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Congestion control in cognitive radio networks with event-triggered sliding mode

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ABSTRACT

The increasing demand for assorted services from extensive wireline and wireless users place a significant burden on the band-limited radio spectrum. To settle the demand, smart reuse and management of the spectrum are necessary. In this contribution, Cognitive Radio being an emerging technology provides a platform to share the same spectrum between Primary Users (licensed) and Secondary Users (unlicensed) for significant improvement in the spectrum efficiency. The coexistence of users for data communications in a band-limited channel calls for a robust congestion controller to maximize throughput. This work presents the design of a robust nonlinear congestion controller based on event-triggered sliding mode for Cognitive Radio Networks. The goal is to maintain desired Quality of Service of the network with optimum bandwidth and resource utilization. The controller has been designed on the notions of sliding mode, better known for its inherent robustness and disturbance rejection capabilities. An event-triggering scheme has been incorporated with the sliding mode for optimum utilization of the available resources. The signal is sampled and control is updated only when a predefined condition gets violated while ensuring acceptable closed-loop behavior of the system. The efficiency of the proposed controllers has been validated using simulations.

1. Introduction

1.1. Overview

The exigent need for high degree of agility, mobility, and flexibility calls for a ubiquitous solution in making wireless networking strategies, a perfect candidate for numerous industrial applications. Our modern lifestyle demands unceasing communication in limited bandwidth. Radio spectrum or bandwidth is assigned by the regulatory body to the license holders called Primary Users. These authorized users are assigned with band limited spectrum and are eligible to access the spectrum over the entire time span. Exponential increase in network traffic and imminent user demands require more bandwidth. Bandwidth being a limited resource, is not abundant and has tremendous scarcity hence further increase in bandwidth is not possible. The bandwidth constraint encourage researchers and regulatory bodies to relook for the optimum radio spectrum usage. Many surveys of Federal Communications Commission (FCC) concludes that most of the time 80–85% of the assigned radio spectrum is idle, i.e., the spectrum is vacant or underutilized [1,2]. The voids in radio spectrum revealed from the survey, encourage the feasibility to embed more traffic in existing (traditional) wireless network. The inefficient usage of the limited spectrum compels the regulatory bodies to review their spectrum policies. The FCC made changes in protocols and has been considering more flexible and comprehensive usage of the available spectrum by allowing dynamic spectrum allocation as opposed to static spectrum allocation, by using Cognitive Radio technology. Cognitive Radios are smart radios with intelligence and are configured dynamically depending on the changing environment. In Cognitive Radio Network (CRN), user traffic has been classified as Primary User (PU) traffic and Secondary User (SU) traffic. PU has the legacy rights to use specific part of the spectrum called licensed band and SU exploit the same spectrum intelligently and use the remnant spectrum for optimum bandwidth utilization. Spectrum sharing strategy is used in CRN to bring about enhancement in

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spectrum utilization. The art of sharing the same spectrum between two different types of traffic users is termed as dynamic spectrum access technique. PUs are given more priorities in all aspects than SUs, such as uninterrupted access to spectrum, unregulated data rate transmission and much more. Unlike PU whose data transmission rate depends on their traffic data services, SU choose to regulate their date rate to the queue as per the height of congestion. A low priority is given to the SU to access the channel, and their service capacity fluctuates over time as effected by the high priority class PU transmission behavior. The dynamic spectrum access approach directs the SU to occupy the left-over channel capacity. Thus, there must be a careful balance between the PUs and SUs to access the same bandwidth of radio spectrum.

The coexistence of PU and SU mitigates spectrum scarcity but comes with a cost of increase in the probability of network congestion. Surge traffic in a network is the root cause of congestion and causes snag like loss of packets, queuing delay, packet collision, reduced throughput, lower energy efficiency and poor Quality of Service (QoS). Occurrence of congestion is due to many reasons like higher data arrival rate than the service rate, staying of packets for a longer time in buffer etc. The higher arrival rate cause buffer overflow resulting in loss of packets and choosing same frequency by several users at the same time cause packet collision. Packet loss demands retransmission of packets more than once until it is successfully transmitted and consumes more power unnecessarily. All the above problems are sufficient enough to degrade the QoS and throughput of a network. To improve QoS in network, proper scheduling, priority in scheduling, collision avoidance, minimal delay even in high queuing condition and increased throughput should be taken care of.

In a network, traffic originates from the sender with a decision of where to send the packets and how many packets are to be sent. Depending on network scenario, packets travel through certain intermediate nodes. The queue size of these nodes increases in the presence of congestion and packet loss occurs if it exceeds a threshold. The final and most important decisions are made at the receiver point, where the goal is to maintain QoS. Traffic can be controlled at sender's end and at intermediate nodes. Measurements can be taken at intermediate nodes and at the receiver. From the point of data traffic regulation and resource management, a data transmission network can be perceived as a feedback system. Therefore, it seems to be a natural choice to apply the concepts of feedback control theory to the design of congestion controllers for network traffic control. The goal of congestion control mechanism is to use the network efficiently in order to attain the highest possible throughput while maintaining QoS, i.e., low packet loss and small packet delay.

In this work, we have investigated the problem of congestion in a dynamic network and its mitigation by the design of a robust congestion controller. In CRN, as PU and SU share the same spectrum, a queue-based model can be used for spectrum scheduling and for the evaluation of network QoS. Among many methodological and mathematical tools, queuing theory has extensively contributed in the modeling of CRN [3,4]. A simple network consisting of single PU and SU has been modeled in our work as M/M/1 priority queue where both users share a single channel. M/M/1 has been adopted in many wireless communication networks traffics [5,6]. In this model input arrival rate and service rates both have Poisson distribution function. The flow dynamics or time varying behavior at each priority queue is mathematically modeled by packet flow conservation principle of fluid flow model. An efficient queue management approach prevents congestion and should be robust against external disturbances such as variations in the number of sources, capacity and arrival rate.

Queue management for congestion control demands stable and sturdy controller. Owing to inaccurate and uncertain nature of the network models, design of a congestion controller is a challenging task. Sliding Mode Control (SMC) is best suited in this case as it can nullify matched uncertainties and bounded disturbances as compared to classical PID controllers [7]. SMC find numerous application [8] due to its conceptual simplicity and robust control of dynamic systems. In CRN, the available channel capacity of the SU varies due to fading, shadowing and by the impact of PU transmissions which proclaims uncertainty in the network. Thus, in a dynamic environment, congestion control using a robust sliding mode controller with an adaptive nature is a natural choice.

