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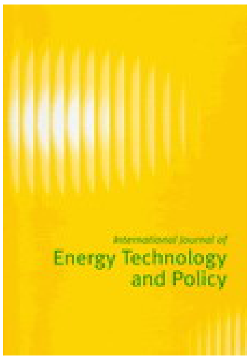

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A multi-objective optimisation configuration method for photovoltaic access microgrid energy storage capacity based on improved genetic algorithm

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Abstract: This study proposes to improve the genetic algorithm and based on the improved genetic algorithm, to complete the optimisation method design of photovoltaic microgrid energy storage configuration. Considering the goal of jointly establishing a new type of energy microgrid, a mathematical model of energy storage is established. Then, determine the configuration constraints of multiple micro energy grid energy storage stations, including battery operation constraints and micro energy grid operation constraints. In the final stage, the genetic algorithm was enhanced using extreme learning machine (ELM), and this improved algorithm was then utilised to address the design model mentioned earlier. The design simulation experiment proves the advanced nature of the proposed method. The experimental results show that after applying the proposed method, the energy efficiency can reach 99.21%, the power balance is only 0.01, and the voltage stability is 0.95, which can guarantee the stability of photovoltaic micro-grid operation to the maximum extent and meet its energy storage needs.

Keywords: genetic algorithm; extreme learning machine; ELM; genetic operators; configuration constraints; multi-objective optimisation.

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1 Introduction

By properly configuring photovoltaic and energy storage capacity, microgrids can better utilise renewable energy (solar energy) and store excess energy (Zhang and Li, 2022; Wang et al., 2022). Photovoltaic integration into microgrid energy storage systems has the characteristics of low carbon emissions and environmental pollution. Through optimisation of configuration methods, sustainable development can be promoted (Li et al., 2023). Therefore, it is necessary to develop this method.

Recently, many researchers have conducted studies. Sun et al. (2021) introduced non cooperative game theory and designed a photovoltaic microgrid storage capacity configuration method. This method first constructs a mathematical model of energy storage equipment for photovoltaic microgrids. Then determine the entities participating in the game, which can be photovoltaic power generation manufacturers, microgrid operators, power users, etc., and define the set of strategies for each entity, that is, the energy storage capacity schemes that can be selected. Finally, define a utility function for each participant to measure their benefits or costs, which is usually related to the selected strategy (energy storage capacity allocation). Using appropriate game theory methods such as Nash equilibrium and Stackelberg games, simulate non cooperative game processes, and each participant selects energy storage capacity allocation schemes based on their own utility function and the actions of other participants. Although this scheme can improve the storage capacity distribution efficiency of photovoltaic microgrid, it has weaknesses in voltage stability. This scheme can effectively improve the energy storage capacity of photovoltaic microgrid, but there are some problems such as poor voltage stability. For example, Wang Hongyan and other scholars adopted IPMOCSA to optimise the capacity of photovoltaic microgrid and energy storage equipment for joint optimisation (Wang et al., 2021). The project intends to use IPMOCSA algorithm to build the optimal distribution strategy of distributed photovoltaic microgrid with energy storage. On this basis, the energy storage optimisation strategy based on energy regeneration mechanism is studied. The scheme not only improves the efficiency of photovoltaic power generation, but also achieves good results. Jiang and Chen (2021) used the improved human work clustering algorithm to strengthen the microgrid energy storage system. Firstly, artificial bee colony algorithm was used to establish the fitness function, and various energy storage schemes were evaluated. Then, through proper optimisation of the objective function, genetic algorithm is used to initialise the parameters, and an initial cluster structure is generated. Finally, the improved artificial bee colony algorithm is run for optimisation search, utilising the foraging behaviour and information exchange of bees to continuously improve the energy storage capacity configuration scheme throughout the entire search process. This method can effectively utilise energy efficiency, but its voltage stability is poor. In view of the shortcomings of the above methods, an advanced algorithm is introduced to optimise the energy storage configuration according to the actual situation of photovoltaic microgrid access.

