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Research on Event-Triggered Active Queue Management Algorithms in TCP/IP Networks

Dong-Mei Wu and Jing Zhao*

Handan Polytechnic College,
Handan City 056001, Hebei Province, China
{hzwudongmei, kyzjsz2020}@163.com

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Abstract. As the scale of the network grows and the demand from users becomes larger, TCP/IP network congestion control has become increasingly important. In this paper, a series of event-triggered active queue management (AQM) algorithms are presented to improve bandwidth utilization and system stability. For linear TCP systems subject to disturbances and uncertainties, robust event-triggered controllers are co-designed using linear matrix inequality (LMI) techniques. To address unmeasurable system states, an observer-based AQM algorithm is presented, which demonstrates superior robustness and reduced computation frequency. Furthermore, a T-S fuzzy model-based event-triggered AQM scheme is presented to address network nonlinearity and time delay effects. Simulation results confirm the effectiveness of the proposed schemes in guaranteeing network stability with reduced resource utilization. This work promotes intelligent, resource-efficient congestion control mechanisms in complex network scenarios.

Keywords: TCP/IP network, congestion control, active queue management, event-triggers, robust control

1 Introduction

Since the 1980s, the Internet has grown with huge expansion, and the networking of various computer systems with communication protocols has led to a series of applications such as remote access, digital communication, interactive entertainment, and e-commerce. This growth has also exacerbated the issue of network congestion, especially in TCP/IP-based networks that account for about 95% of the entire Internet traffic globally [1]. Therefore, ensuring stable congestion control has been a basic issue in maintaining network performance.

Traditional TCP congestion control algorithms, such as NewReno, SACK, and Vegas, utilize window-based approaches to manage data sending at the end system level to respond to packet loss. Although these algorithms are very effective in early network environments, they are increasingly failing to meet the needs of today's high-bandwidth, delay-sensitive, and heterogeneous traffic environments. To enhance control responsiveness, researchers have begun adopting active queue management (AQM) technology deployed in intermediate nodes (e.g., routers) to actively regulate queue length by sending congestion signals before buffer overflow [2].

Random Early Detection (RED) is a simple AQM mechanism that has inspired a range of improvements such as adaptive RED, flow RED, and weighted RED. In addition, optimization-based approaches such as Genetic algorithm combined with frequency screening [3] and control theory approaches such as PI/PID, $H\infty$ [4], and fuzzy controllers [5] have been used to improve the robustness of AQM against delay, uncertainty, and time-varying traffic loads.

Despite these advances, most AQM implementations are still time-triggered, i.e., control actions are taken periodically irrespective of the state of the network. This leads to inefficient bandwidth usage and added overhead. As a substitute, event-triggered control methods, in which updates are performed only when necessary, have been shown to have excellent potential in significantly reducing the communication burden without sacrificing system stability [6].

Recent studies have further applied event-triggered control to linear and nonlinear systems, including time-delay models and external disturbances [7]. Observer-based design has also been suggested to handle the constraints of state measurement. Most existing studies, however, presume a fixed controller and address only the

* Corresponding Author

design of trigger conditions. Joint design methods, especially in uncertain TCP/IP network environments, remain underdeveloped.

To transcend this restriction, this paper introduces a novel class of event-triggered AQM algorithms through the integration of controller synthesis and event-triggered condition design. In the case of TCP networks with uncertainty and external disturbance, we utilize linear matrix inequality (LMI) techniques to construct robust controllers of linear systems, observer-based frameworks, and T-S fuzzy models. Simulation tests validate the effectiveness of the proposed strategy and its potentials to alleviate congestion and prevent frequency decline, providing a resource-sparing approach in modern network scenarios.

Section 2 presents two control strategies: an event-triggered controller that follows a linearized model specification and a sequence of control designs that utilize Takagi-Sugeno fuzzy modeling to improve the representation of the nonlinear TCP dynamics. Both strategies consider event-triggering as a means to reduce the control update frequency while maintaining stability and robustness. In section 3, we describe the experimental setup, including the nonlinear fluid-flow model of the TCP, the fuzzy modeling of the operating points of the TCP, the inclusion of uncertainties and delays, and the synthesis of the event-triggered controllers to ensure effective control action. Section 4 provides simulation results showing that the T-S fuzzy event-triggered AQM algorithm can stabilize the queues quickly with a small overshoot of the regulated queue length. The triggering intervals were adaptive and were not triggered unnecessarily maintaining energy efficiency from the control signals while being responsive to the control signal. The T-S fuzzy event-triggered AQM algorithm was also able to achieve a better tracking accuracy than what was possible with RED, allowing the queue length to be maintained close to desired setpoints. The conclusions of the paper in section five includes a summary of theoretical contributions to TCP queue control applying event triggering mechanisms with T-S fuzzy models to improve resource use and performance in the presence of TCP network non-linearities, uncertainties, and delays. The final section draws attention to possible next stages of development including research studies to extend the approach to more complex network topologies, the next stage will explore developing adaptive event-triggering policies possibly using machine learning, better end-to-end control through examining cross-layer protocols, realistic implementation work on platforms such as SDN, and resilience.