Motivated by the interesting work on differentiated services (DiffServ) network, where the traffic are classified in different classes depending on their priority to enhance QoS of the network, CRN environment has been mapped to the DiffServ architecture. The problem of congestion control in CRN has been dealt with the design of a robust sliding mode controller based on event-triggering.

1.2. Brief survey

Congestion control is a major concern to be addressed in a communication network. However, congestion control in CRN is still a matter of fact finding. In 1993, Benmohamed and Meerkov proposed one of the first successful solutions to congestion control based on classical control by providing a detailed mathematical description of packet switched network [9]. The model was taken to be a linear approximation of the original model and pole placement design approaches were used. This approach ensured the local stability of the system but failed to provide global stability owing to the nonlinear complexities in it. Altman et al. proposed that time-varying bandwidth can be modeled as a truncated auto-regressive moving average (ARMA) process, in which the truncation ensures that the bandwidth cannot exceed certain bounds [10]. However, a linear model was considered where large queue size variation led to inefficient steady state operation. Use of genetic algorithms [11] and neural networks [12] is not very new in traffic management. They use complex nonlinear relationships and predict future behavior from acquired patterns. The biggest drawback in any iterative or learning algorithm is the time lag that restricts the good estimation accuracy. To alleviate network congestion at intermediate nodes active queue management has been proved phenomenal. Active queue management (AQM) scheme generates the explicit feedback information for regulating the inflow of data by observing the state of the nodes. Random Early Detection (RED) [13] gateways are designed to avoid congestion in packet switched networks by computing average queue size based on statistical probabilities. The main drawback of RED is requirement of wide range of parameters to determine correctly the severity of congestion. A fundamentally different active queue management algorithm called Blue has been proposed in [14], where packet loss and link idle events are used to manage congestion. Even though Blue performs extremely well, but number of non responsive flows increases. An adaptive virtual queue (AVQ) algorithm for active queue management has been proposed in [15] to study the robustness in presence of extremely short flows. Here, Proportional Integral (PI) controller is used on a linearized model of the system which fails to prove its benefit in networked systems which is inherently nonlinear.

The Differentiated Service (DiffServ) architecture for internet protocol is proposed to avoid congestion in a node. DiffServ [16] networks provide scalable mechanism for managing network traffic depending on priority queues. The combination of fuzzy logic with integral sliding mode control has been proposed for DiffServ Networks [17], where the premium traffic has been controlled using a fuzzy sliding mode algorithm and an integral sliding mode controller has been used to control ordinary service. An adaptive sliding mode controller has been designed for DiffServ framework based on back stepping algorithm for a model which minimizes the latency in feedback design [18]. On the other hand, to regulate the flow of data in a DiffServ network with delay, a second-order sliding mode technique was applied by Zhang et al. [19], where better performance was obtained at a cost of increase in system complexity. A robust decentralized congestion control strategy has been developed for a large-scale network with DiffServ traffic in [20]. A sliding mode learning control scheme has been proposed to tackle congestion control problem in DiffServ network with a delay in [21]. Though robustness of the sliding mode controllers were used to compensate for network parameter variations and the unmodeled traffic, none of these work has addressed congestion control under less computation, and reduced energy expenses.

CRN is widely used for effective spectrum utilization in limited bandwidth network. The congestion control in CRN could augment network QoS and throughput. The problem of congestion control in CRN is not well addressed till date. A Joint congestion control and routing subject to dynamic interruptions from PU in CRN has been proposed in [22]. The learning procedures were slow, which required a priori knowledge of primary users. Esmaeelzadeh et al. proposed rate-based congestion control schemes in cognitive radio sensor networks [23], although it failed in closed loop formulation for mean sending rate in cognitive radio node. A multiple model predictive congestion control scheme for CRN under disturbances from the time varying service capacity for SU has been proposed in [24]. However, controller updates were based on traditional sample data system.

Recent advancement for QoS enhancement include cloud based radio over optical fiber network (C-RoFN) architecture with multi stratum resources optimization using software defined networking. The proposed architecture globally optimizes radio frequency, optical spectrum, and baseband unit (BBU) processing resources effectively to maximize radio coverage and meet the QoS requirement with vertical integration and horizontal merging [25,26]. A multichannel system using queuing model has been proposed to enhance QoS in preemptive and non-preemptive priority queuing [4]. A stochastic fluid flow model has been used in [27] for effective bandwidth utilization and QoS for multiple PUs and SUs.

In this work, to the best of author's knowledge, an event-triggered control is incorporated for the first time in CRN environment to solve the problem of suboptimal utilization of resources in the networked control system. In general, continuous sampling and transmission along with the occupancy of central processing unit to perform computations, when the signal is constant (not changing too frequently) lead to significant wastage of available resources. The optimum utilization of communication, computing and energy expenses is a concern in various applications with increasing number of systems getting networked. One mitigation strategy adopted is event based control wherein the control is applied only when the system calls for it depending upon some noticeable change, also referred to as an *event*. More formal presentation and earlier works on event based control are presented in [28–31].

It should be noted that the control updates in [17–21] are continuous eventually leading to significant wastage of available resources. This work presents an event-triggered SMC with an aim to curb congestion and to make optimal use of available resources. The main contributions are summarized as:

- This work presents a robust congestion control scheme to maintain desired QoS by reducing the packet loss with optimum bandwidth utilization. The controller updates require minimal computation and thus save energy expenditure. On contrary to periodic sampling and update of controller involved, event triggering has been used.
- The proposed controller is an event-triggered controller designed on the notions of sliding mode control better known for its inherent robustness. An inverse sine hyperbolic reaching law has been used which made the controller gain adaptive and nonlinear. The gain is larger in magnitude when the trajectories are far away from the sliding surface as compared to the gain when trajectories are in the vicinity of the sliding manifold. This helped in shortening the reaching phase and also the control signal is smooth.
- The time interval between two consecutive controller update is bounded below by a finite positive quantity thereby ensuring no Zeno behavior.

The dynamics of the CRN has been described in Section 2. Section 3 presents the problem formulation followed by synthesis of the proposed controller in Section 4. Simulation results are shown in Section 5 followed by conclusion and future work in Section 6.

