Research on Elastic Loads Participating in Demand Response Based on the Price Mechanism and the Demand Elasticity

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Abstract. Elastic load can be regarded as a demand response resource, such as the temperature-controlled loads, the energy storage and the electric vehicles. It participates in the operation and dispatch of the power grid, and its position is becoming more and more important in the future power system. Due to the complex economic environment of the power market, all users involved in demand response are required to interact with each other to obtain an efficient control and dispatch method. From the perspective of user economy, this article takes the minimum total cost of user electricity as the objective function to optimize the load demand response. Two different algorithms, the particle swarm algorithm and the nonlinear algorithm, are used to solve the problem. The results show that the application of particle swarm optimization in the elastic load demand response has obvious characteristics and advantages.

1. Introduction
With the adjustment of the power industry structure and the acceleration of the power system reform, the competitive power market has attracted more and more attention and has become a current research hotspot. Facts have proved that the implementation of load demand response can effectively allocate and adjust the power consumption of electric loads from the time scale and space scale, and reduce energy consumption[1-2]. By increasing users' participation in the implementation of load demand response, the competitiveness and activity of the entire power market can be increased, thereby improving the operating efficiency and operating economy of the entire power system.

To participate in a competitive power market, users must establish an operating mechanism, and formulate interactive forms and strategies for demand response based on available information and business opportunities. How to get a better time for users to participate in demand response, the best way is to obtain results through a large number of calculations through load agents. This is a complex optimization problem and requires a lot of time[3]. Generally, traditional optimization methods cannot handle this type of practical problems. Therefore, some scholars have proposed in the literature the use of artificial intelligence algorithms to solve related problems in the power system and the power market. And there are documents that have successfully applied the particle swarm optimization method (PSO) to the power system[4].

Based on this, this paper applies the particle swarm optimization method to demand response, and proposes a load response management method based on particle swarm optimization. The proposed method takes into account the change relationship between the electricity load and the electricity price when the electricity load needs to be reduced due to some reasons. For example, there is a shortage of power generation or the electricity price is too high. This method will help solve the difficulties in the implementation of fixed planned response quota methods such as direct load control in the initial stage of demand response optimization based on real-time electricity prices.
2. Elastic load response strategy

Demand response is a kind of electricity consumption behavior in which users adjust their power consumption patterns with a purpose. These changes in users' electricity consumption behavior are all related to real-time electricity prices. On the one hand, when electricity prices are low or there is excess power generation, demand response is used to encourage users to increase electricity demand[5]. On the other hand, when electricity prices are too high or power system reliability is threatened, demand response is also used as an incentive to guide users to reduce electricity demand.

In economics, the price elasticity coefficient is a sensitivity index used to measure the quantity changes caused by price changes[6]. It refers to the ratio between the percentage change in the quantity of a certain product or service and the percentage change in its price, or the ratio between the percentage change in demand response volume and the percentage change in electricity price. In electricity load, the price elasticity coefficient is a measure of how electricity consumption changes when the price of electricity changes[7]. Similarly, the demand elasticity coefficient is a measure of how electricity prices change when electricity consumption changes.

The demand price elasticity coefficient is expressed in the form of equation (1).

\[ \varepsilon = \frac{\Delta \text{Quantity}}{\Delta \text{Price}} \]

Where \( \text{Quantity} \) is the amount of goods or services consumed; \( \text{Price} \) is the price of goods or services; \( \Delta \text{Quantity} \) is the change value of the consumption quantity before and after the execution of the demand response; \( \Delta \text{Price} \) is the change value of the electricity price before and after the execution of the demand response.

Demand response is generally divided into two categories. One is price-oriented, and the other is incentive-oriented. In price-based demand response, changes in electricity consumption are related to electricity prices, including three key types of electricity prices[8].

