Delay Sensitive and Power-Aware SMDP-based Connection Admission Control Mechanism in Cognitive Radio Sensor Networks

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Abstract

Due to the opportunistically resource usage of users in cognitive radio sensor networks (CRSNs), the availability of network resources is highly variable. Therefore, admission control is an essential mechanism to manage the traffic of cognitive radio users in order to satisfy the quality of service (QoS) requirements of applications. In this study, a connection admission control (CAC) mechanism is introduced to satisfy the requirements of delay sensitivity and power consumption awareness. This proposed mechanism is modeled through a semi Markov decision process (SMDP) and a linear programming problem is derived with the aim of obtaining the optimal policy to control the traffic of CRSNs and achieving maximum reward. The number of required channels at each network state is estimated through a graph coloring approach. An end to end delay constraint is defined for the optimization problem which is inspired from Kleinrock independence approximation. Furthermore, a power-aware weighting method is proposed for this mechanism. We conduct different simulation-based scenarios to investigate the performance of the proposed mechanism. The experimental results demonstrate the efficiency of this SMDP-based mechanism in comparison to the last CAC mechanism in CRSNs.

Keywords: Cognitive radio sensor networks (CRSNs), admission control, quality of service (QoS), semi Markov decision process (SMDP), graph coloring, Kleinrock independence approximation

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1. Introduction

Cognitive radio (CR) technology is considered as a capable solution of spectrum scarcity in digital communication era. The CR-equipped users can access the available unlicensed spectrum bands opportunistically in the absence of licensed users. These CR-equipped users are named as CR users or CR nodes of the network and also the licensed users are named as primary users (PUs) [1]. The CR users should monitor their using spectrum band periodically in order to be aware of the channel status. When a PU starts to use the related licensed spectrum band, the CR user should stop using the channel, search the other vacant spectrum bands and decide to select one of them to transport information. These operations are CR related operations which are sensing, handoff and spectrum decision, respectively [1].

The CR technology can be highly beneficial for wireless sensor networks (WSNs) because of the resource limited feature of WSNs and various applications of these networks. The WSNs equipped to CR technology are named as cognitive radio sensor networks (CRSNs) [2]. One of the main characteristics of these networks is instable status of the CR channels. Since the PUs have higher priority to use their licensed channels, CR users' activity depends on the PUs' arrival and departure, sensing time and the number of channels. Therefore, traffic management is a precious mechanism for CRSNs because of the highly dynamic nature of these networks. There are some traffic management studies in CRSNs which are about admission control [3] and congestion control [4, 5, 6].

Connection admission control (CAC) is a proactive kind of congestion control that estimates the network resources and prevents the network congestion by controlling the network traffic based on the resource estimation with the aim of providing the network QoS.

Although CRSN is a new research area to be studied for admission control mechanisms, there are some researchs about admission control in cognitive radio networks (CRNs). These studies proposed admission control schemes in addition to cognitive channel allocation, or scheduling, or spectrum handoff or bandwidth management. In [7], the joint admission control, scheduling and spectrum handoff are considered to improve the performance of multimedia transmissions using a Markov model. The authors of [8] introduced a CAC framework by considering reserved channels for CR users' handoff operation and the handoff buffer. Also, the dropping and blocking probabilities are analyzed based on buffer size and number of reserved channels. A joint admission control and channel allocation is proposed in [9] and is formulated through a Markov decision process to support the delay sensitive communications of CR users. In [10], a joint admission control, eviction control and bandwidth management framework is modeled through a semi Markov decision process. The authors of [11] proposed three admission control schemes using discrete-time Markov chain to minimize the forced termination probability of CR users.

The only proposed CAC mechanism in CRSNs is introduced in [3] which decides based on the traffic features of a CRSN, a defined event reliability measure and the approximated correlation of sensors' data. This CAC mechanism

evaluates the network resources based on the average attainable sending rate of CR users and average PU activity parameters without considering the status of the CR channels at decision moments. In addition the delay and power aspects of CRSNs are not take into consideration.

In this study, a CAC mechanism is introduced which decides based on network status, delay and blocking probability bounds at each decision moment. This CAC mechanism is modeled through a semi Markov decision process (SMDP). To the best of our knowledge, there is no SMDP-based CAC mechanism in CRSNs which considers delay, power and blocking probability metrics together. The network state includes the number of active PUs in the network, the CR users who are using the free channels, and the number of free channels. The number of required channels of each data flow is approximated by a graph coloring based formula. The optimal decision policy of this mechanism is achieved by solving the related linear programming (LP) problem of the introduced SMDP. We consider two constraints of blocking probability and end to end delay for the LP problem. In this study, an end to end delay is calculated based on Kleinrock delay approximation [12]. Furthermore, a power-aware weighting method is proposed for source sensor nodes with the aim of reducing the power consumption of network nodes. Therefore, the optimal strategy is obtained based on network limitations (SMDP constraints), new weighting of the sensor nodes, blocking probability and end to end delay bounds. In summary, the main contributions of this paper are:

1. A delay sensitive and power-aware CAC mechanism in CRSNs based on SMDP modeling

2. Approximation formula for the required channel count per data flow through a graph coloring approach

3. An end to end delay constraint of LP problem based on Kleinrock independence approximation

4. A power-aware weighting method for source sensor nodes.

The simulation results represent that the introduced CAC mechanism is more efficient than the last proposed admission control in CRSNs because of including the blocking probability and end to end delay constraints. The delay and blocking probability bounds can be determined based on the requirements of applications in this proposed mechanism. The solution of SMDP-related LP problem with different end to end delay and blocking probability bounds are compared in simulation results in terms of average gained reward, packet loss probability, end to end delay, power consumption and jitter.

The rest of this paper is organized as follows. Section 2 states the system model. The problem definition, formulation and solution are explained in Section 3. Simulation results are presented in Section 5, and finally, the paper concludes with some remarks in Section 6.

2. System Model

This paper considers a cognitive radio sensor network with three types of nodes, CR sensor nodes, CR relay nodes and a sink node that are placed within a certain finite area to provide multiple views. The CR relay nodes relay the CR sensor nodes' data toward the sink. The number of CR sensor users, CR relay nodes and PUs are considered as N_S, N_R and N_{PU}, respectively. With regard to the occurred event in the event area, some sensors request to send a data flow toward the sink. Different weights (w_i) are assumed for requesting sensor nodes (i is the sensor index) because of different importance of their issued data flows. It is assumed that each sensor i generates Poisson data traffic with the average rate of r_i [13].

The sink and sensor nodes negotiate with each other through a common control channel (CCC) so that the sink node has knowledge about the transmission rate and transmission state of CR sensor nodes and also the number of free CR channels. While a primary user leaves or comes back to use its related channel (state is changed), the sink node makes a new decision about the admission of CR sensor nodes and notifies the new decision to CR sensor nodes.

A CR node has two main modes: sensing mode and operating mode. First, a CR node senses the licensed spectrum to decide whether it is idle or occupied by a PU. The sensing time and sensing frequency are denoted by t_s and f_s, respectively. After sensing, the CR node enters in operating mode and sends data in a licensed spectrum channel in the absence of PU.

