Adaptive Multistage Parallel Interference Cancellation for CDMA*

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Abstract

Although multistage interference cancellation detector is simple in structure, its performance degrades when the number of active users becomes large. In some cases, its performance is even worse than that without cancellation due to the lack of the exact knowledge of the interfering signal in cancellation [1]. Partial interference cancellation suggested by D. Divsalar and M. Simon [2] tries to remedy this weakness by reducing the cost of a wrong interference estimation through a weight in each stage. This paper presents an *adaptive* multistage structure based on the partial interference cancellation approach. In this structure, the weights are obtained by minimizing the mean-square error between the received signal and its estimate through a least mean square (LMS) algorithm. The resulting weights contain reliability information for the hard decision made in the previous stage. Neither training sequence nor pilot signal is needed in the proposed scheme and its complexity is much lower than that of linear multiuser detectors. Simulation results show that the proposed scheme can outperform the existing interference cancellation methods in both the additive white Gaussian noise (AWGN) and the multipath fading channels.

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1 Introduction

It is well known that the performance of a code division multiple access (CDMA) system can be limited by the multiple access interference (MAI). Such problem arises from the use of the conventional single-user detector which ignores the existence of other users. The consequence is, when the number of active users increases to a certain level or when some users' signals become extremely strong, weak users with the conventional single-user detection may lose communication because of the overwhelming MAI. The optimal detector [3] that jointly detects all users' signals can significantly eliminate the MAI, and provide a substantial increase in system capacity. However, the complexity of the optimal detector is exponentially proportional to the number of users, and that prohibits its practical implementation.

Various suboptimal detection techniques have been proposed with reduced complexity. These suboptimal approaches can be classified into two categories: linear multiuser detector and subtractive interference canceller. In linear multiuser detection, a linear transformation is applied to the soft outputs of the conventional detectors in order to produce a new set of decision variables with MAI being greatly decoupled or completely decoupled [4, 5]. In subtractive interference cancellation, the interference estimates are generated and removed from the received signal before detection. The cancellation can be carried out either successively [6, 7] or in parallel [8, 9]. Generally, the parallel interference cancellation (PIC) causes much less decision delay than the successive ones. Besides, the structure of the PIC is much simpler than that of the linear multiuser detectors.

As indicated in [10], the optimum detector in the sense of maximum-likelihood (ML) is a one-stage PIC if the data from all interfering users is known *a priori*. In reality, where such data is unknown, the PIC can be implemented in multiple stages [8]. Specifically, in the n-th stage of cancellation, the detector uses the bit decisions in the $(n-1)$-th stage to regenerate the MAI, and then subtracts it completely from the received signal of the desired user. As a result, when the estimates from the previous stage become more accurate, the performance of the multistage PIC will be better. However, the conventional multistage PIC [8] cannot guarantee the performance improvement with more stages, especially when the system load (the ratio between the number of active users and the processing gain of the system) is high

[1]. For instance, a correct estimate of a certain interfering user's bit can lead to a successful removal of this interference, while a wrong estimate may double the power of the interference, introducing more degradation.

In view of the shortcoming associated with the conventional multistage PIC, Divsalar *et al.* [2] suggested a *partial* cancellation of the MAI by introducing a weight in each stage to determine the amount of cancellation. Their results show a considerable capacity increase over the conventional multistage PIC in the additive white Gaussian noise (AWGN) channel.

The lower performance of the conventional multistage PIC stems from the lack of the exact knowledge on whether the hard decisions provided by the previous stage are correct or not. This is also applicable to the scheme proposed by Divsalar *et al.*, where a compromise is made between canceling the MAI and reducing the cost caused by an incorrect estimate without the information on the accuracy of the MAI estimation. Obviously, if certain knowledge about the MAI is available, the performance of the interference cancellation will be enhanced. However, such knowledge is only available at the cost of additional complexity, it is desirable to keep this additional complexity as low as possible.

Intuitively, the weights in the partial cancellation scheme should reflect the reliability of data estimations. Since the reliability of data estimations varies from one user to another and from bit to bit depends on the MAI levels at a particular time instant, it is more reasonable for each user to have its own weight per bit rather than one constant weight for all users in each stage throughout the cancellation. Furthermore, these weights should not be necessarily larger than 0. For instance, with perfect channel information, when a wrong decision is used in reconstructing the interference for binary signal, the optimal weight should be -1 as long as the error is detectable. Motivated by the above thoughts, we can investigate the interference cancellation problem from a different perspective.

At first, we propose a different cost function which takes the weights into consideration to minimize the squared Euclidean distance between the received signal and the weighted sum of the estimates of all users' signals during a bit interval with respect to the weights. The optimal solution is demonstrated to be equivalent to that of the maximum likelihood sequence estimation. For suboptimal solutions, the interference cancellation problem with weights can be solved by means of the least squares (LS) or the mean-squared error (MSE) estimation.

Specifically, we keep the MAI estimates unchanged but update the weights via an adaptive algorithm during each bit. It is interesting to note that when the LS criteria is applied, the suboptimal solution can be found through a recursive least-squares (RLS) algorithm [11]. At convergence this iterative solution is equivalent to the decorrelating detector. However, the computational complexity of the RLS-based decorrelating method is $O(NK^2)$ per bit, where N is the processing gain and K is the number of active users. This complexity is still too high for practical applications.

In this paper, a low-complexity normalized least mean square (LMS) algorithm is employed in searching for the optimal weights. On top of this, the products of the weights and the hard decisions made in the previous stage are used in regenerating the interference. The above procedures can be performed in a multistage manner with the complexity of only $O(NK)$ per stage. Our simulation results show that the proposed technique can provide a superior performance over some of the existing multiuser detectors.

The rest of the paper is organized as follows. The system model adopted in this work, including a transmitter and the single-user matched filters is described in Section 2. Section 3 briefly overviews previous PIC methods. The adaptive multistage PIC approach in the AWGN channel is presented in Section 4 after the introduction of the new perspective of interference cancellation. Section 5 describes the adaptive multistage PIC structure in a multipath fading channel. In Section 6, the bit error rate (BER) performance of various interference cancellation schemes are compared by means of simulation. Section 7 concludes the paper.

2 System Model

Consider a synchronous CDMA system with QPSK modulation in AWGN channel. The transmitter model for the i-th user is shown in Figure 1. The equivalent complex baseband representation of the received signal at the base station can be expressed as

$$\begin{aligned} r(t) &= \sum_{i=1}^{K} s_i(t) + z(t) = \sum_{i=1}^{K} \sqrt{P_i} b_i(t) PN_i(t) [PN^{(I)}(t) + jPN^{(Q)}(t)] + z(t) \\ &= \sum_{i=1}^{K} \sqrt{P_i} b_i(t) c_i(t) + z(t) \end{aligned} \tag{1}$$

where the subscript i denotes the i-th user,

P_i is the signal power,

$b_i(t) = \sum_{m=-\infty}^{\infty} a_i^{(m)} p(t - mT_b)$ is the data signal, where $a_i^{(m)}$ denotes a binary sequence taking values ± 1 with equal probability. $p(t)$ is a rectangular pulse with duration T_b.

$PN^{(I)}(t)$ and $PN^{(Q)}(t)$ are pseudo noise (PN) waveforms in the branches I and Q, respectively.

$PN_i(t)$ is the signature waveform.

$c_i(t)$ denotes the complex-valued PN waveform defined as $c_i(t) = PN_i(t)[PN^{(I)}(t) + jPN^{(Q)}(t)]$.

$z(t)$ is the additive Gaussian noise with double-sided spectrum density $N_0/2$.

K is the number of active users.

We assume all users have purely random PN codes. At the receiver, a matched filter is used for despreading. As a result, the output of the i-th user for its m-th bit is given by

$$\begin{aligned} y_i^{(m)} &= \frac{1}{\sqrt{T_b}} \int_{(m-1)T_b}^{mT_b} r(t) c_i^*(t) dt \\ &= \sqrt{E_{bi}} a_i^{(m)} + \sum_{\substack{j=1 \\ j \neq i}}^{K} \sqrt{E_{bj}} a_j^{(m)} \rho_{ji}^{(m)} + z_i \end{aligned} \tag{2}$$

where "*" represents complex conjugate. $E_{bi} = P_i T_b$ is the bit energy of the i-th user, and

$$\rho_{ji}^{(m)} = \frac{1}{T_b} \int_{(m-1)T_b}^{mT_b} c_j(t) c_i^*(t) dt, \quad i, j = 1, 2, \cdots, K \tag{3}$$

denotes the cross-correlation coefficient between c_i and c_j. z_i is the Gaussian noise component of the i-th user after despreading, which is expressed as

$$z_i = \frac{1}{\sqrt{T_b}} \int_{(m-1)T_b}^{mT_b} z(t) c_i^*(t) dt \tag{4}$$

The second term at the right hand of (2) represents the MAI. For convenience, we will drop the index m in the following discussion. The conventional single-user receiver estimates data a_i as

$$\hat{a}_i = \text{sgn}\{Y_i\} \tag{5}$$

where $\text{sgn}\{\cdot\}$ is the sign function, and

$$Y_i = \text{Re}\{y_i\} \tag{6}$$

3 Parallel Interference Cancellation

Without loss of generality, we assume the first user to be the user of interest.

