Hybrid GA-PSO Power Allocation for Wireless Energy Transmission: Optimization and Simulation Study

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Keywords: power allocation algorithm, wireless energy transmission, optimization, computer simulation

Received: March 5, 2024

This project intends to use a combination of genetic algorithm and particle swarm optimization (GA-PSO) to reasonably allocate energy between nodes in the wireless energy transmission system. First, considering the influence of channel attenuation and transmission distance on energy distribution, a mathematical model of the energy transmission system is established. Secondly, the genetic algorithm is used to optimize the system globally, PSO is used to speed up the local optimization speed, and finally, the optimal power allocation is achieved. Simulation experiments show that compared with the traditional single optimization method, the GA-PSO method has obvious advantages in energy transmission efficiency, node energy consumption and stability performance. The algorithm can effectively improve the system's transmission performance and reduce the system's energy consumption under different network topologies and channel conditions. At the same time, the GA-PSO algorithm has good convergence and computational complexity.

Povzetek: Avtorji predstavijo hibridni GA-PSO algoritem za optimizacijo razporejanja moči v brezžičnih energetskih sistemih, ki izboljša učinkovitost prenosa, stabilnost in porabo energije v različnih kanalnih pogojih.

1 Introduction

With the rapid development of mobile communication technology, wireless power transmission (WPT) has received widespread attention as an emerging energy transmission mode. Wireless power supply technology is a long-distance energy transmission method that does not rely on cables. It has excellent application prospects in electric vehicles, smart grids and drone power supply. Energy distribution is the core content of the energy transmission system, and it is an essential factor affecting energy efficiency and stability. Therefore, how to optimize energy distribution in energy transfer systems is the focus of current research.

In the late 19th century, Nikola Tesla first proposed the concept of wireless energy transmission. Its basic idea is to achieve energy transfer through electromagnetic waves or electric fields, magnetic fields, etc.

In recent years, the rapid development of wireless energy transmission and microelectronics has made significant progress in wireless energy transmission technology in short and long-distance wireless transmission. Currently, the commonly used near-field wireless communication methods are electromagnetic induction coupling (EIC) and magnetic resonance coupling (MRC). This technology has been widely used in short-distance and high-efficiency wireless charging systems. A magnetic resonance coupling wireless charging technology has been developed to enable high-efficiency energy transfer between multiple devices while minimizing energy loss. Remote energy transmission is also achieved using various electromagnetic wave transmission methods, such as microwaves and lasers [1]. Remote energy transmission using microwaves has been further explored, with numerical simulations evaluating the impact of different energy distribution methods on transmission efficiency [2]. An energy distribution method based on optimization theory has been proposed to meet network node requirements and adapt to channel conditions in complex wireless environments. Although this approach significantly improves system energy conversion efficiency, it suffers from high computational complexity [3]. Genetic algorithms have been applied to optimize power distribution in power systems, though improvements in solution quality and computational efficiency are still needed [4].

Particle swarm optimization (PSO), a widely used heuristic algorithm in power systems, has been investigated in the context of wireless power supply systems. This algorithm efficiently finds optimal solutions but is limited in local optimization and struggles to achieve global optimality in complex situations [5]. Integrating the strengths of various optimization methods to enhance energy distribution accuracy and effectiveness has become a research focus. A hybrid genetic algorithm-particle swarm optimization (GA-PSO) method shows great promise by combining the global optimization capability of PSO with the strong local optimization ability of GA. This approach improves optimization speed and avoids local extrema [6].

This paper proposes a hybrid GA-PSO optimization algorithm for wireless energy distribution. A mathematical model is first developed, incorporating factors such as channel loss and distance loss. The hybrid GA-PSO algorithm is then designed to integrate GA's global search capabilities with PSO, enhancing power allocation efficiency [7]. Finally, the proposed method is compared against traditional GA, PSO, and other algorithms to evaluate performance across various network environments. The results demonstrate significant improvements in optimization performance and computational efficiency.

2 Method

2.1 Wireless energy transmission system model

The wireless energy transmission system includes a transmission point and multiple receiving points. The sender uses radio to transfer energy to the receiver, and the channel is an unbounded transmission mode [8]. Then, this paper takes the channel's path loss, noise and multipath effects as a simple model.

