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*Original Article*

# Efficient Estimation Approach for Carrier Frequency Offset in Multiuser OFDMA Uplink Systems

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***Abstract*** *- The performance of uplink OFDMA systems can be severely impacted by Carrier Frequency Offset (CFO), making it a critical impairment to address. While the Maximum Likelihood (ML) estimator, often implemented with an Alternating Projection (AP) algorithm, provides optimal accuracy, its computational burden, specifically the repeated matrix inversions, hinders practical deployment. The novelty of this work lies in leveraging the Woodbury matrix identity to avoid repeated full inversions, thereby cutting computational load by >90% while retaining ML-level estimation accuracy. Unlike prior studies limited to 4 users, this work extends the evaluation up to 16 users to show scalability. This approach avoids re-computing the entire matrix inverse for each trial CFO value, leading to significant computational savings. Simulation results for a 16-user system demonstrate that our proposed method achieves a Mean Squared Error (MSE) performance nearly identical to that of the ML-AP method, while reducing the required complex multiplications for matrix inversion by over 90%. This work provides a scalable and low-latency solution for CFO estimation, making the optimal ML-based approach more feasible for next-generation wireless systems.*

***Keywords*** *- Carrier Frequency Offset, OFDMA Uplink, Multiuser Interference, Maximum Likelihood Estimation, Low-Complexity Estimator, Sparse Signal Processing, 5G Uplink Systems.*

## 1. Introduction

OFDMA has emerged as a key method for enabling multiple users to access wireless networks, particularly in modern technologies like WiMAX and LTE. It works by dividing a single OFDM symbol into separate subcarriers, with each user being allocated their own distinct set of these subcarriers, allowing for simultaneous data transmission. This method enhances immunity to intra-cell interference and offers significant advantages in dynamic resource allocation [1]. These benefits have made OFDMA a cornerstone of 5G New Radio (NR) and future wireless systems, which are characterized by massive connectivity and a diverse range of services. However, in such dense user scenarios, the system becomes even more vulnerable to the cumulative effects of CFOs from numerous users, making efficient and scalable estimation techniques more critical than ever [2, 3].

This paper focuses on improving the computational efficiency of model-based ML estimation. It is essential to recognize the evolving field of modern estimation techniques, which increasingly incorporates data-driven approaches leveraging Deep Learning (DL) [8, 9]. While DL-based estimators have shown impressive performance, particularly in complex and non-linear channel conditions, they often require extensive offline training, large datasets, and can be computationally demanding during inference. In contrast, model-based methods, such as the one enhanced in this work, offer deterministic performance without the need for training data, making them highly relevant for low-latency applications and devices with limited computational resources. Our work builds upon the classical foundation of ML estimation to deliver a solution that is both scalable and practical.

In these systems, Mobile Terminals (MTs) align their frequency with the Base Station (BS) by using a reference signal sent by the BS at the beginning of each downlink period. This process helps keep any frequency mismatches at the MT within acceptable bounds [4]. These frequency estimates assist in receiving downlink signals and act as a reference for uplink transmissions [5]. Yet, residual carrier frequency offsets may persist at the BS owing to Doppler shifts and estimation errors, usually within the limits of subcarrier spacing. However, despite progress in ML-AP methods, a major gap remains in handling the high per-iteration complexity of matrix inversions, particularly for scenarios with 8-16 users. Existing solutions either compromise estimation accuracy or demand impractical computational resources. This motivates our work: reducing complexity without loss of accuracy."

The high sensitivity of OFDMA to synchronization errors is a notable drawback, as any carrier frequency mismatch between transmitter and receiver may lead to inter-carrier and multiple-access interference. Downlink synchronization can be handled using standard OFDM approaches, but uplink synchronization remains particularly demanding [6, 7]. This is primarily because each user's uplink signal may suffer from unique propagation delays and Doppler-induced frequency errors, complicating the synchronization task at the BS [6].

Among the various techniques explored for CFO estimation, Maximum Likelihood (ML) methods are known for their optimal accuracy. However, their practical implementation in multiuser scenarios is hindered by the computational burden of multidimensional searches. To address this, several recent efforts have focused on reducing the complexity of CFO estimation algorithms. This paper contributes to this ongoing research by proposing an enhanced low-complexity CFO estimation technique that integrates the Woodbury matrix identity into each iteration of the existing algorithm presented in [7]. Moreover, this study extends the evaluation beyond the four-user scenario considered in [7], analysing performance for up to 16 users. A comparative analysis between the proposed method and the original ML approach in terms of computational complexity is also provided.

