

Article

A Collaborative Trading Method of Data Center–Power Grid–Energy Storage for Enhancing Spatiotemporal Flexibility

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Abstract

Aiming at the problems of high energy consumption, high carbon emissions from data centers and the difficulty of renewable energy accommodation in distribution networks driven by rapid growth in computing tasks, this paper proposes a collaborative trading method for data center–power grid–energy storage systems to improve spatiotemporal flexibility. Firstly, an integrated mechanism model including IT equipment, HVAC cooling systems, delay-tolerant batch tasks and UPS energy storage is established to quantify multi-dimensional internal flexible regulation potential. Secondly, an improved k-means algorithm is adopted for scenario reduction of wind–PV outputs, and a stochastic-robust collaborative trading optimization model considering carbon emission cost is constructed. Multiple practical constraints are incorporated, including power balance, power flow limits, nodal voltage bounds, task service latency and state of charge limits of energy storage. An improved particle swarm optimization with premature-convergence indicator is developed to solve this nonlinear, non-convex, mixed-variable problem. Simulations are carried out on a modified IEEE 33-node test system over a 24 h scheduling horizon. Numerical results demonstrate that compared with the conventional demand-response strategy, the proposed method reduces total operational cost by 10.7%, curtails wind–PV abandoned power, and achieves 28.6% peak-shaving ratio for data center load. Monte Carlo repeated experiments indicate that the improved Particle Swarm Optimization (PSO) reaches a 95% feasible solution rate with an average computation time of 26.8 s for day-ahead dispatch, which satisfies practical engineering requirements.

Keywords: energy consumption; data centers; collaborative trading method; renewable energy; energy storage



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1. Introduction

With the rapid development of new-generation information technologies such as artificial intelligence, the demand for computing power has experienced explosive growth. The coupling relationship between computing power networks and power grids is becoming increasingly close, and computing-power coordination has attracted widespread attention and reached a developmental consensus [1]. As core infrastructure, data centers constitute a type of large-scale and fast-growing critical load in power grids [2]. The national power consumption of data centers in China reached 150 TW·h in 2023, representing a year-on-year increase of 15.4%, and it is projected to hit 400 TW·h by 2030. Against this backdrop,

incentivizing data centers to consume renewable power and exploring direct renewable power access for data centers have become key components of current computing-power coordination research [3].

With the continuous rise in the penetration rate of new energy sources, data centers have gradually become vital flexible resources for grid regulation and renewable power absorption by virtue of their adjustable loads and migratable computing tasks [4]. Rational scheduling can align the energy consumption demand of data centers with grid operating conditions to realize peak shaving and valley filling. In terms of task scheduling and load flexibility exploitation, Reference [5] establishes a virtual power plant model for multi-data-center coordination. Through wide-area task migration, the model effectively mitigates power fluctuations of regional power grids and achieves low-carbon and economic operation. Nevertheless, the model can be further improved by fully exploiting the internal resource coupling of data centers. Reference [6] puts forward a load scheduling algorithm subject to quality of service (QoS) constraints. It verifies that time shifting of batch tasks can substantially cut electricity costs while guaranteeing user experience, yet it fails to tap into the spatiotemporal migration potential of tasks across different data centers. Reference [7] pioneers the construction of a stochastic programming model for data centers to cope with price uncertainties in electricity markets. For the scheduling problem of multiple data centers, Reference [8] proposes a scheduling scheme that reduces energy consumption while satisfying QoS and other constraints. The performance of this scheme could be further enhanced by additionally conducting collaborative optimization with UPS energy storage, HVAC and other systems at the energy flow level. Reference [9] develops a two-stage distributionally robust optimization-based scheduling strategy for power grid resilience enhancement, which strikes a balance between economic efficiency and system resilience. However, it does not deeply explore the potential of delayed task scheduling in the time dimension. Reference [10] investigates joint load-scheduling and UPS collaborative regulation for data centers, providing technical support for flexible resource coordination under grid operation constraints. Reference [11] explores dispatchable capability evaluation for cross-regional data-center clusters via workload migration scheduling, laying a foundation for the implementation of data-grid collaborative optimization.

Among all power-consuming facilities inside data centers, information technology (IT) equipment and cooling systems account for the largest energy consumption, taking up approximately 56% and 30% of the total power usage, respectively [12]. As core hardware undertaking fundamental functions including computation, storage and communication, servers consume around 70% to 80% of the total energy drawn by IT devices [13]. Reference [13] analyzes load scheduling security risks under high-penetration renewable scenarios, revealing the necessity of introducing robust optimization for data-center dispatch. Accordingly, establishing a refined coupling model between computing power and electric load is critical for accurately characterizing the power demand profiles of data centers. Reference [14] coordinates geographically distributed data-center load scheduling together with UPS regulation under source-side uncertainty, adopting stochastic optimization to improve service performance for grid frequency-regulation. Reference [15] develops a fine-grained and CPU-state-based power modeling approach for IT equipment. Nevertheless, relying merely on CPU utilization or instructions per cycle fails to precisely capture the dynamic power draw of CPUs [16]. The energy consumption of built-in server fans and temperature-dependent leakage power also exert significant impacts on the overall power demand of servers [17]. By incorporating temperature-correlated static leakage power as well as the dynamic power characteristics of CPUs equipped with dynamic voltage and frequency scaling (DVFS) technology, Reference [18] proposes a two-stage distributionally robust optimization framework for data centers with virtual-storage-equivalent UPS re-

sources, realizing spatiotemporal coordinated load operation. Reference [19] constructs an IT equipment power consumption model that accounts for the variation of server fan power consumption against cold aisle pressure. From the perspective of adapting cooling systems to fluctuations in renewable power output, Reference [20] presents a variable-temperature control strategy to guarantee safe operating temperatures for data centers amid volatile cooling capacity supply. Beyond conventional IT hardware and cooling facilities, Reference [21] establishes a data center model considering load fluctuations and designs a regulation strategy for waste heat compensation systems within data centers. Reference [22] addresses non-convex uncertain optimization for flexible-load scheduling of data centers, which can be extended to couple UPS energy storage with stochastic dispatch.

Although numerous scholars have carried out research on the demand-side resource response of data centers, several problems and challenges still remain: (1) Most existing studies only exploit single-dimensional flexible resources of data centers. They often separately consider the regulation capability of IT task migration scheduling, air-conditioning cooling systems or UPS energy storage, while lacking integrated coupled modeling of multiple internal resources including IT equipment, HVAC cooling, delay-tolerant batch tasks and UPS energy storage. Hence, it is difficult to fully unlock the multi-dimensional coordinated regulation potential inside data centers.

(2) Most literature treats data centers as isolated loads for optimal scheduling. Few studies incorporate internal flexible resources of data centers, distribution-network-side distributed renewable energy and grid-side energy storage into a unified trading and regulation framework. Meanwhile, in the face of stochastic fluctuations of wind–photovoltaic outputs, some approaches adopt deterministic scheduling without a stochastic-robust trading strategy combined with multi-scenario generation, which leads to limited renewable-energy accommodation capability.

(3) Some existing optimization solution methods tend to fall into local optima when handling this data center–power grid–energy-storage coupled model with nonlinear and non-convex constraints, and their convergence accuracy needs further improvement. Moreover, most simulation validations focus on the comparison of economic indicators, whereas comprehensive analysis of distribution-network safety indicators such as network loss and nodal voltage fluctuation is insufficient.

