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A Method for Exploring the Flexible Adjustment Potential of Data Centers under the Uncertainty of New Energy Output

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SUMMARY: *The large number of links in the energy system have led to poor stability in the exploration of the flexible adjustment capacity of the entire data centre system. To solve this, a method has been proposed to explore the flexible adjustment capacity of the whole data centre system under uncertainty in new-energy power generation. Probability distribution models, scenario analysis and time-series models are used to quantify the various sources of uncertainty in new energy output comprehensively. A model of the key components of new-energy power generation and energy storage systems is constructed to accurately simulate the operating conditions of the whole data centre energy system. MOPSO is employed to solve the multi-objective optimisation problem, establishes an adjustable plan, and investigates the full range of flexibility in adjustment for the entire data centre system. Experiments have shown that the proposed method can improve the utilisation rate of new energy, significantly enhance the smoothness of adjustment, accelerate the speed of adjustment, and improve the stability of the exploration of the flexible adjustment potential of the entire data centre system compared to the comparison methods.*

KEYWORDS: *New energy output uncertainty; Entire data center system; Multi-objective particle swarm optimization algorithm; Pareto optimal solution set; Flexible adjustment strategy;*

1 Introduction

With the energy transition and digitalisation, the proportion of new energy in the power system is rising, and the uncertainty of its power supply poses a risk to stable power system operation. Data centres are high-energy consumers, and a flexible-adjustment design can be introduced to address variations in new-energy-power generation and improve energy efficiency. To what extent will the full-process adjustment capabilities under the uncertainty of new-energy output in the energy and data centre fields be realised?

Kou and others [1] have proposed a collaborative integration approach of digital twins and sustainable industrial IoT for digital optimisation of energy investment decisions. It is exposed to external interference and therefore relatively unstable. Haiqing and others [2] have built a cooperative game system to coordinate the interests of new-energy power generation enterprises. However, participants' adjustments to their own interests are not uniformly rapid and thus lack stability. Bian and the others [3] reduced carbon emissions and optimised the bidding strategy. However, the returns varied greatly and were unstable. Xin et al. [4] Optimised the energy storage arrangement to enhance the stability of new-energy power supply. However, many reasons may lead to fluctuations in the operation of energy storage

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and thus instability.

Therefore, this paper puts forward a method for investigating the flexible adjustment capacity of data centers under the uncertainty of new energy output, and thus aims to enhance the stability and reliability of the energy system.

2 Quantifying the Uncertainty of New Energy Output

New-energy power generation has been relatively unstable in recent years, and therefore, the continuous operation of data centres and their energy management faces risks, such as irregular power supplies affecting business and increasing operating expenses. Therefore, this paper will study this problem and quantify the uncertainty of new-energy power generation.

The output of new energy sources is significantly affected by natural conditions, and the uncertainty can be quantified using probability distribution models or scenario analysis. Wind power and photovoltaic output follow Weibull and Beta distributions, respectively. This paper takes wind power as an example, assuming its probability density function $g(u)$ can be expressed by formula (1):

$$g(u)=\frac{\alpha}{\beta}\left(\frac{\beta}{u}\right)^{\alpha-1}\cdot\frac{1}{\left(\frac{\beta}{u}\right)^{\alpha}+1}\cdot\frac{1}{\left[\left(\frac{\beta}{u}\right)^{\alpha}+1\right]^{\frac{1}{2}}}\exp\left[-\left(\frac{\beta}{u}\right)^{\alpha}\right]\cdot\nu(u) \tag{1}$$

In formula (1), u represents wind speed, α represents shape parameter, β represents scale parameter, $\nu(u)$ represents a correction factor related to wind speed.

Through statistical analysis of a large amount of actual wind speed data, appropriate α and β values can be determined, and then combined with the correction factor $\nu(u)$ to more accurately describe the probability distribution of wind power output.

Capture the spatiotemporal correlation of new energy output and construct a multi-timescale scenario using the Copula function[5]. Considering the influence of seasonal weather, the joint distribution of wind power and photovoltaic output is set as $G(Q_w,Q_s)$. Based on the properties of the Copula function, its joint probability density function is shown in formula (2):

$$g(Q_w,Q_s)=\tau(a,b)\cdot f\left[\frac{1+G_w(Q_w)}{G_w(Q_w)},\frac{1+G_s(Q_s)}{G_s(Q_s)}\right]\cdot\frac{1+G_w(Q_w)}{g_w(Q_w)}\cdot\frac{1+G_s(Q_s)}{g_s(Q_s)} \tag{2}$$

In formula (2), G_w and G_s represent the edge distribution of wind power and photovoltaic power respectively, f represents the Copula density function, $\tau(a,b)$ represents the comprehensive impact factor of season weather, a represents the season, b represents weather type.