2. Dynamics of the system

We have considered a single queue model and applied the flow dynamics for the mathematical modeling of CRN. The flow dynamics in a queue has been represented with M/M/1 model which find numerous application in wireline and wireless networks [5,6]. Queue dynamics are extensively modeled using probabilistic approaches with the advantage of estimating the network performance under both transient and steady state conditions. However, it is quite cumbersome and computationally complicated to adopt the same approach for analysis of smaller systems. The queue dynamics described here is based on nonlinear time varying differential equations governing the characteristics of mean queue length at sundry network queues. Use of this model in our case is also advantageous as it allows richer techniques of feedback control theory to be incorporated in the development of various control algorithms and evaluation of performance indices.

2.1. Fluid flow model of a single queue

The state model used is based on queue dynamics for a single link. The number of packets at any instant of time t in the system, i.e., *queue + server* is $N(t)$. $x(t)$ is a state variable and also the *ensemble average* of the number of packets in the system, i.e., $x(t) = E\{N(t)\}$. If $a(t)$ is the flow into the queue and $b(t)$ is the flow out of the queue, then $f_{out}(t) = E\{b(t)\}$ and $f_{in}(t) = E\{a(t)\}$. According to the flow conservation principle, the flow dynamics of a single queue is modeled as, the rate of change of the ensemble average number in the system is same as the difference between the flow in and the flow out of the system at time t.

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

The arrival rate at the queue is modeled as a non-stationary Poisson's process and is given as $\lambda(t)$. Under these considerations, $f_{in}(t)$ is just the arrival rate $\lambda(t)$. $f_{out}(t)$ is related to the ensemble average link utilization $\rho(t)$ by

$$f_{out} = \overline{C}\rho(t), \tag{2}$$

where $\overline{C}$ is the link capacity and $\rho(t)$ is the probability of the number of packets at any instant of time t in the system greater than zero, that is, $\rho(t) = P(N(t) > 0)$. Thus, the flow dynamics can also be written as

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

$\rho(t)$ can also be represented in terms of state variable $x(t)$. We assume $\rho(t)$ can be approximated by a function $G(x(t))$, which represents the ensemble average utilization of the queue at time t as a function of state variable. Note that $x \in \mathbb{N} \cup \{0\}$ with $\mathbb{N}$ denoting set of natural numbers. Since, $x(t) = 0 \Rightarrow f_{out}(t) = 0, G(0) = 0$. Also, $x(t) = \infty \Rightarrow f_{out}(t) = \overline{C}, G(\infty) = 1$ (see Fig. 1).

Hence, for any physical model to be described, $G(x(t)) \in [0,1)$ is strictly a non-negative concave function over range $x(t) \in [0,\infty)$, and $\overline{C} \in [0, C_{max}]$. Now the dynamics of queue model represented by a first order nonlinear time varying differential equation is given as:

$$\dot{x}(t) = -\overline{C}G(x(t)) + \lambda(t). \tag{4}$$

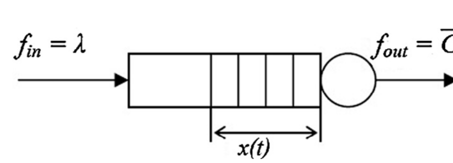

Fig. 1. Simple diagram of a queue and illustration of flow in and flow out.

The link has been modelled as *M/M/1* [5,32] queue for which the following assumptions have been made.

- The packets arrival follows a Poisson distribution.
- The packet length follows an exponential distribution with mean length $1/\mu$.
- The packet transmission time is proportional to the packet length.

Remark 1. A more formal presentation of $G(x(t))$ depends on several factors like queue under consideration, experimental data available, statistical formulations, etc. A commonly used simple approach to determine $G(x(t))$ is by matching the queue length at steady state of M/M/1 model [6,20], i.e.,

$$x(t) = \lambda(t)/(\mu\overline{C} - \lambda(t)), \Rightarrow \lambda(t)/\overline{C} = \mu\frac{x(t)}{1 + x(t)} \tag{5}$$

to the steady state of the fluid flow model in Eq. (4) i.e., when $\dot{x}(t) = 0 \Rightarrow G(x(t)) = \lambda(t)/\overline{C}$. On equating $G(x(t))$ with Eq. (5) we conclude

$$G(x(t)) = \mu\frac{x(t)}{1 + x(t)}, \tag{6}$$

and the dynamics of a single queue model [5,20] can consequently be represented as:

$$\dot{x}(t) = -\overline{C}(t)\mu\frac{x(t)}{1 + x(t)} + \lambda(t). \tag{7}$$

2.2. Primary user traffic

The requirement of PU services is guaranteed delivery of packets but rate regulation is not allowed. Delay and jitters are acceptable but should be kept as minimum as possible. However, the packet loss is unacceptable. The buffer state is regulated to be close to a reference value carefully chosen by the operator such that the packet loss is minimized to get desired QoS [33,34]. The wireless channel is assumed to be noise free with a fixed maximum capacity of C_{max} [4,5]. The Maximum capacity $\overline{C}_p(t)$ of the PU service is dynamically assigned such that $0 \leqslant \overline{C}_p(t) \leqslant C_{max}$. From Eq. (7) and assuming μ (average packet length) as unity, the first order state space equation for PU service can be given as:

$$\dot{x}_p(t) = -\overline{C}_p(t)\frac{x_p(t)}{1 + x_p(t)} + \lambda_p(t). \tag{8}$$

The subscript p denotes that PU services are being dealt with. Without loss of generality, description of the above formulation in functional form (to be used in later stages) is given as:

$$\dot{x}_p(t) = f(x_p(t)) + b(x_p(t))u_p(t), \tag{9}$$

$x_p(t) > 0$ ensures existence of b^{-1} and $u_p(t)$ is the control input for the above case.

2.3. Secondary user traffic

SU services are prohibited to packet loss but can tolerate queuing delay. Whenever maximum capacity is not used by PU services, the leftover capacity is dynamically assigned to SU services which regulate the flow of SU traffic into the network by controlling the queue length to be close to a fixed reference value [33,34]. The bandwidth for SU service can be given as $\overline{C}_s(t) = C_{max} - \overline{C}_p(t)$, where $\overline{C}_s(t) > 0$. The first order state space equation for SU service is represented as:

$$\dot{x}_s(t) = (C_{max} - \overline{C}_p(t))\frac{-x_s(t)}{1 + x_s(t)} + \lambda_s(t). \tag{10}$$

In quite a similar fashion, functional form description of the SU services is given as:

$$\dot{x}_s(t) = f(x_s(t)) + b(x_s(t))u_s(t). \tag{11}$$

3. Problem formulation

The control objective is to regulate queue length in the buffer to the desired reference. In other words, no packet loss should be there in the network irrespective of growing user's request. Thus the error variable can be defined as:

$$e_i(t) = x_i(t) - x_{iref}, \tag{12}$$

where i stands for both PU and SU and x_{iref} is the reference value selected by the operator throughout the discussion. It is required that the error candidate vanishes as fast as possible and an accurate set point tracking is assured. This regulation problem has been dealt separately for PU and SU traffic.