To tackle these problems, this paper proposes a collaborative trading strategy for data center–power grid–energy storage systems to enhance spatiotemporal flexibility. Different from previous research, this method constructs a unified mathematical model for multi-resources inside data centers. It also integrates distribution-network-side distributed renewable energy and energy storage into the regulation system, establishes a stochastic-robust trading model combined with multi-scenario generation, and adopts an improved particle swarm optimization algorithm to address the nonlinear and non-convex characteristics of the model. It reduces operating costs while satisfying safety constraints such as distribution-network voltage and network loss. Overall, the main innovations of this paper can be summarized as follows:

(1) An integrated mathematical characterization model is established for data-center IT equipment, HVAC systems, batch task scheduling and UPS energy storage. It fully describes the multi-link flexible regulation potential within data centers and realizes the coordinated coupling of computing tasks, cooling systems and energy-storage resources. Wind-power and photovoltaic distributed renewable energy as well as grid-side energy storage on the distribution-network side are further integrated into the collaborative trading framework.

(2) An improved PSO algorithm is proposed. A premature-convergence indicator is introduced to adaptively adjust the inertia weight, so as to mitigate the drawback that the original algorithm easily falls into local optima. The coupled optimization model

with nonlinear and non-convex constraints can be solved efficiently. Based on the modified IEEE 33-node test case, the effectiveness of the proposed method is verified from multiple dimensions including scheduling cost, wind–PV curtailment, network loss and voltage fluctuation.

The structure of this paper is organized as follows: Section 2 conducts the flexibility potential evaluation of data centers. The energy-consumption model for IT equipment and the scheduling model for UPS energy storage of data centers are established respectively to quantify the multi-dimensional internal flexible regulation capability of data centers. Section 3 constructs the mathematical model for grid–energy storage–data center cooperative transactions. Targeting the minimization of the comprehensive operation cost of the distribution network and data centers, a stochastic-robust cooperative transaction optimization model considering new-energy uncertainty is established. Section 4 designs an improved PSO-based algorithm to solve the established nonlinear, non-convex coupled model and output the optimal scheduling decision variables. Section 5 presents case-study analysis and simulation validation. Section 6 summarizes the whole paper. The methodological flowchart is shown in Figure 1 below.

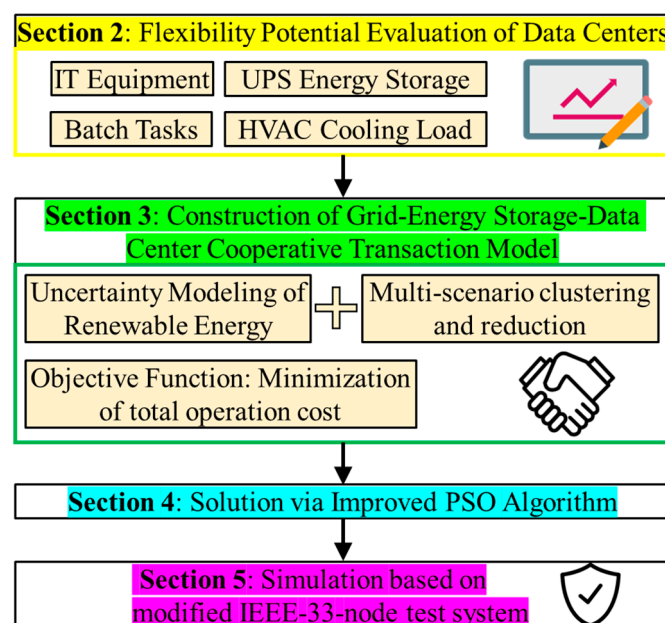


Figure 1. The methodological flowchart of the whole paper.

2. Evaluation of Flexible Regulation Potential of Data Centers

2.1. Energy Consumption Model of IT Equipment in Data Centers

As multi-type flexible resources, data centers have the potential to mobilize internal resources to collaboratively participate in virtual power plants. IT equipment processes batch and interactive tasks submitted by user clusters, while heating, ventilation and air conditioning (HVAC) systems dissipate the heat generated by IT equipment for cooling purposes. A data center consists of IT equipment and auxiliary facilities such as refrigeration systems and lighting systems. At present, the energy efficiency of data centers is measured by Power Usage Effectiveness (PUE) specified in the evaluation criteria for green data centers, which is defined as the ratio of the total energy consumption of a data center to the energy consumption of its IT equipment. The energy consumption models of IT equipment in data centers before and after demand response are presented as follows:

$$\begin{cases} \hat{E}_t^{IT} = (E^{\max} - E^{\text{idle}}) \frac{\hat{\lambda}_t}{\mu} + E^{\text{idle}} M \\ E_t^{IT} = (E^{\max} - E^{\text{idle}}) \frac{\lambda_t}{\mu} + E^{\text{idle}} m_t \\ \hat{E}_t^{DC} = \gamma_{PUE} \sum \hat{E}_t^{IT} \\ E_t^{DC} = \gamma_{PUE} \sum E_t^{IT} \end{cases} \quad (1)$$

where $\hat{E}_t^{IT}$ and E_t^{IT} denote the IT energy consumption of the data center in time period t before and after demand response, respectively; $\hat{E}_t^{DC}$ and E_t^{DC} denote the overall energy consumption of the data center in time period t before and after demand response, respectively; $\hat{\lambda}_t$ and λ_t represent the workload demand of the data center in time period t before and after demand response, respectively; E^{idle} and $E^{\max}$ are the idle power and peak power of a single server, respectively; μ represents the service rate of a single server; m_t is the number of active servers of the data center in time period t ; M is the total number of servers deployed in the data center; and γ_{PUE} represents the energy efficiency level of the data center.

In addition, the computing task carrying capacity of the data center in each time period is subject to utilization constraints and startup state constraints.

$$\begin{cases} \eta_t = \frac{\lambda_t}{\mu m_t} \leq CPU^{\max} \\ 0 \leq m_t \leq M \end{cases} \quad (2)$$

where η_t denotes the average service utilization of the data center during time period t ; $CPU^{\max}$ is the upper limit of CPU utilization.

The delay of workloads induced by demand response during transmission and queuing shall be strictly limited within the maximum delay time $T^{\max}$ specified in the service level agreement, yielding the following constraint:

$$0 \leq \frac{1}{\mu - \frac{\lambda_t}{m_t}} \leq T^{\max} \quad (3)$$

2.2. Energy Consumption Model for HVAC Systems in Data Centers

Servers generate substantial heat during operation, which raises the ambient temperature. Excessively high temperatures will directly impair the stable operation of servers and may even result in hardware failure. For this reason, data centers rely on cooling systems to regulate indoor room temperature. Approximately 90% of the cooling capacity produced by cooling systems is used to offset the heat load generated by IT equipment and its operating environment; this accounts for the majority of the air conditioning cooling load. The specific components of the cooling load are detailed as follows.

$$\begin{cases} L_t^{\text{cool}} = L_t^{IT} + L_{\text{env}} \\ L_t^{IT} = 0.97 E_t^{IT} \\ L_{\text{env}} = -t_1 S (T_t^{\text{in}} - T_t^{\text{out}}) \end{cases} \quad (4)$$

where L_t^{cool} represents the cooling load of air conditioners during period t ; L_t^{IT} denotes the heat generated by IT equipment in period t (0.97 is the heat dissipation ratio); L_{env} represents environmental heat, which is affected by the temperature difference between the inside and outside of the computer room; t_1 is the heat transfer coefficient of the computer room environment; S refers to the heat transfer area inside the computer room; T_t^{out} and T_t^{in} represents the outdoor and indoor temperatures of the computer room.

