

A Novel Iterative Method for I/Q Imbalance Estimation and Calibration in Direct-Conversion Transmitters

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Abstract. *Direct-conversion transmitters (DCTs) have been widely employed in modern communication systems due to their advantages of low cost and high spectral efficiency. However, the inherent problem of in-phase/quadrature (I/Q) imbalance in this architecture significantly limits overall system performance. This paper addresses the I/Q imbalance problem in DCTs by proposing an efficient estimation and calibration method based on an improved swarm intelligence optimization algorithm, which is implemented in software. The algorithm dynamically optimizes the iterative process of pre-distortion coefficients, thereby improving the efficiency of imbalance parameter estimation. To further mitigate the limitations of conventional particle swarm optimization (PSO) algorithms in terms of convergence speed and accuracy, we design a nonlinear exponential parameter update strategy with adaptive focusing characteristics. This strategy adaptively adjusts learning factors during iteration by dynamically evaluating changes in the image rejection ratio (IRR), effectively balancing local exploitation and global exploration capabilities to enhance convergence efficiency. Experimental results demonstrate that the proposed method achieves efficient and precise I/Q imbalance calibration for transmitters, with the IRR improved to over 65 dB for single-tone signals and over 53 dB for broadband signals.*

Keywords

I/Q imbalance, parameter estimation, direct-conversion transmitter, iterative, frequency-dependent, improved PSO

1. Introduction

The rapid advancement of wireless communication technologies, particularly the widespread commercial deployment of fifth-generation (5G) mobile communication systems, has imposed increasingly stringent performance requirements on wireless transmitters [1], [2]. The key met-

rics such as system bandwidth, data transmission rate, and spectral efficiency demand further enhancement [3]. In this context, zero intermediate-frequency (IF) transmitters based on the direct-conversion architecture have emerged as the predominant solution in modern wireless communication systems, owing to their advantages of wide instantaneous bandwidth, low power consumption, and low cost [4]. However, inherent limitations in this architecture—such as non-ideal characteristics of analog components and unavoidable circuit fabrication imperfections—lead to gain and phase mismatch between the in-phase (I) and quadrature (Q) branches, i.e., I/Q imbalance. This mismatch gives rise to image interference, which severely degrades the system performance [5]. Notably, in broadband systems, this imbalance exhibits frequency-dependent (FD) characteristics, meaning the gain and phase mismatch parameters vary with the signal frequency [6]. Consequently, developing efficient and practical calibration techniques is crucial for maintaining high transmitter performance.

Technical approaches for mitigating the performance degradation induced by I/Q imbalance can be broadly categorized into analog-domain compensation and digital-domain compensation [7]. Analog-domain compensation primarily focuses on optimizing analog circuit designs or improving component characteristics to enhance the consistency of I/Q branches, such as the optimized quadrature mixer design [8–13] and local oscillator (LO) mismatch cancellation circuits [14–16]. Nevertheless, such analog-domain calibration methods often face the challenges such as high circuit design complexity and limited compensation accuracy, which restrict their practical applicability. In contrast, digital-domain based I/Q imbalance calibration techniques, which apply digital signal processing algorithms to correct impairments directly in the baseband, have been widely adopted in practice. The digital-domain I/Q imbalance calibration methods can be classified into data-aided calibration, iterative optimization, and self-calibration.

Data-aided calibration, known for its operational simplicity and high calibration accuracy, is commonly employed during system power-up calibration [17–21]. This method

relies on specially designed pilots, from which mismatch information is estimated by analyzing the received response. Liu et al. [19] utilized a Golay sequence for the online estimation and compensation of initial and time-varying (TV) frequency-independent (FI) I/Q imbalance and direct current (DC) offset. However, a common limitation of these approaches, as highlighted in [22], is their susceptibility to practical issues such as time alignment errors, high computational cost, and complex pilot design.

The self-calibration approach fundamentally requires the construction of a hardware loopback path, typically involving additional circuitry in the signal transmission path, enabling the transceiver's receiver to monitor the transmitter's imbalance [7, 23–26]. In [7], X. Cheng et al. proposed an expectation maximization (EM) based approach to jointly estimate the transmitter I/Q imbalance, receiver I/Q imbalance, and real multipath channel for single carrier frequency domain equalization (SC-FDE) system. The work in [23] presented a joint method to estimate and calibrate radio frequency (RF) impairments at both the transmitter and receiver by using frequency-offset binary phase shift keying (BPSK) and quadrature phase shift keying (QPSK) training signals. Neelam and Sahu [24] employed a pseudo-noise (PN) based training sequence for the joint estimation of transceiver I/Q imbalance and channel parameters in the delay time domain. Despite extensive research, these calibration methods impose stringent demands on training sequence design, incur high implementation complexity, and also face time alignment problems.

In comparison, calibration methods based on digital signal processing and corresponding iterative optimization algorithms can also achieve high accuracy imbalance compensation with lower implementation complexity, without relying on known pilot or training sequences [27–32]. M. Tong et al. [28] employed an iterative algorithm that combines frequency-domain minimum mean square error (MMSE) equalization based on an extended-dimension signal model with frame-level decision-driven continuous interference cancellation (DDSIIC) to jointly correct intersymbol interference (ISI) and FD I/Q imbalance in faster-than-Nyquist (FTN) systems. Furthermore, Lagha et al. [32] developed a blind compensation method based on second-order statistics. It employs blind adaptive source separation (BASS) algorithm combined with the globally updated equivariant adaptive separation via independence (EASI) algorithm to perform joint blind source separation and imbalance correction. However, iterative optimization-based methods often face challenges with convergence speed and stability, leading to lengthy calibration times. Thus, an efficient algorithm with stable convergence remains a need.

In this paper, we investigate and develop an adaptive iterative algorithm based on an improved swarm intelligence optimization technique to address the estimation and calibration of I/Q imbalance in direct-conversion transmitter (DCT). The major contributions of this research are given as follows:

- A corresponding structure for the proposed method is designed to estimate and compensate I/Q imbalance coefficients.
- A swarm intelligence optimization algorithm is employed to dynamically adjust the parameters of a pre-distortion module during imbalance factors estimation, minimizing the image component in the output signal and thereby achieving accurate estimation of the imbalance factors.
- A nonlinear exponential parameter update strategy with adaptive focusing characteristics is introduced to mitigate the limitations of conventional particle swarm optimization (PSO) optimization methods, such as their susceptibility to local optima and slow convergence. This strategy enables dynamic balancing between local exploitation and global exploration capabilities during the iterative process: it enhances global exploration in the early stages to rapidly locate potential optimal regions, while intensifying local search in the later stages to improve convergence speed and parameter estimation accuracy.

Furthermore, both simulation and experimental platforms were constructed to validate the proposed calibration method, which is realized in software. The results demonstrate that the proposed approach achieves efficient and high-precision parameter estimation and I/Q imbalance calibration.