3.1 Conventional Multistage PIC [8]

In this method, the MAI in the k-th stage is estimated as

$$\hat{I}_1^{(k)} = \text{Re}\{\sum_{i=2}^{K} \sqrt{E_{bi}} \hat{a}_i^{(k-1)} \rho_{i1}\} \tag{7}$$

The receiver then makes a decision based on the following rule

$$\hat{a}_1^{(k)} = \text{sgn}\{Y_1 - \hat{I}_1^{(k)}\} \tag{8}$$

It is clear that in the conventional multistage PIC, the receiver attempts to completely remove the MAI. Since the hard decisions made in the previous stage may be wrong, such a brute force cancellation can lead to a performance even worse than that without cancellation in some cases [1].

3.2 Partial PIC [2]

Since the estimates of MAI may not be completely correct, Divsalar *et al.* suggest to remove only part of it at one time [2, 10]. Furthermore, observing that the estimates may become more reliable in later stages when most of the interference is canceled, they propose to increase the amount of cancellation for each successive stage. The procedures for the iterative interference cancellation are as follows [2]

$$\begin{aligned} \tilde{a}_1^{(k)} &= p^{(k)}[Y_1 - \hat{I}_1^{(k)}] + [1 - p^{(k)}]\tilde{a}_1^{(k-1)} \\ \hat{a}_1^{(k)} &= \text{sgn}\{\tilde{a}_1^{(k)}\} \end{aligned} \tag{9}$$

where $p^{(k)}$ is the weight for the k-th stage cancellation, which is decided by a trial-and-error computer search [2]. In (9), the estimate $\hat{a}_1^{(k)}$ is based on the soft output $\tilde{a}_1^{(k)}$ which consists of two items, one is similar to that in the conventional PIC but with weight, while the other is a weighted soft output from the previous stage.

4 Adaptive Multistage PIC

4.1 Another Perspective of PIC

Divsalar *et al.*'s work motivates us to find the optimal weights for MAI cancellation. Suppose that the power levels of all users are known to the receiver at the base-station, we define an optimal cost function in terms of the squared Euclidean distance between the received signal $r(t)$ and the weighted sum of the estimates of all users' signals, i.e.,

$$\epsilon = \int_0^{T_b} \left| r(t) - \sum_{i=1}^{K} \lambda_i \sqrt{P_i} \hat{a}_i c_i(t) \right|^2 dt \tag{10}$$

where λ_i is the weight for the i-th user. $\hat{a}_i$ denotes the estimate of a_i. We try to minimize ϵ with a set of optimal weights $\{\lambda_i\}$.

From (10), we observe the following facts:

1. Without noise, the optimal weight should be $\lambda_i^o = a_i/\hat{a}_i$ and equals to 1 or -1 depending on whether the estimate $\hat{a}_i$ is correct or not. With the optimal weights, the weighted sum of all estimated signals is exactly the received signal, and hence ϵ equals to zero.

2. Instead of searching for the optimal weights $\{\lambda_i\}$, we can fix $\lambda_i = 1$ and search for the optimal sequence $(\hat{a}_1, \cdots, \hat{a}_K)$ to minimize ϵ. This results in the maximum-likelihood sequence detector with the complexity exponentially proportional to the number of users.

3. Neither the conventional multistage PIC where $\lambda_i = 1$, nor the partial multistage PIC where $0 < \lambda_i \leq 1$ is the optimal solution to (10).

4. For a suboptimal solution, a modified cost function can be formed in the sense of LS or MSE. We will demonstrate that the corresponding problem can be solved in an iterative manner through the RLS or the LMS algorithms.

Chen and Roy proposed in [11] an adaptive multiuser structure. In their scheme, they try to estimate the discrete received sequence through the PN codes and a set of coefficients $\{\lambda_i(m), m = 1, 2, \cdots, K\}$ during each symbol. The optimal coefficients of $\{\lambda_i(m), m = 1, 2, \cdots, K\}$ can be obtained by solving the LS criterion. The RLS algorithm was used in [11] to find the optimal coefficients. The bit decision is carried out as

$$\hat{a}_i = \mathrm{sgn}[\lambda_i(2N)] \tag{11}$$

As pointed out in [11], when $\{\lambda_i(m), m = 1, 2, \cdots, K\}$ converges to its optimal solution in LS, this approach is equivalent to a matrix inverse decorrelating detector [11].

4.2 LMS Multistage PIC

The main drawback of the aforementioned RLS-based decorrelating method is its complexity, which is $O(NK^2)$ per bit. Since normally $N > K$ for a CDMA system, its complexity is actually $O(K^3)$, similar to that of the matrix inverse decorrelating detector.

To reduce the complexity caused by the RLS algorithm, we suggest the LMS algorithm in the proposed adaptive multistage PIC approach. The received signal is sampled at the chip rate after chip matched filtering. The N samples of the received signal within one bit can be written as

$$r(m) = \sum_{i=1}^{K} \beta_i a_i c_i(m) + z(m) \tag{12}$$

where β_i is the amplitude of the i-th user. a_i and $c_i(m)$ denote the bit and the PN sequence of the i-th user, respectively. $z(m)$ is the noise sample.

Since the LMS algorithm is based on the MSE criteria, the cost function given in (10) is modified as follows

$$\min_{\boldsymbol{\lambda}^{(k)}} \quad E\left[\left|r(m) - \hat{r}^{(k)}(m)\right|^2\right] \tag{13}$$

where $\boldsymbol{\lambda}^{(k)} = (\lambda_1, \lambda_2, \cdots, \lambda_K)^T$ is the weighting vector in the k-th stage. $\hat{r}^{(k)}(m)$ is the estimate of the received signal in the k-th stage which is defined as

$$\hat{r}^{(k)}(m) = \sum_{i=1}^{K} c_i(m) \hat{a}_i^{(k-1)} \lambda_i^{(k)}(m) \tag{14}$$

where $\hat{a}_i^{(k-1)}$ is the estimate of a_i in the $(k-1)$-th stage. Considering the LMS algorithm has a slower convergence rate and is more sensitive to its initial state as compared to the RLS algorithm, the conventional single-user correlators are employed (the reason will be explained later) and their outputs are served as the inputs of the first stage of the LMS PIC, i.e.,

$$\hat{a}_i^{(0)} = \mathrm{sgn}(Y_i) \tag{15}$$

where Y_i is defined in (6). The weighting vector is adjusted via a normalized LMS algorithm that operates in a bit interval and on a chip basis as follows

$$\boldsymbol{\lambda}^{(k)}(m+1) = \boldsymbol{\lambda}^{(k)}(m) + \frac{\mu}{\|\hat{\boldsymbol{s}}^{(k)}(m)\|^2}[\hat{\boldsymbol{s}}^{(k)}(m)]^* e^{(k)}(m) \tag{16}$$

where μ is the step size. $\hat{\boldsymbol{s}}^{(k)}$ denotes the input vector of the LMS algorithm in the k-th stage and its i-th element is defined as

$$\hat{s}_i^{(k)}(m) = c_i(m)\hat{a}_i^{(k-1)} \tag{17}$$

In (16), $e^{(k)}(m)$ is the error between the desired response and its estimate in the k-th stage, namely

$$e^{(k)}(m) = r(m) - \hat{r}^{(k)}(m) \tag{18}$$

For each bit, $\boldsymbol{\lambda}^{(k)}(N-1)$ is used as the weight in the interference cancellation. Consider the i-th user in the k-th stage. The interference cancellation is carried out as follows

$$\xi_i^{(k)}(m) = r(m) - \sum_{\substack{j=1 \\ j\neq i}}^{K} \lambda_j^{(k)}(N-1)\hat{s}_j^{(k)}(m) \tag{19}$$

A more reliable decision is then made based on the less interfered signal $\xi_i^{(k)}(m)$, namely

$$\hat{a}_i^{(k)} = \mathrm{sgn}[Y_i^{(k)}] \tag{20}$$

where

$$Y_i^{(k)} = \mathrm{Re}\left\{\sum_{m=0}^{N-1} \xi_i^{(k)}(m)c_i^*(m)\right\} \tag{21}$$

The block diagram of the LMS-based adaptive PIC scheme is depicted in Figure 2, and the weight updating through the LMS algorithm in the adaptive PIC scheme is illustrated in Figure 3.

