Opportunistic Spectrum Scheduling for Mobile Cognitive Radio Networks in White Space

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Abstract—Recent works have shown that the white-space spectrum opened to cognitive radio devices is far less than what the lobbyists claimed. With fast growing number of secondary users, carefully scheduling the spectrum allocation in cognitive radio networks operating on white space becomes vital. However, the frequent ON/OFF activity of primary users (PU) and the mobility of the cognitive users make the problem of spectrum scheduling extremely hard.

By modeling the PUs activity in an opportunistic manner, this paper studies how to schedule the spectrum assignment for mobile cognitive radio devices. With the mobility information, we formally define the related problem as the Maximum Throughput Channel Scheduling problem (MTCS) which seeks a channel assignment schedule for each cognitive radio device such that the maximum expected throughput can be achieved. We present a general scheduling framework for solving the MTCS. Based on the proposed framework, we then present two polynomial time optimal algorithms to solve the MTCS in the homogeneous and the heterogeneous traffic load cases, respectively. Our algorithms are evaluated by simulations using the mobility trace obtained from a real world public transportation system. On average, the proposed algorithms outperform a greedy algorithm by 21.6%.

Index Terms— Cognitive radio networks, white-space, mobility, spectrum hand-off, scheduling, channel assignment.

I. INTRODUCTION

Communication spectrum is known as one of the most precious and scarce resources for wireless communications. On November, 2008, the FCC released rules opening the digital television bands to the operation of cognitive radio devices. On one hand, the ruling gives opportunistic access of the licensed band to unlicensed users; on the other hand, the FCC also extended protection to adjacent channels and require a no-talk radius larger than the Grade-B protected contour [4]. Recently, studies have shown that the actual amount of available white space is much less than what the lobbyists claimed [2]. With limited spectrum resource and the fast growing number of secondary users, spectrum scheduling in cognitive radio networks operating on white space becomes vital.

Spectrum scheduling in cognitive radio networks involves the secondary users to reserve one portion of the spectrum for certain periods of time [17]. An important factor affecting the spectrum scheduling in cognitive radio networks is the ON/OFF activities of the primary users (PU) [6] [7]. Whenever a PU is detected, the cognitive radio devices have to evacuate from the licensed band possessed by the PU, and transmission link failure could occur. A transmission link failure can be avoided by changing the transmission frequency, i.e., using a different channel. For example, during a period in which a channel on 120MHz is occupied by PUs, another channel on 500MHz can be selected for communications if it is not used by any other PU. However, the frequent ON/OFF activity of the PUs and the mobility of the cognitive users make the problem of selecting an available communication channel on the fly very challenging.

Fortunately, in the white space, the PUs are commonly TV towers whose positions, interference range and operation hours can be profiled [9]. This enables us to model the PUs activity in an opportunistic manner. In this paper, we formally define the Maximum Throughput Channel Scheduling problem (MTCS) which aims at seeking a long-term channel assignment schedule to maximum the expected network throughput. The major contribution of this paper is summarized as follows:
1) We present a general scheduling framework to solve the MTCS; Based on the framework, two polynomial time optimal algorithms are proposed to tackle the homogeneous and the heterogeneous traffic load cases, respectively;
2) The proposed algorithms are evaluated by simulations based on the bus traces in a real public transportation system. Simulation results show that the proposed scheduling algorithms achieve high network throughput and outperform an intuitive greedy algorithm.

The rest of this paper is organized as follows. We discuss related work in Section II. The system model and problem definition are described in Section III. The proposed scheduling framework and algorithms are presented in Section IV. We present simulation results in Section V and conclude the paper in Section VI.

II. RELATED WORK

Recent studies reveal that the lobbyists overestimate the white space availability [2]. For example, only 5 channels in Berkeley, CA are actually available for white space use when the FCC's white space rules are applied, while the FCC website indicates 23 available channels. It is also shown that the average available bandwidth is less than half of the previous estimations [8]. With the fast growing number of secondary users, carefully scheduling the spectrum allocation in cognitive radio networks operating on white space becomes vital.