2 Design of optimisation method of photovoltaic microgrid energy storage configuration

2.1 Optimisation configuration model for photovoltaic access to microgrid energy storage capacity

The multi-objective optimisation allocation method of photovoltaic access micro-grid energy storage capacity is an optimisation engineering problem involving multiple complex factors. In solving this problem, it is crucial to establish an accurate mathematical model of energy storage, which can help us understand and analyse the operating characteristics of the micro-grid system, and then guide the formulation of optimisation decisions. The establishment of energy storage mathematical model needs to follow certain standards and principles. These criteria usually include model accuracy, interpretability, computational efficiency, and practicality. Accuracy means that the model can truly reflect the operation characteristics and behaviour of the energy storage system in the micro-grid. Interpretability means that the structure and parameters of the model have clear physical significance, easy to understand and analysis. Computational efficiency means that the model can run efficiently when solving optimisation problems and avoid excessive consumption of computing resources. Practicability means that the model can adapt to different micro-grid structure and operating conditions, with certain versatility and flexibility.

The multi-target optimal configuration of photovoltaic access to micro-grid energy storage capacity involves the access of photovoltaic system, the operation strategy of micro-grid and the configuration of energy storage capacity. The core goal of this problem is to achieve the optimisation of multiple goals by optimising the configuration of photovoltaic access and energy storage capacity, such as maximising the utilisation of renewable energy, minimising the operation cost and improving the power supply reliability under the premise of meeting the micro grid. Based on this, this engineering problem is transformed into a mathematical problem. The goal of energy storage station is the minimum (Wu et al., 2021) of the annual investment and operation and maintenance cost of energy storage station and the annual operation cost of multiple micro energy networks. Therefore, the objective function is:

$$\min C_{total} = \sum_{m=1}^{M} T_m \left(C_{ESS}^{inv} + \sum_{m=1}^{M} C_{MG,oper,m}^{i} \right) \tag{1}$$

In the formula, C_{total} the total operating cost of the equipment, C_{ESS}^{inv} is the sum of daily investment and maintenance expenses for the energy storage power station; M, T_m represents number of classic days per year, $C_{MG,oper,m}^{i}$ is the total operating cost of a classic day. Next, the operating cost of storage power station is converted to daily equivalent and time value analysis is carried out. The resulting overhead costs are as follows:

$$C_{ESS}^{inv} = \frac{r(1+r)^y}{r(1+r)^y - 1} \frac{\left(\delta_{ESS}^{p} p_{ESS}^{rate} N_{ESS} + \delta_{ESS}^{E} E_{ESS}^{rate} N_{ESS}\right)^y}{MT_m} + \frac{\delta_{ESS}^{OM} P_{ESS}^{rate} N_{ESS}}{MT_m} \tag{2}$$

In the formula, r is the annual interest rate associated with the investment operating cost, y is service life of equipment, δ_{ESS}^{p}, δ_{ESS}^{E} is the investment coefficients related to power and capacity of the equipment, δ_{ESS}^{OM} is the annual maintenance coefficient of the equipment, p_{ESS}^{rate}, E_{ESS}^{rate} is the operating power and capacity of a single battery group in the power station, and N_{ESS} represents the total number of battery packs invested (Wang, 2022).

The operational expenses of the microgrid consist mainly of gas procurement costs and grid electricity procurement costs. Therefore, the following formula can be derived:

$$\begin{cases} C_{MG,oper,m}^{i} = C_{fuel,m}^{i} + C_{grid,m}^{i} \\ C_{fuel,m}^{i} = \sum_{t=1}^{T} \zeta_{gas,t}^{i} \left(\dfrac{P_{MT,mt}^{i}}{\eta_{MT} Q_{MT}} + \dfrac{Q_{GB,m,t}^{i}}{\eta_{GB} Q_{GB}} \right) \Delta t \\ C_{grid,m}^{i} = \sum_{t=1}^{T} \zeta_{grid,t}^{i} P_{grid,m,t}^{i} \Delta t \end{cases} \tag{3}$$

In the formula, $C_{MG,oper,m}^{i}$ is the total cost incurred by microgrid i on the m-th typical day, $C_{fuel,m}^{i}$, $C_{grid,m}^{i}$ is the fuel cost and electricity purchase cost generated on the m-th typical day of microgrid i, $\zeta_{gas,t}^{i}$, $\zeta_{grid,t}^{i}$ is the unit price for purchasing natural gas and electricity from the grid during the m-th typical day and t-th period of the micro energy grid i, $P_{MT,mt}^{i}$, $Q_{GB,m,t}^{i}$, $P_{grid,m,t}^{i}$ respectively gas turbine power and thermal power output during a certain period of a typical day, as well as the power they purchase from the grid (Zhou et al., 2022), η_{MT}, η_{GB} represents the loss coefficient of internal combustion engine and gas turbine in power grid Q_{MT}, Q_{GB} represents the electrical power output of gas turbines and gas boilers, and Δt represents time.

