Optimal Wavelet Threshold De-noising Algorithm of Power Quality Based on Improved Particle Swarm Optimization

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Abstract. For the issues of local optimum and difficult convergence based on traditional Particle Swarm Optimization (PSO), this paper is proposed a new inertia weight which applies to denoise the harmonic of power quality and enhance the precision when selecting threshold in harmonic signal de-noising, and the results show that the method proposed in this paper significantly improves the signal noise ratio. The effect of de-noising is improved through Matlab simulation.

1. Introduction

With the rapid development of power system, more and more non-linear loads and kinds of power electronic equipment put into use and inject a lot of harmonic to power system, which has brought great harm to the normal operation of the power system, so the harmonic detection is particularly important. But for now, the collected harmonic signal contains a lot of noise and it is inconvenient for the follow-up testing, so it should remove the noise of the signal and retain the information of original signal on the maximum extent. The traditional Fourier transform can not be analyzed the signal in the frequency domain, which leads to the deficiency when analyzing the non-stationary signal. The wavelet transform has better local characteristics in time-frequency domain and also has multiple resolution analysis features, which has more obvious advantages when dealing with non-stationary signal. Donoho first proposed the threshold de-noising method and gave the corresponding threshold selecting criteria^[1], he noted that the precision of threshold selection is crucial to the effect of signal de-noising. Literature [2] proposed an improved threshold de-noising method which used different thresholds for wavelet coefficients of different decomposition levels, it is more conducive to denoise than the traditional method which only selects one threshold, but the method is computationally intensive. Literature [3] proposed an improved wavelet threshold de-noising method based on wavelet sym8. Firstly decompose the signal for five layers using wavelet sym8, and then optimally denoise the first layer and the second layer of the wavelet coefficients, but the adaptability of threshold selecting in this method is not better, which can not accurately adjusts the threshold according to the changes of harmonic signal. For this reason, literature [4] proposed an optimal threshold de-noising method based on PSO and established the generalized cross validation criterion in the selection of threshold and adaptively determined the best threshold of each decomposition level based on PSO. Although the adaptability of this method is improved, PSO algorithm is easy to fall into the issues of local optimum and difficult convergence. Shi. Y first introduced the inertia weight ω to PSO algorithm, and pointed out that a large inertia weight is in favor of global search and smaller inertia weight is in favor of local search^[5]. Thus, the inertia weight has a great influence on the capability of algorithm search. In the basis of comparing with common inertia weight, this paper proposes a new inertia weight to power quality of harmonic de-noising. The inertia weight proposed can improve the convergence precision when using PSO to select the threshold and the effect of de-noising is improved through Matlab simulation.

2. The Basic Principle of Wavelet Threshold De-noising

2.1 The basic idea of the wavelet threshold de-noising.

Set up a one-dimensional model of the noisy signal. As shown (1) below:

$$s(t) = f(t) + \sigma n(t)$$

Where s(t) = noisy signal, f(t) = true signal, n(t) = Gaussian white noise signal, σ = noise intensity.

(1)

The basic idea of wavelet threshold de-noising is to select an appropriate wavelet function which decomposes the noise signal and sets threshold for wavelet, the smaller absolute value of coefficients is set to zero, and the larger is set to retain or shrink, and then the estimated wavelet coefficients can be calculated. The estimated wavelet coefficients can be used directly for the signal reconstruction to the purpose of de-noising in the end. The key of threshold de-noising method is to quantify the threshold. The estimated wavelet coefficients which are in favor of the signal reconstruction will be more precise if the selected threshold has a higher precision and the signal de-noised is be able to retain more original information.

2.2 The Basic Steps of Wavelet Threshold De-noising.

The basic steps of wavelet threshold de-noising are shown in Figure 1.



Figure 1 Basic steps of de-noising wavelet threshold

Use orthogonal and symmetrical wavelet 'Meyer' which also has a frequency domain compact support, infinitely differentiable and the other excellent properties when decomposed the signal. This paper uses the threshold function in literature [6] which is continuous derivable and has good adaptability in the process of threshold quantization.

