Extracting Multi-User Diversity in the Cellular Uplink, where Transmission Grants Influence CSI Quality

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Abstract—Modern cellular communication systems facilitate fine-grained resource allocation that can opportunistically exploit the time variations and frequency selectivity of mobile channels by exploiting multi-user diversity. However, extracting such benefits requires the scheduler to have accurate channel state information (CSI). Channel estimation in the uplink direction requires all users to send their own reference signals. For resource allocation purposes, current standards have thus included sounding reference symbols (SRS), which allow simultaneous estimation, but are very sensitive to frequency selectivity and the number of users. Also demodulation reference symbols (DMRS) are used which are always multiplexed with the data during transmission and yield more accurate CSI. However, the information that can be obtained in this way directly depends on the scheduling decisions. In this paper, we propose two new scheduling algorithms that are aware of the channel estimation quality and are thus able to make best use of the available estimation types. Furthermore, through their decisions, the algorithms inherently ensure the right CSI amount to achieve high spectral efficiency. We compare our approaches to conventional scheduling algorithms that rely on estimates from channel sounding based on SRS.

Index Terms—Resource Allocation, Scheduling, Channel Estimation, Channel Sounding

I. INTRODUCTION

The ever increasing demand for high data rate wireless services has led to a paradigm shift in recent generations of wireless systems, in which the fluctuation of channel quality is no longer seen as a threat, but is instead exploited for gains in spectral efficiency.

In cellular wireless communication systems, the medium access within each cell is organized by the base station’s scheduler that assigns transmission resources (e.g., time-slots and/or frequencies) to users that demand access. The use of orthogonal frequency-division multiple access (OFDMA) and single-carrier frequency-division multiple access (SC-FDMA) as medium access schemes in many recent and upcoming standards has not only introduced simple frequency domain equalization, but also enables scheduling algorithms to exploit favorable local channel conditions. For example, facing frequency selective channels, only subcarriers supporting good conditions may be allocated to a user, leaving the remaining worse subcarriers for other users. As the users’ channels fade independently, the residual subcarriers may offer favorable conditions to other users. This is referred to as multi-user diversity, which can be exploited by the scheduler to greatly enhance the overall spectral efficiency [1].

In order to exploit multi-user diversity, scheduling algorithms have to be channel aware and thus require accurate channel state information (CSI) from all users. In the downlink direction, reference symbols are typically inserted into the OFDMA transmission grid to facilitate channel equalization at the users and to allow all users to determine their own channel conditions. Optimal scheduling approaches for downlink transmission were introduced for example in [2]–[4]. The obtained CSI can then be fed back to the base station using the uplink direction. While the feedback load can be high in systems with many users, it has been shown in [5] that not all users’ feedback is required to extract multi-user diversity gains.

Obtaining accurate channel estimates of all users in the uplink direction is more difficult (in FDD systems): each user has to transmit reference symbols occupying the whole bandwidth. In order to reduce interference between reference symbols transmitted from different users, the reference symbols need to be mutually orthogonal. For this purpose the LTE standard has specified so-called sounding reference symbols (SRS) [6], [7], which are transmitted by all users in regular time intervals. Shifted Frank-Zadoff-Chu sequences [8] that extend over multiple subcarriers are used that can be separated at the receiving base station. While all users transmit their SRS at the same time, the obtained CSI quality degrades with the number of users and the frequency selectivity of the channels. This imprecise CSI leads to a low spectral efficiency, like we will describe later. Furthermore, SRS transmission degrades spectral efficiency as it occupies transmission resources.

Another method is to use orthogonal reference symbols (pilot tones) in time and frequency domain for each user. Once a user has been scheduled for transmission, it exclusively occupies the allocated resources. During transmission, data and reference symbols are multiplexed to facilitate channel equalization at the base station. These reference symbols are referred to as demodulation reference symbols (DMRS) in LTE [6], [7] and naturally yield more precise CSI as the SRS-based method.

In this paper, we propose a new uplink scheduling algorithm that solely relies on DMRS-based CSI and thus does not require periodic SRS. By only using DMRS, the scheduler...
decisions directly impact the CSI of each user, which poses an interesting design challenge. Even though the DMRS-based CSI quality is higher, the CSI is naturally more scattered in time and frequency because of the orthogonality requirement of the user transmissions. We are interested to see how well we can exploit multi-user diversity under these conditions and compare it to SRS-based approaches. As we focus on multi-user diversity, our key performance indicator is the systems overall spectral efficiency. Finally, we propose and evaluate an algorithm that is a combination of the two schemes, as it utilizes both, DMRS- and SRS-based CSI.

