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Abstract: With the rapid proliferation of renewable energy sources, particularly photovoltaics (PVs) with the power system, this paper presents a novel PV consumption strategy aimed at maximising PV utilisation while accounting for carbon emission penalties, PV consumption incentives and user experience. In this paper, the carbon emission penalty and PV consumption reward methods are innovative combined and modelled, using a stepwise reward and punishment mechanism to promote renewable energy consumption. Simultaneously, the influence of user experience on PV consumption is fully considered, and the comfort of user electricity consumption is modelled. Subsequently, considering typical scenarios of residential electricity consumption, a multi-objective optimisation model for maximising PV consumption is established. A dynamic adaptive particle swarm algorithm is used to efficiently solve the model and obtain the optimal decision for PV consumption in the distribution network. To validate the soundness of the proposed model and methodology, this work subjected it to rigorous simulation testing using the IEEE33 bus system. The PV consumption strategy obtained provides a strong reference for the operation and planning of high-penetration distributed photovoltaics (DPVs) within distribution networks.

Keywords: power system; carbon emissions; PV consumption incentives; power consumption comfort.

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1 Introduction

As global concerns over the energy crisis and environmental challenges intensify, the prioritisation of green energy development, exemplified by photovoltaics (PVs) and wind power, has garnered unanimous support among nations. China, as the world’s largest energy producer and consumer and the country with the fastest growth in energy utilisation efficiency, has proposed striving to achieve carbon peaking by 2030 and carbon neutrality by 2060 (da Silva et al., 2023). PVs are increasingly integrated into power systems due to growing environmental concerns and the demand for clean energy. The declining costs and improved efficiency of PV technology make it an attractive and

sustainable option. Government policies and incentives further drive the adoption of PV, reducing reliance on fossil fuels and promoting a sustainable future for the global power industry. It can be foreseen that the proportion of PV power generation in future energy supply will gradually increase, and distributed photovoltaic (DPV), which has advantages such as local consumption and small land occupation, has received strong support from various policies (Lu et al., 2022). However, PV power generation presents inherent uncertainty and randomness (Liu et al., 2023; Maghsoodi et al., 2023; Lu et al., 2023). Moreover, the high proportion of access to low-voltage distribution networks will have a dual impact on the network architecture and system operation (Cao et al., 2023) of the original distribution network, and may also lead to the phenomenon of abandoned PV power generation (Ju et al., 2016). Consequently, the simulation of the consumption capacity of PVs by distribution networks and the formulation of judicious access strategies hold significant research significance.

The DPV capacity within distribution networks and its associated development strategy have emerged as a shared focal point for multiple stakeholders. Given the inherent intermittency and stochastic nature of PV power generation, investigations into the PV consumption capacity of distribution networks offer the potential to enhance the rationale and scientific basis of current distribution network scheduling, control strategies and operational paradigms. Furthermore, this research serves as a crucial reference point for the formulation of more technologically and economically sound distribution network development blueprints. By efficiently managing the consumption of solar-generated electricity, we can maximise the utilisation of clean energy, leading to a more sustainable and eco-friendly energy system. This optimisation helps minimise reliance on conventional power sources, subsequently reducing greenhouse gas emissions and mitigating environmental degradation. In addition, an optimised PV consumption strategy contributes to grid stability, as it aligns energy production with demand, reducing wastage and enhancing the overall efficiency of the power system. Ultimately, prioritising the optimisation of PV consumption is crucial for fostering a greener and more resource-efficient approach to energy usage.

Currently, there has been a large amount of research on the planning of DPV power sources. Wang et al. (2019) proposes a maximum PV access capacity planning method for two supply modes by considering the overload risk as a constraint for PV access capacity and combining the operating characteristics of single radiation and hand-pulled power supply structures. Cai et al. (2020) proposes a PV planning model that considers multiple distribution network operation indicators. A combination of multi-attribute decision theory and game theory is used to coordinate and solve the complex relationships between different indicators. Huang et al. (2017) considers the grid reinforcement cost in the optimisation of DPV grids with high penetration. A comprehensive cost-benefit analysis method is proposed to provide a scientific and valuable reference for the planning of DPV grids with high penetration. Mignoni et al. (2023) presents a near-optimal and efficient method for solving PV planning problems, which greatly improves the efficiency of solving the problem. Sun (2022) considers the impact of DPV on relay protection actions and proposes a planning model that considers the configuration cost of relay protection devices; this planning model is more inclined to consider the safety of the system. All of the above studies are biased toward the impact of PV power sources on distribution networks and ignore the issue of PV consumption. Yang et al. (2020) proposes a particle swarm algorithm-based optimisation method for cost-economy evaluation using a whole-life cost management approach. The index of

cost per unit of PV consumption capacity is used to further optimise the cost of the distribution network to achieve the optimisation of the distribution network containing DPV. Fan et al. (2018) proposes a bargaining cooperation model to achieve flexible demand response energy transactions between aggregators and distribution companies. This method can effectively reduce costs, improve the benefits of both parties, increase system flexibility and achieve PV consumption. Jaramillo-Leon et al. (2023) to increase PV consumption in the distribution network by optimising the optimal voltage reactive power control curve of PV inverters. Al-Saffar and Musilek (2020) uses energy storage batteries to improve the PV absorption capacity of the distribution network, while utilising reinforcement learning methods to coordinate distributed batteries in different regions to solve overvoltage problems in the power grid. Huo et al. (2021) promotes the consumption of renewable energy by adjusting the power consumption of air conditioning loads to reduce the fluctuation of the interconnection line power. He et al. (2022) investigates the contribution of electric vehicles to PV consumption. The proximity of PV consumption is achieved by inducing electric vehicles. Liu et al. (2019) proposes a PV consumption strategy for dynamic reconfiguration of distribution networks to improve PV consumption in distribution networks by taking into account load variations, uncertainty of PV, and other factors.

Although the above studies are all established on the basis of fixed capacity of PV power supply location, the consideration of the decision-making for the elimination is not sufficient. PV consumption not only needs to be controlled on the power side, but also on the load side, which is a key link in PV consumption. Therefore, this paper comprehensively considers both power-side and load-side means of consumption, and improves the comprehensive level of consumption of the distribution network. And nowadays, the energy saving and emission reduction efforts are increasing, and the impact of carbon emission reduction policy on the power industry, which is closely linked to the power industry, on the decision-making of consumption should not be ignored. However, at this stage, most researchers consider the use of carbon emission reduction policy to inhibit the pollution of traditional thermal power units on the environment (Cao et al., 2017; Lin and Huang, 2022; Dong et al., 2022; Huang et al., 2022), but ignored the positive effect of carbon emission reduction policy on the consumption of renewable energy. Therefore, this paper considers a more comprehensive implementation of the policy, using the parallel means of punishment and reward for intervention. In the process of policy implementation, frequent demand response will have a serious impact on the user's experience of electricity consumption, which will lead to a large deviation between the ideal method and the actual situation when optimising PV consumption.