Spectrum allocation (channel assignment) and scheduling are very important and challenging problems in cognitive radio networks [3]. In [19], Zheng *et al.* developed a graph-theoretic model to characterize spectrum access. Based on the model, they designed several centralized heuristics to find fair spectrum allocation. Distributed spectrum allocation methods were presented in [14], [16], [18]. In [18], the authors presented optimal and suboptimal distributed spectrum access strategies under a framework of partially observable Markov decision process. In [16], the authors proposed the Dynamic Open Spectrum Sharing (DOSS) MAC protocol, which provides real-time dynamic spectrum allocation and high spectrum utilization.

In this work, we study a mobile cognitive radio network operating on white space where the spectrum resource is not as abundant as that in the previous works. In order to avoid the high overhead caused by real-time spectrum allocation, we design a long-term spectrum scheduling framework to achieve maximum expected network throughput. Therefore, our solution is different from those studied in the related works.

III. PROBLEM DEFINITION

In this section, we will describe the system model and formally define the optimization problem.

We consider a secondary wireless network consisting of a Base Station (BS) and n mobile stations (MS), each of which has a single cognitive radio. According to the IEEE 802.22 standard, the radios usually have long transmission ranges. For example, the 4W EIPR radio has a cell radius of 17km which is basically long enough to cover a town such as Davis, Berkeley and Palo Alto in the State of California, which are 27.1km^2, 45.9km^2 and 61.3km^2, respectively. We assume all the radios work at the fixed transmission power and have the same transmission range r. Therefore, all the MS's can directly communicate with the BS. In such a network, there will be n MS-BS links and every MS/link needs to be assigned a different channel at any instant of time to prevent co-channel interference.

The secondary users share a region with a group of PUs. Both the PUs and the secondary users are aware of their own location through GPS or triangulation techniques [10].

The available spectrum is divided into M non-overlapping channels which are indexed by the integers from 0 to $M-1$. Any proposed spectrum sensing scheme can be used to detect the locally available channels [3]. We assume the existence of a common control channel on a relatively low frequency which can support a long transmission range. Both the location and the sensing information is broadcast by the cognitive radio users through the common control channel periodically. The OFDMA technology is used for media access. Therefore, all MS's are able to communicate with the BS simultaneously if they are assigned different sub-carriers. We assume each mobile station and PU can occupy only one channel at a certain period.

Each MS is assumed to know its own trajectory in the next certain period, say $q \cdot t$ seconds, e.g buses and metros have to follow specific routes and schedules. For every t seconds, the BS will calculate the probability of the existence of PUs by using the activity profile of the PUs. q is a constant which identifies the length of total time period considered for scheduling. The PU's activity is modeled as a two-stage ON-OFF process. The activity profile of PU i is defined as $P_i = \{(0, t, p_i^0), (t, 2t, p_i^1), ..., ((j-1)t, jt, p_i^{j-1}), (jt, (j+1)t, p_i^j), ..., ((q-1)t, qt, p_i^{q-1})\}$, which specifies the probability p_i^j that the PU i is active in each time interval $(jt, (j+1)t)$ $(0 \le j \le q-1)$.

If the PUs are off, the secondary users can operate on the licensed band possessed by the PUs. When the PUs become active in any channel, all the secondary users should evacuate from those channels and switch to other available channels. In the case of limited available licensed bandwidth, some secondary users may fail to detect any available channel and have to stop their transmission until available channels emerge. In this paper, we assume there is always traffic demand on each MS. Therefore, whenever an MS stops transmission, its throughput is degraded.

In this paper, we study the problem of scheduling the channel assignments to maximize the expected network throughput. The expected network throughput is defined as the summation of the expected throughput on each link between the BS and MS. The maximum expected network throughput is the up bound of the average value of the network throughput over a long term such as multiple days or several weeks. The problem is formally defined as follows:

Definition 1 (MTCS): Given a cognitive radio network with one BS, n MS, M channels, N PUs, the MS moving trajectories and the PUs' activity profiles $P = \{P_0, \cdots, P_{N-1}\}$, the **Maximum Throughput Channel Scheduling problem (MTCS)** seeks a feasible channel assignment schedule S_i for each MS i in the time period $(0, q \cdot t)$, such that the expected network throughput is maximized.