The probability of detection (P_d) and the probability of false alarm (P_f) are two metrics which considered for spectrum sensing accuracy [14]. The P_d is the probability that a channel is occupied by a PU and the spectrum sensing has detected that channel is busy. The P_f is the probability that CR user senses a channel is busy but the spectrum is not used by any PUs.

The PUs activity is modeled as exponentially distributed interarrivals thus their arrivals are independent. The traffic of a PU can be modeled as a two-state arrival-departure process with arrival rate r_a and departure rate r_d. A PU has two states: ON and OFF [15]. The ON state represents the period that PU operates on a channel, and CR node cannot use the channel. The OFF state represents the period that the PU does not operate on a channel, and CR nodes can use the channel. There are CH cognitive channels with the same bandwidth. For each channel, there is a PU ($N_{PU} = CH$) and all of the CR channels have similar PU activity. In each channel, a PU operates based on its arrival rate (r_a) and departure rate (r_d). When a PU starts to operate on its licensed channel, the operations of each active CR node on the licensed channel in CRSN will be stopped. In other words, the activity of all CR nodes in CRSN is affected by PUs activity. In Table 1, the notations used in this research are described.

Table 1: Notation Table

Parameter	Meaning
N_S, N_{PU}, N_R	Number of CR sensor users, primary users (PUs), CR relay nodes
CH	Number of CR channels
r_a, r_d	Average arrival rate of each PU to the channel, average departure rate of PU from the channel
w_i	Weight of the i'th sensor node
r_i	Rate of the i'th sensor node
$\mathbf{n}(t)$	Admission condition vector of the flows at decision epoch t
$\mathbf{a}(t)$	Admission decision vector at decision epoch t
$q(t)$	Number of active PUs in the network at decision epoch t
$s(t)$	Network state at decision epoch t
$P_{i,d}$	Probability of using route d related to sensor i
K_i	Number of possible routes between the sensor node i and the sink node
$\Omega(n)$	Minimum number of required channels in each possible routes configuration
$\gamma(n)$	Optimal average required number of channels at state $s = (n, q)$
$P_{sx}(a)$	Probability of transition from state s to state x by selecting the action a
$m_s(a)$	Decision variable of selection the action a at the state s
π	Function of mapping the state space to the acceptable action space
$\tau_s(a)$	Average time after the action a is selected in state s until the next decision epoch (sojourn time)
$R(s, a)$	Earned reward at the state s and selection of the action a
$\psi(CR)$	Worthless CR user who is transmitting data packets toward the sink node

3. Problem Definition and Formulation

In a cognitive radio sensor network, several sensors are deployed in the event area to provide multiple observations of an event. When an event occurs, depending on the event place and sensing radius, some of sensor nodes send data flows toward the sink node. Due to the constraints of the cognitive channels, sending all of these flows cannot be reasonable. Furthermore, it is needed to inform the sink node some information about the event. Therefore, a connection admission control is needed to provide the QoS of the cognitive radio sensor network.

The SMDP is a powerful tool in analyzing stochastic decision control processes satisfying Markov features with random decision epochs. SMDP has a lot of potential applications in telecommunication, reliability control and maintenance [16]. In an SMDP, the system is in one of the states of a finite state set at each decision epoch. There is a finite action set for each state. The system state evolves in different decision epochs according to a transition probability matrix which depends on the current system state and selected action from action set. According to the selected action in each state transition, a cost/reward is obtained. The aim is to optimize the long-term average cost/reward [16].

SMDP is an appropriate theory to model the decision making process for this admission control. It is necessary to identify SMDP components related to this problem that are introduced in the next subsections.

3.1. State Space

The system state represents the network information at the beginning of each decision epoch. We defined row vector $\mathbf{n}(t) = [n_1(t), n_2(t), \ldots, n_{N_S}(t)]$ where $n_i(t) \in \{0, 1\}$ denotes the admission condition of the induced data flow

from sensor i in the event area at the decision epoch t. The $n_i(t) = 1$ represents the sensor node i is sending data flow toward the sink node. Also, the $n_i(t) = 0$ represents the sensor node i has not been admitted to send data. $q(t)$ is defined as the number of active PUs in the network at the decision epoch t. The network state is given by $\mathbf{s}(t) = (\mathbf{n}(t), q(t))$ at the decision epoch t and also, is given by $\mathbf{s} = (\mathbf{n}, q)$ in steady state. The average number of required channels for each network state is considered as function $\gamma(\mathbf{n})$. Thus, the number of used channels by admitted flows plus active PUs should be less than CH. Therefore, the state space S can be defined in Equ. 1.

$$S = \left\{ \mathbf{s} = [\mathbf{n}, q] : n_i \in \{0, 1\}, 0 \le q \le CH, \gamma(\mathbf{n}) + q \le CH \right\} \tag{1}$$

The details of the function $\gamma(\mathbf{n})$ will be described in the next subsection.

3.2. Average Number of Required Channels

The main responsibility of admission control is to estimate the network resources and make decisions based on the users' requirements and available network resources. The number of CR free channels is one of the main network resources in CRSNs that should be estimated in order to decide about the admission of data flows.

In order to send sensors' data toward the sink node, some CR channels are required. The number of these required channels depends on the system state, routing protocol and network topology (contending nodes number). The system state represents which sensors are sending their information toward the sink node. We consider the steady state behavior of routing protocol. In this way, a node selects one of the next hop nodes with a certain probability which does not change rapidly over time [17].

Therefore, for each sensor node, there are several possible routes toward the sink node. In order to decide about the admission of data flows in the network optimally, the optimal number of required channels should be estimated to minimize data packet collision.

It is assumed that there are K_i ($0 \le i \le N_S$) possible routes between the sensor node i and the sink node. The sensor i uses its possible route d with the probability of $P_{i,d}$. Therefore, there are $\prod_{i=1}^{N_S} (K_i)^{n_i}$ possible combinations of routes for the data flows of admitted sensor nodes at each network state. At each network state, the subset of sensor nodes who are sending data packets through selected routs forms a network subgraph. At each considered network subgraph, the nodes have different number of contending nodes in the transmission of data packets to the sink node. In order to decrease the data packet collision, the optimal number of required channels can be considered for each network state. This optimal channel number can be determined according to the maximum number of contending nodes for the nodes of the considered subgraph.

The problem of finding the optimal required number of channels at each possible combination of routes can be modeled by graph coloring approach.

According to vertex coloring, different colors are assigned to each two adjacent vertex of the graph [18]. Each color label is equivalent to a CR free channel. The minimum number of required colors at each possible combination of selected routes can be considered as the minimum number of required channels. Assume the minimum number of required channels at each possible routes configuration is considered as $\Omega(i_1 n_1,\ i_2 n_2, \ldots,\ i_{N_s} n_{N_s})$ where the i_1, i_2, $\ldots$, i_{N_s} are the selected route indexes of sensor 1, sensor 2, $\ldots$ and sensor N_S, respectively and also the $n_i \in \{0,1\}$, $i = 1, \ldots, N_s$ is the admission state of the sensor i which is described before. The value of the product $i_b n_b$ will be zero when sensor b is not admitted and will be i_b when sensor b is admitted. The notation of I_b is considered for the product $i_b n_b$.