Therefore, it is necessary to fully consider the impact of various factors on consumption results when improving DPV consumption.

The contribution of this paper could be listed as follows:

- 1 To improve the consumption capacity of DPV containing distribution networks, a stepped PV consumption incentive model considering carbon emissions is proposed, which combines PV consumption incentives with carbon emission penalties, and uses a stepped incentive and penalty mechanism for modelling in order to improve the system's consumption of renewable energy.

- 2 A global optimisation method for distribution networks containing PVs is proposed, which takes into account carbon emission penalties, PV consumption rewards, and user experience.
- 3 The dynamic self-adaptive particle swarm optimisation algorithm (DAPSOA) is used to solve the new model, and the optimal decision for PV consumption in the distribution network is obtained to achieve maximum PV consumption.

2 DPV consumption strategy for distribution networks

The planning of power grid needs to consider various factors such as economics, environment, etc. Therefore, the planning method proposed in this paper combines all factors as comprehensively as possible. Based on the traditional distributed power generation planning that considers economics, the PV consumption capacity of the system is also included, making the selection and capacity determination of PVs more practical. At the same time, considering the general attention to energy conservation and emission reduction, carbon reduction and PV consumption rewards are also included in the system optimisation (Zhao et al., 2022; Meng et al., 2021; Li et al., 2022; Zhang et al., 2023), and a step-by-step reward and punishment mechanism is used to increase the consumption of PV output. PV consumption is affected by various factors. On the power supply side, measures such as adjusting the transformer ratio can be taken to promote PV consumption. On the load side, measures can be taken to encourage users to use electricity to promote PV consumption. However, frequent power adjustments may cause problems such as poor user experience. Therefore, when adopting measures, this paper takes into account the comfort of user electricity consumption (Cui et al., 2022; Yang et al., 2022; Alfaverh et al., 2023) and not only achieves maximum PV consumption but also meets actual user needs. By considering the power supply side, the load side, and the external environment comprehensively, the optimal DPV connection is achieved. The framework of DPV connection optimisation for the distribution network is shown in Figure 1.

The specific strategy for PV consumption is to use reactive power compensation devices for reactive power compensation on the generation side and to adjust the transformer tap ratio in real-time to promote the PV consumption after the PV is connected to the distribution network. Meanwhile, the government implements a carbon emissions penalty policy to suppress thermal power output and promote user consumption of renewable energy in the system. On the user side, a PV consumption reward policy is implemented to incentivise users to actively participate in demand response while fully considering user experience and improving the user experience. The specific PV strategy is shown in Figure 2. In the model, the carbon emissions penalty and PV consumption reward are combined to form a step-by-step reward and penalty mechanism for a solution. The specific model will be described in Section 2.1.

Figure 1 The framework for optimising DPV integration into the distribution network (see online version for colours)

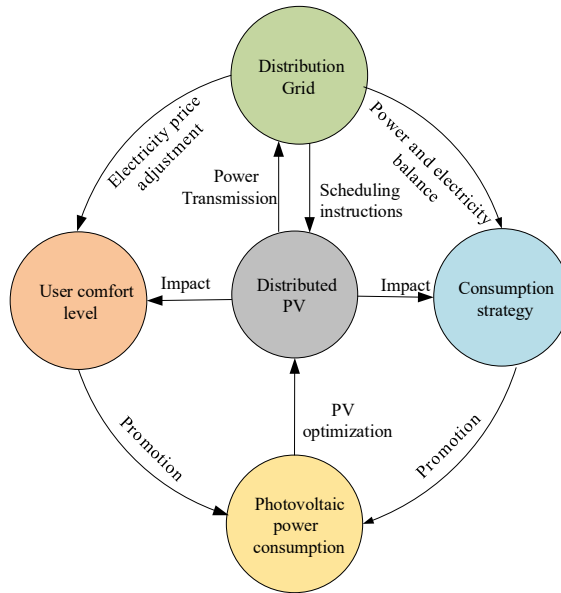
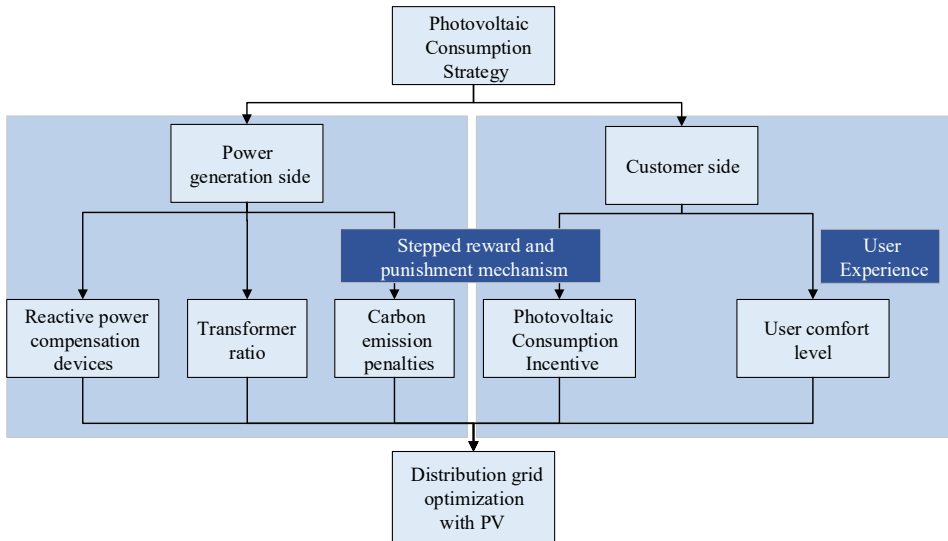


Figure 2 PV power consumption strategy (see online version for colours)



2.1 Staircase PV consumption incentive model considering carbon emissions

This article models a combination of PV consumption incentives and carbon emission penalties in the electricity sector using a tiered mechanism to enhance renewable energy use. This aims to reduce polluting sources, cut greenhouse gas emissions and protect the

environment. A quota-based PV incentive programme encourages grid participants to exceed initial PV consumption quotas for rewards like reduced electricity fees, thereby promoting PV use when resources are plentiful and lowering average electricity costs. Additionally, carbon trading allows manufacturers with emissions below their quotas to trade surplus credits, incentivising rational carbon production and renewable energy consumption (Li et al., 2016). The model, incorporating carbon emission and PV consumption quotas, actual emissions, and tiered incentives, focuses on the synergistic effect of these policies on renewable energy uptake.

2.1.1 Carbon emission quota model

The commonly used quota method currently is the free allocation quota (Li and Jia, 2016). The main source of carbon emissions in the system is from coal-fired power plants, therefore the carbon emission quota is:

$$E_c = \gamma \sum_{t=1}^T \sum_v^{N_v} P_{tp,v} \quad (1)$$

where E_c represents the carbon emission quota within one scheduling period, $P_{tp,v}$ represents the output of the thermal power unit, γ represents the carbon emission quota per unit output of the thermal power unit, T represents the scheduling period, $t = 1, 2, 3, \dots, T$, N_v represents the number of thermal power units, and v represents the thermal power unit number, $v = 1, 2, 3, \dots, N_v$.

