An Efficient Probing Mechanism for Next Generation Mobile Broadband Systems

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Abstract—Opportunistic scheduling exploits multiuser diversity for improving the performance of wireless systems. However, it requires instantaneous channel state information (CSI) to be available at the transmitter side. Since acquiring CSI is resource consuming, it always comes at a cost. We consider the problem of efficient channel state estimation in the context of 4G mobile broadband systems. Our proposed mechanism selects the subcarriers to be probed per user, by estimating the anticipated tentative rate with and without probing. For the latter an informed guess of the channel state is performed. The distinguishing characteristic of this work is that the channel state evolution is assumed Markovian, thus capturing the impact of mobility, contrary to the much simpler i.i.d. case hitherto considered. Based on this probing mechanism we derive a subcarrier allocation algorithm that aims at maximizing the sum rate of the system. Our simulations indicate that the proposed algorithm leads to significant performance benefits.

Index Terms—4G, LTE, probing, sum rate maximization

I. INTRODUCTION

Next generation mobile broadband systems, also known as 4G systems, are soon to become a reality. They are expected to deliver peak rates of 100 Mbit/s to highly mobile users, such as train passengers, and 1 Gbit/s to low mobility ones. In order to achieve these goals, orthogonal frequency division multiple access (OFDMA) schemes have been selected for the downlink, due to their ability to mitigate the effects of inter-symbol interference and to provide robustness to frequency selective fading.

The wideband spectrum is divided into orthogonal narrow-band subcarriers that can be independently allocated to the users, allowing thus the opportunistic scheduling to exploit the multiuser diversity. However, efficient subcarrier allocation requires the base station to be aware of the channel state information (CSI) of each user–subcarrier pair. Such information is usually acquired through a probing mechanism. First, the base station broadcasts a pilot sequence and each receiver estimates the channel quality based on the received signal and the known pilot symbol. Then, the receivers feed back their channel state information to the transmitter.

Clearly, this knowledge comes at a cost; certain resources are “wasted” for CSI acquisition instead of being used for actual communication. This cost may be expressed in energy, bandwidth or time units and increases, most often linearly, with the number of subcarriers probed. Especially in fast-fading scenarios where the channel coherence time is small, the channel state needs to be acquired more frequently. This phenomenon is exacerbated by the Doppler spread due to the movement of the receiver. Mobility, hence, creates a volatile environment and makes the efficient utilization of bandwidth resources a challenging task. Besides, the next generation mobile standards, such as 802.16m [1] and 3GPP LTE [2], allocate only limited bandwidth for CSI feedback that needs to be shared among all the participating users. All the above signify the importance of an efficient probing mechanism that acquires the channel state information in time and with minimum resource consumption.

In this work we focus on the LTE-Advanced scenario, as the typical example of OFDMA based 4G standard. To the best of our knowledge this is the first work that considers the problem of probing and subcarrier allocation in the context of 4G mobile broadband systems for the case of non–i.i.d. channel states for subsequent timeslots. This leads to a more accurate model of channel variation that introduces new challenges. In particular, we model the channel of each user as an uncontrolled Discrete Time Markov Chain (DTMC) of known transition probabilities that captures fading and especially the effect of user mobility. In this context we propose a dynamic probing mechanism that decides which subcarriers should be probed for each user by estimating the future evolution of the channel. Whenever the no-probing strategy is selected, an informed guess of the channel state is performed.

A. Related Work

The importance of the tradeoff between the resources expended for probing and the value of the acquired CSI has been investigated for the case of a single user selecting to transmit over a subchannel out of a set of available ones in [3], [4]. In the former, a 2-approximation algorithm is proposed, whereas in the latter, a two-step look ahead policy that examines only the best two channels is shown to be near-optimal. A generalization where the transmitter may use more than one channels for transmission is considered in [5], where an iterative algorithm that converges to the throughput optimal policy under a total power constraint is derived.