The step size μ plays an important role in the LMS algorithm. For the normalized LMS algorithm deployed in our approach, μ must satisfy $0 < \mu < 2$ to ensure the convergence [12] of the LMS algorithm. A larger step size can result in a faster convergence rate, but also causes a higher excessive gradient noise due to the mis-adjustment of the coefficients [12]. Another important factor that affects the convergence rate of the LMS algorithm is its initial state. When the perfect knowledge of all users' levels is available, the initial value of the weight for each user can be set to its corresponding amplitude. Ideally, with this setting, if all bit decisions from the previous stage are correct, the LMS algorithm will just fine-tune its coefficients due to a small error signal. For a non-ideal situation, more accurate bit and channel estimates can lead to a faster convergence of the weights to their optimal values.

5 Adaptive Multistage PIC for Fading Channel

A cellular CDMA system usually works in a multipath fading environment. The multipath fading channel is often assumed to be wide-sense stationary with uncorrelated scattering [13]. Based on this assumption, the channel model for the i-th user can be written as

$$h_i(\tau;t) = \sum_{l=0}^{L-1} \alpha_{il}(t)\delta(\tau - \tau_{il}) \tag{22}$$

where L is the number of paths of the channel and is supposed to be time-invariant. τ_{il} is the relative delay of the l-th path. $\alpha_{il}(t)$ represents the time-variant complex channel parameter taking into account the amplitude attenuation and the phase shift. In the Rayleigh fading channel, $\alpha_{il}(t)$ is a complex Gaussian random variable with zero mean, while in the Rician fading channel, $\alpha_{il}(t)$ is still a complex Gaussian but with non-zero mean. The largest delay of a multipath channel is also called the multipath spread. Due to the wideband nature of CDMA systems, the multipath spread of a typical outdoor mobile radio channel is usually larger than a chip duration, resulting in the frequency selective fading which can be very hostile to a wideband CDMA system without a special treatment. To combat the frequency selective fading, Price and Green [14] have proposed a RAKE structure which can resolve the multipath and combine their energies as long as the multipath spread is larger than $1/W$, where W is the bandwidth of the transmitted signal [13]. With the same transmitter model illustrated in Figure 1, the received signal through a multipath fading channel given by (22) can be written as

$$r(t) = \sum_{l=0}^{L-1} \sum_{i=1}^{K} \alpha_{il}(t) s_i(t - \tau_{il}) + z(t) \tag{23}$$

Consider the i-th user, the RAKE receiver computes at each of its fingers as follows

$$y_i(l) = \frac{1}{\sqrt{T_b}} \int_{\tau_{il}}^{T_b+\tau_{il}} r(t) c_i^*(t - \tau_{il}) dt \quad l = 0, 1, \cdots, L-1 \tag{24}$$

We assume the channel fading is slow so that $\alpha_{il}(t)$ does not change within a bit interval and thus can be denoted as α_{il}. The outputs from the L fingers are then combined using the maximal ratio rule [13], and we obtain

$$y_i = \sum_{l=0}^{L-1} \alpha_{il}^* y_i(l) \tag{25}$$

For the conventional single-user RAKE receiver, the decision is made as

$$\hat{a}_i = \text{sgn}\{Y_i\} \tag{26}$$

where $Y_i = \text{R}e\{y_i\}$.

Our adaptive multistage PIC scheme can be easily applied to multipath fading channels. To start with, the received signal is sampled as in (12). Then, the resulting samples, the bit decisions in the previous stage, and the PN sequences along with their delayed replicas of all active users are used to compute adaptively the weights through the normalized LMS algorithm. The block diagram of the LMS weight adaptation in the multipath fading environment is illustrated in Figure 4. Unlike the case in the AWGN channel, the PIC here uses L coefficients for each user to track all the paths of the channel. From Figure 4, the estimation of the received signal is given by

$$\hat{r}^{(k)}(m) = \sum_{i=1}^{K} \sum_{l=0}^{L-1} \hat{s}_i^{(k)}(m - l) \lambda_{il}(m) \tag{27}$$

where $\hat{s}_i^{(k)}(m)$ is defined in (17). The coefficients are updated as in (16), but the dimension of the coefficient vector $\boldsymbol{\lambda}$ changes from K to $L \times K$. As in the AWGN channel, the interference cancellation in the k-th stage is performed as

$$\xi_i^{(k)}(m) = r(m) - \sum_{\substack{j=1 \\ j \neq i}}^{K} \sum_{l=0}^{L-1} \lambda_{jl}^{(k)}(N-1) \hat{s}_j^{(k)}(m - l) \tag{28}$$

No channel equalization technique is used here to deal with the intersymbol interference (ISI) caused by the multipath, the ISI is actually treated as noise. Next, the RAKE diversity is carried out based on the less interfered signal $\xi_i^{(k)}(m)$, i.e.,

$$Y_i^{(k)} = \mathrm{Re}\left\{\sum_{l=0}^{L-1}\sum_{m=0}^{N-1}\xi_i^{(k)}(m)c_i^*(m-l)\alpha_{il}^*\right\} \tag{29}$$

Finally, a more reliable decision is made as

$$\hat{a}_i^{(k)} = \mathrm{sgn}[Y_i^{(k)}] \tag{30}$$

The adaptive PIC scheme can cope with unknown user powers, especially when the processing gain N is sufficient large. However, for most situations where N is not large enough, either perfect channel parameters or their estimates must be used as the initial values of $\{\lambda_{il}(m)\}$. Moreover, to ensure the performance improvement with multistage cancellation, the channel estimations need to be sufficiently accurate.

6 Simulation Results

We have carried out simulations to evaluate the performance of various interference cancellation schemes discussed in this paper. The terms *conventional PIC* and *partial PIC* are used in this section for the two schemes discussed in Sections 3.1 and 3.2, respectively. *RLS decorrelating* represents the approach described in Section 4.1, while *LMS PIC* is the proposed adaptive PIC method. The numbers appearing in the legends of the figures in this section stand for the weights in the *partial PIC* or the step sizes in the *LMS PIC*, respectively. For example, the numbers "0.7, 0.8" in the legend "2-stage Partial PIC, 0.7, 0.8" mean the weights for the *partial PIC* are 0.7 in the first stage and 0.8 in the second stage. In all simulations, system model described in Section 2 is adopted with a processing gain of 64. For a system with perfect power control, E_b/N_0=7dB is used for all users. For a power-unbalanced system, the power levels are assumed to be fixed and uniformly distributed over the range from 0 to 15dB. For all cases, only the performance of the weakest user is plotted with E_b/N_0=7dB. All single user bounds in the figures are obtained by simulation.

Figures 5(a)–5(d) show the performance of various multiuser detection schemes in a CDMA system with perfect power control. As shown in Figure 5(a), all methods provide a better performance than the conventional single-user receiver. Among the single-stage schemes, the *LMS PIC* and the *RLS decorrelating* methods have the best performance. For example, to maintain a BER of 0.01, the conventional single-user detector can support 7 users. The *single-stage conventional PIC* and the *single-stage partial PIC* improve the capacity to 17 and 20 users, respectively, while the *single-stage LMS PIC* and *RLS decorrelating* have a comparable performance and can accommodate 26 and 27 active users, respectively (Figure 5(a)). By increasing the number of stages to 2 (Figure 5(b)), the performance of the *LMS PIC* technique is further improved. In particular, the *2-stage partial PIC* offers a capacity of 30 users and the *2-stage LMS PIC* can support 35 users (Figure 5(b)). The introduced adaptive PIC scheme can provide a considerable performance improvement over the *RLS decorrelating* method with much lower complexity. As the number of stages increase to 3 (Figure 5(c)) and 4 (Figure 5(d)), the performance of the *LMS PIC* still outperforms the *conventional PIC* and the *partial PIC* schemes.

Figures 6(a) and 6(b) show the performance of these multiuser detection schemes in a power-unbalanced system. The proposed *single-stage LMS PIC* outperforms both the *single-stage conventional* and *partial PIC*, but has a worse performance than the *RLS decorrelating* due to the fact that the LMS algorithm has a relatively slower convergence rate compared with the RLS algorithm. For a BER of 0.01, the *single-stage conventional* and *single-stage partial PIC* can support 8 and 7 users, respectively. It seems that the weighting in the *partial PIC* scheme does not provide much benefit in this case. In contrast, the introduced *single-stage LMS* can accommodate 18 users and the *RLS decorrelating* has a capacity of 27 users. With an additional stage (Figure 6(b)), the number of active users can be supported by the *2-stage conventional*, *2-stage partial PIC*, and *2-stage LMS* are 18, 19, and 34, respectively. Comparing results in Figures 5(b) and 6(b), the unbalanced power almost has no impact on the performance of the proposed *LMS PIC* and the *RLS decorrelating* schemes while it incurs a drop in capacity of the *2-stage partial PIC* from 30 to 19. Note that in Figure 6(b) the results for the LMS PIC are not monotonic. For instance, the BER decreases as the number of users increases from 10 to 15. This may be incurred by the excessive gradient noise of the LMS algorithm with large step size. Recall (16), the effective step size of the normalized LMS equals to $\frac{\mu}{||\hat{\mathbf{s}}^{(k)}(m)||^2}$. If μ remains constant, the smaller the number of users, the larger the effective step size, and hence the higher the gradient noise. Thus when μ is optimized for a large number of users during simulations, it is possible that the excessive gradient noise may cause a poorer BER when the system load is low.

