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Energy Management in Smart Grids using AI

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Abstract

This paper discusses the design and research of smart grid based on artificial intelligence technology, which realizes automatic control and optimization of power system by applying particle swarm optimization algorithm and multi-objective optimization theory, in order to improve the operation efficiency and stability of power grid. Using particle swarm optimization algorithm and multi-objective optimization theory to design and research smart grid principles and methods, particle swarm optimization algorithm can find the best solution in the search space, and through the multi-objective optimization theory to balance different target requirements, so as to achieve the automatic control of power system. Deep neural networks are trained and utilized with large amounts of data for prediction and classification purposes. By using a variety of means, such as reinforcement learning, we get a diagnosis scheme of intelligent power system, and build relatively perfect intelligent power management software. The results show that the new smart grid design system is more economical and simple than the traditional grid distribution. Better solutions for saving electricity.

Keywords: Artificial Intelligence, Smart Grid, Particle Swarm Optimization, Multi-Objective theory

1. Introduction

The design and research of smart grid based on artificial intelligence is a new exploration method for supply and demand balance, energy optimal distribution, power grid stability and other problems in power system. In this research, it is necessary to use various algorithms and models in artificial intelligence technology, such as deep learning, neural network, genetic algorithm, etc., to analyze and process power system data. By mining the historical data, we can obtain the data information of supply and demand, regulation capacity, reserve capacity and other aspects of the power system, and use clustering, regression and other algorithms to build a multi-dimensional power grid model. At the same time, it is also necessary to take into account the forecast trends under different scenarios, combine real-time monitoring data, and use adaptive control strategies and reinforcement learning models to carry out intelligent prediction and optimal scheduling, so as to achieve efficient, reliable and safe operation of the power grid. In this process, we also need to consider the use of human-machine collaboration, combining human expertise with intelligent algorithms to better understand the interaction and regularity of power systems. For example, through the visual display of data, the operator of the power system can intuitively feel the state changes and trend distribution of the power system, and make decisions and scheduling quickly. This can effectively improve energy efficiency, reduce power consumption, and reduce pollution emissions and other aspects of social, environmental and economic sustainable development to contribute. In recent years, artificial intelligence technology has made remarkable progress in various fields.

In the design and research of smart grid based on artificial intelligence, we use particle swarm optimization and multi-objective optimization theory to achieve more efficient and reliable power grid planning. First, we collect and collate a large amount of historical data about the grid, including power demand, load curves, equipment performance and other information. Next, these data are preprocessed to improve data quality and accuracy. Then, on this basis, a multi-objective optimization model is constructed, taking into account factors such as cost, efficiency, environmental impact and so on. To solve the multi-objective optimization problem, we introduce particle swarm optimization (PSO). PSO is a heuristic search algorithm that finds the optimal solution by simulating the behavior of biological clusters such as birds or fish in nature. In the model training stage, we take the historical data as the training set and train the model according to the multi-objective optimization theory. After many experiments and optimizations, our smart grid design model has evolved into a stable system that can meet a variety of needs. In addition, we also apply deep learning technology to the monitoring and maintenance of smart grids to improve the reliability and security of power grid operation. For example, potential points of failure are detected through neural networks so that preventive measures can be taken in advance. The final experimental results show that our AI based smart grid design and research model can carry out power grid planning and management more accurately and efficiently and provide strong support for the upgrading of traditional power grids.

2. METHODOLOGY

The search for particles in the elementary particle swarm optimization algorithm is very similar to the way birds search for food. Each particle in the particle swarm represents a solution, and each particle will get the corresponding fitness value according to the objective function, which can evaluate the quality of the solution according to the specific problem. The flight space of the particle is determined by the feasible region of the problem to be optimized, and the particle will carry out mobile search in the constrained flight space until the end of the iteration. Before the first iteration begins, several particles are randomly initialized in the search space and the search speed is randomly set for the particles. Each subsequent iteration is based on four elements, namely, the optimal position of the particle's own historical experience, the current position of the particle, the global optimal position of all particles, and the uncertain disturbance generated by the particle's own environment. Among them, the optimal position of the particle's own historical experience can be referred to as the individual extreme value, and the global optimal position of all particles is referred to as the global extreme value. The particle follows the individual extreme value and the global extreme value to change its search speed and direction, and then changes its position. The diagram of its updated position is shown in Fig 1.