3. Fundamental of Improved Particle Swarm Optimization

3.1 Fundamental of Particle Swarm Optimization (PSO).

Particle Swarm Optimization was first proposed by Kennedy and Eberhart in 1995 to solve optimization problems. Suppose in a D-dimensional search space, the population is composed by n particles, where the *ist* particle is represented as a D-dimensional vector, representing the position of the *ist* particle in D-dimensional search space and also representing a potential solution of the problem. It can be calculated the position of each particle x_i and the fitness value of x_i according to

the objective function. The velocity of the *ist* particle is $V = (V_{i1}, V_{i2}, \dots V_{iD})^T$, the extreme value of the individual is $P = (P_{i1}, P_{i2}, \dots P_{iD})^T$, the extreme value of the population is $P = (P_{g1}, P_{g2}, \dots P_{gD})^T$. Each iteration, the particles update their own speed and location through the extreme value of individual and population. As shown below (2), (3) below:

$$V_{id}^{k+1} = \omega V_{id}^{k} + c_{1} r_{1} \left(P_{id}^{k} - X_{id}^{k} \right) + c_{2} r_{2} \left(P_{gd}^{k} - X_{gd}^{k} \right)$$
(2)
$$X_{id}^{k+1} = X_{id}^{k} + V_{k+1id}$$
(3)

where ω =inertia weight; $d = 1, 2, \dots, D$; $i = 1, 2, \dots, n$; k = current number of iterations; c_1, c_2 =acceleration factor; $c_1 = c_2 = 2$; r_1, r_2 are random numbers distributed in the range of [0,1]. **3.2 Selecting of inertia weight.**

The crucial step of wavelet threshold de-noising is to quantify the threshold, the precision of threshold has great influence on the effect of de-noising in the late time. The inertia weight is reflected capability of particles inheriting previous speed and also directly affects the capability of global search and local search. Inertia weight can prevent PSO into the situation of local optimum

when searching the optimal threshold, and have a great impact on the promotion in threshold accuracy. Therefore Shi. Y proposed linear decreasing inertia weight. As shown (4) below:

$$\omega(k) = \omega_1 (\omega_1 - \omega_k) (T_{\text{max}} - k) / T_{\text{max}}$$
(4)

In general, $\omega_1 = 0.9$, $\omega_k = 0.4$, algorithm performance is best, larger inertia weight value is conducive to global search in the early time, smaller inertia weight value is in favor of local search in a more accurate way. But for the non-linear harmonic signal with noise, linear decreasing inertia weight proposed by Shi. Y can not impact the optimal search process in actually. So this paper is proposed a new inertia weight. As shown (5) below:

$$\omega(k) = \omega_{\rm l} - (\omega_{\rm l} - \omega_{\rm k}) \sqrt{\sum_{N}^{k} \left(1 - \frac{N}{T_{\rm max}}\right)^2}$$
(5)

where ω_1 =initial weight; ω_k =the maximum number of iterations of Inertia weight; *k*=the current number of iterations; T_{max} =the maximum number of iterations; $N=1,2,\dots,k$. Equation (5) can be accurately adjusted the inertia weight according to the changes in the number of iterations, and enhances the adaptability of PSO optimization, and reduces the number of local optimization, the accuracy of final threshold is improved.

3.3 Analysis of Inertia Weight to Algorithm Performance.

PSO parameters settings: population size is 40, the dimension of each particle is 2, the maximum number of iterations is 100. Each experiment runs 500 times and sets the average value of 500 times as the optimal threshold result. Use inertia weight proposed in this paper and the traditional linear inertia weight respectively to calculate the results with the threshold function proposed in literature [6], the results are shown in Table 1.

