System-level Modeling and Evaluation of Interference Suppression Receivers in LTE System

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***Abstract*—In this paper we study the performance of linear interference suppression receivers which estimate the interference covariance either from the data symbols or from the reference symbols. For numerical radio system-level simulation purposes, receiver algorithm models are proposed which take into account practical estimation losses caused by the channel and interference covariance estimation. These models are verified using a multi-link simulator, and finally the performance of the receivers is studied using radio system simulations. The results indicate that the algorithm based on the reference symbols can constantly outperform a receiver that assumes white inter-cell interference. Furthermore the modeling proposed in the paper can be utilized in assessing radio system performance when receivers are equipped with interference suppression receivers.**

I. Introduction

Due to heavily increasing data traffic volumes, wireless networks of today are becoming more and more characterized by smaller cell sizes and dense network deployments. In such deployments, the spectral efficiency becomes increasingly limited by inter-cell interference. To alleviate this issue, recently a lot of research effort has been put into inter-cell coordination techniques in which the transmissions from multiple cells are done jointly in a coordinated manner in order to mitigate the impacts of inter-cell interference [1]. These techniques are also being specified for LTE-Advanced in an ongoing 3GPP Work Item on coordinated multi-point transmission (CoMP) [2]. On the other hand, the inter-cell interference can also be mitigated in the receiver side. Therefore, interference suppression receivers are currently studied in the new 3GPP Study Item [3].

Interference suppression techniques can be based on the linear minimum mean square error (LMMSE) estimators [4] or signal-to-interference-and-noise ratio (SINR) maximization [5] and these algorithms are commonly referred to as interference rejection combining (IRC) algorithms. Typically, all these algorithms require information on the interference covariance. Although ideal IRC receivers are efficient, the performance of practical IRC is dependent on the quality of channel and interference covariance estimates. Acquiring the interference covariance information is not straightforward and several different algorithms can be envisioned. For example, one could use the data symbols to calculate a sample mean or one could use the reference signal symbols.

From a single radio link point of view, IRC receivers improve the signal-to-interference-and-noise ratio (SINR) and hence the throughput. However, from the full radio system point of view, aspects such as user scheduling and precoding affect the structure of the interference, and from that perspective it would be beneficial to evaluate IRC receiver performance gain also in system level. Radio system level simulations are typically highly calculation-intensive, thus simplifications on the single radio link modeling are typically made. One conventional method is to generate only the fast fading coefficients and use those to calculate the link SINR which is then mapped to the packet error rates and finally throughput. The lack of baseband samples means that it is difficult to model accurately the estimation losses in the IRC receiver at system level.

In this paper, we study modeling of practical IRC algorithms in system level, and evaluate the performance of two practical IRC algorithms in a macro cellular system. Our contributions can be listed as follows:

- We provide a system-level model for channel and interference covariance estimation errors. We verify the accuracy of the model via simulations.
- We provide a performance comparison of two practical IRC receivers in a macro cellular system based on exact modeling of the receivers in a multi-link simulator.
- Using the proposed error models, we provide system-level evaluation of the benefits of practical IRC algorithms.

The paper is organized as follows. The system model is defined in section II, and the proposed error models are presented in section III. Our simulation results are presented in section IV including the radio system model verification. Finally, our conclusions are drawn in section V.

II. System model

The LTE downlink is based on the OFDM technique where data and reference signal symbols are time and frequency multiplexed on different OFDM symbols and subcarriers. The reference signals are used to obtain the channel state information both for demodulation and link adaptation purposes [6] [7]. Signals on different subcarriers can be assumed