The problem of joint channel state probing and scheduling for the downlink has attracted significant research interest lately. In [6] the problem of scheduling in a single channel under partial state information is considered. The stability region under the assumption that only a limited number of
users can be probed is derived, as well as a throughput optimal scheme based on the MaxWeight scheduling rule. In a similar setting, the authors of [7] introduce the per user cost of probing into the problem description and they show that a generalized stopping problem arises.

However, the generalization of these algorithms to multiple channels is not straightforward. Actually, the proposed approaches would end up probing the same subset of users on each channel, and thus each user would report either the states of all the channels or none. This issue was identified in [8], where the number of subcarrier–user pairs that need to be probed for near-optimal throughput performance is derived. Besides, all these works are based on the simplifying assumption of temporal independence of the channel states, i.e. the channel state within a time frame is assumed to be independent of its state at other timeframes. In contrast, our DTMC model is more accurate and captures the impact of user mobility.

II. SYSTEM MODEL

We consider an OFDMA downlink scenario where the Base Station (BS) serves a set \( N \) of \( N \) users with a set \( C \) of \( C \) available subcarriers. We use the terms subcarrier and channel interchangeably, while by the term link we refer to a subcarrier–user pair. We denote \( L = N \times C \) the set of all the possible links.

Time is slotted, and the state of each link is assumed to be constant within a timeslot. Each link evolves from timeslot to timeslot according to a \( K \)-state stationary Markov chain, independently of the other links. Let \( S^{(\ell)}_t \) denote the state of link \( \ell \) at timeslot \( t \). Without loss of generality we use the same set of channel states \( S = \{1, \ldots, K \} \) for all the links. Thus, the total range of received signal to noise ratio (SNR) is mapped onto the \( K \) states, with each state corresponding to a different range of channel qualities. The states are indexed in order of increasing channel quality, with the \( j \)-th state corresponding to the SNR interval \( \left[ B_{j-1}, B_j \right] \).

For notational simplicity throughout this work we consider the special case of channels evolving as a birth death process, i.e. we constrain transitions to occur only between adjacent states. However, the generalization to the case of a Markov process of arbitrary transitions is straightforward. Let \( r : S \rightarrow \mathbb{R} \) be the function mapping a channel state to the corresponding achievable rate. Then, \( r(S^{(\ell)}_t) \) would be the achievable rate of link \( \ell \) at time \( t \). Next, we consider the parameters that need to be captured towards a realistic 4G system model.

Under the assumption of lognormal fading of mean \( \mu \) and standard deviation \( \sigma \), the steady-state probability of state \( j \) is given by [9]:

\[
\pi_j = Q \left[ \frac{1}{\sigma} \left( \frac{1}{2} \ln B_{j-1} - \mu \right) \right] - Q \left[ \frac{1}{\sigma} \left( \frac{1}{2} \ln B_j - \mu \right) \right]
\]  

(1)

The support of highly mobile users is one of the main characteristics of the next generation systems. Generally the mobility of a user affects significantly the probability of a channel state transition. That is, a fast moving user is more probable to experience a state transition compared to a slowly moving one. In order to capture this, we need to reside at second order statistics, such as the level crossing rate, i.e. the average rate that the received signal crosses a specified threshold level. In our case, and in compliance with [10], the crossing rate of level \( B_j \) downwards will be given by:

\[
N_{B_j} = \frac{f_m}{2B_j \sigma \sqrt{2\pi}} \exp \left( \frac{- \left( \ln B_j - \mu \right)^2 + 1}{2\sigma^2} + 2\mu \right),
\]

(2)

where \( f_m \) is the Doppler frequency due to user mobility. Since the transition probabilities depend on the user speed, we may replace Doppler frequency from its definition:

\[
f_m = \frac{c_0 \pm v}{c_0} f,
\]

(3)

where \( c_0 \) is the velocity of the waves in the medium, \( v \) the speed of the mobile receiver, being positive if the receiver is moving towards the transmitter, and \( f \) the channel frequency.