The rest of this paper is organized as follows: Section 2 introduces the novel I/Q imbalance model for the DCT and formulates the corresponding image rejection ratio (IRR). Section 3 presents the proposed calibration architecture and transforms the imbalance parameter estimation into a constrained nonlinear optimization problem solved by an improved PSO. Section 4 details the simulation setup and presents experimental validation on a hardware platform. Finally, Section 5 concludes the paper.

2. I/Q Imbalance Model

The system model of a DCT with I/Q impairments is illustrated in Fig. 1. The DCT baseband generates ideal digital I/Q sequences, denoted as $x_I(n)$ and $x_Q(n)$, which are then converted into analog waveforms $x_I(t)$ and $x_Q(t)$ by digital-to-analog converters (DACs). The ideal complex baseband signal for the DCT can be expressed as $x(t) = x_I(t) + jx_Q(t)$. Without interference of imbalance, the baseband signal is upconverted to RF using a carrier frequency ω_c , producing the output signal $\tilde{s}(t) = x_I(t)\cos(\omega_c t) - x_Q(t)\sin(\omega_c t)$. In practice, analog imperfections and circuit mismatches between the I and Q branches can lead to amplitude and phase imbalances, which degrade performance by causing image interference. Following the approaches in [7], [23], these I/Q impairments are typically modeled as comprising two parts: FI and FD mismatches.

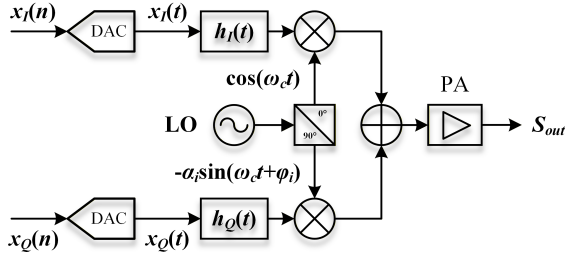


Fig. 1. Block diagram of DCT with IQ impairment.

The FI part is modeled as an impaired LO signal, expressed as $x_{LO}(t) = x_{LO,I}(t) + jx_{LO,Q}(t) = \cos(\omega_c t) + j\alpha_i \sin(\omega_c t + \phi_i)$, where α_i and ϕ_i represent the LO gain mismatch and phase offset factors. Meanwhile, the FD I/Q imbalance originate from the different characteristics of the analog components or transmission paths between the I and Q channels. These mismatches result in distinct frequency responses for the two branches. These impairments can be modeled by incorporating them into the corresponding low-pass filters (LPFs) in the I and Q paths, with impulse responses denoted as $h_I(t)$ and $h_Q(t)$. Thus, the distorted analog signals can be modeled as $x_I(t) = \alpha_{d,I}(\omega) \cdot \cos(\omega t + \phi_{d,I}(\omega))$ and $x_Q(t) = \alpha_{d,Q}(\omega) \cdot \sin(\omega t + \phi_{d,Q}(\omega))$, where $\alpha_{d,I}(\omega)$ and $\alpha_{d,Q}(\omega)$ denote the nonlinear FD gain factors for the I and Q channels, respectively, while $\phi_{d,I}(\omega)$ and $\phi_{d,Q}(\omega)$ represent the nonlinear FD phase shift factors.

Without loss of generality, the FD impairments can be modeled as an equivalent distortion applied solely to the Q branch. Within this model, the FD gain mismatch $\alpha_d(\omega)$ is defined as the amplitude ratio between the I and Q branches [27]

$$\alpha_d(\omega) = \frac{\alpha_{d,I}(\omega)}{\alpha_{d,Q}(\omega)} \quad (1)$$

and the FD phase mismatch $\phi_d(\omega)$ is defined as the phase difference between these branches [27]

$$\phi_d(\omega) = \phi_{d,I}(\omega) - \phi_{d,Q}(\omega). \quad (2)$$

Therefore, the RF signal incorporating I/Q imbalance can be expressed as

$$\begin{aligned} S_{out}(t) &= x_I(t) \cdot x_{LO,I}(t) - x_Q(t) \cdot x_{LO,Q}(t) \\ &= x(t) \exp(j\omega_c t) \cdot k_1(\omega) + x^*(t) \exp(-j\omega_c t) \cdot k_1^*(\omega) \\ &\quad + x^*(t) \exp(j\omega_c t) \cdot k_2(\omega) + x(t) \exp(-j\omega_c t) \cdot k_2^*(\omega) \end{aligned} \quad (3)$$

where the imbalance coefficients $k_1(\omega)$ and $k_2(\omega)$ are denoted as

$$\begin{aligned} k_1(\omega) &= \frac{1 + \alpha_i \cdot \alpha_d(\omega) \cdot \exp(j\phi_d(\omega)) \exp(j\phi_i)}{2}, \\ k_2(\omega) &= \frac{1 - \alpha_i \cdot \alpha_d(\omega) \cdot \exp(j\phi_d(\omega)) \exp(-j\phi_i)}{2}. \end{aligned} \quad (4)$$

The IRR is typically adopted as the evaluation indicator to quantify the impact of I/Q imbalance on the performance of the DCT, which is defined as [33]

$$IRR(\omega) = 10 \log_{10} \frac{|G_+(\omega)|^2}{|G_-(\omega)|^2} \quad (5)$$

where $G_+(\omega)$ and $G_-(\omega)$ denote the power of the main signal component and the image component, respectively, in the transmitter output. As a key metric for I/Q imbalance, the IRR typically ranges from 20 dB to 40 dB without compensation, a level insufficient for advanced DCT.

3. I/Q Imbalance Calibration Method

3.1 Estimation and Calibration Structure

In order to compensate for the inherent I/Q imbalance of the DCT, a pre-distortion module is inserted between the baseband signal generator and the subsequent hardware system. Its output is denoted as $u(n)$. During the initial state of I/Q imbalance calibration, the gain and phase compensation coefficients of the pre-distortion module are set to 1 and 0, respectively. Under this condition, the output of the pre-distortion module is identical to its input, i.e., $x(n) = u(n)$. The structure for DCT I/Q imbalance estimation and calibration is illustrated in Fig. 2.

Within the system design, the I/Q imbalance compensation is configured as a cascade connection of the pre-distortion module and the hardware system. This configuration aims to optimize the final output of the transmitter to closely approximate an ideal quadrature model, i.e., the gain mismatch converges to 1 and the phase mismatch converges to 0. The corresponding block diagram is depicted in Fig. 3. The pre-distortion module that realizes this compensation is given by

$$\begin{aligned} u_I(n) &= x_I(n), \\ u_Q(n) &= \tilde{\alpha} \cdot (\sin \tilde{\varphi} \cdot x_I(n) + \cos \tilde{\varphi} \cdot x_Q(n)) \end{aligned} \quad (6)$$

where $\tilde{\alpha}$ and $\tilde{\varphi}$ are the gain and phase compensation coefficients of the pre-distortion module for the system total imbalance, respectively.