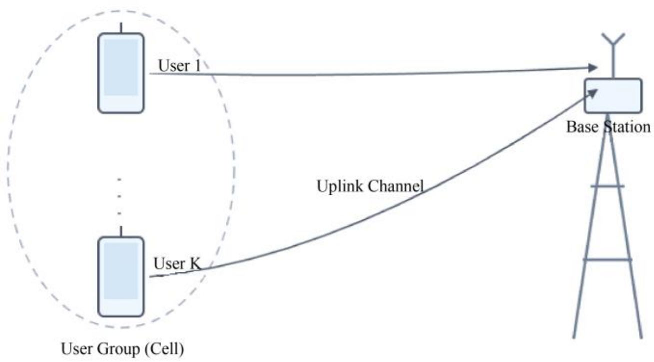


**Fig. 1 OFDMA Uplink system**

Recently, researchers have been exploring the use of machine learning and deep learning methods to enhance the accuracy of CFO estimation, often leveraging neural networks to learn the complex relationship between the received signal and frequency offsets. While these data-driven methods can achieve high estimation accuracy, particularly in complex channel conditions, they typically require extensive offline training, large datasets, and can be computationally intensive during inference, posing challenges for real-time implementation on user-end devices. This highlights the continued relevance of model-based signal processing techniques, which offer a balance of high performance and low complexity without requiring training data. Our work builds on this classical foundation to deliver a solution that is both scalable and practical for next-generation systems [8, 9].

The primary contribution of this work is an enhanced low-complexity CFO estimation algorithm that integrates the Woodbury matrix identity into the ML-AP framework. This significantly reduces the computational cost of the iterative matrix inversions inherent to the ML-AP method. The proposed work extends the performance evaluation to 16-user scenarios to demonstrate scalability and provide a detailed complexity analysis compared to the original ML and ML-AP methods. It should be noted that, as a foundational study, our analysis assumes quasi-static channels and perfect timing synchronization. Acknowledging that factors such as high user mobility, Doppler spread, and timing estimation errors are critical for real-world performance, these aspects are discussed as crucial avenues for future research. This research presents an innovative approach that applies the Woodbury matrix identity, significantly reducing the computational burden by over 90% while maintaining the high estimation accuracy typically associated with machine learning models. In contrast to previous research, which has been limited to evaluating only 4 users, our analysis is extended to 16 users, demonstrating the scalability of our method.

The flow of the paper is arranged to guide the reader through key aspects of the study. It begins in Section II with an overview of existing low-complexity methods used for estimating CFO. Section III outlines the system model that forms the basis of the analysis. In Section IV, the core concepts behind CFO estimation are explained. The new approach introduced by the authors is discussed in detail in Section V. Section VI showcases the simulation outcomes and highlights significant findings. The paper wraps up with final thoughts and conclusions in Section VII.

## 2. Literature Review

Figure 1 illustrates the uplink scenario in an OFDMA system, where the Base Station (BS) receives transmissions from several mobile users simultaneously. Each received signal is usually affected by timing and frequency offsets. While cyclic prefix insertion largely mitigates timing errors, this section concentrates exclusively on the estimation and compensation of CFO.

CFO estimation techniques in research generally fall into two main groups: (a) model-driven approaches that rely on signal structure, and (b) data-driven approaches that leverage machine learning.

### *2.1. Model-Based Estimation Schemes*

Model-based estimation has been the dominant line of research. Among these, Maximum Likelihood (ML)-based methods are widely recognized for delivering near-optimal accuracy [7]. However, their practical adoption in multiuser OFDMA systems is limited due to the high complexity of multi-dimensional searches across all possible CFO values.

To reduce the heavy computational burden, the APFE method [7] simplifies the problem by breaking down the multidimensional frequency estimation into several one-dimensional searches, making the process more efficient and thereby reducing computational requirements. Still, APFE depends on an accurate initial guess, and its scalability diminishes as the number of users grows. Consequently, the ML-APFE approach is treated as a performance benchmark, though its high per-iteration inversion cost remains a barrier to real-time application.

Other studies have pursued different trade-offs. For example, the Von Neumann series has been applied to approximate matrix inversions, which reduces complexity but worsens estimation accuracy. Line search techniques [10] offer computational relief but converge more slowly. EM-based estimators [4] are less complex than ML but demand good initialization for reliable convergence.

