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PSO and ABC based Novel Carrier Frequency Offset Estimation Techniques for Wi-MAX Uplink Transmissions

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Abstract: **Carrier frequency offset (CFO) estimation is a challenging task in Wi-MAX uplink as it uses orthogonal frequency division multiple access (OFDMA) which demands extremely accurate frequency synchronization. In OFDMA uplink, each user may experience a different CFO relative to the base station reference carrier and the estimation of them turn out to be a multiple parameter estimation problem. In this paper, we propose two efficient null subcarrier based CFO estimation techniques based on particle swam optimization (PSO) and artificial bee colony (ABC) techniques which performs the estimation by minimizing a null subcarrier based cost function. As compared to the classical null subcarrier based grid search algorithm available in the literature, the computational complexity of the proposed techniques are very low. The mean square error of the CFO estimator and bit error rate performance of the Wi-MAX base station receiver that employs the proposed estimation methods are studied through computer simulations. It has been shown that the proposed techniques achieve a better performance than the grid search algorithm at low to medium signal to noise ratio (SNR) where the algorithm reliability is extremely important.**

Keywords: Orthogonal frequency division multiple access (OFDMA), Carrier frequency offset (CFO), Particle swam optimization (PSO), Artificial bee colony (ABC), Null subcarriers

I. Introduction

Worldwide Interoperability for Microwave Access (Wi-MAX) has been receiving lots of attention recently due to its ability to support high data rate wireless services with varying quality of service (QoS) requirements at an affordable cost. The standardization activities of Wi-MAX is performed by the IEEE 802.16 task groups [17]. The latest standard belonging to the IEEE 802.16 series is IEEE 802.16m which is designed to support user mobility comparable to the level of current cellular wireless systems and is designated as mobile Wi-MAX. Orthogonal frequency division multiple access (OFDMA) is adopted as the multiple access technique for the uplink of mobile Wi-MAX standard. OFDMA divides the available subcarriers into several mutually exclusive clusters and are allocated to different users for simultaneous transmission. OFDMA can provide protection against multiple access interference (MAI) only if the carrier frequency synchronization is perfectly achieved.

Mobile Wi-MAX systems are designed in such a way that the first stage of carrier frequency offset (CFO) estimation takes place in the downlink transmission where the subscriber stations (SS) estimate the frequency offset using the pilot signals transmitted by the base station (BS). Here the CFO will be a unique offset between the BS and SS and the CFO estimation techniques available for orthogonal frequency division multiplexing (OFDM) can be directly employed for estimating it [1], [2]. The SS use these estimates as a reference for the uplink transmission. But due to Doppler frequency spread and oscillator phase noise, the signals received at the BS from various SS will have small frequency offsets that lies between $-0.5 \leq \Delta_f \leq 0.5$ where Δ_f is the actual CFO in Hz normalized by the subcarrier spacing. Hence the second stage of synchronization is done at the BS by estimating the frequency offsets between the various SS and the BS receiver. The major challenge of OFDMA arises in the uplink where each user may have a distinct CFO which will affect the orthogonality and causes MAI.

Synchronization issues in OFDMA systems are gaining momentum in the literature. A computationally intensive maximum likelihood (ML) technique for the timing and frequency offset estimation in OFDMA system is proposed in [3]. An iterative method with a slightly lower computational complexity is proposed in [4], where timing and frequency offsets are estimated from the training blocks being transmitted by each users at the start of the uplink frame. This results in considerable wastage of bandwidth. A survey of most of the early results in this domain has been compiled in an excellent manner in [5]. One of the authors had proposed a null subcarrier based grid search method [6] that is computationally lighter as compared to [3]. However, its performance is not satisfactory at low SNRs. A joint CFO and channel estimation technique using the variable projection method is proposed in [7]. Though it is computationally lighter, the algorithm converge to a poor mean square error (MSE) which can not be improved further. In [8], a low complexity pilot aided synchronization technique is suggested but it assumes a tile structure for pilot and data subcarriers which may not support the wide quality of service (QoS) requirements in IEEE 802.16e/m based standards. CFO estimation for Wi-MAX OFDMA is discussed in [9] but up to three OFDMA symbols are required for the estimation. A conjugate gradient based algorithm for CFO estimation that is applicable for OFDMA with interleaved carrier assignment scheme (CAS) is proposed in [10]. We have proposed an earlier version of this work in [11]. The method for fractional carrier frequency synchronization of OFDM systems is outlined in [12] does not incorporate the specifics of the joint-estimation involved in an OFDMA uplink. The method proposed in [13] makes use of the Zadoff-Chu sequences as training sequences. There are certain issues related with the dependence of the CFOs on the autocorrelation properties of the sequences used as training preamble. The work given in [14] handles only the CFO estimation problem and is applicable only for an interleaved CAS system.