The channel assignment schedule S_i for each MS i is denoted as a sequence of three-tuples $\{T_1, \cdots, T_k, \cdots\}$. Each three-tuple $T_k = (t_s, t_e, channel_j)$ represents assigning channel j to MS i in the time period (t_s, t_e). The unit of time is second throughout this paper.

IV. PROPOSED SCHEDULING ALGORITHMS

In this section, we present a framework to solve the MTCS. First we will discuss the homogeneous traffic load case in which maximizing the expected network throughput is equivalent to maximizing the expected total available transmission time (ATT) of all MS's. The details of the homogeneous traffic load case is presented in the subsections IV-A and IV-B. The proposed framework is formally presented in the subsection IV-C. An example has also been presented to demonstrate the process of the proposed framework. The heterogeneous traffic load case is discussed in IV-D.

A. Create Base Time Interval

Our approach to solve the homogeneous traffic load case consists of two steps. In the first step, we introduce a method to divide the whole time period $q \cdot t$ into a set of non-overlapped time intervals such that the channel assignment in each time internal is independent. In the second step, an optimal algorithm is proposed to assign channels to each MS in each non-overlapped time interval.

To assist computation, we introduce a *time-channel availability model* which is derived from the activity profiles of the primary users and the trajectories of the MS's. The model is presented as a two dimensional coordinate. The x-axis is time. The MS's are placed on the y-axis. Each point in the first quadrant is corresponding to an instant at which a certain MS moves in or leaves at least one PU's interference range. Since the activities of the PUs will also affect the spectrum availability of the MS's, the whole scheduling period $q \cdot t$ is divided into a group of time slots each of which is equal to t seconds. An example of the time-channel availability model is shown in Fig. 1. In Fig. 1(a), MS0 is moving from the left side of the figure to the right, while MS1 is traversing from right to left. The MS's are moving into or leaving the interference range of the PUs. For example, MS0 enters PU1's interference range at time instant t_1 and leaves at t_4. The corresponding time-channel availability model is shown in Fig. 1(b).

On the time-channel availability model, we define a term **base time interval (BTI)** in which the probability of the BS or any MS being interfered by any PU does not change. For example, in the BTI $(0, t_1)$, the probability of each PU showing up will keep constant. By projecting the points and the time slots to the horizontal axis, the whole time period $(0, qt)$ is divided into a set of base time intervals $B = \{(0, t_1), (t_1, t_2), \cdots, (t_{(j-1)}, t_j), \cdots, (t_{(x-1)}, qt)\}$.

Since each BTI is independent with each other, the channel assignment in each BTI will not affect the assignment in other BTIs. Let ATT_k be the expected available transmission time in the BTI k. Now we are going to prove the following lemma.

Lemma 1: Assuming the time period $(0, qt)$ is divided into x BTIs, the available transmission time over the whole network in the time period $(0, qt)$ is maximized iff the available transmission time is maximized in each time base interval. $\max ATT_{all} = \sum_{k=1}^{x} \max ATT_k$.

Proof: Because each BTI is independent, $ATT_{all} = \sum_{k=1}^{x} ATT_k$. It is trivial to prove the "if" case that maximizing each ATT will maximize the summation of the ATTs. We prove the "only if" case by contradiction. Assume at least one of the $ATTs$, say ATT_i, is not maximized when the summation of the $ATTs$ is maximized. We can always increase that ATT_i to achieve a larger summation of the $ATTs$, which contradicts the assumption. Therefore, if $\sum_{k=1}^{x} ATT_k$ is maximized, each ATT_k is also maximized. So the Lemma is proved. ∎