Several iterative refinements also exist, such as the method in [11], which provides APFE-level accuracy with reduced complexity. Linear estimators like LS and MMSE [12] avoid grid searches altogether but only achieve near-optimal results at high SNR values. Heuristic optimization strategies, including Particle Swarm Optimization (PSO) [16, 17], have also been applied to CFO estimation, improving convergence in multiuser cases, though at the cost of added iterations. In addition to these ML-based methods, non-ML techniques have been proposed [18, 19], which offer lower computational cost but generally do not perform as well.

### 2.2. Data-Driven Estimation Schemes

In recent years, machine learning-based approaches, particularly Deep Learning (DL), have emerged as an attractive alternative [8, 9]. Neural networks can capture the nonlinear mapping between received signals and CFOs, even in difficult channel conditions. For instance, CNN-based methods have been applied to perform joint channel estimation and CFO recovery, showing robustness against channel impairments [9].

Despite these benefits, DL-based approaches face critical challenges:

- They demand large, labeled training datasets and lengthy offline training.
- They require considerable computing power during both training and inference.
- Their performance may degrade in environments that differ from the training set.
- They function as “black boxes,” limiting interpretability and deterministic performance guarantees.

### 2.3. Positioning of This Work

From this survey, a key trade-off becomes clear: DL methods offer adaptability and high accuracy but rely on heavy training and computing resources, while classical model-based methods guarantee deterministic accuracy but suffer from high complexity.

This work positions itself between these extremes. By enhancing the ML-APFE framework with the Woodbury matrix identity, the proposed scheme directly addresses the dominant computational bottleneck of repeated matrix inversions. The method preserves the high accuracy of ML-based estimation while dramatically reducing complexity, making it scalable for scenarios with up to 16 users and suitable for practical real-time applications.

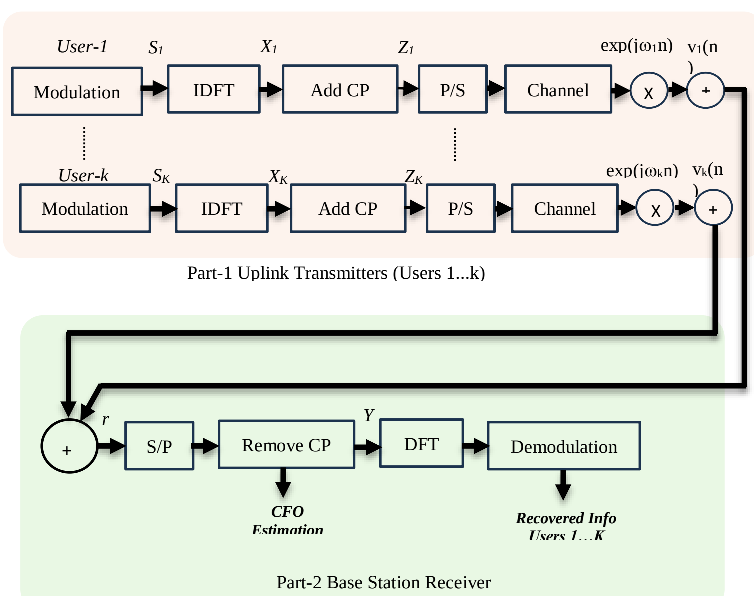


**Fig. 2 System model**

## 3. Uplink Transmission Model in OFDMA Systems

OFDMA uplink transmission involves multiple users simultaneously transmitting data to the BS on their respective subcarrier blocks. Each user's data is baseband-modulated onto assigned subcarriers, with the remaining subcarriers left inactive. Among the available subcarrier allocation strategies, the generalized subcarrier allocation method offers greater adaptability, enabling dynamic resource distribution in accordance with each user's channel conditions. The CFO estimation method developed in this work is specifically designed to function with this allocation scheme.