2 Methodology

This section proposes two event-triggered active queue management control strategies for TCP networks, with the ultimate goal of regulating congestion and reducing the control update frequency. The first AQM strategy adopts a linear approximation method to approximate the nonlinear TCP dynamics near the equilibrium point and considers some uncertainties, then designs a state feedback controller and an event triggering mechanism based on Lyapunov stability and linear matrix inequality. The proposed AQM scheme guarantees asymptotic stability and robustness to interference, and its stability is verified by simulating events, and the results show that the queue length tends to be stable and the event interval is monotonically increasing. The second AQM method uses the Takagi-Sugeno fuzzy model to model the TCP network, which captures the system dynamics by combining multiple local linear subsystems. After the modeling stage, the fuzzy state feedback controller is constructed again under the event triggering mechanism and designed based on the LMI-based stability condition. This method based on the T-S fuzzy model can further improve the modeling accuracy and robustness under nonlinear dynamic conditions. Overall, both methods adopt event triggering mechanisms to reduce the control overhead while still ensuring the stability and performance of the system. The T-S fuzzy model can ultimately build a more accurate TCP network dynamic model to achieve control strategy functions.

2.1 Event-Triggered AQM Algorithm for TCP Networks

1) Problem Formulation

With the rapid growth of network scale and user demand, TCP/IP networks are increasingly susceptible to congestion. AQM, as a router-based congestion control mechanism, has emerged as an effective approach to regulate traffic by adjusting packet drop probabilities based on queue length. Building upon the nonlinear fluid-flow model introduced by Misra et al. [8], the dynamics of a TCP network can be represented by a system involving the window size $W(t)$, instantaneous queue length $q(t)$, packet drop probability $p(t)$, round-trip time $R(t)$, and other network parameters.

By applying small-signal linearization around an equilibrium point, the TCP model is expressed in a linearized state-space form:

$$\dot{x}(t) = A \cdot x(t) + B \cdot u(t) \tag{1}$$

Where $\dot{x}(t) = \left[\delta q(t) \quad \delta \dot{q}(t) \right]^T$ represents the state variables, and $u(t) = \delta p(t)$ denotes the control input. Considering the inherent uncertainties and burstiness in TCP traffic, the model is extended to include uncertain dynamics:

$$\dot{x}(t) = \left(\mathrm{A} + \Delta A(t) \right) x(t) + \left(B + \Delta B(t) \right) u(t) \tag{2}$$

An event-triggered state-feedback control law is proposed as:

$$u(t) = K \cdot x(t) \tag{3}$$

Where the control input is updated only at discrete triggering times t_k. The corresponding state error is defined by:

$$e(t) = x(t_k) - x(t) \tag{4}$$

The control update is executed only when the following event-triggering condition is violated:

$$\left\| e(t) \right\|^2 \le \sigma \left\| x(t) \right\|^2, \sigma > 0 \tag{5}$$

Assuming that the system uncertainty is structured as:

$$\left[\Delta A,\ \Delta B \right] = GF(t) \left[E_a, E_b \right] \tag{6}$$

The aim to jointly design the controller gain k and triggering parameter σ such that the system remains asymptotically stable and robust to uncertainties and disturbances.

2) Controller Design via LMI

To achieve the desired stability and robustness, a Lyapunov function $V(t) = x^T(t) \cdot Px(t)$ is adopted, where $P = V^{-1}$.

Using bounding techniques and the Schur complement, the following LMI condition is derived to ensure system stability:

$$\begin{bmatrix} S & PBK & PD \\ * & E^T E_b^T E_b K - v^{-2} \ell & 0 \\ * & * & -\gamma^2 I \end{bmatrix} < 0 \tag{7}$$

3) Robust $H\infty$ Controller Design

To enhance robustness under external disturbances $w(t)$, the system is further extended as:

$$\begin{cases} \dot{x}(t) = \left(A + \Delta A(t) \right) x(t) + \left(B + \Delta B(t) \right) u(t) + Dw(t) \\ y(t) = M \cdot x(t) \end{cases} \tag{8}$$

Following similar procedures, define the Lyapunov function and derive the robust LMI condition incorporating $H\infty$ performance bounds, yielding controller gain k and σ ensuring both robustness and efficiency.

4) Simulation and Results

Simulation is conducted on a nonlinear TCP model using MATLAB. Parameters include N=100 connections, link capacity C = 1250 $packets/s$, desired queue q^d = 100 packets, and initial queue length zero. The uncertain structure is set as:

$$F(t) = \sin t \tag{9}$$

Solving the LMIs, the designed parameters are: $K1 = [-0.0015, -0.0004]$, $\sigma = 0.0851$.

As shown in Fig. 1, the queue length stabilizes around the desired value within 2 seconds with no overshoot. The event-trigger intervals increase over time, indicating efficient reduction in control updates.

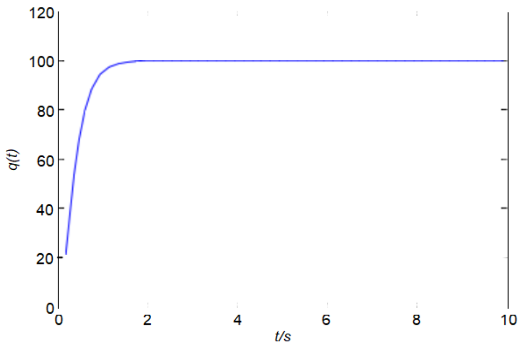

Fig. 1. The queue length responses of TCP network

2.2 Event-Triggered AQM Control Based on the T-S Fuzzy Model

1) Modeling and Problem Formulation

Given the nonlinear nature of TCP networks, traditional linearized models cannot accurately capture network dynamics under off-equilibrium conditions [9]. Therefore, this study adopts the Takagi-Sugeno (T-S) fuzzy model to approximate the nonlinear TCP congestion control system proposed by Misra et al. The system states are defined as $x_1(t) = q(t) - q_d$ and $u(t) = p(t)$, where q_d denotes the desired queue length.