According to these definitions, the optimal average required number of channels at each state ($\gamma(\mathbf{n})$) can be calculated by Equ. 2.

$$\gamma(\mathbf{n}) = \sum_{i_1=1}^{K_1} \sum_{i_2=1}^{K_2} \cdots \sum_{i_{N_s}=1}^{K_{N_s}} (P_{1,i_1})^{n_1} (P_{2,i_2})^{n_2} \ldots (P_{N_s,i_{N_s}})^{n_{N_s}}\ \Omega(I_1,\ I_2, \ldots,\ I_{N_s})$$

(2)

The value of $\Omega(I_1, I_2, \ldots, I_{N_s})$ is calculated by the minimum number of colors required for the network graph while the sensors $1, 2, \ldots, N_S$ are sending data packets in their i_1, i_2, $\ldots$, i_{N_s} routes toward the sink. Therefore, the $\gamma()$ is the function of network state.

3.3. Action Space

At each decision epoch, an action a is selected as the result of the admission control decision for the next epoch. The action a at decision epoch t can be defined as $\mathbf{a}(t) = [a_1(t), a_2(t), \ldots, a_{N_S}(t)]$. The $a_i(t) = 1$ represents the sensor i is admitted for sending data flow at decision epoch t and the $a_i(t) = 0$ represents the rejection decision about this flow. Hence, the action space A can be defined as

$$A = \left\{ \mathbf{a} : a_i \in \{0,1\}, 0 \le i \le N_S, \sum_{i=1}^{N_S} a_i \le 1 \right\}.$$

(3)

The $\mathbf{a} = [0, 0, \ldots, 0]$ means that no data flow is admitted. At each decision epoch, the admission control mechanism decides about the admission of the sensors' sending request and at most admits one of the requesting sensors' data flow. For each state, a subset of the action set A is valid; thus an action space for each state $s \in S$ can be defined as

$$A_s = \left\{ \mathbf{a} \in A : \mathbf{s} = [\mathbf{n}, q], [\mathbf{n} + \mathbf{a}, q] \in S \right\}.$$

(4)

3.4. State Transition

Assuming the states $\mathbf{s} = [\mathbf{n}_s, q_s]$ and $\mathbf{x} = [\mathbf{n}_x, q_x]$, the transition probability $P_{sx}(a)$ is the probability of transition from state $\mathbf{s}$ to state $\mathbf{x}$ by selecting the

action **a**. There are several event types in this admission control mechanism: (1) PU arrival to a channel that is free of CR user, (2) PU arrival to a channel that is using by a CR user and the CR user leaves the channel, (3) PU departure from a channel, and (4) CR user arrival. When a PU departs from related channel, there is at least a CR user request in the queue to use this free channel. The event rate of the mentioned events are $\sum_{i=1}^{N_s} r_a \delta(CH - \gamma(n_x) - q_x)$, $\sum_{i=1}^{N_s} r_a(1 - \delta(CH - \gamma(n_x) - q_x))$, $\sum_{i=1}^{N_s} q_s r_d$, $\sum_{i=1}^{N_s} a_i r_d\ \delta(CH - \gamma(n_x) - q_x)$, respectively, where the function $\delta(i)$ can be defined as follows

$$\delta(i) = \begin{cases} 1; & i \geq 0 \\ 0; & i < 0. \end{cases}$$

These events are independent Poisson processes, thus sum of these events follows the Poisson process too [19]. The total event rate of this system is the sum of event rates of the events (1), (2), (3) and (4). Therefore, the interevent time of this model is the reverse of total event rate. This interevent time can be defined as the expected sojourn time of the SMDP. The sojourn time is the average time after action a is selected in current state **s** until the next decision epoch $(\tau_s(a))$.

$$\tau_s(a); = \left\{ \sum_{i=1}^{N_s} r_a + \sum_{i=1}^{N_s} q\ r_d + \sum_{i=1}^{N_s} a_i\ r_d \right\}^{-1}$$

(5)

The transition probabilities can be derived using the decomposition property of the Poisson process. The transition probabilities between the states of this system can be determined as

$$P_{sx}(a) = \begin{cases} r_a \delta(CH - \gamma(n_x) - q_x)\ \tau_s(a); & if x = s + PU \\ q_s r_d \tau_s(a); & if\ x = s - PU \\ r_a(1 - \delta(CH - \gamma(n_x) - q_x))\ \tau_s(a); & if\ x = s + PU - \psi(CR) \\ a\ r_d\ \delta(CH - \gamma(n_x) - q_x)\ \tau_s(a); & if\ x = s + CR \\ 0; & Otherwise. \end{cases}$$

The **s** + PU and **s** - PU are the arrival and departure of a PU, respectively that are equivalent to **s** + [0,1] and **s** - [0,1], respectively. Also the **s** + CR and **s** - CR are equivalent to **s** + [1,0] and **s** - [1,0], respectively. The $\psi(CR)$ is representative of the worthless CR user who is transmitting data packets toward the sink node. The worth of CR users is determined based on their weight. According to this admission control mechanism, when a PU starts using its related channel while there is no free channel for CR users, the most worthless CR user leaves using CR channel and stops sending data.

3.5. Policy and Reward Function

A policy π is a function that maps state space to acceptable action space. For each state $s \in S$, an action is chosen according to policy π. The Π is

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the acceptable policy space. The reward function $R(s, a)$ is the average reward obtained in the network in current state s after action a is selected until the next decision epoch. The reward function is the reward earned by the weight of new admitted CR user at each decision epoch. This function is defined as the sum of the weights of admitted flows to send to the sink node that can be defined as:

$$R(s, a) = \sum_{i=1}^{N_s} a_i \ w_i. \tag{6}$$

The average reward is considered as a performance measure. Inspiring from [20], the average reward function for $\forall \pi \in \Pi$ is defined as

$$J_\pi(s_0) = \lim_{T \to \infty} \frac{1}{T} E \left\{ \int_0^T R(s(t), a(t)) dt \right\} \tag{7}$$

where the s_0 is the first state that SMDP is started from and $E\{.\}$ is the expectation function. The purpose is to find the optimal policy $\pi^* \in \Pi$ that maximizes the average reward for all initial states. On the other hand, the aim is to find the best policy that maximizes the average value of sent information via the admitted sensors.

3.6. Blocking probability

A request from i'th sensor is blocked if there is not enough free channels and the selected action (a_i) is set zero. The authors of [20] defined the blocking probability for sensor i as the fraction of time the system is in some subset of states that are blocked.

$$P_b^i = \lim_{T \to \infty} \frac{1}{T} E \left\{ \int_0^T (1 - a_i) \tau_{s(t)}(a(t)) dt \right\}. \tag{8}$$

Therefore, the expected blocking probability when action a is selected in state s until the next decision epoch can be obtained as:

$$P_b^i = (1 - a_i). \tag{9}$$

It is desirable to limit the blocking probability according to the sensor network application sensitivity. Therefore, an upper bound for the blocking probability should be considered.