The underlying signal model adopted in this study follows the framework of [7] and is illustrated in Figure 2. Consider an OFDMA uplink scenario where $K$ users that are active transmit at the same time to the BS, illustrated in Figure 2. Consider the total number of subcarriers is N, the $k^{th}$ user transmits a frequency-domain vector $S_k$ containing $N_k$ non-zero elements corresponding to the user's assigned subcarriers, with all other components being zero. Applying the Inverse Discrete Fourier Transform (IDFT) yields the corresponding time-domain signal $\boldsymbol{x_k}$ defined as:

$$\mathrm{x_k} = \mathrm{F^H S_k} \tag{1}$$

Here, F represents the DFT matrix (N-point) with entries

$$[\mathrm{F}]_{\mathrm{m,n}} = \frac{1}{\sqrt{\mathrm{N}}} \exp\left(-\mathrm{j}\frac{2\pi \mathrm{mn}}{\mathrm{N}}\right), \quad 0 \le \mathrm{m,n} < \mathrm{N} \tag{2}$$

and $\mathrm{F^H}$ denotes its Hermitian transpose. A length $N_g$ Cyclic Prefix (CP) is prepended by adding it at the start to $x_k$ to mitigate inter-block interference, resulting in a vector that has the size $N_B = N + N_g$, which is shared through a multipath fading channel.

The channel impulse response for the kth, $\mathrm{h_k}=[\mathrm{h_k}(0), \mathrm{h_k}(1)\ldots \mathrm{h_k}(\mathrm{L_{k-1}})]^{\mathrm{T}}$ includes the combined effects of both filtering and the propagation environment. Since the exact channel order $\boldsymbol{L_k}$ is typically unknown, the response is zero-padded to a maximum expected delay spread $\boldsymbol{L_h}$, resulting in:

$$\mathrm{h}'_{\mathrm{k}} = \begin{bmatrix}\mathrm{h_k^T} & 0^{\mathrm{T}}_{(\mathrm{L_h}-\mathrm{L_k})\times 1}\end{bmatrix}^{\mathrm{T}} \tag{3}$$

At the Base Station (BS), the incoming signal is made up of the combined inputs from every user. When there is a CFO, the discrete-time signal received can be represented as follows:

$$\mathrm{r(m)} = \sum_{\mathrm{k=1}}^{\mathrm{K}} \left(\mathrm{e}^{\mathrm{j}\omega_{\mathrm{k}}\mathrm{m}\sum_{\mathrm{l=0}}^{\mathrm{L_h}-1}\mathrm{h_k(l)x_k(m-l)}}\right) + \upsilon(\mathrm{m}) \tag{4}$$

Here, $\omega_{\mathrm{k}} = \frac{2\pi\Delta \mathrm{f_k}}{\mathrm{N}}$ denotes the CFO of the $\boldsymbol{k^{th}}$ user, standardised relative to the space between subcarriers. The term $\upsilon(\mathrm{m})$ refers to complex white Gaussian noise, which has a variance given by $\sigma_{\mathrm{v}}^2 = 2\mathrm{N_0}$ and zero mean.

The incoming samples are divided into segments, each containing NB samples, which represent one OFDMA symbol. After converting the data from serial to parallel format, the Cyclic Prefix (CP) is removed, leaving a vector $\boldsymbol{y}$ made up of $\boldsymbol{N}$ samples. In a system that is nearly synchronized, users align their timing with the help of a reference signal before sending data in the uplink. At the beginning of each frame, during the training phase, users send predetermined pilot symbols on their assigned subcarriers. Assuming that Inter-Block Interference (IBI) is minimal during this training period, the received signal $\boldsymbol{y}$ can be described as follows:

$$\mathrm{y} = \sum_{\mathrm{k=1}}^{\mathrm{K}} \Gamma(\omega_{\mathrm{k}})\mathrm{A_k}\xi_{\mathrm{k}} + \upsilon \tag{5}$$

Where

- $\Gamma(\omega_k) = \mathrm{diag}\{e^{j\omega_k N_g}, e^{j\omega_k(N_g+1)}, \ldots, e^{j\omega_k(N_g+N-1)}\}$
- $[A_k]_{p,q} = [x_k]_{(p-q)\backslash bmod N}, \quad \text{for } 1 \le p \le N,\ 1 \le q \le N_g]$
- $\xi_k = \begin{bmatrix} h_k'^T & 0^T_{(N_g-L_h)\times 1}\end{bmatrix}^T$

The formula presented in Equation (5) serves as the basis for simultaneously estimating both the CFO and channel parameters. Nonetheless, this research concentrates solely on determining the CFO values.