The energy consumption of air conditioning equipment is expressed in Equation (5).

$$E_t^{\text{cool}} = \frac{L_t^{\text{cool}}}{\gamma_t^{\text{cop}}} = \frac{0.97 E_t^{IT} - t_1 S (T_t^{\text{in}} - T_t^{\text{out}})}{\gamma_t^{\text{cop}}} \quad (5)$$

where γ_t^{cop} is the coefficient of performance defined as the ratio of cooling load to air conditioning energy consumption.

2.3. Workload Scheduling Model

The scheduling horizon is divided into a set of discrete time intervals $\Omega_t = \{1, 2, \dots, T\}$, and all batch tasks arriving at the data center are clustered by type into the set $\Omega_k = \{1, 2, \dots, K\}$. Let $y_{k,t}$ denote the processing demand of type- k tasks arriving at time interval t ; the maximum allowable delay interval for type- k tasks is $E_{delay}^{task,k}$. The 0–1 binary parameter F_j^k represents the executability indicator of type- k tasks at interval j (where $F_j^k = 0$ means such tasks cannot be executed at interval j). The maximum available processing capacity for batch processing at interval j is C_j^{proc} .

The primary decision variable of the model is $x_{t,j}^k$, which represents the actual processing volume allocated at interval j to type- k tasks that arrive at interval t . To ensure all tasks are processed within their permissible delay windows, mass balance constraints and capacity constraints are imposed on the arrival volume at each arrival time. For any k and t , the entire volume of tasks arriving at interval t must be fully allocated within the window spanning intervals t to $t + E_{delay}^{task,k}$:

$$\sum_{j=t}^{\min\{T, t+E_{delay}^{task,k}\}} x_{t,j}^k = y_{k,t} \quad (6)$$

where the left-hand side sums the allocated processing quantities over all feasible processing time intervals, and the right-hand side equals the total demand of the corresponding arrival batch. To explicitly account for the executability of each time interval, the model enforces zero allocation at intervals marked non-executable by parameter F_j^k via the following inequality:

$$x_{t,j}^k \leq y_{k,t} F_j^k \quad (7)$$

In addition, the total processing volume of the data center at any time interval j shall not exceed the available processing capacity of that interval, yielding the capacity constraint as follows:

$$\sum_{k=1}^K \sum_{t=1}^j x_{t,j}^k \leq C_j^{proc} \quad (8)$$

If sequential or consecutive processing block requirements exist between different task types or within a single job, integer-valued start time intervals or binary execution indicators can be introduced on top of the aforementioned continuous variables to characterize precedence and continuity.

Let S_t^u denote the start interval of type- u tasks arriving at interval t , and P_u denotes their required consecutive processing duration. Then the precedence relationship from predecessor task u to successor task v can be linearly formulated as follows:

$$S_t^v \geq S_t^u + P_u, \forall u \rightarrow v \quad (9)$$

To facilitate coupling with the UPS and HVAC subsystems, the total batch processing load D_j^{DW} at time interval j is defined as

$$D_j^{DW} = \sum_{k=1}^K \sum_{t=1}^j x_{t,j}^k \quad (10)$$

It should be noted that D_j^{DW} serves as the direct input for calculating the current-period IT load and energy consumption, and also acts as a coupling variable for subsequent cooling load estimation, power procurement, and UPS charge-discharge decisions.

2.4. Scheduling Model of UPS

The dynamic evolution of the UPS state of charge SOC_{t+1} is described as follows:

$$SOC_{t+1} = SOC_t + \frac{(\eta^{ch}c_t - \frac{d_t}{\eta^{dis}})}{E_{UPS}^N} \Delta t \quad (11)$$

Meanwhile, constraint (12) should also be satisfied.

$$\begin{cases} SOC^{\min} \leq SOC_t \leq SOC^{\max} \\ 0 \leq c_t \leq C_{\max} \\ 0 \leq d_t \leq D_{\max} \end{cases} \quad (12)$$

where η^{ch} and η^{dis} represent the charging and discharging efficiency, respectively; $C_{\max}$ and $D_{\max}$ denote the maximum charging power and maximum discharging power, respectively. SOC_t represents the state of charge of UPS energy storage at time t , with a value range of $[0, 1]$; c_t and d_t represent the charging and discharging power of UPS, respectively, in kW; and E_{UPS}^N represents the rated energy storage capacity of UPS in kWh.

The day-ahead declared capacity R_t is defined in the model as the sum of the instantaneous UPS discharge capability and the schedulable load released via task rescheduling:

$$R_t = D_{\max}(t) + \sum_{k \in K} \phi_k \Delta y_{k,t} \quad (13)$$

$$\Delta y_{k,t} = y_{k,t}^{base} - y_{k,t} \quad (14)$$

where ϕ_k denotes the power consumption corresponding to unit computation volume of type- k tasks, $y_{k,t}^{base}$ represents the baseline scheduling scheme, and $\Delta y_{k,t}$ represents the transferable/reducible load volume in each interval relative to the baseline.

3. Grid-Energy Storage-Data Center Cooperative Trading Model

3.1. Modeling of Renewable Energy Output

The output power of wind turbines is affected by wind speed, and the corresponding relationship is expressed as follows:

$$P_t^{wt} = \begin{cases} 0, v < v_{in}, v \geq v_{out} \\ k_1 v + k_2, v_{in} \leq v < v_r \\ P_N^{WT}, v_r \leq v < v_{out} \end{cases} \quad (15)$$

where P_t^{wt} denotes the wind turbine output power during time interval t ; v is the current wind speed; v_{in} represents the cut-in wind speed; v_{out} represents the cut-out wind speed; v_r represents the rated wind speed; P_N^{WT} is the rated power of the wind turbine; and k_1 and k_2 are the linear transformation coefficients for wind power output.

The wind speed follows a Weibull distribution. The probability density function of wind power output can be derived from the probability density function of wind speed, as shown in (16).

$$f(P_t^{wt}) = \frac{k'}{k_1 c} \left(\frac{P_t^{wt} - k_2}{k_1 c} \right)^{k'-1} \exp \left(- \left(\frac{P_t^{wt} - k_2}{k_1 c} \right)^{k'} \right) \quad (16)$$

where k' and c are the shape parameter and scale parameter of the Weibull distribution for wind speed, respectively.

The output power of photovoltaic units is affected by solar irradiance intensity, and the correlation is given as follows:

$$\begin{cases} P_t^{pv} = \frac{P_N^{pv} G_t [1 - \beta (T_t^{pv} - T_N^{pv})]}{G_N} \\ T_t^{pv} = T_t^{amb} + \frac{G_t (T^{noct} - 20)}{G_N} \end{cases} \quad (17)$$

where P_t^{pv} represents the photovoltaic output power during time interval t ; G_t and G_N are the actual solar irradiance and rated solar irradiance at interval t , respectively; T_t^{pv} , T_N^{pv} , T_t^{amb} and T^{noct} denote the actual temperature of photovoltaic panels, reference temperature, ambient temperature at interval t and nominal operating temperature in sequence; P_N^{pv} is the rated power of photovoltaic equipment; and β represents the power temperature coefficient of photovoltaic cells.

