

# Behavior of a Multi-User MIMO System in Time-Varying Environments\*

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**SUMMARY** We evaluated the behavior of a multi-user multiple-input multiple-output (MIMO) system in time-varying channels using measured data. A base station for downlink or broadcast transmission requires downlink channel state information (CSI), which is outdated in time-varying environments and we encounter degraded performance due to interference. One of the countermeasures against time-variant environments is predicting channels with an autoregressive (AR) model-based method. We modified the AR prediction for a time division duplex system. We conducted measurement campaigns in indoor environments to verify the performance of the scheme of channel prediction in an actual environment and measured channel data. We obtained the bit-error rate (BER) using these data. The AR-model-based technique of prediction assuming the Jakes' model was found to reduce BER. Also, the optimum AR-model order was investigated by using the channel data we measured.

**key words:** multi-user MIMO system, channel state information, time-varying environment, channel prediction, autoregressive (AR) model-based prediction

## 1. Introduction

A tremendous amount of research has been done on multiple-input multiple-output (MIMO) systems over the last decade because they provide transmission at high data rates without increasing the frequency bandwidth [1]–[3]. MIMO systems achieve high-speed wireless transmission through space-domain signal processing. Adaptive antennas that also exploit space-domain signal processing had been studied for various applications before MIMO systems emerged [4]–[6]. MIMO systems are considered to be an extension of adaptive antennas but they have two clearly distinct aspects that are not seen in adaptive antennas.

First, high-speed transmission by MIMO systems is proved from the view-point of information theory [7]. Let us assume that we have a single channel between a transmitter and a receiver, and that the signal-to-noise power ratio at the output of the channel is  $S/N$ . The capacity of the channel is given by  $C = \log_2(S/N + 1) \approx \log_2 S/N$

bps/Hz when  $S/N \gg 1$ . If the transmit (TX) power is doubled, the signal-to-noise power ratio is also doubled, and the capacity is  $\log_2(2S/N + 1) \approx C + 1$  bps/Hz. This means that although the TX power is doubled, the channel capacity is increased by only 1 bps/Hz, which is not efficient. If we have two parallel equivalent channels, the capacity is  $2 \log_2(S/N + 1) \approx 2C$  bps/Hz. MIMO systems achieve parallel channels between a transmitter and a receiver in a space, and achieve high channel capacity.

Second, MIMO systems work properly in multipath-rich environments because the correlations between channels are low, and the previously mentioned parallel transmission effectively improves communication. This means that MIMO systems exploit multipath propagation, which had been a nuisance to wireless communications because it caused fading. The authors believe that exploiting multipath propagation is a distinct paradigm shift.

It is true that MIMO systems are applications of antenna engineering. However, they are closely related with many other fields such as communications, signal processing, information theory, and radio propagation. The development of MIMO systems is a beneficial achievement from these techniques.

If a transmitter has channel state information (CSI), sophisticated transmission such as eigen-beam space division multiplexing (E-SDM) can be applied [8], which is also called a singular value decomposition (SVD) system [9] or MIMO eigenmode transmission system [10]. CSI is needed for downlink (DL) or broadcast transmission in multi-user MIMO systems [11]–[13]. CSI in a frequency division duplex (FDD) system must be fed back from mobile stations (MSs) to a base station (BS). CSI in time-varying environments may be outdated because of feedback delay. The effect of feedback delay is a critical issue, and analytical results have been reported in the literature [14]. Measurement-based considerations on the effect of outdated channels have been done by Wallace et al. [15]. We can obtain downlink CSI from the uplink signal in a time division duplex (TDD) system. We have the outdated CSI issue even in a TDD system when the time interval between the uplink channel and the downlink transmission cannot be neglected.