## 4. Carrier Frequency Offset Estimation via Maximum Likelihood Techniques

Maximum Likelihood (ML) estimation is recognized as the optimal method for CFO estimation in OFDMA systems. Following the derivation in [7], Equation (5) can be reformulated as:

$$y = Q(\omega)\xi + \upsilon \tag{6}$$

Here, $\omega = [\omega_1, \omega_2, \ldots, \omega_K]^T$ is the vector of CFOs and:

$$Q(\omega) = [\Gamma(\omega_1)A_1, \Gamma(\omega_2)A_2, \ldots, \Gamma(\omega_K)A_K] \tag{7}$$

Assuming the presence of Gaussian noise that has a zero mean and a variance of $\sigma_\upsilon^2$, the corresponding log-likelihood function can be written as:

$$\Lambda(\widetilde{\omega}) = -N\ln(\pi\sigma_\upsilon^2) - \frac{1}{\sigma_\upsilon^2}|y - Q(\widetilde{\omega})\xi|^2 \tag{8}$$

To estimate the Carrier Frequency Offset (CFO) using the Maximum Likelihood method, one must identify the value of $\omega$ that minimizes the expression across the entire range of possible values. Alternatively, the ML problem can be posed as a maximization:

$$\widetilde{\omega} = \arg\max_{\widetilde{\omega}} |P_Q(\widetilde{\omega})y|^2 \tag{9}$$

Where the projection matrix $P_Q(\tilde{\omega})$ is given by:

$$P_Q(\tilde{\omega}) = Q(\tilde{\omega})[Q^H(\tilde{\omega})Q(\tilde{\omega})]^{-1}Q^H(\tilde{\omega}) \quad (10)$$

This requires inverting a $KN_g \times KN_g$ matrix for each combination of trial CFO values. Since an exhaustive search over all users' CFOs is computationally intensive, especially with fine resolution, the overall complexity becomes prohibitive-each inversion involves $\mathcal{O}(K^3N_g^3)$ operations.

To address this problem, the approach outlined in [7] uses the Alternating Projection (AP) technique, where the CFO for individual users is refined one at a time while the offsets for the remaining users are held constant during each step of the process. This procedure typically converges in just two iterations, drastically reducing the number of trials. However, even with AP, the computational effort per iteration remains high due to repeated matrix inversions. In this work, an improved method is proposed that significantly reduces the per-iteration computation in the ML-AP approach. The details of the proposed scheme are provided in the next section.

## 5. Reducing Computational Complexity Using Matrix Inversion Lemma

As outlined in the previous section, although the Alternating Projection (AP) technique reduces the number of trials in ML-based CFO estimation, each iteration still requires significant computation. This happens primarily because it involves repeatedly inverting large, complex-valued matrices. A closer inspection of Eq. (9) reveals that the cost function involves inverting a matrix whose structure only changes slightly with each trial CFO value. Considering this, the Woodbury matrix identity, also known as the matrix inversion lemma, can be used to alleviate this computational burden.

This approach is particularly effective when only a small portion of the matrix changes between iterations. Instead of re-computing the full matrix inverse every time, the Woodbury identity allows us to reuse a previously computed inverse and apply a correction with much lower computational overhead. The general form of the identity is as follows [21]:

$$(A + uv^T)^{-1} = A^{-1} - A^{-1}u(I + v^T A^{-1}u)^{-1}v^T A^{-1} \quad (11)$$

Let $\boldsymbol{A}$ be an invertible matrix of size $( N \times N )$. The matrices $u$ and $v$ are both of dimensions $N \times P$, where $P$ is much smaller than $N$ *(i.e., $P \ll N$)*. The symbol $I$ represents the identity matrix of size $( P \times P )$. The identity shows that one can avoid re-computing $(A^{-1})$ entirely if only a few rows or columns change, drastically reducing the total number of required multiplications.

Recalling from Section IV, the matrix $(Q^H(\tilde{\omega})Q(\tilde{\omega}))$ is of size $(KN_g \times KN_g)$ and must be inverted for each trial CFO. However, in each iteration only $(N_g)$ columns (from indices$((K-1)N_g + 1)$ to $(KN_g)$) change, corresponding to the user whose CFO is currently being estimated. Therefore, the unchanged portion can be treated as a matrix$( A )$, and the Woodbury identity can be applied for each new trial.