Literature review indicates that there is demand for novel, computationally lighter, suboptimal approximations to the basic maximum likelihood (ML) problem involved in the CFO estimation, especially in a generalized CAS framework. In the proposed work, we present two bandwidth and computationally efficient CFO estimation technique based on particle swam optimization (PSO) and artificial bee colony (ABC) technique for the Wi-MAX uplink OFDMA system. PSO belongs to the class of stochastic global optimization algorithms, which simulates the social behavior of bird flocking [15]. The PSO algorithm is easy to implement and is computationally efficient, as its memory and CPU requirements are low. ABC algorithm, similar to PSO, uses only common control parameters such as colony size and maximum cycle number. In ABC system, artificial bees fly around in a multidimensional search space and some(employed and onlooker bees) choose food sources depending on the experience of themselves and their nest mates, and adjust their positions [16]. In the proposed work, the cost function for both the techniques are formulated by utilizing a few null subcarriers introduced in just one training preamble, making them bandwidth efficient and thus attractive for Wi-MAX applications. Moreover, the proposed CFO estimation scheme does not require the knowledge of fading channel coefficients. Hence channel estimation can be decoupled from the CFO estimation resulting in simple receiver design.

Rest of the paper is organized as follows. Section II presents the base band model of the uplink OFDMA system and also the CAS schemes used in OFDMA systems. Development of cost function for the ML estimation of CFO is presented in Section III. Proposed CFO estimation techniques using PSO and ABC techniques are presented respectively in Section IV-A and B. Section V illustrates the computational complexities and bandwidth overheads associated with the estimators. Section VI provides a detailed account of the simulation studies conducted for the performance evaluation of proposed techniques. Concluding remarks are given in Section VII.

II. Baseband Model of the Uplink OFDMA System

A. System Model

One of the main differences between OFDM and OFDMA is that in the case of later, the available N subcarriers are divided among the M users. Since the carriers allocated to the M users are to be distinct, $I_k \cap I_j = \emptyset$ for $k \neq j$, where I_k and I_j are the sets of subcarriers allocated to k^{th} and j^{th} users respectively. The baseband signal model of the OFDMA uplink where the individual users communicate with the BS using the subcarriers allocated to them is shown in Fig. 2. For each user, a block $\mathbf{q}_m$ of Q data symbols is fed to the CAS unit and mapped to the Q subcarriers assigned to that particular user. Zeros are padded to the locations of remaining subcarriers. In the training preamble symbol, a set of Z_m subcarriers denoted as Γ_{Zm} among the Q subcarriers assigned to the m^{th} user are imposed as null subcarriers for estimating the m^{th} CFO, ϕ_m. Remaining $W_m = Q - Z_m$ subcarriers as well as Q subcarriers in other OFDMA symbols are used for data transmission of the m^{th} user.

The $N \times 1$ block of frequency domain samples fed to the IDFT modulator can be expressed as

$$\mathbf{s}_m = \mathbf{V}_m \mathbf{q}_m \tag{1}$$

where $\mathbf{q}_m$ is the $W_m \times 1$ vector of symbols transmitted on the active subcarriers and $\mathbf{V}_m$ is an $N \times W_m$ permutation matrix, whose $(n, j)^{th}$ entry is 1 if the j^{th} data symbol is transmitted on the n^{th} subcarrier and zero otherwise. For the OFDMA blocks other than the first one, $\mathbf{q}_m$ will be a $Q \times 1$ vector as all the subcarriers are used for data transmission. The symbol vector $\mathbf{s}_m$ is then pre-coded using the IDFT matrix (F) to

