

Multi-tone Excitation Signal Optimization Based on Particle Swarm Optimization for Lithium-ion Battery EIS Measurement

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Abstract: Electrochemical impedance spectroscopy (EIS) is a vital non-destructive method for lithium-ion battery state detection. Traditional single-tone sweep EIS suffers from long test duration, while fixed multisine excitation causes severe spectrum leakage and low-frequency impedance measurement error, failing to support dynamic online battery monitoring. To address these issues, this paper proposes a particle swarm optimization (PSO) strategy to optimize the amplitude and phase of multisine excitation harmonics. Taking full-band impedance relative error as the optimization objective, safe amplitude constraints are adopted to avoid additional battery polarization. Optimized parameters are embedded into a self-developed differential synchronous sampling EIS hardware system for fast and high-precision measurement. Comparative experiments of three excitation schemes are conducted under static and dynamic working conditions. The results show that the proposed method reduces EIS test time to less than 8 seconds, with static measurement error below 1.0% and dynamic error controlled within 1.6%. This optimized multisine excitation scheme realizes efficient and accurate EIS detection, providing a reliable technical support for online condition monitoring of vehicle and energy storage lithium-ion batteries.

Keywords: Lithium-ion battery; Electrochemical Impedance Spectroscopy; Multisine superposition excitation; Particle swarm optimization.

1. Introduction

With the rapid penetration of lithium-ion batteries in new energy vehicles and grid-scale energy storage, online rapid condition monitoring has become a core research hotspot for battery management systems [1]. EIS separates ohmic resistance, charge-transfer impedance and low-frequency solid diffusion impedance by frequency-domain perturbation signals, quantitatively distinguishing multiple microscopic aging mechanisms such as SEI film growth and active lithium loss, which shows unique advantages over HPPC pulse and static capacity calibration [2].

Traditional EIS measurement adopts single-tone point-by-point sine sweep excitation. Sufficient sampling cycles must be reserved for each frequency point to guarantee signal-to-noise ratio, resulting in excessively long testing periods. For a typical 0.01 Hz–1000 Hz full-spectrum test, single-sine sweep usually costs more than 200 s, which fails to meet real-time monitoring demands under dynamic variable current loads [3]. Multisine superposition excitation simultaneously injects multiple sinusoidal components into batteries and solves full-spectrum impedance via FFT transformation, greatly compressing acquisition time [4]. However, when harmonic amplitude and phase are set as fixed empirical values, mutual frequency-domain interference generates spectrum leakage and signal distortion, especially degrading the precision of low-frequency diffusion impedance below 10 Hz, which directly restricts accurate polarization characterization of lithium iron phosphate cells with flat voltage plateau [5].

Existing research on multisine excitation optimization mainly includes two categories: fixed equal-amplitude multisine and heuristic optimized multisine. Fan et al.

adjusted multisine harmonic power distribution to improve signal SNR, but lacked a targeted error objective function oriented to battery full-band impedance measurement [6]. Guo et al. proposed an amplitude-phase optimization strategy for multisine signals, yet only completed simulation verification without embedded hardware experimental validation under dynamic charge-discharge loads [7]. PSO has been widely applied in lithium-ion battery equivalent circuit parameter identification, which exhibits outstanding global searching ability for multi-dimensional nonlinear optimization problems [8–9]. Nevertheless, few studies construct a PSO optimization model specifically for multisine excitation harmonic parameters taking full-spectrum impedance relative error as fitness value, and lack systematic contrast experiments between optimized and unoptimized multisine signals under complex industrial interference environments [10].

2. Error Mechanism of Fixed Multisine Excitation and Optimization Objective Function

2.1. Time-Domain Mathematical Model of Multisine Superposition Signal

Multisine composite excitation signal overlaps N independent sinusoidal waves with discrete target frequencies, its time-domain expression is defined as:

$$u(t) = \sum_{i=1}^N A_i \sin(2\pi f_i t + \varphi_i)$$

where A_i , f_i , φ_i separately denote the amplitude, frequency and initial phase of the i -th harmonic component. After injecting this perturbation signal to lithium-ion cell terminals, synchronous sampling of battery voltage and

response current is performed. Discrete Fourier transform is utilized to extract amplitude and phase of each target frequency component, then complex impedance at each frequency point can be solved.