2.1.2 PV consumption quota model

The actual consumption of PVs at a node is related to the operation safety of the distribution network, such as network loss and voltage, which can be represented by C_e . The initial allocation of PV consumption incentives adopts a proportional model with the load level of the node, which can be represented as:

$$D_e = \sum_{t=1}^T \sum_{i \in \Omega_G} \eta_i E_i \quad (2)$$

where D_e represents the allocated PV consumption quota for the system, η_i represents the allocation quota of PV consumption reward per unit load at the node i , E_i represents the historical average load at the node, and Ω_G represents the set of system nodes.

2.1.3 Actual carbon emission model

The actual carbon emission model of thermal power units is related to their output (Fang et al., 2022). Therefore, the actual carbon emission model of the unit is as follows:

$$E'_c = \sum_{t=1}^T \sum_v^{N_v} (\tau_v P_{tp,v}) \quad (3)$$

where E'_c is the actual carbon emissions of the thermal power unit, τ_v and is the coefficient of carbon emissions of the unit v .

2.1.4 Staggered PV consumption incentive model considering carbon emissions

Carbon emission trading volume is:

$$E_d = E'_c - E_c \quad (4)$$

where E_d represents the carbon emissions trading amount.

The reward for PV energy consumption

$$\sum_{i \in \Omega_G} \eta_i E_i \quad (5)$$

$$C_d = C_e - D_e \quad (6)$$

where $P_{PV,i}$ is the amount of PV power generation capacity connected to the node i and C_d is the PV consumption incentive.

This paper adopts the PV consumption quota model that considers carbon emissions. The stepped pricing mechanism divides the quota into multiple intervals. As the carbon emission quota and the PV consumption reward quota that needs to be purchased increase, the purchase price or reward in the corresponding interval will increase. The specific model is as follows:

$$C_{tot} = \left\{ \begin{array}{ll} \lambda E_d - \psi C_d, & E_d \leq l, C_d \leq \omega \\ \lambda E_d - \omega(1+\beta)(C_d - \omega) - \psi\omega, & E_d \leq l, \omega \leq C_d \leq 2\omega \\ \lambda E_d - \omega(1+2\beta)(C_d - 2\omega) - \psi(2+\beta)\omega, & E_d \leq l, C_d \geq 2\omega \\ \lambda(1+\alpha)(E_d - l) + \lambda l - \psi C_d, & l \leq E_d \leq 2l, C_d \leq \omega \\ \lambda(1+\alpha)(E_d - l) + \lambda l - \omega(1+\beta)(C_d - \omega) - \psi\omega, & l \leq E_d \leq 2l, \omega \leq C_d \leq 2\omega \\ \lambda(1+\alpha)(E_d - l) + \lambda l - \omega(1+2\beta)(C_d - 2\omega) - \psi(2+\beta)\omega, & l \leq E_d \leq 2l, C_d \geq 2\omega \\ \lambda(1+2\alpha)(E_d - 2l) + \lambda(2+\alpha)l - \psi C_d, & E_d \geq 2l, C_d \leq \omega \\ \lambda(1+2\alpha)(E_d - l) + \lambda(2+\alpha)l - \omega(1+\beta)(C_d - \omega) - \psi\omega, & E_d \geq 2l, \omega \leq C_d \leq 2\omega \\ \lambda(1+2\alpha)(E_d - 2l) + \lambda(2+\alpha)l - \omega(1+2\beta)(C_d - 2\omega) - \psi(2+\beta)\omega, & E_d \geq 2l, C_d \geq 2\omega \end{array} \right\} \quad (7)$$

where C_{tot} is the total cost of carbon emission penalty and PV consumption incentive; λ and ψ are the carbon trading base price and PV incentive base price, respectively; l and ω are the length of carbon emission interval and PV consumption interval, respectively; α and β are the growth rate of the carbon price and PV consumption incentive price, respectively.

2.2 User experience model

After PV is connected to the distribution network, the government can greatly promote the consumption of renewable energy by adjusting the energy consumption behaviour of users through relevant policies. However, while achieving the maximum PV consumption, the impact of government intervention on users' comfort with electricity should be considered. If the actual electricity consumption is lower than the user's demand, then the comfort function value is positive, which means the user is not satisfied, which will in turn affect the actual electricity consumption of residents; if the actual electricity consumption is higher than the user's demand, then the comfort function value is negative, which means the user is satisfied, and with the increase of the function

value, the growth rate should gradually become slower, because the user cannot be satisfied infinitely. Because users cannot be infinitely satisfied.

The residential electricity comfort function in this paper can be expressed in terms of planned residential electricity consumption and actual electricity consumption, and the customer comfort of customer m in the period is expressed by the function $S_{mi}(x_{ami}, x_{mi})$:

$$S_{mi}(x_{ami}, x_{mi}) = \beta_{mi} x_{mi} \left[\left(\frac{x_{ami}}{x_{mi}} \right)^{\alpha_{mi}} - 1 \right] \quad (8)$$

where x_{ami} represents the actual residential electricity consumption, x_{mi} represents the planned residential electricity consumption. α_{mi} , β_{mi} represents the residential comfort parameter, $\alpha_{mi} < 0$, $\beta_{mi} < 0$, which varies to indicate different types of load comfort.

- 1 When $x_{ami} < x_{mi}$, the value of residential comfort is positive, when the value of the function decreases rapidly with the decrease of the actual electricity consumption:

$$S_{mi}(x_{ami}, x_{mi}) > 0 \quad (9)$$

$$\frac{\partial S_{mi}}{\partial x_{ami}} < 0 \quad (10)$$

$$\frac{\partial^2 S_{mi}}{\partial x_{ami}^2} > 0 \quad (11)$$

- 2 When $x_{ami} = x_{mi}$, the resident's comfort value is 0, $S_{mi}(x_{ami}, x_{mi}) = 0$.