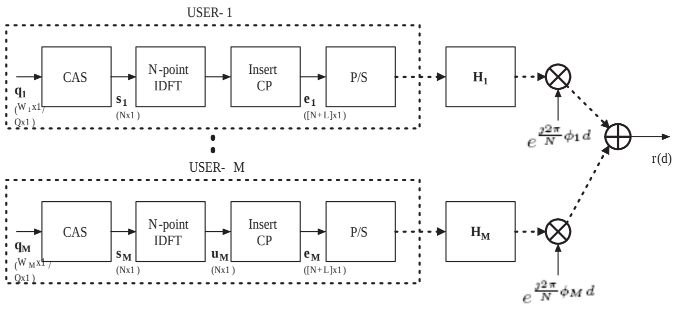

Figure. 1: Block schematic of the OFDMA uplink transmitter

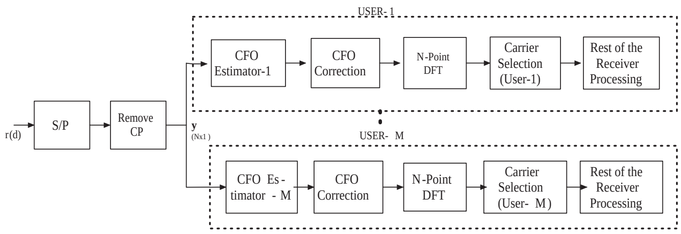

Figure. 2: Block schematic of the OFDMA uplink receiver

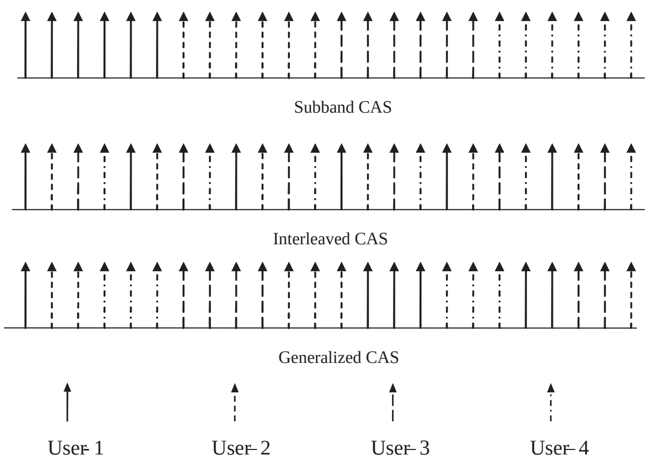

Figure. 3: A pictorial example of the carrier assignment schemes used in OFDMA system (N=24, B=C=4, and Q=6)

generate the time domain symbol of the m^{th} user

$$\mathbf{u}_m = \mathbf{F}\mathbf{s}_m \tag{2}$$

Then a cyclic prefix (CP) of L samples is appended to the vector $\mathbf{u}_m$ to form $\mathbf{e}_m$ of size $(N + L) \times 1$. This OFDMA block is transmitted after RF processing.

The transmitted signals from various subscriber stations (SSs), which are synchronized through a common control signal from the BS, will travel through different fading channels and experience distinct CFOs and timing offsets due to the differences in their local oscillator drifts and Doppler spreads. All the transmitted signals will get implicitly combined at the BS and the sampled baseband received signal is denoted as $r(d)$. It is converted to a parallel stream of samples and the CP is removed. Then the individual CFOs are estimated and corrected, before taking the DFT. Timing offsets can be absorbed in to the channel by assuming a quasi-synchronous scenario where the CP duration is designed to be greater than timing offsets and propagation delay. The subcarrier being received from the different users are separated at the DFT output according to the CAS rules used and are subjected to the remaining receiver processing.

Upon removing the CP samples and by using the vector-matrix notation, the received time domain signal at the BS can be represented as

$$\mathbf{y} = \sum_{m=1}^{M} \mathbf{P}(\phi_m)\mathbf{H}_m\mathbf{F}\mathbf{s}_m + \mathbf{z} \tag{3}$$

where $\mathbf{P}(\phi_m) = Diag(1, \exp(\jmath\frac{2\pi}{N}\phi_m), \ldots, \exp(\jmath\frac{2\pi}{N}(N-1)\phi_m)$ contains the CFO experienced by each sample of the m^{th} user and $\mathbf{H}_m$ is the channel matrix between m^{th} SS and BS which is circulant with $[\mathbf{H}_m]_{k,l} = (h(k-l)\ mod\ N)$. Additive channel noise $\mathbf{z}$ is assumed to be zero mean circular Gaussian with covariance matrix $\sigma^2 I$.

B. Career Assignment Schemes

Three methods are used for the subcarrier assignment in OFDMA systems [5]. In *subband CAS*, a group of P contiguous subcarriers are allocated to each of the users. Adjacent users are usually separated by means of a guard band. Even though this is the easiest allocation policy on a system design point of view, its performance may deteriorate in fading channels at times as it does not exploit the frequency diversity offered by multipath channels. A deep fade can affect large number of subcarriers of a specific user. A better allocation policy is *interleaved CAS* where the subcarriers of each user are uniformly spaced over the OFDM bandwidth with a separation of R subcarriers from each user. But this lacks flexibility for providing variable data rates to the demanding users, which is one of the principal goals of an OFDMA system. Hence the most promising subcarrier allocation policy is the *generalized CAS* which supports dynamic bandwidth allocation where subcarriers are allocated anywhere in the OFDM spectrum, and usually users select the subcarriers with best SNRs. But this enhances the complexity of CFO estimation task. A pictorial representation of the three CAS schemes are shown in Fig. 3 for a total of 24 subcarriers with 4 users in the system allocated with 4 subcarriers/user ($N = 24$, $Q = 6$, and $B = C = 4$). No guard bands are shown. Here an arrow represents one subcarrier and each arrow type represents the subcarriers allocated to a specific user.