2.2 Constraint condition

The constraints that need to be met when multiple micro energy networks jointly build energy storage stations include battery operation constraints for shared energy storage stations, and micro energy network operation constraints (Su, 2023). The specific analysis of these constraints is as follows:

1 Battery pack rate constraint

$$E_{ESS}^{rate} = \beta P_{ESS}^{rate} \tag{4}$$

In the formula, β is the energy ratio of storage device.

2 State of charge constraints for each battery pack

$$Soc_{Ess,m,t}^{k} = (1-\tau)Soc_{Ess,m,t-1}^{k} + \sum_{i=1}^{N_{MG}} \left(\frac{P_{ess,ch,m,t}^{k,i}\Delta t}{E_{ESS}^{rate}} - \frac{P_{ess,dis,m,t}^{k,i}\Delta t}{E_{ESS}^{\max}} \right) \tag{5}$$

$$Soc_{Ess}^{\min} \le Soc_{Ess,m,t}^{k} \le Soc_{Ess}^{\max} \tag{6}$$

$$Soc_{Ess,m,NT}^{k} = Soc_{Ess,m,0}^{k} \tag{7}$$

In the formula, $Soc_{Ess,m,t}^{k}$ represents charging state of k battery pack in a typical day, and τ represents the rate at which the battery is charged and discharged. N_{MG} represents number of microgrid devices, $Soc_{Ess,m,0}^{k}$, $Soc_{Ess,m,t-1}^{k}$, $Soc_{Ess,m,NT}^{k}$ represent charging status of the battery pack during the initial period, $t - 1$ period, and after the end of the schedule, $Soc_{Ess}^{\min}$ represents the minimum charging state of the battery, $Soc_{Ess}^{\max}$ represents the maximum charging state of the battery, $P_{ess,ch,m,t}^{k,i}$ and $P_{ess,dis,m,t}^{k,i}$ are charge and discharge power of a typical day battery pack.

3 Connection constraints between battery packs and micro energy grids

To prevent the occurrence of electromagnetic ring network phenomenon, each group of batteries is only allowed to be connected to one micro energy network at a time, and each group of batteries is not allowed to charge/discharge simultaneously (Su, 2023), with constraints as shown in equation (8).

$$\begin{cases} \sum_{i=1}^{N_{MG}} u_{ess,ch,m,t}^{k,i} \le 1 \\ \sum_{i=1}^{N_{MG}} u_{ess,dis,m,t}^{k,i} \le 1 \\ \sum_{i=1}^{N_{MG}} u_{ess,ch,m,t}^{k,i} + \sum_{i=1}^{N_{MG}} u_{ess,dis,m,t}^{k,i} \le 1 \end{cases} \tag{8}$$

In the formula, $u_{ess,ch,m,t}^{k,i}$ and $u_{ess,dis,m,t}^{k,i}$ respectively represent charging status of the battery pack during t period on a typical day. Both are binary variables, with one of $u_{ess,ch,m,t}^{k,i}$ and $u_{ess,dis,m,t}^{k,i}$ being 1, indicating that battery pack k is connected to the micro energy grid and in a charging/discharging state on the m-th typical day at time slot t. Both are 0, indicating that the battery pack k is not connected to the micro energy grid i (Liu, 2021).