- 3 When $x_{ami} > x_{mi}$, the value of residential comfort is negative, when the value of the function increases slowly with the increase in actual electricity consumption:

$$S_{mi}(x_{ami}, x_{mi}) < 0 \quad (12)$$

$$\frac{\partial S_{mi}}{\partial x_{ami}} > 0 \quad (13)$$

$$\frac{\partial^2 S_{mi}}{\partial x_{ami}^2} < 0. \quad (14)$$

3 DPV grid-connected optimisation model

3.1 Objective functions

Connecting DPV to the distribution network can lead to changes in voltage and increased network loss, subsequently causing a series of power quality problems (Impram et al., 2020; Blaabjerg et al., 2017; Movahhed-Ghodsinya, 2023). Excessive PV grid-connected capacity will increase the tidal flow of the distribution network feeders, making the node voltage fluctuation increase and the distribution network loss increase. Meanwhile, in the optimisation process, the carbon emission reduction and PV consumption incentive decision as well as the user's electricity comfort are fully considered to maximise the PV consumption in the distribution network. Therefore, this part combines the model

established by equations (1)–(14) and establishes a multi-objective PV consumption model by comprehensively considering the three aspects of system operation, government policy, and load demand. The model is as follows:

$$\min F = \begin{cases} \min (C_L, C_U) \\ \min C_{tot} \\ \max (C_e - S_{mi}(x_{ami}, x_{mi})) \end{cases} \quad (15)$$

$$C_L = T_{\max 2} c_1 P_{loss}(t) \quad (16)$$

$$C_u = c_2 \frac{\Delta U(t)}{U_{\Delta}(t)} \quad (17)$$

$$P_{loss}(t) = \sum_{j=1}^L r_j \frac{P_j(t)^2 + Q_j(t)^2}{U_j(t)^2} \quad (18)$$

$$\Delta U(t) = \sum_{i=1}^N \frac{(U_i(t) - U_{iN}(t))^2}{U_{iN}(t)} \quad (19)$$

where C_L is the cost of network loss in the distribution network, C_U is the cost of voltage deviation index, $T_{\max 2}$ is the maximum annual load utilisation hours, c_1 and c_2 are the unit tariff and voltage deviation characteristic index price, respectively, $\Delta U(t)$ is the voltage deviation, $U_{\Delta}(t)$ is the allowable voltage deviation, N_{PV} is the total number of nodes connected to PV in the system, N is the number of nodes in the distribution network, $U_{iN}(t)$ is the rated voltage of nodes at moment t , $P_{loss}(t)$ is the network loss at moment t , L is the number of branches in the system, r_j is the resistance of branch j , $P_j(t)$ is the reactive power at the end of branch j at moment t , $Q_j(t)$ is the reactive power at the end of branch j at moment t , which includes the reactive power compensation power of the system by the reactive power device, and $U_i(t)$ is the actual voltage at the node i at moment t .

3.2 Constraints

1 Node voltage constraint

$$\begin{cases} U_{i\min} \leq U_i(t) \leq U_{i\max} \\ U_{i\min} = 0.93U_{iN} \\ U_{i\max} = 1.07U_{iN} \end{cases} \quad (20)$$

where $U_{i\max}$ and $U_{i\min}$ are the upper and lower limits of the voltage at node i .

2 Current constraint

Excessive currents on the distribution grid lines can generate considerable losses, and even overheating temperatures can lead to line damage, directly affecting the normal operation of the power system. DPV, after being connected to the distribution network, will increase the tidal flow on the line and therefore constrain the branch current.

$$I_i(t) \leq I_{i\max} \quad (21)$$

where $I_i(t)$ is the branch current at moment t and $I_{i\max}$ is the upper limit of the branch current.

3 Line power constraint

$$S_j(t) \leq S_{j,\max} \quad (j = 1, 2, \dots, L) \quad (22)$$

where S_j and $S_{j,\max}$ are the line power at moment t and line power maximum of the line j , respectively.

4 Power flow constraints

This paper's PV consumption strategy, which includes reactive power optimisation using reactive power compensation devices, should also be factored into the power flow constraint.

$$\begin{cases} P_{i+1}(t) = P_i(t) - R_{i+1} \frac{P_i(t)^2 + Q_i(t)^2}{U_{i-1}(t)^2} - P_{Li}(t) + P_{PV,i}(t) \\ Q_{i+1}(t) = Q_i(t) + Q_{in}(t) - X_{i+1} \frac{P_i(t)^2 + Q_i(t)^2}{U_{i-1}(t)^2} - Q_{Li}(t) \\ U_{i+1}(t)^2 = U_i(t)^2 - 2(R_i P_i(t) + X_i Q_i(t)) + (P_i(t)^2 + Q_i(t)^2) \frac{P_i(t)^2 + Q_i(t)^2}{U_{i-1}(t)^2} \end{cases} \quad (23)$$

where $P_i(t)$ and $Q_i(t)$ denote the active and reactive power at node i at moment t , $P_{i+1}(t)$ and $Q_{i+1}(t)$ denote the active and reactive power at node $i + 1$ at moment t , and $Q_{in}(t)$ denotes the reactive power injected by the reactive power compensation device at moment t ; $P_{Li}(t)$ and $Q_{Li}(t)$ denote the active and reactive power of the load at node i at moment t . R_i , R_{i+1} , X_i and X_{i+1} denote the line resistance and reactance values between the nodes.

5 Nodal active power constraint

$$\sum_{i \in \Omega_G} (P_{lp,v,i}(t) + P_{pv,i}(t)) = \sum_{i \in \Omega_G} P_{Li}(t) + P_{loss}(t) \quad (24)$$

6 DPV capacity constraint

Access to DPV in the distribution network can provide more reactive power compensation for the distribution network, and the capacity of reactive power compensation should be constrained.

$$0 \leq S_{PV,i}(t) \leq S_{PV,i\max} \quad (25)$$

where $S_{PV,i}(t)$ and $S_{PV,i\max}(t)$ are the PV capacity of the node i at moment t and the maximum PV access capacity, respectively.

4 Dynamic adaptive particle swarm algorithm

4.1 Dynamic adaptive strategy

Adaptive policy setting based on standard particle swarm algorithm. To better realise the ability of the particles to self-renew and learn from the global optimum, the inertia weight factor needs to be dynamically adjusted so that the acceleration coefficients can be dynamically adjusted to make the particles maintain the ability of global optimum search while maintaining the velocity.

1 Adaptive adjustment of inertia weighting coefficients

$$s_{avg} = \frac{1}{M} \sum_{z=1}^M s_z \quad (26)$$

$$d = \sum_{z=1}^M [s_z - s_{avg}]^2 \quad (27)$$

$$\varepsilon = \sin(\tan^{-1} d) \quad (28)$$

where s_z is the current particle fitness value, s_{avg} is the mean of the population fitness, d is the variance of the fitness function, and ε is the degree of particle aggregation.