The impact of an imperfect amplitude estimation on the performance of the introduced adaptive PIC is depicted in Figure 7. When the amplitudes of all users are unknown, the initial weights for the LMS algorithm are set to 1. The values of the weights at the last iteration of the current bit are used as the initial values of the weights for the next bit. The results shown in Figure 7 indicate that the imperfect power estimation only has a little impact on the performance of the introduced adaptive PIC.

We also study the performance of the aforementioned interference cancellation methods in a single-path Rician fading channel. In our simulation, the power difference between the specular and the diffuse components of the Rician fading channel is set to 7dB. E_b/N_0 remains 7dB. Since coherent channel demodulation is used, perfect amplitude and phase information of all users is assumed to be available. The results are plotted in Figures 8. Figure 8(a) shows the performance comparison of various *single-stage* interference cancellation schemes. To achieve the BER of 0.01, the *conventional* and *partial PIC* schemes can accommodate 18 and 20 users, respectively, while the *RLS decorrelating* and the introduced *LMS PIC* can support 28 users. With an additional stage, a considerable increase in number of users is observed in Figure 8(b). For the BER of 0.01, the number of users can be supported by the *2-stage conventional*, *2-stage partial PIC* and *2-stage LMS PIC* are 27, 37 and above 40, respectively.

The performance of various PIC schemes in a two-path Rayleigh fading channel is plotted in Figure 9 for E_b/N_0 =17dB. The delay of the second path equals to T_c. An even multipath profile is adopted. As can be seen, all PIC techniques provide considerable improvement over the single-user detector. For single-stage detectors, the *conventional PIC* and the *partial PIC* can accommodate 17 and 16 users, respectively, at the BER of 10^{-3}, while the *LMS PIC* can support 20 users (Figure 9(a)). With an additional stage introduced, the *LMS PIC* method still shows its superiority (Figure 9(b)). In particular, at the BER of 10^{-3}, the *2-stage conventional PIC* and the *2-stage partial PIC* can support 34 and 37 users respectively, while the *2-stage LMS PIC* has a capacity of 42 users.

7 Conclusions

In this paper, we propose a new adaptive multistage partial PIC scheme. Unlike the partial PIC in [2, 10], a set of weights are introduced for all users and they can be obtained from the LMS algorithm which tries to minimize the MSE between the received signal and its estimate. Due to the relatively slow convergence rate and the impact of gradient noise, the LMS algorithm may not converge to its optimum solution within one bit interval. The introduction of multiple stages overcomes this problem and greatly improves the system performance. The weights obtained in the proposed method contain additional knowledge on the accuracy of each estimated interference which is indispensable to enhance the performance of multistage PIC. Simulation results show a considerable performance improvement of the proposed adaptive PIC over the existing interference cancellation methods in both AWGN and multipath fading channels.

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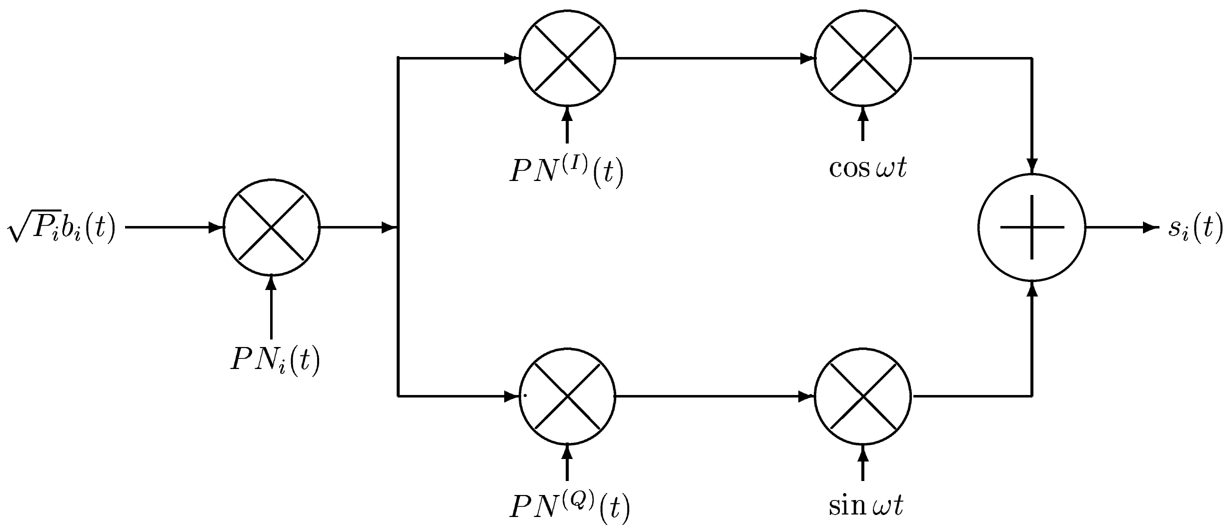