Thus, in order to incorporate into our model the impact of the aforementioned parameters on link state temporal evolution, we propose that the transition probabilities of link \( \ell \) are given for any intermediate state by:

\[
p_{ij}^{(\ell)} = \begin{cases} 
N_{B_{j-1}} / R_j & \text{if } j = i + 1, \\
N_{B_j} / R_j & \text{if } j = i - 1, \\
0 & \text{if } |i-j| > 1, \\
1 - \sum_{k \neq i} p_{ik}^{(\ell)} & \text{if } j = i,
\end{cases}
\]

(4)

where, for a given symbol rate \( R \), \( R_j = \pi_j R \) is the average number of symbols transmitted per second within the interval \( [B_{j-1}, B_j] \) and corresponding hence to state \( j \). Notice that for each of the states 1 and \( K \) only a single transition to adjacent state is valid. In particular, for state 1 the second case of equation 4 is not defined, while for state \( k \) the first case is not defined.

Based on the channel model derived earlier, the BS has to perform the subcarrier allocation towards maximizing the sum rate of the system. However, this decision making requires that the BS knows the state of each link at each timeslot. Such information can only be acquired through a probing mechanism at a certain cost. First, the base station broadcasts a pilot sequence to all the receivers. Then, each receiver estimates channel quality based on its received signal and the known pilot symbol. Next, the receivers forward their CSI back to the transmitter. Once this process is done we say that the scheduler has probed the channel and has acquired its channel state. We assume that it takes a fraction of a slot for the scheduler to probe and acquire the state of each link (channel-user pair).

In this work we assume that acquiring the channel state of a subset of the links \( P \subset L \) costs a proportion \( \alpha = f(P) \) of the timeslot. For example, in a typical scenario the probing cost is proportional to the number of probed links. Then, the actual rate of link \( \ell \) would be \( R_{\ell}^{(\ell)} = (1 - |P|/B) R(S^{(\ell)}_t) \), where \( B \) is the cost of probing a single link. Thus, in order to perform the subcarrier allocation, the BS has to decide the links to be
probed. In the next section we propose a joint probing and subcarrier allocation mechanism.

III. JOINT PROBING AND SUBCARRIER ALLOCATION MECHANISM

Our objective is to derive the probing and subcarrier allocation strategy that maximizes the effective sum rate of the system under the assumption of saturated queues. Since the links evolve independently from each other, we propose a per subcarrier probing mechanism that is executed in each timeslot. Then, based on this probing mechanism we perform a greedy subcarrier allocation.

A. To probe or not to probe? That’s the question

The proposed mechanism operates on a per timeslot and per link basis. Thus, we can focus on the decision making for an arbitrary timeslot $t$ and link $\ell$. In the sequel we discard the link superscript in order to simplify notation. The scheduler has to select one out of two options: probe the link to acquire its exact state $S_t$ or try to guess its state. The former, at a cost $\alpha$, will reveal the exact achievable rate $R_t = (1 - \alpha)R(\hat{S}_t)$, which is a random variable and its value is revealed once probing has been performed. Given that most recent probing of the link was $n$ timeslots earlier and it was found at state $i$, the BS can estimate the current rate for known transition probabilities as:

$$\hat{r}_\text{prob}^{(n)} = (1 - \alpha) \sum_{j \in S} p_{ij}^{(n)} r(j),$$

(5)

where $p_{ij}^{(n)} = P\{S_t = j|S_{t-n} = i\}$ is the $n$-step transition probabilities and $n$ the distance from the latest timeslot that this link was probed. We generally use to denote estimated values.

On the other hand, the “no probing” option requires the BS to guess the current state of the channel. Generally, the expected rate at which the transmitter can successfully transmit data by using link $\ell$, without knowing its current channel state, is less or equal to the expected rate of this specific link. Its exact value is determined by the coding and signaling schemes that are being used in the system under consideration.