4. Synthesis of the proposed controller

The controller synthesized in this work is based on the notions of sliding modes [33,34] with a slight modification. The sliding mode controller design [8,35] is a two step process: design of a sliding surface where trajectories are required to be confined in finite time and a control to force the trajectories onto this surface.

Definition 1. Typical form of sliding surface used in this work is formulated as:

$$\sigma_i = \left(\frac{d}{dt} + h\right)^{n-1} e_i, \tag{13}$$

where n represents the order of the system and h is the scalar coefficient weight.

Remark 2. The surface variable for the first order system as considered in this work reduces to $\sigma_i = e_i$.

4.1. Controller design for primary user services

The control objective discussed earlier requires an accurate tracking of the desired queue length for any PU traffic by dynamically assigning the maximum bandwidth available to the PU, in keeping up with the vacillating incoming traffic rate.

$$\begin{aligned}
&\sigma_p(t) = e_p(t) \Rightarrow \dot{\sigma}_p(t) = \dot{e}_p(t) = \dot{x}_p(t) - \dot{x}_{pref},\\
&\Rightarrow \dot{\sigma}_p(t) = -\overline{C}_p(t)\tfrac{x_p(t)}{1 + x_p(t)} + \lambda_p(t) - \dot{x}_{pref},\\
&\Rightarrow \overline{C}_p(t) = \tfrac{1 + x_p(t)}{x_p(t)}[\lambda_p(t) + K\sinh^{-1}(m + w|\sigma_p(t)|)sign(\sigma_p(t)) - \dot{x}_{pref}],\\
&\Rightarrow \overline{C}_p(t) = \tfrac{1 + x_p(t)}{x_p(t)}[\lambda_p(t) + K_1 sign(\sigma_p(t)) - \dot{x}_{pref}],
\end{aligned} \tag{14}$$

x_{pref} is the constant reference value that needs to be achieved and $sign(\sigma(t))$ is the discontinuous forcing function in the notions of sliding mode. K is tunable controller gain and $K_1 = Ksinh^{-1}(m + w|\sigma_p(t)|) > 0$ is nonlinear controller gain. Here, $w > 0$ is the adjustable gain which can be tuned as per the design specifications and $m > 0$ is a small positive value such that the hyperbolic function does not attain a zero argument, also $m < w$. In functional form,

$$u_p(t) = -b(x_p(t))^{-1}[f(x_p(t)) + K_1 sign(\sigma_p(t))]. \tag{15}$$

4.2. Controller design for secondary user services

In the effort to maintain the specified queue length for SU, flow of traffic in the network is regulated in accordance with the residual capacity. Let us denote the leftover bandwidth by $\overline{C}_s(t)$. Clearly, $\overline{C}_s(t) = C_{max} - \overline{C}_p(t)$.

Remark 3. SU are allocated with the residual bandwidth. $\overline{C}_s(t)$ is required to be strictly positive and $\lambda_s(t)$ is the control signal.

$$\sigma_s(t) = e_s(t) \Rightarrow \dot{\sigma}_s(t) = \dot{e}_s(t) \Rightarrow \dot{\sigma}_s(t) = \dot{x}_s(t) - \dot{x}_{sref},$$
$$\Rightarrow \dot{\sigma}_s(t) = -\overline{C}_s(t)\tfrac{x_s(t)}{1+x_s(t)} + \lambda_s(t) - \dot{x}_{sref},$$
$$\Rightarrow \lambda_s(t) = \overline{C}_s(t)\tfrac{x_s(t)}{1+x_s(t)} - K_1 sign(\sigma_s(t)) + \dot{x}_{sref}. \tag{16}$$

In functional form,

$$u_s(t) = -b(x_s(t))^{-1}[f(x_s(t)) + K_1 sign(\sigma_s(t))]. \tag{17}$$

4.3. Event-driven sliding modes

Sliding mode control is known for its inherent robustness. The switching nature of the control is used to nullify bounded disturbances and matched uncertainties. The switching happens about a surface (hyperplane) in state space known as the sliding surface. The control forces the system monotonically towards the sliding surface and this phase is regarded as reaching phase. When the system reaches the sliding surface it remains there for all future time thereby ensuring the system dynamics remains independent of bounded disturbances and match uncertainties.

The sudden increase of interest in the event-driven design of circuits and systems is due to its better performance in an application where resources are constrained. In networked control system, where bandwidth and processor time is always constrained, event based control can provide better results. The traditional sampled data control system considers periodic update of the controllers even after achieving control objective. This results in wastage of significant computational and communication resources and transmission of redundant data may eventually lead to congestion. An efficient way to reduce communication and computation burden is to use event-triggering scheme. The objective of event-triggering scheme is to sample and update controller only when the local measurement error crosses a predefined threshold while ensuring acceptable closed loop performance of the system. The event based control is a good candidate, if the requirement is to execute different task in time shared manner and also where control is expensive.

Event triggered sampling has often been described as an alternative to periodic sampling owing to its nature. Next sample instant is dependent on the triggering of an *event*. Hence, our control law given in Eqs. (14)–(17) are modified for $\forall\ t \in [t_j, t_{j+1})$ as below.

$$\overline{C}_p(t) = \frac{1 + x_p(t_j)}{x_p(t_j)}[\lambda_p(t_j) + K_1 sign(\sigma_p(t_j)) - \dot{x}_{pref}]. \tag{18}$$

$$\text{or } u_p(t) = -b(x_p(t_j))^{-1}[f(x_p(t_j)) + K_1 sign(\sigma_p(t_j))]. \tag{19}$$

$$\text{and } \lambda_s(t) = \overline{C}_s(t_j)\frac{x_s(t_j)}{1 + x_s(t_j)} - K_1 sign(\sigma_s(t_j)) + \dot{x}_{sref}. \tag{20}$$

$$\text{or } u_s(t) = -b(x_s(t_j))^{-1}[f(x_s(t_j)) + K_1 sign(\sigma_s(t_j))]. \tag{21}$$

with t_j being time instant of jth event.

