

Throughput and Delay Optimal Scheduling in Cognitive Radio Networks under Interference Temperature Constraints

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Abstract: The fixed spectrum assignment policy in today's wireless networks leads to inefficient spectrum usage. Cognitive radio network is a new communication paradigm that enables the unlicensed users to opportunistically use the spatio-temporally unoccupied portions of the spectrum, and hence realizing a dynamic spectrum access (DSA) methodology. Interference temperature model proposed by Federal Communications Commission (FCC) permits the unlicensed users to utilize the licensed frequencies simultaneously with the primary users provided that they adhere to the interference temperature constraints. In this paper, we formulate two NP-hard optimal scheduling methods that meet the interference temperature constraints for cognitive radio networks. The first one maximizes the network throughput, whereas the second one minimizes the scheduling delay. Furthermore, we also propose suboptimal schedulers with linear complexity, referred to as maximum frequency selection (MFS) and probabilistic frequency selection (PFS). We simulate the throughput and delay performance of the optimal as well as the suboptimal schedulers for varying number of cognitive nodes, number of primary neighbors for each cognitive node, and interference temperature limits for the frequencies. We also evaluate the performance of our proposed schedulers under both additive white gaussian noise (AWGN) channels and Gilbert-Elliot fading channels.

Index Terms: Cognitive radio networks, interference temperature, scheduling.

I. INTRODUCTION

Recent studies exhibit that spectrum is sparsely utilized in some frequency bands, whereas it is overcrowded in other frequency bands [1]. The escalating demand for the radio spectrum driven by the continuous growth of wireless technologies and services necessitates new methods to combat the acute shortage of bandwidth by utilizing the spectrum more efficiently. In this respect, dynamic spectrum access (DSA) methods that enable the devices to opportunistically access the licensed frequency bands have been proposed. Cognitive radios, which are computationally intelligent devices that can sense their environment and adapt their communication parameters in accordance with the network and user demands, are able to realize the DSA methodology [2].

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A cognitive radio network consists of primary users (PUs) and secondary users (SUs). The former is a licensed user and hence has exclusive rights to access the radio spectrum, whereas the latter is an unlicensed user that can opportunistically access the temporarily unused licensed spectrum bands, provided that it vacates them as soon as a PU appears [3]. In the rest of this paper, we use the terms cognitive users and SUs interchangeably.

Recently, Federal Communications Commission (FCC) has proposed a new model, referred to as interference temperature model [4], that enables true coexistence between licensed and unlicensed users. In this model, SUs are permitted to simultaneously operate on the same frequencies as the PUs provided that the interference perceived by the PUs is within predefined acceptable limits, quantified by the interference temperature threshold for that particular frequency.

In this paper, we formulate throughput and delay optimal schedulers for cognitive radio networks under interference temperature constraints. Furthermore, we also propose two suboptimal schedulers, referred to as maximum frequency selection (MFS) and probabilistic frequency selection (PFS). To the best of our knowledge, ours is the first study on scheduling in cognitive radio networks meeting the interference temperature constraints of the PUs.

The remainder of the paper is organized as follows: Section II describes the related work, whereas Section III introduces the background and problem formulation. Section IV provides the throughput and delay optimal scheduling formulations, as well as the proposed suboptimal schedulers. Section V discusses the simulation results and finally Section VI concludes the paper.

II. RELATED WORK

The fundamental problems of scheduling schemes have been extensively studied in conventional networks [5]–[8]. However, the appearance of new concepts like cognitive radio brings this topic into the focus of research again. Cognitive radio concept introduces new challenges to the scheduling schemes, since the varying channel availability due to coexistence with PUs requires the cognitive users to determine when and on which channel they should tune to in order to exchange data with their neighbors.

The authors in [9] propose an adaptive downlink packet scheduling algorithm for cognitive radio networks. Their algorithm encompasses QoS and spectrum variation awareness capability. Firstly, they calculate the priority values for the traffic queues in accordance with a priority function with channel adaptive coefficient. Secondly, among the channels that have free

time slots, they determine the best available channel and then make the time slot allocation in the subsequent step. Since they choose among the free channels, their scheme does not enable true coexistence with the primary system introduced in [4].

The authors in [10] modify the existing scheduling schemes in conventional wireless networks that maximize the system capacity, achieve fairness, and satisfy the delay constraints by incorporating interference mitigation to the primary system. Although their approach attempts to reduce interference to the licensed users, they do not guarantee that the interference perceived at the licensed users is within quantified acceptable threshold levels.

The integer linear programming (ILP) formulation for the MAC-layer scheduling introduced in [11] minimizes the schedule length in multi-hop cognitive radio networks. They also propose a distributed heuristic to determine the channels and time slots for the cognitive nodes. However, both in their optimization formulation and the suboptimal heuristic, they do not consider the interference to the PUs.

The list-coloring problem introduced in [12] is a general resource allocation issue but it can also be considered as a scheduling problem by adding time indices to the variables in the optimization procedure. Their formulated problem assigns different frequencies to the cognitive users that are in the interference range of each other. However, the interference to the primary system is again avoided by using only the free channels of the licensed users and hence, true coexistence introduced in [4] is again not considered in [12].

The studies on interference temperature concept mainly revolve around methods that optimize various objectives such as QoS, transmission power allocation or channel capacity subject to the interference temperature constraints. For instance, the authors in [13] provide an analysis of the achievable capacity by the interference temperature model. They model the RF environment and derive the probability distributions governing the interference temperature.

