Joint Maximum-Likelihood CFO and Channel Estimation for OFDMA Uplink Using Importance Sampling

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***Abstract*—In this paper, the optimal carrier frequency offset (CFO) and channel estimator for an orthogonal frequency-division multiple-access (OFDMA) uplink based on a joint maximum-likelihood (ML) criterion is derived. Direct implementation of the resultant estimation scheme is challenging due to the need for a multidimensional exhaustive search in multi-CFO estimation. To solve this problem, an optimization theorem is exploited, and a computationally efficient method using an importance sampling technique is proposed. Without the need to provide an initial estimate, the proposed estimator guarantees the generation of the global optimal solution. Simulation results clearly verify the effectiveness of the proposed estimation scheme.**

***Index Terms*—Carrier frequency offset, channel estimation, importance sampling, maximum likelihood, orthogonal frequency-division multiple-access (OFDMA).**

I. Introduction

SINCE orthogonal frequency-division multiple access (OFDMA) is widely regarded as a promising technique for broadband wireless networks [1], it has recently attracted a lot of attention. In OFDMA, all users simultaneously transmit their data to the base station by modulating an exclusive set of orthogonal subcarriers; thus, the receiver at the base station can easily separate each user's signal in the frequency domain.

In OFDMA uplink transmissions, there are two challenging issues. The first one is frequency synchronization since OFDMA, which is an orthogonal frequency-division multiplexing (OFDM)-based technique, is particularly sensitive to carrier frequency offsets (CFOs). Moreover, in an OFDMA uplink, different users introduce different CFOs; therefore, the CFO estimation at the base station is a multivariable estimation problem, which is computationally expensive. The second challenge is channel estimation since a large number of channel parameters need to be estimated for coherent detection.

Depending on the specific carrier-assignment schemes (CASs), different algorithms for frequency synchronization have been proposed for OFDMA uplink in the literature. For systems with subband-based CASs, two methods are proposed in [2] and [3]. The first scheme tries to use the redundancy that is offered by the cyclic prefix (CP), whereas the second one exploits the virtual subcarriers. To maximize the frequency diversity and increase the capacity of OFDMA systems, an interleaved CAS is required. For this kind of an OFDMA system, a frequency estimation scheme exploiting the periodic structure of the signals that are transmitted by each user is proposed in [4]. Coping with the requirements for dynamic resource allocation and scheduling in future wireless systems, the generalized CAS is desired, which provides more flexibility than subband-based or interleaved schemes. For OFDMA systems with a generalized CAS, several schemes are proposed in [5]–[7]. In [5], synchronization is only performed on one new user while assuming that all existing users have already been synchronized. However, this situation may be restrictive in practical systems. A more general case where all users need to be synchronized is considered in [6] and [7], in which iterative programming techniques (e.g., expectation maximization and alternating projection) are used, and good performance can be achieved. However, in these iterative estimators, the global optimality cannot be guaranteed, and the initial guess point is critical.

In this paper, the problem of joint CFO and channel estimation for all users in an OFDMA uplink transmission is addressed. Similar to the frame structures in many standardized multicarrier systems, we assume that a training block is available for the estimation task. Without loss of generality, it is assumed that the training block is composed of only one OFDM symbol. Based on the maximum-likelihood (ML) criterion, the joint CFO and channel estimator is derived. It is found that the solution to this problem is very challenging due to the need of a multidimensional exhaustive search. To overcome this problem, an importance sampling-based estimation scheme is proposed. In this scheme, based on an optimization theorem, the closed-form solution to the multi-CFO estimation is derived first, which is guaranteed to be the global optimal solution. Due to the presence of a multidimensional integral in the explicit solution, the importance sampling method is exploited to remove the difficulty in evaluation. With the CFO estimates, the channel responses for all users are then recovered. Compared with the existing methods in the literature, the proposed scheme does not need an initial estimate and can guarantee the solution to be the global optimal solution. Moreover, the

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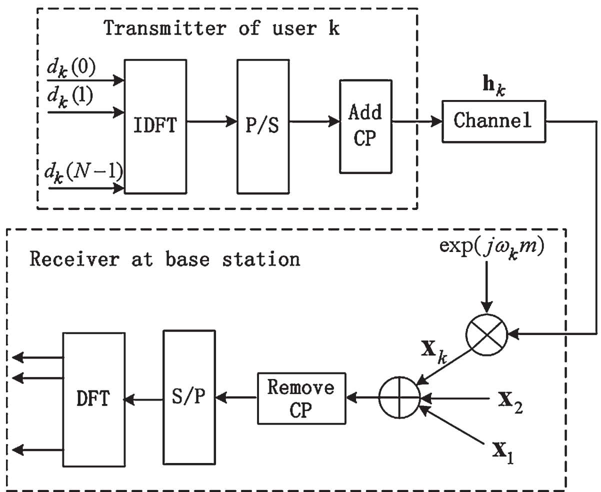

Fig. 1. Baseband diagram for OFDMA uplink.

computational complexity of the proposed scheme is lower than the scheme based on alternative projection [7]. Furthermore, it should be stressed that the proposed scheme is suitable for any CAS, which is required for practical OFDMA systems, such as IEEE 802.16 [1].

The rest of this paper is organized as follows. In Section II, the considered OFDMA system model is presented. In Section III, the ML estimator for the joint CFO and channel estimation is derived, and an efficient algorithm based on importance sampling is proposed. Section IV presents simulation results to verify the effectiveness of the proposed scheme. Conclusions are drawn in Section V.

Notations used are as follows. $(\cdot)^{-1}$, $(\cdot)^T$, and $(\cdot)^H$ denote the inverse, the transpose, and the conjugate transpose operations, respectively. The $k \times k$ identity and zero matrices are denoted by $\mathbf{I}_{k\times k}$ and $\mathbf{0}_{k\times k}$, respectively, and $\|\mathbf{x}\|$ represents the norm operation for vector $\mathbf{x}$. Throughout this paper, MATLAB notations for matrices and vectors are used.

II. Signal Model

In the considered OFDMA system, as shown in Fig. 1, K users simultaneously transmit different data streams using an exclusive set of subcarriers to the base station. Before initiating the transmission, the timing for each user is acquired by using the downlink synchronization channel from the base station. Consequently, the transmissions from all users can be regarded as quasi-synchronous. The total number of subcarriers is denoted as N, and one block of frequency-domain symbols that are sent by the kth user is denoted as $d_k = [d_k(0), \ldots, d_k(N-1)]^T$, where $d_k(i), i = 0, \ldots, N-1$, is nonzero if and only if the ith subcarrier is modulated by the kth user. The frequency-domain block is first modulated onto different subcarriers by left-multiplying an N-point inverse fast Fourier transform (FFT) matrix $\mathbf{F}^H$, where $\mathbf{F}$ is the FFT matrix with $\mathbf{F}(k,l) = (1/\sqrt{N})\exp(-(j2\pi kl/N))$. After inserting a CP of length L_{cp} into each block of the time-domain signal (denoted as $\mathbf{F}^H\mathbf{d}_k$), the augmented block is serially transmitted through the multipath channel. Let the channel impulse response (including all transmit/receive filtering effects) between the kth user and the base station be denoted as $\boldsymbol{\xi}_k = [\xi_k(0), \ldots, \xi_k(L_k-1)]^T$, where L_k is the channel length. Denoting the timing offset that is caused by propagation delay as μ_k, the compound channel response can be written as $\mathbf{h}_k \triangleq [\mathbf{0}^T_{\mu_k\times 1}\ \boldsymbol{\xi}_k^T\ \mathbf{0}^T_{(L-\mu_k-L_k)\times 1}]^T$, where L is the upper bound on the compound channel length. For user k, the normalized CFO and the phase offset (between the oscillator at user k and that of the base station) are denoted as ε_k and θ_k, respectively. At the base station, after timing synchronization and removal of CP, the signal from user k is given by