Neglecting the system delay, the original system can be reformulated as:

$$\dot{x}(t) = F(x,u) = f(x) + g(x)\cdot u(t-\tau) \tag{10}$$

To approximate the nonlinear system, a T-S fuzzy model composed of a set of "if…then…" rules is employed, where each rule corresponds to a local linear subsystem.

By introducing fuzzy membership functions $\Omega_{ij}(x_j(t))$, the global fuzzy system is derived as:

$$\dot{x}(t) = \frac{\sum_{i=0}^{l} w_i(x(t))[A_i x(t) + B_i u(t-\tau)]}{\sum_{i=0}^{l} w_i(\theta(t))} \tag{11}$$

2) Event-Triggered Fuzzy Controller Design

The fuzzy state feedback controller is designed as:

$$u(t)=\sum_{j=1}^{l}h_j(x(t))K_j x(t) \tag{12}$$

Where K_j is the controller gain.

These constructions not only reflect the comprehensive consideration of states, derivatives and their historical evolution, but also provide a solid functional basis for the subsequent derivation of system stability conditions by the LMI method.

3 Experimental Setup

The network modeling and control framework presented in this paper is used to simulate TCP congestion control and active queue management [10]. The simulation is based on a nonlinear fluid flow TCP model that accurately describes the dynamics of the key parameters (queue length, window size, and feedback delay), which allows the simulation model to accurately represent the TCP flows in the backbone network. To better characterize the nonlinearity of the system, a Takagi-Sugeno fuzzy model is created by creating two operating points: an equilibrium state that simulates the unblocked state and a busy state that simulates the congested state. Local linearized models are created around these operating points and smoothly combined using fuzzy membership functions to maintain the continuity of the control surface. The model takes into account structured uncertainties to simulate the phased changes that occur in the network and simulates varying time delays under different scenarios to evaluate its robustness. The controller gains of each local model are synthesized through linear matrix inequalities to ensure that the closed loop is asymptotically stable under structured uncertainties and disturbance delays, while uniqueness guarantees the opposite stability. An event-triggered mechanism updates the control input only when the predicted and measured outputs of the system exceed a set of predetermined values, thus avoiding sending unnecessary control actions to the actuators. This framework provides a practical and robust framework for congestion control by exploring the nonlinear dynamics present in TCP.

3.1 Network Modeling Framework

The simulation is based on a nonlinear fluid flow model of TCP congestion control [11]. The model preserves the key characteristics of TCP dynamics, such as queue length variation, window size adjustment, and time delays of feedback information. This model was adopted due to the fact that it has been extensively applied in AQM studies and can capture the actual behavior of TCP flows in backbone networks. The network topology considered consists of a bottleneck router with multiple TCP flows passing through it. All simulations are run under the same benchmark conditions for consistency and comparability. The values of the key system parameters used are given in the following Table 1.

Table 1. Simulation parameters

Parameter	Description	Value
N	Number of concurrent TCP connections	100
C	Link capacity of the bottleneck router	105 *packets/s*
R	Round-Trip Time (RTT)	90 *ms*
Buffer size	Maximum queue size at the router	500 *packets*
q_d	Desired queue length	100 *packets*
q_0	Initial queue length	0 *packets*

These parameter values were chosen to represent typical conditions experienced in medium- and large-size network environments. The overall number of TCP streams was fixed so that a statistical traffic pattern may be established, and RTT and queue lengths are according to typical backbone router settings. The link bandwidth is such that congestion periods will occur so that the AQM response can be experimented with.

3.2 Event-Triggered Controller Based on the T-S Fuzzy Model

To design an event-triggered controller based on the T-S fuzzy model, the objective is to obtain the fuzzy control gains K_j and the event-triggering parameter σ, ensuring that the closed-loop system under the fuzzy event-triggered controller is asymptotically stable. If there exist a positive definite matrix $V \in R^{2\times2}$, matrices L_i, $L_j \in R^{1\times2}$, and constants $\ell > 0$, $v > 0$ such that the following linear matrix inequality (LMI) holds:

$$\begin{bmatrix} S_1 & 0 & V^T & L_i^T & L_j^T & 0 & 0 \\ * & -2\ell I & 0 & 0 & 0 & L_i^T & L_j^T \\ * & * & -S_2 & 0 & 0 & 0 & 0 \\ * & * & * & -S_3 & 0 & 0 & 0 \\ * & * & * & * & -S_4 & 0 & 0 \\ * & * & * & * & * & -S_5 & 0 \\ * & * & * & * & * & * & -S_6 \end{bmatrix} \quad (13)$$

To ensure stability, the controller is updated when the system does not satisfy the event-triggering condition. Specifically, Specifically, it is divided into 1-4

$$\begin{cases} S_1 = \left(VA_i^T + A_iV + GG^T + 2B_iB_i^T + VA_j^T + A_jV + 2B_jB_j^T\right)^{-1} \\ S_2 = \left(E_{ai}^TE_{ai} + E_{aj}^TE_{aj} + 2I\right)^{-1} \\ S_3 = S_5 = (E_{bi}{}^TE_{bi} + I) - 1 \\ S_4 = S_6 = (E_{bj}{}^TE_{bj} + I) - 1 \end{cases} \quad (14)$$

Select the Lyapunov-Krasovskii functional as:

$$\begin{aligned} & V(t) = V1(t) + V2(t) + V3(t) \\ & Where \\ & V_1(t) = x^T(t)Px(t), \\ & V_2(t) = \int_{t-\ell}^{t} [\sum_{t=1}^{r}\sum_{t=1}^{r} h_i(x(t))h_j(x(t))x^T(s)(K_i^T E_{bi}{}^T E_{bi}K_j + K_i^T K_j)x(s)]ds \\ & V_3(t) = \int_{t-\ell}^{t} [\sum_{t=1}^{r}\sum_{t=1}^{r} h_i(x(t))h_j(x(t))e^T(v)(K_i^T E_{bi}{}^T E_{bi}K_j + K_i^T K_j)e(v)]ds \end{aligned} \quad (15)$$