Multi-user MIMO systems are much more affected by outdated CSI than single-user ones. A BS needs to send signals using TX or beamforming weights that suppress inter-user interference (IUI) and inter-stream interference (ISIt) because MSs have fewer antennas than a BS and cannot sup-

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press this interference. The channels in time-varying environments at the actual time of transmission differ from those used to determine the TX weights. Thus, MSs suffer from interference, and transmission is seriously degraded.

A transmission scheme based on channel distribution information has been proposed to mitigate the effect of outdated CSI. Although communication is not optimum, it is stable in time-varying environments because the transmission scheme does not need CSI [16], [17]. Another countermeasure against time-variant environments is achieved by predicting channels. If we can predict future channels, the outdated CSI issue is resolved. Several schemes have been reported for channel prediction [18]–[25]. Of these, an autoregressive (AR) model-based method, which is often referred to as a linear predictor, is a typical scheme. Detailed considerations on the AR-model-based method are stated in the literature [18] and the references therein. We need to obtain AR coefficients to apply the method and knowledge about channel autocorrelations is required to compute these. One method of obtaining the autocorrelations is to calculate them from past channel information. If we have many channel data, we have accurate channel autocorrelations. However, if we do not have enough data, we may have poor autocorrelations. An other method is to calculate the channel autocorrelations assuming the Jakes’ model. If we know the maximum Doppler frequency, the channel autocorrelations can easily be obtained. However, the Jakes’ model is not always valid in actual radio environments.

We examined the prediction of channels with the AR-model-based method for multi-user MIMO downlink transmission. We conducted measurement campaigns in the 5.2-GHz frequency band in indoor environments and obtained a large number of statistically stationary time-varying channels [26]. We investigated the bit error rate (BER) by using the data.

The paper is organized as follows. The next section briefly describes the prediction of channels with the AR-model-based method. Section 3 then presents the measuring setup for our experiment. Section 4 shows autocorrelations and Doppler spectra of the measured channels, and Sect. 5 explains our evaluation of BER. Finally, Sect. 6 presents the conclusions we drew.

## 2. AR-Model-Based Prediction of Channels

We represent the channel from the  $j$ th TX antenna of the BS to the  $i$ th receive (RX) antenna of the  $k$ th MS at time  $t$  by  $h_{i,j,k}(t)$ . Future channel  $h_{i,j,k}((n+1)T_f)$  is predicted in AR-model-based algorithms using  $p$  previous channel values  $h_{i,j,k}(nT_f)$ ,  $h_{i,j,k}((n-1)T_f)$ ,  $\dots$ ,  $h_{i,j,k}((n+1-p)T_f)$ , which are given by

$$\hat{h}_{i,j,k}((n+1)T_f) = \sum_{m=1}^p a_m h_{i,j,k}((n+1-m)T_f). \quad (1)$$

Here,  $a_m$  are AR coefficients, and  $p$  is called the AR-model order [18], [27]. Although the AR coefficients are time-

variant values, we assume channels are slowly varying and we can consider that they are independent of time for a certain period. The optimum AR coefficients are given by the Yule-Walker equation

$$\mathbf{R}\mathbf{a} = \mathbf{r}. \quad (2)$$

$\mathbf{a}$  is the  $p$ -dimensional vector in the above equation defined as

$$\mathbf{a} = [a_1 \ a_2 \ \dots \ a_p]^T, \quad (3)$$

where  $[\ ]^T$  denotes the transpose.  $\mathbf{R}$  is the  $p \times p$  correlation matrix whose  $l_1$ th row and  $l_2$ th column element is given by

$$\begin{aligned} r(l_1 - l_2) &= r^*(l_2 - l_1) \\ &= E \{ h_{i,j,k}^*((n+1-l_1)T_f) h_{i,j,k}((n+1-l_2)T_f) \} \\ &= E \{ h_{i,j,k}^*((n+1-(l_1-l_2))T_f) h_{i,j,k}((n+1)T_f) \}, \end{aligned} \quad (4)$$

where  $*$  denotes the complex conjugate and  $E\{\}$  denotes the ensemble average. Also, correlation vector  $\mathbf{r}$  is defined as