In Section II we detail our system model, before we describe the new scheduling algorithm in Section III. Finally, numerical evaluation results are presented in Section IV, before the paper is concluded in Section V.

In the following, we use bold face lower case letters to denote vectors and bold face upper case letters to denote matrices. $x[n]$ selects the $n$-th element of vector $x$. With $X^H$ we denote the hermitian of matrix $X$ and with $x^*$ the conjugate value of $x$. A diagonal matrix $X$ with entries $x$ is denoted as $X = \text{diag}(x)$ and vice versa, i.e., $x = \text{diag}^{-1}(X)$. Furthermore, we use $\mathbb{E}\{\cdot\}$ to denote the expected value, $\text{Cov}\{\cdot\}$ to denote the covariance and $I$ for the identity matrix.

II. SYSTEM MODEL

We consider a single-cell uplink scenario, in which $N_u$ users want to transmit to a single base station. All communication entities, base station and users, are equipped with a single antenna each.

For the transmission, a time-frequency orthogonal medium access scheme like OFDMA is considered, as for example used in LTE. In a multi-carrier system, the spectral efficiency is maximized w.r.t constant transmit power if it is maximized at each subcarrier. Thus, scheduling can be done in parallel for all subcarriers. Even though channel estimation and hence the system performance benefits from coherent subcarriers, we for now want to consider one flat channel (one subcarrier) for resource allocation. This consideration is only done for the resource allocation, not for the channel estimation. During each transmit time interval (TTI), the subcarrier may be occupied by only one user transmission. It is the task of the scheduler to grant medium access to the users. If user $i$ has been selected, the received signal at the base station can be expressed as

$$y = h_i x_i + n,$$

where $h_i$ denotes the channel coefficient with variance $\sigma_{h_i}^2$, $x_i$ denotes the transmit symbol drawn from a Gaussian distribution with unit variance, and $n \sim \mathcal{N}(0, \sigma_n^2)$ denotes the noise. Given this transmission, the maximum achievable rate of user $i$ is its Shannon Capacity

$$R_i = \log_2 \left(1 + \frac{|h_i|^2}{\sigma_n^2}\right) \text{[bits]}.$$  \hspace{1cm} (1)

A. Channel Model

For the single subcarrier considered, we assume correlated Rayleigh fading using the well-known Jakes model. To compare our results with SRS-based scheduling, we also need to consider the neighboring subcarriers that will impact the quality of the channel estimates. Thus, we model a time-varying and frequency-selective channel grid. To characterize the channel’s variability in time and frequency, we define the coherence time $T_c$ and coherence bandwidth $B_c$ as the time range and frequency range, respectively, at which the correlation function drops below 0.5 [9]. Finally, because we want to analyze the multi-user diversity gain, we assume a transmit power control mechanism to compensate the pathloss differences of the users like in [10]. In effect, the channels of different users are i.i.d. .

B. Channel Estimation

As described before, we consider SRS- and DMRS-based channel estimation that yield different CSI qualities. We focus on the effect of mutual interference between the users during channel estimation and therefore neglect thermal noise and other effects that would impact both estimation types.

1) DMRS: DMRs are multiplexed with the data. For simplicity, we assume that we can perfectly estimate the user channels using DMRS. Hence, whenever a user is selected for scheduling, it transmits DMRS at the allocated subcarrier during one TTI and the scheduler obtains perfect CSI. Overall per subcarrier and TTI only one reference signal is transmitted.

2) SRS: SRS are code orthogonal reference signals spread over multiple subcarriers (frequency domain) and used to estimate CSI of all users simultaneously. To enable separation at the receiver, each SRS is a copy of the same constant amplitude zero autocorrelation (CAZAC) Frank-Zadoff-Chu root sequence [8] with a unique cyclic shift for each user. All users transmit their SRS simultaneously using the same $N_s$ subcarriers. Hence, in total $N_x \times N_y$ up-link channel coefficients are estimated based on $N_s$ received symbols. The estimation accuracy clearly depends on $B_c$.