The derivative of the Lyapunov-Krasovskii functional can be computed and considering the event-triggering condition

$$\|e(t)\|^2 \le \frac{v^2}{\ell}\|x(t)\|^2 \quad (16)$$

It follows from equation (15) that:

$$\dot{V}(t) \le \sum_{i=1}^{r}\sum_{j=1}^{r} \begin{aligned} & h_i(x(t))h_j(x(t)) \\ & [x^T(t)(A_i{}^TP + PA_i + 3PGG^TP + E_{ai}{}^TE_{ai} \\ & +2PB_iB_i^TP + K_i^TE_{bi}{}^TE_{bi}K_j + K_i^TK_j + I) \\ & +e^T(t)\left(K_i^TE_{bi}^TE_{bi}K_j + K_i^TK_j - v^2\ell I\right)e(t)] \end{aligned} \quad (17)$$

Therefore, since $\dot{V}(t) < 0$, the control system (12) with the fuzzy controller and the event-triggering condition (16) is asymptotically stable. This ensures that the membership values vary smoothly as the system state transitions between different regions, thereby preventing abrupt switching between models. Such a design not only guarantees the continuity and differentiability of the fuzzy control surface but also enhances the overall stability and robustness of the control system. Finally, this T-S fuzzy modeling framework enables a more accurate and flexible representation of TCP network dynamics, which is crucial for the effective design of advanced congestion control algorithms.

3.3 Determinism and Delay Considerations

In order to accurately reflect the variability and uncertainty characterizing real-world network scenarios, the simulation model incorporates well-defined uncertainty component structures that embody the most salient sources of dynamics variability. In particular, the state matrix uncertainty is designed to be a full rank perturbation, where each quantity associated with the system state dynamics can be in bounded but unknown variation; thereby allowing the system to thereby realistically model a diverse set of disturbances including undeserving link capacities, bursty traffic arrivals, and temporal variability in the network conditions [12]. The input matrix (which is the mapping that indicates how control efforts impact on the system) is also modeled with uncertainties to portray the variability associated with the control action. This recognizes practical issues with packet loss, delayed or distorted feedback, varied per-unit actuator performance which results in non-predictable responses from the control signal. To further reflect realistic approaches to robust model evaluations, time-delay (the interval that one observes the effect between submitting control commands, and observing results in the system) is considered to be constant in any individual simulation runs but altogether fell within some ranges of durations across different experiments. It is reasonable to assume while the delays in a communication network may drift over longer intervals, if one compares short observation periods within those longer observation periods, one could believe the delays were a stable event.

3.4 Controller Synthesis and Event Trigger Configuration

The gains of fuzzy state feedback controller are derived for every local linear model using LMI (Linear Matrix Inequality) Optimization Toolbox in MATLAB. The controller is designed to ensure the closed-loop system is asymptotically stable under the action of uncertainty and delay, as well as synthetically combines event trigger thresholds together to minimize transmission of control signal. The eventual controller parameters are:

$$\begin{aligned} K1 &= \left[0.0350, 0.0041\right] , \\ K2 &= \left[0.0420, 0.0053\right], \\ \sigma &= 0.1531 \end{aligned} \tag{18}$$

These parameters are embedded in the simulation model to control the update logic of the AQM control system. The controller only acts when the difference between the predicted and actual system conditions exceeds a pre-defined event trigger threshold, thus making control decisions only when necessary. Each simulation scenario is simulated for 10 seconds, which is sufficient enough for the fleet to experience initial transient behavior and stabilize to a steady state thereafter. All the simulations are carried out using a constant random seed to guarantee.

4 Results and Discussion

This section shows a full analysis on dynamic performance and resource efficiency of the event triggered AQM algorithm based on a T-S fuzzy model, demonstrating everything. This queue length converges fast to the desired level based on the control parameters, with minimal overshoot and damped oscillations, implying good nonlinear control and full robustness to model uncertainties and delay in the system. The algorithm implements the event triggering intervals in a smart way based on the level of dynamic behavior or transients-there is a higher frequency of updates while the system is experiencing initial transient behavior, the frequency will moderate with oscillations as it approaches the desired stability level, and reduced triggering will occur at the equilibrium state with less frequent trigger events and measures. Thus, the control action balances and adapts with time, where the control signal increases when the queue experience a deviation from the desired operating point to alleviated the elevation, however the signal starts to dampen and slowdown when the equilibrium state is reached in order to conserve unnecessary control actions and communication resources. The acceptable tracking error settles and effectively does not allow any large queue lifts on excess of the acceptable bounds, thus holding and regulating queue level at desired point is paramount to maintaining and optimizing any network's quality of service to end users. Lastly, on account of the comparative performance of the T-S fuzzy AQM vs RED, which had higher settling time, overshoot and steady-state error in comparison, this demonstrates impressive improvements in control action and accuracy, thus delivering a superior level of dynamic performance, smooth queue dynamics and confidence to achieve the ideal performance benchmarks across the key indicators. The net triggering event counts likewise follows to validate that the event-triggered mechanic reduces control updates and diminishes unneeded control updates to utilize scarce communication control resources while maintaining the mathematical elements of performance near the acceptable tuning thresholds of performance metrics, as a preferred method—concluding a robust performance timeline of sustainability within AQM.