4 Constraints on the number of investment groups for battery packs

$$\begin{cases} \sum_{i=1}^{N_{MG}} u_{ess,ch,m,t}^{k,i} + \sum_{i=1}^{N_{MG}} u_{ess,dis,m,t}^{k,i} \leq u_{ess,m}^{k,i} \\ N_{ESS} \geq \sum_{k=1}^{K} u_{ess,m}^{k} \end{cases} \tag{9}$$

In the formula, K is the initial number of battery packs for an energy storage power station, $u_{ess,m}^{k}$ is the usage of battery pack k on the m-th typical day, which is a binary variable. Taking 1 indicates that battery pack k was used on that typical day. According to equation (9), if the battery pack k undergoes overcharging/discharging at any time during the mrd typical day, then $u_{ess,m}^{k}$ is 1. In addition, the number of battery packs invested should be greater than the number of battery packs used in that typical day (Zhong et al., 2023).

5 Configuration model constraint design

The design of battery pack charge and discharge constraint function is as follows:

$$\begin{cases} 0 \leq P_{ess,ch,m,t}^{k,i} = P_{ESS}^{rate} u_{ess,ch,m,t}^{k,i} \\ 0 \leq P_{ess,dis,m,t}^{k,i} = P_{ESS}^{rate} u_{ess,dis,m,t}^{k,i} \end{cases} \tag{10}$$

Moreover, the charge and discharge power of the battery pack should be in balance with the power used by the power station and the power grid. This requirement leads us to equation (11).

$$\begin{cases} \sum_{k=1}^{K} P_{ess,ch,m,t}^{k,i} = P_{sell,m,t}^{i} \\ \sum_{k=1}^{K} P_{ess,dis,m,t}^{k,i} = P_{buy,m,t}^{i} \end{cases} \tag{11}$$

In the formula, $P_{buy,m,t}^{i}$, $P_{sell,m,t}^{i}$ represents the electrical power obtained from the energy storage station by Microenergy Network i on the m-th typical day at 55 hours (Li et al., 2022). The microgrid transmits electricity to the energy storage station for charging and vice versa, which can be expressed as:

$$\begin{cases} P_{change}^{\min} \leq u_{sell,m,t}^{i} P_{change}^{\max} \\ P_{change}^{\min} \leq u_{buy,m,t}^{i} \leq P_{change}^{\max} \\ u_{sell,m,t}^{i} + u_{buy,m,t}^{i} \leq 1 \end{cases} \tag{12}$$

In the formula, $u_{sell,m,t}^{i}$, $u_{buy,m,t}^{i}$ represents the state variable of the input and output power from the classical daily grid to the power station, $P_{change}^{\min}$, $P_{change}^{\max}$ represents the upper and lower limits of the interaction power between the grid and the energy storage. Therefore, a larger value of $P_{change}^{\max}$ can be taken within a reasonable range.

6 Balance constraints of micro energy grid power supply system

$$P^i_{MT,m,t} + P^i_{WT,m,t} + P^i_{PV,m,t} + P^i_{grid,m,t} + P^i_{buy,m,t} = P^i_{sell,m,t} + P^i_{EC,m,t} + P^i_{cut,m.t} + P^i_{Load,m,t} \quad (13)$$

In the formula, $P^i_{Load,m,t}$ is the electricity load during the *m*nd typical day *t* period of the micro energy grid *i*, $P^i_{MT,m,t}$, $P^i_{WT,m,t}$, $P^i_{PV,m,t}$, $P^i_{grid,m,t}$, $P^i_{EC,m,t}$, and $P^i_{cut,m.t}$ respectively represent the electrical loads of gas turbines, wind turbines, photovoltaic generators, power procurement, energy storage systems, and distribution transformers during the *m*rd typical day *t* period in the micro energy grid *i*.