In this context:

- $( A )$ is the initial matrix $(Q^H(\tilde{\omega})Q(\tilde{\omega}))$
- $( u )$ is an $(KN_g \times N_g)$ matrix capturing the updates due to the new CFO trial
- $( v )$ is a structured $(KN_g \times N_g)$ matrix with an identity matrix embedded at rows $((K-1)N_g + 1)$ to $(KN_g)$

The multiplication count for the Woodbury-based update is significantly lower:

$$2N^2P + NP^2 + P^3 \quad \text{vs.} \quad N^3 \quad (12)$$

In the case of CFO estimation, $(N = KN_g)$, $(P = N_g)$, so the benefit becomes more prominent with increasing $( K )$.

This computational saving becomes especially impactful for scenarios with high user counts and larger DFT sizes. The performance and complexity comparisons are provided in the next section.

## 6. Simulation-Based Evaluation and Performance Analysis Materials and Methods

To validate the efficiency and accuracy of the proposed low-complexity CFO estimation scheme, simulations were conducted in MATLAB. The cost function applied follows the ML-based formulation described in Eq. (9). To assess how precise the CFO estimation is, the MSE is used as a metric for evaluation, calculated as:

$$\text{MSE} = E|\omega - \hat{\omega}|^2 \quad (13)$$

The main variables applied in our simulation tests are outlined in Table 1.

**Table 1. Simulation parameters and settings for CFO Estimation in a rayleigh fading environment**

| Parameter | Values |
|---|---|
| User Count | Simulations conducted with 8 and 16 users |
| DFT Size | Set to 512 |
| Cyclic Prefix Length | Fixed at 8 samples |
| Modulation Type | QPSK (Quadrature Phase Shift Keying) |
| Channel Conditions | Rayleigh fading environment with four distinct paths |

| | |
|---|---|
| CFO Category | Fractional Carrier Frequency Offset |
| Iteration Count | Adjusted based on scenario requirements |
| CFO Resolution Step | Precision set at 0.001 |
| Total Search Points | 1000 evaluation points are used in the frequency search process |

While [7] evaluated MSE performance for up to 4 users, our study considers 8 and 16 users to demonstrate scalability. Figure 3 displays MSE performance as a function of SNR. As expected, MSE degrades with an increase in user count due to enhanced multiple-access interference. Still, the proposed scheme yields MSE results comparable to those of the original ML with the AP method, while requiring substantially fewer computations.

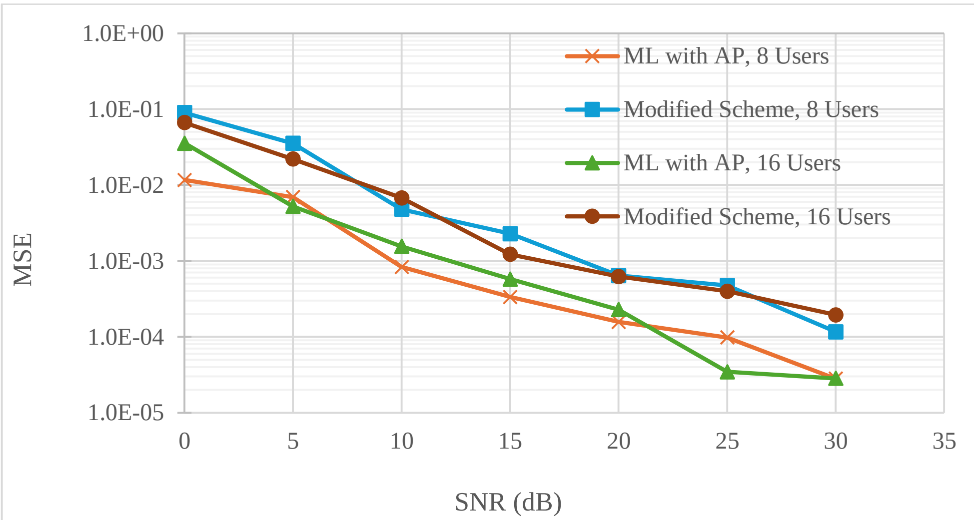


**Fig. 3 MSE Performance comparison for varying user counts**

Table 2 presents the total number of complex multiplications required to perform matrix inversion using three different techniques: the standard ML method, ML combined with AP, and the proposed method. It highlights the exponential growth in ML's computational cost due to its multi-dimensional CFO search space. The AP technique mitigates this by converting the search to one dimension per user, while our approach goes further by applying Woodbury's identity to reduce the per-iteration burden.

Figure 4 shows how the complexity benefit of our method increases with larger user counts and longer cyclic prefix lengths. This supports the method's practical viability in real-world high-capacity OFDMA systems.