The authors in [14] formulate a nonlinear social rate optimization problem with QoS and interference temperature constraints. Note that unlike our work, their problem does not consider the frequencies that each SU will be using but only determines the rate and transmission power of the users. Hence, unlike our study, the work in [14] is not a scheduling issue that determines the frequency and time slot allocation of the cognitive users. Moreover, they only consider a single interference temperature measurement point, whereas we satisfy the constraints in all the measurement points in our work.

The work in [15] concentrates on the power control problem in cognitive radio networks under interference temperature constraints. The authors firstly examine the power control problem without interference temperature constraints. Subsequently, they reformulate the same problem by taking interference temperature constraints into account and model it as a concave minimization problem with linear constraints.

The authors in [16] consider the interference temperature model from a different perspective. Binary and transmitter centric constraints are often used in the literature, where a reuse distance between pair-wise sets of transmitters are considered and the reuse of a set of channels is prohibited within this reuse

distance. On the contrary, the work in [16] proposes non-binary and receiver-centric constraints, where the aggregate interference at the receiver is considered and multiple transmitters are allowed to use the same set of channels as long as they satisfy the interference temperature limit at the receiver.

The optimization problem formulated by the authors in [17] considers interference constraints and channel heterogeneity, which implies that different channels support different transmission ranges. Our work also has this channel heterogeneity feature since we model the maximum transmission power of different frequencies with respect to their interference temperature characteristics. Different maximum transmit power values imply different transmission ranges for the frequencies. However, our work is different from [17] in numerous ways. Firstly, we focus on an *underlay* model, where the SUs transmit at the same time and frequency with the PUs while ensuring that the interference that they impose on any PU does not increase the aggregate interference perceived by that PU above the interference temperature limit. In contrast, the authors in [17] focus on an *overlay* model, where the SUs opportunistically utilize the spatio-temporally unoccupied portions of the spectrum without causing any interference on the PUs. Secondly, they base their model on an ad hoc cognitive radio network architecture, while we focus on an infrastructure based cognitive radio network. Thirdly, they consider only frequency domain channel assignment, whereas we consider both frequency and time domain channel assignment, i.e., our proposed model determines the assignment of both time slots and frequencies to the SUs. Fourthly, the objective function in their model maximizes the total spectrum utilization, whereas we maximize the total network throughput. Their objective function tries to establish as many links between the SUs as possible. In other words, all frequencies have the same weight in their work, whereas there is a maximum rate constraint for each frequency in our work. Fifthly, they use a simple linear expression for the relation between the transmission range and interference range, while we guarantee the reliable communication with the base station in our transmission range formulation and consider the interference temperature constraints in the interference range.

In this paper, we consider scheduling in cognitive radio networks under interference temperature constraints. We formulate the problems of throughput maximization and delay minimization as optimization problems. Our work differentiates itself by incorporating the interference temperature constraint, which is specific to cognitive radio networks, and hence making it distinct in principle from past works about scheduling in conventional wireless networks [5]–[8]. Besides, none of the work in the literature about scheduling in cognitive radio networks [9]–[12], [17] considers interference temperature constraints. Similarly, the research studies about interference temperature constraints [13]–[16] do not consider scheduling in terms of frequency and time slot allocation to the cognitive users. To the best of our knowledge, ours is the first work on scheduling in cognitive radio networks under interference temperature constraints.

III. PROBLEM FORMULATION

Interference temperature is the temperature equivalent of the

RF power available at a receiving antenna per unit of bandwidth. It is formally defined as [18]:

$$IT(f^c, B) = \frac{P_{IF}(f^c, B)}{kB} \quad (1)$$

where $IT(f^c, B)$ is the interference temperature for channel c with central frequency f^c and bandwidth B , $P_{IF}(f^c, B)$ is the average interference power in Watts centered at frequency f^c and covering the bandwidth B in Hz, and k is Boltzmann's constant (1.38×10^{-23} J/K). Under this model, a channel is available at a cognitive node m if the transmission due to m does not increase the interference temperature at any other primary node in the interference range of m beyond a predefined threshold. This constraint can be conveyed as [18]:

$$IT(f^c, B) + \frac{L_{mn}^c P_m(f^c, B)}{kB} < IT_c^{th}. \quad (2)$$

In the above formulation, L_{mn}^c refers to the distance dependent path loss in transmission from node m to n on channel c , $P_m(f^c, B)$ is the transmission power of m , and IT_c^{th} is the interference temperature threshold for channel c . The threshold values should be determined by the regulatory bodies for each frequency band in a given geographic region.

We consider a time slotted IEEE 802.22 system, where the cognitive devices are managed by the base station (BS) [19]. The scheduler resides at the BS and determines how many packets and with which frequency each cognitive user will transmit in each time slot. If we denote the number of packets in the buffer of SU i at the beginning of time slot t by $x_{i,t}$, the number of packets transmitted by user i in time slot t by $u_{i,t}$, the fading coefficient of the channel between user i and the BS in time slot t by $A_{i,t}$, the frequency used by user i in time slot t by $f_{i,t}$, the vector of buffer states for a total number of N cognitive nodes as $\bar{x}_t = [x_{1,t}, x_{2,t}, \dots, x_{N,t}]$, the vector of transmitted packets as $\bar{u}_t = [u_{1,t}, u_{2,t}, \dots, u_{N,t}]$, the vector of channel states as $\bar{A}_t = [A_{1,t}, A_{2,t}, \dots, A_{N,t}]$, and the vector of transmission frequencies as $\bar{f}_t = [f_{1,t}, f_{2,t}, \dots, f_{N,t}]$, then the scheduler's mapping is $\alpha: [\bar{x}_t, \bar{A}_t] \rightarrow [\bar{u}_t, \bar{f}_t]$.