3.7. Linear Programming Solution of the SMDP

The optimal policy π^* can be obtained by solving a constrained linear programming optimization problem which named as $OPT1$. This linear program-

ming problem can be formulated as follows [16]:

$$\max_{\substack{m_{sa} \geq 0 \\ s \in S, a \in A_s}} \sum_{s \in S} \sum_{a \in A_s} \sum_{i=1}^{N_S} w_i a_i \tau_s(a) m_{sa}$$

subject to

$$\sum_{a \in A_s} m_{sa} - \sum_{a \in A_s} \sum_{i=1}^{N_S} P_{sx}(a) m_{sa} = 0, \quad x \in S,$$

$$\sum_{a \in A_s} \sum_{i=1}^{N_S} m_{sa} \tau_s(a) = 1,$$

$$\sum_{a \in A_s} \sum_{i=1}^{N_S} (1 - a_i) m_{sa} \tau_s(a) \leq \Psi_i, \quad i = 1, \ldots, N_S. \tag{10}$$

where the m_{sa} is the decision variable for $\forall s \in S$, $\forall a \in A_s$. The term $\tau_s(a) m_{sa}$ is equivalent to the steady state probability of being in state s and the selection of action a. The objective is the maximization of reward function that is the maximization of the average value of admitted flows. The first and second constraints are balance and normalization equations, respectively. The optimal solution m_{sa}^* is obtained through this linear programming. The optimal policy π^* is given by

$$\pi_a^* = \frac{m_{sa}}{\sum_{a \in A_s} m_{sa}}, \quad \forall s \in S, \ \forall a \in A_s [16]. \tag{11}$$

The optimal policy can be specified as a policy matrix $M_{(dim(S),dim(A_s))}^*$. Each entry of M^* equals to $M^*(i,j) = \pi_j^*(i)$. The (i,j)th entry for matrix M^* represents the probability that action j is selected when the system is in state i. The M^* is calculated offline and the admission control chooses actions at each decisions epoch, according to the corresponding probabilities of this matrix. The sink node notifies the CR sensor nodes about the optimal policy.

4. Average end to end Delay

Due to the delay sensitivity level of the CRSNs applications, delay is one of the critical measures in CRSNs. Especially, in multimedia applications, the end to end delay is vital. Therefore, calculation of this metric is necessary in these applications. To calculate the average end to end delay of packets in the network, the delay of the network and transport layers can be ignored by considering the determined routes for data packets and UDP transport protocol. According to [12], the link delay consists of four components: processing delay, queuing delay, propagation delay and transmission delay. processing and propagation delays are independent of traffic amount carried by the link. Transmission

delay depends on the transmission rate of bits of a packet on the link. Because of considering the equal bandwidth and MAC parameters for all links of the network, the transmission delay of all links are considered equal. Therefore, the average delay per packet in the network can be expressed using queuing delay analysis of the network links.

In this study, the Kleinrock independence approximation [12] is considered to approximate the average end to end delay of packets in the network. This approximation considers an $M/M/1$ queuing model for each communication link in the network irrespective of the interaction of traffic on each link with traffic on other links. In the considered network, there are several sensor sources generating packet streams toward the sink node. Assume R_i is the arrival rate of the $i'th$ sensor source and $f_{pq}(i)$ denotes the transmission probability of packets generating from the $i'th$ sensor that pass through link (p, q). The arrival rate and service rate of a queue is considered as λ, μ, respectively, in the queuing theory. The arrival rate at link (p, q) is approximated as [12]

$$\lambda_{pq} = \sum_{\substack{all\ packet\ stream\ i \\ crossing\ link\ (p,q)}} f_{pq}(i)R_i. \tag{12}$$

Based on the $M/M/1$ model, the average number of packets in queue at link (p, q) is

$$Num_{pq} = \frac{\lambda_{pq}}{\mu_{pq} - \lambda_{pq}} \tag{13}$$

where the $1/\mu_{pq}$ is the average transmission delay on link (p, q). Thus the average number of packets in all queues of the network links are

$$Num = \sum_{(p,q)} \frac{\lambda_{pq}}{\mu_{pq} - \lambda_{pq}}. \tag{14}$$

If ω is considered as the total arrival rate of the network ($\omega = \sum_{i=1}^{N} R_i$), according to the Little's Law [12], the average end to end delay per packet in the network is

$$T = \frac{1}{\omega} \sum_{(p,q)} Num_{pq}. \tag{15}$$

Since, a CR user can use cognitive channels in the absence of PUs thus the queue of CR users can not be modeled as a pure M/M/1. In this study, the average number of packets in the queue of each link (p, q) of the considered network (Num_{pq}) is calculated by the simulation experiments for different states of the network. According to the equation 15, the average end to end delay of the data packets is approximated in different states of the network. In order to transmit the event information toward the sink in a tolerable time, the end

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to end delay should be approximated and controlled by admission control in different states of this network. The tolerable delay in different application of the sensor networks is different. Thus a delay constraint is added to this admission control mechanism. The delay constraint is defined as

$$\frac{1}{\omega} \sum_{(p,q)} Num_{pq} \leq \Xi. \tag{16}$$

According to this delay constraint, the bound Ξ_i is considered for the average end to end delay of data packets induced from the sensor i.

Therefore, the linear programing problem associated with this delay constraint, named $OPT2$, is as follows

$$\max_{\substack{m_{sa} \geq 0 \\ s \in S, a \in A_s}} \sum_{s \in S} \sum_{a \in A_s} \sum_{i=1}^{N_S} w_i a_i \tau_s(a) m_{sa}$$

subject to

$$\sum_{a \in A_s} m_{sa} - \sum_{a \in A_s} \sum_{i=1}^{N_S} P_{sx}(a) m_{sa} = 0, \quad x \in S,$$

$$\sum_{a \in A_s} \sum_{i=1}^{N_S} m_{sa} \tau_s(a) = 1,$$

$$\sum_{a \in A_s} \sum_{i=1}^{N_S} (1 - a_i) m_{sa} \tau_s(a) \leq \Psi_i, \quad i = 1, \ldots, N_S,$$

$$\sum_{a \in A_s} \sum_{i=1}^{N_S} \frac{1}{\omega} \sum_{(p,q)} Num_{pq} \, m_{sa} \tau_s(a) \leq \Xi_i, \quad i = 1, \ldots, N_S.$$

4.1. Power

Due to the power limited nature of most wireless sensor networks (WSNs), considering the power efficiency aspects of the proposed protocols and mechanisms is significant. Accordingly, this measure is critical in the most CRSNs. In this study, the residual power of sensor nodes can be considered as a power metric to increase the network lifetime. The source node with higher residual power have the higher priority to send the sensed information toward the sink node. In order to use the residual power amount of sensor nodes at decision moments in different states of the network, the state of the SMDP should be changed.