$$\begin{aligned}\mathbf{x}_k &\triangleq [x_k(0), \ldots, x_k(N-1)]^T\\ &= \exp(j\theta_k)\boldsymbol{\Gamma}(\omega_k)\mathbf{A}_k\mathbf{h}_k\\ &= \boldsymbol{\Gamma}(\omega_k)\mathbf{A}_k\left(\exp(j\theta_k)\mathbf{h}_k\right) \qquad (1)\end{aligned}$$

where

$$\boldsymbol{\Gamma}(\omega_k) \triangleq \operatorname{diag}\left(1, \ldots, \exp\left(j(N-1)\omega_k\right)\right) \qquad (2)$$

$$\mathbf{A}_k = \mathbf{F}^H\mathbf{D}_k\mathbf{F}_L \qquad (3)$$

$$\mathbf{D}_k \triangleq \operatorname{diag}(\mathbf{d}_k) \qquad (4)$$

$$\mathbf{F}_L = \mathbf{F}(:, 1:L) \qquad (5)$$

$$\omega_k \triangleq 2\pi\varepsilon_k/N. \qquad (6)$$

In the above signal model, the phase offset $\exp(j\theta_k)$ (a complex scalar) can be incorporated into the channel response $\mathbf{h}_k$. This renders the estimation of the phase offset dispensable since only the combined channel $\exp(j\theta_k)\mathbf{h}_k$ is needed in the equalization. Based on this fact, the CFO estimation will not be influenced by the presence of the common phase offset. Thus, without loss of generality, we assume that $\theta_k = 0, \forall\ k$, for simplicity.

Since the received signal at base station $\mathbf{x}$ is a superposition of the signals from all the users plus noise, we have

$$\mathbf{x} = \sum_{k=1}^{K}\boldsymbol{\Gamma}(\omega_k)\mathbf{A}_k\mathbf{h}_k + \mathbf{n} \qquad (7)$$

where

$$\mathbf{n} = [n(0), \ldots, n(N-1)]^T \qquad (8)$$

is the complex white Gaussian noise vector with zero mean and covariance matrix $C_{\mathbf{n}} = E\{\mathbf{n}\mathbf{n}^H\} = \sigma^2\mathbf{I}_{N\times N}$.

Denoting $\mathbf{h} = [\mathbf{h}_1^T \ldots \mathbf{h}_K^T]^T$, signal model (7) can be rewritten as

$$\mathbf{x} = \mathbf{Q}(\boldsymbol{\omega})\mathbf{h} + \mathbf{n} \qquad (9)$$

where $\mathbf{Q}(\boldsymbol{\omega}) = [\boldsymbol{\Gamma}(\omega_1)\mathbf{A}_1\quad \boldsymbol{\Gamma}(\omega_2)\mathbf{A}_2\quad \ldots\quad \boldsymbol{\Gamma}(\omega_K)\mathbf{A}_K]$.

Remark 1: In this paper, only the case where the base station equips with one antenna is considered; however, the above signal model can be easily generalized to the case where the base station equips with more than one antenna due to the fact that the multiple antennas that are equipped on the OFDMA base station always share the same oscillator.

Remark 2: Although there is an implicit assumption that the upper bound of the sum of the channel delay spread and the propagation delay for each user (L) is less than the length of CP L_{cp}, the considered system model is practical. The reason is that the timing offsets due to different propagation delays are limited to several samples only, and, in practical OFDM systems, the CP is always longer than the exact channel order.

III. Joint CFO and Channel Estimation

A. ML Estimation

Based on the signal model in (9), the ML estimate of parameters $\{\mathbf{h}, \boldsymbol{\omega}\}$ is given by maximizing

$$\psi(\mathbf{x}; \tilde{\mathbf{h}}, \tilde{\boldsymbol{\omega}}) = \frac{1}{(\pi\sigma^2)^N} \cdot \exp\left\{-\frac{1}{\sigma^2}\left[\mathbf{x} - \mathbf{Q}(\tilde{\boldsymbol{\omega}})\tilde{\mathbf{h}}\right]^H \left[\mathbf{x} - \mathbf{Q}(\tilde{\boldsymbol{\omega}})\tilde{\mathbf{h}}\right]\right\} \quad (10)$$

or equivalently minimizing

$$\Lambda(\mathbf{x}; \tilde{\mathbf{h}}, \tilde{\boldsymbol{\omega}}) = \left[\mathbf{x} - \mathbf{Q}(\tilde{\boldsymbol{\omega}})\tilde{\mathbf{h}}\right]^H \left[\mathbf{x} - \mathbf{Q}(\tilde{\boldsymbol{\omega}})\tilde{\mathbf{h}}\right] \quad (11)$$

where $\tilde{\mathbf{h}}$ and $\tilde{\boldsymbol{\omega}}$ are trial values of $\mathbf{h}$ and $\boldsymbol{\omega}$, respectively. Due to the linear dependence of parameter $\mathbf{h}$ in (9), the ML estimate for channel vector $\mathbf{h}$ (when $\tilde{\boldsymbol{\omega}}$ is fixed) is given by

$$\hat{\mathbf{h}} = \left(\mathbf{Q}^H(\tilde{\boldsymbol{\omega}})\mathbf{Q}(\tilde{\boldsymbol{\omega}})\right)^{-1} \mathbf{Q}^H(\tilde{\boldsymbol{\omega}})\mathbf{x}. \quad (12)$$

Putting $\hat{\mathbf{h}}$ into (11), the estimate of $\boldsymbol{\omega}$ can be obtained as

$$\hat{\boldsymbol{\omega}} = \arg\max_{\tilde{\boldsymbol{\omega}}} \left\{L'(\tilde{\boldsymbol{\omega}}) \triangleq \|\mathbf{P}_{\mathbf{Q}}(\tilde{\boldsymbol{\omega}})\mathbf{x}\|^2\right\} \quad (13)$$

where $\mathbf{P}_{\mathbf{Q}}(\tilde{\boldsymbol{\omega}}) = \mathbf{Q}(\tilde{\boldsymbol{\omega}})(\mathbf{Q}^H(\tilde{\boldsymbol{\omega}})\mathbf{Q}(\tilde{\boldsymbol{\omega}}))^{-1}\mathbf{Q}^H(\tilde{\boldsymbol{\omega}})$.