Given the time correlation of new energy output, an autoregressive moving average model (ARMA) is used to model the time series as in formula (3).

$$S_t=\sum_{i=1}^{r}\omega(i)\cdot\delta_i\cdot\frac{1+S_{t-i}^2}{S_{t-i}}+\xi_t+\sum_{j=1}^{s}\omega(j)\cdot\eta_j\cdot\frac{1+\xi_{t-j}^2}{\xi_{t-j}} \tag{3}$$

In formula (3), S_t represents the output of new energy at time t, δ_i represents the degree of impact of past renewable energy output on current output, η_j represents the impact of random errors in the past on the current output, ξ_t represents the random fluctuations in new energy output that cannot be explained by models, r represents the order of autoregression, s represents the order of the moving average, $\omega(m)$ represents historical data weight factors, m represents the time interval between the historical moment and the current moment.

Formula (3) can be used to show the fluctuations in the time-varying components of new-energy-output. In conjunction with the description of the probability distribution of new energy output in formula (1) and the characterisation of spatiotemporal correlation in formula (2), all these factors can be used together to measure the uncertainty in new energy output.

3 Build a Comprehensive Energy System Model for the Entire Data Center Process

After quantifying the uncertainty in new-energy power generation, this paper starts to build a full-fledged model of the energy system for data centers. The four parts of this model are new-energy generation, energy storage, backup power sources and loads, etc.; they are intended to accurately simulate the actual operating conditions of the power system and help with energy management and optimization.

3.1 New Energy Generation Module

The new-energy generation module is a wind-power and photovoltaic-power-generation type. Considering the uncertainties in the new-energy-output factors, this module will dynamically adjust its output according to the uncertainty model determined earlier.

Let the output of wind power at time s be $Q_{\text{wind}}(s)$. It is affected by the combined effects of wind speed, wind direction, and wind turbine performance. Wind speed fluctuations affect blade rotation speed and power generation, and wind direction changes reduce power generation efficiency. The power generation capacity of wind turbines of different models and maintenance conditions varies.

The output of photovoltaic power at time s is $Q_{\text{solar}}(s)$, the output of photovoltaic power depends on the light intensity, solar altitude angle, and photovoltaic panel efficiency. The stronger the light, the greater the power generation; the solar altitude angle affects the effective light-receiving area; the photovoltaic panel efficiency is related to materials, processes, and service life.

The total output $Q_{\text{renewable}}(s)$ of new energy at time s can be calculated using Equation (4):

$$
\begin{aligned}
Q_{\text{renewable}}(s) = {} & \frac{1+\mu_1}{\dfrac{Q_{\text{wind}}(s)^2}{Q_{\text{wind}}(s)^2+Q_{solar}(s)^2}+\dfrac{\sqrt{Q_{\text{wind}}(s)^2+Q_{solar}(s)^2}}{2\mu_2}} \cdot \frac{Q_{\text{wind}}(s)^2}{Q_{\text{wind}}(s)^2+Q_{solar}(s)^2} + \\
& \mu_1 \cdot Q_{\text{wind}}(s)\cdot\sin(\alpha_{\text{wind}})\cdot\frac{Q_{\text{wind}}(s)^2}{Q_{\text{wind}}(s)^2+Q_{solar}(s)^2} + \mu_2 \cdot Q_{solar}(s)\cdot\cos(\alpha_{solar})\cdot\frac{Q_{solar}(s)^2}{Q_{\text{wind}}(s)^2+Q_{solar}(s)^2}
\end{aligned}
\tag{4}
$$

In formula (4), μ_1 represents the wind power output correction coefficient of the entire data center, μ_2 represents the photovoltaic output correction coefficient of the entire data center, α_{wind} represents the angle parameter related to wind speed and wind direction, and α_{solar} represents the parameter related to solar altitude angle.

3.2 Energy Storage System Module

Modules of energy storage systems are required by the power supply systems of data centers to regulate variations in electricity produced by renewable sources. When renewable energy generation exceeds the demand, it is stored; when generation falls short of the demand, stored energy is released to ensure a stable power supply for the data centre.

Let the charging and discharging power of the energy storage system at time s be $Q_{storage-power}(s)$, and the energy storage state be represented as $SOC'(s)$ [6]. The state of charge of the energy storage system changes dynamically with the charging and discharging process. The dynamic relationship can be described by formula (5) and formula (5):

$$SOC'(s+1) = SOC'(s) + \frac{F_{\text{capacity}}}{\Delta s'} \cdot \frac{1+e^{-\beta_1 \cdot s} + e^{-\beta_2 \cdot s}}{1+e^{-\beta_1 \cdot s} + e^{-\beta_2 \cdot s}} \cdot \frac{\mu_{\text{charge}} \cdot Q_{\text{charge}}(s) \cdot e^{-\beta_1 \cdot s} + \mu_{\text{discharge}} \cdot Q_{\text{discharge}}(s) \cdot e^{-\beta_2 \cdot s}}{\sqrt{Q_{\text{charge}}(s)^2 + Q_{\text{discharge}}(s)^2}} \tag{5}$$