Define row vector $\mathbf{p}(t) = [p_1(t), p_2(t), \ldots, p_{N_S}(t)]$ where $p_i(t) \in \{0, \ldots M\}$ denotes the residual power level of the sensor i at the decision epoch t. Similar to the defined state in 3.1, the network state is given by $\mathbf{s}(t) = (\mathbf{n}(t), \mathbf{p}(t), q(t))$ at the decision epoch t and also, is given by $\mathbf{s} = (\mathbf{n}, \mathbf{p}, q)$ in steady state. According to this new state of the network, the priority of sensor nodes should be changed. As mentioned in 2, the sent information by the sensor nodes toward

the sink node has different value because of different condition of sensor nodes relatively and the value of induced data streams by sensor i are determined by w_i. According to new defined state, the new priority of sensor i can be defined as $w_i p_i$.

Since the number of the residual power levels in this model is $M + 1$, the size of state space equals to $(M + 1)^{N_S} 2^{N_S} CH = CH(2M + 2)^{N_S}$. Actually, the value of M is great in real applications and hence with big values of M, the state space grows very much. Finding the related policy for the related state from this very big state space is very time consuming at decision moments and this is not efficient in the big networks.

This model can be replaced by an approximation with the aim of reducing the computational complexity and also increasing the network lifetime. Instead of using the new SMDP model, the weighting method of the first SMDP model can be changed. There are several power consumption elements in CR sensor nodes such as power usage in spectrum sensing, event area sensing and packet transmission. Since the proposed mechanism manages the network traffic, the power usage of event sensing and spectrum sensing is not related to this mechanism. We focus on the amount of power consumed because of data transmission.

The priority of sensor node i can be considered as $\frac{w_i}{r_i}$. According to this weighting method, the sensor nodes with higher information value and also lower data rate have higher priority to send data toward the sink node. Sending low data rate and high value data streams leads to save the energy of all nodes in the route of those data streams.

5. Experimental Results

In this section, the performance of the proposed mechanism is evaluated through CogNS that is a simulation framework based on NS-2 [21] for cognitive radio networks [22]. Due to the practical issues of memory and computational complexity, a small-scale [23] CRSN with $50m \times 50m$ coverage area is considered in this research.

The number of the PUs (N_{PU}) and CR channels (CH) is taken as 6. It is assumed each PU individually has the license of using related frequency channel. The values of N_S and N_R are set as 18 and 7 respectively. The sensing time and operating time are considered as 0.025 and 0.6 sec, respectively. It is assumed that in ideal sensing conditions, the values of P_f and P_d are 0 and 1, respectively. The default values of PUs' arrival and departure rates are considered as 1; these two rates are changed for different experiments. The packet size is considered 100 bytes. The simulation time is 200 second. Each experiment is run five times, and results are averaged.

The proposed admission control mechanism is evaluated in this section by several experiments in different PU activity settings. The PU activity (r_d, r_a) is determined based on the length of ON and OFF periods of PU transmissions. When the PU arrival rate (r_a) is greater than the PU departure rate (r_d), this state is considered as a "high PU activity" state. Furthermore, when the PU

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Table 2: The list name of considered mechanisms

Mechanism	Description
AD_0	The network without applying any admission control mechanism.
AD_1	The proposed mechanism in [3].
AD_2	The obtained mechanism from $OPT1$ problem
AD_3	The obtained mechanism from $OPT2$ problem

arrival rate is smaller than the PU departure rate, this state is considered as a "low PU activity" state. Also, when the PU arrival rate is equal to PU departure rate, this state is considered as a "medium PU activity" state [3]. According to these definitions, the PU activities (3,1) and (5,1) belong to the low PU activity state, the PU activities (1,1), (3,3) and (5,5) belong to the medium PU activity state, and the PU activities (1,3) and (1,5) belong to the high PU activity state.

In this section, the performance of the introduced mechanisms which obtained from OPT1 and OPT2 problems is evaluated and compared with the proposed mechanism in [3] and the network without applying any admission control. The list of considered names of the compared mechanisms are summarized in Table 2. According to this table, not using any admission control mechanism in the network and the proposed mechanism in [3] are named as AD_0 and AD_1, respectively. Furthermore, the obtained mechanism from $OPT1$ and $OPT2$ problems are named as AD_2 and AD_3, respectively.

Since the networks with different PU activities parameters have different behavior, these networks have different values of blocking probability and end to end delay. Thus, different blocking probability and end to end delay constraints can be considered for these networks. In this study, the considered blocking probability constraints are represented in Table 3. According to this table, five different considered blocking probability constraints are named as $Pb_1, \ldots, Pb_5$. At each blocking probability constraint vector Pb_k ($1 \leq k \leq 5$), seven values of the average blocking probability constraint of different data flows are considered in the networks for seven considered PU activity (r_a, r_d): (1,5), (1,3), (1,1), (3,3), (5,5), (3,1) and (5,1). For example, the average blocking probability constraint of data flows in Pb_5 in all considered PU activity conditions is 1. This constraint is equivalent to the condition that there is no blocking probability limitation for admission control mechanism. This means that there is no limitation in the number of blocked sensors to send data flows toward the sink node.

Furthermore, the considered end to end delay constraints are represented in Table 4. Six different considered end to end delay constraints are named as D_1, $\ldots, D_6$. At each end to end delay constraint vector D_t ($1 \leq t \leq 6$), seven values of the average end to end delay constraint of different data flows are considered in the networks for seven considered PU activity (r_a, r_d): (1,5), (1,3), (1,1), (3,3), (5,5), (3,1) and (5,1). Thus, in the experiments, the mechanism AD_2 with the constraint of the blocking probability Pb_k ($1 \leq k \leq 5$) are represented by $AD_2 - Pb_k$ notation. Also the mechanism AD_3 with the constraints of the blocking probability Pb_k ($1 \leq k \leq 5$) and end to end delay D_t ($1 \leq t \leq 6$) is represented by $AD_3 - Pb_j - D_t$ notation.

Table 3: The list of considered blocking probability constraints

Constraint	Description
Pb_1	[0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.01]
Pb_2	[0.7 0.65 0.55 0.15 0.15 0.15 0.02 0.02]
Pb_3	[0.8 0.8 0.7 0.4 0.4 0.4 0.3 0.3]
Pb_4	[0.9 0.9 0.9 0.4 0.4 0.4 0.4 0.4]
Pb_5	[1 1 1 1 1 1 1 1]

Table 4: The list of considered end to end delay constraints

Constraint	Description
D_1	[0.7 0.7 0.4 0.3 0.3 0.3 0.15 0.1]
D_2	[0.6 0.55 0.2 0.1 0.1 0.1 0.07 0.07]
D_3	[0.2 0.2 0.2 0.2 0.2 0.2 0.2 0.2]
D_4	[0.1 0.1 0.1 0.1 0.1 0.1 0.1 0.1]
D_5	[0.01 0.01 0.01 0.01 0.01 0.01 0.01 0.01]
D_6	[0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005]

5.1. Power-Aware Weighting Method

Due to practical issues of proposed power-aware model in section 4.1 a power-aware weighting is considered as an approximation of the proposed model. In this section, the obtained mechanism from $OPT1$ problem considering the power-aware weighting method and the blocking probability constraint Pb_4 is named as *Power-aware AD_2-Pb_4*. In order to demonstrate the efficiency of this weighting method, the Fig. 1 illustrates the average end to end delay, the average power consumption and the average gained reward per second in the AD_2-Pb_4 and *Power-aware AD_2-Pb_4*. As depicted in this figure, the network in the *Power-aware AD_2-Pb_4* mechanism in comparison with the AD_2-Pb_4 mechanism, average gained reward is reduced in contrast with reaching to lower average power consumption and average packet end to end delay. Hence, with the aim of having a power-aware CRSN, this power-aware weighting is applied to all the considered mechanisms in the next experiments. It is assumed that all the listed mechanisms in Table 2 use the power-aware weighting for source sensor nodes. Therefore, all of used mechanisms in the next experiments are power-aware.