The solar irradiance follows a Beta distribution. The probability density function of photovoltaic output power can be derived from the probability density function of solar irradiance, as illustrated in (18).

$$f(P_t^{pv}) = \frac{\Gamma(\xi + \psi)}{\Gamma(\xi)\Gamma(\psi)} \left(\frac{P_t^{pv}}{P_{\max}^{pv}} \right)^{\xi-1} \left(1 - \frac{P_t^{pv}}{P_{\max}^{pv}} \right)^{\psi-1} \quad (18)$$

where ξ and ψ are the shape parameters of the Beta distribution; $P_{\max}^{pv}$ denotes the maximum power generation of photovoltaic systems.

Feature extraction and cluster analysis of wind and photovoltaic power output scenarios are critical procedures for investigating the uncertainty of renewable energy generation. In this paper, an improved k-means algorithm is adopted to implement scenario reduction, with characteristic indicators constructed including daily output ratio, daily peak-to-valley difference ratio, peak and valley output time instants, and daily average power output. Compared with conventional indicators such as average power output and power fluctuation rate, the selected indicators in this paper can effectively characterize the uncertainty of wind and photovoltaic generation from the perspectives of temporal distribution and amplitude discrepancy, while efficiently reducing data dimensionality. The construction method for the proposed indicators is presented as follows:

$$\begin{cases} a_1 = P_{av}^{renew} / P_{\max}^{renew} \\ a_2 = (P_{\max}^{renew} - P_{\min}^{renew}) / P_{\max}^{renew} \\ a_3 = \operatorname{argmax}_{t \in [1, 2, \dots, T]} \{P_t^{renew}\} \\ a_4 = \operatorname{argmin}_{t \in [1, 2, \dots, T]} \{P_t^{renew}\} \\ a_5 = P_{av}^{renew} = \frac{1}{24} \sum_{t=1}^{24} P_t^{renew} \end{cases} \quad (19)$$

where a_1 , a_2 , a_3 , a_4 and a_5 represent the daily output ratio, daily peak-valley difference ratio, peak output time, valley output time, and daily average output of renewable energy, respectively; P_{av}^{renew} is the daily average output of renewable energy; $P_{\max}^{renew}$ and $P_{\min}^{renew}$ are the maximum and minimum renewable energy output.

To eliminate the influence of dimensional differences, normalization is adopted for data preprocessing, so that all indicators can be compared under uniform dimensions.

$$y_{s,m}^* = \frac{y_{s,m} - \min(y_m)}{\max(y_m) - \min(y_m)} \quad (20)$$

where $y_{s,m}^*$ and $y_{s,m}$ are the standard value and indicator value of the m -th renewable energy output indicator under the s -th scenario, respectively; y_m represents the dataset composed of the m -th renewable energy output indicator.

3.2. Mathematical Model for Collaborative Trading

In this paper, an uncertainty set is constructed using typical scenarios obtained via scenario reduction based on improved k-means clustering [23,24]. The original stochastic-robust optimization problem is transformed into a tractable deterministic equivalent formulation. Scenario-probability weights are explicitly introduced in Objective Function (21),

and the expected comprehensive operating cost of the system is calculated by weighting each typical scenario with its corresponding occurrence probability. The objective function of collaborative trading is to minimize the comprehensive operating cost of the power grid and data centers, as shown below:

$$\min F = \sum_{t=1}^T \pi_s (C_t^{grid} + C_t^{loss} + C_t^p + C_t^{DC} + C_t^{carbon}), \quad s \in \Omega_s \quad (21)$$

$$C_t^{grid} = \lambda_t^{grid} P_t^{grid} \quad (22)$$

$$C_t^{loss} = \lambda_t^{loss} \sum a_{l,t} r_l \quad (23)$$

$$C_t^p = \lambda_t^{pv} \sum (P_{\max}^{pv} - P_t^{pv}) + \lambda_t^{wt} \sum (P_{\max}^{wt} - P_t^{wt}) \quad (24)$$

$$C_t^{DC} = \lambda_t^{DC} P_t^{DC} \quad (25)$$

$$C_t^{carbon} = \lambda_{carbon} e_{grid} P_t^{grid} \quad (26)$$

where π_s represents the probability of scenario s ; Ω_s represents the scenario set; C_t^{grid} , C_t^{loss} , C_t^p and C_t^{carbon} represent the power purchase cost of the distribution system (DS) from the upper-level grid, network loss cost, renewable energy curtailment cost and carbon emission cost during time period t , respectively; C_t^{DC} represents the total operation cost; λ_t^{grid} denotes the electricity price for the DS purchasing power from the upper-level grid in period t ; P_t^{grid} is the power purchased by the DS from the upper-level grid during time period t ; λ_t^{loss} represents the network loss cost per unit transmission power; $a_{l,t}$ is the square of the current flowing through branch l in period t ; r_l represents the resistance of branch l ; λ_t^{wt} and λ_t^{pv} are the wind power curtailment cost and photovoltaic power curtailment cost, respectively; P_t^{wt} and P_t^{pv} represent the active power output of wind turbine w and photovoltaic unit v in period t ; $P_{\max}^{wt}$ and $P_{\max}^{pv}$ are the predicted maximum output of wind turbines and photovoltaics in period t . λ_{carbon} represents the carbon price and its value is set as 150\$/tCO₂; and e_{grid} represents the carbon-emission factor for the grid power purchase side with a value 0.58 tCO₂/MWh. Then, the total carbon-dioxide emissions E_{total} over the entire scheduling time horizon can be calculated by Equation (27):

$$E_{total} = \sum_{t=1}^T \pi_s e_{grid} P_t^{grid}, \quad s \in \Omega_s \quad (27)$$

In addition to the conventional constraints of data centers, the following operational constraints shall also be satisfied. The system active power balance constraint can be formulated as

$$P_t^{pv} + P_t^{wt} + P_t^{grid} + d_t = P_t^{DC} + c_t + P_t^L + \sum P_{b,t}^{DN} - \sum (P_{l,t}^{DN} - a_{l,t} r_l) \quad (28)$$

In the above formula, $P_{l,t}^{DN}$ and $P_{b,t}^{DN}$ represent the active power flowing through line b and line l at time t , respectively.

The system reactive power balance constraint can be expressed as

$$Q_t^{grid} = \tan \phi \sum P_{b,t}^{DN} + Q_t^L + \sum Q_{b,t}^{DN} - \sum (Q_{l,t}^{DN} - a_{l,t} x_l) \quad (29)$$

where Q_t^{grid} is the reactive power purchased by the distribution network from the upper-level grid at time t ; $\tan \phi$ represents the power factor of data center loads; $Q_{b,t}^{DN}$ and $Q_{l,t}^{DN}$ represent the reactive power flowing through line b and line l at time t , respectively; and x_l is the reactance of line l .

The line voltage constraint can be expressed as

$$U_{l,t} - 2(r_l P_{l,t}^{DN} + Q_{l,t}^{DN} x_l) + a_{l,t} (r_l^2 + x_l^2) = U_{n,t} \quad (30)$$

where $U_{n,t}$ represents the square of the voltage magnitude at node n at time t .

The line current constraint can be expressed as

$$0 \leq a_{l,t} \leq a_{l,\max} \quad (31)$$

where $a_{l,\max}$ is the upper limit of the square of the current on branch l .

The node voltage constraint can be formulated as

$$U_{n,\min} \leq U_{n,t} \leq U_{n,\max} \quad (32)$$

where $U_{n,\max}$ and $U_{n,\min}$ are the upper and lower limits of the voltage magnitude at bus n , respectively.