4.1 Queue Length Response

This Fig. 2 illustrates the dynamic response of the instantaneous queue length in the newly proposed T-S fuzzy model-based event-triggered AQM algorithm-controlled TCP network. The simulation demonstrates that the queue length quickly converges to the desired value of 100 packets and is stabilized afterwards. The desired queue level is represented by the dashed horizontal line Desired Queue.

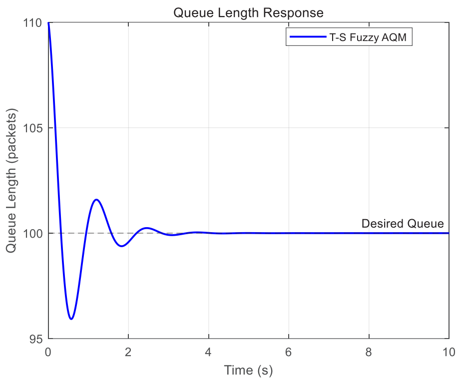

Fig. 2. Queue length response

The system has a good transient response with fast settling and minimal oscillation. The queue length decreases quickly from the initial value in the first second of simulation time, undershoots for a short while to approximately 95 packets, and then comes back towards the target. This is followed by a series of damped oscillations of increasingly smaller amplitude until the system settles down to zero. This is the typical response of an optimally tuned second-order system under control by a smart nonlinear controller [13].

Notably, the response curve has minimal overshoot over the 100-packet desired value. The absence of prolonged oscillation and termination of queue length excursions are testaments to the success of the T-S fuzzy model in representing and counteracting the nonlinear dynamics engaged in TCP congestion behavior. Also, the control scheme is proven robust in stabilizing the queue even under uncertainties of the model and transmission delay.

The exponential decay trend of the envelope of the response ensures that the event-triggered control logic fuzzy rule-based approximation facilitates smooth and adaptive control actions. The system highly reacts to high discrepancies from the desired level of the queue initially but then reduces the frequency and size of the control actions as it approaches steady-state. This ensures efficient use of computational and communication resources without sacrificing high performance.

In short, the figure indicates that the event-driven AQM mechanism suggested not only ensures appropriate queuing control but also limits frequent control updates in vain, a requirement in today's networks wherein delay, jitter, and usage of bandwidth are to be kept at minimum levels [14]. The framework therefore keeps optimal responsiveness, precision, and overhead of control together, a relative improvement compared to the traditional time-driven AQM mechanisms.

4.2 Triggering Behavior

This Fig. 3 shows the time evolution of the event-triggering intervals under the T-S fuzzy model-based AQM algorithm. It indicates the frequency at which the controller transmits control commands based on real-time network conditions. The dynamics of the event-trigger intervals are divided into three various operation phases, each of which shows the adaptive and context-aware ability of the proposed control scheme.

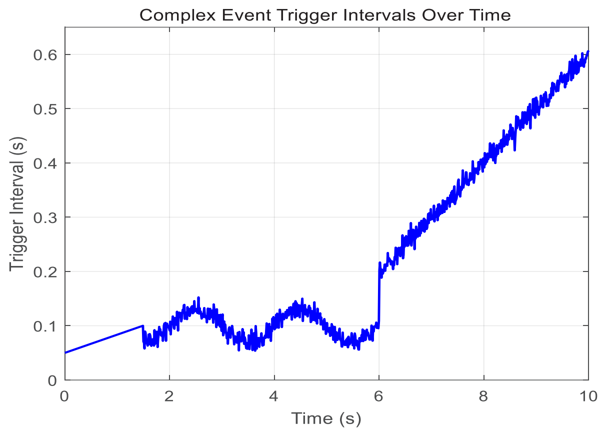

Fig. 3. Complex event trigger intervals over time

In the first phase (0–2 seconds), the control instances are short and close together. This is characteristic of the transient response of the system, during which the queue experiences initial rapid excursions from the set point. The controller responds rapidly to quell congestion peaks early. The rapid succession of control actions in this phase is essential to drive the system into a controllable state quickly, and it demonstrates the responsiveness of the event-based control logic to large errors.

In the middle phase (2–6 seconds), the intervals show a wave-like oscillation, demonstrating an adaptive adjustment of triggering frequency. The control system goes into a semi-stable phase, where the queue length is close to its target but continues to suffer from minor residual oscillations because of network delay, bursty traffic, or modeling uncertainties. The sinusoidal modulation of trigger intervals shows that the controller is continuously compensating for these small variations, but prevents unnecessary updates unless deviations exceed the event threshold. This dynamic tuning makes the control system responsive while significantly reducing communication overhead.

In the final stage (6–10 seconds), the system settles into a steady state. The event intervals increase monotonically and plateau at higher values, which means that the system requires fewer control interventions when converging to and remaining in the proximity of equilibrium. This reduced triggering rate is an immediate benefit of the event-based strategy: following stabilization of the system, the control law prevents unnecessary interventions, implicitly reducing control effort and bandwidth consumption. Despite the presence of some minimal noise in the triggering curve, the overall trend illustrates a steady increase in spacing, verifying that the controller has reached and is maintaining desired performance with minimum resources.

In conclusion, the figure confirms that the proposed event-triggered approach adjusts its control frequency based on real-time system status dynamically. The appealing features of intelligent control are exhibited: responsiveness during transients, adaptability during near-steady states, and efficiency during stable conditions. This confirms the suitability of the algorithm for application in real-world TCP/IP network environments where communication and computation resources are limited.