- Peak-valley time-of-use electricity price. According to the load change of the power grid, the 24 hours a day is divided into peak, flat, low and other periods, and different power prices are set for each period. It reflects the power generation and power supply in each period. The average cost.
- Real-time electricity price. It is the price of electricity in a short period of time, usually one hour as a period, reflecting the price of electricity in each hour. Usually, users are provided with electricity price information for one day or one hour in advance.
- Critical peak price. It is a hybrid electricity pricing method that combines peak-valley electricity prices and real-time electricity prices. Compared with the peak-valley price, the peak price of electricity is higher than the ordinary peak-valley price under certain conditions, for example, when the reliability of the system is threatened or the cost of power supply is high.

Price-based demand response is entirely the participation of users according to their own wishes. In the price-based demand response, for different times or time periods, if the electricity price changes significantly, users can make corresponding demand responses by changing the electricity consumption or the electricity consumption strategy.

Incentive-based demand response is carried out by signing demand response contracts with users, and provides users with fixed or time-varying incentive mechanisms and compensation. This demand response method is more commonly used in public utilities, load management service agencies, and regional power grid operators. If the relevant event in the pre-signed contract occurs, but the user who signed the relevant response contract does not respond, he will be punished accordingly. These responses usually include: direct load control, interruption/reduction of services, demand bidding/repurchase, emergency demand response, auxiliary market services, etc.

Direct load control is also a method of load demand response, which is a demand response model that can directly control user equipment. This control method has the positive effect of avoiding additional power generation, and is mostly used to control air conditioners and water heaters. In the future, with the further development of smart grids with two-way communication capabilities, users will
be able to better control target response devices. In this way, the smart grid is combined with the Internet of Things. The manager provides users with electricity price signals through smart pricing schemes, and the users decide whether to control the target response equipment to participate in the current demand response based on these price signals.

3. Model construction
The demand response problem considered in this paper refers to that after a load reduction instruction is given, the total load reduction of users participating in this load reduction response can meet the requirements of the instruction through demand response. For the users participating in the response, the amount of load that needs to be reduced is determined by the load agent, and strives to achieve the lowest total cost of electricity for all users. In order to achieve this goal, load agents also need to take into account user price elasticity coefficients related to electricity prices and demand.

3.1 Optimal modeling
The problem to be solved in this paper is to manage the user's load through the load agent to achieve the optimal global cost of the user's electricity. Due to the characteristics of the problem, a nonlinear model needs to be established and solved.

In practice, when electricity demand needs to be reduced, based on the understanding of each user by the load agent, the electricity price is increased at the electricity price level expected by the user, so as to achieve the purpose of reducing the user's electricity consumption by the user.

The objective function of the optimization model is expressed in the form of equation (2).

$$\text{Min Cost} = \sum_{c=1}^{nc} \left( (E_{L(c)} - E_{LR(c)}) \times \left( Price_{EL(c)} + Price_{EV(c)} \right) \right)$$

Where $Cost$ is the cost of all loads consumed; $nc$ is the number of users; $E_{L(c)}$ is the initial power consumption of user $c$; $E_{LR(c)}$ is the amount of change in power consumption for user $c$; $Price_{EL(c)}$ is the initial electricity price for user $c$; $Price_{EV(c)}$ is the amount of change in the electricity price for user $c$. Equation (2) is the objective function, which means that the user's total electricity cost is the smallest when the electricity demand changes.

According to the demand response contract signed by each user and the accepted price elasticity coefficient, the constraints of the change in electricity demand and the change in electricity price are expressed as equations (3) and (4), respectively. The energy balance constraint of the power system is expressed as equation (5).

$$P_{LR(c)} \leq \text{Max} P_{LR(c)}$$

$$Price_{EV} \leq \text{MaxPrice}_{EV}$$

$$P_{Main} - P_{Reserve} = \sum_{c=1}^{nc} P_{L(c)} - \sum_{c=1}^{nc} P_{LR(c)}$$

Where $Max P_{LR(c)}$ is the maximum change in demand acceptable to user $c$; $MaxPrice_{EV}$ is the maximum change in electricity price acceptable to user $c$; $P_{Main}$ is the power provided by the grid; $P_{Reserve}$ is the power required to be cut by the grid; $P_{L(c)}$ is the initial power consumption of user $c$; $P_{LR(c)}$ is the electric power cut by user $c$.