Figure 1: Transmitter model for the i-th user

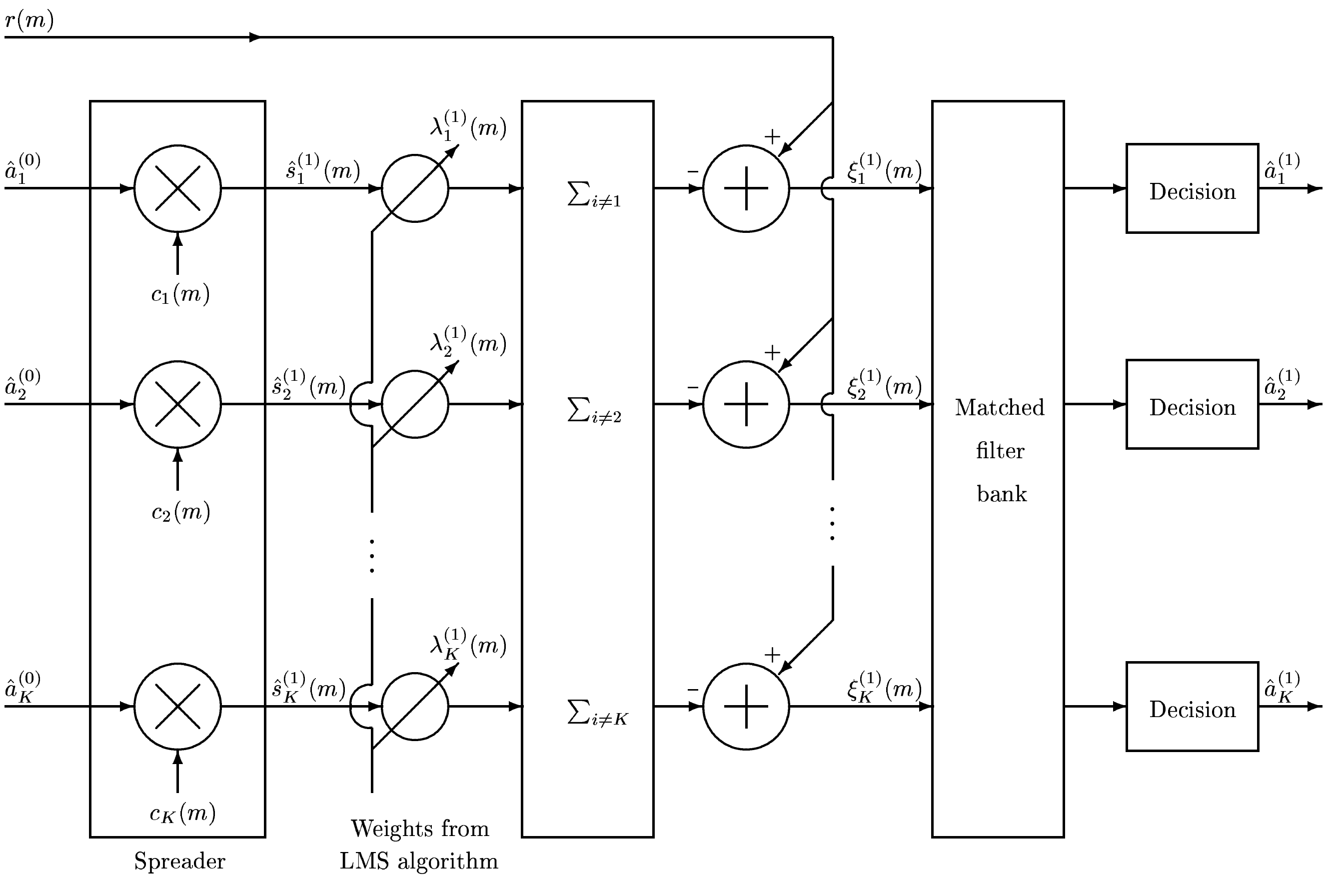


Figure 2: One stage of the adaptive multistage PIC detector in the AWGN channel

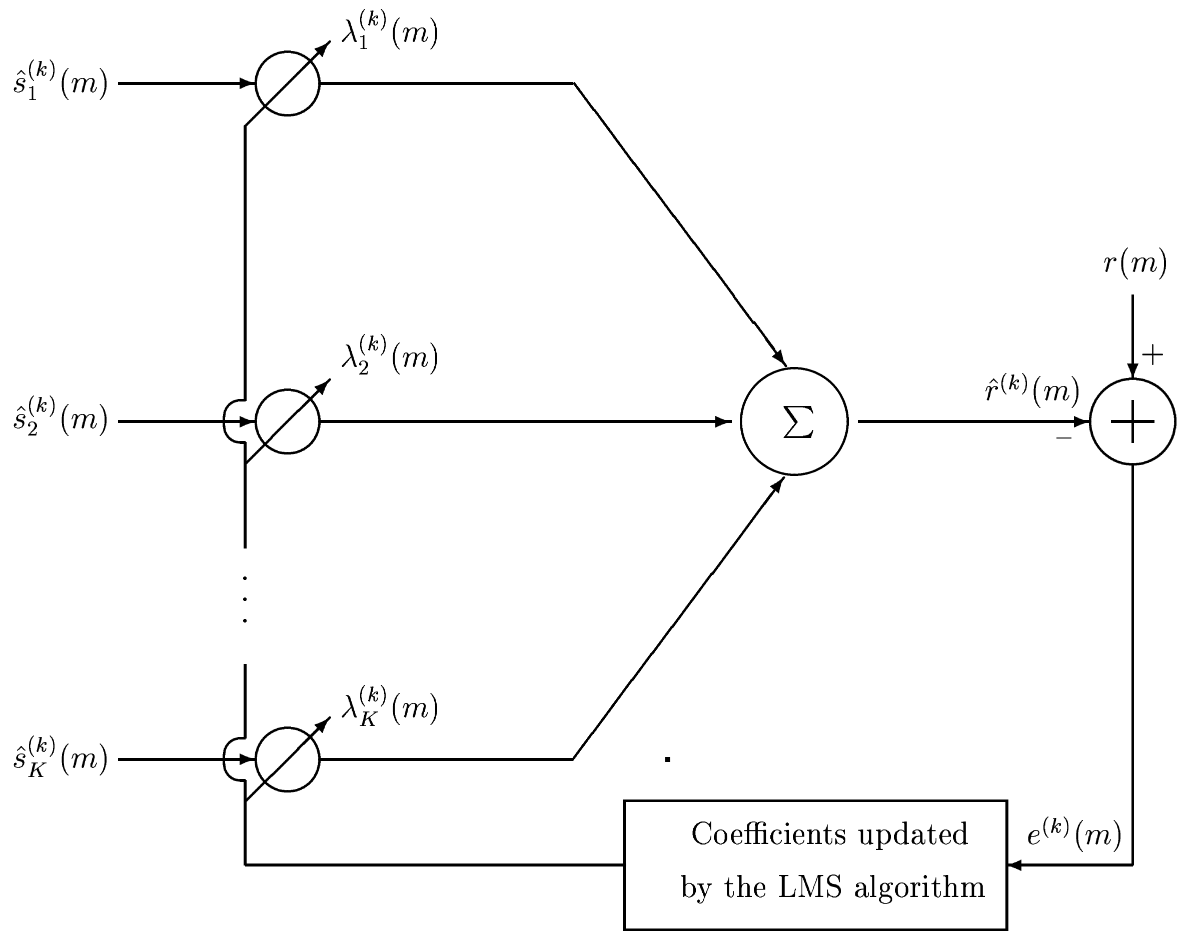


Figure 3: Weight updating in the adaptive multistage PIC in the AWGN channel

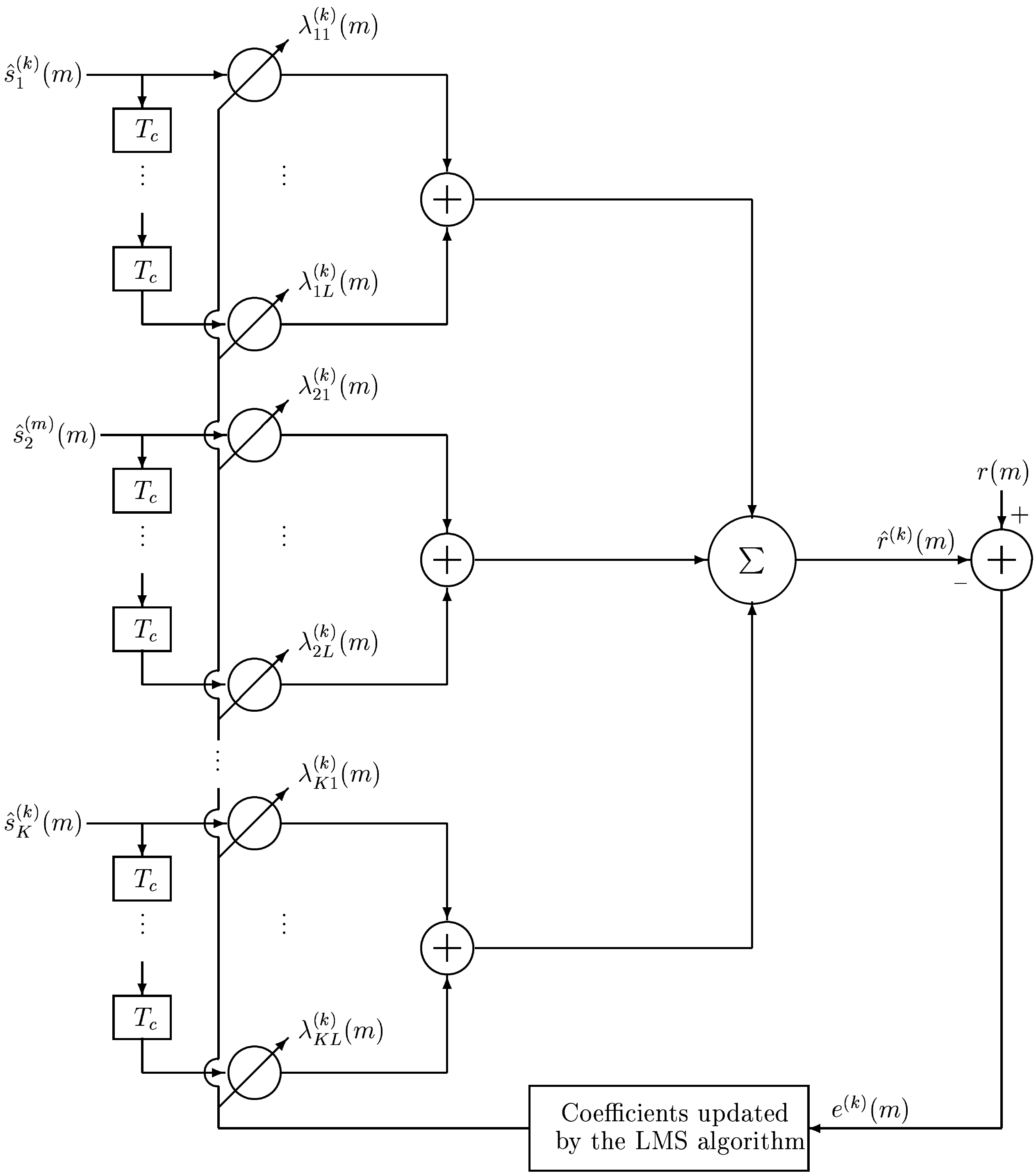
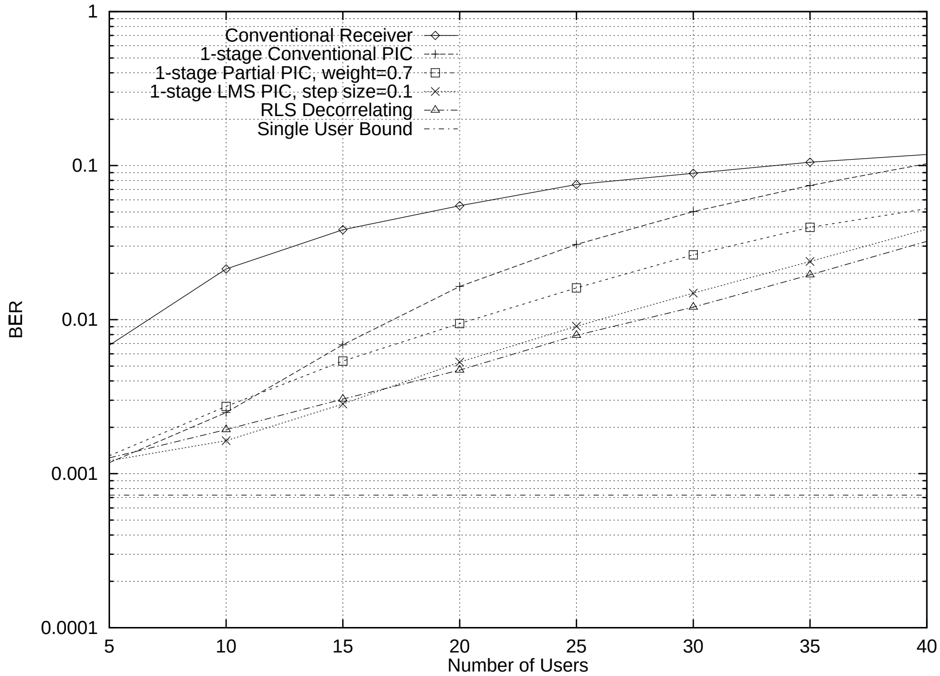
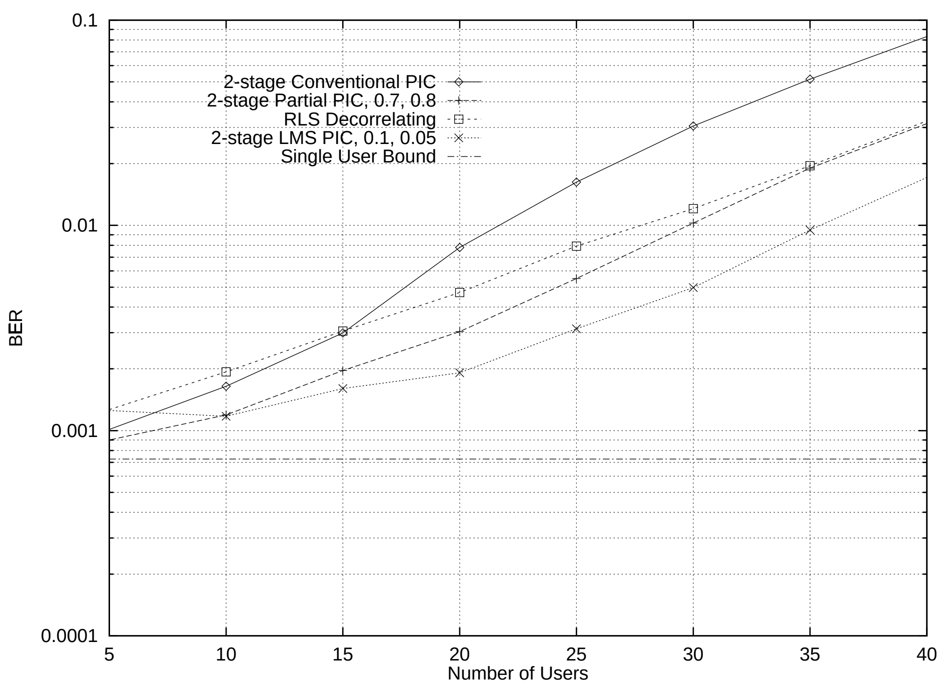