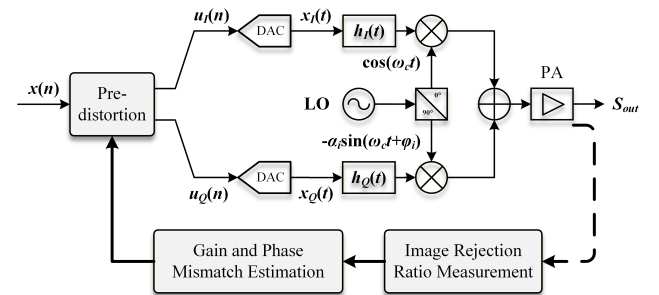


Fig. 2. Block diagram of DCT with IQ imbalance estimation and calibration structure.

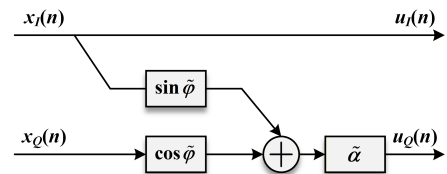


Fig. 3. Block diagram of pre-distortion for I/Q imbalance calibration.

3.2 Optimization Problem

In this paper, the core objective of the calibration process is to optimize the pre-distortion module coefficients $(\tilde{\alpha}, \tilde{\varphi})$ so that the distortion they introduce compensates for the system's inherent I/Q imbalance (α, φ) . Thus, the estimation of DCT imbalance parameters can be formulated as a nonlinear optimization problem, with the loss function $J(\alpha, \varphi)$ defined as IRR. This optimization objective is achieved by iteratively adjusting the pre-distortion coefficients via an adaptive feedback loop, thereby obtaining estimates of the system's gain and phase mismatch at the baseband angular frequency ω_0 . The process essentially performs a global search over the parameter space (α, φ) to find the imbalance parameters $(\tilde{\alpha}, \tilde{\varphi})$ that minimize the IRR. Consequently, the I/Q imbalance calibration problem can be formally expressed as the following constrained optimization problem

$$\begin{aligned} & \min J(\alpha, \varphi), \\ & \text{s.t. } \alpha \in [0, 2], \varphi \in \left(-\frac{\pi}{2}, \frac{\pi}{2}\right). \end{aligned} \quad (7)$$

When the global optimum is attained by the objective function under the specified constraints, the image signal power is minimized. The corresponding optimal imbalance parameter $(\tilde{\alpha}, \tilde{\varphi})$ that achieves this condition constitutes the global minimum point in the solution space, satisfying

$$\begin{aligned} (\tilde{\alpha}, \tilde{\varphi}) = \arg \min_{\substack{\alpha \in [0, 2] \\ \varphi \in (-\pi/2, \pi/2)}} J(\alpha, \varphi). \end{aligned} \quad (8)$$

Under ideal conditions, the IRR exhibits a single global optimum. For such a unimodal problem, algorithms like gradient descent can reliably converge to the globally optimal solution [34]. However, in practical hardware systems, the presence of noise introduces multiple local optima within the solution space. As shown in Fig. 4, the corresponding contour lines of the resulting surface exhibit multiple undulations. This compromises the convergence stability of gradient-based algorithms, making them susceptible to becoming trapped in local optima and thus failing to achieve global parameter optimization.

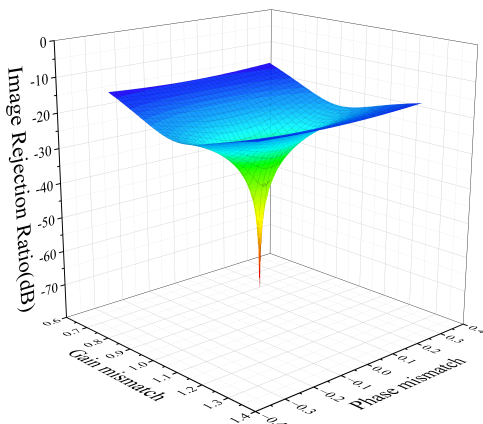


Fig. 4. Relationship between IRR and I/Q imbalance in the presence of system noise.

3.3 Swarm Intelligent Algorithm

PSO, a population-based intelligent optimization algorithm, was introduced by R. C. Eberhart and J. Kennedy in 1995 [35]. The algorithm draws inspiration from the collective behavioral patterns observed in natural bird flocking activities. It emulates the cooperative foraging behavior and information sharing mechanisms within bird populations, enabling the swarm to effectively locate the global optimum solution.

In the PSO algorithm, each individual within the search space is abstracted as a massless and volumeless particle characterized solely by two fundamental attributes: velocity and position. Each particle thereby represents a potential solution within the solution space. The core principle of the algorithm is founded upon a swarm-based information-sharing mechanism. Throughout the iterative process, each particle dynamically updates its velocity vector and position vector based on its own historical best solution (personal best) and the swarm's current best solution (global best). This interactive information mechanism guides the entire particle swarm to gradually converge toward the vicinity of the global optimum. The quality of a solution is quantitatively evaluated by a fitness value derived from a predefined fitness function.

The standard velocity and position update equations governing the PSO algorithm can be represented as [35]

$$\begin{cases} \mathbf{V}_i^{k+1} = w\mathbf{V}_i^k + c_1r_1(\mathbf{P}_{i,\text{pbest}}^k - \mathbf{X}_i^k) + c_2r_2(\mathbf{P}_{\text{gbest}}^k - \mathbf{X}_i^k) \\ \mathbf{X}_i^{k+1} = \mathbf{X}_i^k + \mathbf{V}_i^{k+1} \end{cases} \quad (9)$$

where $\mathbf{V}_i^k$ and $\mathbf{X}_i^k$ represent the velocity vector and position vector, respectively, of the i -th particle at the k -th iteration. Both $\mathbf{V}$ and $\mathbf{X}$ can be multidimensional vectors, specifically defined as $\mathbf{V} = [v_1, v_2, \dots, v_d]^T$ and $\mathbf{X} = [x_1, x_2, \dots, x_d]^T$. Here, w represents the inertia weight factor; c_1 and c_2 are the cognitive (individual) learning factor and social (group) learning factor, respectively; r_1 and r_2 are two independent random numbers uniformly distributed in the interval $[0, 1]$. $\mathbf{P}_{i,\text{pbest}}^k$ signifies the personal best position (individual optimum) of the i -th particle up to the k -th iteration, while $\mathbf{P}_{\text{gbest}}^k$ denotes the global best position (population optimum) achieved by the entire swarm after k iterations. Similarly, $\mathbf{P}_{\text{pbest}}$ and $\mathbf{P}_{\text{gbest}}$ are also d -dimensional column vectors.