If the current particle's fitness is greater than the average, the part of the particle is considered to have better performance and is more likely to approach the optimal solution, and the inertia weight factor at this time is

$$\omega_z = \omega_{\max} - \frac{(\omega_{\max} - \omega_{\min}) |s_z - s'_{avg}|}{|s_z - s'_{avg}|} \quad (29)$$

If the current particle fitness is between the mean values, the inertia weighting factor at this point is

$$\omega_z = \omega_{\min} + (\omega_{\max} - \omega_{\min}) \frac{1 + \cos \frac{k}{T} \pi}{2} \quad (30)$$

If the current particle is weakly adapted, the performance of that part of the particle is poor, and the inertia weighting factor at that time is

$$\omega_z = 1 - \frac{1}{p \cdot \exp(-q\varepsilon)} \quad (31)$$

2 Acceleration factor adjustment

$$c_{z1} = \frac{\omega_z}{\omega_{\max}} \times (\omega_z + \sqrt{\omega_z} + 1) \quad (32)$$

$$c_{z2} = \frac{\omega_{\max} - \omega_z}{\omega_{\max}} \times (\omega_z + \sqrt{\omega_z} + 1). \quad (33)$$

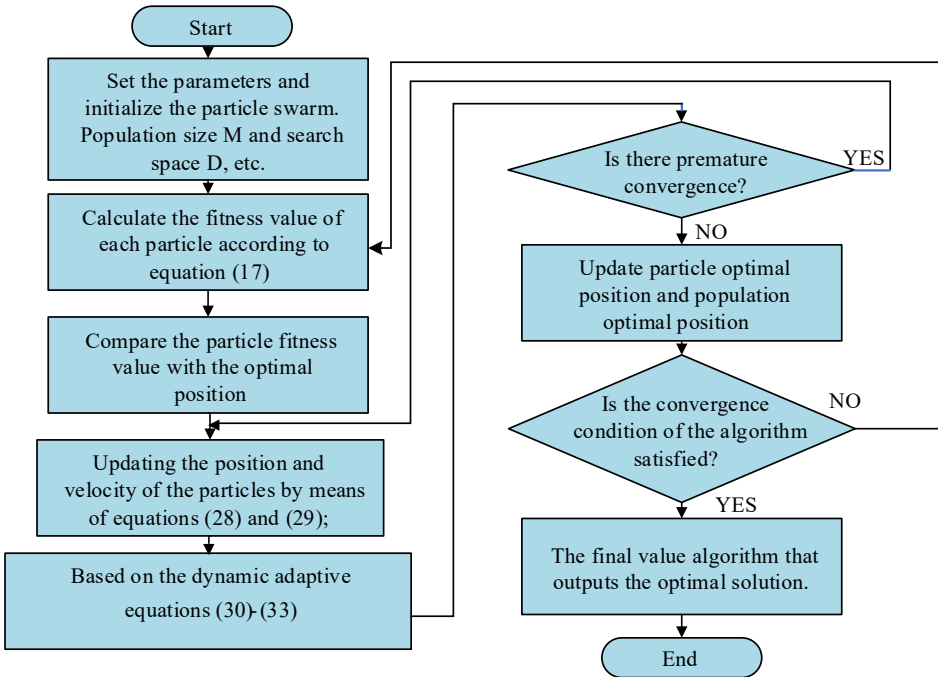
4.2 Particle swarm algorithm process

Based on the above study, the specific steps and flow chart of DAPSOA are as follows:

- Step 1 Set the parameters and initialise the particle swarm. Setting the population size M , the search space D dimension, the maximum number of iterations of the algorithm, and other parameters.
- Step 2 Calculate the fitness value of each particle based on equation (17).
- Step 3 Comparing the particle fitness values with the optimal positions.
- Step 4 Updating the position and velocity of the particles by equations (28) and (29).
- Step 5 Updating the inertia weight factor and acceleration coefficient by equations (30)–(33) based on the dynamic adaptive strategy.
- Step 6 Repetition of Steps 4 and 5.
- Step 7 Judge the convergence condition of the algorithm, if the condition is satisfied, the final value algorithm and output the optimal solution. If the condition is not satisfied, return to Step 2 to continue the algorithm iteration.

The specific algorithm flow chart is as shown in Figure 3.

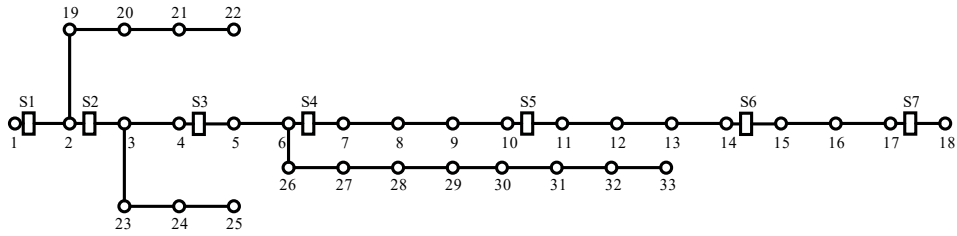
Figure 3 Dynamic adaptive particle swarm algorithm flow chart (see online version for colours)



5 Case study

In this paper, a modified IEEE-33 bus system is used for simulation verification, and the maximum number of iterations of the algorithm is set to 500.

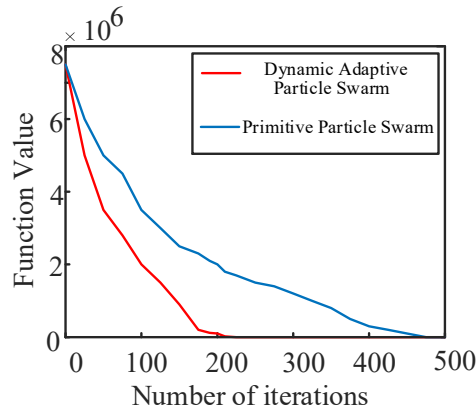
Figure 4 IEEE-33 standard node system



5.1 Algorithm validation

The original particle swarm algorithm and the dynamic adaptive particle swarm algorithm are used to perform several operations and take the average value, and the final result of the two algorithms is shown in Figure 5. It can be seen that the original particle swarm algorithm requires about 480 iterations to reach convergence, while the dynamic adaptive particle swarm algorithm can converge quickly after about 200 iterations, which shows the superiority of the dynamic adaptive particle swarm algorithm in the optimisation search process.

Figure 5 Comparison of particle swarm algorithms (see online version for colours)



5.2 Optimisation results

In this paper, PV is connected at node 21 of the IEEE-33 nodes, and reactive power compensation devices are connected at nodes 15 and 31 to participate in the distribution network operation. The variable ratio k of the transformer is adjusted at node 1 to achieve

reactive power optimisation of the whole distribution network after the PV connection and to promote PV consumption at the same time.

By considering the carbon emission penalty and PV consumption incentive as well as the user experience in the model, the dynamic adaptive particle swarm algorithm is used to optimise the solution, and the results are shown in Figure 6.

