Power optimization method for wireless power transmission system based on improved differential evolution algorithm

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Abstract. In this paper, we propose a power optimization algorithm in view of the Differential Evolution algorithm (DE) in order to reduce the transmission power due to the frequency split of the electromagnetic coupling resonant radio energy transmission system in the over-coupled state. Simulation experiments in MATLAB environment verify the effectiveness of the algorithm for power optimization of transmission system. Simulation experiments show that compared with the standard Differential Evolution algorithm and adaptive control parameter Differential Evolution algorithm (JDE), a new adaptive Differential Evolution algorithm (NDE) is improved based on the standard Differential Evolution algorithm. The new algorithm enables the system to find the optimal load power faster, which is conducive to increasing the output power of the system.

1. Introduction

There are two main types of wireless energy transmission technology: Electromagnetic coupling induction wireless energy transmission system and electromagnetic coupling resonance wireless energy transmission system. Magnetically coupled inductive wireless energy transmission systems have low efficiency and are not suitable for medium and long-distance wireless energy transport, while magnetic coupling resonance wireless energy transport system use non-radiative electromagnetic fields in the near field to complete power transport. On the one hand, there are It has been greatly improved, so that electrical equipment has a greater degree of freedom in the transmission of electrical energy [1]; on the other hand, the energy in the near-field region is non-radiative and has better safety [2].

Last few years, magnetic coupling resonance wireless power transmission has turn into a hot topic at home and abroad. Some studies have shown that when the distance between the two coils is reduced to a certain extent, the system is in over coupling state. In this state, the system will have frequency splitting [3]. At this time, operating frequency of the system will be inconsistent with resonance frequency, the energy conversion efficiency will be reduced, and the power received by the load will be reduced. Therefore, performing power optimization on the system can effectively alleviate the frequency split phenomenon caused by changes in conditions such as distance. Tracking the resonance frequency further improves the load receiving power and receiving efficiency [4-6].

Based on the above research on improving transmission power through power frequency optimization in wireless power transmission, this article proposes a new power optimization algorithm in view of an improved algorithm. Simulation experiments with MATLAB software verify the effectiveness of this algorithm in power optimization during wireless power transmission.
2. Analysis of Wireless Power Transmission System

Electromagnetic coupling resonant radio energy transmission technology originates from the concept of strong coupling in the near-field region of electromagnetic energy. The basic principle of this technology is that when two non-contact objects have the same resonance frequency, efficient energy transmission can be achieved between the two, but when the resonance frequencies of the two are different, the energy conversion between them is very weak. Taking the double coil structure as an example, its equivalent circuit diagram is shown in Figure 1.

![Figure 1. Equivalent circuit](image)

Among them, \( U_s \) and \( R_1 \) are the equivalent induced electromotive force and impedance of the transmitting coil, respectively; \( R_4 \) is the equivalent impedance of load end coil reflecting to the receiving end coil. \( R_2 \) and \( R_3 \) are the sum of the loss resistance and radiation resistance of the transmitting coil and the receiving coil, respectively. It is assumed that the current values passing through resonance coil of transmitter and receiver are \( I_1 \) and \( I_2 \) respectively. The current direction is shown in Figure 1.

\[
\begin{align*}
U_s &= (R_1 + R_2 + j\omega L_2 + \frac{1}{j\omega C_2})I_1 - j\omega M_{23}I_2 \\
0 &= (R_3 + R_4 + j\omega L_3 + \frac{1}{j\omega C_3})I_2 - j\omega M_{23}I_1
\end{align*}
\]  
(1)

Analyze it and solve equation (1) to get

\[
\begin{align*}
I_1 &= \frac{(1+j\xi)U_s^1}{(1+j\xi)^2+\delta^2} \\
I_2 &= \frac{j\xi U_s^1}{(1+j\xi)^2+\delta^2}
\end{align*}
\]  
(2)

Among them, \( \xi \) is a detuning factor, and \( \xi = Q\left(\frac{\omega}{\omega_0}\right) \); \( \delta \) is a coupling factor, and \( \delta = \frac{\omega M}{R} \).

A wireless power transmission system model is established by formulas (1) and (2). Frequency splitting and other phenomena in wireless power transmission systems where resonance occurs through magnetic coupling, problems such as low power and efficiency will occur during transmission. In this paper, an improved DE algorithm is used to carry out simulation experiments to realize the power optimization of wireless power transmission systems.

3. Differential Evolution Algorithm

The differential evolution algorithm is an optimization algorithm proposed by Rainer Storn and Kenneth Price in 1997 to solve the Chebyshev polynomial [7]. At present, differential evolution algorithms have attracted widespread attention and widely used in many research fields at domestic and foreign.
3.1. Standard algorithm

The standard DE algorithm is mainly embodied in the three important operations of "mutation, crossover and selection", and the conversion from the parent individual to the child individual is achieved through these three operations [8]. The main process of the algorithm is as follows.

3.1.1. Initialization. The DE algorithm usually uses N D-dimensional vectors as the population of each generation, and \( x_{i,g} = (x_{1,i,g}, \ldots, x_{D,i,g}) \), \( i = 1, 2, \ldots, N \). The population is initialized in a random manner. Taking the j-th initial parameter value of the i-th vector as an example, the expression is:

\[
    x_{j,i,0} = x_{j,\min} + \text{rand} \cdot (x_{j,\max} - x_{j,\min})
\]

(3)

Among them, rand represents a random integer uniformly distributed in the interval (0, 1).