B. Channel Assignment In Each BTI

Using the activity profile set P, the probability p_{ij}^k at which each MS i will be able to use each channel j in each BTI k
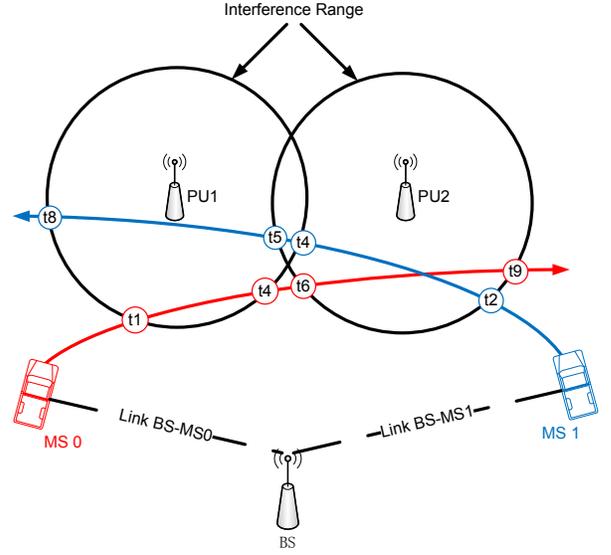
(a) MS trajectory. The letters in the small circles are the time the MS's arrive at that point
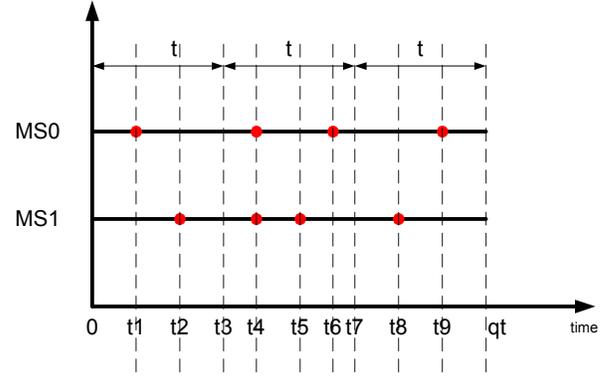
(b) Time-channel availability model

Fig. 1.   MS trajectory to Time-channel availability model.

can be pre-calculated. We say an MS can communicate with the BS if neither the BS nor the MS is affected by any PU. For example, suppose there are three PUs will be turned on in the channel j and interfere with the BS (or the MS i) with probability 0.5, 0.2 and 0.3, respectively. The probability of the MS i being able to communicate with the BS in channel j is $(1 - 0.5)(1 - 0.2)(1 - 0.3) = 0.28$. The probabilities in each BTI can be denoted as a matrix. Each row of the matrix is corresponding to a MS while each column is corresponding to a channel. Each number at the ith row jth column is corresponding to the probability p_{ij}^k. An example of 3 MS and 3 channels is shown in Table. I.

To achieve a maximum ATT in each BTI k, the MS's are not necessary to switch channels in the whole BTI. The proof is trivial. Let us first consider any given time instant. If this is an optimal assignment at the instant, the total probability should be the highest. According to the construction of the BTIs, the

TABLE I
MS vs. Channel in one BTI

	CH0	CH1	CH2	
MS0	0.5	0.9	1.0	
MS1	0.5	1.0	1.0	
MS2	0.5	0.9	1.0	

activity profile of the primary users do not change in each BTI. In other words, each instant is equivalent to each other in the BTI k. Therefore we can always use the same assignment in the whole BTI k to achieve a maximum ATT. Since there may not always be enough number of available channels, only one part of the MS's can be assigned a channel in each BTI. Moreover, co-channel interference is not allowed in the system. In other words, at any instant each two MS's can not be assigned the same channel. Thus the problem is equivalent to find a maximum weight matching between channels and MS's, where the weight of an assignment of MS i to channel j is the probability p_{ij}^k.

To solve the matching problem, we use the bipartite graph model. For each BTI k, a bipartite graph is created with two columns of vertices. Each vertex u on the left corresponds to a MS i. Each vertex v on the right corresponds to a channel j. Each vertex on the left is connected with each vertex on the right by an edge with weight p_{ij}^k. An example of the constructed bipartite graph is shown in Fig. 2. There are a number of algorithms which can be used to optimally solve the maximum weight matching problem in bipartite graphs in literature. The maximum weight matching problem can be solved by using a modified shortest path search in the augmenting path algorithm. In our simulation, the modified Bellman-Ford algorithm with running time $O((n + M)^3)$ is used [13].