The CFO estimation in (13) requires an exhaustive search over the multidimensional space spanned by $\tilde{\boldsymbol{\omega}}$, which may be too computationally expensive in implementation.

B. Estimation Scheme Using Importance Sampling

For the problem in (13), although the alternative projection approach [7] can be used, a good initial guess of the CFOs is required. Furthermore, there is no guarantee that an estimate that is iteratively obtained will be the global maximum. In [8], Pincus showed that it is possible to obtain a closed-form solution for such problems that are guaranteed to be the global optimum. Based on the theorem given by Pincus, the $\boldsymbol{\omega}$ that yields the global maximum of $L'(\tilde{\boldsymbol{\omega}})$ is given by

$$\hat{\omega}_k = \lim_{\rho_1\to\infty} \frac{\int\cdots\int \omega_k \exp\left(\rho_1 L'(\boldsymbol{\omega})\right) d\boldsymbol{\omega}}{\int\cdots\int \exp\left(\rho_1 L'(\boldsymbol{\omega})\right) d\boldsymbol{\omega}}, \quad k = 1, \ldots, K \quad (14)$$

where ρ_1 is a design parameter. If we denote $L(\boldsymbol{\omega}) = \exp(\rho_1 L'(\boldsymbol{\omega}))$, the normalized version of $L(\boldsymbol{\omega})$ can be obtained by

$$\bar{L}(\boldsymbol{\omega}) = \frac{L(\boldsymbol{\omega})}{\int\cdots\int L(\boldsymbol{\omega})d\boldsymbol{\omega}}. \quad (15)$$

Here, function $\bar{L}(\boldsymbol{\omega})$ has all the properties of a probability density function (pdf); therefore, it is referred to the pseudo-pdf in $\boldsymbol{\omega}$. With this definition and (14), the optimal solution of $\boldsymbol{\omega}$ for (13) is

$$\hat{\omega}_k = \int\cdots\int \omega_k \bar{L}(\boldsymbol{\omega})d\boldsymbol{\omega}, \quad k = 1, \ldots, K \quad (16)$$

for some large value of ρ_1. Due to the fact that the frequency offsets $(\omega_k, k = 1, \ldots, K)$ have the properties of a circular random variable, the estimate for ω_k in (16) can be rewritten as

$$\hat{\omega}_k = \frac{1}{2\pi}\angle \int\cdots\int \exp(j2\pi\omega_k)\bar{L}(\boldsymbol{\omega})d\boldsymbol{\omega}, \quad k = 1, \ldots, K \quad (17)$$

where $\angle$ denotes the operation of finding the angle of the complex number. The advantage of using (17) instead of (16) is that (17) eliminates a potential bias in $\hat{\omega}_k$.

In [9], importance sampling is used to compute the multidimensional integral in (17). This approach is based on the observation that integrals of the type $\int\cdots\int h(\boldsymbol{\omega})\bar{L}(\boldsymbol{\omega})d\boldsymbol{\omega}$ can be expressed as

$$\int\cdots\int h(\boldsymbol{\omega})\bar{L}(\boldsymbol{\omega})d\boldsymbol{\omega} = \int\cdots\int h(\boldsymbol{\omega})\frac{\bar{L}(\boldsymbol{\omega})}{\bar{g}(\boldsymbol{\omega})}\bar{g}(\boldsymbol{\omega})d\boldsymbol{\omega} \quad (18)$$

where

$$\bar{g}(\boldsymbol{\omega}) = \frac{g(\boldsymbol{\omega})}{\int\cdots\int g(\boldsymbol{\omega})d\boldsymbol{\omega}} \quad (19)$$

with $g(\boldsymbol{\omega}) > 0$. Function $g(\boldsymbol{\omega})$ is called the importance function, and its normalized version $\bar{g}(\boldsymbol{\omega})$ has all the properties of a pdf. Then, the right-hand side of (18) can be expressed as the expected value of $h(\boldsymbol{\omega})(\bar{L}(\boldsymbol{\omega})/\bar{g}(\boldsymbol{\omega}))$ with respect to the pseudo-pdf $\bar{g}(\boldsymbol{\omega})$. If we can generate realizations of $\boldsymbol{\omega}$ according to $\bar{g}(\boldsymbol{\omega})$, the value of the integral in (18) can be found by the Monte Carlo approximation as

$$\int\cdots\int h(\boldsymbol{\omega})\bar{L}(\boldsymbol{\omega})d\boldsymbol{\omega} \approx \frac{1}{T}\sum_{i=1}^{T} h(\boldsymbol{\omega}^i)\frac{\bar{L}(\boldsymbol{\omega}^i)}{\bar{g}(\boldsymbol{\omega}^i)} \quad (20)$$

where T is the number of realizations, and $\boldsymbol{\omega}^i$ is the ith realization of the vector $\boldsymbol{\omega}$ that is generated according to the pseudo-pdf $\bar{g}(\boldsymbol{\omega})$. With $h(\boldsymbol{\omega}) = \exp(j2\pi\omega_k)$, we can obtain the estimate of the CFO using importance sampling as

$$\hat{\omega}_k = \frac{1}{2\pi}\angle\frac{1}{T}\sum_{i=1}^{T}\frac{\bar{L}(\boldsymbol{\omega}^i)}{\bar{g}(\boldsymbol{\omega}^i)}\exp\left(j2\pi\omega_k^i\right), \quad k = 1, \ldots, K. \quad (21)$$

Note that $\hat{\omega}_k$ is only related to the angle of the complex value in (21); the equivalent but simplified estimator is given by

$$\hat{\omega}_k = \frac{1}{2\pi}\angle\frac{1}{T}\sum_{i=1}^{T}\frac{L(\boldsymbol{\omega}^i)}{g(\boldsymbol{\omega}^i)}\exp\left(j2\pi\omega_k^i\right), \quad k = 1, \ldots, K \quad (22)$$

in which the integrals that are needed to compute $\bar{L}(\boldsymbol{\omega})$ and $\bar{g}(\boldsymbol{\omega})$ can be avoided.

C. Choosing the Importance Function $g(\boldsymbol{\omega})$

In general, estimator (22) converges to (14) by the strong law of large numbers, regardless of the choice of function $g(\boldsymbol{\omega})$. However, there are, obviously, some choices of $g(\boldsymbol{\omega})$ that are better than others in terms of computational complexity. From [11], the $g(\boldsymbol{\omega})$ that minimizes the variance of the estimator for a fixed number of realizations T is given by

$$\bar{g}_o(\boldsymbol{\omega}) = \frac{|h(\boldsymbol{\omega})|\,\bar{L}(\boldsymbol{\omega})}{\int\cdots\int |h(\boldsymbol{\omega})|\,\bar{L}(\boldsymbol{\omega})d\boldsymbol{\omega}}. \tag{23}$$

Here, because $h(\boldsymbol{\omega}) = \exp(j2\pi\omega_k)$ and $|\exp(j2\pi\omega_k)| = 1$, we have

$$g_o(\boldsymbol{\omega}) = \frac{\int\cdots\int g_o(\boldsymbol{\omega})d\boldsymbol{\omega}}{\int\cdots\int L(\boldsymbol{\omega})d\boldsymbol{\omega}} L(\boldsymbol{\omega}) \propto L(\boldsymbol{\omega}). \tag{24}$$

It is obvious that optimal importance function $g_o(\boldsymbol{\omega})$ for the estimator at hand should be a scaled version of $L(\boldsymbol{\omega})$. However, when $g(\boldsymbol{\omega})$ is chosen like this, the implementation of the estimator in (22) will be challenging due to the difficulty in sample generation from a multidimensional pdf. Considering the performance and the ease of sample generation, exploited importance function $g(\boldsymbol{\omega})$ is relaxed to be a close approximation of $L(\boldsymbol{\omega})$, and, at the same time, it should be as simple as possible to facilitate sample generation [12].