We denote by $\hat{S}_t$ our guess about the current state of the link. If $n$ is the time elapsed from the latest timeslot that this link was probed and was found at state $i$, our guess strategy can be described by:

$$\hat{S}_t = \arg \max_{j \in S} p_{ij}^{(n)}$$

(6)

We assume that the achievable rate $\hat{r}$ at our guessed state is given by:

$$\hat{r}(\hat{S}_t) = \begin{cases} r(\hat{S}_t) & \text{if } S_t \geq \hat{S}_t, \\ r(\hat{S}_t) - \gamma & \text{otherwise} \end{cases}$$

(7)

In particular, we assume that whenever the actual state of the link is at the same or a better state than the guessed one the transmission is totally successful. Otherwise the achievable rate is equal to the actual rate reduced by $\gamma$. Based on the above, we may derive the estimated transmission rate of the no probing strategy as:

$$\hat{r}_\text{no-prob}^{(n)} = \sum_{j \in S} p_{ij}^{(n)} \hat{r}(\hat{S}_t)$$

(8)

By comparing the estimated transmission rates of the probing and no-probing policy, the BS may decide which policy is expected to provide the best transmission rate for each link.

B. Subcarrier allocation

Based on the estimated achievable rates with and without probing, we propose a subcarrier allocation mechanism that is executed in each timeslot and greedily schedules for transmission the link of maximum estimated rate. In particular, each subcarrier is assigned to the user for which that estimated rate is the highest among users. Whenever a link that needs to be probed is scheduled, a new round of estimation of the achievable rates is performed with updated information of the probing cost. The algorithm terminates once every subcarrier has been assigned to a user. The steps of the mechanism are described in Algorithm 1.

Algorithm 1 Greedy subcarrier allocation and probing scheme

Input: $p^\ell_j$ $\forall \ell \in S, j \in S$ // transition probabilities
$
\mathcal{T} \leftarrow \emptyset$

repeat

for all $\ell \in \mathcal{L}$ do // for each link (subcarrier–user pair)

// calculate estimated rate with and without probing

$\hat{r}_\text{prob}^{(\ell,n)} \leftarrow (1 - \alpha) \sum_{j \in S} p_{ij}^{(\ell,n)} r(j)$

$\hat{r}_\text{no-prob}^{(\ell,n)} \leftarrow \sum_{j \in S} p_{ij}^{(\ell,n)} \hat{r}(\hat{S}_t)$

rate($\ell$) $\leftarrow \max\{\hat{r}_\text{prob}^{(\ell,n)}, \hat{r}_\text{no-prob}^{(\ell,n)}\}$

end for

$\mathcal{T} \leftarrow \mathcal{T} \cup \{k : \arg \max_{(i,k) \in \mathcal{N}, k \in \mathcal{C}, \mathcal{T}} \text{rate}(i,k)\}$ // allocate subcarrier $k$ to user $i$, the one of maximum rate

if $k$ has to be probed then

update probing cost $\alpha$

end if

until $\mathcal{T} = \mathcal{C}$

IV. NUMERICAL RESULTS

In order to quantify the performance of the proposed schemes we performed MATLAB simulations using the following system parameters, unless otherwise stated. We assume a per user probing cost of $\alpha = 0.2$, and the evolution of each link is modeled by a birth death process consisting of 5 states with the achievable rate at state $i$ being equal to $r(i) = 20i$ Mbps. On the other hand, the cost of guessing is assumed to be equal to $\gamma = 2$ Mbps. The frequency band of 1.8 GHz is considered, in compliance with the 3GPP LTE-Advanced standard. We consider several scenarios with the speed of the users ranging from 5 km/h to 120km/h. Each depicted value is the average of thousands of simulation runs.

Initially, we consider a system of a single user in an attempt to quantify the performance of the probing mechanism. This
allows us to exclude any performance loss caused by the subcarrier allocation mechanism. In particular, we examine the impact of user mobility on the achievable transmission rate of a single user. For comparison purposes we consider also the ideal scenario of zero probing cost, for given transition probabilities the expected achievable rate of a link would be:

$$E[r(S_t)] = \sum_{j \in S} \pi_j r(j),$$  \hfill (9)

This is actually an upper bound of the achievable rate of each subcarrier and will serve as a benchmark, since it is not achievable. Besides, in each figure we depict the performance of two extreme strategies, the “full-probing” one where all the links are probed in each timeslot and the “no–probing” which never performs probing, but always transmits at the rate of the most probable state, as this is calculated by the steady state probabilities.