III. Cost Function for CFO Estimation

A cost function needs to be formulated for the estimation of CFO using the PSO and ABC techniques. The PSO technique employs a set of feasible solutions called a “swarm of particles” that are populated in the search space with random initial locations. The values of the cost function corresponding to the particle locations are evaluated. Then the particles are moved in the search space obeying rules inspired by bird flocking behavior. Each particle is moved towards a randomly weighted average of the best position that the particle has come across so far (p_b) and the best position encountered by the entire particle population (g_b). In ABC algorithm used here, the position of a food source represents a possible solution to the estimation of CFO value of a particular user and the nectar amount of a food source corresponds to the quality of the solution assessed through the term "fitness", where fitness is calculated from the cost function. The proposed method uses a cost function that tries to minimize the total inter carrier interference (ICI) power at the null subcarrier locations due to the CFO. Firstly we shall formulate the cost function mathematically and later on explain the PSO and ABC based implementations of it.

In (3), if we diagonalize the channel circulant matrix by premultiplying and post multiplying it by DFT and IDFT matrices, we get

$$\mathbf{y} = \sum_{m=1}^{M} \mathbf{P}(\phi_m)\mathbf{F}\mathbf{D}(H_m)\mathbf{s}_m + \mathbf{z} \tag{4}$$

where $\mathbf{D}(H_m) = Diag(H_m(0), H_m(1), \ldots, H_m(N-1))$ contains the frequency domain channel coefficients with $H_m(k) = \sum_{l=0}^{L-1} h_m(l)\exp(-\frac{\jmath 2\pi kl}{N})$ denoting the frequency response of the channel at frequency $\frac{2\pi k}{N}$ between m^{th} SS and BS. The impact of a frequency selective channel on the OFDM symbol can be completely absorbed in to the data symbols by multiplying them with the channel coefficients at the specified subcarrier frequencies. Hence (4) can be re-written as

$$\mathbf{y} = \sum_{m=1}^{M} \mathbf{P}(\phi_m)\mathbf{F}_{W_m}\mathbf{x}_m + \mathbf{z} \tag{5}$$

where $\mathbf{F}_{W_m} = \mathbf{F}\mathbf{V}_m$ is an $N \times W_m$ matrix with $[\mathbf{F}_{W_m}]_{n,k} = \frac{1}{\sqrt{N}}\exp(\frac{\jmath 2\pi}{N}(n-1)k)$ and $\mathbf{x}_m \equiv \mathbf{D}(H_{W_m})\mathbf{q}_m$ with $\mathbf{D}(H_{W_m})$ representing the $W_m \times W_m$ diagonal matrix containing the actual excited channel coefficients between m^{th} SS and BS corresponding to the W_m data symbols transmitted on the first OFDMA symbol in a frame.

A cost function for the ML estimation of ϕ_m can be constructed using (5) as,

$$J(\acute{\phi}_m) = \sum_{r \in \Gamma_{Z_m}} {\mathbf{v}_{r_m}}^H \mathbf{P}^H(\acute{\phi}_m)\mathbf{y}\mathbf{y}^{\mathbf{H}}\mathbf{P}(\acute{\phi}_m)\mathbf{v}_{r_m} \tag{6}$$

where $\acute{\phi}_m$ represents the trial value of CFO for the m^{th} user, $\mathbf{v}_{r_m}$ is an $N \times 1$ vector given by $\frac{1}{\sqrt{N}}\left[1, \exp(\frac{-\jmath 2\pi}{N}r_m), \ldots, \exp(\frac{-\jmath 2\pi}{N}(N-1)r_m)\right]^T$ and Γ_{Z_m} is the set containing the indices of null subcarriers imposed in the first OFDMA symbol of m^{th} user. This cost function computes the total energy spilled over to the preassigned null subcarriers due to the ICI introduced by CFO. Thus the minimization of (6) over the possible trial CFO values will lead to the estimation of true CFO of m^{th} user.

A. CFO Estimation by Grid Search Algorithm

Grid search algorithm is an optimization technique used with null subcarrier based CFO estimation techniques[6]. Here the cost function $J(\acute{\phi}_m)$ in (6) is computed for each trial fractional offset value in the range of $-0.5 \leq \acute{\phi}_m \leq 0.5$, with increments of $1/N_f$ by initializing $\mathbf{P}(\acute{\phi}_m)$ each time with the corresponding trial value. Here N_f refers to the number of fractional points for which the cost function is computed. If it is decided to have a resolution of 0.001, the cost function has to be computed 1000 times for each user. The estimated value of CFO experienced by the m^{th} user is that value of $\acute{\phi}_m$ which results in the minimum cost function magnitude when put into (6). Similarly the CFO experienced by other $(M-1)$ users of the OFDMA system are estimated by using the specific set of null subcarriers $\{\Gamma_{Z_m}\}$ for $m = 1, 2 \ldots, M-1$. This results in an exorbitantly high computational complexity. In the proposed work, we suggest two feasible solutions to this problem by applying the PSO and ABC algorithms.