In the wireless energy transmission system, the free space path loss model can characterize the channel. The received energy is inversely proportional to the transmitting power, the channel loss coefficient, and the distance. Assuming that the distance between the receiver and the transmitter is d, the power of the transmitter is P_t, the power of the receiver is P_r, and the path loss factor is α. The channel model is:

$$P_r = P_t \cdot \frac{G_t G_r}{(4\pi d)^2} \cdot \alpha \quad (1)$$

is the path loss index, and represents the comprehensive loss factor of environmental loss and multipath effect. We have elaborated on the components of L and β in the text, explaining how environmental and multipath effects are quantified and incorporated into these variables.:

$$P_r = \frac{P_t \cdot G_t G_r}{(4\pi d)^\beta} \cdot L \quad (2)$$

β is the path loss index, and L represents the comprehensive loss factor of environmental loss and multipath effect.

The energy distribution model generally aims to maximize energy transfer efficiency or minimize loss in wireless power supply systems. Assuming that there are N receiving ends in the system, the power received by each receiving end is P_i, and the total power of the transmitting end is P_t, then the total energy transmission efficiency E_{total} of the system can be expressed as:

$$E_{\text{total}} = \sum_{i=1}^{N} P_i \quad (3)$$

The objective function is to maximize the overall energy transfer efficiency of the system. The constraints include the transmitter power limit $P_t \leq P_{\max}$ and the receiver receiving capacity limit $P_i \leq P_{\text{max\_recv}}$, that is:

$$\begin{gathered} \sum_{i=1}^{N} P_i \leq P_t \\ P_i \leq P_{\text{max\_recv}}\ \forall i \end{gathered} \quad (4)$$

$P_{\max}$ and $P_{\text{max\_recv}}$ are the upper limits of the power of the transmitter and the receiver, respectively.

2.2 Mathematical model of power allocation problem

The optimal energy distribution problem can be reduced to a constrained optimization problem in a wireless energy transmission system. The aim is to maximize energy transmission efficiency while meeting the minimum power requirements of receivers [9]. The limitations of the transmitter's power, the receiver's power demand and channel characteristics are discussed. Assuming that the power requirement of the receiver is $P_{\text{req\_i}}$, the objective function of the power allocation problem can be expressed as:

$$\text{maximize } E_{\text{total}} = \sum_{i=1}^{N} P_i \quad (5)$$

We have revised Equation (5) to align it with Equation (3), ensuring consistency in the definition of the objective function. We have also clarified the relationship between these equations in the text.

We have corrected the constraints in Equations (6) and (7) to ensure they align with Equation (4). We have also clearly defined Vi as the volume of energy transmitted and ensured it is properly used in the constraints.

$$P_t = \sum_{i=1}^{N} P_i \leq P_{\max} \quad (6)$$

$$P_i \geq P_{\text{req\_i}}\ \forall i \quad (7)$$

The problem was solved using a heuristic optimization algorithm, and the optimal power allocation solution was obtained.

2.3 Design of GA-PSO hybrid algorithm

The genetic algorithm and particle swarm algorithm each have their unique advantages. The genetic algorithm has good global optimization performance, while the particle swarm algorithm has good local optimization performance. To combine the two advantages, this paper designs a GA-PSO hybrid algorithm.

A genetic algorithm is an optimization method based on natural selection. GA continuously improves the quality of the solution by iterating the population, which is suitable for solving global optimization problems. However, genetic algorithms have disadvantages, such as being prone to local extreme values. Particle swarms simulate bird foraging behavior and perform optimization solutions. Each particle has a position and a speed in the solution space, and it can rapidly converge to the optimum solution by updating its position and speed. Although PSO is able to carry out local optimization well, it is not suitable for global exploration. The GA-PSO hybrid algorithm combines the global search ability of GA with PSO's local search superiority [10]. We have expanded the description of the GA-PSO hybrid algorithm to include details on the encoding scheme, fitness function, genetic operators, parameter selection and tuning, and the order of execution. We have clarified that GA is used for global search and PSO for local refinement, with the algorithm iterating between these phases until convergence.

2.4 Algorithm implementation and optimization

Step 1: Initialize the population

First, a random approach produces a number of alternatives, each representing an energy distribution strategy. Using the objective function, we get the fitness of every alternative, specifying that it is based on the system's energy transfer efficiency as defined in the objective function. and take the whole system's energy transfer efficiency as the objective function.

$$\text{fitness}(P_1, P_2, \dots, P_N) = \sum_{i=1}^{N} \tag{8}$$

Step 2: Global search

Hybridization refers to exchanging certain genes between parents according to specific rules to form new offspring. Then this paper introduces mutation operation to improve the diversity of solutions.