$$\mathbf{r} = [r(1) \ r(2) \ \dots \ r(p)]^T. \quad (5)$$

The  $l$ th element is given by

$$r(l) = E \{ h_{i,j,k}^*((n+1-l)T_f) h_{i,j,k}((n+1)T_f) \}. \quad (6)$$

We have assumed a TDD system such as HIPERLAN/2 in the remainder of this paper [28]. TDD systems are also standardized in addition to FDD ones in 3GPP LTE and mobile WiMAX [29], [30]. As seen in Fig. 1, uplink and downlink signals are transmitted with a period of  $T_f$ , which is the frame duration in the TDD system. The BS estimates the channels for the MSs using uplink ACK packets, and sends DL packets using the multi-user MIMO E-SDM scheme [26]. The above mentioned inter-user interference (IUI) is suppressed by block diagonalization [31]–[33]. We assumed that the ACK and DL packets were so short that we could neglect channel changes in the duration of packets.

Using the previous  $p$  channels at  $nT_f$ ,  $(n-1)T_f, \dots, (n+1-p)T_f$  estimated by the ACK packets, we predict the DL channel at  $nT_f + \tau$ , which is given by

$$\hat{h}_{i,j,k}(nT_f + \tau) = \sum_{m=1}^p a'_m h_{i,j,k}((n+1-m)T_f). \quad (7)$$

In this case, AR coefficients  $a'_m$  are obtained by using a slightly modified Yule-Walker equation

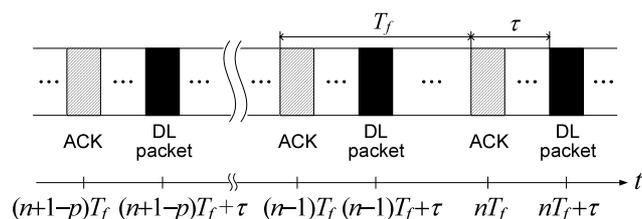


Fig. 1 TDD transmission frame format.

$$\mathbf{R}\mathbf{a}' = \mathbf{r}'. \quad (8)$$

Here, the  $p$ -dimensional vectors,  $\mathbf{a}'$  and  $\mathbf{r}'$ , are defined as

$$\mathbf{a}' = [a'_1 \ a'_2 \ \cdots \ a'_p]^T \quad (9)$$

$$\mathbf{r}' = [r'(1) \ r'(2) \ \cdots \ r'(p)]^T. \quad (10)$$

The  $l$ th element of  $\mathbf{r}'$  is given by

$$r'(l) = E \left\{ h_{i,j,k}^* \left( (n+1-l)T_f \right) h_{i,j,k} \left( nT_f + \tau \right) \right\}. \quad (11)$$

The channel correlation in the Jakes' model, without a constant coefficient, is given by

$$E \left\{ h_{i,j,k}^* (t-T) h_{i,j,k}(t) \right\} = J_0(2\pi f_D T), \quad (12)$$

where  $J_0(\cdot)$  is the zeroth-order Bessel function of the first kind and  $f_D$  is the maximum Doppler frequency. Thus, the  $l_1$ th row and  $l_2$ th column element of correlation matrix  $\mathbf{R}$  is written as

$$\begin{aligned} r(l_1 - l_2) &= r(l_2 - l_1) \\ &= J_0(2\pi f_D (l_1 - l_2) T_f). \end{aligned} \quad (13)$$

Also, the  $l$ th element of correlation vector  $\mathbf{r}'$  is given by

$$r'(l) = J_0(2\pi f_D (\tau + (l-1)T_f)). \quad (14)$$

CSI in TDD systems is obtained by uplink ACK packets at the BS. However, downlink channel  $h_{i,j,k}(kT_f + \tau)$  required for correlation  $r'(l)$  given by (11) cannot be directly observed at the BS. The channel information must be fed back from the MS to the BS. This is a serious problem. However, if the channels can be approximated with the Jakes' model, we can calculate correlation matrix  $\mathbf{R}$  and vector  $\mathbf{r}'$  using maximum Doppler frequency  $f_D$ . We will demonstrate BER performance with the AR-based prediction of channels assuming the Jakes' model later.