The SRS are transmitted during one TTI. With $x_i \in \mathbb{C}^{N_s}$ containing the Frank-Zadoff-Chu sequence of user $i$, we can denote the received sequence $y \in \mathbb{C}^{N_x}$ at the base station as

$$y = \sum_{i=1}^{N_s} X_i h_i,$$ \hspace{1cm} (2)

where $X_i = \text{diag}(x_i) \in \mathbb{C}^{N_x \times N_s}$ and $h_i \in \mathbb{C}^{N_s}$ holds all subcarrier channel coefficients of user $i$. Given this received signal and assuming a vector LMMSE estimator [11] (neglecting thermal noise), we estimate the subcarrier channel coefficients as

$$\hat{h}_i = C_{hh,i} X_i^H C_{yy}^{-1} y$$

with error covariance matrix

$$C_{ee,i} = C_{hh,i} - C_{hh,i} X_i^H C_{yy}^{-1} X_i C_{hh,i}.$$
where
\[ C_{yy} = \sum_{i=1}^{N_c} X_i C_{hh,i} X_i^H. \]

\( C_{hh,i} = \mathbb{E}\{h_i h_i^H\} \) is the channel’s covariance matrix and \( C_{yy} = \mathbb{E}\{yy^H\} \) the received symbols’ covariance matrix. Finally, we obtain the vector with the estimation error variances for all subcarriers by
\[ \sigma_{e,i}^2 = \text{diag}^{-1}(C_{ee,i}) \in \mathbb{R}^{N_c}. \]

As we can see from the equations above, the estimation error variance using SRS depends on the combination of \( N_u \), \( N_s \), \( B_c \), and the location of the subcarrier of interest within the sounding bandwidth.

![Figure 1: Normalized SRS-based channel estimation error variance depending on the subcarrier location. \( N_u = N_s = 24 \) and \( B_c = 10 \) subcarriers.](image)

![Figure 2: Normalized SRS-based channel estimation error variance depending on the coherence bandwidth \( B_c \). \( N_u = N_s = 24 \), at \( B_c = 10 \) subcarriers.](image)

We illustrate two main trends in Fig. 1 and Fig. 2. The minimum estimation error, denoted by \( \sigma_{e,\text{min}}^2 = \min\{\sigma_{e,i}^2\} \), is achieved at the middle subcarrier and the maximal estimation error \( \sigma_{e,\text{max}}^2 = \max\{\sigma_{e,i}^2\} \) at the edges. Note that these estimation error values are equal for all users for a given frequency selective channel. As expected, the estimation error increases as the coherence bandwidth \( B_c \) decreases. In the remainder of this paper we concentrate on the best and worst estimation performance, \( \sigma_{e,\text{max}}^2 \) and \( \sigma_{e,\text{min}}^2 \), achieved by the SRS-based estimation, according to the middle and edge subcarrier locations.

III. SCHEDULING

Optimal scheduling with respect to spectral efficiency implies that the scheduler fully exploits multi-user diversity. In order to do so, the algorithm has to be aware of all CSI. Scheduling algorithms often try to maximize an objective function and can thus be denoted as
\[ t = \arg \max_{i \in \{1, \ldots, N_u\}} \Omega(i), \]
where \( t \) denotes the scheduled user and \( \Omega(\cdot) \) the objective function. As we are interested in maximizing the spectral efficiency, the objective function has to depend on the available CSI.

In the following, we will describe four different scheduling algorithms that all try to maximize spectral efficiency assuming different degrees of channel knowledge. While the first two algorithms are common approaches, we propose the last two algorithms to better cope with the specific CSI availability.

A. Max-Rate Scheduler with perfect CSI (upper bound)

The highest spectral efficiency can be achieved under the assumption of perfect CSI at the scheduler. In this case the user with the highest instantaneous rate is always selected for transmission. Hence,
\[ \Omega(i) = R_i, \]
with \( R_i \) defined in (1). Thus, for each TTI the scheduler selects the user
\[ t = \arg \max_{i \in \{1, \ldots, N_u\}} R_i \]
for transmission. This will serve us as the upper bound throughout our analysis.

B. Max-Rate Scheduler with imperfect CSI (MR-SRS)

As discussed before, perfect CSI is not available in our system. For comparison, we will analyze the performance of the max-rate scheduler with imperfect CSI, solely based on SRS. As CSI accuracy is not accounted for by the max-rate algorithm, it is to be expected that this approach will not maximize spectral efficiency. Here we neglect DMRS-based CSI because the algorithm performance does not converge and strongly depends on the initial conditions.