5.2. Comparison of Considered Mechanisms

In this section, the performance of the considered mechanisms of AD_0, AD_1, AD_2-Pb_4 and AD_3-Pb_5-D_5 are compared. In the mechanism of AD_2-Pb_4, some loose bounds of blocking probability are considered for considered PU activity states. Also, a tight bound of end to end delay is considered for different PU activity states in the mechanism of AD_3-Pb_5-D_5. The aim of this section is the illustration of two different conditions of introduced CAC mechanism in comparison with the mechanisms of AD_0 and AD_1. The performance metrics are average packet end-to-end delay, average packet loss ratio, average gained reward per second, average jitter of data packets and average power consumption.

5.2.1. Reward

The average reward of the network has a direct relation with the amount of admitted sensors' request to send data flows toward the sink node. As depicted in Fig. 2(a), the network with AD_0 mechanism receives the most reward due to all sensor nodes can send their data toward the sink node. The AD_2-Pb_4 mechanism with the blocking probability constraint Pb_4 which is a loose blocking probability constraint has the second rank of receiving reward. The AD_3-Pb_5-D_5 mechanism, with delay constraint 0.1 second and blocking probability constraint 1 for all experiments with different PU activities, has the less average receiving reward. Also, the AD_1 mechanism has third rank at the receiving reward toward the considered mechanisms. As depicted in this figure, based on the different sensitivities of applications (blocking probability and delay), different reward values are achieved in the proposed CAC mechanism.

5.2.2. Power

Similarly, the average power consumption of nodes has a direct relation with the amount of sensors' sent data packets toward the sink node. Therefore, the trend of plots representing the average power consumption of nodes in different considered mechanisms is similar to the average gained reward of theses comparing mechanisms which are described before. As illustrated in Fig. 2(b), average power consumption of network nodes in "low PU activity" states are more than the "high PU activity" states because of the more availability of cognitive channels and then sending more data packets by the sensor nodes.

5.2.3. End to End Delay

As depicted in Fig. 2(c), the network with the AD_3-Pb_5-D_5 mechanism, with delay constraint 0.1 second and blocking probability constraint 1 for all experiments with different PU activities, has the least average end to end delay and the AD_0 mechanism has the most end to end delay. The AD_2-Pb_4 mechanism has the constraint of Pb_4 which is not a strict blocking probability constraint. Apparently, because of this blocking probability constraint in AD_2-Pb_4 mechanism, more sensors are admitted to send data flows toward the sink node rather than the AD_1 mechanism. Therefore, the end to end delay in the network with AD_2-Pb_4 mechanism is more than AD_1 mechanism.

5.2.4. Packet Loss Ratio

According to Fig. 2(d), the network with the AD_0 mechanism has the most packet loss ratio because of sending all data packets toward the sink node without any evaluation and estimation of network resources. In the network with AD_3-Pb_5-D_5 mechanism, because of the delay constraint of 0.1 second, a few number of sensor nodes are admitted to send data toward the sink node, thus sending these admitted data flows leads to least number of packet loss in comparison with the networks with other considered mechanisms.

5.2.5. Jitter

The jitter is considered as the variance of packet end-to-end delay in the literature. According to Fig. 2(e), the AD_0 mechanism has the most average jitter of data packet because of transmitting the most data packets toward the sink node. The average amount of jitter in AD_2-Pb_4 mechanism is more than AD_1 mechanism and also the average amount of jitter in AD_2-Pb_1 mechanism is more than AD_3-Pb_5-D_5 mechanism. As depicted in this figure, the amount of jitter in "high PU activity" states is more than the jitter values in "low PU activity" states because of the more unstable availability of cognitive channels.

5.3. End to End Delay Bounds

In this section, a network with the AD_3 mechanism without any blocking probability bound (Pb_5 constraint) with different end to end delay constraints is considered with the aim of investigating the effect of different delay thresholds on the obtained policy of this mechanism. The considered end to end delay constraints are D_1, D_2, D_4 and D_5. The average packet end to end delay, power consumption, packet loss ratio, jitter and gained reward per second metrics of the networks are illustrated in Fig. 3. According to Table 4, the delay constraint D_5 is tighter than D_4, the D_4 is tighter than D_2 and the D_2 is tighter than D_1. This fact can be seen in Fig. 3(a) too. The tighter end to end delay constraint leads to admit lower number of sensor nodes to send data and thus the lower average power consumption, lower packet loss ratio, lower average gained reward and lower average jitter of data packets which are depicted in Fig. 3(b), Fig. 3(c), Fig. 3(d) and Fig. 3(e), respectively.

5.4. End to End Delay and Blocking Probability Bounds

Investigating the effect of both end to end delay and blocking probability bounds on the obtained policy of OPT2 problem is the aim of this section. Therefore, some different combination of end to end delay and blocking probability constraints are considered for AD_3 mechanism (Tables 3 and 4). Several experiments are performed based on these considerations and the results are illustrated in Fig. 4. The considered mechanisms are AD_3-Pb_1-D_1, AD_3-Pb_2-D_2, AD_3-Pb_3-D_4, AD_3-Pb_4-D_4 and AD_3-Pb_4-D_6. As mentioned before, according to these considered end to end delay and blocking probability bounds, the OPT2 problem is solved and the optimal policy is obtained. The OPT2 problem cannot be converge to desirable solution in some of theses end to end delay and blocking probability bounds in some PU activity conditions. The average packet end-to-end delay, the average gained reward per second and the average power consumption of the networks with these applied considered mechanisms are depicted in Fig. 4(a), Fig. 4(b) and Fig. 4(c), respectively.

As illustrated in these figures, some curves of these plots are not completed because there is no answer for the problem with these considerations. For example, there is no solution for the OPT2 problem with average end to end delay bound 0.7 sec and blocking probability bound 0.01 at PU activity of (1,5). Also, there is no solution for the OPT2 problem with average end to end delay bound

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0.005 sec and blocking probability bounds 0.9, 0.9, 0.4, 0.4 and 0.4 at PU activities of (1,5), (1,3), (1,1), (3,3) and (5,5). In addition, there is no solution for the OPT2 problem with average end to end delay bound 0.01 sec and blocking probability bounds 0.8 and 0.7 at PU activities of (1,5) and (1,3) and there is no solution for the OPT2 problem with average end to end delay bound 0.2 sec and blocking probability bound 0.9 at PU activity of (1,5).