The second-order cone formulation of power flow constraints [25] can be expressed as (33).

$$\left\| \begin{array}{c} 2P_{ij,t} \\ 2Q_{ij,t} \\ I_{ij,t} - U_{i,t} \end{array} \right\|_2 \leq I_{ij,t} + U_{i,t} \quad (33)$$

The output constraints of renewable energy sources can be expressed as (34).

$$\begin{cases} 0 \leq P_t^{pv} \leq P_{\max}^{pv} \\ 0 \leq P_t^{wt} \leq P_{\min}^{wt} \end{cases} \quad (34)$$

The power purchase constraint from the upper-level grid can be expressed as

$$\begin{cases} 0 \leq P_t^{grid} \leq P_{\max}^{grid} \\ 0 \leq Q_t^{grid} \leq Q_{\max}^{grid} \end{cases} \quad (35)$$

The stored energy of energy storage equipment during operation is subject to upper and lower limit constraint (36).

$$E_{\min}^{ess} \leq E_t^{ess} \leq E_{\max}^{ess} \quad (36)$$

where E_t^{ess} represents the energy stored in the energy storage device during period t ; $E_{\max}^{ess}$ and $E_{\min}^{ess}$ are the upper and lower limits of stored energy for the energy storage device, respectively.

The stored energy of the energy storage device is continuous in each time period. To ensure a consistent initial state for each operating day, a constraint (37) that enforces equal initial and final energy states of the energy storage system should be incorporated.

$$\begin{cases} E_t^{ess} = E_{t-1}^{ess} + \eta^{char} P_t^{char} \Delta t - P_t^{dischar} \Delta t / \eta^{dischar} \\ E_0^{ess} = E_{24}^{ess} \\ 0 \leq P_t^{char} \leq P_{rated}^{ess} I_{t,char} \\ 0 \leq P_t^{dischar} \leq P_{rated}^{ess} I_{t,dischar} \\ 0 \leq I_{t,char} + I_{t,dischar} \leq 1 \end{cases} \quad (37)$$

where η^{char} and $\eta^{dischar}$ are the charging and discharging efficiencies of the energy storage device, respectively; P_t^{char} and $P_t^{dischar}$ represent the charging and discharging power of the energy storage device in period t , respectively; E_0^{ess} and E_{24}^{ess} represent the initial and final stored energy of the energy storage device, respectively; P_{rated}^{ess} is the rated charge-discharge power; and $I_{t,char}$ and $I_{t,dischar}$ are the binary variables corresponding to charging and discharging of the energy storage device in each period, respectively.

4. Solution Algorithm Based on Improved PSO

PSO is a widely used algorithm for solving mathematical optimization models with multiple constraints [26], and its general search process is illustrated in Figure 2. In Figure 2,

t is the iteration number; x_t is the current position of the particle; v_t is the current velocity of the particle; x_{t+1} is the particle position in the next iteration; v_{t+1} is the particle velocity in the next iteration; p_{best} is the personal best position; and g_{best} is the global best position [27].

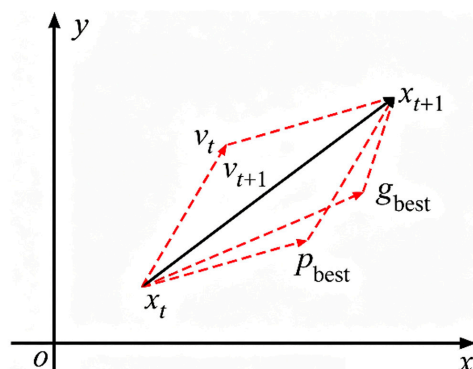


Figure 2. General search process of the PSO.

Let M denote the dimensionality of the particle swarm search space. For the i -th particle, its position vector x_i , velocity vector v_i , and personal best position vector $p_{best,i}$ can be written as

$$x_i = (x_{i1}, x_{i2}, \dots, x_{iM}) \quad (38)$$

$$v_i = (v_{i1}, v_{i2}, \dots, v_{iM}) \quad (39)$$

$$p_{best,i} = (p_{i1}, p_{i2}, \dots, p_{iM}) \quad (40)$$

The search procedure of the basic PSO algorithm is as follows:

$$V_{im}^{t+1} = w^t V_{im}^t + C_1 r_1 (p_{im}^t - X_{im}^t) + C_2 r_2 (p_{gm}^t - X_{im}^t) \quad (41)$$

$$X_{im}^{t+1} = X_{im}^t + V_{im}^t \quad (42)$$

In Equations (41) and (42), w^t represents the adaptive inertia weight of the t -th generation, which is dynamically updated according to the premature-convergence index; r_1 and r_2 are random numbers uniformly distributed in the interval $[0, 1]$; c_1 and c_2 denote learning factors; V_{im}^t represents the velocity of particle i in the m -th dimension at the t -th iteration; X_{im}^t denotes the position of particle i in the m -th dimension at the t -th iteration; p_{im}^t represents the personal best position of particle i up to the t -th iteration; and p_{gm}^t is the global best position found by the swarm up to the t -th iteration.

The basic PSO algorithm tends to fall into local optima during iteration, which results in premature convergence. Therefore, an inertia weight is introduced in this paper to adaptively adjust the iterative process of the algorithm. Let η denote the premature-convergence index of the particle swarm, whose calculation formula is given by

$$\eta = |E_g - E_{avg}^*| \quad (43)$$

In Equation (43), E_g denotes the optimal adaptive fitness value of particles; E_{avg}^* represents the portion where the fitness value E_i outperforms its average adaptive fitness value E_{avg} . The calculation formula of E_{avg} is expressed as

$$E_{avg} = \frac{1}{N} \sum_{i=1}^n E_i \quad (44)$$

During the iteration process, the particle swarm adjusts the weight according to the fitness values.

(1) When $E_i > E_{avg}$

$$w = w_{\max} - (w_{\max} - w_{\min}) \left| \frac{E_i - E_i^*}{E_g - E_i^*} \right| \quad (45)$$

In Equation (45), E_i^* denotes the historical personal best fitness value of particle i . At this moment, the particle corresponds to the optimal individual within the swarm. Equations (41) and (42) are adopted to drive the particle into subsequent iterations, so as to moderately reduce its flight velocity.

(2) When $E_{avg} > E_i > E_{avg}^*$

To avoid the problem that the output weight may exceed the reasonable value range, weight truncation constraints are added:

$$w^t = clip \left\{ w_{\max} + (w_{\max} - w_{\min}) \times \frac{1 + \cos \frac{t-1}{t_{\max}-1} \pi}{2}, w_{\max}, w_{\min} \right\} \quad (46)$$

In Equation (46), $t_{\max}$ represents the preset maximum iteration number of the algorithm. At this time, the particle is an ordinary individual in the population. Equation (47) enables particles to accelerate the search speed in the early iteration stage. The weight truncation function is defined as follows:

$$clip\{x, L, U\} = \begin{cases} U & x > U \\ x & L \leq x \leq U \\ L & x < L \end{cases} \quad (47)$$

Here, $clip\{\}$ denotes the clipping function, which forces the calculated inertia weight to be bounded between the preset upper and lower limits to avoid numerical overflow.

(3) When $E_i < E_{avg}^*$

$$w^t = 1.5 - \frac{1}{1 + k_1 \times \exp(-k \times \Delta)} \quad (48)$$

In Equation (48), k_1 is a constant greater than 1, which determines the upper limit of w and is used to amplify the inertia weights of inferior-solution individuals; Δ denotes the adjustment factor.