7 Balance constraints of micro energy grid cooling system

$$COP_{EC} P^i_{EC,m,t} + Q^i_{AC,m,t} = C^i_{Load,m,t} \quad (14)$$

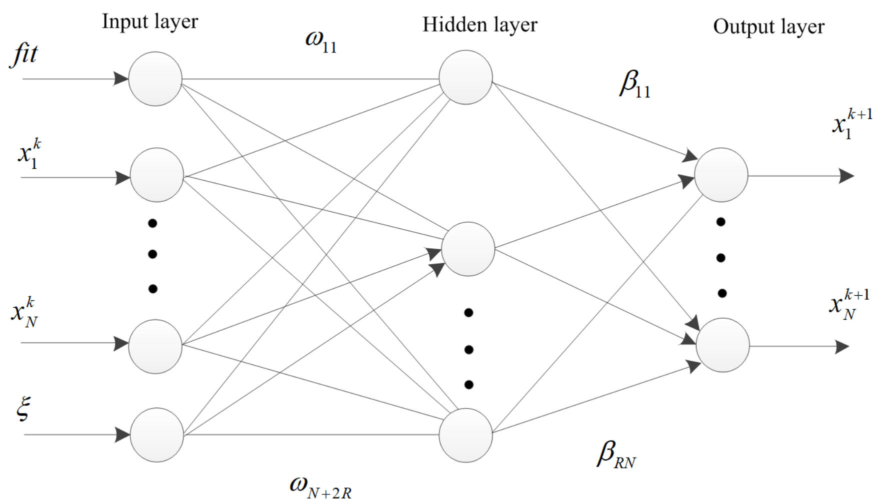
In the formula, $P^i_{EC,m,t}$ is the power consumption of the classic daily grid during the *t* period, and COP_{EC} is the refrigeration energy efficiency ratio of the electric refrigeration unit, $Q^i_{AC,m,t}$ represents the energy consumption during the *m*rd typical day and *t* time periods in the micro energy network *i*, and $C^i_{Load,m,t}$ is the cooling load of the *m*-th typical day during the *t*th period of the micro energy network *i*.

Energy storage technology is adopted to achieve energy interconnection between multi-energy networks, give full play to the asynchronous role of regional loads, improve the absorption efficiency of new energy in multi-power areas, improve the economic efficiency of low-power areas, and achieve multi-energy complementarity. On the basis of equations (1)–(14), the optimal microgrid cooperative configuration model is constructed.

2.3 Multi-objective optimisation design of energy storage configuration model

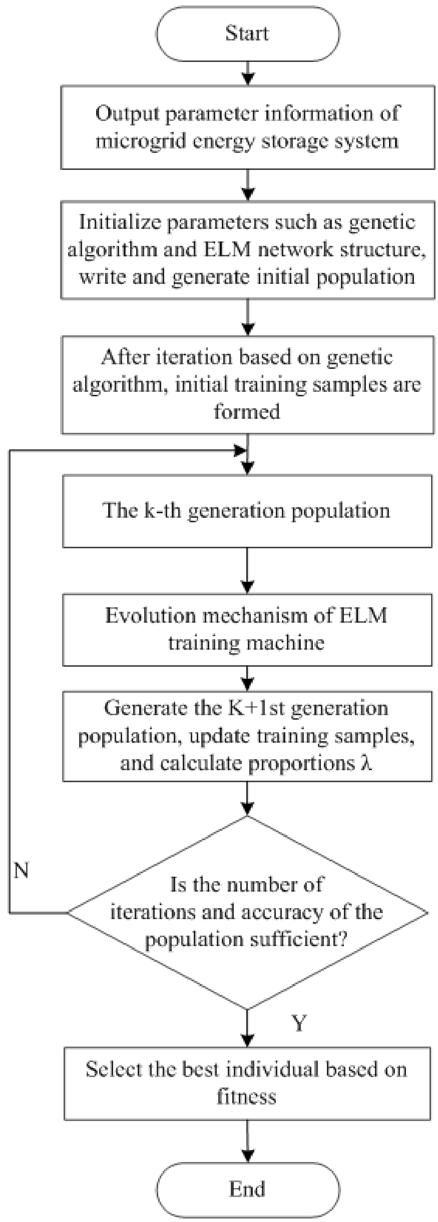
Traversing method is a commonly used method in solving problems such as optimising the configuration of independent microgrids. However, the traversal method searches for the best solution by examining each possible scenario in the plan one by one, which leads to issues of high computational intensity and low efficiency. Due to the limitations of its search scope, it usually only conducts surveys on a small scale, which may miss the global optimal solution and waste a lot of time in the process of finding the best solution. Although the traversal method has a clear idea and is relatively simple to write and debug programs, its efficiency issue cannot be ignored. To overcome the limitations of traversal methods, genetic algorithms have been introduced as a more effective solution. Genetic algorithm is based on the principles of natural selection and genetics, and through the ability to self-organise, adapt, and learn, it can create more suitable offspring according to environmental changes. This method does not require explaining all the characteristics of the problem, but rather seeks the optimal solution by simulating the evolution process in nature. The advantage of genetic algorithm over existing algorithms lies in its powerful global search ability and adaptive ability. By simulating natural selection and genetic mechanisms, genetic algorithms can effectively explore the solution space, find individuals close to the optimal solution, and continuously optimise the population through genetic operations such as selection, crossover, and mutation. This selforganising and adaptive feature makes genetic algorithms more efficient and robust in dealing with complex optimisation problems. To further optimise the solving performance of genetic algorithms, the fitness of the population is introduced to reflect the characteristics of survival of the fittest in the selection process. By evaluating the fitness of individuals, excellent individuals can be selected for genetic operations, thereby accelerating the convergence speed of the algorithm. In addition, chaotic perturbations were introduced to reflect the randomness of mutation operations, in order to increase the diversity of the population and avoid falling into local optima. In order to improve the accuracy and speed of genetic algorithm, extreme learning machine (ELM) is also introduced. ELM is a fast learning algorithm with excellent generalisation ability and learning speed. By combining ELM with genetic algorithms, we can use ELM to guide and optimise the search process of genetic algorithms. Specifically, ELM can construct an efficient network model by training a large amount of sample data to evaluate the fitness of individuals in genetic algorithms. In this way, we can more accurately select excellent individuals for genetic operations, thereby improving the solving performance of the algorithm. The training structure diagram for improving the genetic algorithm using ELM is shown in Figure 1.