IV. Proposed CFO Estimation Methods

A. CFO estimation using the PSO Algorithm

PSO conducts its solution searching in a non-linear fashion by employing a population of particle swarms where each particle represents a potential solution (trial value for CFO estimation). The single particle will keep track of the position of its *individual best solution* (p_b) and the *global best solution*(g_b) among the achieved p_bs of all swarms. The particles are accelerated towards p_b and g_b over the iterations, by combining the cognition model and social model. The cognition model represents private thinking from its own previous experience/memory of the particle itself toward p_b. On the other hand, the social model represents collaboration of all the particles toward g_b, according to the belief of the best experience of the population.

The basic elements of PSO algorithm for the CFO estimation of a particular user can be defined as following.

1. Population size NP: It will give us the number of the particle swarms employed in PSO.

2. Particle x_k^i: Let the k^{th} particle position at the i^{th} iteration is denoted as x_k^i and each particle is one of the trial value of CFO of a particular user.

3. Particle velocity v_k^i : Let the velocity of the k^{th} particle at the i^{th} iteration is denoted as v_k^i and it is used for the movement of particles.

4. Inertia weight w^i: It will control the impact of the velocity of previous iterations on the velocity of current iteration. For the initial stage of the search process, large inertia weight is recommended to enhance the global exploration, whereas for the later stage, the inertia weight is reduced for better local exploration.

5. Cost function F: Here the energy on the null subcarriers is taken as cost function. The problem addressed here is to find the particle position x_k^i that minimizes the objective function given in (6)

6. Individual Particle Best pb_k^i: The individual best position of the k^{th} particle at the i^{th} iteration is denoted as pb_k^i, which is determined by $J(pb_k^i) \leq J(x_k^j)$ for all $j \leq i$.

7. Global Best gb^i: It is the global best particle position among all the individual best particle positions pb_k^i at the i^{th} iteration such that $J(gb^i) \leq J(pb_k^i)$ for $k = 1, 2, \ldots, N_p$.

Based on the ingredient knowledge of PSO algorithm, the steps of PSO-based CFO estimation of a particular user can be described as follows.

1) Initialization and Evaluation

First we will set the iteration counter as $i = 0$ and the initial position x_k^0 $(k = 1, 2, \ldots, N_p)$ is randomly generated from the range $[-0.5, 0.5]$. Next set $pb_k^0 = x_k^0$ and evaluate $J(pb_k^0)$. Let pb_{min}^0 is denoted as the individual best position such that $J(pb_{min}^0) \leq J(pb_k^0)$ for $k = 1, 2, \ldots, N_p$. Set $gb^0 = pb_{min}^0$. The initial velocity v_k^0 is also randomly chosen from range $[-0.5, 0.5]$.

2) Swarm Update

Firstly, we update the inertia weight w^i (in accordance with step-4) and then the velocity of the k^{th} particle at the i^{th} iteration is then changed by

$$v_k^i = w^i \times v_k^{i-1} + c_1 \times r_1 \times (pb_k^{i-1} - x_k^{i-1}) + c_2 \times r_2 \times (gb^{i-1} - x_k^{i-1}) \quad (7)$$

In (7), the first term accounts for the influence of the previous velocity to the current velocity. The second term corresponds to the cognition part, and the third term is the social part. Thus, (7) calculates the particle's current velocity according to its previous velocity, the distance of its current particle position from its own individual best particle position pb, and the global best particle position gb. Both r_1 and r_2 are random numbers that are uniformly distributed in the interval $[0, 1]$. c_1 and c_2 are the acceleration coefficients, respectively corresponding to the weighting of the stochastic acceleration terms to pull the particle to pb and gb. A commonly adopted strategy is to set both c_1 and c_2 to a constant. In our case, both c_1 and c_2 can be appropriately set to 1.
Each particle will update its position based on v_k^i by using following relation

$$x_k^i = x_k^{i-1} + v_k^i \quad (8)$$

3) Fitness Update

After finding the new particle positions, evaluate them using the objective function shown in (6). If $J(x_k^i) < J(pb_k^{i-1})$, then set $pb_k^i = x_k^i$. Else, if $J(x_k^i) \geq J(pb_k^{i-1})$, then set $pb_k^i = pb_k^{i-1}$. Set $gb^i = pb_{min}^i$ if $J(pb_{min}^i) < J(gb^{i-1})$. Else, if $J(pb_{min}^i) \geq J(gb^{i-1})$, then set $gb^i = gb^{i-1}$.

4) Termination Condition Check

Let I denote the maximum number of iterations. If the number of iterations reach I, terminate the search algorithm with the gb^I; otherwise, set $i = i + 1$ and repeat Step -B.