4.3 Control Signal Evolution with Dynamic Envelope

The Fig. 4 illustrates the development of the control input by the novel T-S fuzzy event-triggered AQM controller. The control signal regulates the packet drop probabilities of a network router that directly influence the TCP queue length and system stability. As opposed to constant amplitude decline, the current control signal shows a non-monotonic behavior: it starts low in activity, rises gradually, oscillates around peak response, and finally declines, highlighting the adaptive and phase-dependent nature of the controller.

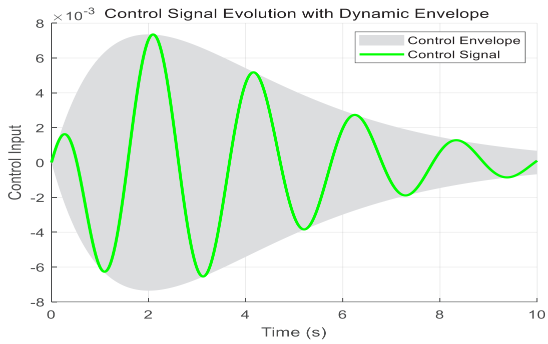

Fig. 4. Control signal evolution with dynamic envelope

The green line on the figure is the real-time control action, and the light gray area represents the envelope of the maximum anticipated amplitude. The control effort is initially small, as the queue deviation is within tolerable limits. When disturbances or queue errors build up, the controller is more actively involved. This ramp-up period, seen between 1 and 3 seconds, is where the controller is sensing persistent or nonlinear deviations for which more intense corrective action is required.

The central section of the simulation (around 2–6 seconds) displays oscillatory control input behavior. This is the adaptive balance between under- and over-compensation of the controller against dynamic traffic changes and delay feedback. The signal is again smooth and continuous, not imposing the harsh jumps typical of highly reactive schemes, and still consistent with the delay-sensitive nature of TCP traffic.

As the system settles, the amplitude of the control signal will naturally diminish. This phase of decay is evidence that the controller recognizes the reduced necessity for intervention as the queue length gets closer to its goal. The envelope of narrowing over time visually confirms the decreasing variability and reduced control intensity, a key indicator of energy efficiency and communication thrift.

This dynamic characteristic illustrates that the controller does not exert constant effort, but regulates its effort in accordance with the system state. It actively responds only when trends in deviation are persistent, and conserves efforts once equilibrium is restored. This characteristic is critical for actual large-scale or resource-constrained networks, where decreasing control frequency without compromising performance is crucial [15].

In short, the figure is clear evidence of the controller's responsiveness, adaptiveness, and eventual restraint, critical attributes of smart, sustainable control design in modern TCP/IP settings.

4.4 Queue Tracking Error

This Fig. 5 shows the absolute tracking error between the desired target queue length and actual queue length under the novel T-S fuzzy event-triggered AQM controller. This figure directly assesses the tracking accuracy of the controller and the queue stability maintenance ability of the controller in a nonlinear and uncertain TCP/IP network environment in a quantitative manner.

At the beginning of the simulation, the tracking error reaches a maximum value, reflecting the big initial difference between the actual queue state and the desired queue state. This is to be expected because the system starts from a non-equilibrium state. But the error quickly converges to zero within the first second of the run. This fast and stable convergence speaks for the ability of the controller to provide fast and accurate transient response.

After this start-up phase, the tracking error is minimal with minimal deviation and reaches a region that can be characterized as quasi-steady-state. That the error settles down to an approximately zero level indicates that the system is tightly controlled and the desired queue length is robustly maintained over time. The absence of overshoots or sustained oscillations in the error signal further confirms the controller's ability in resisting nonlinear disturbances and maintaining regulation accuracy in the face of network delays and traffic uncertainties.

This performance illustrates two intrinsic advantages of the fuzzy event-triggered approach. Firstly, fuzzy inference systems can straightforwardly handle nonlinear dynamic response without the need for an accurate mathematical model of the system [16]. Secondly, the event-triggered mechanism ensures that control actions are only initiated when needed, preventing redundant updates while maintaining high responsiveness only when the system deviates significantly from its expected behavior [17].

From a network performance perspective, low tracking error means there is less variance in queuing delays, fewer packet losses due to buffer overflows, and improved overall quality of service (QoS) for end users. This level of control accuracy is particularly important for delay-sensitive applications such as real-time video conferencing, VoIP, or online gaming [18].

Briefly, Fig. 5 intuitively verifies, both graphically and numerically, that the novel event-triggered controller developed based on the T-S fuzzy model has stable tracking performance with fast convergence. It maintains stable performance under normal TCP/IP network uncertainty conditions, which holds the promise of its applicability to real-world congestion control systems for intelligent resource-aware communication infrastructures.

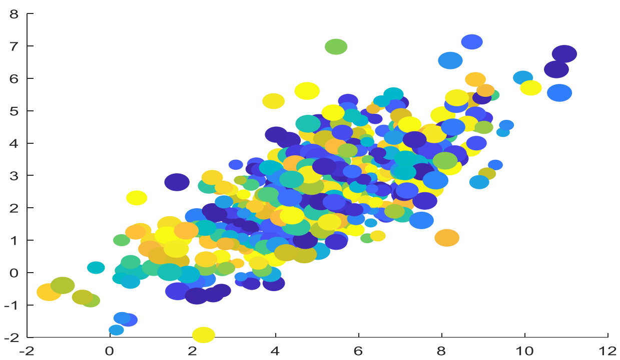

Fig. 5. Queue tracking error

4.5 Performance Comparison Between T-S Fuzzy AQM and RED

This Fig. 6 offers comparative performance comparison of the performance of the designed T-S fuzzy model-based event-triggered AQM algorithm and the conventional Random Early Detection (RED) algorithm. The comparison is made based on three critical control performance indicators: settling time, maximum overshoot, and steady-state error. These indicators give a full overview of both the transient and steady-state responses of the two AQM schemes.