The degree of demand response is determined by the elasticity of the response, which is expressed in the form of equation (6). Since the elastic value is a fixed constant value for each load, the optimal
value can be determined according to the relationship between the load, electricity price and the elastic value in equation (6) during optimization. At present, most studies adopt the same price change for the same type of load, as shown in equation (7).

\[
Elasticity_{(c)} = \frac{P_{LR(c)}}{P_{L(c)}} \times \frac{Price_{EI(c)}}{Price_{EV(c)}} 
\]  

(6)

\[
Price_{EV(c)} = Price_{EV(T)}, \quad \forall c \in T 
\]  

(7)

Where \( Elasticity_{(c)} \) is the price elasticity coefficient of user \( c \); \( T \) is the load type.

### 3.2 Solution

In the past ten years, artificial intelligence technology has developed into a set of effective methods that can solve complex computing time problems. The artificial intelligence algorithm searches for a specified solution space and finally obtains the optimal solution. Particle swarm algorithm is a kind of artificial intelligence algorithm. Because particle swarm algorithm can solve the difficulties in nonlinear optimization problems well, this paper adopts this method to deal with demand response problems. The algorithm flow of the demand response optimization problem based on particle swarm optimization proposed in this paper is shown in Fig. 1, and the results obtained by the particle swarm optimization method are compared with the results obtained by the traditional nonlinear optimization method.

![Algorithm Flowchart](image)

Fig. 1. The algorithm flowchart
4. Case Study

4.1 Case Introduction

An example of a 32-node distribution network model is taken for simulation in this paper. Two simulation scenarios were established, consisting of 32 users and 320 users respectively.

Table 1 shows the initial load information of 32 users in the first simulation scenario, including the large commercial load (LCL), the medium business load (MBL), the small business load (SBL), the industrial load (IL), and the resident load (RL). Compared with the first scenario, the second scenario has 10 identical users under each node, and the initial load information of a single user is also shown in Table 1.

| Node | Power (kW) | Load type            |
|------|------------|----------------------|
| 1    | 169.1      | Medium business load |
| 2    | 148.9      | Small business load  |
| 3    | 147.1      | Small business load  |
| 4    | 145.5      | Small business load  |
| 5    | 94.2       | Resident load        |
| 6    | 311.1      | Large commercial load|
| 7    | 308.7      | Large commercial load|
| 8    | 89.3       | Resident load        |
| 9    | 90.6       | Resident load        |
| 10   | 67.0       | Resident load        |
| 11   | 91.1       | Resident load        |
| 12   | 91.3       | Resident load        |
| 13   | 181.3      | Medium business load |
| 14   | 91.1       | Resident load        |
| 15   | 91.1       | Resident load        |
| 16   | 91.9       | Resident load        |
| 17   | 135.5      | Small business load  |
| 18   | 152.4      | Medium business load |
| 19   | 151.7      | Medium business load |
| 20   | 151.6      | Medium business load |
| 21   | 151.5      | Medium business load |
| 22   | 147.3      | Small business load  |
| 23   | 674.8      | Industrial load      |
| 24   | 669.3      | Industrial load      |
| 25   | 93.8       | Resident load        |
| 26   | 93.2       | Resident load        |
| 27   | 92.2       | Resident load        |
| 28   | 183.0      | Medium business load |
| 29   | 295.3      | Medium business load |
| 30   | 225.4      | Medium business load |
| 31   | 315.1      | Large commercial load|
| 32   | 89.8       | Resident load        |
| Total | 5,831.3    | —                    |

In both scenarios, this article uses the same price change for all loads of the same type. This article utilizes two methods to simulate each scenario, including particle swarm optimization method and nonlinear programming method. Discuss and compare the results from the two aspects of time scale and optimized value. The price elasticity coefficients of each type are 0.14 for residential users, 0.12 for small commercial users, 0.12 for medium commercial users, 0.2, 0.28 for large commercial users, and 0.38 for industrial users. The corresponding electricity prices are 1.26, 1.33, 1.4, 1.12 and 0.84 yuan per kilowatt hour respectively. And the upper limit of the electricity price change and the power change are set, where the upper limit of electricity price change is 150% of energy price, and the upper limit of power change is 15% of each user's load.
In the simulation, 7 sets of load reduction plans were set for each simulation scenario. For each set of load reduction values, there is an optimization result, that is, the electricity price for each load type and the amount of load reduced by each load type.