3.1.2. Variation. The DE algorithm introduces the difference idea into the mutation strategy, randomly selects 2 parent individuals from the population to perform the difference operation, and then weights the difference vector and sums it with the third parent individual to obtain the offspring individuals generated by the mutation. The specific operations are as follows:

\[
    v_{i,g} = x_{r0,g} + F \cdot (x_{r1,g} - x_{r2,g}), \quad i \neq r0 \neq r1 \neq r2
\]

(4)

Among them, \( i, r0, r1, \) and \( r2 \) are mutually different random integers in \([1,2, \ldots, D]\), and \( F \) is a mutation factor.

3.1.3. Crossover. The purpose of the cross operation is to increase population richness. Cross the target vector \( x_{i,g} \) with its corresponding mutation vector \( v_{i,g} \) to generate a test vector \( u_{i,g} \).

\[
    u_{ij,g} = \begin{cases} 
    v_{ij,g}, & \text{rand} \leq CR \ or \ j = r, \\
    x_{ij,g}, & \text{otherwise}.
    \end{cases}
\]

(5)

Among them, \( CR \) is a crossover factor, and the value of \( r \) is a stochastic integer of \([1,2, \ldots, D]\).

3.1.4. Select. The DE algorithm uses a "greedy" strategy in the selection operation. The specific operations are as follows:

\[
    x_{i,g+1} = \begin{cases} 
    u_{i,g}, & f(u_{i,g}) \leq f(x_{i,g}), \\
    x_{i,g}, & \text{otherwise}.
    \end{cases}
\]

(6)

3.1.5. Termination. Output results when the algorithm meets the termination condition. Otherwise go back to step 2 and perform a series of operations again.

4. Algorithm improvement

The NDE algorithm mainly improves mutation factors and mutation strategies. These two points will be described in detail below.

4.1. Adaptive mutation factor

The mutation operation is a key step of the DE algorithm, and play an significant part in the growth of the algorithm's population diversity and search space. The worth of the mutation factor has a big affect on the algorithm optimization range. If the value of the variation factor is large, the search range of the algorithm is larger. At this time, it is beneficial to global search and avoids premature convergence during the search process. However, when the variation factor is too small, the algorithm search limit is smaller, the local search capability is stronger, and the convergence rate is faster.

In the std DE algorithm, the worth of the mutation factor is a natural number and cannot take into account both convergence speed and global search capabilities [9]. For the sake of make the algorithm have a faster convergence speed and better global convergence ability, the value of F needs to be larger at the beginning of operation, and then gradually decreases with the number of iterations. The values of the adaptive mutation factor F put forward in this paper is shown below.

\[
    F = F_0 \cdot 2^\lambda
\]

(7)

\[
    \lambda = \exp \left( 1 - \frac{g_m}{g_{m+1}-G} \right)
\]

(8)

Among them, $F_0$ represents the initial values of the factor. The values of this article is $F_0 = 0.9$, $G_m$ indicate the maximum developmental generation number, $G$ indicate the current number of iterations. It can be known from equations (7) and (8) the mutation operator shows a decreasing trend.

4.2. Random perturbation strategy

The mutation strategy in mutation stage has an important influence on the optimization of the algorithm. Different strategies will lead to different optimization results. Equation (4) is the most common used mutation strategy, but later in the algorithm, it will always fall into partial optimal value, which greatly reduces the astringent velocity and is easy to premature convergence. In view of the formula (4), propose a random disturbance effect on two parents who perform different actions, and substitute for the regular stage with a stochastic stage. The specific expression is as follows.

$$v_{i,g} = x_{r0,g} + F \cdot (\text{rand}x_{r1,g} - \text{rand}n_{r2,g}), \quad i \neq r0 \neq r1 \neq r2$$  \hspace{1cm} (9)

Among them, $\text{rand}$ is a random number in the range of minimum 0 and maximum 1, and $\text{rand}n$ is a stochastic number with a normal distribution with a indicate of 0 and a variance of 1.

5. Simulation Results and Analysis

For the purpose of inspect the superiority of the NDE in power optimization, it is compared with the simulation curves of the standard DE algorithm and JDE algorithm in the same model, as shown in Figure 2.

![Figure 2. Comparison results of the three algorithms](image_url)

Can be concluded from Figure 2 that the NDE performs better in the maximum power optimization. Starting from the 9th iteration, the tracking results of the NDE algorithm are larger than the other three algorithms. When the population iteration is 15 times, the NDE algorithm results tend to be stable. That is convergence, while the standard DE algorithm requires 40 iterations, and the JDE algorithm requires 30 iterations.
6. Conclusion

Analysis of the factors influencing the optimization effect of DE algorithm, this article proposes an improved DE algorithm with an adaptive mutation factor and a random perturbation mutation strategy, and the feasibility of the algorithm is verified by simulation with MATLAB software. Compared with the standard DE algorithm and JDE algorithm, the experimental consequent indicate that the NDE algorithm has improved astringent function and astringent velocity. In the future, a wireless power transmission hardware platform will be used to further examine the method validity in power optimization of wireless power transmission systems.

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