6. Conclusions

Admission control is one of the critical mechanisms in cognitive radio sensor networks (CRSNs) with the aim of managing the network traffic of unstable cognitive channels. In this study, a connection admission control (CAC) has been introduced and modeled based on a semi Markov decision process (SMDP). This proposed CAC mechanism considers both end to end delay constraint of applications and power consumption aspect of CRSNs. An optimal strategy has been acquired by solving an SMDP-derived linear programming problem with the considered weighting method, blocking probability bound and delay bound. This mechanism maximizes network reward and also improves the average jitter of data packets, average power consumption of network nodes and packet loss ratio. The NS-2 based experimental results demonstrate the efficiency of the proposed CAC mechanism compared to the previous proposed admission control mechanism.

References

[1] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, S. Mohanty, Next generation/dynamic spectrum access/cognitive radio wireless networks: A survey, Computer Networks 50 (13) (2006) 2127–2159.

[2] O. Akan, O. Karli, O. Ergul, Cognitive radio sensor networks, IEEE Network 23 (4) (2009) 34–40.

[3] E. S. Hosseini, V. Esmaeelzadeh, R. Berangi, O. B. Akan, A correlation-based and spectrum-aware admission control mechanism for multimedia streaming in cognitive radio sensor networks, International Journal of Communication Systems, in press,`doi:10.1002/dac.2986`.

[4] A. O. Bicen, V. C. Gungor, O. B. Akan, Delay-sensitive and multimedia communication in cognitive radio sensor networks, Ad Hoc Networks 10 (5) (2012) 816–830.

[5] V. Esmaeelzadeh, R. Berangi, E. S. Hosseini, O. B. Akan, Stochastic Backlog and Delay Bounds of Generic Rate-based AIMD Congestion Control Scheme in Cognitive Radio Sensor Networks, Pervasive and Mobile Computing 22 (C) (2015) 46–57.

[6] V. Esmaeelzadeh, R. Berangi, On the optimality of generic rate-based AIMD and AIAD congestion control schemes in cognitive radio sensor networks, International Journal of Distributed Sensor Networks, 2015, Article ID 614643 (2015) 9 pages. `doi:10.1155/2015/614643`.

[7] M. Li, T. Jiang, L. Tong, Spectrum Handoff Scheme for Prioritized Multimedia Services in Cognitive Radio Network with Finite Buffer, in: 2013 IEEE 11th International Conference on Dependable, Autonomic and Secure Computing (DASC), pp. 410–415.

[8] J. Wang, A. Huang, W. Wang, T. Quek, Admission Control in Cognitive Radio Networks with Finite Queue and User Impatience, IEEE Wireless Communications Letters 2 (2) (2013) 175–178.

[9] F. Wang, J. Huang, Y. Zhao, Delay Sensitive Communications over Cognitive Radio Networks, IEEE Transactions on Wireless Communications 11 (4) (2012) 1402–1411.

[10] T. Guo, K. Moessner, Optimal Strategy for QoS Provision under Spectrum Mobility in Cognitive Radio Networks, in: 2012 IEEE Vehicular Technology Conference (VTC Fall), pp. 1–5.

[11] C. An, H. Ji, P. Si, Dynamic Spectrum Access with QoS Provisioning in Cognitive Radio Networks, in: 2010 IEEE Global Telecommunications Conference (GLOBECOM 2010), pp. 1–5.

[12] D. Bertsekas, R. Gallager, Data Networks (2Nd Ed.), Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 1992.

[13] R. Dai, I. Akyildiz, A Spatial Correlation Model for Visual Information in Wireless Multimedia Sensor Networks, IEEE Transactions on Multimedia 11 (6) (2009) 1148–1159.

[14] S. Tang, B. L. Mark, Modeling and analysis of opportunistic spectrum sharing with unreliable spectrum sensing, IEEE Trans. Wireless Communications 8 (4) (2009) 1934–1943. `doi:10.1109/T-WC.2008.080213`. URL `http://dx.doi.org/10.1109/T-WC.2008.080213`

[15] W.-Y. Lee, I. Akyildiz, Optimal spectrum sensing framework for cognitive radio networks, IEEE Transactions on Wireless Communications 7 (10) (2008) 3845–3857.

[16] H. C. Tijms, A First Course in Stochastic Models, Wiley, 2003.

[17] Y. Wang, M. C. Vuran, S. Goddard, Cross-Layer Analysis of the End-to-End Delay Distribution in Wireless Sensor Networks, IEEE/ACM Transactions on Networking 20 (1) (2012) 305–318.

[18] R. L. R. T. H. Cormen, C. E. Leiserson, C. Stein, Introduction to Algorithms, MIT Press, 2009.

[19] K. S. Trivedi, Probability and Statistics with Reliability, Queueing, and Computer Science Applications, 2nd Edition, Wiley-Interscience, 2001.

[20] F. Yu, V. Krishnamurthy, V. Leung, Cross-Layer optimal connection admission control for variable bit rate multimedia traffic in packet wireless CDMA networks, IEEE Transactions on Signal Processing 54 (2) (2006) 542–555.

[21] Network simulator version 2, `http://www.isi.edu/nsnam/ns/`.

[22] V. Esmaeelzadeh, R. Berangi, S. M. Sebt, E. S. Hosseini, M. Parsinia, CogNS: a simulation framework for cognitive radio networks, Wireless Personal Communications 72 (4) (2013) 2849–2865.

[23] A. J. D. Rathnayaka, V. M. Potdar, Review: Wireless sensor network transport protocol: A critical review, J. Netw. Comput. Appl. 36 (1) (2013) 134–146.
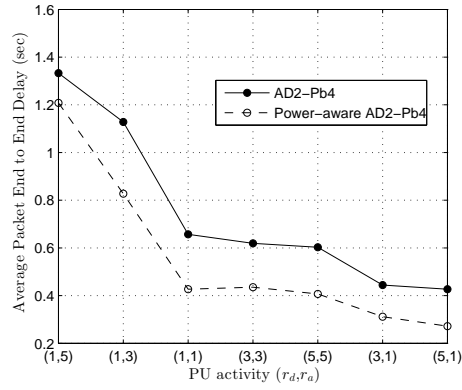
(a) Average packet end-to-end Delay
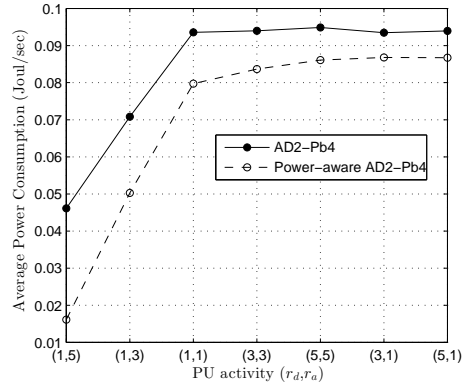
(b) Average power consumption
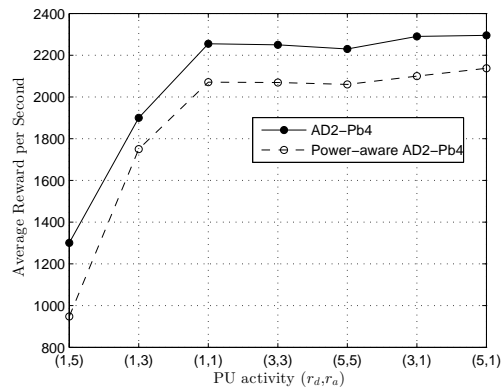
(c) Average gained reward per second