Remark 4. The control is updated at t_j instants only. For the time instants in $[t_j, t_{j+1})$, trajectories deviate from the sliding surface. However, this deviation is assumed to be bounded by a small finite quantity.

Determination of triggering instant is given by the following relation:

$$t_{j+1} = \inf\{t \in [t_j, \infty): x_i(t) \geqslant x_{iref}\}. \tag{22}$$

Assumption 4.3.1. Delay Δ might occur during sampling due to hardware characteristics. In such cases the control is maintained constant $\forall\ t \in [t_j + \Delta, t_{j+1} + \Delta)$. It has been assumed that Δ is negligible and has been ignored. Hence in this case, control is constant in the interval $[t_j, t_{j+1})$.

4.4. Stability analysis

Stability analysis is carried out to affirm the asymptotic stability in Lyapunov sense. Negative definiteness of the derivative of Lyapunov candidate ensures stability. Let us propose a potential Lyapunov candidate $V_i = \frac{1}{2}\sigma_i^2$. The task is to show that $\dot{V}_i < 0$ for the proposed law. It should be noted that the reference x_{iref} is taken to be a constant positive value in both cases, so $\dot{x}_{iref} = 0$. The functions used in functional form description of PU and SU services are assumed to be locally Lipschitz with Lipschitz constant L_i.

$$\dot{V}_i = \sigma_i(t)\dot{\sigma}_i(t) = \sigma_i(t)\dot{x}_i(t) = \sigma_i(t)[f(x_i(t)) + b(x_i(t))u_i(t)]. \tag{23}$$

Thus $\forall\ t \in [t_j, t_{j+1})$, it can be written as

$$\begin{aligned}
\dot{V}_i &= \sigma_i(t)[f(x_i(t)) - b(x_i(t))b(x_i(t_j))^{-1}f(x_i(t_j)) \\
&\quad - b(x_i(t))b(x_i(t_j))^{-1}K_1 sign(\sigma_i(t_j))] \\
\dot{V}_i &\leqslant -\sigma_i(t)b(x_i(t))b(x_i(t_j))^{-1}K_1 sign(\sigma_i(t_j)) + \|\sigma_i(t)\|\|f(x_i(t)) \\
&\quad - b(x_i(t))b(x_i(t_j))^{-1}f(x_i(t_j))\|,
\end{aligned}$$

As long as $\sigma_i(t) > 0$ or $\sigma_i(t) < 0$, the condition $\sigma_i(t) = \sigma_i(t_j)$ is strictly satisfied $\forall\ t \in [t_j, t_{j+1})$. Hence, when trajectories are just outside the sliding manifold,

$$\begin{aligned}
\dot{V}_i &\leqslant -\|\sigma_i(t)\|b(x_i(t))b(x_i(t_j))^{-1}K_1 + \|\sigma_i(t)\|\|f(x_i(t)) \\
&\quad - b(x_i(t))b(x_i(t_j))^{-1}f(x_i(t_j))\| \\
\dot{V}_i &\leqslant -\|\sigma_i(t)\|(b(x_i(t))b(x_i(t_j))^{-1}K_1 - \|f(x_i(t)) \\
&\quad - b(x_i(t))b(x_i(t_j))^{-1}f(x_i(t_j))\|) \\
&\Rightarrow \dot{V}_i \leqslant -\eta\|\sigma_i(t)\|,
\end{aligned}$$

with $\eta > 0$. This completes the proof of reachability for both the services.

For stability, it is required to be shown that $\dot{V}_i < 0$. At $t = t_j$, $\|x_i(t) - x_i(t_j)\| \to 0$ and the control signal is updated. Also $b(x_i(t))b(x_i(t_j))^{-1} = \mathbf{1}$. Thus, $\dot{V}_i \leqslant -\|\sigma_i(t)\|(K_1 + L_i\|x_i(t) - x_i(t_j)\|)$. Since, $\|x_i(t) - x_i(t_j)\| \to 0 \Rightarrow \dot{V}_i \leqslant -K_1\|\sigma_i(t)\| \Rightarrow \dot{V}_i < 0$. This completes the proof of stability for both the services.

Remark 5. Let us define the inter-event time by T_j such that

$$T_j = t_{j+1} - t_j. \tag{24}$$

For finite lower bound of inter-event time, the following inequality holds good.

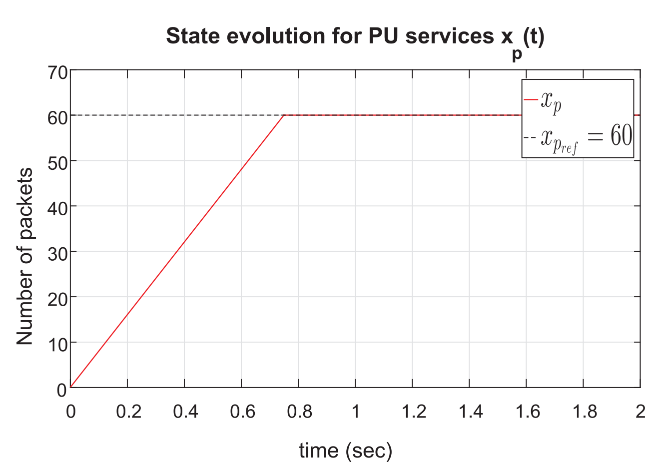

Fig. 2. Queue for PU using event based sliding mode control.

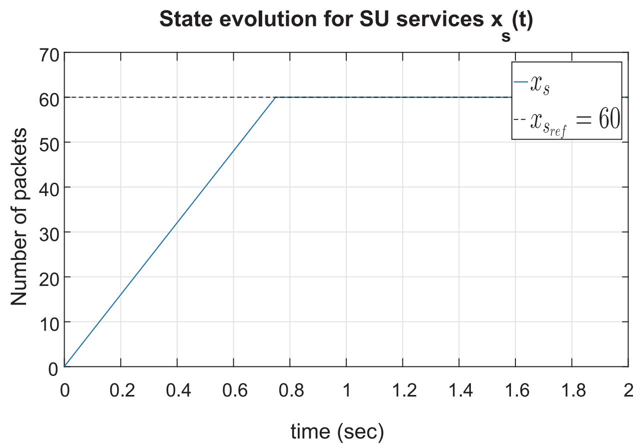

Fig. 3. Queue for SU using event based sliding mode control.