C. Scheduling Framework

The proposed scheduling framework is formally presented as Algorithm 1.

Algorithm 1 Optimal Scheduling Framework

Step 1 Construct the time-channel availability model;
Step 2 Divided the whole time period qt to a set B of BTIs;
Step 3 **foreach** element BTI_k of B
    Calculate the probability p_{ij}^k of each channel j being available for each MS i;
    Construct the bipartite graph G_k;
    if G_k is not a complete bipartite graph;
      Make G_k a complete bipartite by inserting edges with weight 0;
    endif
    Compute a maximum weight matching MWM_k of G_k;
    Get the corresponding assignment ASS_k of MWM_k;
    endforeach
Step 4 **foreach** MS;
    Combine its corresponding assignment in each BTI and output;
    endforeach

In Step 1 and 2, this algorithm simply construct time-channel availability model for each MS and compute the BTIs. Assume the number of the joints of each MS $i's$ trajectory and the inference range boundaries of all PUs is a constant C_i. Let $C_{max} = max\{C_i | \forall i \in \{1, \cdots, n\}\}$. The Step 1 and 2 take $O(nM(q + nC_{max}))$. The maximum number of BTIs is $q + nC_{max}$. Step 3 is to construct a bipartite graph and compute maximum weight matching for each BTI. The maximum weight matching algorithm takes $O((n+M)^3)$ [13]. So Step 3 takes $O((n + M)^3(q + nC_{max}))$. In Step 4, each MS combines their assignment together to make a full channel assignment schedule. The running time of Step 4 is $O(n)$. The total running time of Alg. 1 is $O((n + M)^3(q + nC_{max}))$.

Next, we use an example to demonstrate how the proposed approach works. In this example, we consider 3 MS's, 2 PUs(PU) and 3 channels. The scheduling duration is 90 seconds. Assume the BS is not in any PUs interference range. PU0 uses channel 0 and PU1 operates in channel 1. Assume the activity profile of PU0 in the next 90 seconds is $P_0 = (0s, 30s, 0.4), (30s, 60s, 0.5), (60s, 90s, 0.7)$. The activity profile of PU1 is $P_1 = (0s, 30s, 0.6), (30s, 60s, 0.1), (60s, 90s, 0.8)$. MS0 is in PU0's interference range in the time periods $(0s, 15s)$ and $(45s, 75s)$ and in PU1's interference range in the time period $(30s, 60s)$. MS1 is in PU0's interference range in the time periods $(45s, 75s)$ and in PU1's interference range in the time periods $(30s, 45s)$ and $(75s, 90s)$. MS2 is in PU0's interference range in time periods $(15s, 60s)$ and in PU1's interference range in time period $(30s, 60s)$.

According to the MS's trajectories and the PUs' activity profiles, we can get the set of BTIs $B = \{(0s, 15s), (15s, 30s), (30s, 45s), (45s, 60s), (60s, 75s), (75s, 90s)\}$. We pick the BTI $(45s, 60s)$ as an example to compute a channel assignment schedule. The constructed bipartite graph is shown in Fig. 2. One of the maximum weight matching of this graph is consist of 3 edges (MS0, CH2), (MS1, CH1) and (MS2, CH0) with a total weight 2.5. Then in this BTI, channels 2, 1 and 0 should be assigned to MS's 0, 1 and 2, respectively, in order to get the maximum expected $ATT = 2.5 \times 15s = 37.5s$.
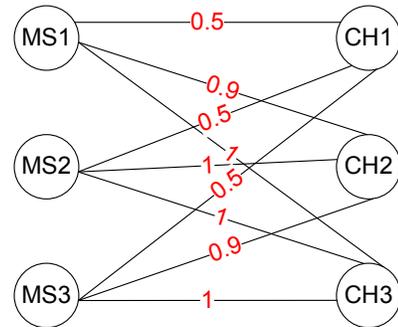

Fig. 2. A bipartite graph with 3 MS's and 3 Channels (CH). The numbers are the weight of the edges.