### 4.2 Analysis

The demand response model described in this article has five control variables. These five control variables are the electricity prices of the five load types, and the constraints are the upper limit of each load constraint. In the particle swarm optimization algorithm, each particle is a five-dimensional variable. The maximum position of each particle dimension is the upper limit of the price change of each load type, and the minimum position is zero. In the case study, 60 particles and 200 iterations were used, and the maximum and minimum velocities were 0.01 and -0.1, respectively. The penalty method is used to satisfy the energy balance constraint, and the equation constraint is controlled by adding a penalty function to the fitness function, so that the energy of the power system can be balanced.

Table 2 shows the sensitivity analysis results of the simulation parameters. It can be seen from Table 2 that the simulation parameter configuration scheme A for this research example is the best and is adopted.

**Table 2. Sensitivity analysis of particle swarm optimization simulation parameters**

| Program | A   | B   | C   | D   |
|---------|-----|-----|-----|-----|
| Maximum rate | 0.01 | 0.01 | 0.01 | 0.01 |
| Minimum rate  | -0.1 | -0.01 | -0.1 | -0.01 |
| Number of iterations | 200 | 200 | 100 | 100 |
| Correctness (%) | 94 | 93 | 82 | 82 |
| Average fitness | 1422.2 | 1427 | 1426.6 | 1433.1 |
| Worst fitness | 1482 | 1534 | 1527.1 | 1654.7 |
| Optimal fitness | 1379.8 | 1377.5 | 1366.7 | 1378.5 |
| Average time | 0.0716 | 0.0715 | 0.0387 | 0.0382 |

Fig. 2. (a) and (b) are the changes in the electricity price of each load type under the maximum load reduction plan in scenario 1, and the actual maximum change in the electricity price under each load reduction plan.
From Fig. 2, we can get the electricity price changes of 32 users in the first scenario under each load type and the electricity price changes under each plan. In Fig. 2(a), the results of electricity price changes in the maximum load reduction plan are grouped and compared according to load types. It can be seen that there is a slight difference between the two methods. This is because the particle swarm optimization method is a random search method. Although the objective function value obtained by the particle swarm optimization method is close to the result obtained by the NLP optimization method, for each specific demand response event, the users participating in the load reduction are different, so the results themselves may show certain differences. In Fig. 2(b), for each load reduction plan, the actual maximum change in the electricity price is within the maximum allowable change in the electricity price. This is because both the electricity price ceiling and the power ceiling are considered in the demand response model. Therefore users The response is restricted to a certain extent.

Finally, from Fig. 3, we can get the situation of user participation in demand response in two simulation scenarios. In terms of the number of users participating in demand response, for each load reduction scheme, the participation of users in the particle swarm optimization method is higher than that in the nonlinear optimization method. In terms of the number of users that reach the maximum response load, the nonlinear optimization method seems to implement a reasonable command-based load scheduling management. That’s to say, when the current user does not have more scheduling capacity, the next user will be considered for scheduling. In contrast, the particle swarm optimization method transfers load change information between users. Therefore, when the load change is constrained, unless there is a greater load reduction demand, the user will not reach the maximum response to the load change.

5. Conclusion
In terms of the number of users participating in demand response, the particle swarm optimization method for each load reduction requires a higher degree of load participation. The results obtained by the particle swarm optimization method often do not make the users participating in the response reach the maximum load change. Instead, more participating users are used to disperse the total response demand, thereby reducing the load change borne by each participating user. Therefore, it can be concluded that the particle swarm optimization method achieves the expected demand response target value through the participation of a large number of users, and achieves the lowest total user cost.

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