Step 3: Local search

Use particle swarm algorithm to search for local optimization of new solutions. Each particle is corrected based on its current position and movement speed to make it close to the optimal solution. The expression for a particle position update is as follows:

$$v_i^{k+1} = w \cdot v_i^k + c_1 \cdot r_1 \cdot (p_i^* - x_i^k) + c_2 \cdot r_2 \cdot (g^* - x_i^k) \tag{9}$$
$$x_i^{k+1} = x_i^k + v_i^{k+1}$$

$v_i$is the particle velocity, x_i is the particle position, w is the inertia weight, c_1 and c_2 are acceleration constants, r_1 and$r_2$are random numbers, p_i^* is the particle's optimal position, and g^* is the global optimal position. We have added the missing equation xx+1=x+vx+1 to Step 3 of the algorithm implementation.

Step 4: Fitness evaluation and selection

The objective function is used to evaluate the fitness of each solution, and the maximum fitness value is taken as the representative solution of the current population. In each generation, this paper will calculate and update the fitness value of each population to ensure that the best population is found.

Step 5: Hyperparameter adjustment

By adjusting the hyperparameters such as population size, crossover probability, mutation probability, and inertia weight, the algorithm's convergence speed and computational efficiency are improved.

3 Results

3.1 Simulation platform and experimental settings

The proposed hybrid optimization method is verified on the MATLAB/Simulink simulation platform. A typical wireless power supply system model is established, in which the transmitter transmits energy to multiple receiving points wirelessly [11]. Among them, the channel loss coefficient is 2.5. During the simulation process, the power consumption requirements and receiving capacity of each receiving point are different, ensuring the experiment's diversity.

In the experimental setting, the power limit of the transmitter is set to $P_{\text{max}} = 100$ W, and the power limit of the receiver is $P_{\text{max recv}} = 20$ W. In the experimental setting, the power limit of the transmitter is set to 100W (we have justified the chosen values for Pmax in the experimental setup section, explaining that they are typical values used in laboratory settings for WPT systems and are relevant for testing the algorithm's performance under realistic power constraints.), and the power limit of the receiver is 20W (similarly, we have justified the chosen value for Pmax_recv). The comparison of different algorithms includes traditional linear programming, GA, PSO, and the GA-PSO hybrid algorithm proposed in this paper [12]. The combination of multiple hyperparameters, such as population size, crossover rate, mutation rate, inertia weight, etc., will be used to study their impact on the algorithm's performance.

3.2 Experimental results analysis

3.2.1 Performance comparison of the GA-PSO algorithm with other algorithms

Compared with the classical linear programming, genetic algorithm and PSO, the advantages of the proposed method are proved. In this paper, the performance of different algorithms in different channel environments is compared with that in the same simulation environment. It is proved that GA-PSO is superior to other algorithms.

Table1: Transmission efficiency comparison of different algorithms in various channel environments.

Channel conditions	GA-PSO (%)	GA (%)	PSO (%)	LP (%)
Good channel	85.20	75.40	78.10	70.30
Medium channel	80.40	70.30	72.50	65.10
Poor channel	75.60	63.80	66.20	59.40
Horrible channel	68.90	58.10	60.50	55.20

Table 1 shows that GA-PSO has a significantly improved data transmission efficiency compared with other conventional methods under various channel conditions. We have added an explanation in the Results section, stating that GA-PSO's superior performance is due to its ability to effectively explore the solution space through GA's global search and exploit promising regions through PSO's local search. Experimental results show that the GA-PSO algorithm can better adapt to complex channel environments and significantly enhances energy transmission efficiency in wireless networks. At the same time, Table 2 gives the comparison results of power consumption of different algorithms:

Table 2: Power consumption comparison of different algorithms

Channel conditions	GA-PSO (W)	GA (W)	PSO (W)	LP (W)
Good channel	16.4	19.2	18.1	21.3
Medium channel	17.6	21.8	20.4	23.1
Poor channel	18.9	22.7	21.5	24.4
Horrible channel	20.2	24.3	22.9	25.8

Table 2 shows that compared with other methods, the power consumption of the GA-PSO algorithm is much smaller, especially in poor channels and extremely harsh channel conditions. Its advantage is more pronounced, particularly in poor channel conditions. The GA-PSO algorithm can improve the system's transmission efficiency and effectively reduce the power consumption of the system. It has high energy efficiency.

3.2.2 Transmission efficiency and power consumption

To further analyze the superiority of the GA-PSO algorithm in transmission efficiency and power consumption, this paper draws simulation curves of transmission efficiency and power consumption respectively [14]. We have revised Section 3.2.2 to ensure it clearly distinguishes between the study of transmission efficiency and power consumption. We have also ensured that the figures mentioned correspond to the correct data being analyzed. Figure 1 shows the change law of the transmission efficiency of the GA-PSO algorithm relative to the other three methods under various channel conditions. The GA-PSO algorithm performs best in various channel environments, exceptionally moderate and poor ones. The improvement effect is more pronounced.