D. Heterogenous Traffic Load Case

In the heterogenous traffic load case, each MS i is assumed to generate traffic at a constant rate f_i over the scheduling during $q \cdot t$. Once a MS can not find any available channel to communicate with the BS, it has wait and stop generating traffic. Thus the heterogeneous traffic load case is very similar to the homogeneous traffic load case. The only difference is each MS has different traffic demand. Then based on the framework proposed in Section. IV-C, we use a modified version of the algorithm proposed in Section. IV-B to assign the channels to each MS.

First notice the scheduling duration $q \cdot t$ can also be divided into a set of BTIs by the same method introduced in Section. IV-A, because the assignment in each BTI will not affect the performance of the assignment in other BTIs. In each BTI k, the probability p_{ij}^k at which each MS i will be able to use each channel j is also calculated.

Then we construct the bipartite graphs and solve the maximum weight matching problem following the framework presented in subsection IV-C. The only difference is the weight assigned to each edge on the bipartite graphs is equal to the expected throughput on that link if a certain channel is assigned to the link. Assume the time duration of a BTI k is L_k, the expected throughput is $p_{ij}^k \times f_i \times L_k$. The final step is to combine each channel assignment in all BTIs for each MS to create its own channel assignment schedule. The running time of the algorithm is also $O((n+M)^3(q+nC_{max}))$.

V. NUMERICAL RESULTS

We evaluate the performance of the proposed algorithms and compare them with the theoretical expected value and a greedy algorithm. The greedy algorithm always tries to assign each MS the channel with the highest available probability in each BTI.

We used a real bus system UNITRANS as the simulation model. UNITRANS is a public bus service system opened in 1972 serving the city of Davis, California with 14 different routes. Each bus of the UNITRANS system is equipped with a GPS which is tracked by the terminal monitor [11]. The map of the UNITRANS system is shown in Fig. 3. The rectangle blocks with an arrowhead inside are the real-time locations of the buses. The BS is placed at the Silo Bus Terminal of latitude $38.539345°$, longitude $-121.753077°$. The PUs are randomly placed on a square region of $80km \times 80km$ centering at the Silo Bus Terminal. The MS's follow the real bus schedule.

The other important simulation settings are the transmission range $r = 17km$, the interference range $R = 34km$ [12]. The profiles of the PUs activity are built by setting $t = 30$. The schedule during $q \cdot t$ is set to 4500 seconds.

Intuitively, the following parameters play a key role in the system performance: the number of MS's n, the number of PUs N, the number of channels M and the traffic load. We conducted our performance evaluation by setting those parameters to different values in different scenarios. In the homogeneous traffic load case, since maximizing the expected network throughput is equivalent to maximizing the expected

Fig. 3.   UNITRANS Bus Routes

total available transmission time (ATT), the summation of the ATT of all MS's was used as a performance metric. In the heterogeneous traffic load case, each MS generates traffic with a random data rate between 1Mbps and 10Mbps. The network throughput is used as the evaluation metric in the heterogeneous traffic load case. In Fig. 4(a) and Fig. 5(a), $n = 30, M = 40$ and N was changed from 10 to 50 with a step size of 10. In Fig. 4(b) and Fig. 5(b), $N = 30, M = 40$ and n is increased from 10 to 50. In Fig. 4(c) and Fig. 5(c), $N = 30, n = 30$ and M was increased from 20 to 60. The corresponding results are presented in Fig. 4 and Fig. 5. Each point on the figures is the average value of 10 simulation runs.