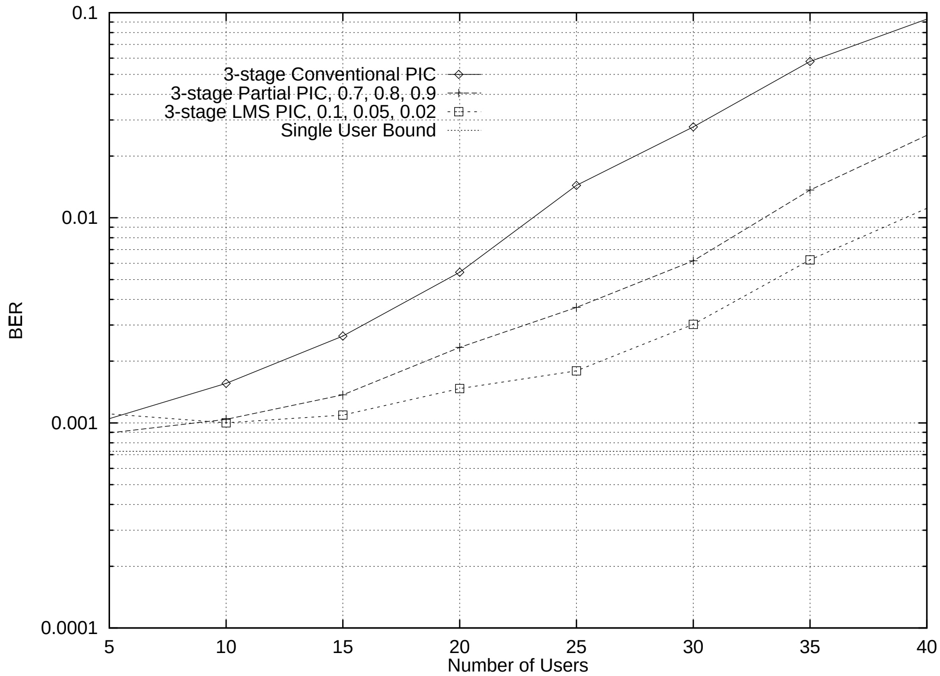
Figure 4: Weight updating in the adaptive multistage PIC in a multipath fading channel