Since this problem aims to minimize the comprehensive operating cost, a lower cost corresponds to a better fitness. Accordingly, the particle fitness function is defined as $Fit(x) = \min F$. The update criteria for individual and global optima are given in Equation (49).

$$\begin{cases} \text{if } Fit(x_i^{t+1}) < Fit(pbest_i^t) \Rightarrow pbest_i^{t+1} = x_i^{t+1} \\ \text{if } \min Fit(pbest_i^{t+1}) < Fit(gbest^t) \Rightarrow gbest_i^{t+1} = \operatorname{argmin} Fit(pbest_i^{t+1}) \end{cases} \quad (49)$$

The proposed model includes 0–1 binary charge-discharge indicator variables, branch power-flow inequality constraints, and SOC upper- and lower-bound constraints. Particle iterations of meta-heuristic algorithms generate numerous infeasible particles that violate constraints. This paper adopts a combined strategy of external penalty function and variable-bound repair for constraint handling:

(1) **0–1 binary variables:** After continuous-valued outputs from particles, rounding mapping is adopted to enforce mapping onto the set $\{0, 1\}$.

(2) **SOC constraint:** If the calculated value exceeds the interval after particle iteration, direct clipping repair is performed: $SOC_t = clip\{SOC_t, 0, 1\}$.

(3) **Power-flow, voltage and power inequality constraints:** Particles are not discarded directly. Penalty terms are added to the fitness function:

$$Fit(x) = F + \rho_p \cdot [\sum h_j(x)] \quad (50)$$

where $h_j(x)$ denotes the violation magnitude of each constraint; ρ_p is the penalty coefficient. Larger constraint violations lead to a sharp increase in fitness (cost), guiding the population away from the infeasible region.

(4) **Handling of infeasible particles:** Particles are not directly deleted and remain within the population. Nevertheless, the large penalty prevents them from being selected as p_{best} / g_{best} . Feasible-region particles gradually dominate in the later iteration stage.

The details such as algorithm parameter configuration and termination criteria are shown in Table 1.

Table 1. Parameter configuration of the improved PSO algorithm.

Parameters	Value
Population size	60
Maximum number of iterations	120
Learning factors c_1 and c_2	2.0, 2.0
Inertia weight interval $[w_{\min}, w_{\max}]$	$[0.4, 0.9]$
Adjustment coefficient k_1	1.2
Convergence threshold	0.001
Constraint penalty coefficient ρ_p	10^5

The flowchart of the improved PSO algorithm is shown in Figure 3.

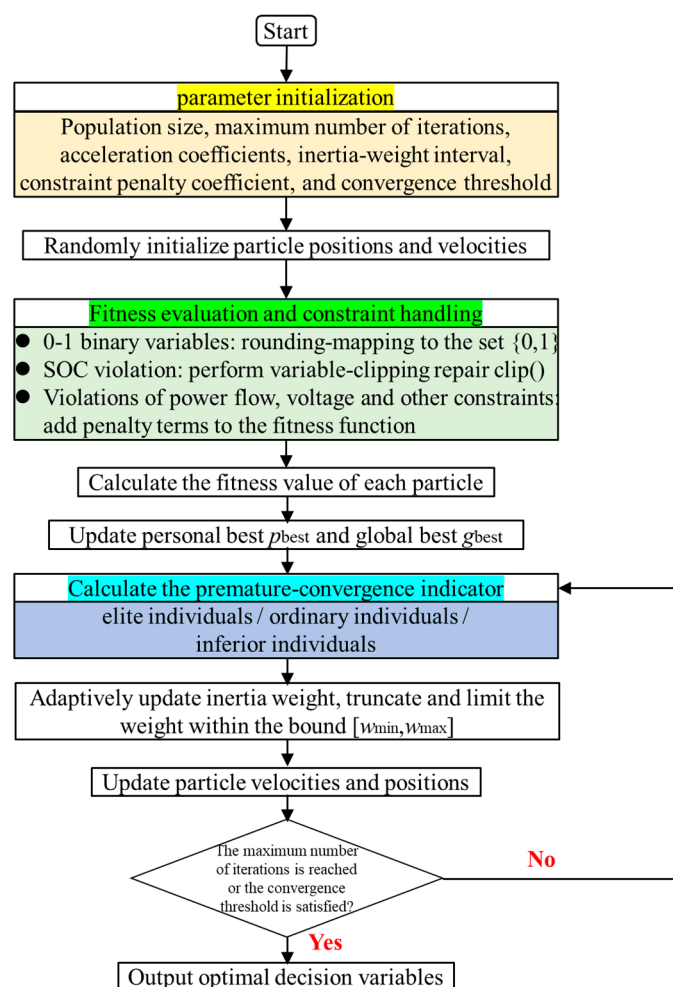


Figure 3. The flowchart of the improved PSO algorithm.

5. Case Study

5.1. Introduction to Test System

To verify the effectiveness and feasibility of the algorithm proposed in this paper, an improved IEEE 33-node test system is adopted for verification and analysis, whose topology is illustrated in Figure 4. Two data centers are deployed at node 19 and node 30. The typical output curves of renewable energy are presented in Figure 5. The detailed parameter settings of the simulation system are as follows: The IEEE 33 distribution network system adopted in this paper has a base total active load of 3.715 MW and a base total reactive load of 2.300 Mvar. The operating range of each node voltage is constrained within 0.95–1.05 p.u. Wind power and photovoltaic units are connected to node 7 and node 22 with rated outputs of 2.2 MW and 1.8 MW, respectively, and the grid-side energy storage is installed at node 4. The test case includes two data centers. The no-load power and peak power of a single server are 0.12 MW and 0.45 MW. The maximum allowable delay for batch-processing tasks is set to 4 h. The PUE of the data center is 1.42 and the COP of air-conditioning equipment is 3.2. The rated UPS capacities of Data Center 1 and Data Center 2 are 2.0 MWh and 1.6 MWh, with the corresponding maximum charging-discharging powers of 0.6 MW and 0.5 MW. The power consumption coefficient per unit computing task is 0.08 MW/(1000 tasks). For the grid-side energy storage, the rated capacity is 3.0 MWh, the maximum charging-discharging power is 1.0 MW, and both charging and discharging efficiencies are set to 0.95. In terms of economic parameters, the peak-hour and valley-hour electricity purchase prices are 85 \$/MWh and 32 \$/MWh, and the curtailment penalty coefficient for wind and photovoltaic power is 120 \$/MWh. Six typical renewable-energy scenarios are selected, whose corresponding scenario occurrence probabilities are [0.18, 0.22, 0.14, 0.16, 0.15, 0.15].

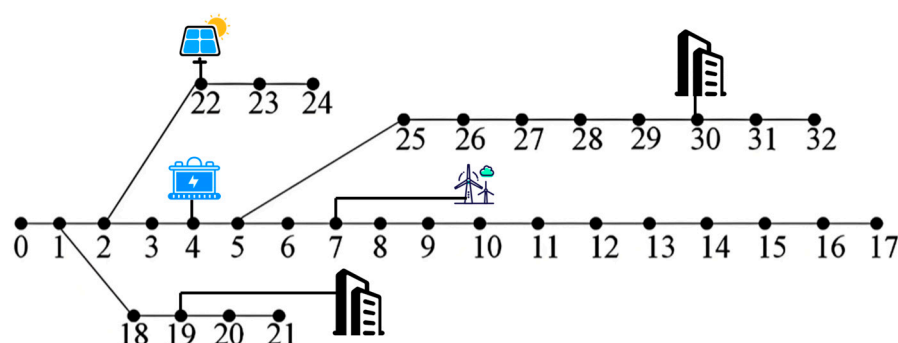


Figure 4. Topology of the testing system.