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orthogonal among each other. Furthermore, the cyclic prefix removes the time-domain inter-symbol interference. Hence, it is sufficient to consider the received signal after the FFT transformation. In other words, received signal at subcarrier k in OFDM symbol j equals

$$\bar{\boldsymbol{r}}_{k,j} = \boldsymbol{H}_{k,j}\bar{\boldsymbol{s}}_{k,j} + \bar{\boldsymbol{n}}_{k,j} \tag{1}$$

where the length of vector $\bar{\boldsymbol{r}}_{k,j}$ equals the number of receive antennas, N_r, and the length of vector $\bar{\boldsymbol{s}}_{k,j}$ equals the number of transmitted symbol streams, N_s. Vector $\bar{\boldsymbol{n}}_{k,j}$ consists of inter-cell interference and thermal noise. Thus, assuming i.i.d. transmitted symbols from interfering cells, the spatial interference covariance $\boldsymbol{C}_{nn,k,j}$ can be written as

$$\begin{aligned} \boldsymbol{C}_{nn,k,j} &= \mathrm{E}[\bar{\boldsymbol{n}}_{k,j}\bar{\boldsymbol{n}}_{k,j}^H] \quad (2)\\ &= \sum_{i\in\mathcal{S}_I} \boldsymbol{H}_{k,j}^{(i)}\boldsymbol{H}_{k,j}^{(i)H} + \sigma_v^2\boldsymbol{I}. \quad (3) \end{aligned}$$

where $\mathcal{S}_I$ denotes the set of interfering cells, matrix $\boldsymbol{H}_{k,j}^{(i)}$ is the channel corresponding to interfering cell i and σ_v^2 is the thermal noise variance. It is noted that we assume possible precoding to be embedded into the channel, i.e. matrices $\boldsymbol{H}_{k,j}$ and $\boldsymbol{H}_{k,j}^{(i)}$ in fact represent the effective radio channel taking into account precoding.

III. Estimation error models

A conventional method of using an LMMSE receiver leads to interference suppression. The interference from a modulation symbol point of view can be originating from other transmitted symbol streams in the same cell or from other cells. A general LMMSE symbol estimate

$$\hat{\boldsymbol{s}}_{k,j} = \boldsymbol{H}_{k,j}^H(\boldsymbol{H}_{k,j}\boldsymbol{H}_{k,j}^H + \boldsymbol{C}_{nn,k,j})^{-1}\bar{\boldsymbol{r}}_{k,j} \tag{4}$$

suppresses both sources. Assuming that the data in the serving cell and in the interfering cells are independent, the model can also be expressed as

$$\hat{\boldsymbol{s}}_{k,j} = \boldsymbol{H}_{k,j}^H(\boldsymbol{C}_{rr,k,j})^{-1}\bar{\boldsymbol{r}}_{k,j} \tag{5}$$

with

$$\boldsymbol{C}_{rr,k,j} = \boldsymbol{H}_{k,j}\boldsymbol{H}_{k,j}^H + \boldsymbol{C}_{nn,k,j}. \tag{6}$$

In non-MIMO systems this receiver is also known as interference rejection combining.

In practical systems, the channel and received signal covariance information need to be estimated and the ideal LMMSE solution is replaced by

$$\hat{\boldsymbol{s}}_{k,j} = \hat{\boldsymbol{H}}_{k,j}^H(\hat{\boldsymbol{C}}_{rr,k,j})^{-1}\bar{\boldsymbol{r}}_{k,j} \tag{7}$$

using the estimates of channel and received signal covariance $\hat{\boldsymbol{H}}_{k,j}$ and $\hat{\boldsymbol{C}}_{rr,k,j}$ respectively. As mentioned, since in system-level simulations the baseband samples are typically not available, error models for $\hat{\boldsymbol{H}}_{k,j}$ and $\hat{\boldsymbol{C}}_{rr,k,j}$ are needed to be able to simulate practical IRC.