On the other hand, reliable communication can be guaranteed by having the scheduler to choose the power level $P_m(f^c, B)$ in time slot t such that the number of packets transmitted $u_{i,t}$ is equal to the Shannon capacity function for a Gaussian channel [20]. If the noise variance is $\sigma^2/|A_{i,t}|^2$ and the average power is $P_{i,t}$, then,

$$u_{i,t} = B \frac{T_s}{S} \ln \left(1 + \frac{|A_{i,t}|^2 P_{i,t}}{\sigma^2} \right) \quad (3)$$

where B is the bandwidth, S is the packet size and T_s is the time slot length. For simplicity, we assume that $S = BT_s$. Therefore,

$$P_{i,t} = \frac{\sigma^2 (e^{u_{i,t}} - 1)}{|A_{i,t}|^2}. \quad (4)$$

In line with the above information, the scheduling problem that maximizes the network throughput while satisfying the interfer-

ence temperature constraints can be formulated as follows:

$$\max_{\bar{u}_t, \bar{f}_t} E \left\{ \sum_{i=1}^N u_{i,t} \right\} \quad (5)$$

$$\text{s.t. } P_{IF}(f_i, B) + L_{ij}^{f_i} \frac{\sigma^2 (e^{u_{i,t}} - 1)}{|A_{i,t}|^2} < IT_{f_i}^{th} kB; \quad \forall j \in \Phi_i, \forall i \in \{1, \dots, N\}, \quad (6)$$

$$f_{i,t} \neq f_{i',t}; \quad \forall i, i' \in \{1, \dots, N\}, i \neq i', \quad (7)$$

$$u_{i,t} \leq x_{i,t} \quad (8)$$

where $P_{IF}(f_i, B)$ denotes the average sensed interference power at frequency f_i over bandwidth B , $L_{ij}^{f_i}$ is the distance dependent path loss from node i to node j with frequency f_i , $IT_{f_i}^{th}$ is the interference temperature threshold for frequency f_i , Φ_i is the set of primary nodes in the interference range of cognitive node i , N is the total number of cognitive nodes, and $f_{i,t}$ is the frequency used by node i in time slot t . In the above formulation, (5) maximizes the expected value of the total number of packets transmitted by all the cognitive users, (6) satisfies the interference temperature constraint, (7) ensures that at most one cognitive user can transmit using a certain time slot and frequency combination, and (8) represents the fact that a user cannot transmit more than the number of packets in its buffer at the beginning of the time slot.

How the cognitive nodes know the already existing interference temperature in the neighboring primary nodes is an open issue in [4]. Therefore, as in [18], we assume a specialized environment where cognitive radios can locate licensed signals and measure the interference temperature. In other words, the cognitive nodes learn about the interference perceived by their neighboring primary nodes through their local spectrum sensing observations, which we denote here by $P_{IF}(f_i, B)$.

IV. PROPOSED SCHEDULERS

A. Throughput Optimal Scheduler

Our solution to the problem formulated in Section III consists of two stages. In the first stage, every cognitive node i computes the maximum number of packets that can be transmitted for every frequency by solving the following problem for each frequency f_i :

$$D(f_i) = \min(C(f_i, j)); \quad \forall j \in \Phi_i \quad (9)$$

$$\text{s.t. } IT_{f_i}^{th} kB - P_{IF}(f_i, B) > 0 \quad (10)$$

where $C(f_i, j) = \ln \left((IT_{f_i}^{th} kB - P_{IF}(f_i, B) |A_{i,t}|^2) / \sigma^2 L_{ij}^{f_i} + 1 \right)$. In the above formulation, $\lfloor D(f_i) \rfloor$ equals the maximum number of packets that can be transmitted by cognitive node i using frequency f_i while not violating the interference temperature constraints for all the primary nodes that are in the interference range of node i . Afterwards, all the cognitive nodes send their $\lfloor D(f_i) \rfloor$ values to the BS. We assume here that the cognitive nodes have a priori knowledge about the number of primary nodes in their interference range as well as the path loss values to their neighbors. How the nodes acquire this information is beyond the scope of this paper.

In the second stage of the algorithm, the BS constructs a matrix called $\mathbf{U} = [U_{if}]$, where U_{if} is the maximum number of packets that can be transmitted by user i using frequency f , and hence being equal to the $\lfloor D(f_i) \rfloor$ value. The BS, then, executes the following binary integer linear program:

$$\max \left(\sum_{i=1}^N \sum_{f=1}^F \sum_{t=1}^T \frac{U_{if} X_{ift}}{T} \right) \quad (11)$$

$$\text{s.t.} \quad \sum_f \sum_t X_{ift} \geq 1; \quad \forall i \in \{1, \dots, N\}, \quad (12)$$

$$X_{ift} + X_{i'ft} \leq 1; \quad \forall i, i' \in \{1, \dots, N\}, i \neq i', \forall f, \forall t \quad (13)$$