In formula (5), $\Delta s'$ represents the time step of the entire data center, F_{capacity} represents the total capacity of the energy storage system of the entire data center, μ_{charge} represents the charging efficiency of the energy storage system of the entire data center, $\mu_{\text{discharge}}$ represents the discharging efficiency of the energy storage system of the entire data center, $Q_{\text{charge}}(s)$ and $Q_{\text{discharge}}(s)$ represent the charging power and discharging power of the energy storage system of the entire data center at time s respectively, β_1 and β_2 represent the parameter[7]related to the energy loss during the charging and discharging process of the energy storage system of the entire data center.

The relationship between the charging and discharging power $Q_{storage-power}(s)$ of the energy storage system at time s and the charging power and discharging power can be expressed by Equation (6):

$$Q_{\text{storage - power}}(s) = \begin{cases} Q_{\text{charge}}(s) \cdot \dfrac{2\,|\,Q_{\text{charge}}(s)\,|}{|\,Q_{\text{charge}}(s)\,| + \sqrt{Q_{\text{charge}}(s)^2}} \\ -Q_{\text{discharge}}(s) \cdot \dfrac{2\,|\,Q_{\text{discharge}}(s)\,|}{|\,Q_{\text{discharge}}(s)\,| + \sqrt{Q_{\text{discharge}}(s)^2}} \end{cases} \tag{6}$$

During charging, $Q_{\text{storage - power}}(s) = Q_{\text{charge}}(s) \cdot \dfrac{2\,|\,Q_{\text{charge}}(s)\,|}{|\,Q_{\text{charge}}(s)\,| + \sqrt{Q_{\text{charge}}(s)^2}}$, during discharging, $Q_{\text{storage - power}}(s) = -Q_{\text{discharge}}(s) \cdot \dfrac{2\,|\,Q_{\text{discharge}}(s)\,|}{|\,Q_{\text{discharge}}(s)\,| + \sqrt{Q_{\text{discharge}}(s)^2}}$.

3.3 Backup Power Module

The backup Power Supply Unit of the data centre's energy system serves as a final safeguard.

When the output of new energy is too low and the energy storage system cannot meet the demand, diesel generators and other equipment are used to provide stable power promptly [8].

The power supply for the equipment at time s be $Q_{\text{backup - power}}(s)$, its start-up condition can be expressed by formula (7):

$$Q_{\text{backup - power}}(s)=\begin{cases}\dfrac{\sqrt{Q_{\text{demand}}(s)^2+Q_{\text{renewable}}(s)^2+Q_{\text{storage - power}}(s)^2}}{Q_{\text{demand}}(s)^2+Q_{\text{renewable}}(s)^2+Q_{\text{storage - power}}(s)^2}\cdot\dfrac{Q_{\text{demand}}(s)^2}{\sqrt{Q_{\text{demand}}(s)^2+Q_{\text{renewable}}(s)^3+Q_{\text{storage - power}}(s)^3}} \\ 0\end{cases} \quad (7)$$

In formula (7), $Q_{\text{demand}}(s)$ represents the load demand of the entire data center at time s. This formula calculates the output of the backup power supply in a relatively complex form. When the load demand of the data center is greater than the sum of the output of new energy and the output of the energy storage system, the backup power supply is activated and provides corresponding power support according to certain calculation rules.

3.4 Data Center Load Module

The data center load module dynamically adjusts the load according to actual business needs. Let the load demand at time s be $Q_{\text{demand}}(s)$, and estimate its changing pattern by analyzing historical data and establishing a business forecasting model.

Mine and analyse historical load data to find the periodicity (e.g., daily cycle, high load in the day and low load at night) and trend (e.g., increasing trend with business development) of load variations. In conjunction with a business forecasting model, predict the future demand for electricity and provide corresponding support for optimisation in the operation of the energy system.

The architecture diagram of the full-process energy system model for the data centre is shown in Figure 1.