A. Channel estimation error modeling

A conventional channel estimation algorithm can be based on an LMMSE interpolator using reference signals. For each receive antenna r, the corresponding channel estimate is generated by interpolating over the initial channel estimates obtained using the reference signals (RS) in RS locations (k, j), see e.g. [8]. This is expressed as for each subcarrier-symbol pair (k, j) as

$$\hat{\boldsymbol{h}}_{r,k,j} = \boldsymbol{W}_{k,j}\hat{\boldsymbol{h}}_{r,p} = \boldsymbol{C}_{(k,j),p}\boldsymbol{C}_{pp}^{-1}\hat{\boldsymbol{h}}_{r,p}. \tag{8}$$

Here, $\boldsymbol{C}_{pp}$ equals the covariance of the channel in the RS locations and $\boldsymbol{C}_{(k,j),p}$ equals the cross correlation of the channel in RS locations and in the desired channel estimate locations (k, j). Matrix $\boldsymbol{W}_{k,j}$ is the LMMSE interpolation filter for estimating the channel in location (k, j). The initial channel estimates for RS locations for receive antenna r are included in $\hat{\boldsymbol{h}}_{r,p}$. The interpolation input sample from each receive antenna is limited to the RS locations. The covariances can be calculated based on the channel coherence bandwidth and the signal-to-noise ratio of the reference signal. Assuming that the UE is moving slowly, these paramters are relatively stable.

As mentioned, in the system simulator the basedband samples are not available, which means that the input samples for the interpolator have to be generated by other means. Essentially, interference and noise will imply an error term on top of the ideal channel in the estimation process. The interference and noise contribution can be generated by creating spatial correlation to uncorrelated noise samples. It is known from the modeling that the interference and noise covariance equals $\boldsymbol{C}_{nn,p}$ at the reference signal locations p. An actual realization of the interference and noise contribution can be created for example by using a Cholesky factorization of the covariance matrix, i.e. $\boldsymbol{C}_{nn,p} = \boldsymbol{F_p}\boldsymbol{F_p}^H$, and uncorrelated Gaussian distributed noise samples $\bar{\boldsymbol{w}}$, i.e.

$$\bar{\boldsymbol{e}}_p = \boldsymbol{F_p}\bar{\boldsymbol{w}}. \tag{9}$$

Based on the ideal channel and the generated error terms, we obtain the model for the initial estimates as $\hat{\boldsymbol{h}}_{r,p} = \bar{\boldsymbol{h}}_{r,p} + \bar{\boldsymbol{e}}_{r,p}$.

The interpolation can be written as

$$\hat{\boldsymbol{h}}_{r,k,j} = \boldsymbol{W}_{k,j}\hat{\boldsymbol{h}}_{r,p} = \boldsymbol{W}_{k,j}(\bar{\boldsymbol{h}}_{r,p} + \bar{\boldsymbol{e}}_{r,p}) \tag{10}$$

where the input samples consist of the ideal channel coefficients and the interference and noise contribution. The receive antenna specific, interpolated channel estimates are concatenated as the estimated channel matrix

$$\hat{\boldsymbol{H}}_{k,j} = [\hat{\boldsymbol{h}}_{1,k,j} \ \hat{\boldsymbol{h}}_{2,k,j} \ \cdots \ \hat{\boldsymbol{h}}_{N_r,k,j}] \tag{11}$$

The error of the channel estimate is then $\boldsymbol{\epsilon}_{k,j} = \hat{\boldsymbol{H}}_{k,j} - \boldsymbol{H}_{k,j}$, and the covariance of the estimation error is

$$\boldsymbol{C}_{\epsilon\epsilon,k,j} = E\Big\{(\hat{\boldsymbol{H}}_{k,j} - \boldsymbol{H}_{k,j})(\hat{\boldsymbol{H}}_{k,j} - \boldsymbol{H}_{k,j})^H]\Big\}. \tag{12}$$

B. Interference covariance estimation error modeling

In this paper we study two different approaches on estimating the received signal covariance matrix. First method is based on using the data symbols and the second method is based on using the reference signal symbols. In both cases, the estimated covariance matrix is modeled by taking the ideal covariance and adding an error term drawn from a certain distribution. These distributions are discussed below.