B. CFO estimation using the ABC Algorithm

In ABC algorithm, the colony of artificial bees consists of three groups of bees: employed bees, onlookers and scouts. First half of the colony consists of the employed artificial bees and the second half includes the onlookers. An employed bee whose food source has been abandoned by the onlooker bees becomes a scout. In the first step, the algorithm generates a randomly distributed initial population containing S solutions where S is the number of food sources and it is equal to the number of employed bees. An onlooker bee chooses a food source depending on the probability value p_i associated with that food source given by

$$p_i = \frac{fit_i}{\sum_{n=1}^{S} fit_n} \quad (9)$$

where fit_i is the fitness value of the i^{th} solution which is proportional to the nectar amount of the food source in the position i. A new candidate solution v_i from an old solution x_i can be generated as

$$v_i = x_i + \varphi_i(x_i - x_k) \quad (10)$$

where $k \in 1, 2, \ldots, S$ is a randomly chosen index which has to be different from i; and φ_i is a random number in the range $[-1, 1]$.
After each candidate source position is produced and evaluated by the artificial bee, its performance is compared with that of its old one. If the new food source has equal or better quality than the old source, then the old one is replaced by the new one. Otherwise the old position is retained. If a position cannot be improved further through a predetermined number of cycles, then that food source is assumed to be abandoned. The corresponding employed bee becomes a scout. The abandoned position will be replaced with the position of a new food source found by the scout. Assuming that the abandoned source is x_i, and then the scout discovers a new food source as

$$x_i = x_{min} + rand(0, 1)(x_{max} - x_{min}) \quad (11)$$

where x_{max} and x_{min} are the upper and lower bounds of the variable x_i.
Based on the fundamental knowledge of ABC algorithm, the steps of ABC-based CFO estimation of a particular user can be described as follows.

1. Initialize the population of solutions x_i for $i = 1, 2, \ldots, S$
2. Evaluate the population
3. set *cycle=1*
4. repeat
5. Produce new solutions v_i for the employed bees by using (10) and evaluate them
6. Apply the greedy selection process
7. Calculate the probability values p_i for the solutions x_i by means of (9)
8. Produce the new solutions v_i for the onlookers from the solutions x_i selected depending on p_i and evaluate them
9. Apply the greedy selection process
10. Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution x_i by using (11)
11. Memorize the best solution achieved so far
12. set *cycle=cycle+1*
13. until *cycle=MNC*, where MNC is the maximum number of cycles

V. Computational Complexity and Bandwidth Overhead

The computational complexity of the proposed PSO and ABC based algorithms and that of the classical null subcarrier based grid search method are compared in this section in terms of the required number of real multiplications (RM) and real additions (RA). The number of subcarriers used is N and null subcarriers is Z. The number of trials in grid search method is taken as T. The population size in PSO is taken as P and the number of iterations as C. In ABC algorithm, the food number is denoted as P and maximum number of cycles as C. For the grid search method, computation of cost function magnitude for one trial value of CFO requires $2NZ$ complex multiplications, $2Z$ RM, $Z(N-1)$ complex additions and $(2Z-1)$ RA. By converting complex operations into equivalent real operations, it requires $Z(8N+2)$ RM and $(6NZ-1)$ RA for one iteration and T times these figures are required for the complete iteration. In the PSO based algorithm, the cost function is evaluated $P(C+1)$ times and it requires $(P(C+1)Z(8N+2))$ RM and $(P(C+1)(6NZ-1))$ RA whereas in ABC based algorithm, the cost function is evaluated $(C(P+1)+P)$ times and it requires $(C(P+1)+P)Z(8N+2))$ RM and $(C(P+1)+P)(6NZ-1))$ RA.

As an illustrative example, consider a typical specification like $N = 512$ and $Z = 11$ used in the simulation studies reported in Section VI. For the PSO based algorithm, a population size of $P = 20$ and number of iterations $C = 20$ are used. The food number is taken as $P = 20$ and maximum number of cycles as $C = 20$ for the ABC based algorithm. For a comparable performance, the number of trial values used in grid search technique is $T = 1000$. For these values, the proposed PSO algorithm requires $18,935,160$ RM and $14,194,220$ RA and ABC algorithm needs $19,834,320$ RM and $14,868,040$ RA only. This is very low as compared to the grid search approach which requires $45,078,000$ RM and $33,791,000$ RA.

Apart from the computational efficiency, the proposed methods are advantageous in terms of the bandwidth overhead required for CFO estimation as compared to methods like [4], [9]. The only overhead required for the proposed method is that of a few null subcarriers imposed in the first OFDMA block of each user in a frame. This is an attractive feature of the proposed techniques in the context of bandwidth starving wireless communication applications.