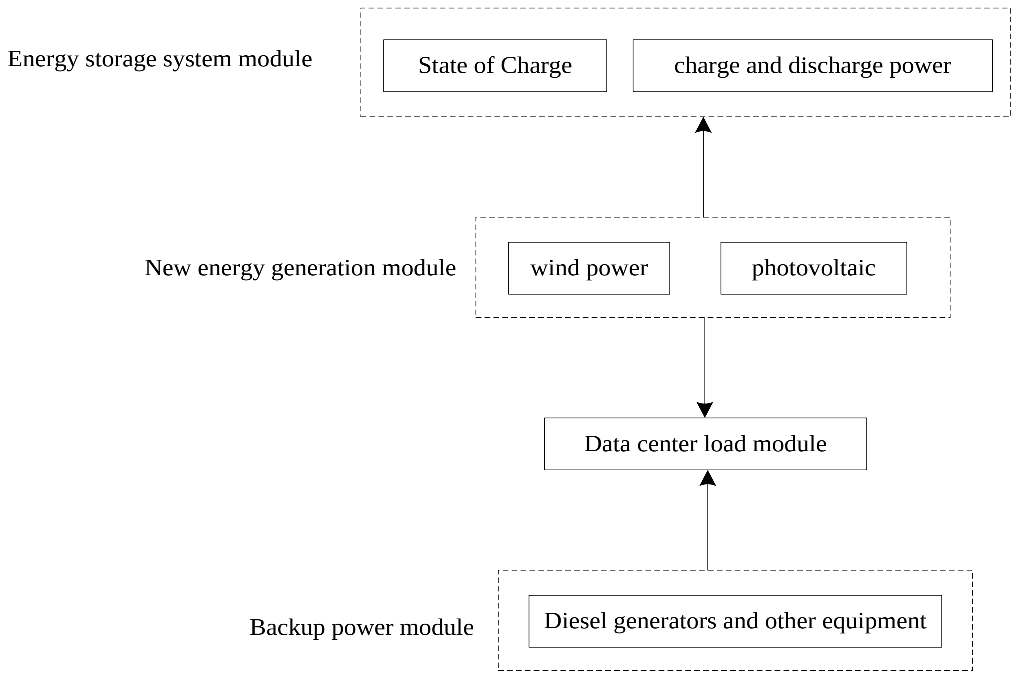

Figure 1: Architecture Diagram of the Full-Process Energy System Model for a Data Center

Based on this model, all parts of the data centre energy system can be addressed comprehensively in this paper, and an analysis framework will be provided for further exploration of flexible adjustment potential.

4 Realizing the Potential for Flexible Adjustment of the Entire Data Center

Quantify the uncertainty of new-energy power generation, build an energy system model, and set three main optimisation objectives to balance the stability, economy and environmental protection of energy supply.

Stability Goal: To ensure that there is a stable and continuous power supply for the data centre in the event of fluctuations in new-energy output, preventing business interruptions. The deviation is given by the sum of the absolute values of the load and power supply deviations of the entire process multiplied by the weight. The formula for the deviation is (8).

$$C = \alpha_1 \cdot \left(\sum_{t=1}^{T} \gamma_t \cdot \left(E_t - Q_{t,\text{total}} \right)^2 \right) \tag{8}$$

In formula (8), α_1 represents the deviation weight coefficient, γ_t represents the time weight factor, E_t represents the load demand of the entire data center at time t, $Q_{t,\text{total}}$ represents the actual total power supply of the entire data center at time t.

A small deviation indicates that the power supply to all parts of the data centre is relatively stable.

Economic goal: Committed to reducing the energy operating costs of the entire data center process, which includes multiple aspects such as new energy generation costs, energy storage system charging and discharging costs, and backup power operation costs[9]. The economic objective can be measured by the absolute difference between the total energy cost of the data center and a benchmark cost, and then taking the natural logarithm of its ratio to the benchmark cost. Considering the possible fluctuations in energy market prices, a price fluctuation adjustment coefficient σ_{t2} is introduced. At the same time, considering that the proportion of different energy costs in the total cost is different, the weight $\zeta_{i,t}$ of energy cost proportion is introduced (i represents wind power, photovoltaic power, energy storage, and backup power), the total energy cost of the entire data center can be calculated using formula (9):

$$F_{\text{total}} = \ln \left(\frac{\left| F_0 - \sum_{t=1}^{T} \sigma_{t2} \cdot \sum_{i} \zeta_{i,t} \cdot \left(F_{t,\text{wind}} + F_{t,\text{solar}} + F_{t,\text{storage}} + F_{t,\text{backup}} \right) \right|}{F_0} \right) \tag{9}$$

In formula (9), $F_{t,\text{wind}}$ and $F_{t,\text{solar}}$ represent the cost of wind and photovoltaic power generation at time t, $F_{t,\text{storage}}$ represents the charging and discharging cost of the energy storage system at time t, $F_{t,\text{backup}}$ represents the operating cost of the backup power supply at time t.

Environmental protection goal: improve the utilization rate of new energy in all aspects of the data center, reduce the dependence on traditional fossil energy, and thus reduce carbon emissions. The environmental protection goal can be measured by the absolute value of the difference between the proportion of new energy in the total energy consumption of the data center and a certain ideal proportion, and then taking the square of the ratio of the new energy to the ideal proportion. Considering that there may be a certain energy loss in the process of new energy power generation, and considering that the environmental benefits of different new energy sources may be different in the process of power generation, the environmental benefit weight $\iota_{i,t}$ of new energy is introduced. The proportion of new energy in the entire process of the data center can be expressed by formula (10):

$$\mathrm{H} = \left(\frac{\sum_{t=1}^{T} G_{t,\text{total}} \cdot \sum_{i} \iota_{i,t} \cdot G_{t,\text{renewable},i}}{\sum_{t=1}^{T} G_{t,\text{total}} \cdot S_0} - 1 \right)^2 \times 100\% \tag{10}$$

In formula (10), $G_{t,\text{renewable},i}$ represents the power generation of new energy i at time t, $G_{t,\text{total}}$ represents the total energy consumption of the entire process of the data center at time t, S_0 represents the ideal proportion.