Figure 6 100 group particle iterative solutions (see online version for colours)

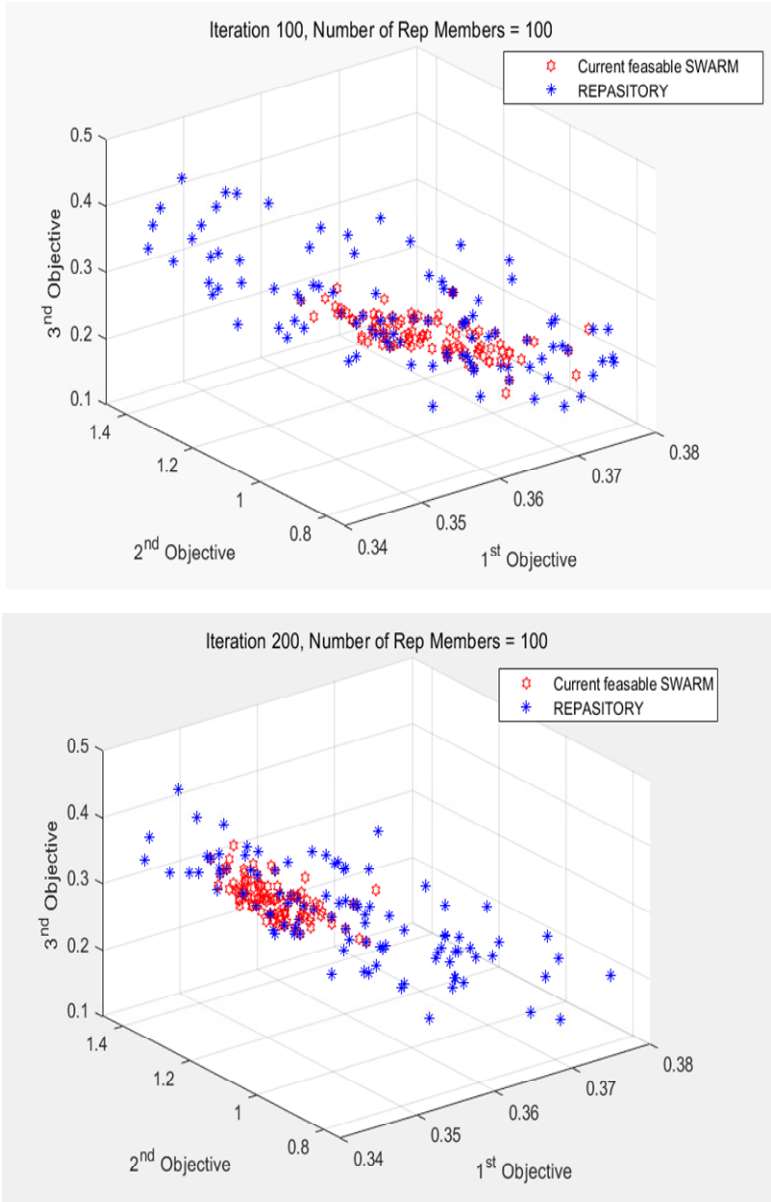
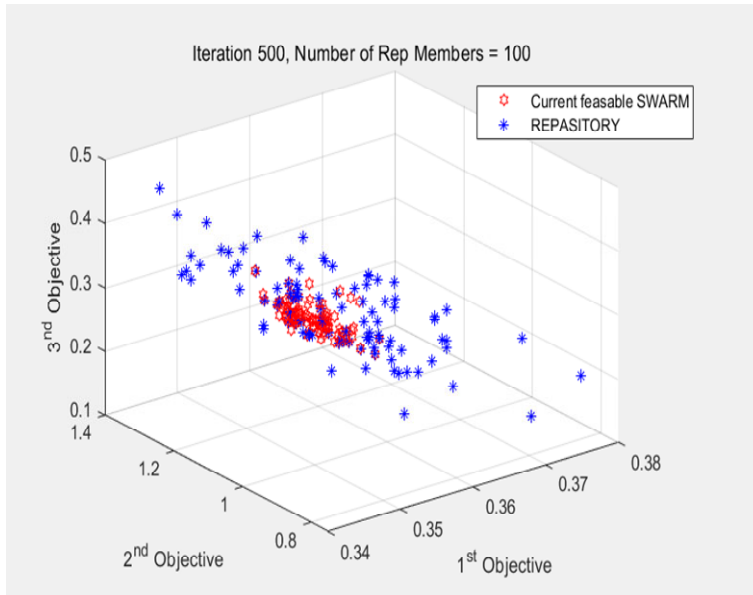


Figure 6 100 group particle iterative solutions (continued) (see online version for colours)

Among the 100 sets of solutions, the optimal solution is found as the optimal output, and the optimal decision is derived.

This paper is divided into four scenarios for simulation validation:

- Case 1 no consideration of carbon emission penalty and PV consumption incentive and user experience
- Case 2 considering only user experience
- Case 3 considering only carbon emission penalty and PV consumption incentive
- Case 4 considering carbon emission penalty and PV consumption incentive as well as user experience.

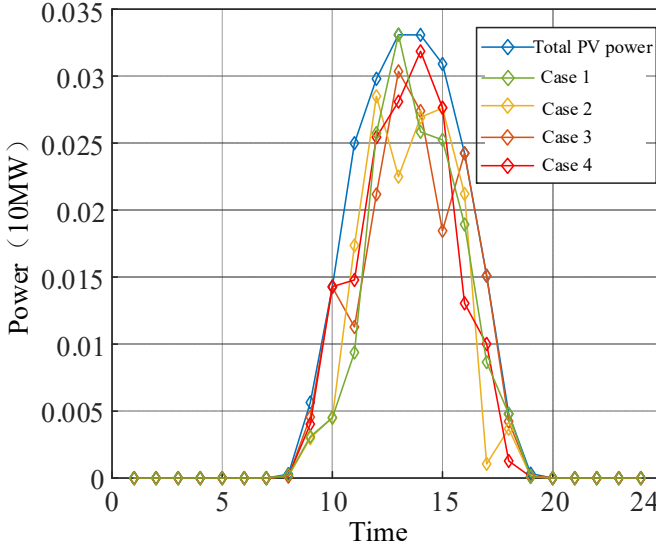
Table 1 Comparison of case results

Case	Photovoltaic consumption rate	Comfort level	Balancing node power
Case 1	73.68%	0.80	$0.4045 + 0.2188i$
Case 2	72.33%	0.83	$0.4048 + 0.2209i$
Case 3	79.10%	\	$0.3994 + 0.1424i$
Case 4	78.83%	0.79	$0.3996 + 0.1641i$

The results are shown in Table 1, and the PV consumption ratio can reach 78.83% at this time, which is 6.99% higher than the consumption ratio of 73.68% in Case 1, which shows the effectiveness of the model in this paper. Meanwhile, in Case 1, the customer comfort is 0.80. After considering the PV dissipation incentive, some transferable loads change their electricity consumption time, which not only improves PV dissipation but also hardly reduces the residents' comfort with electricity consumption because it is the residents' independent behaviour. However, in Case 2, compared with Case 1, since only

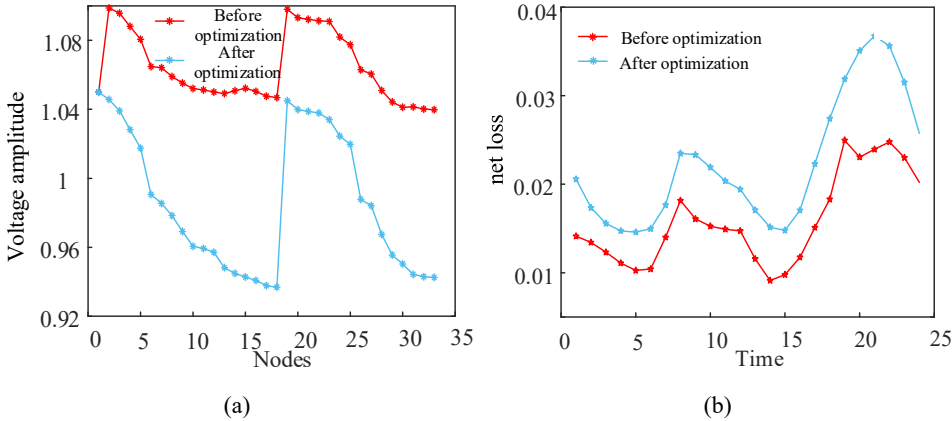
customer comfort is considered, there is a more significant increase in comfort, but there is a certain inhibitory effect for PV consumption. This can also be reflected in the comparison of Cases 3 and 4.