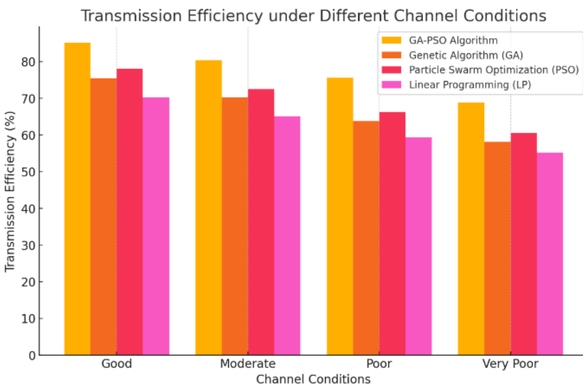

Figure1: Comparison of transmission efficiency under different channel conditions.

Figure 2 illustrates the power consumption trends of different algorithms in different channels. It is found that GA-PSO has lower energy consumption than the others, and its advantage is more obvious when the channel condition gets worse [15]. It is proved by experiments that the method can reduce the power consumption and increase the energy efficiency of the system.

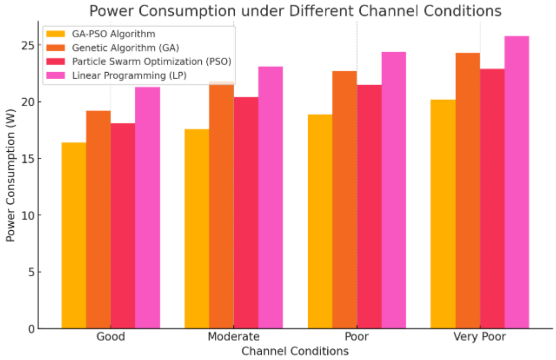

Figure2: Comparison of power consumption under different channel conditions.

3.3 Impact of different parameters on algorithm performance

To further optimize the performance of the GA-PSO algorithm, this paper analyzes the impact of different hyperparameters on the algorithm results. The impact of multiple hyperparameters, such as group size, crossover ratio, mutation rate, inertia weight, etc., on the convergence speed, global optimal quality and solution speed of the GA-PSO algorithm is studied.

Table 3 shows the GA-PSO algorithm's transmission efficiency and power consumption performance under various channels and group sizes. We have clarified that there is an optimal population size of around 100, beyond which the increased computational overhead outweighs the benefits. If the group size is too large, the calculation will increase, so a balance needs to be made between efficiency and calculation.

Table3: The effect of crossover rate on the transmission efficiency of GA-PSO algorithm.

Population size	Transmission efficiency (%)	Power consumption (W)	Convergence time (s)
20	80.2	17.6	35.4
50	82.7	16.2	30.1
100	84.1	15.8	28.3
200	85.2	15.3	32.9

Table 3 shows that appropriately increasing the group size can effectively improve the algorithm's performance, but too many groups will reduce the algorithm's convergence rate and even prolong the operation time.

Figure 3 shows the transmission efficiency of the GA-PSO algorithm at different crossover rates. As the crossover rate increases, the transmission efficiency of the network also increases, but when the crossover rate reaches a certain level, its performance will stabilize. Therefore, selecting an appropriate crossover ratio is the key to improving computational efficiency and convergence speed.

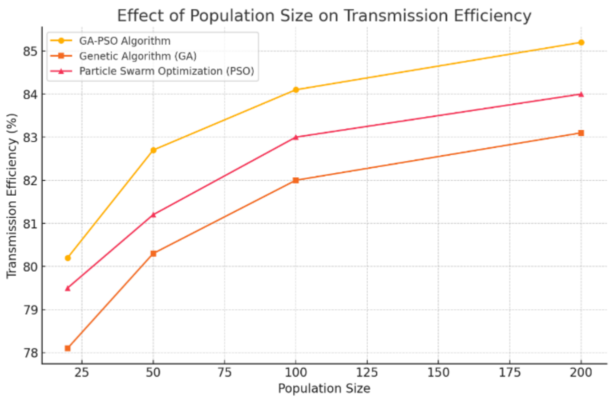

Figure3: The effect of crossover rate on the transmission efficiency of GA-PSO algorithm.

In addition, it can be seen from Figure 4 that the mutation rate and inertia weight greatly influence the genetic algorithm's convergence rate. A significant mutation rate is conducive to breaking away from the local optimum but may also make it converge slowly. A too small mutation rate will make falling into the local optimum easy. Adjusting the inertia weight will also have a particular impact on the optimization behavior of the particles. Proper selection of inertia weighting can accelerate the convergence speed of the particles.