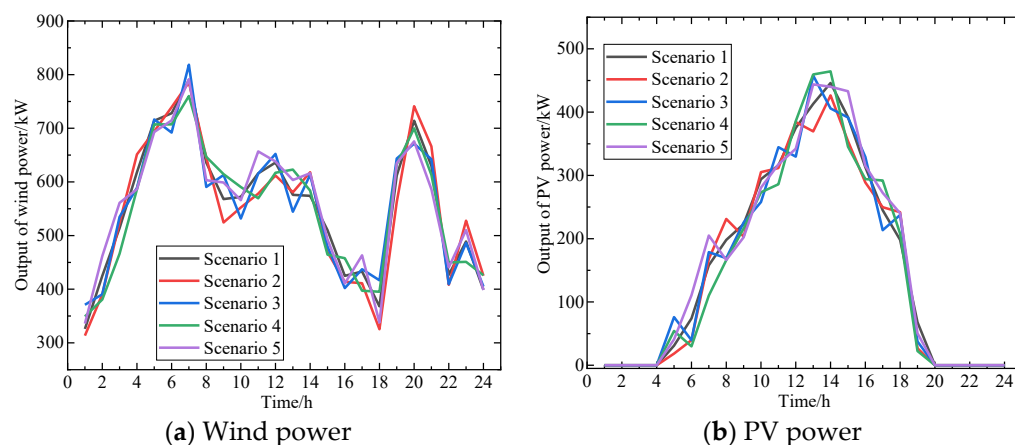


Figure 5. Typical scenarios of new energy output.

5.2. Feasibility Verification of the Proposed Method

Figure 6 illustrates the power demand profiles of the two data centers before and after optimization. The collaborative scheduling strategy proposed in this paper can fully exploit the multi-dimensional flexible regulation potential within data centers, including IT loads, air-conditioning cooling systems, delayable batch tasks, and UPS energy storage. Relying on the optimized cross-time shifting of tasks, the scheme realizes flexible transfer of electric loads. Combined with an adaptive adjustment mechanism, it dynamically modulates the power demand of the data center in each time interval. Under the premise of satisfying the service delay constraints of business operations, peak load shaving and valley filling are achieved. By comparing the power demand curves of the data center before and after optimization, it can be clearly observed that the proposed scheduling method smooths internal power consumption fluctuations, effectively cuts the peak power demand and flattens the all-day power output curve. The scheme fully unlocks the adjustable load resources inherent to data centers, markedly reduces electricity expenses and comprehensive energy consumption, and demonstrates outstanding capabilities for flexible internal power regulation as well as prominent economic operation benefits.

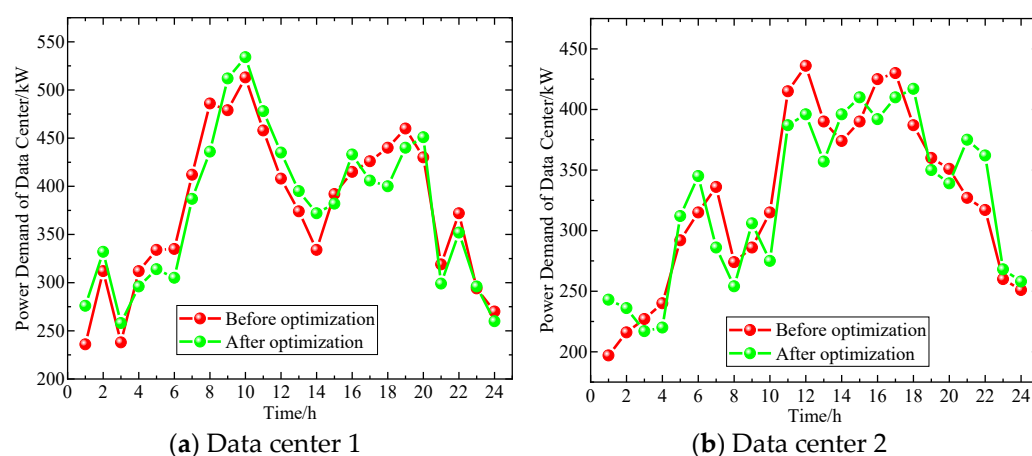


Figure 6. Power response of data centers.

The charging and discharging power of energy storage devices in the system is presented in Figure 7. Within the collaborative scheduling framework of data centers, both UPS energy storage and grid-side energy storage can give full play to their flexible charging and discharging regulation advantages. During the peak power consumption periods of the data center, stored electric energy is discharged to cut down instantaneous peak power, while charging is conducted to store surplus electricity during off-peak hours. Cooperating with shiftable computing tasks, they jointly smooth the all-day power demand curve of the data center, effectively alleviating the short-term high-power electricity pressure and reducing the high electricity purchase cost caused by peak power consumption. Meanwhile, relying on the continuous power regulation capability of energy storage to absorb load fluctuations induced by task time shifting, the internal flexible regulation margin of the data center is fully tapped. On the basis of meeting service delay constraints, the time-series distribution of power consumption is further optimized, and the operating losses arising from drastic power fluctuations are reduced. Overall, the economy of collaborative utilization of internal resources and the stability of power regulation inside the data center are comprehensively improved.

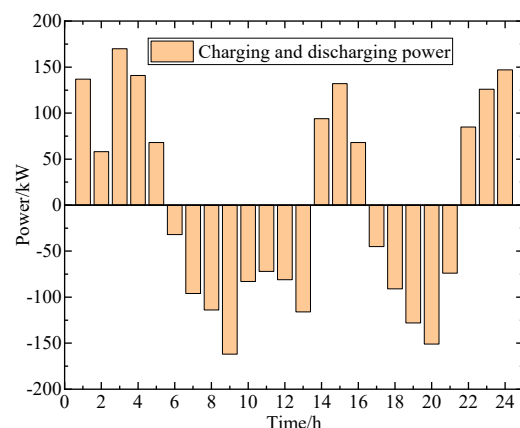


Figure 7. Charging and discharging power of energy storage devices.

Figures 8 and 9 illustrate the network loss and voltage fluctuation before and after optimization, respectively. The collaborative transaction scheduling method proposed in this paper leverages the schedulable loads of data centers and the coordinated charging/discharging of energy storage to adjust the time-series distribution of power consumption. Guided by dynamic electricity prices, data centers shift power consumption away from grid peak periods and raise load demand during valley periods with abundant new energy generation. This approach effectively balances the active power flow distribution across all nodes in the distribution network, curtails current losses caused by heavy power transmission on lines, and thereby reduces system network losses. Meanwhile, the load power at each node becomes smoother after optimization, eliminating severe node voltage deviations induced by concentrated short-duration high power consumption at local nodes. Real-time fast charging and discharging of energy storage suppress voltage fluctuations triggered by sudden load changes and improve the overall voltage operation performance of the entire network. Ultimately, simultaneous reductions in system network loss and voltage fluctuation rate are achieved.

