Simulation of Carbon Footprint Calculation Model of Power Enterprises Based on Particle Swarm Optimization

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Abstract. The purpose of this study is to develop a carbon footprint calculation model of power enterprises based on PSO(particle swarm optimization) to help power enterprises quantify their carbon emissions and optimize their carbon emission reduction strategies. In this study, considering the user-side carbon emission quota constraint model, a Fuzzy SPSO (Fuzzy Self-Correcting PSO) is proposed to solve this optimization problem. Fuzzy SPSO is an optimization algorithm that combines PSO and fuzzy logic to improve the adaptability and global search ability of the algorithm. Through the introduction of fuzzy rules, the algorithm can better adapt to the characteristics of different problems, deal with uncertainty and diversity, and find a better solution. The simulation results show that the algorithm can effectively deal with multiple influencing factors, including power supply structure, energy efficiency and carbon emission factors, so as to find the best emission reduction strategy. This study provides a powerful tool, which is helpful for power enterprises to achieve carbon emission reduction targets, promote sustainable development, and provide valuable experience and methods for research and practice in the field of carbon emission reduction. This is of great significance for coping with climate change and achieving the goal of carbon neutrality.

Keywords.particle swarm optimization; carbon footprint; power enterprises

1.Introduction

With the increasing prominence of global climate change and the emergence of sustainable development goals, reducing carbon emissions has become the common responsibility of the government, enterprises and individuals. As the main participants in the energy field, power companies have produced a lot of carbon emissions in energy production and distribution, and become one of the important contributors to the global carbon footprint [1]. Therefore, it is an urgent task for the power industry to accurately measure the carbon footprint of power enterprises and find feasible ways to reduce carbon emissions.

Measuring carbon footprint helps individuals, organizations and governments to better understand their contribution to climate change, make emission reduction plans and take measures to reduce greenhouse gas emissions. At the same time, it also helps to monitor the progress of emission reduction and promote climate action. Different countries and organizations may use different methods and tools to measure carbon footprint, but the overall

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goal is to reduce the adverse impact on climate change [2-3]. In reference [4], the optimal operation model of carbon capture unit under carbon emission trading is established, but the carbon emission trading is not considered in the actual example analysis. Literature [5] considers the carbon transaction cost in the objective function of optimal power flow to realize the coordinated optimization of economy and low carbon of dispatching. Traditional carbon footprint measurement models often rely on historical data and complex model equations. These methods may be limited by data incompleteness and model complexity, resulting in inaccurate results. By introducing PSO(particle swarm optimization), we can better deal with the uncertainties and changeable factors in carbon footprint calculation, and improve the robustness and prediction accuracy of the model.

In this study, we will introduce the carbon footprint calculation model of power enterprises based on PSO, and discuss its working principle in detail. We will also show the simulation results of this model and compare it with traditional methods to verify its performance and accuracy. The goal of this study is to provide an innovative tool for power enterprises to better understand their carbon footprint, provide strong support for reducing carbon emissions, and push the power industry to a more sustainable and environmentally friendly future.

2.Research Method

2.1.Calculation model of carbon footprint of electric power enterprises

Climate change has become an urgent problem on a global scale, and one of its fundamental reasons is the emission of greenhouse gases. Power industry is one of the main sources of global greenhouse gas emissions, so power companies bear great responsibility for reducing carbon footprint. Carbon footprint measurement is a key tool, which can help electric power enterprises to assess, monitor and reduce their carbon emissions and achieve sustainable energy production. Reducing carbon emissions is an important step to curb climate change. Power companies play a key role in reducing carbon emissions, because they supply energy and directly affect the carbon emissions of other industries. Consumers pay more and more attention to the sustainable performance of enterprises. Power companies with low-carbon footprints are more likely to attract customers and investment.

Power companies need to measure their direct and indirect carbon emissions, including carbon emissions of coal, gas and renewable energy during power generation, as well as energy losses during transmission and distribution. An effective data collection and monitoring system should be established to track carbon emissions and find potential problems in time. Increasing renewable energy and energy efficiency is an effective way to reduce carbon footprint. Power companies can invest in solar energy, wind energy and other clean energy technologies. For carbon emissions that are difficult to completely eliminate, power companies can consider purchasing carbon offset projects to neutralize their emissions. The calculation of carbon footprint of power enterprises involves many complicated factors, including energy sources, transmission networks, electricity demand and supply chain [6-7]. Therefore, it may be challenging to accurately measure the carbon footprint.

The calculation of carbon footprint of power enterprises is a key step, which is helpful to achieve the goal of climate change response, abide by laws and regulations, and attract customers and investment. Although facing some challenges, power companies can reduce their carbon footprint by adopting clean energy, improving data collection and monitoring systems and actively participating in carbon emission reduction efforts. This will help to ensure a sustainable and environmentally friendly power supply and create a cleaner living environment for future generations.