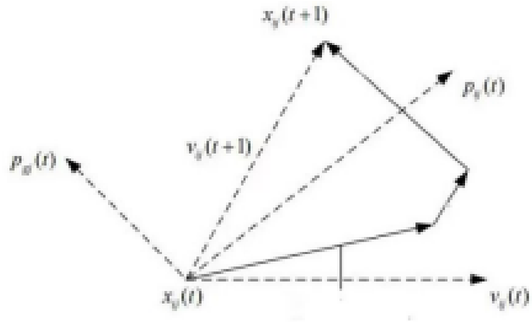

Fig.1. Update the location map

The historical inertia of the particle is due to the particle flying in the search domain, and the inertia of the previous flight is inherited, and the next flight is affected by its velocity and direction. If the group cognition of particles is not considered in the evolution of PSO algorithm, then the velocity equation of particles only contains historical inertia and self-cognition of particles and the velocity equation can be expressed as:

$$v_{ij}(t+1) = v_{ij}(t) + c_1 r_1[p(t) - x(t)] \qquad (1)$$

In the PSO algorithm, each particle exerts an influence among all particles by affecting the particles around it, that is, the particles in its neighborhood. This way of interacting between particles can be called the topology of particle swarm. It is through the topology of each particle that multiple neighborhoods in the group are connected, so that all particles search the search space together. Therefore, the topology between particles has a significant impact on the search of the whole group. There are two types of elementary particle swarm algorithms, namely local and global. In the global PSO algorithm, the position update of each particle is affected by the current optimal position, and all particles have access to the global extreme value. In the local PSO algorithm, each particle can only access the particles in its neighborhood, which refers to the particles on different sides of the topology diagram. Fig 2 shows the common topology structure of particle swarm. In the fully connected topology, every particle is connected with other particles. The advantage of this topology is that particles can transfer information quickly and efficiently, and convergence speed is fast. The disadvantage is that the faster convergence speed leads to incomplete search and premature fall into the local optimal solution. In the ring topology, particles can only connect with other particles in their neighborhood, and the speed of information transfer is relatively slow, but more detailed search can be carried out in the search domain, and it is easier to find the global optimal solution. In the star topology, with one particle as the center, the central particle can directly exchange information with the other particles, and the information transmission between the other particles must pass through the central particle as the transmission hub. Therefore, the dependence on the central particle in this structure is too large, and when the central particle falls into the local optimal, the whole particle swarm will be misled into the local optimal solution. There is no specific rule to follow for information transfer between random topological particles, and there may be any form of fully connected topology, ring topology or star topology among different particles. When dealing with optimization problems of different complexity, different types of particle swarm topology should be selected. When the problem to be optimized is more complex, it is suitable to adopt a topology with a small neighborhood, such as a ring topology, because in the case of small neighborhoods, particles can converge slowly, search is more refined, and it is easy to solve complex problems. When the problem to be optimized is relatively simple, it is suitable to adopt a topology structure with a large neighborhood, in which all particles can be fully connected, efficient information exchange, and simple problems can be solved faster.