C. Max-Probability with DMRS-based CSI (MP-DMRS)

To make use of the high quality DMRS-based CSI, we introduce a new scheduling algorithm which is an evolution of the max-rate scheduler. As mentioned earlier, CSI achieved by DMRS-based channel estimation is obtained during the transmission of individual users and thus directly depends on the scheduling decision. Therefore, a scheduling algorithm based purely on DMRS also has to consider its effect on (future) CSI. In fact, it needs to find the right balance between the contradicting goals of CSI completeness and spectral efficiency. In other words, the scheduler has to generate just enough CSI to schedule the UEs as spectral efficient as possible.
To cope with these two tasks, we base the scheduling decision on expected transmission rates rather than on actual ones. In this way, the CSI accuracy can directly be taken into account in the scheduling decision. Based on the observations of the user channels in the past and the knowledge of the general channel statistics, we derive an expectation for the performance of each user. As we consider a single flat channel (for the reasons given above), we leave the exploitation of frequency correlation to future work. Without loss of generality, we use the analogy of transmission rate and received power in (1) to denote our new statistics, we derive an expectation for the performance of each user, and prediction error variance according to (8) which is represented by the error covariance matrix

\[
C_{nn} = \text{diag}(\sigma_n^2), \quad \text{with} \quad \sigma_n^2 = \left[ 0 \right] \quad \in \mathbb{C}^{L_i + M_i},
\]

where \(\sigma_n^2[n_s]\) is the estimation error variance given in (3) according to subcarrier location \(n_s\). The expected users’ channel coefficients are again of Gaussian nature with

\[
\hat{h}_i = c_{h,\kappa_i} \left( C_{h,\kappa_i} + C_{nn} \right)^{-1} \kappa_i \quad \text{and the prediction error variance}
\]

\[
\sigma_i^2 = 1 - c_{h,\kappa_i} C_{h,\kappa_i}^{-1},
\]

where \(c_{h,\kappa_i} = E\{h_i \cdot \kappa_i\} \in \mathbb{C}^{L_i}\), and \(C_{h,\kappa_i} = E\{\kappa_i \kappa_i^H\} \in \mathbb{C}^{L_i \times L_i}\) for a scalar LMMSE estimator [11]. With (5) and (6) we rewrite (4) to

\[
\Omega(i) = E \left\{ |h_i|^2 \mid \kappa_i \right\} = E \left\{ h_i \hat{h}_i \mid \kappa_i \right\} = E \left\{ h_i \mid \kappa_i \right\} E \left\{ h_i \hat{h}_i \mid \kappa_i \right\} - \text{Cov} \left\{ h_i, h_i \hat{h}_i \mid \kappa_i \right\}
\]

\[
= |\hat{h}_i|^2 + \sigma_i^2.
\]

Considering (7), the scheduling decision does not only depend on the channel prediction value \(\hat{h}_i\), but also on the prediction error variance \(\sigma_i^2\) which is directly related to the CSI accuracy. If the CSI accuracy is high \((\sigma_i^2 \approx 0)\) the objective function solely depends on the predicted channel value. But with previous CSI becoming out-dated, \(||c_{h,\kappa_i}|| \rightarrow 0\), the prediction error monotonically increases towards one while the predicted channel value converges to zero, \(\sigma_i^2 \rightarrow 1\) and \(h_i \rightarrow 0\). Consequently, users are either selected by the scheduling algorithm if their predicted channel is very high (to increase spectral efficiency), or if their CSI accuracy is very low (to counteract that, which is guaranteed by an increasing \(\sigma_i^2\)). This mechanism dynamically regulates the amount of CSI available for every UE. Due to its design, our proposed algorithm should perform well for a low number of users \(N_u\) and high coherence time \(T_c\), as it could easily keep track of the channel states of all users.