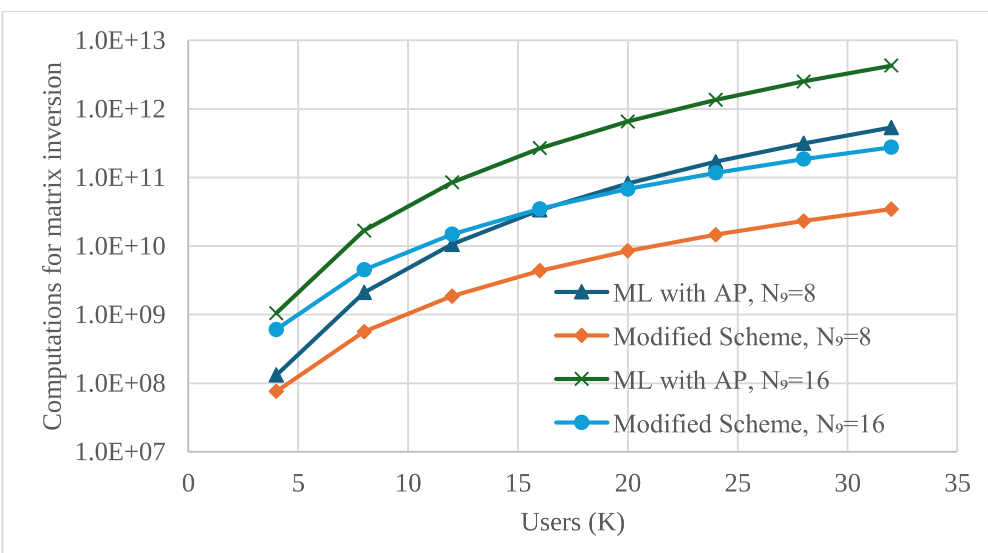


**Fig. 4 Complexity comparison for different CP lengths and user counts**

**Table 2. Comparison of total complex multiplications required**

| Method | Complex Multiplication Count for Matrix Inversion |
|---|---|
| ML | $(SP)^K \cdot (KN_g)^3$ |
| ML with AP | $N_c \cdot K \cdot SP \cdot (KN_g)^3$ |
| Proposed Scheme | $N_c \cdot K \cdot (KN_g)^3 + N_c \cdot K \cdot (SP - 1) \cdot \left(N_g^3 + 2N_g \cdot (KN_g)^2 + N_g^2 \cdot KN_g\right)$ |

## 7. Conclusion and Directions for Future Research

### 7.1. Conclusion

This study tackles the significant issue of excessive computational demands in ML-based CFO estimation for multiuser OFDMA uplink systems. To improve efficiency, a modification to the existing ML-Alternating Projection method is introduced by incorporating the Woodbury matrix identity. This modification directly targets the primary computational bottleneck—the repeated inversion of large matrices—by updating the inverse incrementally rather than recomputing it from scratch.

The results from our simulations clearly demonstrate that this method works well. In a 16-user OFDMA setup, the new approach achieves MSE performance nearly identical to the highly precise ML-AP standard. At the same time, it cuts down the computational effort needed for matrix inversion by about ten times. This significant drop in complexity makes the ML estimation technique, which was once thought to be too demanding for practical use, much more feasible for real-world applications.

### 7.2. Limitations and Future Work

Acknowledging the limitations of this study, which pave the way for important future research.

Simulation Realism: Our analysis was conducted under the assumption of perfect timing synchronization and quasi-static channels. Future work must evaluate the robustness of the proposed method in more realistic, dynamic environments, including those with timing offsets and high-mobility vehicular channels (e.g., ITU-R models) that introduce significant Doppler spread.

Scalability and Performance Metrics: While the analysis was extended to 16 users, future systems like 5G and 6G will serve much higher user densities. Further investigation is needed to confirm scalability for dozens or hundreds of users. Moreover, the evaluation should be expanded beyond MSE to include link-level performance metrics, such as Bit Error Rate (BER), which would provide a more comprehensive picture of the estimator's impact on end-to-end communication quality.

Hardware Feasibility and Comparative Analysis: This work focused on algorithmic complexity. A crucial next step is to conduct a real-time feasibility analysis, estimating latency and implementation costs on hardware platforms like FPGAs or DSPs. It would also be very useful to directly compare our approach with the top data-driven (Deep Learning) CFO estimators to clearly understand how our method stacks up against the current best techniques.

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