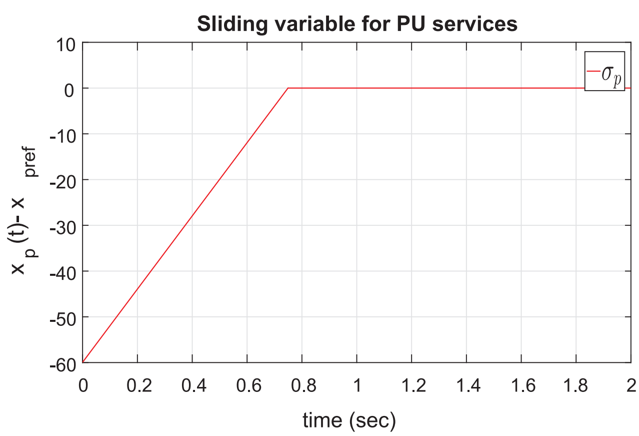

Fig. 4. Sliding surface variable for PU service.

$$t_{j+1} - t_j \geqslant T_j. \tag{25}$$

This also implies that there exists a positive inter execution time and triggering instants are admissible. Moreover, there is no *Zeno* phenomenon.

4.5. Proof of event-triggering with minimum bound of T_j for PU

Let us formulate the discretization error introduced by implementing event based control as

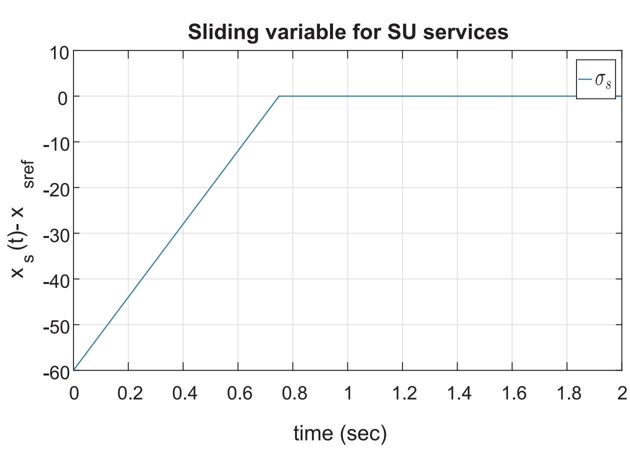

Fig. 5. Sliding surface variable for SU service.

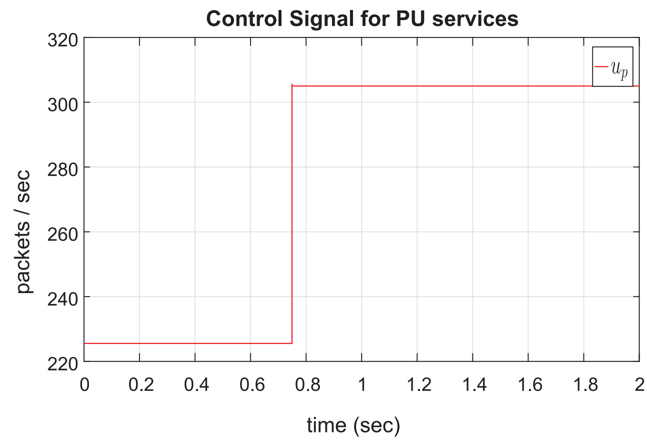

Fig. 6. Control signal for PU service.

$$\epsilon_p(t) = x_p(t) - x_p(t_j). \tag{26}$$

From (9) and (19), we have

$$\dot{x}_p(t) = f(x_p(t)) + b(x_p(t))u_p(t)$$
$$u_p(t) = -b(x_p(t_j))^{-1}[f(x_p(t_j)) + K_1 sign(\sigma_p(t_j))].$$

Between j^{th} and $(j+1)^{th}$ sampling instant during the execution of control, the discretization error (26) is non zero. T_j is the time taken by the discretization error to rise from 0 to some finite value. Thus,

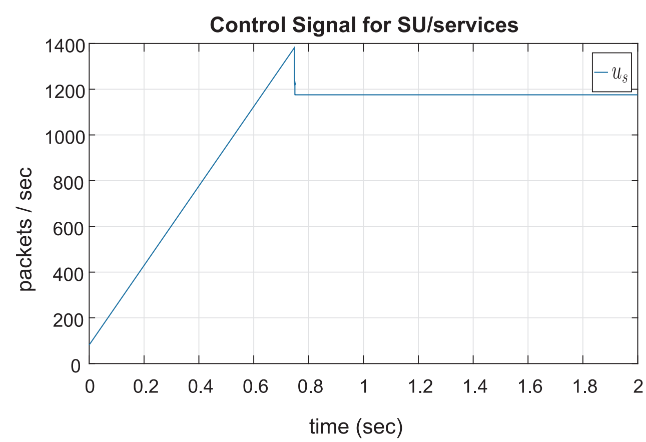

Fig. 7. Control signal for SU service.

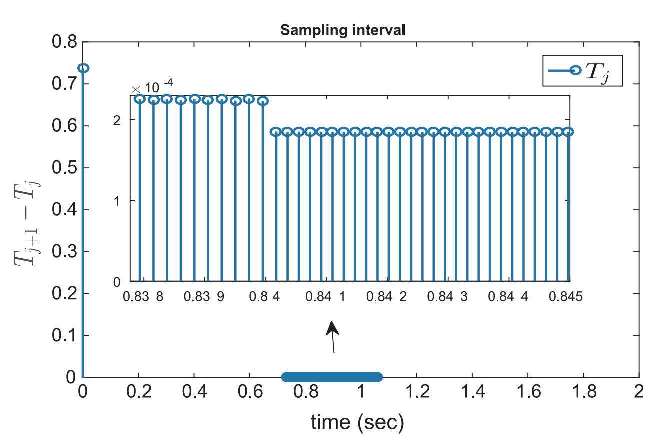

Fig. 8. Sampling intervals.

Table 1
Numerical values of parameters used in simulation.