Creating a user-side carbon emission quota constraint model needs to consider many factors, including users' carbon emission targets, constraints and data sources. Define users' carbon emission targets, for example, reducing carbon emissions by 10% every year. Determine the constraints on carbon emissions, which may include regulations, policies and individual/organization restrictions. Determine the unit of measurement of carbon emissions, usually using tons of carbon dioxide equivalent. Consider renewable energy and carbon offset.

At present, the calculation formula of the total carbon emission F at the user side in the project is as follows [8]:

$$F = eG \tag{1}$$

Where: G is the electricity consumption of users; e is the average emission factor of power grid, generally taking the weighted average of carbon dioxide emissions per unit power generation of generators.

However, using the average emission factor of power grid is not conducive to users to understand the actual carbon footprint of high energy consumption behavior, and it has a weak incentive and punishment effect on users to reduce carbon [9]. Therefore, this paper adopts the carbon flow theory to measure the carbon emissions of users through the carbon emission intensity e_x (that is, the carbon emissions generated by each user's unit electricity consumption).

The calculation formula of e_x is as follows:

$$e_x = \frac{\sum_{i \in x^+} \left(P_i \rho_i\right) + P_{G,x} e_{G,x}}{\sum_{i \in x^+} \left(P_i\right) + P_{G,x}} \tag{2}$$

Where: x^+ is the set of branches flowing into the node x; P_i is the active power of the branch i; ρ_i is the carbon emission intensity of branch i; $P_{G,x}$ is the active power of the generator of node x; $e_{G,x}$ is the carbon emission intensity of the generator at node x.

Considering that CO2, SO2 and NOx are produced at the same time in the actual operation process, the emissions of SO2 and NOx can be converted into equivalent CO2 by comparing the emissions of various gases per unit capacity [10]. The environmental cost model of combined cooling, heating and power supply system in a certain period is obtained as follows:

$$f(t)=W\left[\sum_{i=1}^{N_P}E_{pi}(P_i(t))+\left(1+\frac{1}{\rho}\right)\sum_{j=1}^{N_P}E_{cj}(P_j(t))+\left(1+\frac{1}{\rho}\right)\sum_{k=1}^{N_h}E_{hk}(P_k(t))\right] \tag{3}$$

Where: ρ is the equivalent performance coefficient of heating; $P_i(t)$ is the active output of the i generator at time t; $E_{pi}(P_i(t))$ is the total CO2 emission of power supply only; $E_{cj}(P_j(t))$ is the total CO2 emission corresponding to the CCHP system; $E_{hk}(P_k(t))$ is the total CO2 emission corresponding to the heating (cooling) part only; W is the penalty coefficient, including emission penalty and environmental value.

2.2.Model solving

PSO is a heuristic optimization algorithm, which was first proposed by American social psychologists James Kennedy and Russell Eberhart in 1995, and was inspired by the behavior of biological groups such as birds and fish. PSO is widely used to solve various optimization problems, including function optimization, machine learning, neural network training, engineering design and other fields.

The core idea of PSO is to find the optimal solution by simulating the cooperation and information sharing of individuals in a group. In PSO, each individual is called a particle. These particles search for the optimal solution in the solution space and constantly update their positions and velocities to approach the global optimal solution.

The algorithm process of PSO can be briefly described as follows:

Initialization: randomly generate a group of particles, each particle has a position and velocity, and evaluate its fitness according to the objective function defined by the problem.

Searching for individual optimum: each particle determines its best position (individual optimum solution) according to its fitness value.

Searching for global optimum: according to the best particle (global optimum solution) in the whole population, update the speed and position of all particles. This process is influenced by two main factors, namely, the historical experience of the particles themselves and the information of the best particles in the group.

Update speed and position: according to the global and individual optimal solutions, update the speed and position of particles to make them move to the optimal solution.

Termination condition: the algorithm iterates until a predetermined termination condition is met, such as the maximum number of iterations or a certain convergence condition.

Output result: Return the global optimal solution, or take corresponding actions according to the requirements of the problem.

The advantages of PSO include easy implementation, independent of gradient information, and suitable for multidimensional and nonlinear problems. However, it also has some challenges, such as falling into local optimal solution and being sensitive to parameter setting. Therefore, researchers and engineers usually need to optimize parameters and improve algorithms according to specific problems in order to obtain the best performance. PSO is a powerful optimization tool, which can be used to solve various practical problems, especially those that lack explicit mathematical models or gradient information [11].