A three-object multi-objective particle swarm optimisation algorithm (MOPSO) is used for the three optimisation objectives. A swarm intelligence-based algorithm that can handle multi-objective problems and find the non-dominated set. Particles in the algorithm are the operating strategies of the data centre energy system; their positions are set by the output or state parameters of each module, and their velocities are the directions of solution updates.

Initialize Particle Swarm: Randomly generate a set of initial particles and set their positions and velocities in a reasonable range. Simultaneously, set an initial fitness value for each particle. Given that different levels of influence are exerted by various parameters on the entire data centre system, set distinct initial range weights for each parameter based on how much that parameter affects the initial position and velocity.

Calculate Fitness Value: Based on the set optimisation objectives, compute the fitness value of each particle, which is the function value of the three optimisation objectives.

At the same time, to improve the comparison and optimisation of objective functions with different dimensions, they are normalised.

Update Individual and Global Optimum: For each particle, compare its current fitness value with its previous best fitness value. If the current value is better, update the individual optimal solution; at the same time, compare the fitness values of all particles, find the maximum fitness value, and update the global optimal solution [10].

Update Particle Velocity and Position: Based on the individual optimal solution and the global optimal solution, update the particle velocity and position according to certain rules to modify the size of the velocity update. At the same time, to avoid very high or very low particle velocities that would reduce the search efficiency, upper and lower limits are set to constrain the velocity.

A constraint handling mechanism is added to ensure that the position of a particle meets the constraints of the data centre energy system during particle updates, such as the charge state range of energy storage and backup power start-up conditions. Otherwise, it will be returned to the feasible solution space according to the rules. For example, if the energy storage charge exceeds the range, then the charging and discharging power will be reduced based on whether it is charging or discharging.

Iterative Optimisation: Repeat steps 2-5 until convergence of the fitness value.

Iteratively optimise with the MOPSO algorithm to obtain a set of Pareto-optimal solutions finally. The above solutions are the best operating modes of the whole data centre's energy system for various purposes. Based on the Pareto-optimal solution set obtained by the MOPSO algorithm, the following flexible adjustment strategies are proposed in this paper:

Pre-adjustment Strategy based on new energy output prediction: Based on the prediction results of the new energy output of the entire data center system over a future period (using the previously quantified uncertainty of new energy output), a suitable operational strategy is selected from the Pareto optimal solution set to adjust the charging and discharging plan of the energy storage system and the startup status of the backup power supply in advance in response to fluctuations in new energy output. For instance, if it is expected that the output of wind power will increase substantially in the near future, and considering the fluctuations of wind power generation, the charging rate of the energy storage system can be raised to store the excess electricity. At the same time, based on the remaining capacity of the energy storage system and the status of the backup power supply, the activation threshold of the backup power supply can be reasonably adjusted to correct the adjustment range.

Real-time dynamic adjustment strategy: Observe the output of renewable energy, energy storage and load demand in the system during operation in real time. Select an optimal strategy dynamically from the set of Pareto-optimal solutions to adjust the output or status of each module. If the output of renewable energy drops sharply and the energy storage capacity is sufficient, then discharge power will be increased according to the demand; if the capacity is too small, a backup power supply needs to be activated, and the output power will be adjusted according to the remaining capacity and the expected recovery of renewable energy.

According to the demand for data centre operators, the set of Pareto optimal solutions is ordered to select an all-encompassing optimal strategy. If economic efficiency is to be achieved, a solution with a relatively low total energy cost and a renewable energy ratio that meets the basic requirements will be selected; if environmental protection is prioritized, then a solution with a high renewable energy ratio and an acceptable total cost will be chosen. Weighting of the solutions during sorting is based on how much attention operators pay to both factors.

5 Experiments

5.1 Experimental Environment Setup and Parameter Configuration

A laboratory of about 200 square meters with a stable power supply and good ventilation was selected as the site for constructing a simulated data centre, and it will have two racks, each supporting 10 Dell PowerEdge R740 servers. The Test Parameters are as follows:

Processor: Intel Xeon Scalable Processor, 2.6GHz Clock Speed, 20 Cores.

Memory: 256GB DDR4 RAM.

Storage: Four 960GB Solid-State Drives (SSDs) are used in a RAID 5 array to improve the reliability of data storage and read/write speed.