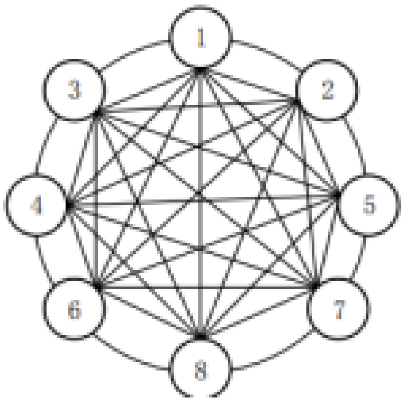

Fig.2. Topological structure model

Since the current velocity of the particle in the equation at this time follows its own historical optimal extreme value, and does not refer to the search situation of other particles in the population, it indicates that no matter how many particles there are in the whole particle population, each particle cannot exchange information with other particles, and only focuses on its own speed and individual extreme value, so it is difficult to find the global optimal solution by searching for an individual. If the self-cognition of particles is not considered in the evolution of PSO algorithm, then the velocity equation of particles only contains historical inertia and particle group cognition, and its velocity equation can be expressed as:

$$v_{tj}(t+1) = v_{tj}(t) + c_2 r[p_{gj}(t) - x_{ij}(t)] \qquad (2)$$

At this time, the particle will blindly explore the entire search space because of the lack of reference to its own individual extreme value, and although the development ability of new regions will be enhanced and the convergence rate will be faster, it is very easy to fall into the local optimal solution in advance. The introduction of inertia weight in the algorithm greatly improves the overall performance of the particle swarm optimization algorithm and can better solve practical application problems. Therefore, this particle swarm optimization algorithm with inertia weight is also called the standard particle swarm optimization algorithm, and its rate and displacement expressions are as follows:

$$v_{ij}(t+1) = \omega v_{sj}(t) + c_1 r_1[p_{gj}(t) - x_{ij}(t)] \qquad (3)$$

In addition, through the in-depth study of inertia weight and combining with the characteristics of particle swarm optimization search, it is found that should be assigned a large value at the initial stage of particle swarm search, so that particles can be efficiently searched in the feasible domain with a large step. In the later stage of particle swarm search, due to the extensive exploration in the early stage, the value is reduced in the later stage to ensure that the algorithm can carry out fine search around particles. The method of adjusting the size in different particle search stages to improve the convergence performance of PSO is called dynamic inertial weight PSO. Shi proposed a dynamic inertial weight particle swarm optimization algorithm, whose weight changes with the number of iterations as follows:

$$\omega = \omega_{\max} - \frac{(\omega_{max} - \omega_{\min})t}{T} \qquad (4)$$

The increase or decrease of the parameter with the increase of the number of iterations should not be completely linear, because the particles have to be packed into the optimal particle. The characteristics of the particle, the linear increase or decrease of the inertia weight, the algorithm is difficult to judge the characteristics of the optimal particle it searches. Therefore, at the beginning of the iteration, the particles should be dispersed in the solution space as much as possible to diffuse the particles and prevent premature aggregation. In addition, the change of inertia weight factor should be from a large value in the initial iteration, with the increase of the number of iterations, its value should be smaller and smaller, and the function form should be convex. Considering the search characteristics of particle swarm optimization algorithm and the influence of inertia weight factor on the algorithm in the search process, a dynamic nonlinear inertia weight factor adjustment formula is proposed, which is as follows:

$$\omega = \omega_{ini} + (\omega_{end} - \omega_{ini}) \tag{5}$$

The three-dimensional image of Rastrigin test function is shown in Fig 3, from which it can be seen that the function has multiple peaks and multiple local extreme values, and the dimension of the independent variable also has a great influence on the complexity of the problem. When the dimension is higher, the number of local extreme values increases and the optimization algorithm is more likely to fall into the local optimal solution. Rastrigin test function is a classic multimodal test function, and its fluctuating image is very challenging for optimization algorithms. This test function is often used to test the convergence performance of an algorithm.