### 3. Measurements of Time-Varying Channels

The measurement campaign for the multi-user MIMO system was carried out in a meeting room in a building of the Graduate School of Information Science and Technology at Hokkaido University, as shown in Fig. 2. The measurement was the same as that in Bui et al. [26]. We will repeat almost the same description here. The walls of the room were mostly plaster-board. The room also had reinforced concrete pillars, metal doors, and a metal whiteboard, where a 4-element TX and two 2-element RX linear arrays were placed on three tables. The TX and RXs corresponded to the BS and MSs stated in the previous sections. The arrays consisted of omnidirectional collinear antennas. The nominal gain of these antennas on the horizontal plane was about 4 dBi. The distances from the TX to RX1 and RX2 were 4 m, while the spacing between RX1 and RX2 was 3 m. The channels were measured for all the TX and the RX antenna pairs with a vector network analyzer. The measurement band was from 5.15 to 5.40 GHz (bandwidth =

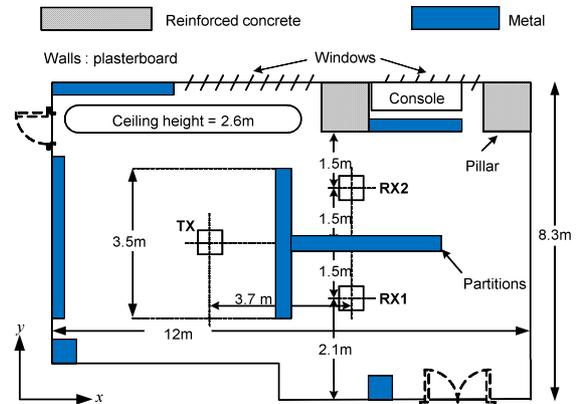


Fig. 2 Measurement site (top view). (Reprinted from Bui et al. [26] ©2013 IEEE).

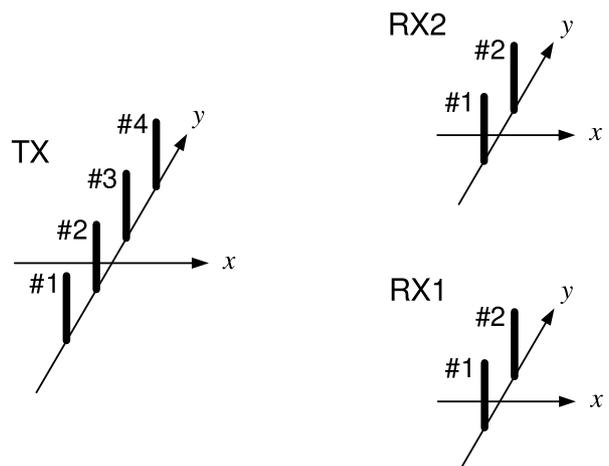


Fig. 3 Array orientations.

250 MHz), and we obtained 1,601 frequency domain data with 156.25 kHz intervals. The antenna spacing was 3 cm (half-wavelength at 5 GHz).

The array orientation was along the  $y$ -axis as shown in Fig. 3. When there were no metal partitions between the TX and RXs, we had a line-of-sight (LOS) environment, as seen in Fig. 4(a). When there were partitions, we had a non-LOS (NLOS) one, as shown in Fig. 4(b).