1) Data-based estimation: In the data-based estimation method, received data samples are used to calculate a sample average of the interference covariance. The benefit of the data-based estimation is that typically there are a lot more data symbols in the received block of information than there are reference symbols. Conditioned on a set $\mathcal{S}_d$ such each (k, j)-pair in $\mathcal{S}_d$ is a data symbol location, the received signal covariance is estimated as

$$\hat{\boldsymbol{C}}_{rr,d} = \frac{1}{N_d} \sum_{(k,j)\in\mathcal{S}_d} \bar{\boldsymbol{r}}_{k,j}\bar{\boldsymbol{r}}_{k,j}^H \tag{13}$$

where N_d is the number of data samples in $\mathcal{S}_d$. From system-level simulator modeling point of view, as also pointed out in [9], this matrix can be assumed to be a Wishart-distributed random matrix conditioned on that the channel does not change within the estimation block. In other words, $\hat{\boldsymbol{C}}_{rr,d} \sim \mathrm{W}_n(N_d, \boldsymbol{C}_{rr,d})$ [10]. In a conventional system simulator, this property can be exploited because in a system simulator the baseband data samples do not exist. A method of generating the Wishart-distributed random matrices can be found for example from [11].

2) Reference signal -based estimation: In the reference signal based estimation method, the N_p demodulation reference signal (DMRS) positions in the set $\mathcal{S}_p$ are used for the covariance matrix estimation. These reference symbols as defined in [12] are precoded with the same precoder as the data symbol and should also experience the same interference as the actual data symbols. The algorithm subtracts the serving cell DMRS signal before performing the covariance estimation. In other words, the inter-cell interference and noise covariance is estimated as follows:

$$\begin{aligned}\hat{\boldsymbol{C}}_{nn,p} &= \frac{1}{N_p} \sum_{(k,j)\in\mathcal{S}_p} (\bar{\boldsymbol{r}}_{k,j} - \hat{\boldsymbol{H}}_{k,j}\bar{\boldsymbol{p}}_{k,j})(\bar{\boldsymbol{r}}_{k,j} - \hat{\boldsymbol{H}}_{k,j}\bar{\boldsymbol{p}}_{k,j})^H \\ &= \frac{1}{N_p} \sum_{(k,j)\in\mathcal{S}_p} (\bar{\boldsymbol{r}}_{k,j} - (\boldsymbol{H}_{k,j} + \boldsymbol{\epsilon}_{k,j})\bar{\boldsymbol{p}}_{k,j}) \cdot \\ &\quad (\bar{\boldsymbol{r}}_{k,j} - (\boldsymbol{H}_{k,j} + \boldsymbol{\epsilon}_{k,j})\bar{\boldsymbol{p}}_{k,j})^H \end{aligned} \tag{14}$$

where $\bar{\boldsymbol{p}}_{k,j}$ is the DMRS symbol vector and the final covariance matrix estimate is formed as

$$\hat{\boldsymbol{C}}_{rr,p} = \hat{\boldsymbol{H}}_{k,j}\hat{\boldsymbol{H}}_{k,j}^H + \hat{\boldsymbol{C}}_{nn,p}. \tag{15}$$

Note that again the interference covariance matrix could be considered to be Wishart distributed (W) with N_p degrees of freedom. i.e. $\hat{\boldsymbol{C}}_{nn,p} \sim \mathrm{W}_n(N_p, \boldsymbol{C}_{nn} + \boldsymbol{C}_{\epsilon\epsilon})$ if the channel estimation error $\boldsymbol{\epsilon}$ is independent from the DMRS samples. This in fact is not entirely true since the same samples are used for the channel estimation.

TABLE I
SIMULATION ASSUMPTIONS.