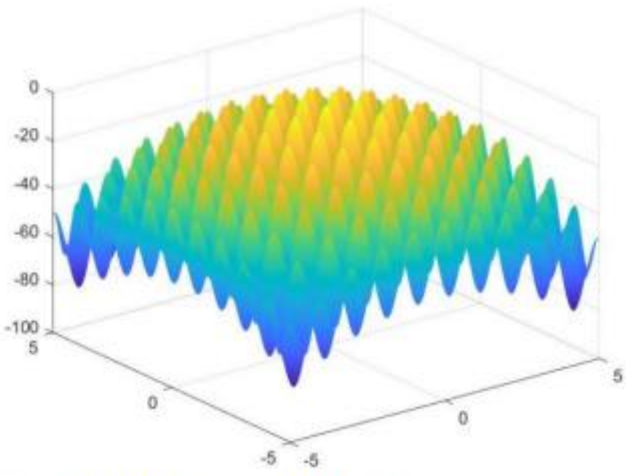

Fig.3. Algorithm convergence demonstration

The Metropolis sampling method is an important solution selection method and the core of simulated annealing algorithm. Moreover, this method can be combined with particle swarm optimization algorithm to be used in the case that the particle swarm algorithm has been iterated many times but the fitness value of the objective function has not been improved, which includes two cases: One is that the fitness value of the objective function deteriorates, and the other is that the algorithm falls into a local optimal solution. In this case, updating the PSO equations of position and velocity cannot help the particles converge to the global optimal solution, so the simulated annealing mechanism will be called to help the particle swarm optimization algorithm escape from the local optimal. The algorithm is as follows: When the energy state of the system changes from state A to state B, the corresponding energy changes from R to E, and the probability of this change is:

$$p = e^{\left(-\frac{R-E}{T}\right)} \quad (6)$$

With the introduction of simulated annealing mechanism, the improved PSO can accept both the solution that makes the objective function better and the solution that makes the objective function worse with a certain probability in the iterative process. In the process of algorithm update iteration, it is not required that the solution of the later generation must be better than the solution of the previous generation, and the probability of accepting the poor solution is gradually reduced. In this way, the certainty of the original particle swarm optimization algorithm is effectively avoided and a certain degree of uncertainty is increased. There are two methods for moving from one location to another, one is deterministic and the other is uncertain. The deterministic method tends to greatly hinder the particle exploration process, and on the contrary, the algorithm cannot find the optimal solution efficiently. Searching with a certain probability increases the flexibility of particle swarm, so that particle swarm can find the optimal solution more quickly.

$$T(n+1) = K * T(n) \quad (7)$$

In order to model the economic cost function more reasonably and accurately, the above cost function expression 8 needs to be modified appropriately. The increase of heat loss in the process of valve opening and closing in the generator set of multi-valve steam turbine is called valve point effect. The economic cost generated by the valve point effect cannot be ignored in the long run, so the cost generated by the valve point effect is included in the economic cost function.

3. EXPERIMENT

The main objective function method selects one of the N objective functions as the main objective function, takes the remaining N-1 objective functions as the secondary objective function, and transforms the secondary objective functions into new constraints through certain methods, and finally forms a single objective function with multiple constraints to complete the transformation from the multi-objective optimization problem to the single-objective optimization problem. The disadvantage of this method is that the choice of the main objective function is subjective. Several objective functions in multi-objective optimization problems are mutually contradictory and mutually restrictive, and most of the time they are equally important. At this time, choosing one of them as the main objective function is more subjective, and different people make different choices, resulting in a large gap between the optimal solutions. The traditional method to solve the multi-objective optimization problem is to transform the objective function into a constraint condition or form a single objective function by weight aggregation, and then solve the single objective problem. The traditional method can only find one optimal solution, and cannot find multiple solutions to provide multiple choices for decision makers. Particle swarm optimization (PSO) can solve this problem well. By searching in decision space, the algorithm finds several non-dominant solutions, and finally forms a Pareto optimal solution set.