A programmable solar-wind hybrid power generation simulation device will be employed to introduce uncertainty in the new-energy output. Solar simulator

Rated Power: 10kW.

Light Intensity Simulation Range: 0-1200W/m^2, can simulate changes in light under various weather conditions (sunny, cloudy, rainy, etc.).

Time resolution: 1 minute; adjust to change in light intensity over time accurately.

Wind Turbine Simulator

Rated Power: 8kW.

Range of wind speed simulation: 0-25 m/s; can simulate wind power generation at various wind speeds.

Time resolution: One minute, and can show changes in wind speed relatively accurately.

Power Monitoring Equipment

Power Analyzer: Fluke 435 series power analyser with a measurement accuracy of $\pm$0.1% is employed.

Current Transformer and Voltage Transformer: Ratio of current transformer is 1000:1, ratio of voltage transformer is 10000:100.

Data Center Management System: Custom-built based on the open-source OpenStack platform for resource management, task scheduling and power consumption monitoring of servers. Scripts can be written to change the server's operating state dynamically according to the amount of renewable energy generation and data centre load, for example, turning off servers or reducing CPU frequency.

Energy Management System: A Python-based system that integrates simulated renewable energy generation data, data centre power consumption monitoring data, and energy storage system status data.

Set up a lithium-ion battery energy storage system, and the specific parameters are as follows:

Rated Capacity: 20kWh.

Rated Voltage: 48V.

Charge and Discharge Efficiency: $\geq$95%.

Maximum Charge/Discharge Power: 10kW.

Battery Management System (BMS): Transmit the current status of the battery and receive control commands from the energy management system.

The data centre has high-precision air conditioning and the particular parameters are as follows:

Cooling Capacity: 30kW.

Air Supply Method: Bottom Supply and Top Return.

Variable-frequency Control: Can vary the operating frequency according to fluctuations in the heat load of the data center to reduce energy consumption through automatic frequency regulation of the compressor.

Energy Efficiency Ratio (EER): ≥ 3.0.

Matlab is employed to show the effects of all corrections on the data.

5.2 Experimental Scenario Design

To comprehensively evaluate the impact of the uncertainty in new-energy output on the flexible-adjustment capability of a data center, this paper designs 8 typical experimental scenarios, and the specific scenario classification and parameters are shown in Table 1.

Table 1: Classification of Data Center Experimental Scenarios Under Uncertainty of New Energy Output.

Scene Number	Scene Name	Characteristics of new energy output	Load characteristics of data center
C1	Stable and high permeability on sunny days	Photovoltaic output accounts for 80% (10kW), wind power is stable (6kW), and the total output fluctuates by ± 5%	Fixed load (70% utilization, IT load 8.4kW)
C2	Penetrating in cloudy fluctuations	Photovoltaic output accounts for 40% (4kW), wind power fluctuates (3-7kW), and total output fluctuates by ± 20%	Dynamic load (60% -80% utilization, IT load 7.2-9.6 kW)
C3	Low permeability on rainy days	Photovoltaic output accounts for 10% (1kW), wind power is inefficient (2kW), and the total output fluctuates by ± 30%	High load (90% utilization, IT load 10.8kW)
C4	Gust impact	Photovoltaic stability (5kW), sudden drop in wind power (8kW → 3kW, lasting for 5 minutes)	Sudden computing task (load increases from 70% to 95%, lasting for 10 minutes)
C5	No photovoltaics at night	Only wind power generation (0-4kW, low nighttime wind speed), with a total output of less than 5kW	60% of non interruptible tasks (IT load of 7.2kW)
C6	Rapid cloud cover	Sudden drop in photovoltaic output (10kW → 4kW, lasting for 2 minutes), stable wind power (5kW)	Mixed load (50% computing tasks+50% storage tasks, IT load 7.2kW)
C7	Extreme wind speed cutting out	Wind turbines are cut off due to high wind speeds (8kW → 0kW), resulting in fluctuations in photovoltaic output (2-6kW)	Low load (40% utilization, IT load of 4.8kW)
C8	Comprehensive fluctuation	Joint fluctuation of photovoltaic and wind power (photovoltaic 3-9kW, wind 2-7kW, total output fluctuation ± 25%)	Random load (50% -90% utilization, IT load 6-10.8kW)

5.3 Experimental Results and Analysis

Based on the experimental environment, the method introduced in this paper was employed to investigate the possible range of flexible adjustments for all parts of a data center under uncertainty of new energy output. The results are as follows: Figure 2.