**D. Max-Probability with DMRS- and SRS-based CSI (MP-DMRS+SRS)**

To combine the best of both worlds, we simply extend the previously introduced max-probability scheduler to take advantage of SRS- and DMRS-based channel estimations. Since we are still dealing with CSI uncertainty, we do not need to modify the objective function, but need to incorporate the “noisy” SRS-based CSI in the prediction. First we redefine the vector of CSI history to be

\[
\kappa_i = \begin{bmatrix} \kappa_i,\text{DMRS} \\ \kappa_i,\text{SRS} \end{bmatrix} \in \mathbb{C}^{L_i + M_i},
\]

We then adjust the prediction in (5) and (6) to take SRS-based CSI into account. Therefore, we incorporate the channel estimation error variance according to (8) which is represented by the error covariance matrix

\[
C_{nn} = \text{diag}(\sigma_n^2), \quad \text{with} \quad \sigma_n^2 = \left[ 0 \right] \quad \in \mathbb{C}^{L_i + M_i},
\]

where \(\sigma_n^2[n_s]\) is the estimation error variance given in (3) according to subcarrier location \(n_s\). The expected users’ channel coefficients are again of Gaussian nature with

\[
\hat{h}_i = c_{h,\kappa_i} \left( C_{h,\kappa_i} + C_{nn} \right)^{-1} \kappa_i
\]

and the prediction error variance

\[
\sigma_i^2 = 1 - c_{h,\kappa_i} C_{h,\kappa_i}^{-1},
\]

At the expense of a higher computational effort, this scheduling algorithm can easily accumulate and exploit all available CSI.

**IV. SIMULATION RESULTS**

In this section we present numerical evaluation results of all four scheduling algorithms introduced in Section III. We compare how well the algorithms can exploit multi-user diversity under varying conditions like user velocity, coherence bandwidth, number of users and subcarriers.

Additionally to the “one subcarrier assumption” we make a few assumptions and simplifications to ease the complexity and reduce computational effort.

We consider two mobility scenarios: pedestrian and vehicular, where all users move at 3 km/h and 30 km/h, respectively. The user channels are assumed to be block static within one TTI of length 1 ms and frequency-flat on each subcarrier. Furthermore, we assume Rayleigh fading channels and compute the time/frequency channel grid for each user with the well-known Jake’s Doppler power spectrum and an exponential power delay profile according to the considered coherence bandwidths \(B_c\). Among different users, the channel coefficients are assumed to be i.i.d. All numerical results originate from Monte-Carlo simulations, where we average 100 runs each with 1000 channel realizations. The simulation parameters are summarized in Table I.

We model our SRS-based CSI estimates, which we have described in Section II-B, by adding Gaussian noise with the variance according to (3) to the perfect channel coefficients \(\hat{h}_i\). The estimate for all subcarriers is modeled as

\[
\hat{h}_i = \text{diag}(\alpha) (h_i + n_{e,i}) \in \mathbb{C}^{N_c},
\]

where \(h_i\) is the actual user channel coefficient vector for all subcarriers, \(n_{e,i} \sim \mathcal{CN}(0, \text{diag}(\sigma_{e,i}^2))\) is the estimation error and \(\alpha[n_s] = 1/(1 + \sigma_{e,i}^2[n_s]/\sigma_n^2)\) ensures at each subcarrier \(n_s\) that the variance of the estimate is equal to that of the
channel coefficient. $\sigma^2_{e,i}$ is computed under the assumption of a sounded bandwidth of $N_s := N_u$ subcarriers. This framework allows us to simulate the whole frequency selective fading channel with little computational effort. As discussed above, we pick only two subcarriers to analyze the impacts of the position of the subcarrier. We consider the following two cases with the estimation errors $\sigma^2_{\text{min}} = \min(\sigma^2_{e,i})$ and $\sigma^2_{\text{max}} = \max(\sigma^2_{e,i})$ and compare the scheduling algorithms separately for each of them. The chosen subcarrier is denoted by $n_s$.

The net-transmission rate reduction due to the transmission of reference symbols instead of data is considered in our simulation. We assume the frame structure of LTE, which we illustrate for one subcarrier in Fig. 5. Because DMRS are needed for demodulation anyway, they have to be transmitted with all algorithms and we do not take into account their resulting loss in spectral efficiency. However, SRS are only required for some of the considered algorithms. Depending on the user speed, the SRS frequency is adjusted. For the pedestrian and vehicular case, we assume a SRS transmission repeat frequency of 1/10ms and 1/2ms, respectively. The net-transmission rate reduction is calculated accordingly.