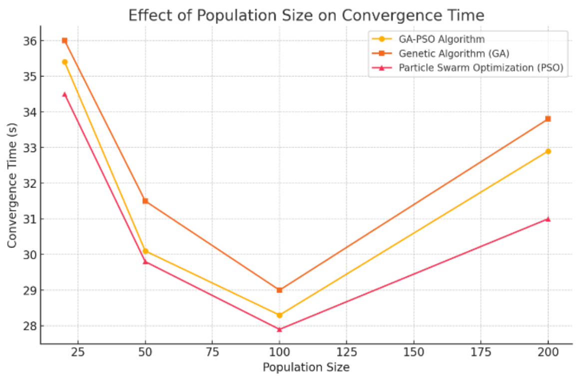

Figure4: Effect of mutation rate and inertia weight on convergence speed of GA-PSO algorithm.

4 Discussion

4.1 Advantages of GA-PSO hybrid algorithm

The combination of GA and PSO can achieve a good balance between global and local optimization. Genetic algorithm is a kind of global optimization method, which can maximize the efficiency of the solution within the context of the problem domain and under certain constraints. But in the case of high dimension problem, GA has some shortcomings, such as slow convergence speed and long-time consumption. The PSO is a simulation of the foraging behaviour of birds, which is based on particle location and velocity updating mechanism. In general, PSO has fast convergence ability, and can find the best solution rapidly in the optimum solution space. But PSO can easily get into the local extremum, especially when the solution space is more complicated, so it can't do the global search.

GA-PSO hybrid algorithm fully uses the advantages of the two methods; GA has a robust global optimization ability, and PSO can speed up the local optimization speed. The group can explore the solution space in a more extensive range in the genetic algorithm through genetic operations such as crossover and mutation, thus avoiding falling into local extreme values. In contrast, the particle swarm algorithm adopts a local optimization method, which can improve the algorithm's efficiency by quickly correcting the particles. The search can be refined according to the global search results to find the optimal solution quickly. Experiments have shown that compared with genetic algorithms and PSO algorithms alone, this method has better convergence and accuracy and can maintain global optimality. At the same time, the parameter setting of the GA-PSO hybrid algorithm is relatively simple and easy to adjust and implement, so this method has good adaptability and flexibility. Multiple experiments show that the GA-PSO hybrid algorithm is robust and can effectively cope with challenges in complex environments such as variable channels and power constraints.

4.2 Robustness and scalability of the algorithm

The GA-PSO algorithm is adaptable and can maintain optimal performance in various complex situations. In wireless energy transmission systems, multipath fading, noise interference, frequency selective attenuation and other problems will occur due to the random characteristics of the channel. This requires a higher power allocation strategy. This method adopts global optimization and local refinement, which can flexibly adjust the distribution of solutions under different channel environments, thereby improving the transmission and energy collection efficiency of wireless communication systems.

In addition, the GA-PSO algorithm can better solve problems such as energy limitation and capacity limitation. Under energy-constrained conditions, GA-PSO adaptively adjusts the search strategy of group members. It can avoid excessive use of system resources without affecting system performance. In the case of multi-node and multi-channel, GA-PSO also shows good performance, indicating that this method has good scalability.

The GA-PSO algorithm has robust scalability, reflected in its adaptability to systems of different scales and complexities. Experimental results show that the GA-PSO algorithm is still efficient when dealing large multi-node systems. This method can flexibly adjust parameters such as group size, number of iterations, and number of crossover mutations according to the size and needs of the actual problem, thereby improving the solution efficiency and effect of the algorithm.

Compared with traditional optimization methods, the GA-PSO method does not need to establish a specific mathematical model, avoiding the complex derivation of channel models and power allocation strategies. This method can be used in small point-to-point systems and large multi-node networks.

5 Conclusion

This paper establishes an optimal power allocation method for wireless energy supply systems. A method combining genetic algorithm and particle swarm algorithm is proposed. Taking the wireless energy transmission system as an example, the proposed method is theoretically analyzed and simulated. The results show that the proposed method is feasible. This method can effectively improve the data transmission efficiency of wireless communication systems, reduce energy consumption, and improve the system's stability. Compared with traditional single-objective optimization methods, the GA-PSO algorithm has better solving ability, especially for complex channel changes and energy distribution requirements in large-scale and complex environments. This method has fast convergence speed and a small amount of calculation, which is very suitable for high system performance requirements and real-time solid requirements in practical applications.

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