Figure 7 Four cases of PV consumption comparison chart (see online version for colours)



The results of distribution network node voltage and line network loss optimisation are shown in Figures 8–11.

Figure 8 Comparison of the results before and after the optimisation of Case 1, (a) comparison of voltage optimisation results (b) comparison of network loss optimisation results (see online version for colours)



In Figure 8, the optimisation leads to a reduction in voltage offset and a 28.7% reduction in network loss, which shows the necessity of over-reactive power optimisation of the distribution network after the PV is connected to the distribution network. From Figure 11(a), it can be seen that the voltage offset is further reduced after considering the

demand-side response, which is due to the enhanced consumption of PV, resulting in more reactive power compensation input to the node, which further optimises the voltage in its vicinity. However, it can be seen from Figure 11(b) that the increase in system power consumption leads to a higher network loss result compared to that of Case 1. Case 4 reduces the network loss by 27.16% compared to the pre-optimisation network loss, but the network loss result of Case 4 is higher than its 2.21% compared to Case 1, which is the result of load shifting due to load demand response.

Figure 9 Comparison of the results before and after the optimisation of Case 2, (a) comparison of voltage optimisation results (b) comparison of network loss optimisation results (see online version for colours)

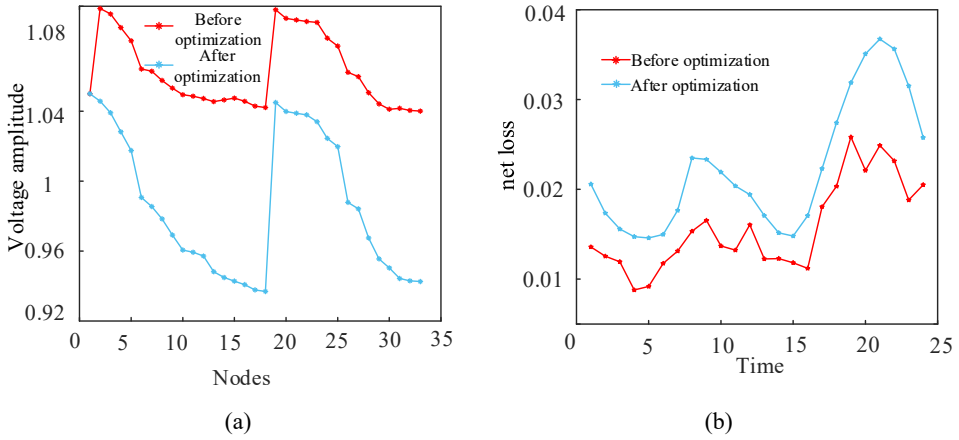


Figure 10 Comparison of the results before and after the optimisation of Case 3, (a) comparison of voltage optimisation results (b) comparison of network loss optimisation results (see online version for colours)

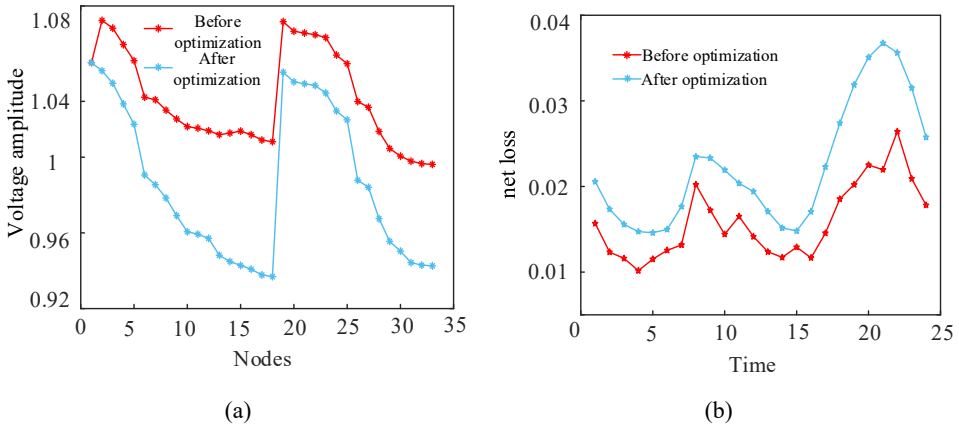
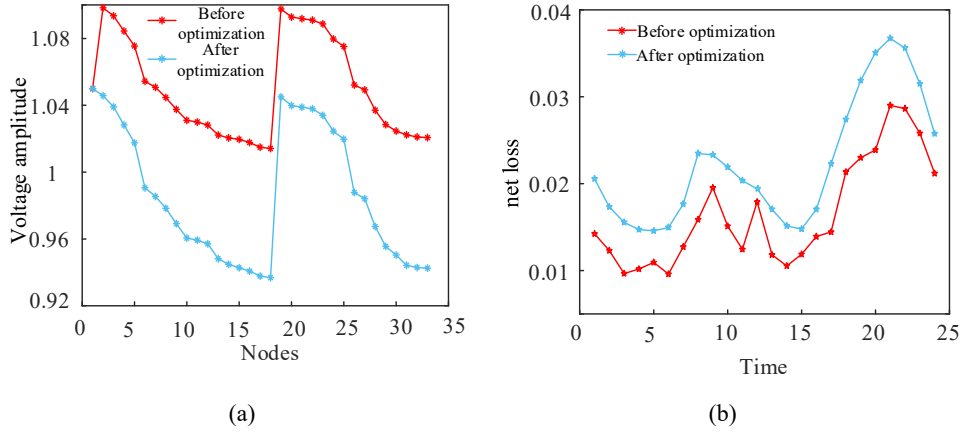


Figure 11 Comparison of the results before and after the optimisation of Case 4, (a) comparison of voltage optimisation results (b) comparison of network loss optimisation results (see online version for colours)



5.3 Optimisation strategies

In this paper, when considering PV consumption, not only the strategy of dynamic adjustment at the load side is used, but also the adjustment strategy of increasing reactive power compensation device and changing transformer ratio is applied, and the final obtained strategy is shown in Table 2 to Table 3.