We can make the following observations from these results:
1) In terms of the total available transmission time and the network throughput, the average difference between the proposed MTCS Framework and the numerical expectation are 2.7% and 3.6%, respectively. Since the results obtained from the MTCS framework is an average value of only 10 simulation runs, it is reasonable to have some shift from the theoretical value. On average, the proposed framework outperforms the greedy algorithm by 14.7% in the aspect of ATT and 21.6% in the aspect of network throughput.
2) From the Fig. 4(a) and Fig. 5(a), we can see that the total ATT and the network throughput decreases if the number of PUs increases. When additional PUs are introduced to the network, the BS and the secondary users are more likely to be affected and have less opportunity to get access to the licensed spectrum. Thus the throughput in the cognitive radio network is reduced.
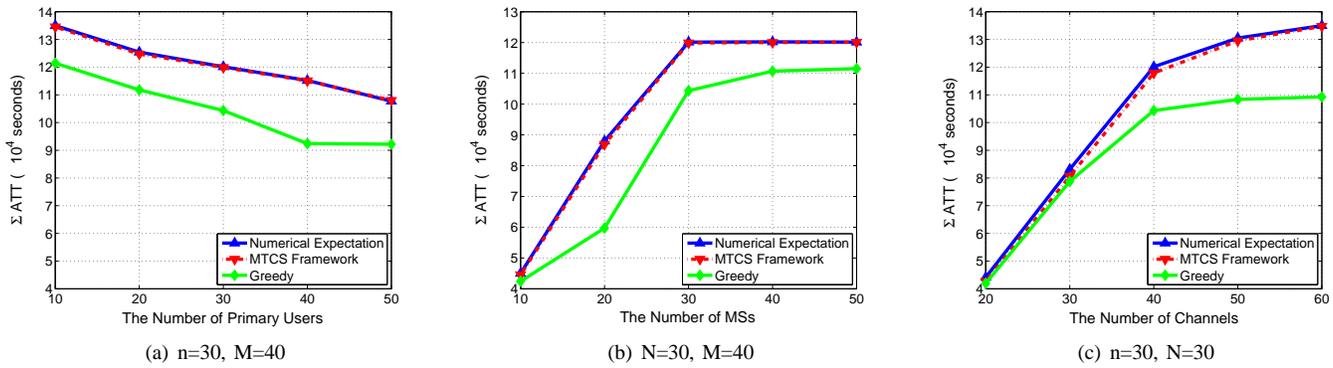
Fig. 4. Simulation and Theoretical Results: UNITRANS System, Homogeneous Traffic Load.
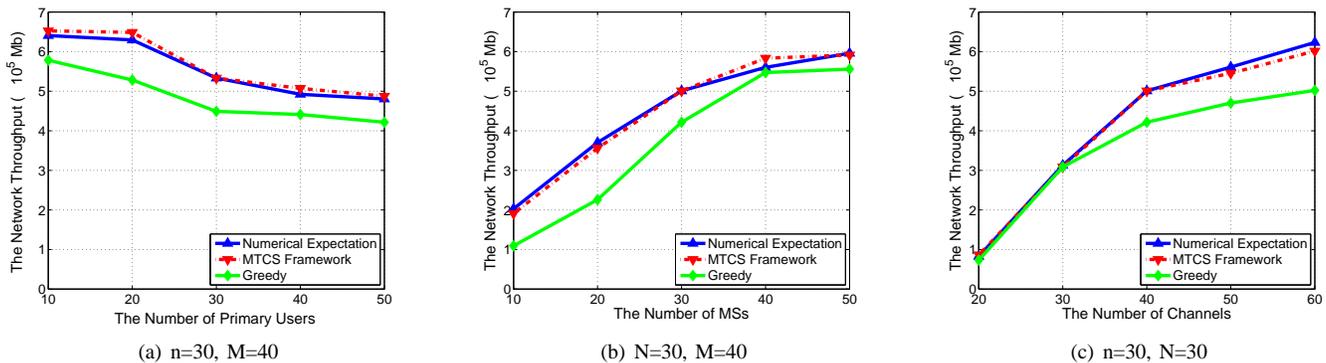

Fig. 5. Simulation and Theoretical Results: UNITRANS System, Heterogeneous Traffic Load.

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we formally define the Maximum Throughput Channel Scheduling problem (MTCS) and proposed a general scheduling framework to solve the MTCS. Based on the proposed framework, two optimal algorithms are developed to solve the MTCS problem in the homogeneous and the heterogeneous traffic load cases respectively. Simulation results show that the performance of the proposed algorithms is close to the optimal value. The aim of this paper is to maximize the network throughput. Actually there are multiple other important metrics to evaluate the network performance. In the future, we will study the fairness and the delay issues in the spectrum scheduling problem.

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