where N is the total number of cognitive nodes, F is the total number of frequencies, T is the total number of time slots, and X_{ift} is a binary variable such that $X_{ift} = 1$ if user i transmits with frequency f in time slot t , and 0 otherwise. In the above formulation, (12) ensures that each cognitive user is assigned at least one time slot, whereas (13) guarantees that at most one user can transmit in a certain time slot and frequency pair, thereby avoiding collisions among the secondary nodes. Consider the case that a PU is in the interference range of two cognitive users. Since the cognitive users determine their $\lfloor D(f_i) \rfloor$ values, and consequently the U_{if} values by taking only their own transmissions into account, having more than one cognitive user transmit in the same frequency and time slot may increase the aggregate interference perceived at the PU beyond the interference temperature limit. Therefore, in addition to avoiding collisions among the secondary nodes, (13) is also necessary to ensure that the aggregate interference temperature at the PUs is within the pre-determined limits. Besides, the schedule length T is the duration of time in which the changes in the sensed interference values, denoted by $P_{IF}(f_i, B)$, as well as the path loss values to the PUs in the interference range are small enough not to have any impact on the U_{if} values. Note that because of the floor operator in $\lfloor D(f_i) \rfloor$, the schedule length T does not mandate $P_{IF}(f_i, B)$ and the path loss values to remain constant in that time period, but only requires that the change in their values does not alter U_{if} . The value of T , in general, depends on the characteristics of the spectrum environment. For instance, a slowly varying spectrum environment like the TV broadcast bands utilized by an IEEE 802.22 network allows T to have a fairly large value. In the simulations of this paper, we set $T = N$ because $T = N$ is sufficiently large to ensure the fulfillment of constraint (12), which prescribes that at least one time slot is assigned to each cognitive user.

Once the scheduler determines the U_{if} values, each node i transmits $\min(x_{i,t}, U_{if})$ number of packets in time slot t . We consider traffic in which all flows are continuously backlogged such that the achieved throughput is entirely related to the scheduling process and channel conditions without any variation due to traffic fluctuation.

B. Delay Optimal Scheduler

The first stage of the scheduler that minimizes the scheduling delay is the same as the throughput optimal scheduler. However, in the second stage the delay optimal scheduler implements

the following nonlinear binary integer program with linear constraints:

$$\min \left(\frac{\sum_i \sum_f \sum_t t U_{if} X_{ift}}{\sum_i \sum_f \sum_t U_{if} X_{ift}} \right) \quad (14)$$

$$\text{s.t.} \quad \sum_i \sum_f \sum_t U_{if} X_{ift} > 0, \quad (15)$$

$$\sum_f \sum_t X_{ift} \geq 1; \quad \forall i \in \{1, \dots, N\}, \quad (16)$$

$$X_{ift} + X_{i'ft} \leq 1; \quad \forall i, i' \in \{1, \dots, N\}, i \neq i', \forall f, \forall t. \quad (17)$$

In the above formulation, when $X_{ift} = 1$, each one of U_{if} number of packets waits for t number of time slots, starting from the beginning of the schedule. We use the term *scheduling delay* to refer to the number of time slots that a packet has to wait for until its determined transmission time comes, given that the packet is scheduled for transmission in that particular schedule. Therefore, the total scheduling delay of these U_{if} number of packets is equal to tU_{if} . Hence, $\sum_i \sum_f \sum_t t U_{if} X_{ift}$ denotes the total scheduling delay experienced by all the transmitted packets in the schedule. Because the total number of transmitted packets equals $\sum_i \sum_f \sum_t U_{if} X_{ift}$, the objective function in (14) minimizes the scheduling delay in terms of time slots experienced per packet. Moreover, (15) is necessary to avoid the situation that the scheduler always selects the frequencies with which the nodes can send at most zero packets for the sake of reducing the average delay. Without (15), the scheduler can arrive at the irrational decision of having none of the nodes being able to transmit any packets, which would result in zero throughput. The two optimization problems starting with (11) and (14) are binary integer programming problems, which are known to be NP-hard and can be solved via branch-and-bound algorithms [21], [22].

C. Maximum Frequency Selection (MFS) Suboptimal Scheduler

In the first stage of the MFS scheduler, each cognitive node i sends the frequency with which it wishes to transmit to the BS. The nodes make their selection by finding $\max_{f_i} D(f_i)$. In the second stage, the BS makes the time slot assignments by first grouping the nodes with respect to the frequencies that they wish to transmit with. Among the cognitive nodes in the same frequency group, the BS assigns the node with the maximum number of packets to the first time slot, the second maximum to the second time slot etc. This way, the condition that at most one cognitive node can be assigned a certain time slot and frequency combination is ensured. Furthermore, the scheduling delay is also reduced by doing the time slot assignment in the decreasing order of their allowable number of packets to transmit.

D. Probabilistic Frequency Selection (PFS) Suboptimal Scheduler

As in the MFS scheduler, in the first stage each node sends the frequency with which it wishes to transmit to the BS. However,

the selection of the desired frequency is made probabilistically as follows: A cognitive node i chooses frequency f_i with probability $p_{f_i} = \lfloor D(f_i) \rfloor / \sum_{f_i} \lfloor D(f_i) \rfloor$. In order to reduce the average delay, if frequency f_i was selected in the previous schedule and node i waited for T_{f_i} time slots with a schedule length of T , then as a penalty metric p_{f_i} is updated as $p_{f_i}(1 - T_{f_i}/T)$. The selection probability of the frequency that has the highest number of packets among the remaining ones is increased by $p_{f_i}T_{f_i}/T$, which makes the total probability equal to 1. The second stage of the PFS scheduler is the same as MFS.