During the joint optimization process of the gain mismatch factor $\tilde{\alpha}$ and the phase mismatch factor $\tilde{\varphi}$, strong global exploration capability is required in the initial stage to locate potential optimal regions. As the IRR progressively approaches the global optimum, the precision requirements for the factors $\tilde{\alpha}$ and $\tilde{\varphi}$ increase accordingly. Simulation results are shown in Figs. 5 and 6, which illustrate the combined influence of $\tilde{\alpha}$ and $\tilde{\varphi}$ on the IRR, respectively. Figure 5 demonstrates that when $\tilde{\varphi}$ is at its global optimum ($\tilde{\varphi} = 0.22$), a minimal variation in $\tilde{\alpha}$ (as small as 0.001) significantly impacts the IRR. Figure 6 further reveals that when $\tilde{\alpha}$ resides within the neighborhood of its optimal value, even a slight change in $\tilde{\varphi}$ also induces a substantial fluctuation in the IRR.

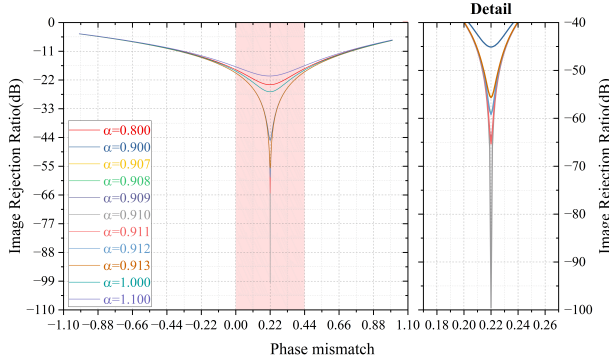


Fig. 5. The variation curve of IRR with φ under different α values.

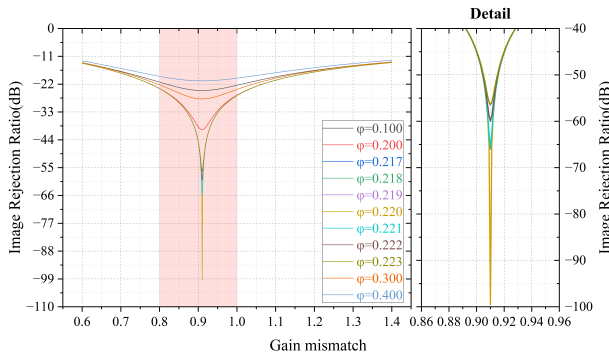


Fig. 6. The variation curve of IRR with α under different φ values.

These results indicate that the local search ability must be enhanced during the later stages of the optimization process to achieve high-precision identification of the imbalance parameters.

3.4 Adaptive Learning Factor Update Strategy

Population-based intelligent optimization algorithms, exemplified by the conventional PSO algorithm, are fundamentally classified as stochastic search methods [36]. However, they may face limitations during parameter optimization, including a tendency to converge to local optima, slow convergence speed, and limited final accuracy. To overcome these performance limitations, numerous improved strategies have been investigated, primarily including dynamic adjustment mechanisms for inertial weight, adaptive optimization methods for learning factors, and various population distribution optimization techniques [36–38].

The learning factor is a critical parameter in PSO, governing both the direction and step size of particle movement toward the individual best position and the global best position. To address these limitations and further enhance the performance of the PSO algorithm in terms of both iterative efficiency and convergence accuracy, we propose a nonlinear learning factor update strategy with focusing characteristics. The core mechanism of this strategy lies in adaptively updating the individual learning factor c_1 and social learning factor c_2 based on the dynamic evolution of the relative distance be-

tween the current particle fitness value and the initial fitness value. The specific update rules for the learning factors are defined as follows

$$c_1 = \exp\left(-\frac{F_0 - F_c}{F_0} p_1\right), \quad (10)$$

$$c_2 = \exp\left(\frac{F_0 - F_c}{F_0} p_2\right) \quad (11)$$

where F_0 denotes the initial fitness value, F_c represents the current fitness value, and the fitness value satisfies $F = 10^{\frac{\text{IRR}}{10}}$. Here, p_1 and p_2 are introduced random numbers uniformly distributed in the interval $[0, 1]$. With the introduction of this update strategy, the learning factors no longer exhibit a simple monotonic variation. Instead, they demonstrate an adaptive, nonlinear evolution that dynamically adjusts according to the progression of the mismatch factor search. This mechanism enables a dynamic balance between the algorithm's local exploitation and global exploration capabilities during the iterative process, thereby synergistically optimizing both the convergence rate and the final solution accuracy.

Algorithm 1 details the implementation framework for gain and phase mismatch factors estimation and calibration in the DCT, which is based on an improved PSO approach.

In this framework, each particle's position vector $\mathbf{X}_i^k$ is mapped to a parameter space defined by (α, φ) , and the resulting parameter pair is applied to the pre-distortion module. At the end of each iteration, the parameter pair corresponding to the current optimal particle is immediately applied to the pre-distortion module. The algorithm uses the IRR as its core performance metric and constructs a fitness function F_c based on this metric to guide the particle swarm toward minimizing the IRR. Finally, the estimated values $\tilde{\alpha}$ and $\tilde{\varphi}$ are obtained by mapping the global optimum position $\mathbf{P}_{\text{gbest}}^k$ to the parameter space, and are then used for calibration of the I/Q imbalance.

Algorithm 1. Proposed I/Q imbalance estimation and calibration scheme.

Input: ω_0

Output: $\tilde{\alpha}$ and $\tilde{\varphi}$

- 1: Initialize particles, iterations, w , c_1 , c_2 and set $[v_{\min}, v_{\max}]$, $[x_{\min}, x_{\max}]$.
 - 2: Initialize the particles velocity, distribution and fitness, $\mathbf{P}_{\text{pbest}}$ and $\mathbf{P}_{\text{gbest}}$.
 - 3: **for** $k = 2$ to iterations **do**
 - 4: **for** $i = 1$ to particles **do**
 - 5: update $\mathbf{V}_i^k$ and $\mathbf{X}_i^k$ by using (9);
 - 6: map $\mathbf{X}_i^k$ onto the parameter pair (α, φ) ;
 - 7: update (α, φ) to pre-distortion module;
 - 8: update IRR;
 - 9: calculate F_c ;
 - 10: update $\mathbf{P}_{i,\text{pbest}}^k$;
 - 11: update $\mathbf{P}_{\text{gbest}}^k$;
 - 12: **end for**
 - 13: update c_1 by using (10);
 - 14: update c_2 by using (11);
 - 15: **end for**
 - 16: map $\mathbf{P}_{\text{gbest}}$ onto the parameter pair $(\tilde{\alpha}, \tilde{\varphi})$.
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4. Simulation and Experimental Results