From the signal model, it is straightforward to show that $\mathbf{A}_i^H\mathbf{A}_j = \mathbf{0}_{L\times L}$, $\forall i \neq j$. Thus, for the OFDMA system with a large number of subcarriers, we have $\lim_{N\to\infty}\mathbf{A}_i^H\boldsymbol{\Gamma}(\omega_j - \omega_i)\mathbf{A}_j = \mathbf{0}$, $\forall i \neq j$ [10]. Then, if N is large enough, we obtain the following approximation:

$$\begin{aligned}
&\left(\mathbf{Q}^H(\boldsymbol{\omega})\mathbf{Q}(\boldsymbol{\omega})\right)^{-1} \\
&= \left(\begin{bmatrix} \mathbf{A}_1^H\boldsymbol{\Gamma}^H(\omega_1) \\ \vdots \\ \mathbf{A}_K^H\boldsymbol{\Gamma}^H(\omega_K)\end{bmatrix} [\boldsymbol{\Gamma}(\omega_1)\mathbf{A}_1 \ldots \boldsymbol{\Gamma}(\omega_K)\mathbf{A}_K]\right)^{-1} \\
&= \begin{bmatrix} \mathbf{A}_1^H\mathbf{A}_1 & \ldots & \mathbf{A}_1^H\boldsymbol{\Gamma}(\omega_K-\omega_1)\mathbf{A}_K \\ \vdots & \ddots & \vdots \\ \mathbf{A}_K^H\boldsymbol{\Gamma}(\omega_1-\omega_K)\mathbf{A}_1 & \ldots & \mathbf{A}_K^H\mathbf{A}_K \end{bmatrix}^{-1} \\
&\approx \begin{bmatrix} \left(\mathbf{A}_1^H\mathbf{A}_1\right)^{-1} & \ldots & \mathbf{0} \\ \vdots & \ddots & \vdots \\ \mathbf{0} & \ldots & \left(\mathbf{A}_K^H\mathbf{A}_K\right)^{-1} \end{bmatrix} \triangleq \mathbf{B}.
\end{aligned} \tag{25}$$

If we choose the importance function $g(\boldsymbol{\omega})$ as

$$\begin{aligned}
g(\boldsymbol{\omega}) &= \exp\left(\rho_2\mathbf{x}^H\mathbf{Q}(\boldsymbol{\omega})\mathbf{B}\mathbf{Q}^H(\boldsymbol{\omega})\mathbf{x}\right) \\
&= \exp\left(\sum_{k=1}^{K}\rho_2\mathbf{x}^H\left\{\boldsymbol{\Gamma}(\omega_k)\mathbf{A}_k\left(\mathbf{A}_k^H\mathbf{A}_k\right)^{-1}\mathbf{A}_k^H\boldsymbol{\Gamma}^H(\omega_k)\right\}\mathbf{x}\right) \\
&= \prod_{k=1}^{K}\exp\left(\rho_2\mathbf{x}^H\boldsymbol{\Gamma}(\omega_k)\mathbf{A}_k\left(\mathbf{A}_k^H\mathbf{A}_k\right)^{-1}\mathbf{A}_k^H\boldsymbol{\Gamma}^H(\omega_k)\mathbf{x}\right) \\
&\triangleq \prod_{k=1}^{K} g_k(\omega_k)
\end{aligned} \tag{26}$$

where ρ_2 is a design parameter, then the generation of realizations of $\boldsymbol{\omega}$ reduces to the generation of K independent realizations of ω_k following the pseudo-pdf's, i.e.,

$$\bar{g}_k(\omega_k) = \frac{g_k(\omega_k)}{\int_{-2\pi\alpha/N}^{2\pi\alpha/N} g_k(\omega_k)d\omega_k}, \quad k = 1,\ldots,K \tag{27}$$

where α is the normalized estimation range of CFOs.

Remark 3: There are three considerations when choosing ρ_1 and ρ_2. First, although the theorem in [8] states that the global optimum is attained for the limiting case $\rho_1 \to \infty$, in practice, the theorem holds for large but finite ρ_1. In fact, if the global optimum is attained for some finite value of ρ_1, then it will be attained for all values of ρ_1 that are above that finite value. In implementation, design parameter ρ_1 should be chosen as large as possible. Second, since realization $\boldsymbol{\omega}$ is generated from importance function $g(\boldsymbol{\omega})$ in (26), $g(\boldsymbol{\omega})$ should be a close approximation of $L(\boldsymbol{\omega})$. Thus, ρ_2 should also be chosen as large as possible. Third, to make the estimator have a finite variance, parameter ρ_1 should be set larger than ρ_2 such that the tail of $g(\boldsymbol{\omega})$ is thicker than that of $L(\boldsymbol{\omega})$ [11]. Following the above criteria, in implementation, design parameters ρ_1 and ρ_2 should be chosen as large as possible with $\rho_1 > \rho_2$, and, at the same time, the whole expression $[L(\boldsymbol{\omega}) = \exp(\rho_1\|\mathbf{P}_{\mathbf{Q}}(\boldsymbol{\omega})\mathbf{x}\|^2)$, $g(\boldsymbol{\omega}) = \exp(\rho_2\mathbf{x}^H\mathbf{Q}(\boldsymbol{\omega})\mathbf{B}\mathbf{Q}^H(\boldsymbol{\omega})\mathbf{x})]$ should not overflow the hardware limit [the exponential expressions $L(\boldsymbol{\omega})$ and $g(\boldsymbol{\omega})$ are very large].

Remark 4: Based on the approximation in (25), the CFO estimates for all users in (13) can be decoupled as

$$\hat{\omega}_k = \arg\max_{\tilde{\omega}_k}\left\{\mathbf{x}^H\boldsymbol{\Gamma}(\tilde{\omega}_k)\mathbf{A}_k\left(\mathbf{A}_k^H\mathbf{A}_k\right)^{-1}\mathbf{A}_k^H\boldsymbol{\Gamma}^H(\tilde{\omega}_k)\mathbf{x}\right\} \quad k = 1,\ldots,K \tag{28}$$

and the solution can be found by K 1-D searches. Unfortunately, (25) and (28) hold only when the number of subcarriers is infinite. For a practical system with finite subcarriers, (28) only offers approximated solutions to the original estimation problem. In Section IV, we will show that the decoupled estimator in (28) suffers a great performance loss when the number of subcarriers is not large enough. Thus, an efficient algorithm that can find the exact solutions of (13) with affordable complexity is needed.