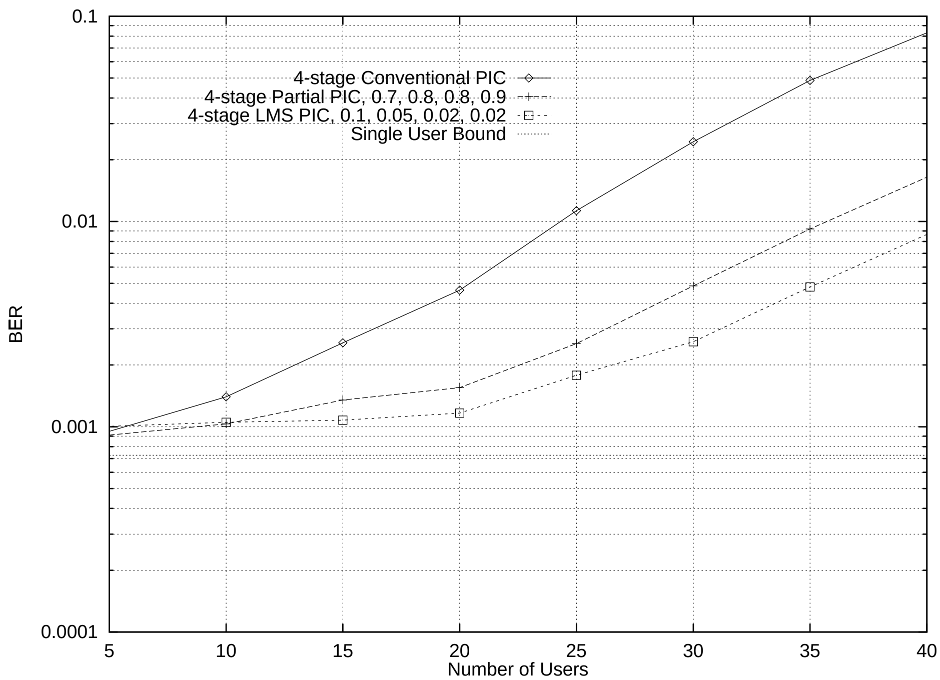
(a) single stage, perfect power control



(b) 2-stage, perfect power control

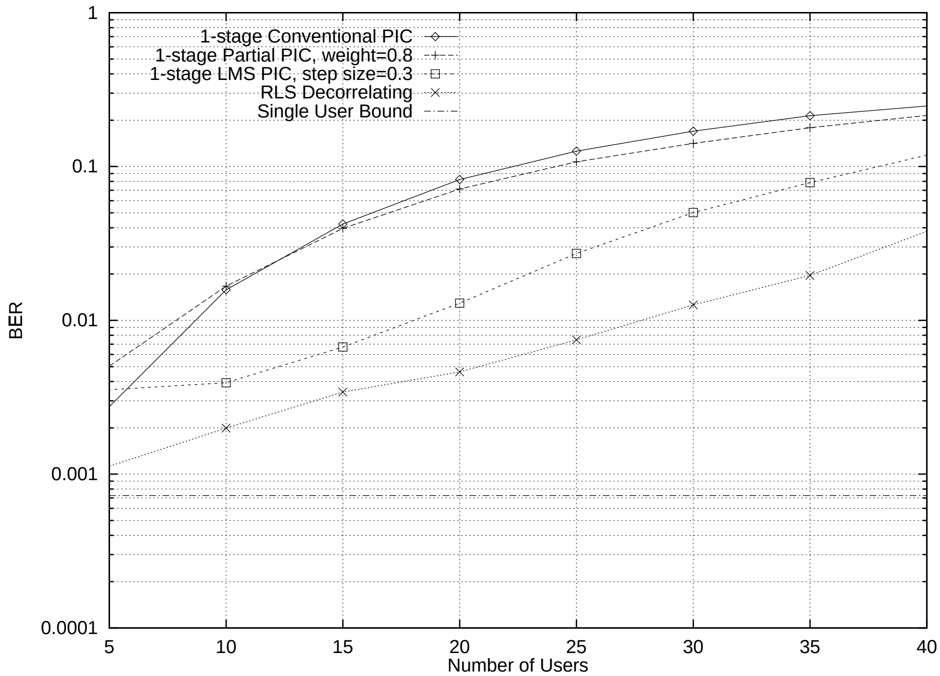


(c) 3-stage, perfect power control

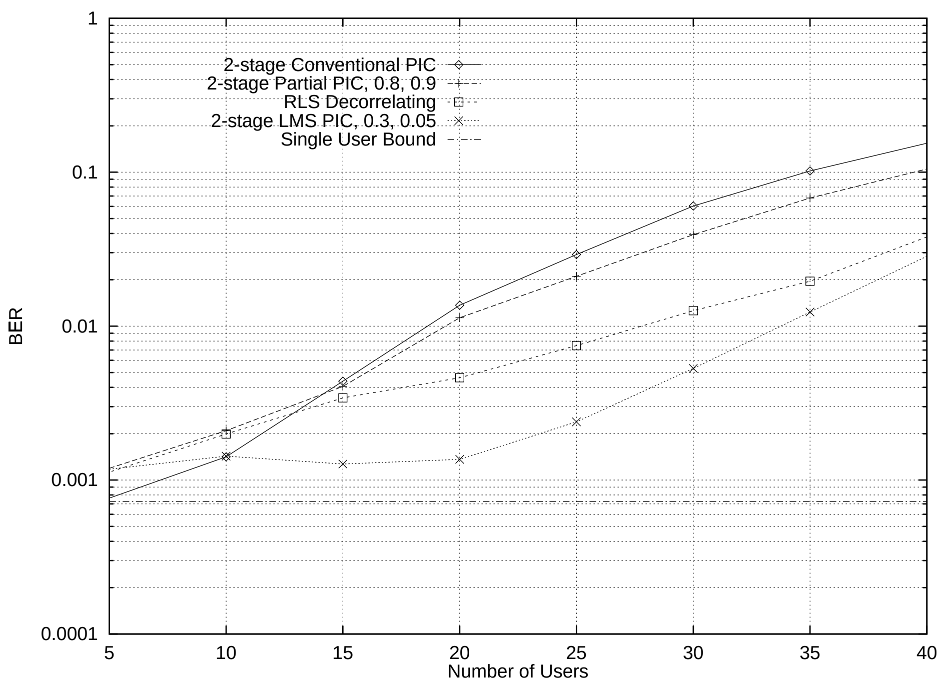


(d) 4-stage, perfect power control

Figure 5: Performance comparison of various multiuser detection schemes in an AWGN channel with perfect power control (E_b/N_0 =7dB)

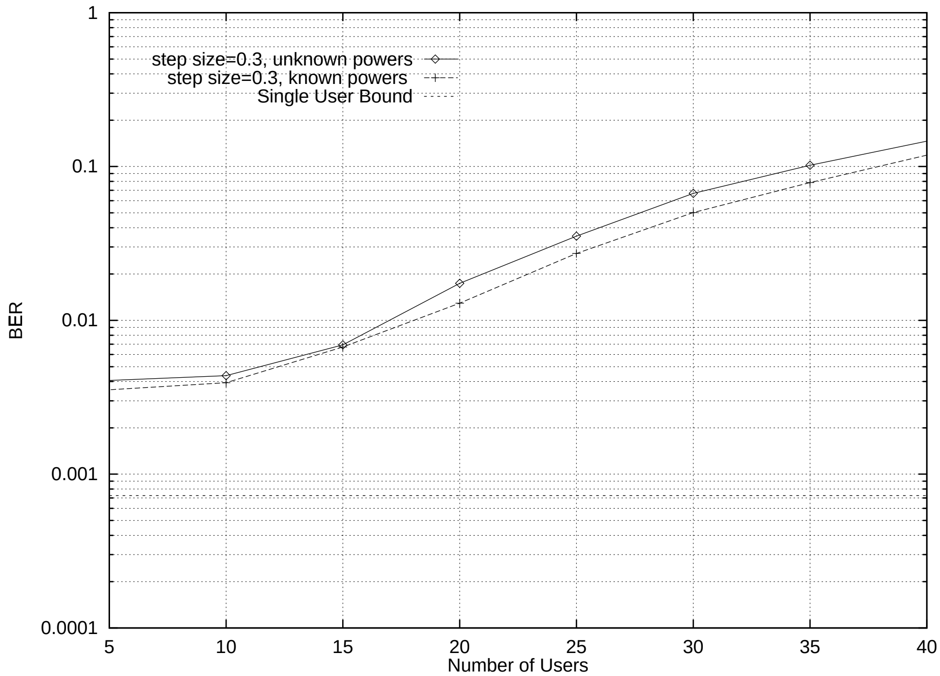


(a) single-stage, unbalanced power

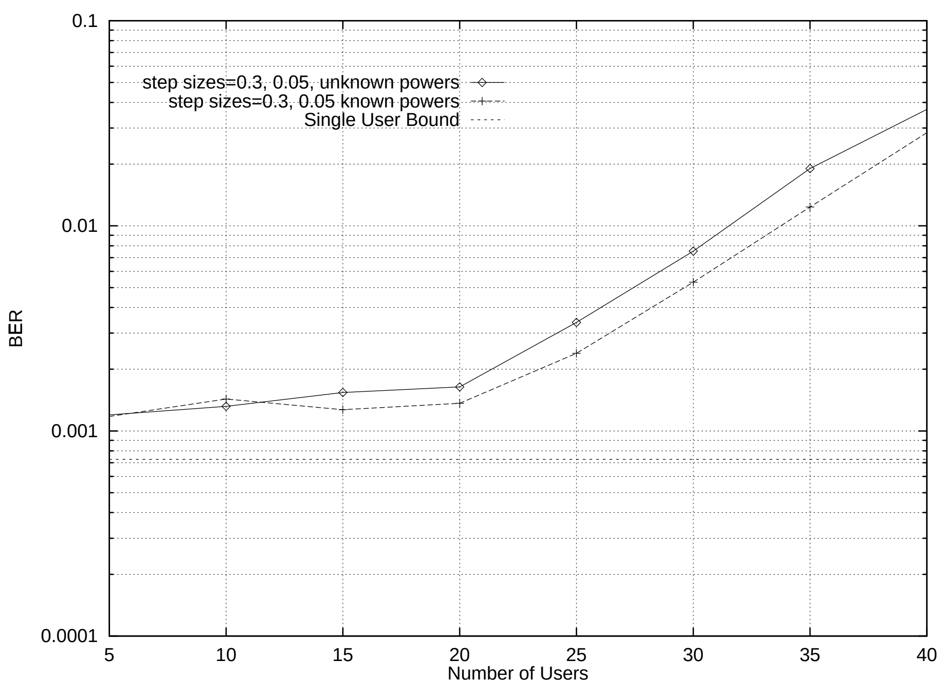


(b) 2-stage, unbalanced power

Figure 6: Performance comparison of various multiuser detection schemes in an AWGN channel with unbalanced power (E_b/N_0 =7dB)