4.1 Simulation Results

In order to verify the effectiveness of the I/Q imbalance estimation and calibration method proposed in Sec. 3, a DCT simulation platform incorporating I/Q impairment was developed using MATLAB 2015b. The system operated with a sampling rate of 1.25 GHz. The specific parameter configurations are detailed as follows: The baseband signal frequency was swept from -500 MHz to 500 MHz, with a frequency step of 10 MHz. The cutoff frequency of the baseband LPF was set to 500 MHz. The LO frequency was configured as $f_{LO} = 3$ GHz. To model practical hardware impairments, equivalent gain and phase mismatches, including both FI and FD parts, were embedded in the DCT model, as shown in Fig. 7 (a) and (b). Specifically, the FD gain mismatch was set to be approximately even-symmetric, while phase mismatch was modeled as approximately odd-symmetric. Additionally, the number of points for the fast Fourier transform (FFT) was set to 2048 points to calculate the power of the signal and image components. The estimation accuracy was quantified by the relative errors (RE) of the gain and phase mismatch factors, denoted as e_g and e_ϕ , respectively, defined as

$$RE = \left| \frac{u - p}{p} \right| \cdot 100\% \quad (12)$$

where u and p denote the estimated value and preset value, respectively, and $|\cdot|$ represents the absolute value operation.

The simulation results for I/Q imbalance estimation and calibration are presented in Fig. 7 and Fig. 8. Figure 7 indicates that, within a wide baseband frequency range from -500 MHz to 500 MHz, despite the system's preset nonlinear gain and phase mismatches, the proposed method still demonstrates strong tracking capability, achieving accurate parameter estimation with RE maintained below 1×10^{-2} and 3×10^{-1} , respectively. This confirms that the method achieves high estimation accuracy across a wide frequency band. Figure 8 shows the IRR performance before and after I/Q imbalance calibration. Due to the presence of I/Q imbalance in the system, the uncorrected IRR varied between 10 dB and 45 dB over frequency band. After applying the proposed calibration method, the IRR was consistently improved to over 80 dB across the entire frequency band, representing a significant improvement compared to the uncorrected value, thereby verifying the proposed method's effective compensation capability for DCT I/Q imbalance.

The fitness convergence curve, which tracks the evolution of the optimal fitness value over iterations, indicates the algorithm's convergence speed and stability. The convergence efficiency of the proposed improved PSO was compared with the conventional PSO [35] and the improved PSO methods in [36], [39] under the same experimental conditions. The comparison results of fitness convergence curves are presented in Fig. 9.

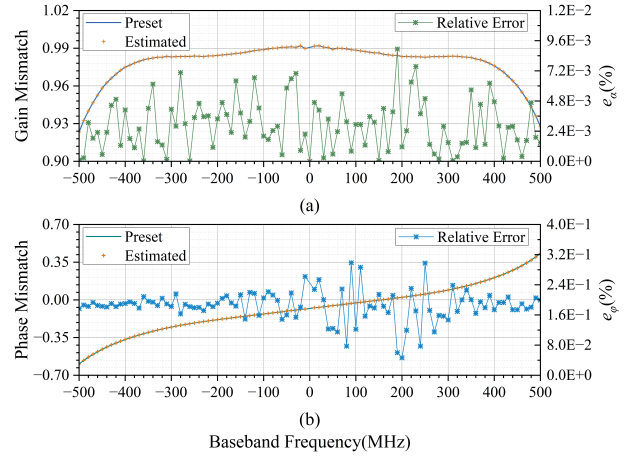


Fig. 7. Simulation results of (a) DCT I/Q gain mismatch, and (b) DCT I/Q phase mismatch estimation at different baseband frequencies.

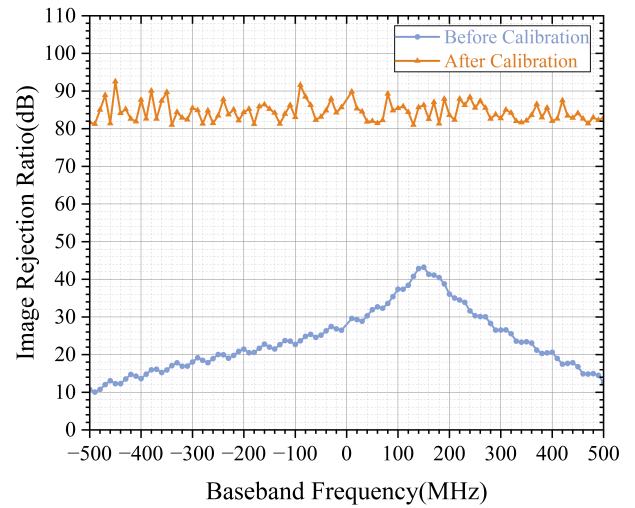


Fig. 8. Simulation results of I/Q imbalance calibration at different baseband frequencies. The frequency range spans from -500 MHz to 500 MHz with a step size of 10 MHz.

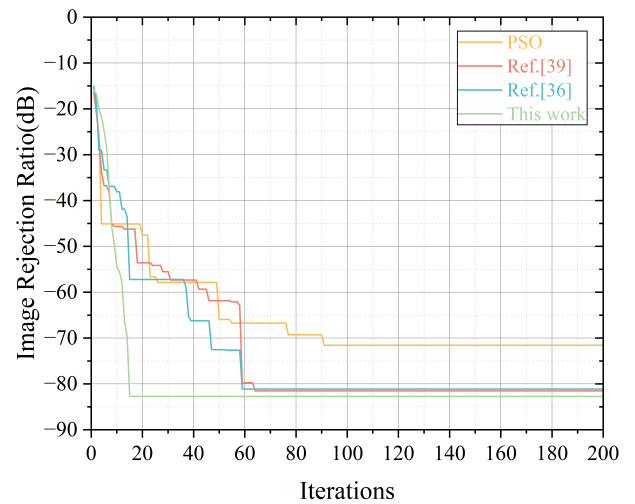


Fig. 9. Simulation results of convergence performance for different algorithms.

From the observation of Fig. 9, the conventional PSO converges to its minimum fitness value at the slowest rate and exhibits premature convergence, indicating that it is likely to get stuck in a local optimum and yielding suboptimal solutions. In contrast, the convergence curve of the improved PSO guarantees stronger global search capability and converges faster to the global optimum. Simulation results confirm that the improved PSO converges more rapidly than conventional PSO and its variants, achieving higher efficiency in locating the global optimum.

To ensure statistical reliability, we performed multiple independent replicates for all algorithms. Each algorithm was independently executed 100 times with a maximum of 500 iterations per run. The RE of the gain and phase mismatch was evaluated for each trial. The mean, standard deviation (SD), best, and worst RE values from these 100 independent runs served as the key performance metrics for comparing the algorithms. The statistical results are presented in Figs. 10 and 11.