Figure 1 Training structure diagram of genetic algorithm improved by ELM



As shown in Figure 1, the ELM used in this article has an input node of $N + 2$ and an output node of N. The fitness of the parent population, random number, parent population, and offspring population are represented by *fit*, $(x_1^k, x_2^k, ..., k_n^k)$ …, $(x_1^{k+1}, x_2^{k+1}, ..., k_n^{k+1})$ respectively. Firstly, in the first stage of evolution, basic genetic algorithms are used to evolve the initial population to obtain training samples for ELM. Next, use the basic genetic algorithm to train the L-generation population, and use the previous and L-generation as inputs and outputs for ELM, namely the training samples for the parent population and ELM. Through this approach, the nonlinear mapping function of ELM can overcome the limitations of traditional genetic algorithms, determine better search directions, expand search ranges, and significantly improve the speed and quality of population evolution. Then, in order to accelerate the global convergence speed, ELM is retrained using the previously generated population and evolutionary parameters are adjusted. Finally, in order to improve the search space of the ELM evolution mechanism, the next generation population consists of two parts: one part is generated by traditional genetic algorithms through selection, mutation, and crossover operations; The other part evolved from the previously trained ELM of the previous generation population.

Figure 2 Flowchart of energy storage capacity configuration



The ratio of these two parts is λ, λ is determined based on the average fitness of these two evolutionary mechanisms. By optimising parameter value λ as mentioned above, a population of $kfit_2^k$ is generated. Based on the above, complete the improvement of genetic algorithm. The solution process of applying the modified algorithm is shown in Figure 2.

In summary, the photovoltaic microgrid energy storage capacity configuration design is completed to achieve efficient utilisation of renewable energy.

3 Experiment

3.1 Experimental design

Taking an independent DC micronetwork as an example, an empirical analysis of the proposed capacity allocation strategy is carried out, and its main parameters are shown in the table.

Table 1 Main parameters of microgrid model

Parameter	*Parameter*
Photovoltaic nominal power (kW)	800
Fan nominal power (kW)	750
Maximum load (kW)	600
Data sampling time (s)	5
Maximum power outage rate allowed by microgrid (%)	2
DC bus voltage (kV)	11

Based on the above parameters, some necessary assumptions were made during the simulation process to simplify the problem and make it easier to handle. This includes assuming that the load demand within the microgrid is stable and predictable, which helps us to more accurately evaluate the capacity requirements of energy storage systems. Meanwhile, it is also assumed that the output of renewable energy generation is stable and can be scheduled as expected. Although these assumptions simplify the problem, they to some extent reflect the actual operation of microgrid systems. Based on this, verify the effectiveness of energy storage capacity configuration. In order to further verify the progressiveness of the proposed method, the energy utilisation efficiency, power balance rate and voltage stability are selected as evaluation indicators, and the methods of Sun et al. (2021) and Wang et al. (2021) are used as evaluation methods to complete the comparative experimental design.