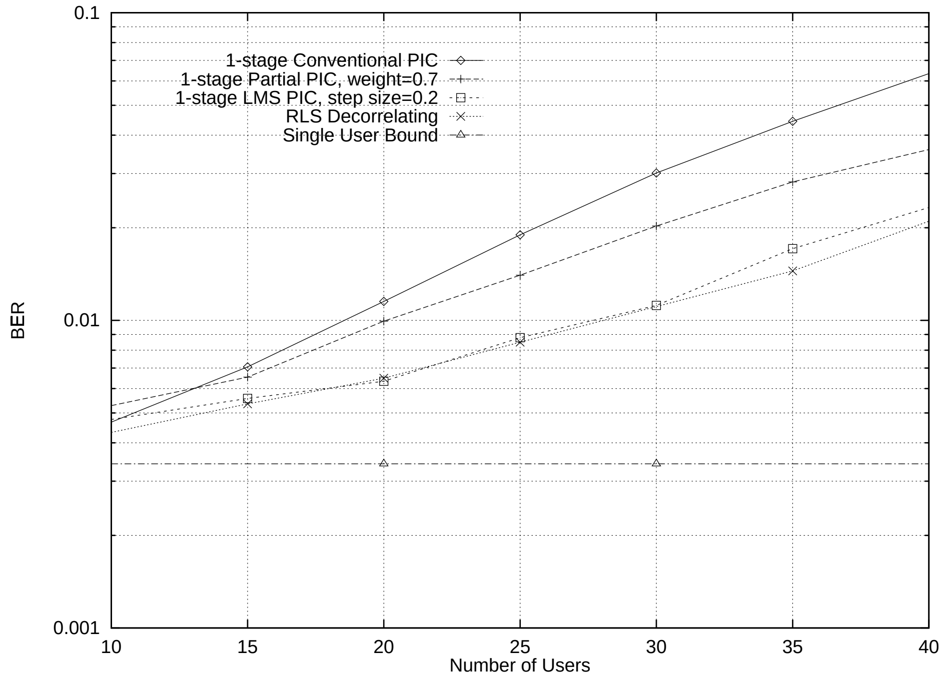


(a) single-stage, unbalanced power

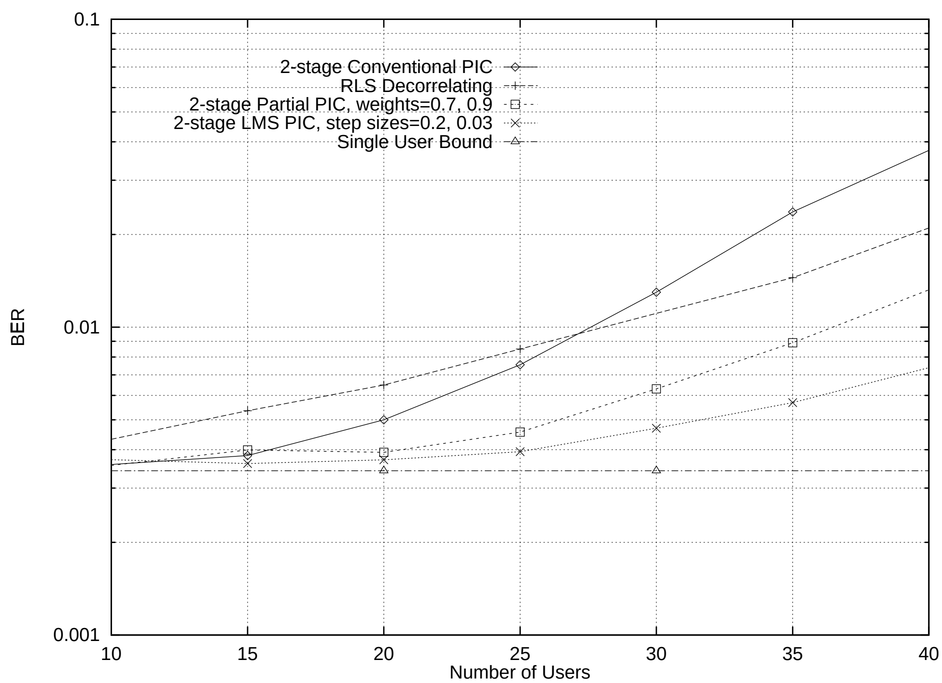


(b) 2-stage, unbalanced power

Figure 7: Effect of imperfect power estimation on the performance of the adaptive PIC scheme in an AWGN channel (E_b/N_0 =7dB)

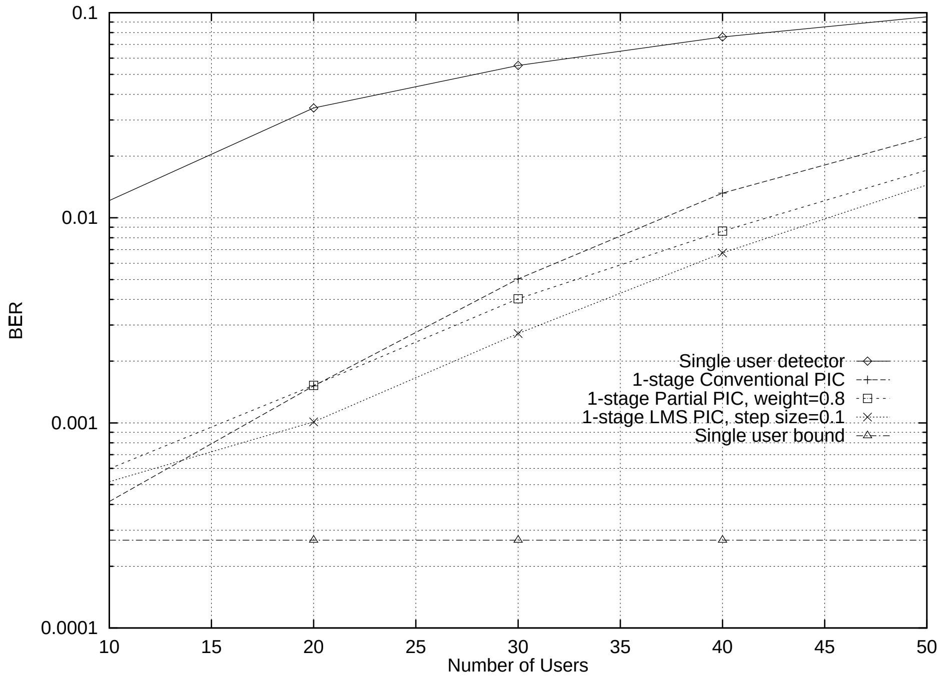


(a) single stage

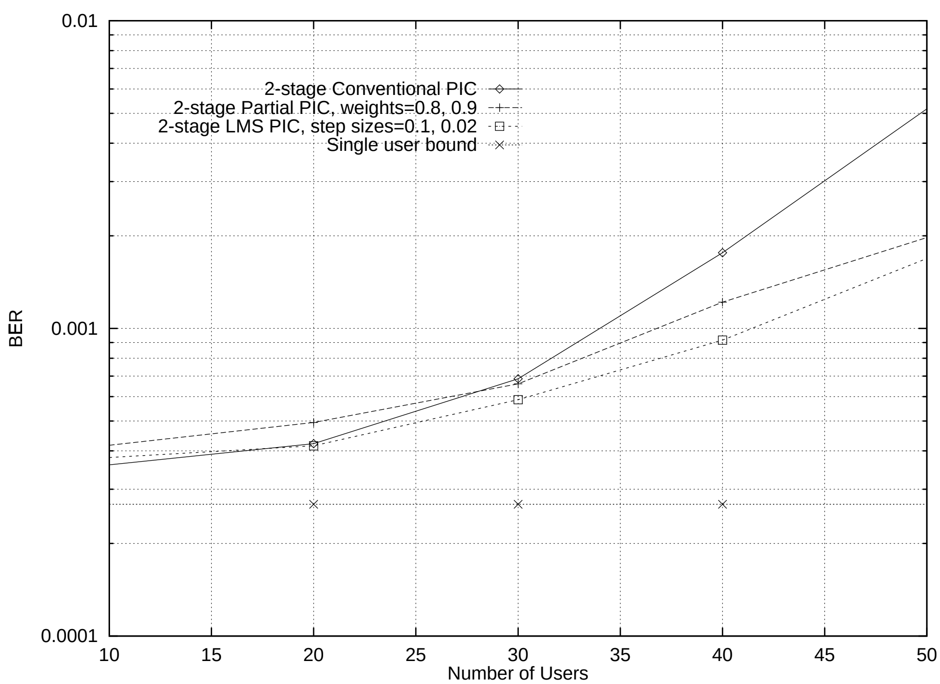


(b) 2-stage

Figure 8: Performance comparison of various interference cancellation schemes over a single-path Rician fading channel ($E_b/N_0 = 7$dB)



(a) single stage



(b) 2-stage

Figure 9: Performance comparison of various interference cancellation schemes over a 2-path Rayleigh fading channel (E_b/N_0 =17dB)