Two stepping motors were used on the RX side to move the two RX arrays along the  $x$ - or  $y$ -axis during the experiments. These motors were controlled by a personal computer. Each step of the motors corresponded to 0.0088 cm, and the RX arrays were stopped at every 10 steps (equal to 0.088 cm). The channels were measured at intervals of 0.088 cm, and we had a total of 500 spatial measuring points. As a result, channel response matrices were obtained for each case of direction of RX motion and LOS/NLOS condition. A large number of channel data was measured to find reliable BER. Note that the measurement campaign was conducted while no one was in the room to ensure statistical stationarity of propagation.



(a) LOS environment.



(b) NLOS environment.

**Fig. 4** Measurement environments. (Reprinted from Bui et al. [26] ©2013 IEEE).

#### 4. Channel Autocorrelations and Doppler Spectra

We assumed that RXs were moving at constant velocity  $v$ . We will discuss our examination of channel autocorrelations and Doppler spectra in this section using the measured data. As stated in the previous section, the channels were measured at intervals of 0.088 cm. Assuming that the time interval between adjacent measuring points is 0.833 ms, then the velocity is  $v = 0.088 \text{ cm} / 0.833 \text{ ms} = 1.06 \text{ m/s}$ . This motion causes maximum Doppler frequency  $f_D$  of 18.6 Hz for the center frequency of 5.275 GHz.

We have considered two cases in this paper:

- (a) The NLOS environment and RX motion along the  $x$ -axis
- (b) The LOS environment and RX motion along the  $y$ -axis

The channel autocorrelations and Doppler spectra for RX1 are shown in Fig. 5. We had 4×2 MIMO channels. The channel autocorrelations were obtained by averaging over the eight channels as well as the spatial domain and 1,601 frequency domain data. Autocorrelation assuming the Jakes' model is also provided in Fig. 5. If we divide the measuring distance (abscissa) by velocity  $v = 1.06 \text{ m/s}$ , we have the channel autocorrelations versus time. The Doppler spectra of both the measured data and the Jakes' model were cal-

culated by applying a 450-point discrete Fourier transform (DFT) process to the time domain channel autocorrelations after multiplying them by the Hamming window [34].

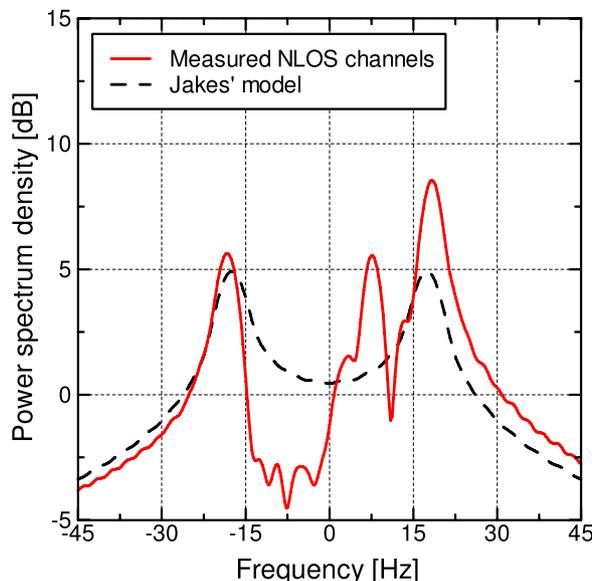
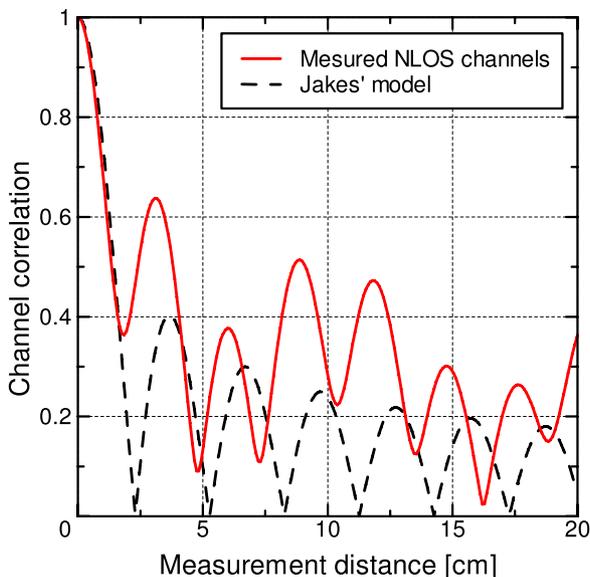
The Doppler spectrum in the NLOS environment shown in Fig. 5(a) has peaks at  $\pm 18.6 \text{ Hz}$ , which correspond to  $\pm f_D$ . This is similar to the Doppler spectrum of the Jakes' model. However, we can see another peak at about 7.5 Hz. A strong reflection corresponding to the peak was considered to be at the site, which is different from the Jakes' model.