D. Efficient Algorithms for Sample Generation

It is pointed out in [9] that there are two major sources of computations in the importance sampling approach. The first one is the generation of realizations using pseudo-pdf (27), and the second one is the calculation of coefficient $L(\boldsymbol{\omega}^i)/g(\boldsymbol{\omega}^i)$ in (22). Since the complexity of the second step is constant for a fixed T, to reduce the complexity of the whole algorithm, it is critical to focus on the first one.

To generate realizations of ω_k according to pseudo-pdf $\bar{g}_k(\omega_k)$, several methods are available in the literature [13]–[15]. The conceptually simplest one is the inverse cumulative density function (cdf) approach, which is employed in [9]. For the inverse cdf approach, a random variable U uniformly distributed in (0, 1) is generated first, and then, the realization of ω_k can be obtained by solving $U = G_k(\omega_k)$, where $G_k(\omega_k) = \int_{-2\pi\alpha/N}^{\omega_k} \bar{g}_k(x)dx$ can be regarded as the cdf of pseudo-pdf $\bar{g}_k(\omega_k)$. To solve this equation, 24 evaluations of $G_k(\omega_k)$ are needed, even if the golden search is exploited [9]. Moreover, for one evaluation of $G_k(\omega_k)$, $\bar{g}_k(\omega_k)$ has to be evaluated for many times due to the inherent complexity in numerical integration. Thus, the complexity for the inverse cdf method is very high and not suitable for the problem at hand. It is desirable to exploit other techniques that can reduce the evaluation times of pdf $\bar{g}_k(\omega_k)$ to generate ω_k.

Here, we propose to use the ratio-of-uniform method since this technique is quite fast and has moderate performance [15]. This method is based on the fact that, if (U, V) is uniformly distributed over the set $C = \{(u, v); 0 \leq u \leq \sqrt{\bar{g}_k(v/u)}\}$, then v/u has $\bar{g}_k(\omega_k)$ as the pdf. To implement this method, the following procedures are needed [15].

1) Choose a rectangle E that encloses C. From [16], a simple form of the rectangle E that encloses C can be obtained by

$$E = \left\{(u, v); 0 \leq u \leq \max_{\omega_k} \sqrt{\bar{g}_k(\omega_k)} \right.$$
$$\left. \min_{\omega_k} \omega_k \sqrt{\bar{g}_k(\omega_k)} \leq v \leq \max_{\omega_k} \omega_k \sqrt{\bar{g}_k(\omega_k)} \right\} \quad (29)$$

where $\omega_k \in [-2\pi\alpha/N, 2\pi\alpha/N]$.

2) Generate two random variables (u, v) in the domain E under a uniform distribution.

3) If the generated random variables (u, v) satisfy $u^2 \leq \bar{g}_k(v/u)$, one realization of ω_k is generated as $\omega_k = v/u$; otherwise, reject (u, v), and go back to step 2).

This method is efficient if estimation range α is small. However, when estimation range α is large, the range for random variable v in (29) may be large. In this case, after generating (u, v), the chance to reject this pair is large such that step 2) has to be repeated many times to generate one realization of ω_k. In other words, the number of evaluations of $\bar{g}_k(\omega_k)$ may be significant to successfully generate one ω_k.

To avoid this problem, we revised the first step of the above method as follows. Denoting $\bar{\omega}_k$ as an estimate of the maximal point of $\sqrt{\bar{g}_k(\omega_k)}$, we define

$$E' = \left\{(u', v'); 0 \leq u' \leq \max_{\omega_k} \sqrt{\bar{g}_k(\omega_k)}, \right.$$
$$\left. \min_{\omega'_k} \omega'_k \sqrt{\bar{g}_k\,(\omega'_k + \bar{\omega}_k)} \leq v' \leq \max_{\omega'_k} \omega'_k \sqrt{\bar{g}_k\,(\omega'_k + \bar{\omega}_k)} \right\} \quad (30)$$

where $\omega'_k \in [-2\pi\alpha/N - \bar{\omega}_k, 2\pi\alpha/N - \bar{\omega}_k]$. If generated (u', v') satisfies $u'^2 \leq \bar{g}_k(v'/u' + \bar{\omega}_k)$, the value of $(v'/u' + \bar{\omega}_k)$ will be accepted as a realization of ω_k. This idea can be illustrated by Fig. 2. Since $\bar{\omega}_k$ corresponds to the maximal point of function $\bar{g}_k(\omega_k)$, which is normally near the real CFO value, most realizations of ω_k will be around $\bar{\omega}_k$. If we shift the zero point to $\bar{\omega}_k$ and construct a new axis framework, the bounds of v' in (30) can always be small values, even if the real CFO is large.

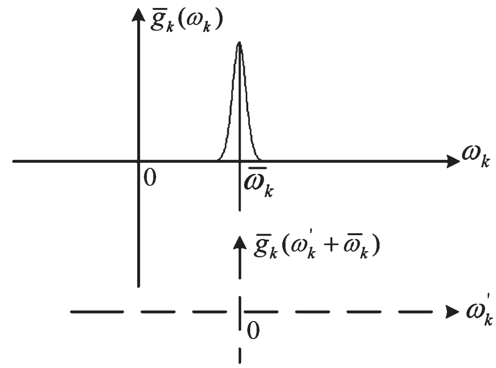

Fig. 2. Idea of the proposed sample generation method.

Remark 5: Although a matrix inverse $(\mathbf{A}_k^H \mathbf{A}_k)^{-1}$ [see (26)] is included in $g_k(\omega_k)$, this term can be calculated offline. Furthermore, in a practical system, the knowledge of α is possible if we know the accuracy of the oscillators in transceivers. For example, if the OFDM system, which has 64 subcarriers and 20-MHz signal bandwidth, is operating over the 5-GHz frequency band, the accuracy of the transceiver oscillators is 30 ppm, and the maximum CFO is 150 kHz, then the normalized CFO is in the range [−0.48, 0.48] ($\alpha = 0.48$). Thus, with known α, the term $\int_{-2\pi\alpha/N}^{2\pi\alpha/N} g_k(\omega_k)d\omega_k$ in (27) can also be precalculated once and stored.

Remark 6: It is noticed that searching the maximum of function $\bar{g}_k(\omega_k)$ in step 1) is equivalent to finding the solution of (28). The complexity is affordable since only multiple 1-D searches are needed. This step can be regarded as a coarse search for the parameters to be estimated.

Remark 7: Using the proposed method, the generation of ω_k is only loosely coupled with the estimation range through the bound of v'. It is shown in Section IV that, with the increase in the estimation range α, the complexity of the proposed estimator is only marginally increased. This is a significant advantage over the conventional CFO estimation schemes, in which the required computation increases very quickly in proportion to the estimation range.