Although PSO has been successful in many application fields, it also has some shortcomings and limitations, including: PSO is easy to fall into local optimal solutions, especially in highly nonconvex or multimodal optimization problems. Because the movement of particles is influenced by neighboring particles, the global optimal solution may be missed. PSO algorithm has some important parameters, such as learning factor and inertia weight, and the selection of these parameters is very sensitive to the performance of the algorithm. Improper parameter setting may lead to slow convergence or failure of the algorithm. Compared with some other optimization algorithms, PSO usually converges slowly. This means that more iterations may be needed to find the optimal solution. PSO usually doesn't adjust the parameters of the algorithm adaptively during its execution, which may lead to great differences in the performance of the algorithm at different stages.

Considering the user-side carbon emission quota constraint model, a Fuzzy SPSO(Fuzzy self-correcting PSO) is proposed to solve this optimization problem. Fuzzy SPSO is an optimization algorithm that combines PSO and fuzzy logic to improve the adaptability and global search ability of the algorithm. Through the introduction of fuzzy rules, the algorithm can better adapt to the characteristics of different problems, deal with uncertainty and diversity, and find a better solution.

Fuzzy logic is a mathematical tool for dealing with uncertainty and fuzziness, which introduces fuzzy sets and fuzzy rules for fuzzy reasoning and decision-making [12]. In Fuzzy SPSO, fuzzy logic is used to enhance the adaptability of particles to better adapt to the uncertainty and diversity of problems.

Fuzzy SPSO introduces fuzzy logic to adjust the speed and position update of particles. Fuzzy logic allows each particle to adaptively adjust its behavior according to the nature of the problem. This can effectively deal with the uncertainty and diversity of the problem and make the algorithm more robust. Fuzzy rules define how to update the speed and position of particles according to the current state and problem characteristics. These rules are designed based on the nature of the problem and the historical performance of particles. For example, fuzzy rules can adjust the speed of particles to better explore unknown areas, or reduce the speed to accelerate convergence to local optimal solutions. The goal of Fuzzy SPSO is to minimize or maximize a given fitness function, which describes the nature of the problem. The algorithm improves the value of fitness function by constantly optimizing the position of particles, so as to find the best solution.

Suppose there is a fuzzy membership function, which represents the degree of particle velocity update in a specific problem. This fuzzy membership function can be designed according to the characteristics of the problem. Then, the speed update can be adjusted adaptively according to this membership function, and the speed update formula is as follows:

$$V_i(t+1)=V_i(t)+\alpha\cdot\mu(x)\cdot\Delta V_i \tag{4}$$

In this formula: $V_i(t)$ is the velocity of the particle i at the time step t. $V_i(t+1)$ is the velocity of the particle i at the time step $t+1$. α is a learning factor, which is used to control the amplitude of speed update. $\mu(x)$ is a fuzzy membership function, which indicates the velocity update degree of particles at position x. ΔV_i is a basic speed update, which is usually given by the traditional PSO formula.

This fuzzy membership function $\mu(x)$ can be designed according to the nature of the problem, so that particles have different speed updates in different positions. This adaptability can help the particle swarm to better adapt to the uncertainty and diversity of the problem, thus improving the performance of the algorithm.

The inertia weight of Fuzzy SPSO is calculated by the following formula:

$$W(t)=\frac{W_{\max}-W_{\min}}{\max\_iter}*(\max\_iter-t)+W_{\min} \tag{5}$$

Where: $W(t)$ is the inertia weight at the iteration number t. $W_{\max}$ is the maximum value of inertia weight. $W_{\min}$ is the minimum value of inertia weight. $\max\_iter$ is the maximum number of iterations of the algorithm.

This formula can be used to dynamically adjust the inertia weight in PSO according to the current iteration times to balance the trade-off between global search and local search. In the early stage of the algorithm, larger inertia weight is helpful to promote global search, while in the later stage, smaller inertia weight is helpful to strengthen local search. This weight change process can help the algorithm better adapt to the problem optimization needs in different stages.

The algorithm flow of Fuzzy SPSO is shown in Figure 1 below:

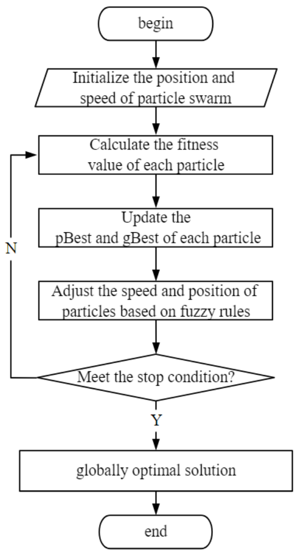

Fig. 1. Algorithm flow of Fuzzy SPSO

3.Simulation And Result Analysis

The program tested in this paper is written based on MATLAB R2018a and MATPOWER 7.0, and runs on the 64-bit Windows10 operating system. The CPU used in the test is IntelCore i5-7300HQ, running at 2.50 GHz. The inertia weight of PSO is set to 0.7201, and the two learning factors are set to 1.4038. The basic load parameters of combined cooling, heating and power supply system in power enterprises are analyzed.