In order to better comprehend the different behavior of MFS and PFS schedulers, suppose that there are three SUs and three frequencies in the network. Assume that $\max_{f_i} D(f_i) = f^3$ for all the three nodes and $\lfloor D(f_i) \rfloor = 22, 21, 20$ for node 1, 2, and 3, respectively. Thus, MFS scheduler selects node 1 for the first time slot, node 2 for the second time slot and node 3 for the third time slot. Assume that node 3 can transmit 19 and 18 packets with the other frequencies f^1 and f^2 . Note that node 3 could have used f^1 and f^2 in the first and second time slots, while other nodes used f^3 . This would decrease the scheduling delay for node 3 because the packets would wait for less number of time slots by being able to transmit earlier. Nevertheless, MFS scheduler does not allow this frequency and time slot usage pattern by always selecting $\max_{f_i} D(f_i)$. In contrast, PFS scheduler probabilistically allows node 3 to select frequencies f^1 or f^2 as the frequency that it wishes to transmit with, hence enabling node 3 to transmit in earlier time slots. This way, PFS scheduler disperses the selected frequencies and avoids the above situation, which could occur with MFS scheduler. Because of this behavior of the PFS scheduler in addition to the penalty metric that it introduces, we intuitively expect PFS scheduler to have less scheduling delay on the average. Nevertheless, since PFS scheduler probabilistically allows the selection of frequencies whose maximum number of packets for transmission is smaller, we intuitively expect the average throughput of PFS scheduler to be smaller than the throughput of MFS scheduler.

E. Computational Complexity Comparison

If the number of frequencies is F and each cognitive node has M primary neighbors in its interference range, the first stage of all the schedulers requires MF computations at each node. Since M and F are fixed in our case, the computational complexity of the first stage is $O(1)$. Since the optimal schedulers have binary integer programming models, they are NP-hard problems. On the other hand, there is one value for the maximum allowable number of packets to transmit corresponding to a certain frequency for each secondary node in the sub-optimal schedulers. Since the number of cognitive nodes is N , the computational complexity of the suboptimal schedulers is $O(N)$.

V. NUMERICAL EVALUATION

We simulated the suboptimal schedulers using OPNET Modeler 14.0 [23]. While the first stage of the optimal schedulers were also simulated and the $U_{i,f}$ values were obtained in OP-

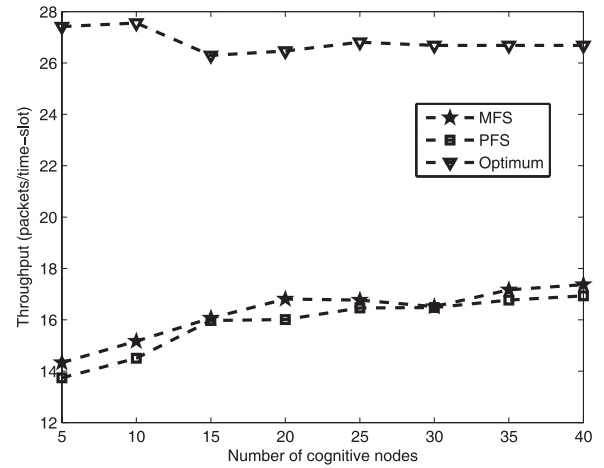


Fig. 1. Average network throughput for the proposed scheduling schemes with varying number of cognitive nodes.

NET, the optimization procedures in the second stages were implemented using CPLEX [24]. Firstly, we consider AWGN channels, i.e., $|A_{i,t}| = 1, \forall i$ and $\forall t$. Secondly, we evaluate the performance of our proposed schedulers under Gilbert-Elliot fading channel model. The bandwidth is $B = 10$ MHz and the noise variance is $\sigma^2 = 10^{-10}$. The PU activity is modeled such that the initially sensed interference for each frequency f_i is uniformly distributed in $[0, 2IT_{f_i}^{th}kB/\sigma^2]$. If the sensed interference at the beginning of a certain schedule is $P_{IF}(f_i, B)$, then the sensed interference in the next schedule is uniformly distributed in $[P_{IF}(f_i, B) - \delta, P_{IF}(f_i, B) + \delta]$, where δ was selected to be 0.65 mW. Besides, path loss of the cognitive nodes to each primary neighbor is uniformly distributed between 0 and 1. The average values in all of the results were obtained using 10 different seeds and 10000 schedules for each seed.

In the first set of simulations, each cognitive node has three primary neighbors in its interference range. The channel between the SUs and the BS is AWGN channel. There are three frequencies with interference temperature thresholds of 1000 K, 2000 K, and 3000 K.

Figs. 1 and 2 illustrate the average network throughput and average scheduling delay values where the number of cognitive nodes varies between 5 and 40. For all the three schemes, the throughput values remain almost invariant as the number of secondary nodes increases, whereas the average scheduling delay increases almost linearly. Furthermore, PFS scheduler has a slightly less average scheduling delay than MFS at the expense of a little decrease in average network throughput compared to MFS. This improvement in delay is due to the penalty metric introduced in PFS in order to decrease the scheduling delay. Note here that because of the scale of the graph, the difference between the throughput values of MFS and PFS schedulers for 15 and 30 nodes is not visible. The actual average network throughput values for 30 nodes are 16.51 packets/time-slot for MFS and 16.47 packets/time-slot for PFS. Similarly, the average throughput for 15 nodes is 16.07 packets/time-slot for MFS and 15.97 packets/time-slot for PFS.