We start to evaluate the results for pedestrian UEs in Fig. 3. The plots depict the spectral efficiency over the number of UEs of all four scheduling algorithms, considering minimum SRS estimation error in Fig. 3a and maximum SRS estimation error in Fig. 3b. The performance results are depicted for different coherence bandwidths. As DMRS-based scheduling is not influenced by the coherence bandwidth, only one curve is provided.

As expected, we can observe in both plots, that the solely SRS-based algorithm degrades with decreasing coherence bandwidth. While it is able to extract a certain degree of multi-user diversity, the gains degrade for large numbers of users, as the estimation errors increase. The proposed DMRS-based algorithm only outperforms SRS-based scheduling, if the SRS estimation error is high due to low coherence bandwidth and/or high user numbers and/or unfavorable subcarrier location. Different from SRS-based scheduling, it is however able to maintain multi-user diversity to a certain degree (non-degrading performance). The performance curves saturate above a certain
number of users, as the limited coherence time bounds the amount of up-to-date CSI that can be obtained. Even though the DMRS-based algorithm cannot outperform the SRS-based one, we can see clearly that it is worth to consider DMRS as a source for CSI.

The proposed combination of both algorithms, DMRS+SRS-based scheduling, shows superior performance for all considered cases. Making use of the information obtained through DMRS, it is able to significantly reduce the degrading influence of small coherence bandwidths. Likewise, the sensitivity towards the subcarrier location is almost eliminated. Furthermore, DMRS+SRS-based scheduling continues to benefit from additional users, even for high amounts.

Observing the results in Fig. 4 for vehicular UEs, we can observe, that especially all algorithms using DMRS show lower performance, when compared to the pedestrian case. Due to the smaller coherence time in this scenario, outdated channel information becomes less valuable for the DMRS-based approaches, since the channel prediction horizon has decreased significantly. However, also the SRS-based algorithms show slight degradation when compared to the pedestrian case, as the sounding transmission repeat frequency is 5 times higher leading to reduced net-rates.

Figure 5: Simplified reference signal framework of LTE. Data and DMRS symbols are transmitted by the scheduled UE only over the allocated subcarriers no.1 and $N_S/2$. SRS symbols are transmitted by all UEs over all subcarriers.

<table>
<thead>
<tr>
<th>Subcarriers</th>
<th>Transmission symbols</th>
</tr>
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<tbody>
<tr>
<td>1</td>
<td>RE DATA DMRS SRS</td>
</tr>
<tr>
<td>2</td>
<td></td>
</tr>
<tr>
<td>...</td>
<td></td>
</tr>
<tr>
<td>$N_S/2$</td>
<td></td>
</tr>
<tr>
<td>$N_S$</td>
<td></td>
</tr>
<tr>
<td>TTI</td>
<td></td>
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Table I: Simulation parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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<tr>
<td>channel realizations per run</td>
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<td>carrier frequency</td>
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<tr>
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<td>-174 dBm</td>
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<tr>
<td>subcarrier bandwidth</td>
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<tr>
<td>TTI duration</td>
<td>1 ms</td>
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<tr>
<td>average receive SNR at BS</td>
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<tr>
<td>number of users $N_u$</td>
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<tr>
<td>user velocity</td>
<td>3 km/h, 30 km/h</td>
</tr>
<tr>
<td>SRS interval</td>
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</tr>
</tbody>
</table>

V. Conclusions

In this contribution, we have proposed two new algorithms for spectral efficient scheduling in the cellular uplink that account for channel information quality. Two types of channel estimation techniques are taken into account. Demodulation reference symbols are multiplexed with data transmission and yield high quality estimates. Sounding reference symbols are transmitted simultaneously by all users and hence yield low quality channel estimates, especially for small coherence bandwidths and/or high user numbers. We have introduced a scheduling algorithm relying solely on demodulation reference symbol based channel knowledge, that is able to exploit multi-user diversity by finding the right balance between the contradicting goals of channel knowledge completeness and spectral efficiency. Our evaluation has shown that combining channel information from demodulation reference symbols and channel sounding yields the highest performance and adds robustness against frequency selectivity to the system. Quality-awareness of the different estimation types is key in this approach. With numerical evaluation, we have shown that the proposed algorithms continuously benefit from additional users as they extract multi-user diversity gains. This is not true for algorithms that solely rely on channel sounding information.

In this study, we have focused on a single subcarrier of a multi-carrier system. In the future, our algorithms could be extended to multiple carriers and could then potentially also benefit from frequency correlation.

References