Ø	Ontimal	Augraga	number of local	number of global
6	value	value	ontima	optimum
	value	value	optinia	optillulli
$\omega = \omega_1 + (\omega_k - \omega_1)(t_{\max} - t)/t_{\max}$	32.75	31.22	28	472
$\omega(k) = \omega_1 - (\omega_1 - \omega_k) \sqrt{\sum_{N}^{k} \left(1 - \frac{N}{T_{\text{max}}}\right)^2}$	32.75	32.23	19	481

Table 1 PSO algorithm performance under different inertia weights

From Table 1, the inertia weight mentioned in this paper improves the accuracy of the threshold, although it will fall into the solution of local optimal, the numbers has been reduced obviously.

4. Simulation of Harmonic Signal De-noising

4.1 Evaluation of Signal de-noising.

In this paper, set the amplitude error ε and SNR (Signal Noise Ratio) as the evaluation index. As shown equation (6), equation (7) below:

$$\varepsilon = \frac{A_0 - A_D}{A_0} \times 100\% \tag{6}$$

Where A_0 = amplitude of original signal; A_D = amplitude of de-noised signal.

$$SNR = \frac{A_s}{A_N} \tag{7}$$

Where A_s = amplitude of disturbance signal; A_N = amplitude of the Gaussian white noise.

4.2 Simulation analysis

Using wavelet transform to decompose the two transient harmonic signals with the 'Meyer' Wavelet function and the maximum levels of decomposition is 6.Denoise the signals with traditional

PSO and IPSO (Improved Particle Swarm Optimization) respectively. Two types of noisy signals which are added 20dB noise to the original signals are shown as Figure 2(a), Figure 2(b) respectively.



Figure 2(b) signal of transient inter-harmonic added 20dB noise The waveforms of harmonic signal de-noised using PSO and IPSO are shown as Figure 3(a) and Figure 3(b) respectively.



Figure 3(b) signal of transient harmonic de-noised by IPSO

The waveforms of inter-harmonic signal de-noised using PSO and IPSO are shown as Figure 4(a) and Figure 4(b) respectively.



Figure 4(b) signal of transient inter-harmonic de-noised by IPSO

The results of de-nosing evaluation parameters of different harmonic signals after added different SNR Gaussian white noise which are calculated by using PSO and IPSO, and the results are respectively shown in Figure 5(a) and Figure 5(b).



Figure 5(b) amplitude error and SNR of de-noised signal of transient inter-harmonic From the Simulink results, the amplitude of the de-noised signals using IPSO is smaller than the de-noised signals using PSO under different SRN.IPSO can remain more original information of the signals than PSO.

5. Summary

This paper mainly focuses on power quality of harmonic de-noising problem, and describes the effect of inertia weight on threshold selection based on PSO wavelet de-noising method. On the basis of this, it proposes a new inertia weight and gives the specific expression. Inertia weight proposed in this paper can improve accuracy of threshold through Matlab simulation. Finally, by comparing with the traditional inertia weight on the effect of de-noising, the amplitude error and signal distortion rate have declined and it is verified that the method has better effect on power quality of harmonic de-nosing.

References

- [1]. Donoho D L, 1995, De-noising by Soft-thresholding, J.IEEE Transaction on Information Theory. 41(3)613-627.
- [2]. Wan Hong, Jiang Fengru, 2008, An algorithm study of electrocardiogram signal de-noising by wavelet threshold method, J. Microcomputer Information. 24(3)156-158.
- [3]. Wang Qingqing, Huang Yourui, Chen Zhenping, Qu Liguo, Li Nan, 2015, Harmonic detection based on improved threshold de-noising, J. Electrical Measurement & Instrumentation. 52(13) 20-24.
- [4]. Wu Juzhuo, Niu Haiqing ,Ye Kaifa,2015,Application of the optimum threshold method based on particle swarm optimization to partial discharge signal de-noising, J. Electrical Measurement & Instrumentation.52(10) 100 -104.
- [5]. Shi, Y. H., Eberhart R.C.A, A modified particle swarm optimizer, J. Proceedings of the IEEE Congress on Evolutionary Computation. Piscataway, USA, IEEE Service Center, 1998, PP. 69-73.
- [6]. Zhang X.P., Desai, M.D,1998, Adaptive de-noising based on sure risk, J. IEEE Signal Processing Letters. 5(10) 265-267.