Both autocorrelation and the Doppler spectrum were completely different from those of the Jakes' model for LOS and RX motion along the  $y$ -axis (Fig. 5(b)). We can see that the power spectral density is mainly distributed around the Doppler frequency of 7 Hz, which is caused by a direct wave from the TX in the LOS environment. If we compensate for the Doppler frequency of 7 Hz, the effect of time-varying channels is largely mitigated. This will be shown in the next section.

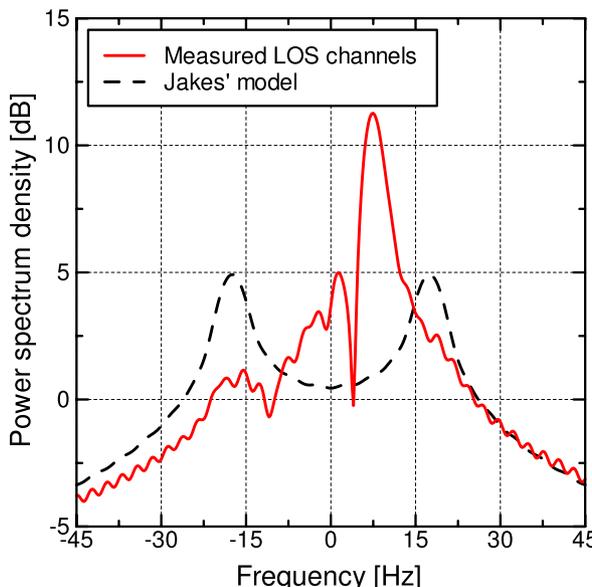
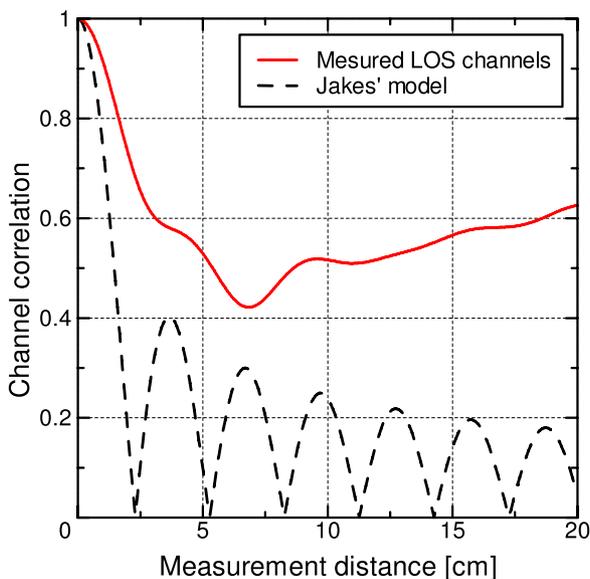
#### 5. Accuracy of Channel Prediction