TABLE I. RESULT OF MPCMPPSO COMPARED WITH OTHER ALGORITHMS

Problems	*SPEA2*	*PMODE*	*DEMO/ (parent)*	*ADEA*	*MPCMPPSO*
ZDT1	0.33482	0.023285	0.005800	0.001083	0.002741
	0.00475	0	0	0.000113	0.0000385
ZDT2	0.114500	0.018409	0.021560	0.001178	0.002741
	0.007940	0	0	0.000059	0.000120
ZDT4	0.513053	4.9271	0.638950	0.001037	0.100100
	0.118460	2.703	0.500200	0.000134	0.446200
ZDT6	0.296564	0.232551	0.026230	0.000629	0.000624
	0.013135	0.004945	0.000861	0.000044	0.000060

Therefore, using particle swarm optimization algorithm to solve multi-objective optimization problems has great advantages. Among the four multi-objective test functions, the non-dominated solutions obtained by MPCMOPSO algorithm are uniformly distributed, and the Pareto frontier formed by MPCMOPSO algorithm is particularly close to the real Pareto frontier, which has good convergence and distribution. As shown in TABLE I, for ZDT1, MPCMOPSO's convergence is much better than NSGA-II and SPEA2 and is close to the convergence of the other three algorithms. The variance of MPCMOPSO is better than that of NSGA-II, DEMO/(parent) and ADEA. For ZDT3, MPCMOPSO has better convergence than the first three algorithms, and the convergence order is the same as the last two algorithms. For ZDT4, MPCMOPSO has the same degree of convergence as DEMO/(parent), and is better than the other four algorithms, with better variance than the remaining five algorithms. For ZDT6, MPCMOPSO convergence is better than the first three algorithms and variance is better than the other five algorithms.

4. DISCUSSION

In the design and research of smart grid based on artificial intelligence, we can adopt particle swarm optimization algorithm and multi-objective optimization theory to jointly achieve more efficient and stable smart grid operation. Specifically, we use the global search capability of particle swarm optimization algorithm and the tradeoff mechanism of multi-objective optimization theory to optimize scheduling and equipment configuration in different power grid scenarios to achieve a more reliable and energy-saving power supply. In terms of data processing, we first need to collect a large amount of power grid operation data and equipment information, and use data cleaning and preprocessing technology to process and screen it. Then, we design particle swarm optimization model and multi-objective optimization problem for different types of power grid structure and operation mode. By weighing and integrating each optimization objective, we can find the optimal solution that meets various constraints, so as to realize the intelligent scheduling and optimal configuration of the power grid. In terms of model application and evaluation, we can apply particle swarm optimization and multi-objective optimization theory to such fields as load forecasting, power equipment scheduling, energy management, etc., so as to effectively improve the operation efficiency and reliability of power grid. At the same time, we can use a series of performance indicators and evaluation methods, such as system loss, stability indicators, etc., to evaluate and optimize the model in an all-round way. In addition, visualization and interpretative analysis can be used to explore and excavate the internal structure and key factors of the model. In short, the design and research of smart grid based on artificial intelligence can make use of the technical advantages of particle swarm optimization algorithm and multi-objective optimization theory to achieve more efficient and environmentally friendly power scheduling and management, and make important contributions to the development of the power industry and the sustainable development of social economy.

5. CONCLUSION

Remarkable progress has been made in the design and research of smart grid based on artificial intelligence, in which particle swarm optimization and multi-objective optimization theory are very important methods. This method realizes the automatic control and optimization of power system, and can greatly improve the operation efficiency and stability of power grid. However, there are still some problems to be solved. First of all, PSO requires a large amount of data support, which requires high requirements for data collection and processing, and requires professional personnel to maintain and manage. Secondly, the multi-objective optimization theory also has some limitations, which cannot fully consider the complex interaction and uncertainty factors in the power system. In future research, the design and research of smart grid based on artificial intelligence can be combined with technical means in other fields, such as deep learning and reinforcement learning. At the same time, more abundant feature extraction methods and feature selection optimization algorithms can be used to improve the accuracy and effectiveness of smart grid design from multiple dimensions. In short, the future is expected to use more effective algorithms and model architectures to further explore the value of data and promote the application of intelligent technology in the power system to improve the performance and application value of smart grid. At the same time, it is also necessary to pay attention to the practical degree and adaptability of the research results to ensure that they are widely used in power system practice and provide more intelligent and efficient solutions for the power industry.

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