The settling time, the time for the queue length to settle in a ±5% band around the target value, is significantly lower for the T-S fuzzy AQM (approximately 1.2 seconds) compared to RED (3.8 seconds). This rapid settling is a reflection of the improved transient response of the fuzzy controller, which dynamically adjusts its output according to system nonlinearities and prevailing event conditions.

Maximum overshoot, measuring the largest variation of the target queue length in the transient stage, is also notably smaller in T-S fuzzy AQM (2 packets) than in RED (10 packets). This smaller overshoot indicates that the fuzzy controller avoids buffer overflow more and the bursty packet losses decrease, thereby smoothing out the queue dynamics.

As far as steady-state error, the T-S fuzzy controller performs better than RED with a zero-like long-term deviation from the target queue (0.2 packets vs. 1.5 packets). Such precision supports the robustness of the fuzzy logic controller to hold regulation irrespective of modeling uncertainty and dynamic network fluctuations.

The Fig. 6 representation gives an easy and intuitive understanding of the performance difference between the two approaches. For all three performance metrics, the event-triggered fuzzy AQM proposal shows significant improvements in both control speed and accuracy of regulation, as well as maintaining stable operation with low control effort.

Overall, this comparison emphasizes the limitations of static, time-triggered controls like RED in reacting to dynamic, nonlinear traffic conditions [19]. By contrast, the T-S fuzzy AQM, via adaptive inference and demand-based control updating, offers greater responsiveness, reduced variability, and better resource utilization. These characteristics make it a superior choice for congestion control in modern, high-speed TCP/IP networks.

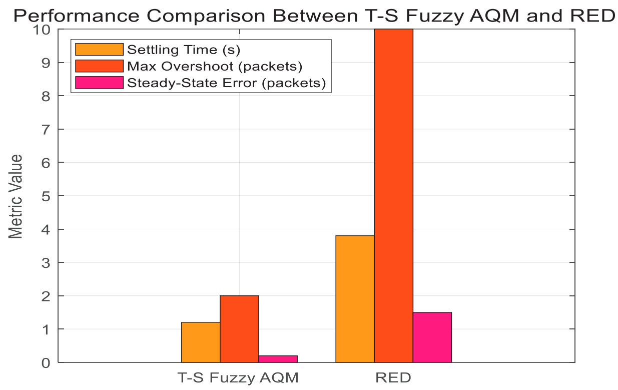

Fig. 6. Performance comparison between T-S fuzzy AQM and RED

4.6 Cumulative Trigger Events Over Time

This Fig. 7 indicates the cumulative number of event-triggered control updates executed by the T-S fuzzy AQM controller during a 10-second simulation period. The cumulative trigger trace is an easy-to-view representation of the activity level of the controller across different stages of the system and illustrates how the event-triggering mechanism adapts dynamically based on the network state.

In the initial transient phase (0–3 seconds), the curve rises rapidly, indicating frequent triggering. This corresponds to the initial response of the system to excessive queue imbalances from the desired level. At this period, the control mechanism operates under stringent error conditions demanding regular corrective action to dampen oscillations and reach equilibrium rapidly.

Under intermediate regulation (3–7 seconds), the gradient of the curve begins to alter with visible oscillations. This shows that the controller is dynamically varying its rate of intervention based on localized perturbations, possibly because of traffic bursts or residual nonlinearities. The oscillatory nature of the triggering rate suggests that the controller is always active, but selectively, in the sense that it intervenes only when system deviations cross the desired event threshold.

In the last stabilization period (7–10 seconds), the overall trigger curve is significantly flattened. This shows how with the queue reaching and lingering around the target value, the controller will not output any further updates. The event-triggering condition naturally filters out minor fluctuations, thereby removing unnecessary computational and communication overhead once stability is achieved.

This adaptive nature clearly distinguishes event-triggered AQM from the traditional time-triggered approaches that continuously transmit control action at fixed intervals regardless of need. By reducing control frequency selectively in the stable regime, the approach outlined here greatly improves efficiency without degrading performance.

Furthermore, the cumulative trigger curve enables quantitative measurement of control burden [20]. The decreasing slope as a function of time suggests diminishing control effort, validating the method's scalability and its suitability for resource-constrained settings such as embedded routers, IoT edge nodes, or wireless sensor gateways.

In summary, Fig. 7 attests to the effectiveness of the proposed controller in achieving precise queue length control with minimal control effort. Time-varying triggering frequency not only represents a manifestation of adaptive intelligent system response but also embodies a practical advantage in today's network environments demanding low-latency, energy-efficient, and responsive congestion control schemes.

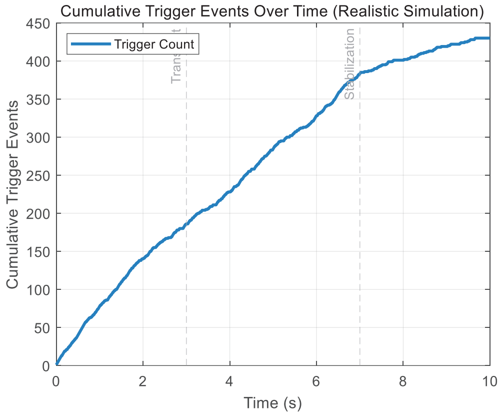

Fig. 7. Cumulative trigger events over time

4.7 Contributions

This paper systematically analyzes event-triggered AQM algorithms of TCP/IP network congestion control from the perspective of improving control effectiveness in nonlinear, delayed, and uncertain network situations. In response to the weakness of traditional time-triggered AQM policies of periodic update nature and unawareness of network state, this paper proposes an adaptive control approach based on the T-S fuzzy model and event-triggered scheme.