Based on the statistical results shown in Figs. 10 and 11, the overall performance of each algorithm in estimating gain and phase mismatches can be evaluated. The results indicate

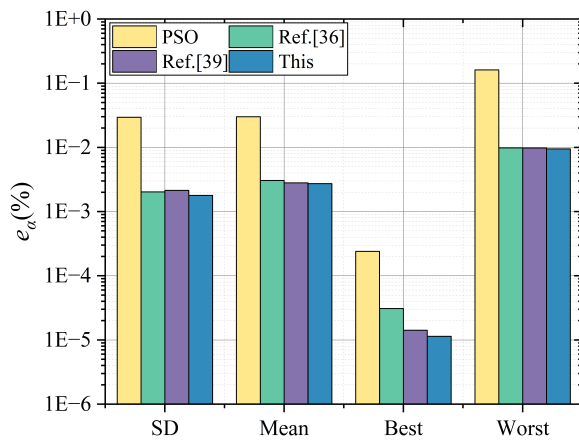


Fig. 10. Statistical results of different algorithms for the RE of gain mismatch.

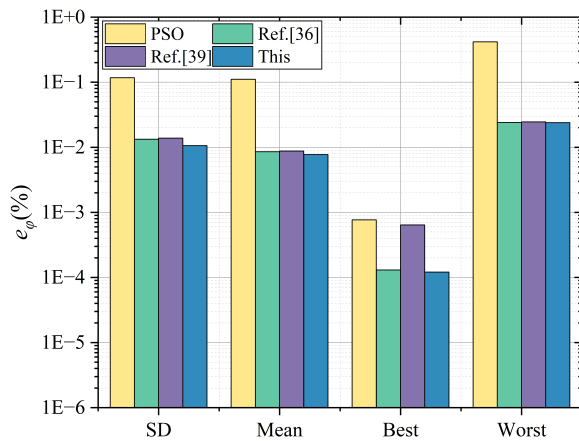


Fig. 11. Statistical results of different algorithms for the RE of phase mismatch.

that the proposed method outperforms the other algorithms across all statistical metrics, confirming its ability to approximate the global optimal solution. Specifically, in terms of mean values, the proposed method achieves RE of 2.73×10^{-3} and 1.06×10^{-2} for e_{α} and e_{φ} , respectively, representing a significant improvement over the conventional PSO algorithm. This advantage stems from enhancements in the search strategy, particularly the integration of global exploration and local exploitation, which effectively avoids the inherent limitations of the PSO algorithm—getting trapped in local optima due to premature loss of population diversity. SD is a key metric for measuring algorithm stability. The proposed method achieves significantly lower SD values for both e_{α} and e_{φ} compared to the conventional PSO algorithm and also outperforms the methods described in [36], [39], indicating that it can yield stable, high-precision estimates under different initial particle distributions. Notably, regarding the worst-case performance, the proposed method still achieves e_{α} and e_{φ} of 9.51×10^{-3} and 2.39×10^{-2} , respectively, outperforming the other methods. This demonstrates that even under the most unfavorable conditions, the proposed method maintains high accuracy in parameter estimation. In contrast, the conventional PSO algorithm performs the worst in terms of both mean RE and best RE values, reflecting its tendency to get stuck in local optima and its limited convergence accuracy for this problem.

4.2 Measurement Results

In addition to software simulation, we constructed an experimental platform to verify the I/Q imbalance estimation and calibration method proposed in this paper. As illustrated in Fig. 12, the setup consisted of a host computer (NI PXIe-8133) with an Intel Core i7 Q820 central processing unit (CPU) @1.73 GHz and 4 GB random-access memory (RAM), a Keysight MXA signal analyzer (N9020A), an NI PXIe-1062Q chassis, and a laboratory-built prototype vector signal generator (VSG) serving as the target calibration transmitter. The basic parameters of the VSG are listed in Tab. 1.

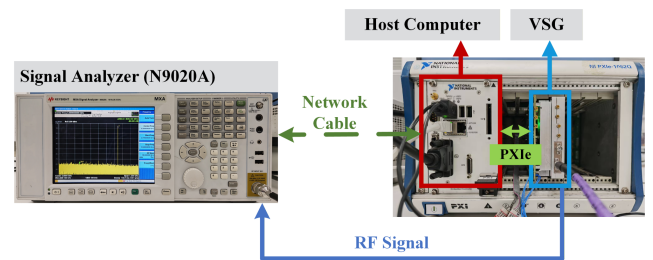


Fig. 12. The experimental platform of this work.

Parameters	Value
Frequency Range	65 MHz to 6 GHz
LO Frequency Range	20 MHz to 6 GHz
Sampling Rate	1.25 GSPS
Instantaneous Bandwidth	1 GHz
Typical Uncalibrated IRR	25 dB to 45 dB

Tab. 1. Parameters value of the VSG

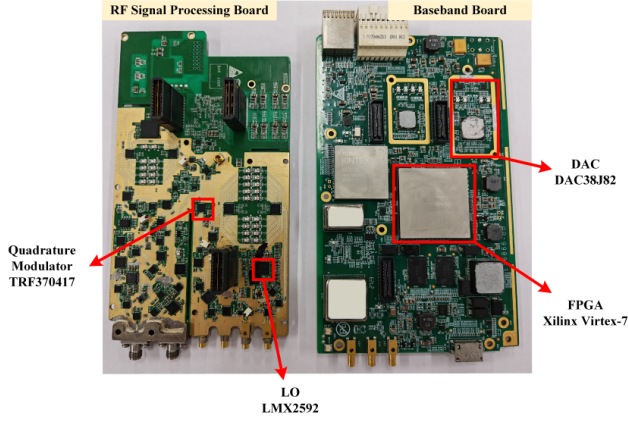


Fig. 13. Block diagram of the VSG prototype hardware.

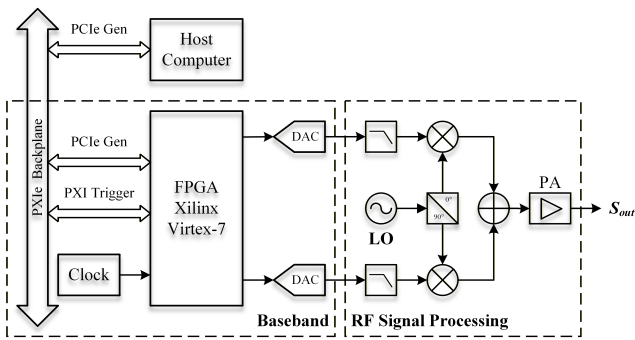


Fig. 14. Block diagram of the VSG experimental platform.

The VSG, installed in the PXIe chassis, was controlled by the host computer via the PXIe backplane to generate signals at specified frequencies. Its hardware architecture is presented in Figs. 13 and 14, comprising a baseband board and an RF signal processing board. The baseband board houses the core components: a field programmable gate array (FPGA) for signal processing and a dual-channel, 16-bit DAC38J82. The DAC was operated at 1.25 GSPS to support the 1 GHz instantaneous bandwidth requirement. The RF signal processing board houses the core components: an LO signal generator LMX2592 and a quadrature modulator TRF370417 used to upconvert the signal from IF to RF. The IF bandwidth of the TRF370417 exceeds 1 GHz, making it suitable for broadband signal processing.