3.2 Experimental result

3.2.1 Energy efficiency

The energy utilisation results of the three methods were obtained through testing, as shown in Table 1.

Table 1 Energy utilisation efficiency of photovoltaic connected microgrid energy storage capacity system

Iterations/time	*System energy efficiency/%*		
	Sun et al. (2021) method	*Wang et al. (2021) method*	*Proposed method*
1,000	66.23	65.82	99.29
2,000	69.61	66.36	99.36
3,000	68.52	69.08	98.63
4,000	72.16	65.15	99.68
5,000	73.62	72.18	98.75
6,000	76.20	73.26	99.21

As can be seen from Table 1, after 1,000 tests, the energy utilisation efficiency of the solar cell system connected to the microgrid by the method described in Sun et al. (2021) is 66.23%, compared with 65.82% for the method described in Wang et al. (2021). The algorithm proposed in this project has a remarkable application effect in the grid-connected microgrid with photovoltaic, and the energy utilisation rate reaches 99.29%. Under the conditions of 3,000 tests, the energy utilisation rate of photovoltaic connected to the microgrid can reach 68.52% by using the method of Sun et al. (2021), 69.08% by using the method of Wang et al. (2021), and 98.63% by using the proposed method. In 6,000 tests, the energy utilisation rate of the photovoltaic energy storage system calculated by the method of Sun et al. (2021) can reach 76.20%, the energy utilisation rate calculated by the method of Wang et al. (2021) can reach 73.26%, and the proposed method can reach 99.21%. The findings clearly indicate that the proposed method has the capability to enhance the energy utilisation rate of a microgrid photovoltaic power generation system with electric storage capacity. Through the analysis, we can find that the main parameters affecting the optimisation performance may include the scale of the micro-grid system, the access ratio of renewable energy, the configuration mode of the energy storage system and the selection of the optimisation algorithm. In this paper, the energy utilisation efficiency of the photovoltaic access micro-grid energy storage capacity system is significantly improved through reasonable energy storage capacity configuration and optimisation algorithm design. This will not only help to improve the economy of the micro-grid system, but also help to promote the wide application and sustainable development of renewable energy.

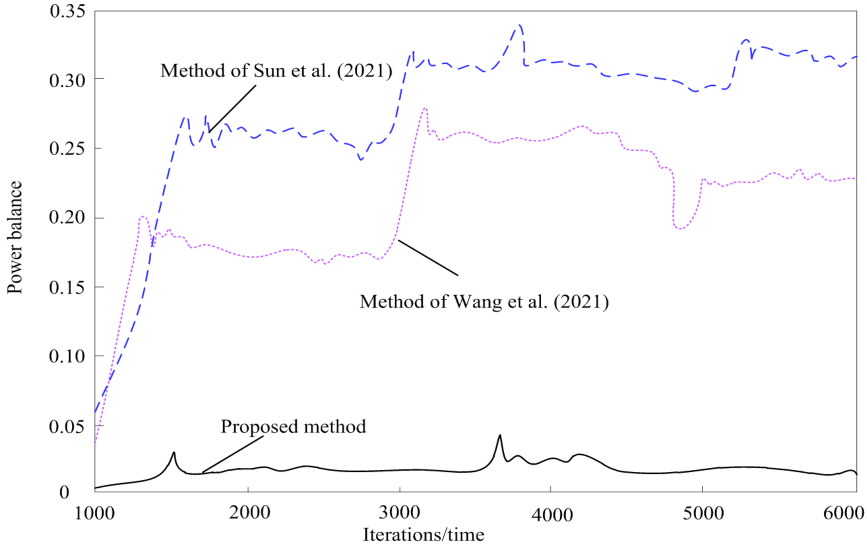
3.2.2 Power balance

The calculation formula for power balance is:

$$Power\ balance = \left(actual\ output\ power - rated\ output\ power\right) / rated\ output\ power$$