VI. Simulation Studies and Discussion

Performance of the proposed CFO estimators have been studied through computer simulation of an OFDMA uplink. An OFDMA system with 512 subcarriers and a subcarrier spacing (Δ_F) of 10.9375 kHz, which meets one of the specifications of IEEE 802.16m Wi-MAX standard is considered for the simulation [17]. We assume that four users are present in the system and 128 subcarriers are allocated to each user. In the first OFDMA symbol of a frame, 11 subcarriers are imposed as nulls to aid the CFO estimation. All simulations are conducted under simultaneous presence of AWGN and multipath fading channels. SUI-5 channel model proposed by the IEEE 802.16 broadband wireless access working group for the performance evaluation of Wi-MAX transmission schemes is considered for the realization of the multipath fading channel [18]. We assume a quasi-synchronous scenario with a CP length of 32 samples. Subcarriers are allocated to the users by employing generalized career assignment scheme. The null subcarrier pattern information can be transmitted to the BS through the uplink control channels. The normalized CFOs of four users considered for the simulation are [0.45, 0.2, -0.3, 0.4].

In the grid search method [6], which is shown for the sake of comparison, CFO is estimated using one dimensional search over a range of [-0.5, 0.5] for 1000 number of trials. In PSO, we have taken a population size of 20 and maximum number of iterations of 20. The constant factor for the vector in the direction of the local best, c_1, is set to 1. The constant factor for the vector in the direction of the global best, c_2, is set to 1. In ABC algorithm, we have taken the food number as 20 and maximum number of cycles as 20. 500 Monte-Carlo iterations were used for each SNR values.

Figure 4 shows the mean square error (MSE) performance of the proposed PSO and ABC based techniques and that of the grid search method. At low to medium SNRs, performance of the proposed algorithms is much superior to [6]. They achieve an MSE better than 10^{-4} from 7-8dB onwards. The typical accuracy requirement of the CFO estimator for practical implementations is 1-2% of subcarrier spacing. While PSO based algorithm yields a better performance than ABC at low SNRs, ABC consistently performs better than PSO from medium to high SNRs. At very high SNRs, [6] performs better than the proposed methods. But at these SNRs, marginal differences in MSE will not contribute a notable difference in bit error rate (BER) performance as illustrated in the next figure. Also the proposed methods achieve this better performance with lesser computational complexity as that of [6].

The uncoded BER performances of the uplink OFDMA system with the proposed CFO estimation schemes are shown in Fig. 5. The modulation scheme used is QPSK with perfect channel estimation and zero forcing equalization. The assumption of ideal channel estimation takes the focus on to studying of the impact of synchronization errors introduced by various estimators under consideration. PSO and ABC methods achieve a BER of 10^{-3} at SNRs of 13.5dB and 13 dB respectively. It is approximately better than 4dB as compared to [6] for the same BER level. This performance can be further improved by applying suitable forward error control coding schemes. Although there is a flattening at high SNRs as compared to the grid search method, the better performance at low to medium SNRs will make the proposed method an attractive choice for practical applications.

It is important to check whether the CFO estimator ensures reliable performance for the entire range of $[-0.5, 0.5]$ for possible normalized frequency offsets. Hence, in the above range, CFOs are introduced with increments of 0.1 and the proposed algorithms are used to estimate it. The estimated CFO versus the actual CFO at an SNR of 12 dB is plotted for the designated range of values. Figure 6 shows the performance of PSO based technique while Fig. 7 shows the performance of ABC based method. While Fig. 7 depicts a close match between the actual and estimated CFOs, Fig.

6 shows a little higher difference between the estimated and actual CFOs. However all the variations are within $1 - 2\%$ of subcarrier spacing which is the synchronization accuracy requirement of a practical implementation. Figures 6 and 7 also show the identifiability of CFO over the entire range of possible frequency offsets in a typical uplink OFDMA communication system.

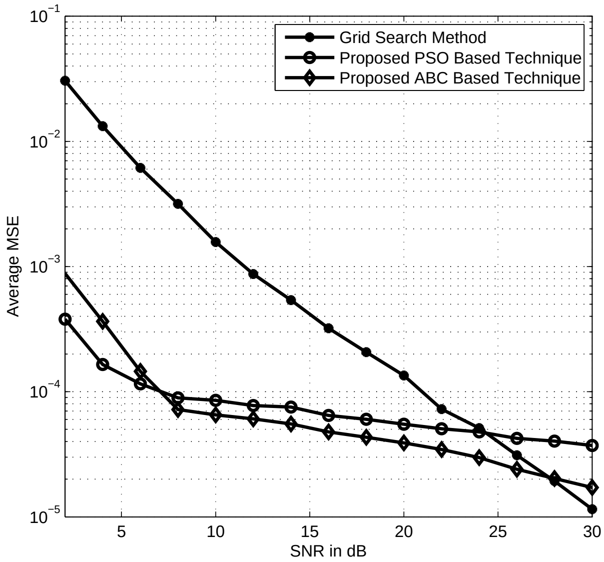

Figure. 4: The Mean Square Error of the Proposed Methods and that of [6] as a function of SNR