IV. Simulation Results and Discussions

A. Simulation Setup

In this section, simulation results are presented to demonstrate the effectiveness of the proposed scheme. The considered OFDMA system has the following parameters: $N = 64$ and $L_{\text{cp}} = 16$. Since, for coherent data detection, only the estimates of the compound channels $\mathbf{h}_k$ are required, the estimation of timing offsets becomes dispensable. By combining the timing offsets μ_k and the exact channel $\boldsymbol{\xi}_k$, the system can be regarded as a perfectly synchronous system with compound channels $\mathbf{h}_k$. Thus, without loss of generality, in the simulation, we assume that $\mu_k = 0, \forall k$, for simplicity. The channel response for each user is generated according to the HIPERLAN/2 channel model with eight paths ($L = 8$) [18]. In detail, the channel taps are modeled as independent and complex Gaussian random variables with zero mean and an exponential power delay profile. In the simulation, it is assumed that the subcarriers are randomly allocated to all users with a generalized CAS, and the users' signals arrive at the base station with equal average power. Without loss of generality, the normalized CFOs for all users $(\varepsilon_k, k = 1, \ldots, K)$ are generated as random variables that are uniformly distributed in $[-N/2, N/2]$. Notice that this corresponds to a very large CFO range.

The proper choice of design parameters ρ_1 and ρ_2 can significantly reduce the number of realizations T that are needed for one estimation. Following the suggestions in [8], [11], and Remark 3, in the simulation, we choose $\rho_1 = 2/K$ and $\rho_2 = 1/K$. For each CFO estimate, 2000 realizations $(T = 2000)$ are generated for importance sampling estimation (22). The SNR that is used in the simulation is defined as $\mathrm{SNR} = E\{\|\mathbf{x} - \mathbf{n}\|^2\}/\sigma^2$. Since there are multiple CFOs and channels to be estimated in the scheme, the MSE performance that is used here is defined as

$$\mathrm{MSE}_{\mathrm{CFO}} = \sum_{k=1}^{K} (\hat{\omega}_k - \omega_k)^2$$
$$\mathrm{MSE}_{\mathrm{channel}} = \|\hat{\mathbf{h}} - \mathbf{h}\|^2.$$

All the simulation results of the proposed algorithm are averaged over 200 Monte Carlo runs.

B. Efficiency of the Proposed Estimation Scheme

To establish the performance limit of the CFO and channel estimators, we first present the Cramer–Rao bounds (CRBs) for $\boldsymbol{\omega}$ and $\mathbf{h}$. In [7], the CRB for $\boldsymbol{\omega}$ is derived and given by

$$\mathrm{CRB}(\boldsymbol{\omega}) = \frac{\sigma^2}{2} \left(\Re \left\{ \mathbf{Z}^H \mathbf{\Pi}_Q^{\perp} \mathbf{Z} \right\} \right)^{-1}$$

where

$$\begin{aligned} \mathbf{Z} &= [\mathbf{Z}_1 \quad \mathbf{Z}_2 \quad \cdots \quad \mathbf{Z}_K] \\ \mathbf{Z}_k &= \mathbf{M}\mathbf{\Gamma}(\omega_k)\mathbf{A}_k\mathbf{h}_k \\ \mathbf{M} &= \mathrm{diag}(0, 1, \ldots, N-1) \\ \mathbf{\Pi}_Q^{\perp} &= \mathbf{I}_{N\times N} - \mathbf{Q}(\mathbf{Q}^H\mathbf{Q})^{-1}\mathbf{Q}^H. \end{aligned}$$

For the CRB of $\mathbf{h}$, [7] does not provide an explicit result. However, following similar mathematical manipulations as those in [17, App. I], the CRB for $\mathbf{h}$ can be derived as

$$\mathrm{CRB}(\mathbf{h}) = \frac{\sigma^2}{2} \cdot \Big(2(\mathbf{Q}^H\mathbf{Q})^{-1} + (\mathbf{Q}^H\mathbf{Q})^{-1}\mathbf{Q}^H\mathbf{Z} \times \left(\Re \left\{ \mathbf{Z}^H \mathbf{\Pi}_Q^{\perp} \mathbf{Z} \right\} \right)^{-1} \mathbf{Z}^H \mathbf{Q}(\mathbf{Q}^H\mathbf{Q})^{-H} \Big).$$

The simulated MSEs of the CFO and channel estimators and the CRBs are plotted versus the SNR (with two and four users) in Figs. 3 and 4. It is noticed that for the proposed CFO and channel estimator, the MSEs always coincide with the respective CRBs in all the SNR range of interest, which means that the proposed estimation scheme is efficient. Notice that for the previously proposed alternating projection-based frequency estimator (APFE) in [7], the same CRBs as those of the proposed estimator are shared due to the fact that the

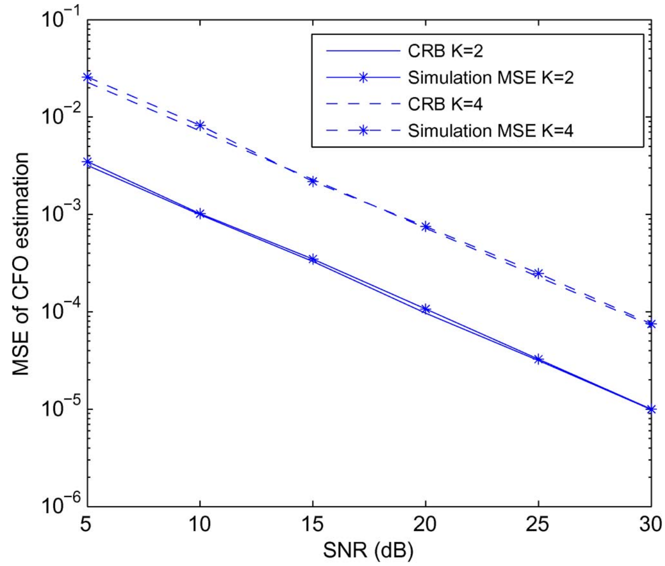

Fig. 3. MSE performance of the proposed CFO estimator; $K = 2, 4$.

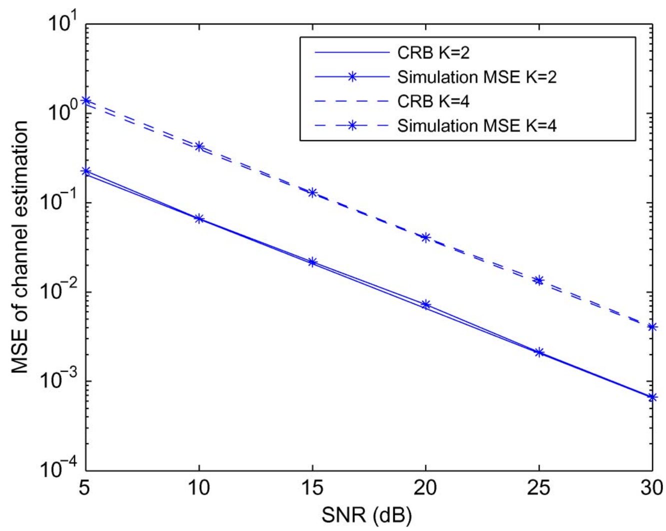

Fig. 4. MSE performance of the proposed channel estimator; $K = 2, 4$.

same signal model and the ML criterion are exploited in both estimators. Thus, the performance of the APFE, at best, is equal to that of the proposed scheme (note that, in general, global optimal solution cannot be guaranteed in the APFE) and is not presented here.