If A_i and φ_i are manually fixed as constant values without global optimization, mutual superposition interference exists among different harmonics in frequency domain, inducing spectrum leakage noise components. The extra frequency-domain noise distorts the amplitude and phase of response current at each target frequency, leading to obvious deviation between solved impedance and true impedance value measured by high-precision single-sine sweep. This error amplification effect is most severe in low-frequency bands corresponding to solid-phase diffusion dynamics, causing inaccurate characterization of battery real-time polarization state.

2.2. Full-Band Impedance Error Optimization Objective Function

To quantitatively evaluate the measurement performance of multisine excitation signals, the sum of relative measurement errors of all characteristic frequency points is defined as the fitness objective function of PSO optimization. Let $Z_{true}(f_i)$ represent standard true impedance value obtained by commercial high-precision single-sine sweep workstation, $Z_{meas}(f_i)$ denote impedance solved under multisine excitation:

$$\min J = \sum_{i=1}^N \frac{|Z_{meas}(f_i) - Z_{true}(f_i)|}{|Z_{true}(f_i)|}$$

During optimization iteration, strict amplitude constraint $0 < A_i < A_{max}$ is added to the optimization variables, limiting total excitation perturbation amplitude within safe range to avoid triggering additional polarization loss and capacity attenuation of lithium-ion batteries.

3. PSO Optimization of Multisine Excitation Harmonic Parameters

3.1. Fundamental Principle of Particle Swarm Optimization

Particle swarm optimization imitates the group foraging behavior of bird flocks. Each particle corresponds to a set of multisine harmonic parameter combination $[A_1, \varphi_1, A_2, \varphi_2, \dots, A_N, \varphi_N]$. Each particle continuously updates velocity and position according to individual historical optimal fitness ($pbest$) and global population optimal fitness ($gbest$), searching the amplitude-phase combination that minimizes the impedance error objective function J . The standard velocity and position iteration formulas are expressed as:

$$v_{k+1} = wv_k + c_1r_1(pbest - x_k) + c_2r_2(gbest - x_k)$$

$$x_{k+1} = x_k + v_{k+1}$$

where w represents inertia weight balancing global and local searching ability; c_1, c_2 are learning factors; r_1, r_2 are uniform random numbers ranging from 0 to 1; $pbest$ is the optimal parameter position of single particle in all historical iterations; $gbest$ is the optimal parameter combination of the entire particle swarm.

3.2. Complete Implementation Flow of PSO Multisine Optimization

Confirm the multisine frequency set covering ohmic impedance (kHz band), charge-transfer impedance (10–100

Hz) and solid diffusion impedance (0.01–10 Hz) characteristic bands of lithium-ion batteries.

Initialize PSO hyperparameters including population scale, maximum iteration number, inertia weight and learning factors according to battery EIS measurement characteristics.

Randomly generate initial amplitude and phase values of each harmonic component within the safe amplitude constraint boundary.

Reconstruct time-domain multisine excitation signal based on particle parameter combination, simulate spectrum leakage interference and calculate objective function J representing total full-band impedance relative error.

Update $pbest$ and $gbest$ of all particles, iterate particle velocity and position until reaching preset maximum iteration times.

Output the globally optimal amplitude-phase combination of each harmonic component, store optimized parameters into embedded lookup table of EIS testing hardware for real-time DDS signal generation.

3.3. Matching with Embedded Differential Synchronous Sampling Hardware

After PSO offline optimization, the optimal multisine harmonic parameters are solidified into the flash storage of embedded main control chip on self-developed EIS equipment. The main control chip generates composite multisine perturbation signal via DDS and DA conversion module. A differential synchronous adaptive sampling circuit is matched to collect battery terminal voltage and response current synchronously, sharing the same homologous clock with excitation signal generator to eliminate phase offset error introduced by asynchronous sampling. The differential input topology suppresses 50 Hz industrial power frequency common-mode noise and lead wire voltage drop interference, further improving the overall impedance measurement precision under complex field working conditions.

