathbf{Q}}(n) \equiv \hat{\mathbf{Q}}_u(n) - \hat{\mathbf{Q}}_{u,0}$, it is shown in [10] that if $0 < \mu < 2$ and certain other assumptions are met, then

$$\lim_{n\to\infty} E[\tilde{\mathbf{Q}}(n)] = \mathbf{0} \text{ and } \lim_{n\to\infty} \sum_{i=1}^{dQ+1} E[(\tilde{Q}_i(n))^2] < \alpha, \alpha < \infty \tag{17}$$

Global stability is addressed in [10].

5.5 Complete Control Architecture

Figure 6 shows the complete control architecture. The Identification section uses NLMS adaptation to determine $\hat{\mathbf{Q}}(n)$ (shown with $\hat{q}_{DC}(n)$ separated from the remaining linear taps, $\hat{\mathbf{Q}}_{lin}(n)$, and with y_{DC}=1) by creating estimate $\hat{u}(n-V-d)$ (Section 5.4). $\hat{\mathbf{Q}}(n)$ is copied into the Controller, which produces $u(n)$ from the set point $y^*(n+V+d \mid n)$ (with $\breve{\mathbf{y}}^*$ replacing $\mathbf{y}^*$ in (5)). The Plant is represented by (2).

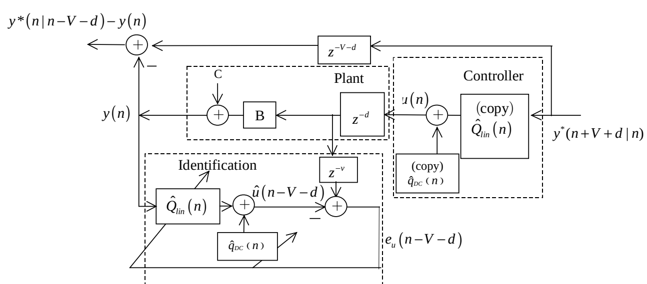

Figure 6 – Complete Control Architecture ($y_{DC} = 1$)

Convergence and other issues pertaining to this control architecture are discussed in [10]. Simulation results will be reported shortly.

6 Conclusions and Future Work

After presenting the ATM ABR congestion plant in Section 2, four control mechanisms based on adaptive linear control theory were presented. The first, described in Section 3, is a previously published controller that approximates the inverse of the MA plant with a BIBO stable FIR filter. This approach is an indirect controller and was judged to be unnecessarily computationally complex, yet it inspired the ensuing three controllers. The first two of these three are fatally flawed, as discussed in Section 4, but provide intuition to the proposed controller in Section 5. The final controller can be viewed as a direct adaptive controller based on the first controller. This controller can employ a NLMS adaptation mechanism and is known to be stable.

Further discussion of the proposed controller can be found in a sequel paper, [10]. Methods to speed convergence are currently being studied and will be reported shortly along with results from simulative experiments.

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