Table 2 Node 15 in Case 4 is connected to reactive power compensation

Time	1	2	3	4	5	6
Reactive power compensation (Mvar)	0.790	0.304	0.627	0.484	0.415	0.183
Time	7	8	9	10	11	12
Reactive power compensation (Mvar)	0	0.431	0.800	0.457	0.100	0.334
Time	13	14	15	16	17	18
Reactive power compensation (Mvar)	0.184	0.217	0.193	0.664	0.431	0.156
Time	19	20	21	22	23	24
Reactive power compensation (Mvar)	0.148	0.719	0.218	0	0.174	0.440

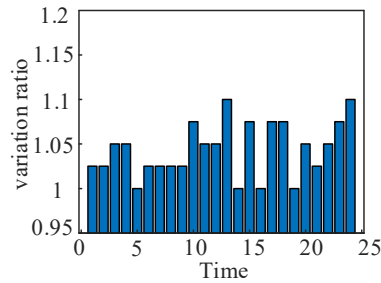
Table 3 Node 31 in Case 4 is connected to reactive power compensation

Time	1	2	3	4	5	6
Reactive power compensation (Mvar)	0.191	0.084	0.374	0.119	0.656	0.681
Time	7	8	9	10	11	12
Reactive power compensation (Mvar)	0.543	0.473	0.171	0.596	0.219	0.569
Time	13	14	15	16	17	18
Reactive power compensation (Mvar)	0.473	0.443	0.576	0.268	0.061	0.014
Time	19	20	21	22	23	24
Reactive power compensation (Mvar)	0.602	0.404	0.456	0.311	0.692	0.447

The connection of reactive power compensation devices in the distribution network helps to improve the quality of the power supply and has a very important role in stabilising the voltage and reducing the network loss. From the results, it can be seen that at the moment when the PV output is high, the reactive power compensation is less in this period because the PV also provides part of the reactive power to the distribution network. At the same time, due to the balance of reactive power compensation for system reactive power, the system can receive more PV access, which greatly promotes PV consumption.

The transformer ratio k adjustment strategy is shown in Figure 12.

Figure 12 Transformer ratio change trend graph (see online version for colours)



By adjusting the voltage on the low-voltage side of the distribution transformer and cooperating with the reactive power compensation device, the system voltage stabilisation can be achieved together. This method can well smooth out the impact of PV access on the system voltage fluctuation, thus improving the system's consumption of PV.

6 Conclusions

This paper proposes a PV consumption method that considers carbon emission penalties and PV consumption rewards as well as user experience. A combination method of carbon emission penalty and PV consumption reward is used to change the user-side energy use behaviour and achieve the maximum PV consumption of the distribution network. Through the experimental study, the following conclusions are drawn:

- 1 In the operation planning of the power grid, the feelings of residential electricity consumption on the load-side should be fully considered, which will play a very positive role in PV consumption.
- 2 The combination of carbon emission penalty and PV consumption incentive is a good incentive policy, which can be used as a load-side incentive policy in the case of large-scale renewable energy access in the future, not only to meet the residents' comfortable electricity consumption but also to achieve the purpose of peak shaving and valley filling.
- 3 For multi-objective model solution problems, compared with the traditional particle swarm algorithm, using the dynamic adaptive particle swarm algorithm can achieve faster and more accurate convergence and global optimum.

- 4 PV consumption is a problem affected by a variety of factors, and requires the coordination of multiple parties in the power grid, including source, network, load, and storage, to achieve better results. There are some shortcomings in the current research.

There may be a degree of simplification in modelling that considers user experience, as it involves complex human behaviours and preferences, and these may be difficult to be fully and accurately reflected in the model. The implementation of the strategy of combining carbon emission penalties with PV consumption incentives may be affected by changes in policies and regulations, and thus its long-term effectiveness may need to be verified by further empirical studies. Dynamic adaptive particle swarm algorithms may face the challenge of slower convergence when dealing with more complex or larger-scale problems, and future research could explore improvements to the algorithm to enhance its applicability in a wider range of contexts.

Although this study provides a reference for maximising the consumption of this clean energy, the grid will face more and more renewable energy access in the future. How to maximise the consumption of this clean energy while ensuring stable access also requires consideration of the overall stability of the grid, the availability of energy storage devices, and coordination with conventional energy sources. This model provides valuable insights at the current stage, but may require further adaptation and optimisation in future scenarios where grid size and complexity grow.

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Nomenclature

Variable	
E_c	Carbon emission quota within one scheduling period
$P_{tp,v}$	Output of the thermal power unit
η_i	Allocation quota of PV consumption reward per unit load at the node i
E_i	Historical average load at the node
Ω_G	Set of system nodes
E_c'	Actual carbon emissions of the thermal power unit
τ_v	Coefficient of carbon emissions of the unit v
E_d	Carbon emissions trading amount
$P_{PV,i}$	Amount of PV power generation capacity connected to the node i
C_d	PV consumption incentive

Nomenclature (continued)

<i>Variable</i>	
C_{tot}	Total cost of carbon emission penalty and PV consumption incentive
λ and ψ	Carbon trading base price and PV incentive base price
l and ω	Length of carbon emission interval and PV consumption interval
α and β	Growth rate of the carbon price and PV consumption incentive price
x_{ami}	Actual residential electricity consumption
x_{mi}	Planned residential electricity consumption
$\alpha_{ami}, \beta_{ami}$	Residential comfort parameter
C_L	Cost of network loss in the distribution network
C_U	Cost of voltage deviation index
$P_{i+1}(t)$ and $Q_{i+1}(t)$	Active and reactive power at node $i + 1$ at moment t
$Q_{in}(t)$	Reactive power injected by the reactive power compensation device at moment t
$P_{Li}(t)$ and $Q_{Li}(t)$	Active and reactive power of the load at node i at moment t
R_i, R_{i+1}, X_i and X_{i+1}	Line resistance and reactance values between the nodes
$SPV_i(t)$ and $SPV_{i,max}$	PV capacity of the node i at moment t and the maximum PV access capacity
γ	Carbon emission quota per unit output of the thermal power unit
T	Scheduling period
N_v	Number of thermal power units
D_e	Allocated PV consumption quota for the system
T_{max2}	Maximum annual load utilisation hours
c_1 and c_2	Unit tariff and voltage deviation characteristic index price
$\Delta U(t)$	Voltage deviation
$U_{\Delta}(t)$	Allowable voltage deviation
$P_{loss}(t)$	Network loss at moment t
L	Number of branches in the system
r_j	Resistance of branch j
$P_j(t)$	Reactive power at the end of branch j at moment t
$Q_j(t)$	Reactive power at the end of branch j at moment t
$U_i(t)$	Actual voltage at the node i at moment t
N_{PV}	Total number of nodes connected to PV in the system
U_{imax} and U_{imin}	Upper and lower limits of the voltage at node i
$I_i(t)$	Branch current at moment t
S_j and $S_{j,max}$	Line power at moment t and line power maximum of the line j
$P_i(t)$ and $Q_i(t)$	Active and reactive power at node i at moment t
<i>Abbreviations</i>	
PV	Photovoltaic
DPV	Distributed photovoltaic
DAPSOA	Dynamic self-adaptive particle swarm optimisation algorithm