Network model	3GPP Case 1 [13], inter-site dist. 500 m
Network basestation timing	synchronous
Channel model, UE velocity	Flat fading, 3 km/h
	SCM Urban Macro, 3 km/h
Transmission bandwidth	10 MHz
eNB antenna configurations	2-Tx co-polarized, $\lambda/2$ -spaced (link)
	4-Tx co-polarized, $\lambda/2$ -spaced (system)
UE antenna configuration	2-Rx co-polarized, $\lambda/2$ -spaced
Number of MIMO streams	Max. 2 precoded codewords
OFDM parameters	According to LTE specifications [12]
CSI-RS	as in [12], periodicity of 5 ms
Feedback	4-bit LTE codebook [12]
Precoding granularity	1 PRB (12 subcarriers)
Link and rank adaptation	based on maximum throughput
HARQ	Incremental redundancy
	Max. 4 transmissions
Channel estimation	MMSE estimator
Rx covariance estimation	Data or DMRS sample estimator
	Wishart distribution -based error model

IV. SIMULATION RESULTS

Simulations were run first to verify the validity of the error models by comparing the estimates obtained using the error model to estimates obtained in a true multi-link estimation. Then, we ran system-level simulations in order to see the system-level benefits of practical IRC algorithms. Our simulation assumptions are summarized in table I.

A. Error model verification

The simulations to verify the error model were made using a multi-link simulator where a single user is uniformly dropped to a hexagonal cell network. The cell having the smallest path loss is the serving cell and the other cells are assumed to be fully loaded by the traffic generating interference. Baseband sample level signals are generated enabling to simulate the interference suppressing receiver performance. Note that in a multi-link simulator, the true interference estimation can be performed, hence one can assess the accuracy of Wishart error model which is to be applied in system level simulations. Furthermore, a more complete algorithm model where the signal samples are used for the parameter estimation can be compared to the simplified algorithm model where the estimation error is generated to the interference covariance matrix estimates by the Wishart random matrix model.

The subcarriers in the LTE system are divided into physical resource blocks (PRB) which can be used for user scheduling. The base station scheduler may allocate different user signals with a PRB granularity. This means that for example MIMO precoding could change from one PRB to another. This constraints the DMRS channel estimation and especially the interference covariance estimation as it can not be assumed that the interference is continuous over multiple PRBs. In these simulations, the interfering cells change precoding in the PRB level, hence, the wider estimation bandwidth is not necessarily better even if the channel is flat fading.

Following algorithms are compared as also labeled in the accompanying figures:

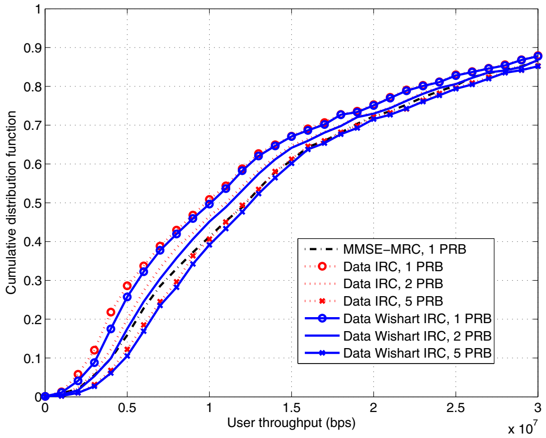

Fig. 1. Performance of data symbol -based IRC receiver compared to proposed error model in a flat fading channel.

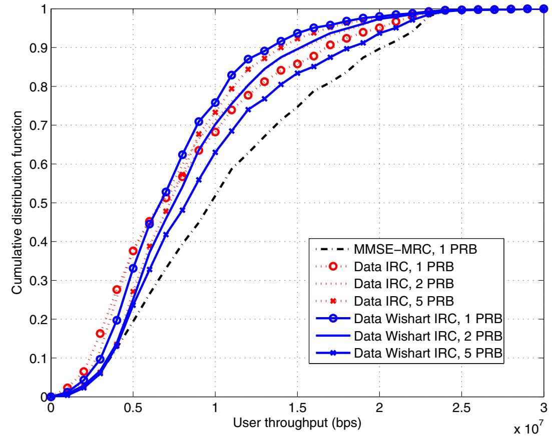

Fig. 2. Performance of data symbol -based IRC receiver compared to proposed error model in frequency-selective SCM channel.