In the second set of simulations, again there are three fre-

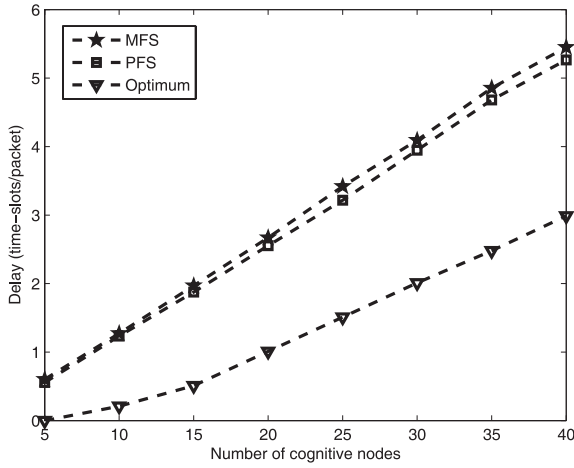


Fig. 2. Average scheduling delay for the proposed scheduling schemes with varying number of cognitive nodes.

quencies with interference temperature thresholds of 1000 K, 2000 K, and 3000 K, and the channel between the SUs and the BS is AWGN channel. However, this time we vary the number of primary neighbors of each cognitive node while keeping the total number of cognitive nodes constant. Figs. 3 and 4 illustrate the average network throughput and average scheduling delay for 15 cognitive nodes with varying number of primary neighbors for each node. For all the scheduling schemes, throughput decreases as the number of primary neighbors for each secondary node increases. However, the rate of decrease diminishes as the number of primary neighbors increases. The reason for this is that the cognitive nodes have more interference temperature constraints as the number of their primary neighbors increases. Therefore, their $[D(f_i)]$ values and consequently $[U_{if}]$ values decrease and hence the average network throughput diminishes. Fig. 4 illustrates that the average scheduling delay decreases as the number of primary neighbors for each cognitive node increases and the rate of decrease diminishes as the number of primary neighbors increases. This behavior in average scheduling delay is in line with the throughput performance results of Fig. 3.

In the third set of simulations, we again model the channel between the SUs and the BS as an AWGN channel. We vary the interference temperature limits of the frequencies, while keeping the total number of cognitive nodes and the number of primary neighbors of each cognitive node constant. Fig. 5 illustrates the average network throughput for 15 cognitive nodes, each having 3 primary neighbors in its interference range, with increasing values of interference temperature limit. In this figure, the values on the x -axis correspond to the interference temperature limit for the first frequency. That is to say, if the value on the x -axis is A K, then the limits for the second and third frequencies are $A + 1000$ K and $A + 2000$ K, respectively. This figure indicates that the network throughput increases as the interference temperature limit increases. The results in Fig. 6 are essentially the same as the ones in Fig. 5 with the only difference that we do not show the results of the throughput optimal scheduler in Fig. 6 in order to provide a better visualization of the through-

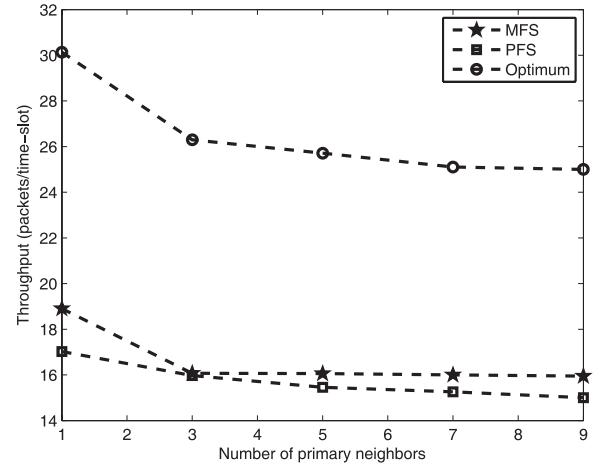


Fig. 3. Average network throughput for the proposed scheduling schemes with varying number of primary neighbors for the cognitive nodes.

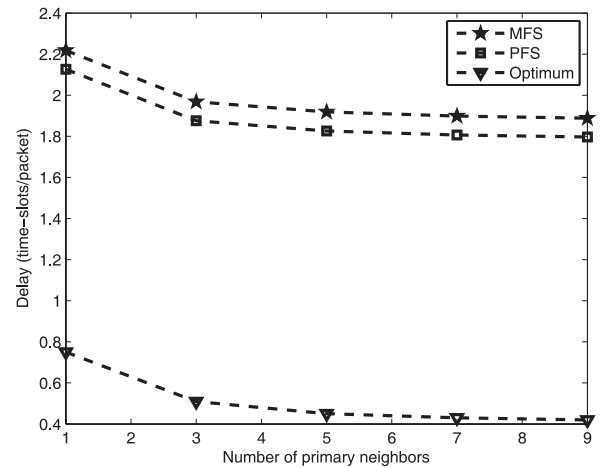


Fig. 4. Average scheduling delay for the proposed scheduling schemes with varying number of primary neighbors for the cognitive nodes.

put increase in the MFS and PFS schedulers as the interference temperature limit increases. This increase in average network throughput is due to the fact that the $[D(f_i)]$ values and consequently the $[U_{if}]$ values of the cognitive nodes increase as the interference temperature limits increase because increasing the interference temperature limit represents the FCC allowing more interference from unlicensed devices. Furthermore, the rate of increase decreases for the optimum scheduler as the interference temperature limit increases. The observed decrease in the rate of increase is consistent with the results in [25], where the network capacity saturates at a certain level after an initial increase as the interference temperature limit increases.