To evaluate the calibration performance, we employed the signal analyzer to measure the IRR of the output signal from the VSG. The signal analyzer was remotely controlled via a local area network (LAN) by the host computer, allowing the acquisition of the output signal's IRR. The pre-distortion module is implemented within the FPGA, and its structure is shown in Fig. 15. The module consists of three multipliers, an adder, and a delay unit. The delay unit ensures time alignment of the I and Q signals after pipeline establishment, thereby preventing additional phase mismatch.

The I/Q imbalance estimation and calibration software runs on the host computer, and its operational flowchart is shown in Fig. 16. The process comprises two main stages: initialization and iterative optimization. In the initialization

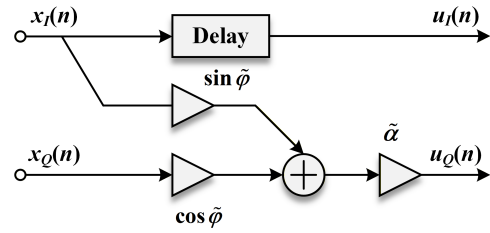


Fig. 15. Block diagram of the pre-distortion module implementation.

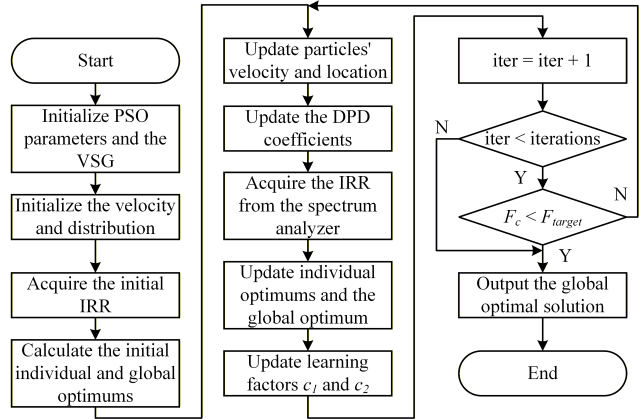


Fig. 16. Software flowchart for I/Q imbalance estimation and calibration on the experimental platform.

stage, the system configures the VSG to generate an RF signal at the specified frequency and initializes parameters for the pre-distortion module and the PSO algorithm. In the iterative optimization stage, the host computer dynamically adapts the pre-distortion coefficients based on the signal analyzer measurements and the imbalance parameters estimated by the PSO, thereby achieving closed-loop adaptive I/Q imbalance calibration. The iteration continues until either the maximum iteration count is reached or the current global optimal fitness F_c exceeds the target F_{target} , at which point the global optimal solution is found and the calibration process completes. Measurements were performed using a single-tone signal with the LO frequency of 3 GHz and the baseband tone at 300 MHz.

The experimental results are shown in Figs. 17–22. Figs. 17 and 18 present the output RF spectrum of the single-tone signal generated by the VSG, respectively. Figure 17 shows the transmitter's RF spectrum before I/Q imbalance calibration. The image component is clearly visible, with an IRR of only 34.93 dB, indicating significant gain and phase mismatch in the system. Figure 18 shows the spectrum after applying the proposed I/Q imbalance calibration scheme. The image component is now significantly suppressed, and the IRR has improved to 70.40 dB, a 35.47 dB increase compared to before calibration, demonstrating a substantial reduction in gain and phase mismatch.

To verify the applicability and stability of the proposed calibration scheme in broadband scenarios, a single-tone frequency sweep from -500 MHz to 500 MHz with a step size

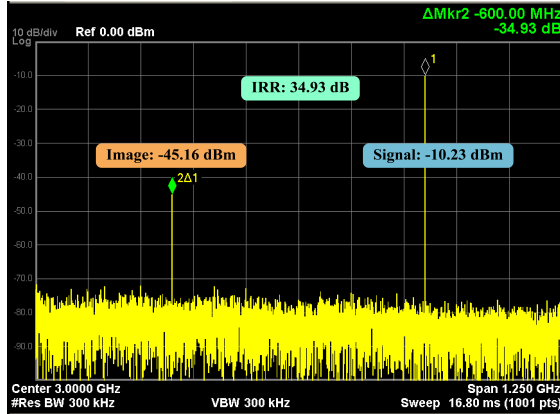


Fig. 17. Output RF spectrum of the VSG before I/Q imbalance calibration. The measured signal and image component powers are -10.23 dBm and -45.16 dBm, respectively, yielding an IRR of 34.93 dB.

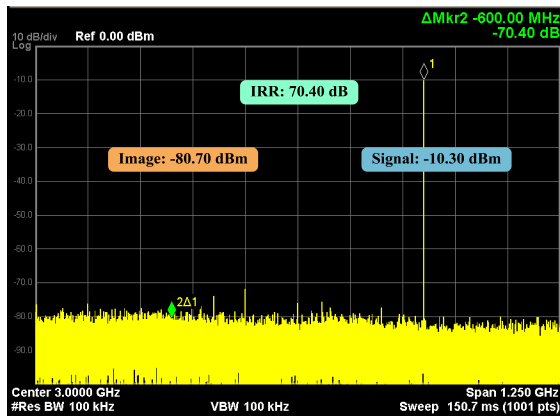


Fig. 18. Output RF spectrum of the VSG after I/Q imbalance calibration. The measured signal and image component powers are -10.30 dBm and -80.70 dBm, respectively, yielding an IRR of 70.40 dB.

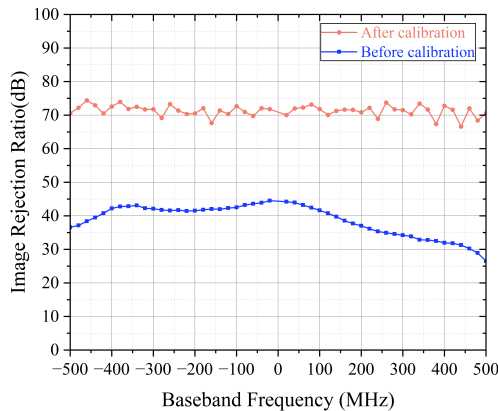


Fig. 19. Calibration results under different baseband frequencies. The frequency range spans from -500 MHz to 500 MHz with a step size of 10 MHz.

of 10 MHz was conducted. The compensation effect was quantified by comparing the IRR before and after calibration. The experimental results are shown in Fig. 19. Before calibration, the VSG's IRR ranged from only 25 dB to 45 dB

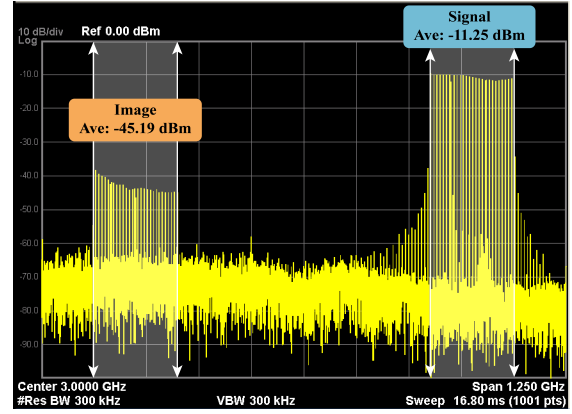


Fig. 20. RF spectrum of the broadband test signal output from the VSG before I/Q calibration. The average measured signal and image component powers are -11.25 dBm and -45.19 dBm, respectively, yielding an average IRR of 33.94 dB.