Among them, actual output power refers to the power value provided by the actual generator, power grid or power system, and rated output power refers to the rated capacity or design power of the equipment or system. Power balance is expressed as a dimensionless index, used to describe the level of deviation between actual output and rated output. Through comparative analysis with the methods described in Sun et al. (2021) and Wang et al. (2021), the results are as follows:

Figure 3 Power balance of photovoltaic connected microgrid energy storage capacity system (see online version for colours)



As shown in Figure 3, the power balance degree of photovoltaic access microgrid obtained by Sun et al. (2021) is 0.06, the power balance degree of photovoltaic access microgrid obtained by Wang et al. (2021) is 0.04, and the power balance degree of photovoltaic access microgrid calculated by this method is 0.01. After 3,000 iterations, the power balance of the PV grid-connected system calculated by the method described in Sun et al. (2021) is 0.30, while the power balance obtained by the method described in Wang et al. (2021) is 0.22. In stark contrast, the research results of this project will enable the power balance of the photovoltaic power generation system to reach 0.02. After the number of iterations is extended to 6,000 times, the power balance value obtained by the method described in Sun et al. (2021) is 0.32, while the power balance value obtained in Wang et al. (2021) is 0.23, and the power balance value obtained by the method presented in this paper is 0.01. Through the research of this topic, the energy balance of distributed photovoltaic access microgrid can be effectively reduced, and the multi-objective optimisation allocation efficiency can be improved.

3.2.3 Voltage stability

The verification study of photovoltaic grid connected microgrid energy storage capacity based on multi-objective optimal configuration effect can be used as a reference for the research results of this project. The results are listed in Table 2.

Table 2 shows the voltage stabilisation effect of photovoltaic microgrid energy storage device obtained by using three methods. Compared with 0.52 in Wang et al. (2021), the measured value of voltage stability in Sun et al. (2021) is 0.36. In sharp contrast, the solution can significantly improve the voltage stability of the photovoltaic microgrid, which is 0.99. After 3,000 iterations, the voltage stability obtained in Sun et al. (2021) and Wang et al. (2021) is 0.58 and 0.46, respectively. By using this method, the voltage stability of the microgrid with photovoltaic access can reach 0.92.After 3,000 iterations, the voltage stability of photovoltaic grid-connected micro-grid energy storage system obtained by referring to the method described Sun et al. (2021) is 0.40, which is 0.50 compared with the method described according to Wang et al. (2021). The voltage stability of the system is better with this method. Voltage stability is related to the normal operation of each equipment in the microgrid and the power quality of users. By optimising the energy storage capacity configuration, this method not only reduces the power balance, but also helps to improve the voltage stability of the microgrid. This is because a reasonable energy storage capacity configuration can smooth the fluctuations of renewable energy, reduce the impact on the microgrid voltage, and thus improve the voltage stability level of the microgrid.

Table 2 Voltage stability of photovoltaic connected microgrid energy storage capacity system

Iterations/time	*System voltage stability*		
	Sun et al. (2021) method	*Wang et al. (2021) method*	*Proposed method*
1,000	0.36	0.52	0.99
2,000	0.42	0.49	0.98
3,000	0.58	0.46	0.92
4,000	0.42	0.56	0.96
5,000	0.49	0.51	0.99
6,000	0.40	0.50	0.95

4 Conclusions

In order to facilitate the further application of photovoltaic micro-grid, this paper is the research object to carry out the optimisation of micro-grid storage configuration. This project aims to develop an energy storage optimisation model for a photovoltaic microgrid. It involves creating the objective function for energy storage and identifying various constraints on energy distribution. The optimisation process utilises ELM with a genetic algorithm to determine the optimal output weight. Additionally, the least square method is applied to refine the optimal control strategy, ultimately leading to the best control approach. Comparison experiments show that the energy efficiency, power balance and voltage stability of the proposed algorithm reach 99.21%, 0.01 and 0.95 respectively during 6,000 iterations, which are obviously better than the comparison method. It can be proved that this method has high practical value and has certain guiding significance for energy storage optimisation of photovoltaic microgrid.

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