Figure 1: Average packet end to end delay, power consumption and reward per second in different PU activities in the network with AD_2-Pb_4 and *Power-aware AD_2-Pb_4* mechanisms
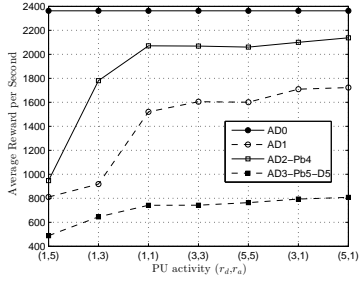
(a) Average gained reward per second
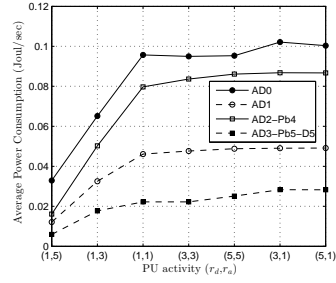
(b) Average power consumption
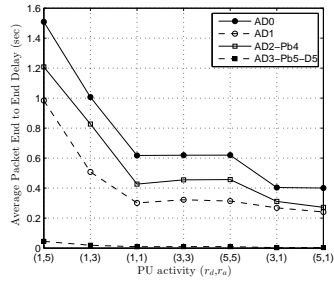
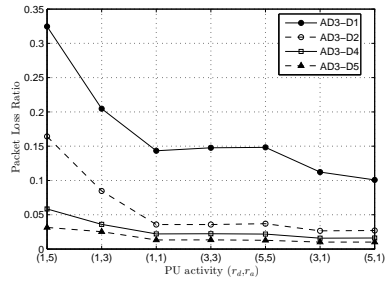(c) Average packet end-to-end Delay
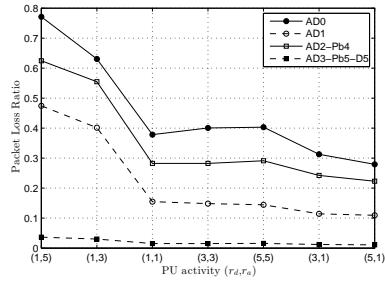
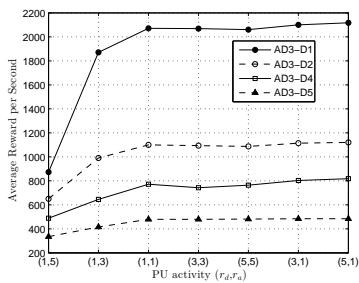(d) Average packet loss ratio
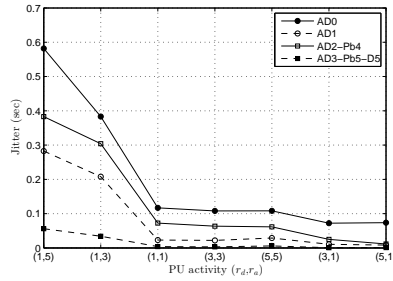
(e) Average jitter of data packets

Figure 2: Average packet end to end delay, power consumption, packet loss ratio, jitter and reward per second in different PU activities in the network with AD_0, AD_1, AD_2-Pb_4 and AD_3-Pb_5-D_5 mechanisms
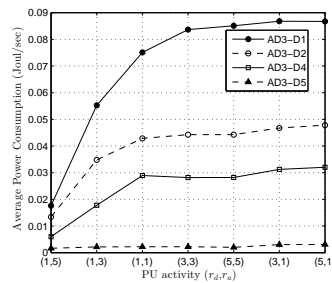
22
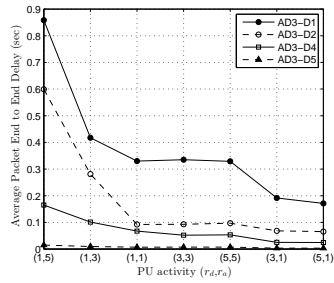
(a) Average packet end-to-end Delay

(b) Average packet loss ratio
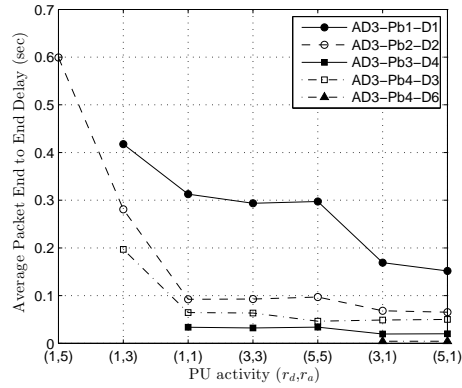

(c) Average gained reward per second
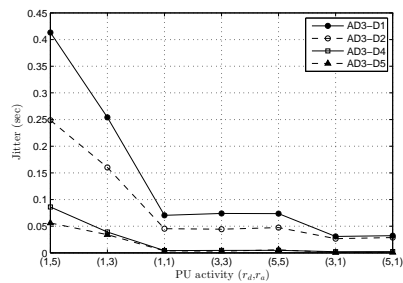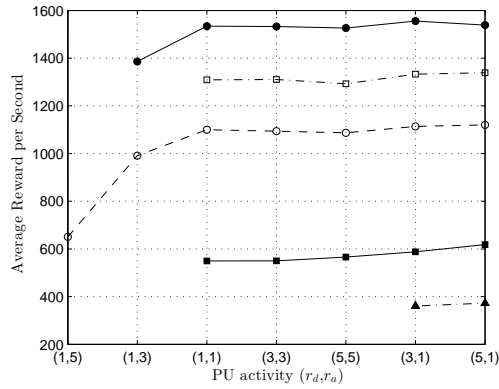

(d) Average jitter of data packet
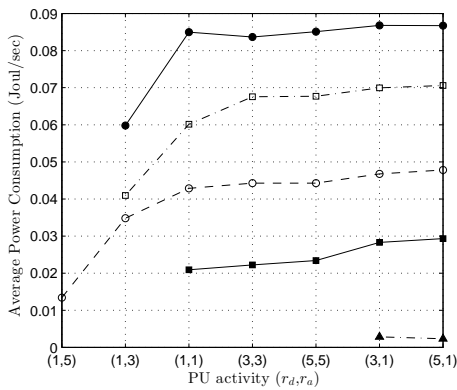

(e) Average power consumption per second

Figure 3: Average packet end to end delay, power consumption, packet loss ratio, jitter and reward per second in different PU activities in the network with AD_3-D_1, AD_3-D_2, AD_3-D_4 and AD_3-D_5 mechanisms without any blocking probability constraint (Pb_5).

(a) Average packet end-to-end Delay

(b) Average gained reward per second

(c) Average power consumption

Figure 4: Average packet end to end delay, power consumption, packet loss ratio, jitter and reward per second in different PU activities in the network with AD_3-Pb_1-D_1, AD_3-Pb_2-D_2, AD_3-Pb_3-D_4, AD_3-Pb_4-D_4 and AD_3-Pb_4-D_6 mechanisms