On the basis of the baseline scenario, carbon emission constraints are introduced, and the emission intensity is lowered by 20% on the basis of the baseline scenario. Each cost curve of multi-objective fuzzy optimization unit is shown in Figure 2.

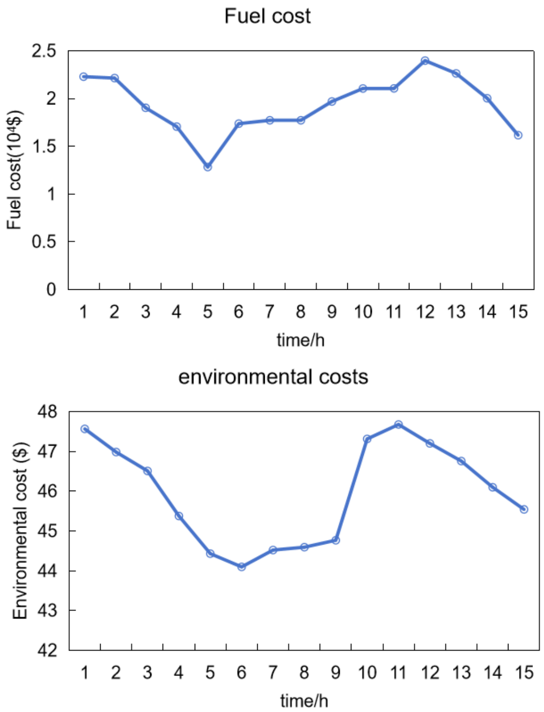

Fig. 2. Multi-objective fuzzy optimization of each cost curve of unit

From the results of multi-objective optimization, it can be seen that after considering the carbon emission constraints, the emissions in each period have decreased, which makes the overall carbon emissions low. This is because after considering the carbon emission constraints and the trading of carbon emission rights, the pollution emission and energy consumption characteristics of the unit will be fully weighed and its output will be reasonably distributed during optimization, thus changing the production and scheduling methods of different energies and realizing reasonable low-carbon economic scheduling.

The time period with the largest load demand is selected for comparative analysis without considering carbon emission constraints and carbon emission rights trading. The comparison of convergence characteristics between Fuzzy SPSO and traditional PSO is shown in Figure 3.

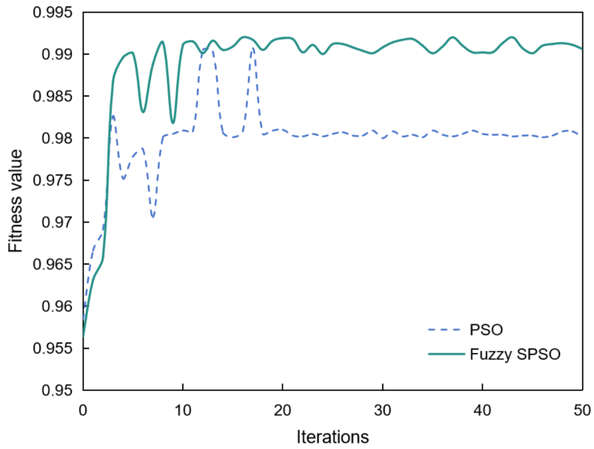

Fig. 3. Comparison of convergence characteristics of algorithms

It can be seen that PSO falls into local optimum in less than 10 times. Fuzzy SPSO can self-correct, jump out of the local optimal region and search for a better target value. This is because PSO adopts a linear decreasing correction strategy, and the inertia weight values show a linear decreasing trend, while Fuzzy SPSO fully considers the performance of particles, and obtains the corresponding weight values according to the actual situation of each particle's performance, so as to give full play to the actual performance of particles; Making particles have self-correcting ability is helpful to find better target values and enhance their global search ability.

4.Conclusion

The research on the simulation of carbon footprint measurement model of power enterprises based on PSO provides important insights for power enterprises in reducing carbon emissions and sustainable development. By using Fuzzy SPSO algorithm, our model can estimate the carbon emissions of power enterprises more accurately and provide reliable results. This will help enterprises to better understand their carbon footprint and formulate effective emission reduction strategies. The model based on PSO can not only be used to measure the carbon footprint, but also be used as a decision support tool to help enterprises formulate long-term carbon emission reduction strategies to meet the requirements of government regulations and social sustainable development. It is helpful to reduce its carbon emissions and realize sustainable development, and also provides valuable methods and experiences for the research and practice in the field of carbon emission reduction.

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