We investigated the BER performance of multi-user MIMO downlink transmission using the measured channel data. We conducted simulations of the multi-user MIMO E-SDM system by assuming the parameters listed in Table 1. Some parameters and transmission schemes stated below are the same as those in Bui et al. [26]. Because the TX had four antennas and each RX had two antennas, we had either single-stream or two-stream transmission for each RX. We assumed that the data rate for each MS was fixed constantly at 4 bps/Hz (4 bits/symbol). The modulation scheme was either 16QAM for the single-stream transmission or QPSK for the two-stream one. The control of resources for E-SDM transmission, viz., determining the number of streams, modulation scheme, and transmit power, was done in such a way that the Chernoff upper bound of BER for each MS had the lowest value [8]. The total transmit power per MS was equal. The uplink channels in this study were assumed to be perfectly estimated at the TX using ACK packets, and the effective downlink channels for E-SDM transmission were also assumed to be perfectly estimated at both RXs. Each RX determined the MMSE weights using its own effective downlink channels.

Figure 6 shows the average BER performance of RX1 versus normalized TX power for RX motion along the  $x$ -axis in the NLOS case. The normalized TX power is the TX power per MS normalized to the power yielding average  $E_s/N_0$  of 0 dB in single-user SISO-LOS measurements in an anechoic chamber. Here,  $E_s$  is the received signal energy per symbol, and  $N_0$  is the noise power density. In addition to the BER performance with the prediction of channels for different values of AR-model order  $p$ , performance without prediction and that of the ideal case are also plotted in the figure. The ideal case in the figure indicates behavior in accurately predicting channels. As indicated in Table 1, all the curves are for delay  $\tau$  of 5 ms from the ACK packet. The



(a) NLOS environment with RX motion along  $x$ -axis.



(b) LOS environment with RX motion along  $y$ -axis.

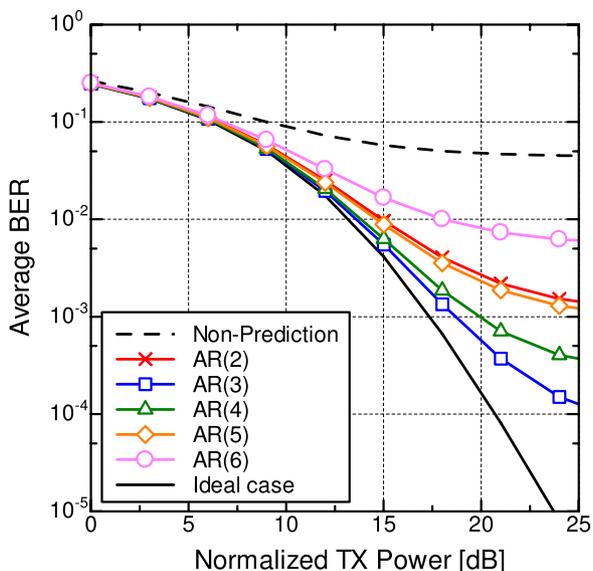
**Fig. 5** Channel autocorrelations and Doppler spectra for RX1.

figure reveals that when we do not use the scheme of channel prediction, we have a high error floor. This means that if we use outdated channels when ACK packets are received, we have poor BER performance. The distance traveled during 5 ms for the velocity of 1.06 m/s or  $f_D$  of 18.6 Hz is 0.53 cm or 0.093 wavelengths. It should be noted that only a fraction of channel transition significantly affected the BER performance even though the RX weights were determined by the MMSE criterion using CSI without delay. As can be seen from Fig. 5(a), we have strong components at the Doppler frequencies of  $\pm 18.6$  and 7.5 Hz. These cause channel changes and deteriorate the BER performance. When we use channel prediction, on the other hand, BER is re-

duced depending on AR-model order  $p$ . Especially, when  $p = 3$ , BER is reduced close to the ideal case. It should be noted that the channel autocorrelations required for the AR-model-based prediction of channels are obtained assuming the Jakes' model. As can be seen from the Doppler spectra in Fig. 5(a), the actual radio environment is different from that of the Jakes' model. However, prediction is very effective for  $p = 3$ . We assumed frame duration  $T_f$  of 10 ms in the simulations, which corresponds to 1.06 cm for the velocity of 1.06 m/s. We used autocorrelations up to 2.12 cm apart when  $p = 3$ . We can see from Fig. 5(a) that the autocorrelations in the Jakes' model and the actual channels are the same up to about 2 cm. We conjectured that this was