Maximum channel capacity (packets/s)	Incoming traffic for PU (packets/s)	Desired queue length for PU (packets)	Desired queue length for SU (packets)	Controller gain	Reaching law bias	Additional gain factor
C_{max}	λ_p	x_{pref}	x_{sref}	K	m	w
1500	300	60	60	60	0.01	10

$$\frac{d}{dt}\|\epsilon_p(t)\| \leqslant \|\frac{d}{dt}\epsilon_p(t)\| \leqslant \|\frac{d}{dt}x_p(t)\| \tag{27}$$

$$\Rightarrow \|\frac{d}{dt}\epsilon_p(t)\| \leqslant \|f(x_p(t)) + b(x_p(t))u_p(t)\|, \tag{28}$$

Substituting the control input (19) in the above inequality, we get

$$\begin{aligned}\|\tfrac{d}{dt}\epsilon_p(t)\| &\leqslant \|f(x_p(t)) - b(x_p(t))b(x_p(t_j))^{-1}[f(x_p(t_j)) + K_1 sign(\sigma_p(t_j))]\|\\ &\leqslant L_p\|x_p(t)\| + \|b(x_p(t))b(x_p(t_j))^{-1}\|\, L_p\|x_p(t_j)\|\\ &\quad + \|b(x_p(t))b(x_p(t_j))^{-1}\|\|K_1\|\\ &\leqslant L_p(\|x_p(t_j)\| + \|\epsilon_p(t)\|) + \gamma\, L_p\|x_p(t_j)\| + \gamma\|K_1\|\\ &= L_p\|\epsilon_p(t)\| + (1+\gamma)\, L_p\|x_p(t_j)\| + \gamma\|K_1\|\\ &= L_p\|\epsilon_p(t)\| + \Omega\|x_p(t_j)\| + K_2,\end{aligned} \tag{29}$$

Where γ is $\|b(x_p(t))b(x_p(t_j))^{-1}\|$, $(1+\gamma)L_p = \Omega$ and $\gamma\|K_1\| = K_2$.

The solution to the above differential inequality $\forall\ t \in [t_j, t_{j+1})$ can be understood by using Comparison Lemma [36] with initial condition $\|\epsilon_p(t)\| = 0$ and is given as:

$$\|\epsilon_p(t)\| \leqslant \frac{\Omega\|x_p(t_j)\| + K_2}{L_p}(exp\{L_p(t-t_j)\}-1) \tag{30}$$

$$\leqslant \frac{\Omega\|x_p(t_j)\| + K_2}{L_p}(exp\{L_p(T_j)\}-1). \tag{31}$$

Comparison Lemma [36] is particularly useful when information on bounds for the solution is of greater significance than the solution itself.

$$T_j \geqslant \frac{1}{L_p}ln\left(\frac{L_p\|\epsilon_p\|_\infty}{\Omega\|x_p(t_j)\| + K_2} + 1\right). \tag{32}$$

Since, the right hand side of (32) is always positive, it is, therefore concluded that inter-event execution time is bounded below by a finite positive quantity [37], which ensures no Zeno behavior. This concludes the proof.

A similar proof also follows for SU services and hence it has been omitted here.

5. Numerical simulation and results

Network congestion has a direct impact on energy efficiency and QoS of the network. Packet loss not only degrades the reliability and link utilization but also demand retransmission of packets, resulting in wastage of limited source energy. To validate the responsiveness of our proposed controller, reference queue set point has been fixed. The chosen reference point indirectly guaranteed acceptable bounds for the packet loss and delay in each traffic. From Figs. 2 and 3, we can observe the behavior of both the traffic queues. It can be inferred that transient response is fast and there are no overshoot and undershoot with respect to the reference set point. Further it can be noticed that no cyclic behavior or oscillations are observed at the steady state, thus it implies the network is well controlled. Good transient response (fast convergence) and smooth steady state response proved the robustness of the proposed controller. By dynamically controlling the buffer queue to its stable operating point (queue set point), the proposed controller not only avoids packet loss and delay but also utilizes the queue effectively. Effective queue utilization guarantees no retransmission of packets by avoiding queue overflow and helps in maximum link utilization by avoiding buffer emptiness. Figs. 4 and 5, depicts the surface variable for both the service class, which also happens to be the error variable. The faster convergence of error variable to zero shows desirable close loop dynamics of the system and proves the effectiveness of the controller. The control objective in PU traffic is to allocate appropriate capacity for data communication, depending on the constraint of unknown arrival rate by keeping controlled buffer length close to the set-point. Fig. 6 depicts the chattering free control signal for the corresponding service. The propinquity of unwanted chattering with controller gain has been obviated and acceptable closed loop behavior has been achieved. The control objective for SU is to use remnant spectrum effectively and transmit at allowable rate to avoid congestion. It can be inferred from Fig. 7 that the proposed scheme not only avoids congestion but also optimally utilizes the available spectrum. Fig. 8 shows inter event time interval wherein it is clear that sampling is non-uniform. In Fig. 8, a magnified sectional view is also embedded to represent controller updates. On contrary to periodic sampling and controller update, event-triggering helped in optimum use of available resources and saving energy expenses. When the sliding mode is enforced, an increase in sampling is observed. During this period, the number of packets in the system is maintained in close proximity of the desired reference.

Numerical simulations have been carried out in Mathworks MATLAB™ and parameters of interest are tabulated here (see Table 1).

6. Conclusion and future work

In this paper, the congestion control problem in CRN has been addressed with an event based sliding mode controller to allocate the maximum possible capacity for the PU traffic and the leftover capacity for SU traffic. The dynamics of the network has been presented as fluid flow model. This allowed to reduce computation complexities and incorporate the richer theory of control systems in the development of congestion controller for CRN. Negative definiteness of the Lyapunov candidate proved stability. The superiority of the proposed controller guarantees both robustness and stability thus providing smaller queue fluctuation, lower packet loss, optimum bandwidth utilization and desired QoS. The control has been updated only based on some noticeable change (event) on contrary to periodic update. This helped to achieve low computation power and control by exception, thus reduced communication burden. Inter-event time i.e the time difference between two consecutive controller update has been separated by a finite positive value. Finally, results are shown to prove the effectiveness of the proposed control.

In future, a robust congestion controller with dynamic event driven triggering can be incorporated in CRN. The effects of time varying delay on performance metrics can be addressed as extensions to the current work. A rate based congestion control scheme based on consensus of multiple PUs and SUs can be formulated.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.aeue.2018.04.013.

References

[1] Akyildiz IF, Lee W-Y, Vuran MC, Mohanty S. Next generation/dynamic spectrum access/cognitive radio wireless networks: a survey. Comput Networks 2006;50(13):2127–59.

[2] Wang B, Liu KJR. Advances in cognitive radio networks: a survey. IEEE J Select Top Signal Process 2011;5(1):5–23.