Fig. 7 shows the average scheduling delay of 15 cognitive nodes, again each having 3 primary neighbors in its interference range, for increasing values of interference temperature limit. This figure illustrates that the average scheduling delay increases as the interference temperature limit increases. Fig. 8 better illustrates the increase in MFS and PFS schedulers. Similar to the situation between Figs. 5 and 6, the only difference

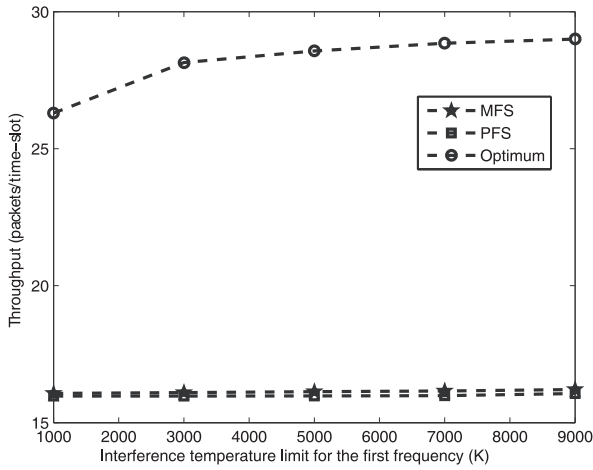


Fig. 5. Average network throughput for the proposed scheduling schemes with varying values of interference temperature limit.

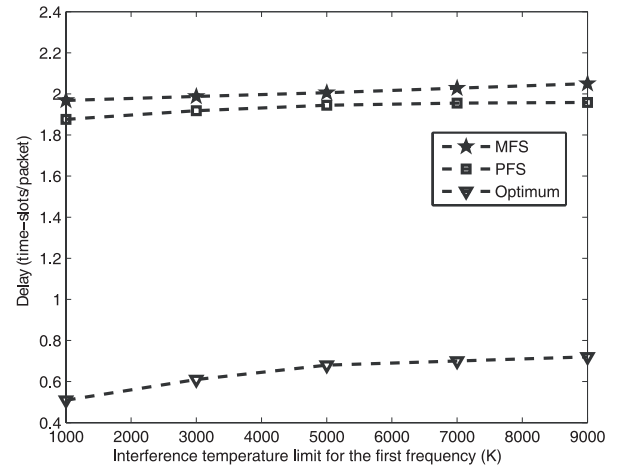


Fig. 7. Average scheduling delay for the proposed scheduling schemes with varying values of interference temperature limit.

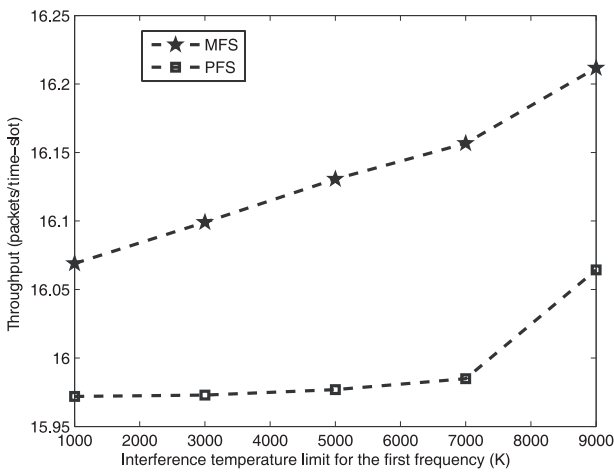


Fig. 6. Average network throughput for the proposed scheduling schemes with varying values of interference temperature limit.

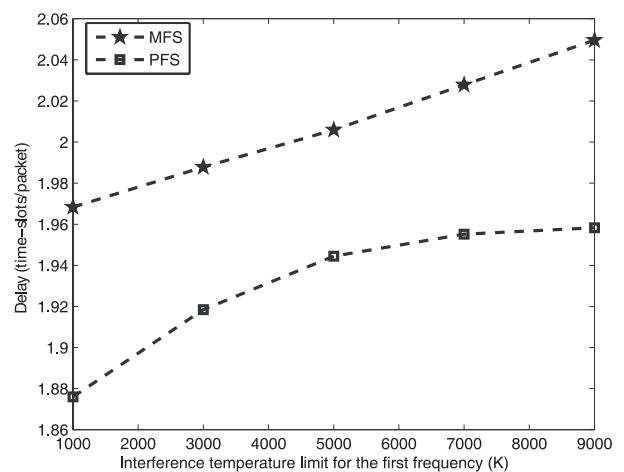


Fig. 8. Average scheduling delay for the proposed scheduling schemes with varying values of interference temperature limit.

between Figs. 7 and 8 is that we do not show the performance results of the delay optimal scheduler in Fig. 8 in order to provide a better visualization of the increase in the average scheduling delay as the interference temperature limit increases. Moreover, the results also indicate that the average scheduling delay values of the optimal as well as the MFS scheduler stabilize around 7000 K. This increase in average scheduling delay is consistent with the increase in average network throughput as the interference temperature limit increases.

The fourth set of simulations investigate the impact of channel fading on the performance of our proposed schedulers. We model the fading process as a Gilbert-Elliot channel, which we illustrated as a 2-state Markov process in Fig. 9. The fading coefficient is high when the channel is in the good state, whereas it is low in the bad state. We have chosen the state transition probabilities as 0.1, which is a small number compared to 0.9, the probability of staying in the same state. We have made this selection in order to reflect the slow fading channel process. The rest of the simulation conditions is the same as the ones in the

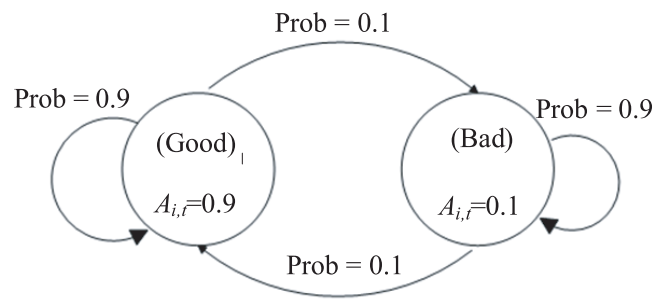


Fig. 9. Gilbert-Elliot channel model.

first set of simulations, where we evaluated the AWGN channels.