In Fig. 1 we depict the achievable transmission rate of each probing policy as a function of the user speed. We observe that our probing policy performs better than the full probing one up to the speed of 85 km/h. Beyond this value the ordering is reversed, since as the speed increases the probability of a successful guess diminishes. Besides, in this case our algorithm almost always probes the links due to the ever-changing channel state. The no–probing mechanism being a fixed policy cannot adapt to evolving channel states and thus performs significantly worse than the other two.

Next, in Fig. 2 we depict the user rate as a function of the per user probing cost $\alpha$ for a user moving with a speed of 40 km/h. Notice that the cost of probing of a user generally increases with the number of available subcarriers. We observe that as the probing cost increases, the transmission rate of our proposed probing policy slightly decreases initially but then stabilizes. This indicates the robustness of our approach to the cost of probing, since the guessing mechanism performs quite well for any value of the probing cost. On the other hand, the rate of the full probing policy as expected is declining significantly for increasing probing cost. Obviously the no–probing mechanism is not affected by the cost of probing.

Towards quantifying the probing behaviour of our mechanism we depict in Fig. 3 the probing frequency for increasing speed and for two different values of probing cost. For low cost of probing our approach prefers to carry out probing more frequently, since this causes insignificant loss. The opposite holds for the case of increased probing cost. From this figure one may also observe that our algorithm is highly adaptive to changes of the speed of the mobile. In particular, as the speed increases the probability of a channel state change increases and hence the BS faces an increased risk of guessing. To avoid this, it selects probing more frequently.

Next, we consider the generic scenario where the BS serves a number of users by using a set of available subcarriers. So as to be able to keep track of the results, we consider a toy system of three users and five subcarriers. In Fig. 4 we show the total system rate achieved by our joint probing and subcarrier allocation scheme for increasing speed. In this experiment all the users are characterized by the same speed. Since the probing cost is an increasing function of the number of links,
we notice that in this scenario the full probing mechanism exhibits the worst performance. This indicates that in a real life system, consisting of several subcarriers and users, full probing is not an option. On the other hand, our probing policy performs generally well, due to its ability to select which channels have to be probed.

Finally, we consider the impact of the number of subcarriers on the performance of the schemes under consideration. Additional channels increase the available bandwidth. In Fig. 5 we see that our algorithm follows the performance of the upper bound. The rate of the no probing strategy is also increasing, whereas the performance of the full probing one deteriorates.

V. CONCLUSION

This work is a first step towards understanding the impact of mobility on the problem of probing and subcarrier allocation. We focused on the LTE-Advanced scenario and we modeled the channel of each user as an uncontrolled Discrete Time Markov Chain of known transition probabilities, which capture the effect of fading and user mobility. The distinguishing characteristic of this work is that the channel state evolution is assumed to be Markovian, in contrast to the much simpler but less accurate i.i.d. case generally considered.

Our dynamic probing mechanism decides which subcarriers should be probed for each user by estimating the evolution of the channel. Whenever the no-probing strategy is selected, an informed guess of the channel state is performed. Based on this, we derive a subcarrier allocation algorithm that aims at maximizing the sum rate of the system. In our work we assumed that the transition probabilities are known at the BS. Although this may seem to limit the applicability of our scheme, several mechanisms for estimating the transition probabilities exist, such as the maximum likelihood approach (see [11]). Thus, our algorithms can be easily extended to capture scenarios that such information is not available a priori, but has to be estimated.

Alternatively, a low complexity reinforcement learning mechanism can be considered. For example Q-learning based on current estimates of the system parameters selects the action that maximizes the so-called Q function most of the time, but also random ones from time to time for exploration purposes. These directions will be considered in some future work.

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REFERENCES