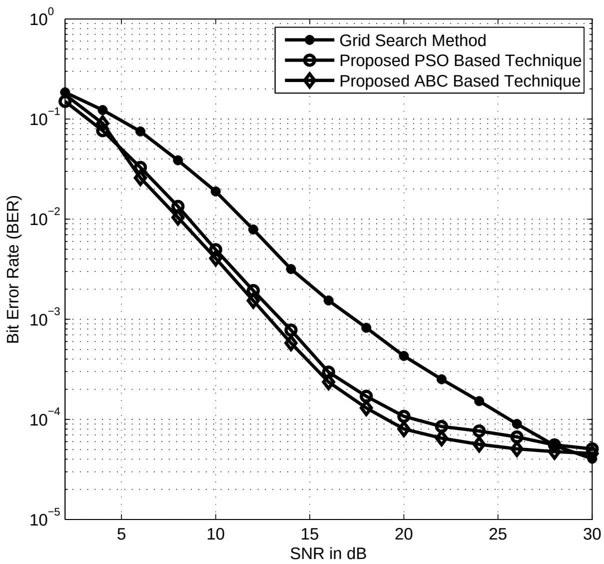

Figure. 5: Bit Error Rate versus SNR of the Proposed Techniques and that of the classical grid search method

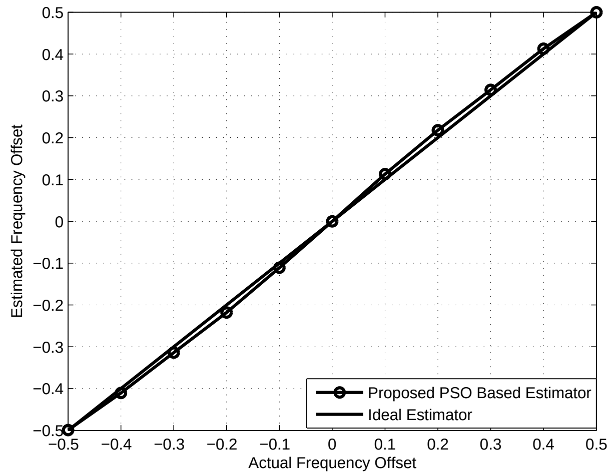

Figure. 6: Estimated CFO against actual CFO of the Proposed PSO based method

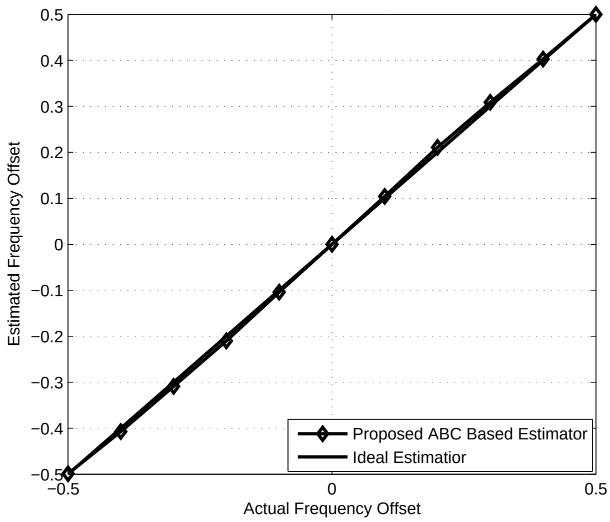

Figure. 7: Estimated CFO against actual CFO of the Proposed ABC based method

VII. Conclusions

VIII. Conclusions

In this paper, we proposed two efficient CFO estimation techniques for the challenging uplink of Wi-MAX networks where OFDMA is used as the transmission technique. Proposed schemes use the principles of bio-inspired optimization techniques such as PSO and ABC algorithms and are able to estimate multiple CFOs from a single composite received signal using a few null subcarriers. Also the proposed methods have a significantly small training overhead compared to some state of the art techniques. The MSE and BER performances of the proposed techniques are studied and found to be acceptable for practical Wi-MAX links. It has been shown that both PSO and ABC based methods outperform the null subcarrier based grid search algorithm, that uses one dimensional grid search, in terms of performance and computational complexity. As OFDMA has gained popularity as a default choice for mobile Wi-MAX networks and is an active candidate for 4G cellular systems, CFO estimation techniques which ensure good performance with small training overhead and computational complexity, like the methods proposed in this paper, have special relevance especially in the context of inexpensive receiver designs.

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