C. Asymptotic Performance

In Figs. 5 and 6, the CRB and the MSE for the CFO and channel estimation $(K = 2)$ using the proposed scheme are presented versus the different number of subcarriers (N). The SNR in this simulation is set as 10 dB. In both figures, the MSEs from simulations meet the respective CRBs quite well, which shows that the proposed scheme is efficient. The performance of the joint CFO and channel estimation scheme using the decoupled CFO estimator in (28) is also included in the two figures for comparison. It is noticed that for the decoupled estimator, a significant performance loss occurs when the number of subcarriers is small. On the other hand, the gap between

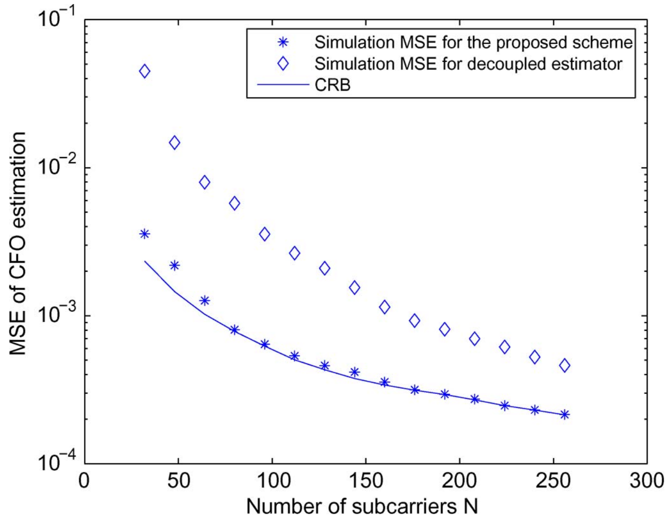

Fig. 5. CRB and MSE of the proposed CFO estimator versus different numbers of subcarriers.

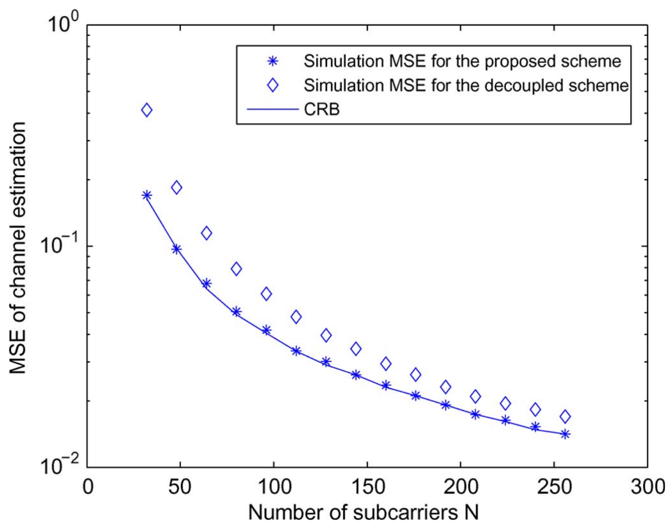

Fig. 6. CRB and MSE of the proposed channel estimator versus different numbers of subcarriers.

the decoupled estimator and the proposed estimator decreases when the number of subcarriers increases. This implies that when the number of subcarriers is large, we can use the decoupled estimator, which is computationally efficient, with only a marginal loss of performance.

D. Complexity Analysis

Here, the computational complexity of the proposed scheme is assessed. As mentioned in Section III-C, when the number of samples that are required in one estimation (T) is fixed, the complexity of the proposed importance sampling-based CFO estimator is only determined by the efficiency of sample generation. Therefore, we first analyze the complexity for the proposed sample generation scheme, which is characterized by averaged pdf $\bar{g}_k(\omega_k)$ evaluations for generating one realization of ω_k (denoted as N_a). In Fig. 7, N_a for the proposed scheme is plotted versus different estimation ranges α at an SNR of 10 dB. The corresponding results for the inverse cdf method and the original ratio-of-uniform method are also included as

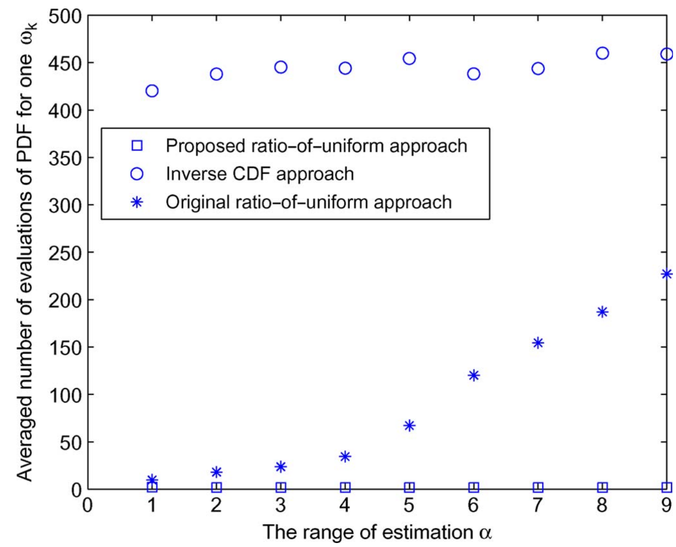

Fig. 7. Averaged pdf evaluation times for generating one realization of ω_k.

comparisons. It is noticed that the average number of $\bar{g}_k(\omega_k)$ evaluations N_a for the proposed sample generation method is far smaller than other methods and remains constant for all estimation ranges. This shows that the proposed method is more efficient than the other methods. In fact, although it cannot be seen in Fig. 7 because of the scale of the figure, $2 \leq N_a \leq 3$ always holds in the proposed method, regardless of the estimation range α (simulations at other SNRs of interest give similar results).

Next, we compare the complexity of the proposed CFO estimator, the decoupled estimator, and the APFE in [7].

- For the decoupled CFO estimator in (28), since multiple 1-D searches are required, the complexity is donated as $\mathcal{O}(KN_wN^2)$, where N_w is the number of $\tilde{\omega}_k$ values over which the cost function is evaluated. In practical implementation, the value of N_w is determined by the estimation range α and the estimation resolution. For example, if a normalized frequency resolution 0.001 is required (such that the estimation accuracy is not limited by the search resolution) and the estimation range α is 0.5, the value of N_w is, therefore, 1000.
- For the proposed estimator, two steps should be considered. In the first step, searching for the maximum of function $\bar{g}_k(\omega_k)$ is required in (30), which has the same complexity as the decoupled estimator. After that, the sample generation only needs multiplications between an $N \times 1$ vector and an $N \times N$ matrix in (26) since the term $\mathbf{A}_k(\mathbf{A}_k^H\mathbf{A}_k)^{-1}\mathbf{A}_k^H$ can be precalculated and stored. Thus, the complexity for this step is found to be $\mathcal{O}(KN_wN^2 + KTN_aN^2)$. In the second step, T evaluations of the coefficient $L(\boldsymbol{\omega}^i)/g(\boldsymbol{\omega}^i)$ in (22) have complexity of order $\mathcal{O}(T((KL)^3 + N(KL)^2 + KN^2))$. Summing the two steps and taking only the dominant order term, the entire complexity for the proposed estimator is obtained as $\mathcal{O}(KTN_aN^2 + KN_wN^2 + T(KL)^3 + TN(KL)^2)$. Note that, in general, the relative order of these terms can be determined only when the system specification is fixed.