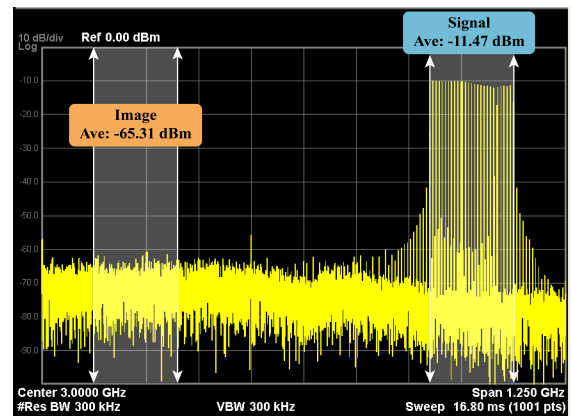


Fig. 21. RF spectrum of the broadband test signal output from the VSG after I/Q calibration. The average measured signal and image component powers are -11.47 dBm and -65.31 dBm, respectively, yielding an average IRR of 53.84 dB.

and exhibited significant FD. Nevertheless, after calibration, it improved to over 65 dB across the entire frequency band. Furthermore, the estimated full-band gain and phase mismatch coefficients were applied to the finite impulse response (FIR) filter structure proposed in [40] to achieve broadband calibration. The VSG's LO was set to 3 GHz, and the baseband generated a linear frequency modulation (LFM) signal with a starting frequency of 300 MHz and a bandwidth of 200 MHz. The broadband compensation effectiveness was evaluated by comparing the IRR before and after calibration. The comparison results are shown in Figs. 20 and 21, respectively. It can be seen that when the VSG output a broadband baseband signal, the average IRR was only 33.94 dB without calibration, which improved to 53.83 dB after calibration. In fact, analog components such as the LPF introduce FD I/Q imbalance. Consequently, although the IRR can exceed 65 dB under narrowband conditions, the same level of performance cannot be guaranteed for broadband signals. Nevertheless, the performance after calibration still satisfies the requirements of communication systems [3], [8].

Figure 22 compares the convergence efficiency of different algorithms on the experimental platform. The results indicate that the proposed improved algorithm achieves significantly faster convergence, reaching the optimum solution in fewer iterations.

The FPGA resource usage of the pre-distortion module is shown in Tab. 2. Regarding the time complexity of the I/Q imbalance estimation process, since the number of particles N remains constant per iteration, the total computational cost can be expressed as $N \times k \times T_D$, where k is the actual number of iterations and T_D is the computation time per particle per iteration. In the worst-case scenario, the number of iterations reaches the preset upper limit. As the convergence rate improves, the estimation time decreases accordingly. As shown in Fig. 22, the proposed improved method significantly outperforms other algorithms in terms of estimation time.

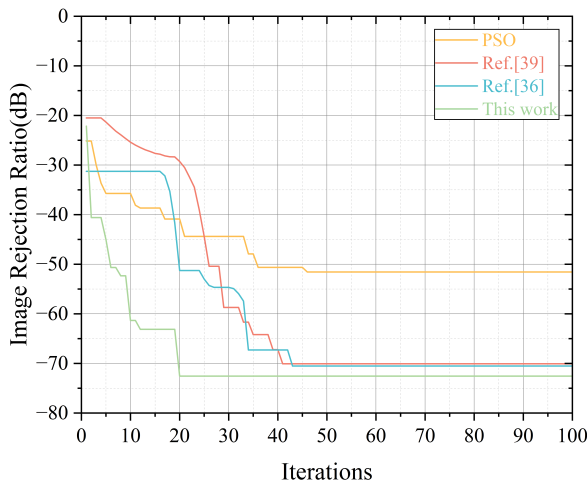


Fig. 22. Experimental results of convergence performance for different PSO algorithms.

Resource	LUTs	Registers	RAM	DSPs
Usage	144	221	0	12

Tab. 2. The Usage of FPGA Resource

Ref.	[23]	[26]	[27]	This work
Imbalance estimation	Loopback	Loopback	Loopback	Feedback
Bandwidth [MHz]	60	20	100	200
LO [MHz]	1000	2900 3000	2000–3500 step: 300	3000
Method	Self-calibration	Hybrid	Self-calibration	Iterative
Modulation	16QAM	QPSK	/	LFM
Single-tone IRR	52 dB	65 dB	50 dB	65 dB
Broadband IRR	/	65 dB	/	53 dB
Implementation	Least squares, Parallel filters, Inv. Matrix	Squaring circuit, Variable delay line, Digital correction	Spectral analysis, FIR, Iteration	Pre-distortion module, Iteration

Tab. 3. Performance comparison of related works.

A comparison of recent I/Q imbalance calibration methods is provided in Tab. 3. The method proposed in this work is implemented entirely in the digital domain via iterative optimization. It offers advantages in terms of implementation complexity and accuracy, while simultaneously achieving superior IRR.

5. Conclusion

This paper presents a method for I/Q imbalance parameter estimation and calibration in DCTs, leveraging a swarm intelligence optimization algorithm. By utilizing swarm intelligence algorithms to iteratively optimize the parameters of the pre-distortion module, this method achieves efficient estimation of the imbalance parameters. Furthermore, in order to overcome the limitations of the conventional PSO algorithm, such as its tendency to converge to local optima and its relatively slow convergence speed, an adaptive focusing strategy featuring a nonlinear exponential parameter update mechanism is introduced. This strategy dynamically adjusts the individual and social learning factors to balance local exploitation and global exploration capabilities, thereby enhancing the overall convergence efficiency of the algorithm. Simulation and experimental results demonstrate that the proposed method achieves accurate and efficient estimation of the transmitter's imbalance parameters.

After calibration, the system's IRR improves to over 65 dB for single-tone signals and over 53 dB for broadband signals, thus confirming a significant performance enhancement and validating the method's effectiveness. Currently, this method has been implemented and validated in software. In future work, we plan to implement the improved PSO algorithm on an FPGA platform to further enhance real-time parameter estimation.

Data Availability

The data and source code that support the findings of this study are available from the corresponding author upon reasonable request.

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