**Table 1** Simulation parameters.

No. of MSs	2
No. TX & RX antennas	4 × 2
Data rate for each MS	4 bits/symbol
Modulation schemes	QPSK, 16QAM
Resource control	Minimum BER criterion based on Chernoff upper bound
Data burst length	128 symbols
Frame duration ( $T_f$ )	10 ms
Delay from ACK ( $\tau$ )	5 ms
Max. Doppler frequency ( $f_D$ )	18.6 Hz
Channels	Frequency flat-fading estimated perfectly at TX, RX1 and RX2
Thermal noise	Additive white Gaussian noise
RX signal processing	MMSE weight

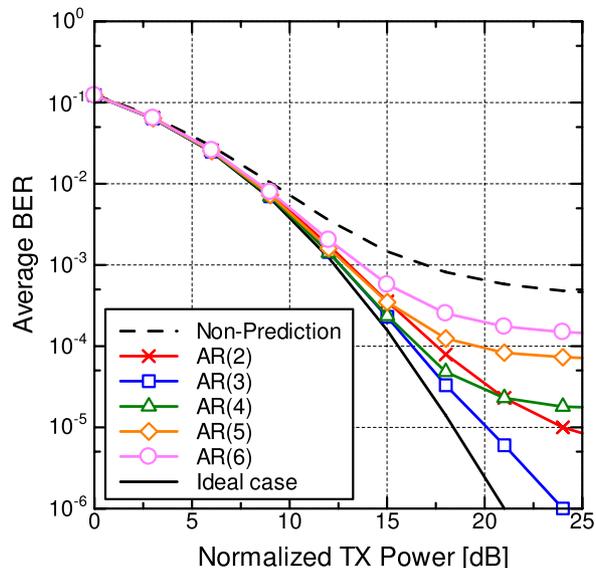


**Fig. 6** BER performance with channel prediction assuming the Jakes' model (1). NLOS, RX1, RX motion along  $x$ -axis,  $v = 1.06$  m/s,  $f_D = 18.6$  Hz.

the reason why we could reduce BER assuming the Jakes' model.

Figure 7 shows the average BER performance of RX1 versus normalized TX power for RX motion along the  $y$ -axis in the LOS environment. We can see that BER is reduced more than that in Fig. 6. As stated in the previous section, the Doppler spectrum is almost concentrated around 7 Hz in this scenario, and the effect of the time-varying channels can easily be mitigated. Also in this LOS environment, the AR-model-based prediction of channels with  $p = 3$  reduces BER so that it is close to that of the ideal case. It is interesting that although channel autocorrelation for the LOS case is different from that for the Jakes' model, as seen from Fig. 5(b), the BER performance is improved assuming the Jakes' model.

The optimum value of  $p$  was 3 for both the cases. The value, however, may be different depending on environments and parameters such as  $T_f$  and  $\tau$ . The method of determining the optimum  $p$  has not been available.



**Fig. 7** BER performance with channel prediction assuming the Jakes' model (2). LOS, RX1, RX motion along  $y$ -axis,  $v = 1.06$  m/s,  $f_D = 18.6$  Hz.

### 6. Conclusions

We investigated the behavior of multi-user MIMO systems in time-varying environments. We found that BER was seriously degraded depending on channel scenarios. However, if we predicted future channels using the AR-model-based scheme, performance was largely improved. We also found that we could assume the Jakes' model for calculations of AR coefficients. The reason for this was not clear, and this is an issue that needs to be resolved in future work. Here, we treated the prediction range of 0.53 cm or 0.093 wavelengths, and evaluated the average BER. The prediction of channels for longer ranges also remains for future work.

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