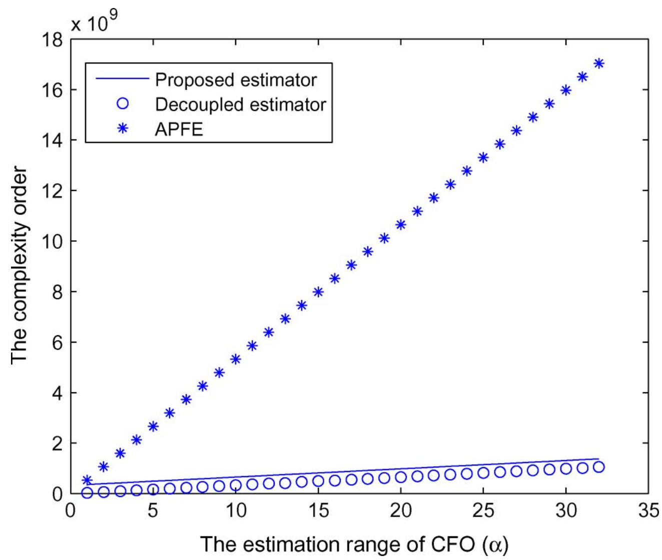

Fig. 8. Complexity order comparison versus the estimation range.

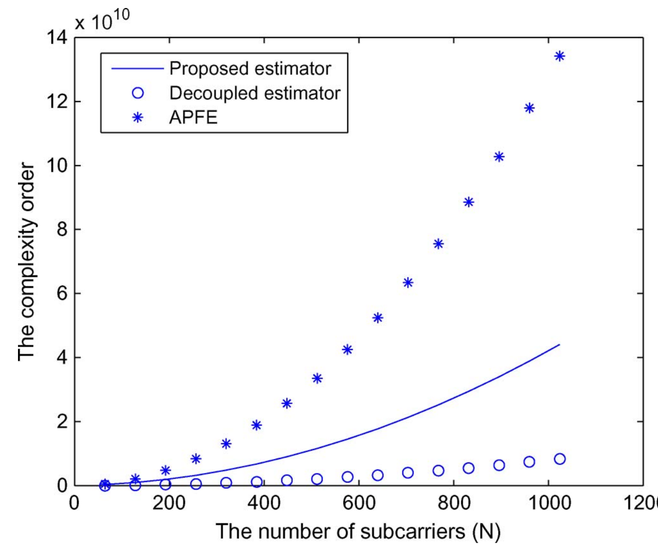

Fig. 9. Complexity order comparison versus the number of subcarriers ($\alpha = 1$).

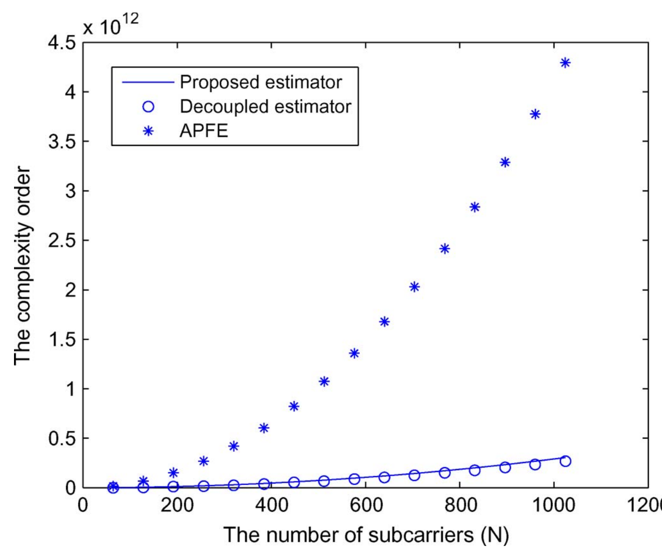

Fig. 10. Complexity order comparison versus the number of subcarriers ($\alpha = 10$).

- For the APFE, the complexity analysis given in [7] only considers the matrix inversion $(L \times L)$. From this analysis, the complexity of the APFE is constant if the length of channel L is fixed. However, the complexity of the APFE is also sensitive to the number of subcarriers N. To obtain a more complete picture, we reconsider the computations that are required in the APFE. After some calculations, the complexity of this estimator is found to be $\mathcal{O}(KN_cN_w(L^3 + LN^2))$, where N_c is the number of cycles that are needed in the estimation. If LN^2 is ignored, this reduces to the complexity expression that is given in [7].

In Fig. 8, the complexity orders (the value in the bracket of $\mathcal{O}()$) of the three estimators are plotted versus estimation range α, and the other parameters are chosen as $N_c = 2$, $N_a = 3$, $T = 2000$, $K = 4$, and $N_w = 2\alpha/0.001$. It is found that the APFE and the decoupled estimator always have the highest and lowest complexity, respectively. With the increase in the estimation range, the complexity of the APFE increases significantly, whereas that of the proposed estimator is only increased marginally, which means that the proposed estimator is not as sensitive to the estimation range α as the APFE. To investigate the effects of the subcarrier number N on the complexity, we plot the complexity orders versus N with different estimation ranges. In Figs. 9 and 10, the number of subcarriers is varied from 64 to 1024, and α is set to be 1 and 10, respectively. It is noticed that the complexity of the proposed estimator is consistently below that of the APFE. When compared with the decoupled estimator, the complexity of the proposed estimator can approach that of the decoupled estimator when α is large.

V. Conclusion

In this paper, the problem of joint CFO and channel estimation for an OFDMA uplink has been considered, and the ML joint CFO and channel estimator has been derived. However, direct implementation of the ML estimator is impractical due to a multidimensional search that is required in the CFO estimation. Unlike the conventional iterative algorithms that are usually used in multidimensional optimization, an importance sampling-based estimator has been proposed to solve this problem. To further reduce the complexity, a novel sampling generation algorithm has also been presented. Different from the iterative methods, in the proposed scheme, the global optimality can always be guaranteed without the need to provide an initial estimate. Compared with other schemes in the literature, the proposed scheme has three advantages.

1) Global optimality is guaranteed naturally.
2) The complexity of the algorithm is not sensitive to the estimation range.
3) The scheme is applicable for any subcarrier allocation scheme.

Simulation results have clearly verified that the proposed scheme is efficient.

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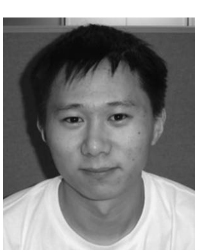

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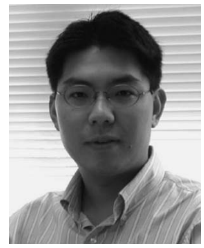

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