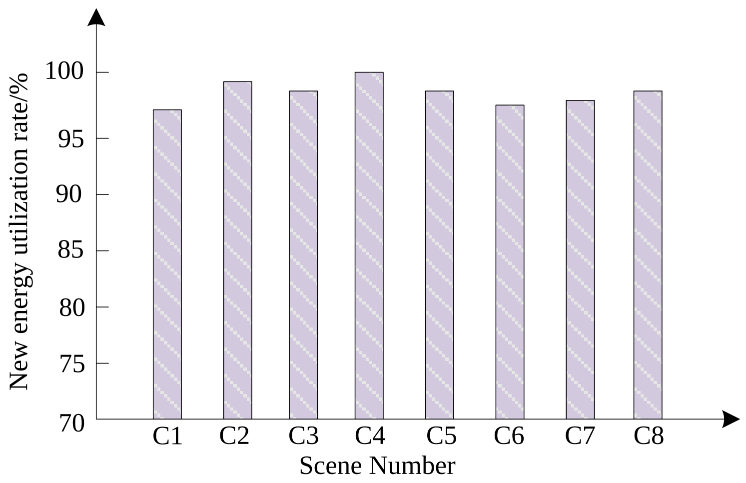

Figure 2: Results of Exploring the Potential for Flexible Adjustment Across All Aspects of the Data Center under Uncertainty of New Energy Output

Figure 2 is the utilization rate of new energy in the data centre after using the method presented in this paper under different experimental conditions. As shown in the figure, the proportion of new energy utilisation in each scenario is generally above 95 per cent; thus, the way in which it supports all parts of the data centre is highly feasible. Given the problem of unknown new-energy power output and fluctuations in data centre load, this paper accurately quantifies the uncertainty of new-energy power generation, builds a complete model of the entire energy system, uses a multi-objective particle swarm optimisation algorithm to solve the problem, and establishes a reasonable adjustment strategy to enhance the efficiency of new-energy use.

Although the proportion of new-energy resources under different conditions is relatively variable, it is still in a narrow range, and thus the method introduced in this paper has good robustness and general applicability. Whether the output of new energy sources is relatively stable in a certain situation, whether it fluctuates greatly, or whether there is a fixed data center load that changes dynamically or suddenly spikes, this method can still accurately select a suitable operating strategy from the set of Pareto-optimal solutions based on the quantified uncertainty information and the constructed model. Thus, a dynamic equilibrium will be achieved among the new-energy output, energy-storage systems, backup power sources and data centre loads; by adjusting these elements flexibly, all links in the data centre's process can be optimised to support the smooth application of new-energy sources in data centres.

The method in this paper is set as the experimental group, which is method 1. The ways in references [2], [3] and [4] were selected for comparison and set as method 2, method 3 and method 4, respectively. Four ways are used in the same experimental conditions to explore the feasibility of flexible adjustment for the whole process of a data center under the uncertainty of new energy generation. The results of the adjustment smoothness for the four methods are shown in Table 2.

Table 2: Comparison of Adjustment Smoothness for Data Center under Uncertainty in New Energy Output Using Different Methods.

Experimental scenario	Method 1 adjust smoothness	Method 2 adjust smoothness	Method 3 adjust smoothness	Method 4 adjust smoothness
C1 (Clear Sky High Penetration)	98.5%	88.2%	90.1%	85.3%
C2 (Cloudy Fluctuations Penetration)	96.7%	82.5%	85.0%	80.7%
C3 (low permeability on rainy days)	95.8%	78.9%	81.3%	76.2%
C4 (gust impact)	97.3%	83.4%	84.7%	81.1%
C5 (no photovoltaics at night)	96.1%	80.0%	82.8%	77.5%
C6 (rapid cloud cover)	97.0%	84.1%	86.4%	82.3%
C7 (extreme wind speed cut out)	95.5%	77.6%	80.9%	75.8%
C8 (comprehensive fluctuation)	96.4%	81.3%	83.7%	79.0%

Based on the adjustment smoothness data of all methods under different experimental conditions shown in Table 2, it can be seen that method 1 of this paper has excellent performance. In various situations where the new-energy output has extremely high uncertainty, such as high penetration in sunny weather to meet high demand, output fluctuation in cloudy and rainy conditions, gust impact and extreme wind speed cut-outs, method 1 can maintain exceptionally high adjustment smoothness. This is because it has accurately quantified the uncertainty of new energy output, comprehensively characterized features with a multi-dimensional model, laid the foundation for adjustment strategy formulation, and the constructed full-process energy system model covers the key parts of data center energy, considers the mutual influence of each link, and the adjustment is more holistic and coordinated.

Methods 2-4 in the literature have shown substantially poorer adjustment smoothness under various conditions. This may be because the uncertainty of the new energy output has not been fully quantified and analysed, or the model of the entire data centre process in the energy system has not fully accounted for complex interdependencies. However, the method in this paper uses a multi-objective particle swarm optimisation algorithm to solve multi-objective optimisation problems, forms scientific and flexible adjustment strategies, effectively handles various changes, fully explores the potential of the entire process, and shows excellent adjustment smoothness.

This paper will also examine the performance of the four methods in terms of the main indicator for adjustment speed, and the results are shown in Figure 3.