4. Experimental Platform and Result Analysis

4.1. Construction of Experimental Test Platform

The integrated test platform consists of self-designed embedded EIS detection device with dual-mode excitation circuit, commercial high-precision Gamry electrochemical workstation, 314 Ah large-format lithium iron phosphate square cell, programmable constant temperature chamber and programmable battery charge-discharge tester. The Gamry workstation provides standard single-sine sweep impedance data as Z_{true} reference value for error calculation. Three excitation schemes are tested separately: conventional single-frequency sine sweep, unoptimized fixed multisine excitation, and PSO optimized multisine excitation proposed in this paper. The test temperature is set as 25 °C for static experiments, and random dynamic charge-discharge current profiles are loaded to simulate vehicle and energy storage variable load working conditions for dynamic experiments.

4.2. Static Standing Measurement Experimental Results

Under 25 °C static battery standing condition, full-spectrum impedance measurement comparison of three excitation modes is carried out. The single-tone sequential

sine sweep costs 218 s to complete 0.01 Hz–1000 Hz full-band scanning, while both multisine excitation schemes finish the same frequency range measurement within 7.2 s, greatly improving testing efficiency. For unoptimized fixed multisine signal, the relative impedance error of low-frequency diffusion band reaches 3.1% due to severe spectrum leakage interference. As show in Fig. 1, the PSO optimized multisine excitation effectively suppresses harmonic mutual interference and spectrum distortion, restricting full-band static impedance relative error below 1.0%. Experimental results prove that the proposed optimization strategy significantly enhances the measurement accuracy of low-frequency impedance closely related to battery polarization state under static steady-state conditions.

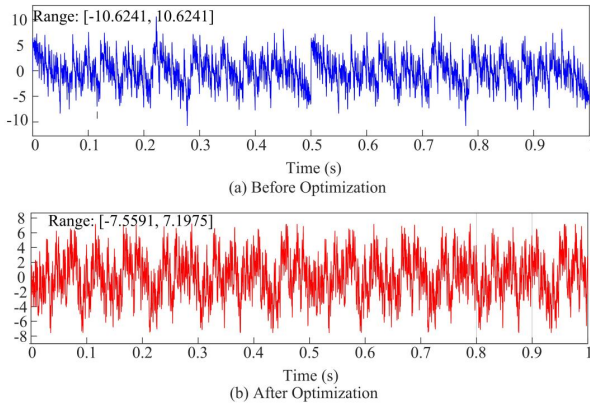


Fig. 1 The PSO optimization performance

4.3. Dynamic Charge-Discharge Working Condition Test Results

The lithium iron phosphate cell is operated under random dynamic charge-discharge current cycles to simulate real variable load interference of energy storage clusters and vehicle power batteries. Under dynamic time-varying polarization and industrial electromagnetic noise interference, the full-band average impedance relative error of fixed unoptimized multisine excitation rises to 2.8%. For the PSO optimized multisine excitation scheme, the overall dynamic measurement error is controlled within 1.6%. Comparative test data verify that the optimized composite multisine signal possesses stronger anti-interference ability, maintaining high impedance measurement precision under variable polarization and complex industrial noise environments.

5. Conclusion

Aiming at the drawbacks of long measurement time of single-tone sweep EIS and large low-frequency impedance error caused by spectrum leakage of fixed multisine excitation, this paper proposes a multisine excitation harmonic parameter optimization method based on particle swarm optimization. Taking the sum of full-band impedance relative error as the PSO fitness objective function, the amplitude and phase of each sinusoidal harmonic component in composite excitation signal are globally optimized to restrain time-domain waveform distortion and frequency-domain mutual harmonic interference. Static standing and dynamic variable charge-discharge comparative experiments demonstrate that the PSO optimized multisine excitation can complete full-wide EIS spectrum measurement within less than 8 seconds. Static full-

band impedance measurement error is lower than 1.0%, and dynamic working condition measurement error is suppressed within 1.6%. The optimized multisine parameter table can be directly embedded into embedded EIS testing equipment equipped with differential synchronous sampling circuit, offering a fast high-precision measurement technical route for online field EIS diagnosis of lithium iron phosphate energy storage batteries and automotive power batteries.

Future research will focus on multi-objective PSO optimization simultaneously considering measurement time, impedance error and battery excitation power consumption, and further deploy the optimized multisine excitation algorithm into low-cost vehicle-grade BMS chips for on-board real-time impedance monitoring.

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