Fig. 10 illustrates the average network throughput with Gilbert-Elliot channel as the number of cognitive nodes increases from 5 to 40 for all the three schedulers. To facilitate the visual comparison with the AWGN channel performance, we have

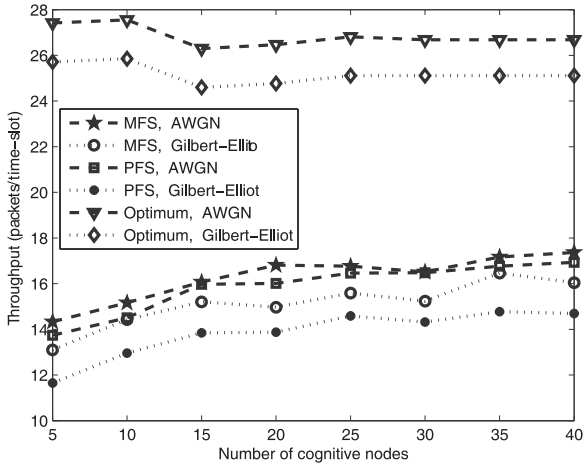


Fig. 10. Average network throughput for the proposed scheduling schemes with Gilbert-Elliot channel.

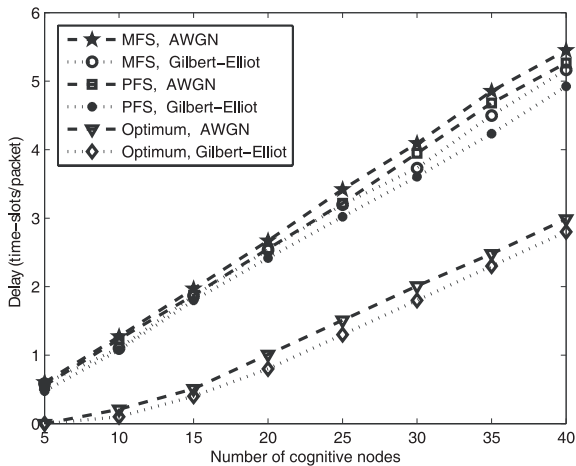


Fig. 11. Average scheduling delay for the proposed scheduling schemes with Gilbert-Elliot channel.

also shown in Fig. 10 the performance results previously displayed in Fig. 1. In line with the theoretical expectations, the average network throughput decreases as the fading conditions in the channel deteriorate. Hence, Gilbert-Elliot channel for all the three schedulers yields reduced average network throughput when compared to their AWGN channel counterparts.

Fig. 11 shows the average scheduling delay with Gilbert-Elliot channel as the number of cognitive nodes increases from 5 to 40 for all the three schedulers. For better visual comparison with the AWGN channel performance, we have also shown here the performance results previously illustrated in Fig. 2. The reason that the average scheduling delay of the Gilbert-Elliot channel is less than the AWGN channel for all the three schedulers is that the $\lfloor D(f_i) \rfloor$ values and consequently the $\lceil U_{if} \rceil$ values decrease as the fading condition of the channel deteriorates. The reasoning here is the same as the one where we varied the number of PUs in the interference range of each SU: The decrease in $\lceil U_{if} \rceil$ values leads to reduced average scheduling delay due to the formulation in (14). As in the preceding simulation results,

the decrease in the average scheduling delay is consistent with the decrease in the average network throughput.

To put it in a nutshell, the average network throughput of the MFS scheduler is slightly higher than that of the PFS scheduler in all the simulation results. Furthermore, the average scheduling delay of the PFS scheduler is slightly lower than that of the MFS scheduler in all the results. These two observations are consistent with our theoretical expectations, which we outlined in Section IV-D. On the one hand, the reason for the superior throughput performance of the MFS scheduler is that MFS scheduler always selects the channel with the maximum allowable number of packets to transmit per time slot, whereas the PFS scheduler may select the channel with reduced allowable number of packets to transmit per time slot owing to its probabilistic selection of the channels. On the other hand, the delay performance of the PFS scheduler is better than that of MFS scheduler due to the penalty metric introduced in the design of PFS. Besides, the throughput and delay performance of the optimal schedulers are significantly better than that of suboptimal schedulers. As a research challenge, the simulation results indicate that better performing, yet computationally efficient suboptimal schedulers are needed.

VI. CONCLUSION

In this paper, we propose throughput and delay optimal schedulers with exponential complexity as well as suboptimal schedulers with linear complexity for cognitive radio networks under interference temperature constraints. We have simulated the throughput and delay performance of the optimal schedulers as well as the suboptimal schedulers for varying number of nodes, number of primary neighbors for each cognitive node, and interference temperature limits. Moreover, we have investigated the impact of channel fading on the performance of our proposed schedulers by providing comparative simulation results for both AWGN and Gilbert-Elliot fading channels. While the performance results of the optimal schedulers serve as a baseline, the suboptimal schedulers have significantly less computational complexity at the expense of reduced throughput and increased delay performance.

Although the computational simplicity of the suboptimal schedulers makes them attractive, better performing suboptimal schedulers might be needed. Therefore, as a future work, we are planning to design suboptimal schedulers whose performance is closer to the optimal schedulers. We envision that the binary variables X_{ift} , whose values are to be determined by the scheduling algorithm, can be easily encoded to a binary string, and this property can make genetic algorithms (GA) [26] suitable for implementation. Hence, we are planning to design GA-based suboptimal schedulers for the throughput maximizing and delay minimizing problems formulated in this paper.

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