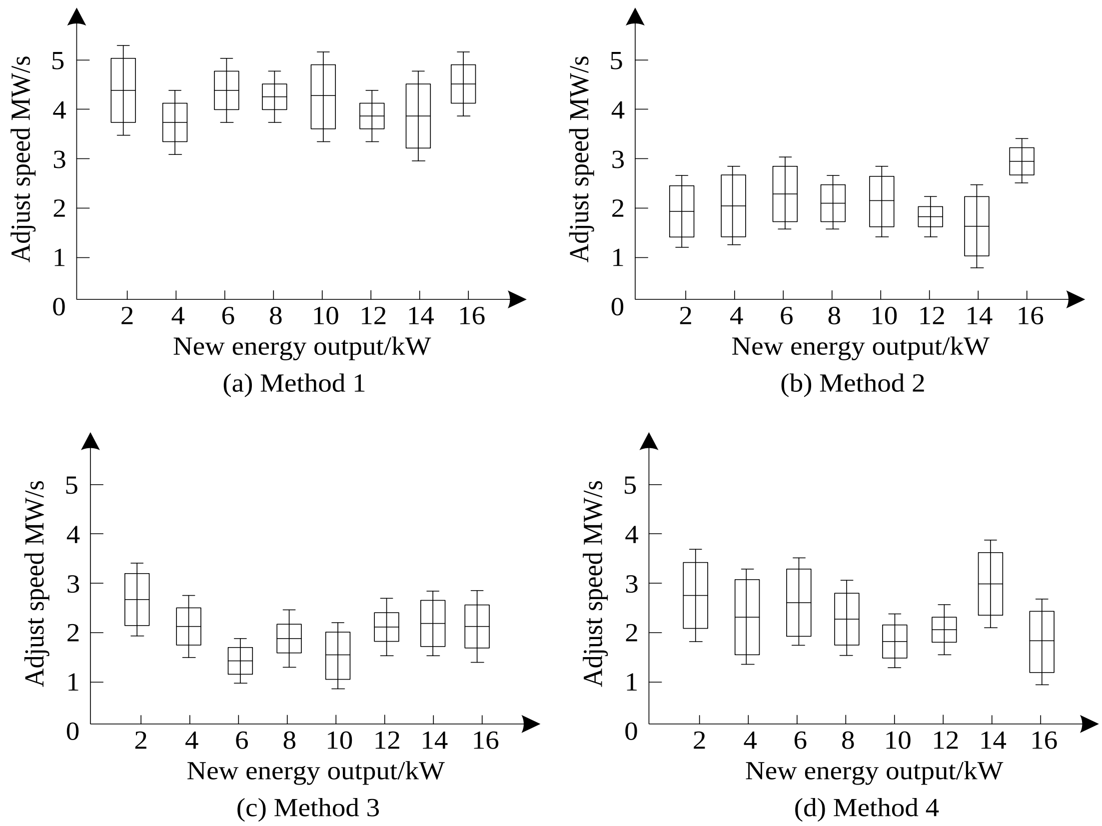

Figure 3: Comparison of Data Center Adjustment Speed under New Energy Output Uncertainty with Different Methods

As shown in Figure 3, at different levels of new energy output, Method 1 of this paper has good response speed. When the output of new energy increases from 2kW to 16kW, the adjustment speed of Method 1 is generally high and relatively stable, and it is also stable. It has accurately quantified the uncertainty in the new-energy-output and improved the construction of the energy-system model at all levels. Precise determination can be made of the future changes in the output of new energy, and a better model can promptly provide support for adjusting the plan according to changes in new energy output conditions and achieve high-speed, stable response.

On the other hand, methods 2, 3 and 4 generally have a slower adjustment speed than method 1 within the same range of new energy output changes, and they are not very stable. This may be due to deviations in the quantification of new-energy uncertainty or a model for the energy system that does not fully consider the complex coupling relationships among all parts of the data centre process. Method 1 is a multi-objective particle swarm optimisation algorithm that considers stability, economy and environmental protection simultaneously in the multi-objective optimisation problem; it can quickly generate suitable adjustment strategies for different situations, explore the flexible adjustment capacity of the entire process, and have good adjustment speed.

6 Conclusion

This paper studies the feasibility of all-around flexible adaptation for data centers in the event of a fluctuation in renewable energy output. Based on the above theory and experiments, a high utilization rate of renewable energy can be achieved in data centers; most cases have reached more than 95 per cent and thus exploited the advantages of new energy fully. Compared with the methods in the literature, this study has shown better smoothness and speed of adjustment, maintained power stability, quickly responded to changes, and promptly adjusted strategies.

Through model construction in this paper, we have provided theoretical support for data center energy management, solved related theoretical problems, offered reliable solutions for practical engineering applications, and promoted the stable and economical development of new-energy applications in data centers and green development.

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