[3] Kumar V, Minz S, Kumar V. Performance analysis of cognitive radio networks under spectrum sharing using queuing approach. Comput Electr Eng 2016;52:390–8.

[4] N. Khedun, V. Bassoo, Analysis of priority queueing with multichannel in cognitive radio network, in: IEEE EUROCON 2015 - International Conference on Computer as a Tool (EUROCON), 2015, pp. 1–6.

[5] Xu K, Tipper D, Qian Y, Krishnamurthy P, Tipmongkonsilp S. Time-varying performance analysis of multihop wireless networks with cbr traffic. IEEE Trans. Veh. Technol. 2014;63(7):3397–409.

[6] Tipper David, Sundareshan Malur K. Numerical methods for modelling computer networks under non stationary conditions. IEEE J Select Areas Commun 1990;8(9):1682–95.

[7] Lin C-L, Chen C-H. Robust control of interconnected network schemes subject to random time-varying communication delays. AEU – Int J Electron Commun 2006;60(9):647–58. http://dx.doi.org/10.1016/j.aeue.2006.01.001.

[8] David Young K, Utkin Vadim I, Ozguner Umit. A control engineer's guide to sliding mode control. IEEE Trans Control Syst Technol 1999;7(3):328–42.

[9] Benmohamed L, Meerkov SM. Feedback control of congestion in packet switching networks: the case of a single congested node. IEEE/ACM Trans Network 1993(1):693–708.

[10] E. Altman, F. Baccelli, J.-C. Bolot, Discrete-time analysis of adaptive rate control mechanisms, in: In Proc. 5th Int. Conference on Data and Communications, 1994, pp. 121–140.

[11] A. Pitsillides, A. Sekercioglu, Congestion control, Tech. Rep., 2000.

[12] Douligeris C, Develekos G. Neuro-fuzzy control in atm networks. IEEE Commun Magaz 1997(35):154–62.

[13] Floyd S, Jacobson V. Random early detection gateways for congestion avoidance. IEEE/ACM Trans Netw 1993(1):397–413.

[14] Feng W-C, Shin KG, Kandlur DD, Saha D. The blue active queue management algorithms. IEEE/ACM Trans Netw 2002;10(4):513–28.

[15] Kunniyur SS, Srikant S. An Adaptive Virtual Queue (AVQ) algorithm for active queue management. IEEE/ACM Trans Netw 2004(12):286–99.

[16] Demoor T, Walraevens J, Fiems D, Bruneel H. Performance analysis of a priority queue: expedited forwarding phb in diffserv. AEU – Int J Electron Commun 2011;65(3):190–7.

[17] N. Zhang, Y. Jing, M. Yang and S. Zhang, Robust AQM controller design for DiffServ network using sliding mode control, in: Proc. 17th IFAC World Congress, Seoul, South Korea, 2008, pp. 5635–5639.

[18] X. Zheng,N. Zhang, G.M. Dimirovski and Y. Jing, Adaptive sliding mode congestion control for diffserv network, in: Proc. 17th IFAC World Congress, Seoul, South Korea, 2008, pp. 12983–12987.

[19] Zhang N, Yang M, Jing Y, Zhang S. Congestion control for diffserv network using second-order sliding mode control. IEEE Trans Industr Electron 2009(56):3330–6.

[20] Chen R, Khorasani K. A robust adaptive congestion control strategy for large scale networks with differentiated services traffic. Automatica 2011;47(1):26–38.

[21] Do MT, Jin J, Wang H, Man Z. Sliding mode learning based congestion control for diffserv networks. IET Control Theory Appl 2016;10(11):1281–7.

[22] H. Li, L. Qian, Joint congestion control and routing subject to dynamic interruptions in cognitive radio networks, in: 2012 7th International ICST Conference on Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM), 2012, pp. 275–279.

[23] Esmaeelzadeh V, Hosseini ES, Berangi R, Akan OB. Modeling of rate-based congestion control schemes in cognitive radio sensor networks. Ad Hoc Netw 2016;36:177–88.

[24] Xiao K, Mao S, Tugnait JK. Maq: A multiple model predictive congestion control scheme for cognitive radio networks. IEEE Trans Wireless Commun 2017;16(4):2614–26.

[25] Yang H, Zhang J, Ji Y, Lee Y. C-rofn: multi-stratum resources optimization for cloud-based radio over optical fiber networks. IEEE Commun Mag 2016;54(8):118–25.

[26] H. Yang, J. Zhang, Y. Ji, Y. He, Y. Lee, Experimental demonstration of multi-dimensional resources integration for service provisioning in cloud radio over fiber network, Scientific Reports 6, article.

[27] Safavi SE, Subbalakshmi KP. Effective bandwidth for delay tolerant secondary user traffic in multi-pu, multi-su dynamic spectrum access networks. IEEE Trans Cognit Commun Network 2015;1(2):175–84.

[28] Shi Dawei, Shi Ling, Chen Tongwen. Event Based State Estimation – A Stochastic Perspective. Springer; 2016.

[29] Mazo M, Tabuada P. Decentralized event-triggered control over wireless sensor/actuator networks. IEEE Trans Autom Control 2011;56(10):2456–61.

[30] Tabuada P. Event-triggered real-time scheduling of stabilizing control tasks. IEEE Trans Autom Control 2007;52(9):1680–5.

[31] Aström KJ. Event Based Control. Berlin, Heidelberg: Springer; 2008. pp. 127–147.

[32] Kumar L, Sharma V, Singh A. Feasibility and modelling for convergence of optical-wireless network - a review. AEU – Int J Electron Commun 2017;80(Supplement C):144–56. http://dx.doi.org/10.1016/j.aeue.2017.06.027.

[33] Tirtha Majumder, P.K. Sahu, S.S. Singh, Abhinav Sinha, Rajiv Kumar Mishra, Robust nonlinear congestion controller for cognitive radio based wireless network.

[34] T. Majumder, R.K. Mishra, S.S. Singh, A. Sinha, P.K. Sahu, CRC Press, 2016. Ch. Congestion control in Cognitive Radio networks using fractional order rate reaching law based sliding modes, pp. 91–94.

[35] Żak SH. Systems and Control. 198 Madison Avenue, New York, New York, 10016: Oxford University Press; 2003.

[36] Khalil HK. Nonlinear Systems. 2nd ed. Englewood Cliffs, NJ: Prentice-Hall; 1996.

[37] Girard A. Dynamic triggering mechanisms for event-triggered control. IEEE Trans Autom Control 2015;60(7):1992–7.