- MMSE-MRC 1 PRB: Interference covariance is assumed to be diagonal but still the interference is estimated from DMRS locations. DMRS based channel estimates are used.
- Data-IRC x PRB: IRC receiver which estimates the interference covariance from the data symbols as shown in the previous section. Estimation is done over x PRBs, where x is mentioned in each figure legend. DMRS based channel estimates are used.
- Data Wishart IRC x PRB: IRC receiver whose ideal covariance matrix is perturbated by the proposed error model. Estimation is assumed to be done from the data symbols over x PRBs. DMRS based channel estimates are used (no error model needed in link level).
- DMRS IRC x PRB: IRC receiver which estimates the covariance from the DMRS resource elements as shown in the previous section. Estimation is done over x PRBs. DMRS based channel estimates are used.
- DMRS Wishart IRC x PRB: IRC receiver whose ideal covariance matrix is perturbated by the proposed error model. Estimation is assumed to be done from the DMRS REs over x PRBs. DMRS based channel estimates are used (no error model needed in link level).

Figures 1-4 present the performance of the interference suppression algorithms in flat fading and SCM urban macro channels. Wider estimation blocks in frequency can be used effectively to improve the estimation quality of the IRC receivers only in the flat channel. In the SCM channel, the channel coefficients change during the estimation block causing distortion.

The first aspect in the results is the quality of the system level modeling utilizing the Wishart distributed random matrices. In the simulations, LMMSE filtered channel estimates were used since they can be calculated in the multi-link simulator. Only the quality of the covariance matrix error emulation is studied. Note also that $\boldsymbol{C}_{\epsilon\epsilon}$ was ignored assuming that the channel estimates achieve a very good quality. It can be observed that applying the Wishart random matrix model in the

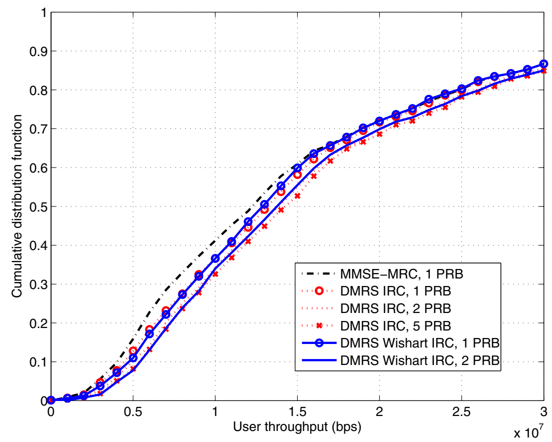

Fig. 3. Performance of DMRS symbol -based IRC receiver compared to proposed error model in a flat fading channel.

IRC receiver instead of the real covariance estimate provides similar performance despite the significant simplification in the assumptions. It can also be observed that although the error model is less accurate in the frequency selective channel the performance is relatively well replicated by the system level model. To summarize, the proposed error model provides a very good match with real algorithm performance.

Another aspect in the simulations is the actual receiver performance. The main problem in the IRC receiver is the signal covariance estimation. The data symbol based algorithm performs poorly even though very large number of symbols is available for the estimation. Even the receiver assuming white noise typically outperforms this IRC receiver. The IRC algorithm based on the DMRS symbol estimates on the other hand performs very well even though the number of samples for the covariance estimation is very small compared to the data based algorithm. This may be caused by the different way of constructing the LMMSE filter. The same channel estimation error sample impacts both the nominator and the denominator in the LMMSE calculation. Furthermore, the cross-correlation between the data symbols and interference is more clearly zeroed out.