The most important contribution of this research is the presentation of an AQM controller that combines the T-S fuzzy approximation of TCP queueing dynamics with a state-dependent event-triggered design. This integrated method enables the controller to handle the inherent nonlinearity of TCP traffic and reduce useless packet loss interventions by updating the control actions only under certain threshold violation conditions. The controller adapts its dynamics in real time, significantly improving the bandwidth usage and computational performance of the router.

The other contribution is the concurrent optimization of fuzzy controller gains and event-triggered conditions using Lyapunov-Krasovsky functionals and LMI techniques. The formulation ensures asymptotic stability of the closed-loop system and the capacity to cope with uncertainty and communication delays, two central problems in modern TCP/IP-based systems.

The scheme has been confirmed by a series of accurate simulations, which cumulatively embody its engineering merits. The simulation results show that event-triggered fuzzy AQM can achieve faster queue stabilization, implement smart adjustments on the triggering rate according to the network status, provide smooth control inputs during the transition phase, minimize tracking errors in the steady state, and significantly outperform RED in terms of control precision, stability, and efficiency.

In summary, this work is a valuable contribution to the intelligent and resource-efficient design of congestion control mechanisms in TCP/IP networks. By combining event-triggered logic with a nonlinear fuzzy control scheme, the proposed AQM algorithm provides a scalable and high-performance alternative to traditional congestion control techniques, and thus it is a promising candidate for next-generation Internet infrastructure.

5 Conclusion

This paper presents a comprehensive theoretical investigation of an event-triggered active queue management algorithm specifically designed to address several persistent challenges in TCP/IP network congestion control. Conventional AQM approaches typically adopt a time-triggered mechanism that periodically updates control actions regardless of changes in network status, which can lead to unnecessary control signaling and inefficiencies. In contrast, the proposed approach leverages the Takagi-Sugeno fuzzy modeling framework to more accurately capture the inherent nonlinear and complex dynamics of TCP queue behavior. This modeling choice enables a detailed characterization of the nonlinear characteristics of the system, which are often oversimplified or ignored in classical linear models. In addition, the algorithm integrates an event-triggered control strategy that updates the control input only when certain conditions are violated, significantly reducing the frequency of redundant control signals. This selective update mechanism not only saves network and computational resources, but also enhances the system's responsiveness by precisely focusing control effort when needed, thereby improving the overall efficiency of congestion regulation. The controller design is based on a rigorous mathematical framework that combines the Lyapunov-Krasovsky function approach with linear matrix inequality techniques. This combined approach ensures that the closed-loop system remains asymptotically stable even in the presence of uncertainties in the model parameters and inherent time delays in the network feedback loop. This robustness is critical in real-world TCP/IP networks, where changing traffic patterns, unpredictable interference, and transmission delays are common. Extensive simulation studies validate the performance of the proposed event-triggered active queue management algorithm under different network conditions. Results show that the proposed controller is able to quickly control the queue length to the desired setpoint with minimal overshoot, maintaining very low tracking error throughout the process. Notably, the peak overshoot of the queue length is significantly reduced compared to traditional approaches such as the random early detection algorithm. In addition, the event-triggered mechanism effectively reduces the total number of control updates, thereby reducing the frequency of control operations, but with more significant control effects, which ultimately translates into improved network resource utilization. The cumulative triggering events recorded during the simulation further demonstrate the effectiveness of the event-triggered strategy, highlighting its ability to dynamically adjust control operations based on network state changes without incurring unnecessary overhead. In summary, the event-triggered active queue management algorithm provides a robust, intelligent, and resource-efficient solution for congestion control in TCP/IP networks. By addressing nonlinearity, uncertainty, and delay issues while minimizing the control workload, the algorithm provides a promising alternative to traditional periodic active queue management methods and lays a solid foundation for developing more adaptive, scalable, and energy-efficient queue management protocols that are better suited to the evolving Internet architecture.

6 Future Work

Given the positive results of this research, future research will continue to enhance the applicability, flexibility, and robustness of event-triggered AQM algorithms to TCP/IP networks. A main avenue is to generalize the current single-router model to more sophisticated network topologies involving multiple queues, interconnected routers, and distributed traffic scenarios. This extension will facilitate testing the scalability and coordination ability of the algorithm in multi-node congestion scenarios. Concurrently, adaptive event-triggering scheme development will be investigated. Instead of fixed thresholds, dynamic triggering policies that adapt in real-time according to queue behavior, network traffic load, or link usage will be investigated in future research [21]. Machine learning techniques such as reinforcement learning can be employed to learn to optimize these thresholds over the internet.

Moreover, more cross-layer integration at a lower level with transport-layer protocols is planned. This will enable the AQM controller to match more closely with end-to-end congestion control behavior and react better in delay-sensitive applications. Realistic implementation will also be prioritized. The algorithm will be tested and assessed in network simulation environments and programmable routers using Software-Defined Networking (SDN) platforms to assess its real-world performance in dynamic network conditions and packet-level impairments [22]. Lastly, because of the potential for security attacks in dynamic queue control, future research will also investigate the resilience of the proposed event-triggered mechanism against denial-of-service (DoS) or adversarial attacks, potentially with the addition of lightweight anomaly detection to guarantee stability and fairness

[23]. These studies aim to push the developed AQM framework to a fully adaptive, intelligent, and deployable solution for future-proof TCP/IP network infrastructure.

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