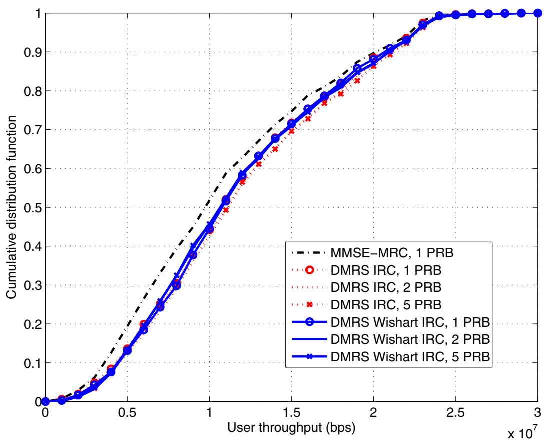

Fig. 4. Performance of DMRS symbol -based IRC receiver compared to proposed error model in frequency-selective SCM channel.

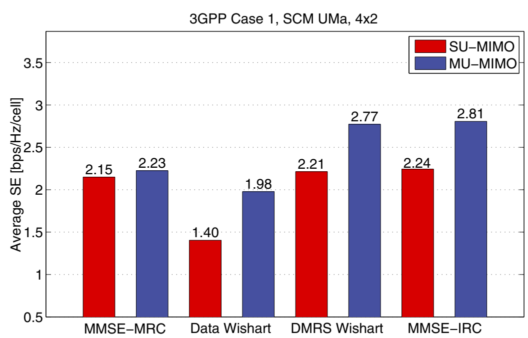

Fig. 5. Average spectral efficiency in SCM urban macro scenario with different receivers.

B. System-level performance of IRC receivers

System-level simulations are conducted in this section using the error model proposed in previous sections in order to evaluate the performance of practical IRC receivers. Simulations assume 10 UEs per cell in the 4x2 3GPP SCM urban macro scenario. We simulated both SU-MIMO and MU-MIMO transmission schemes assuming proportional fair scheduling algorithm both in time and frequency domain.

Average spectral efficiency is presented in figure 5 whereas figure 6 shows the cell edge performance for the lowest 5 percentile of user throughputs.

The results are aligned with the results shown in previous section. It can be observed that only the DMRS based algorithm can outperform the receiver assuming white noise (denoted MMSE-MRC in the figures). The DMRS-based IRC provides 24.2% and 2.8% gains in average spectral efficiency for MU-MIMO and SU-MIMO respectively. Similarly, 18.5% and 11.7% coverage gains are observed for MU-MIMO and SU-MIMO. Furthermore, the loss compared to the ideal algorithm which has ideal information on the signal covariance (denoted MMSE-IRC in the figures) is small.

V. Conclusion

In this paper we have studied the system-level modeling and performance of IRC receivers which estimate the in-

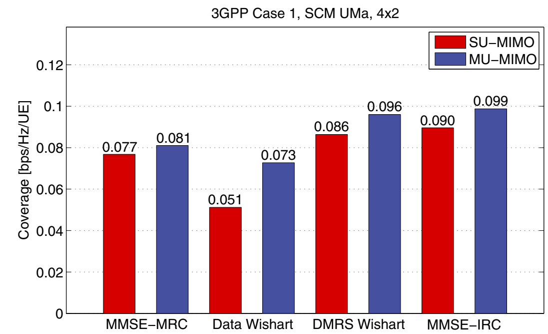

Fig. 6. Spectral efficiency at 5 percentile of UEs in SCM urban macro scenario.

terference covariance either from the data symbols or the DMRS symbols. We proposed modeling methodology for IRC receivers applicable to radio system simulations. The model is verified in a multi-link simulator showing a reasonable match to the fully modeled IRC receiver. We also studied the performance of different IRC receivers: It was observed that different estimation methods have significant impact on the performance. Only the algorithm based on the DMRS symbols can constantly outperform a receiver that assumes white other cell interference. Up to 24% spectral efficiency gains were observed from practical IRC receivers in our system-level evaluations.

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