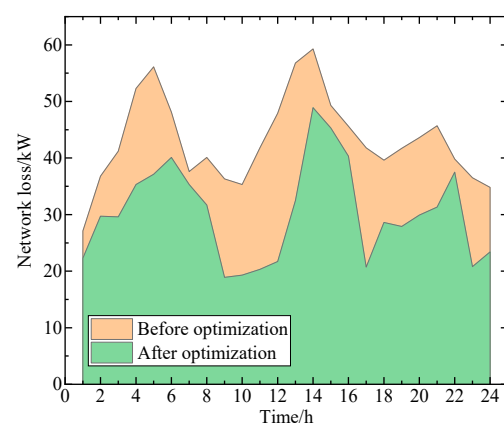


Figure 8. Network loss before and after optimization.

This paper further selects several typical strategies for comparison, and their calculation results are listed in Table 2. Only relying on grid-side energy storage for power regulation, this scheme does not activate the multi-dimensional flexible resources inside the data center including IT loads, batch tasks, UPS and HVAC, leading to a single means for load regulation. When wind and solar power generation is abundant, new energy is accommodated merely by the capacity of energy storage. Restricted by the upper limit of energy storage capacity, the wind–solar curtailment ratio remains high, and the comprehensive operation cost is relatively high. It only implements simple time shifting of

data center loads without coordinating the charge and discharge of energy storage and thus lacks continuous power regulation capability. Without modeling the uncertainty of wind–solar generation, it shows the poorest adaptability to new energy fluctuations and achieves the highest curtailment ratio. Its total scheduling cost ranks the highest among the five schemes.

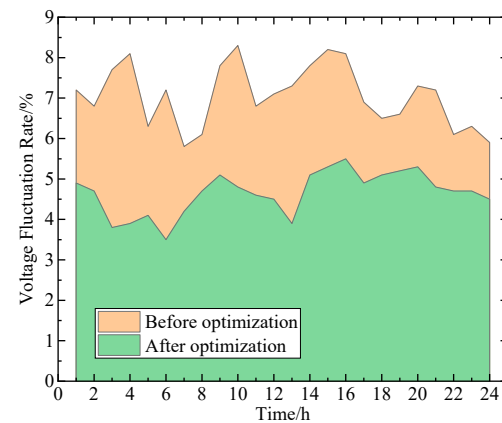


Figure 9. Voltage fluctuation before and after optimization.

Table 2. Performance comparison of optimization strategies with different methods.

Performance Indicators	Energy-Storage-Only Scheduling	Conventional Demand-Response Strategy	Deterministic Optimization Scheduling	Two-Stage Stochastic Programming Scheduling	The Proposed Method
Total scheduling cost (\$)	13,151.4	13,879.6	134,22.7	12,764.2	12,397.4
Wind–solar curtailment ratio (%)	5.1	6.3	5.7	4.1	3.2
Load peak-shaving ratio of data centers (%)	14.7	19.2	16.3	23.5	28.6
System network loss reduction ratio (%)	8.3	11.5	9.6	14.2	17.4
Maximum node voltage fluctuation (p.u.)	0.072	0.064	0.068	0.053	0.041
24 h carbon emission reduction (t CO ₂)	1.82	0	1.13	2.54	3.47
Single-run computation time of algorithm (s)	21.6	17.3	14.1	34.2	26.8

Scheduling is performed using the expected forecast values of wind and solar outputs without considering stochastic output fluctuations. Although multiple types of data center resources are introduced, the model possesses no robustness against practical deviations between real wind–solar outputs and forecasts, which easily gives rise to resource mismatch in actual operation. Its curtailment and cost outperform those of energy-storage-only scheduling and the conventional demand-response strategy, yet they are inferior to those of the stochastic scheme and the proposed method.

Multi-scenario representation is adopted to characterize wind–solar uncertainty, and the operation cost can be optimized in an expected sense. The curtailment and cost are evidently improved compared with the deterministic scheme. Nevertheless, this method heavily relies on the accurate probability distribution of wind–solar outputs. If a deviation exists between the practical distribution and the assumed one, the performance of the scheduling solution will degrade significantly. Besides, numerous variables are required to cover a large number of scenarios. The proposed approach couples multi-dimensional internal flexible resources of the data center with grid-side energy storage. The improved k-means algorithm is utilized for scenario reduction to construct the stochastic-robust model, which does not require strictly known probability distributions. Time delay-tolerant batch tasks are transferred across time intervals. The power consumption of the data center

is actively increased during periods of abundant wind–solar generation to maximize local new energy accommodation. Meanwhile, dynamic electricity prices are exploited for peak-avoiding power consumption. Consequently, the power purchase cost and curtailment penalty are greatly suppressed. Compared with the conventional demand-response strategy, the total cost is reduced by 10.7%, and the wind–solar curtailment ratio drops by 3.1%.

Deterministic optimization generates scheduling solutions purely based on forecast values. Once wind–solar outputs fluctuate, the power-consumption schedule of the data center and the energy-storage strategy cannot respond accordingly, resulting in limited performance in peak shaving, network-loss mitigation and voltage fluctuation suppression. Two-stage stochastic programming realizes balanced optimization over multiple scenarios and yields better peak-shaving and voltage improvement than the deterministic scheme; however, the number of scenarios is limited such that extreme fluctuation conditions cannot be fully covered. The proposed method simultaneously activates multiple regulation means including the time-delay flexibility of batch tasks, UPS charge-discharge and HVAC temperature control. Multi-dimensional resources are coordinated to smooth power-consumption peaks. The power flow across the whole network is co-optimized to balance power flow at each node and mitigate line overload. Fast charge-discharge of energy storage dampens abrupt load disturbances. Therefore, it achieves the optimal performance in peak-shaving ratio, network-loss reduction and voltage quality among the five schemes. Carbon emission reduction originates from two aspects: ① local accommodation of clean wind–solar energy to replace power purchased from thermal power units and ② reduction of network losses to cut down total system energy consumption. Conventional demand-response strategy barely brings additional new-energy accommodation and serves as the emission-reduction benchmark. Deterministic optimization has limited capability to handle fluctuations, so the improvement in new-energy accommodation is marginal. Two-stage stochastic programming achieves decent accommodation performance but is constrained by scenario samples. Benefiting from the deep coordination between load-side resources and energy storage, the proposed method maximizes wind–solar power absorption. A carbon emission reduction of 3.47 t CO₂ within a 24 h cycle is achieved compared with the conventional demand-response strategy, demonstrating the most prominent low-carbon benefit.

In this paper, two key variables, namely the maximum delay of batch tasks and carbon price, are selected for sensitivity analysis. The upper limit of batch-task delay determines the flexibility margin on the load side of data centers, while the carbon price characterizes the strength of low-carbon incentives. All other parameters are kept constant. The results of the sensitivity analysis are shown in Figures 10 and 11.

A larger upper-limit delay corresponds to a wider schedulable time window for batch tasks, which yields greater flexibility potential on the data-center load side and enables more clean-energy consumption during high wind–solar output periods. The total cost, curtailed energy and carbon emissions continuously decrease, and the peak-shaving performance is further improved. Nevertheless, the delay is constrained by business-level SLA requirements and cannot be infinitely enlarged in practical engineering. A baseline value of 4 h is adopted in this work.

As the carbon price rises, the weight of the carbon-emission cost term in the model increases. The model will prioritize the consumption of wind and solar power and reduce the purchase of thermal-power electricity, leading to a continuous drop in the total system carbon emissions. Nevertheless, partial economic performance has to be sacrificed to accommodate renewable energy, and the overall scheduling cost increases accordingly.

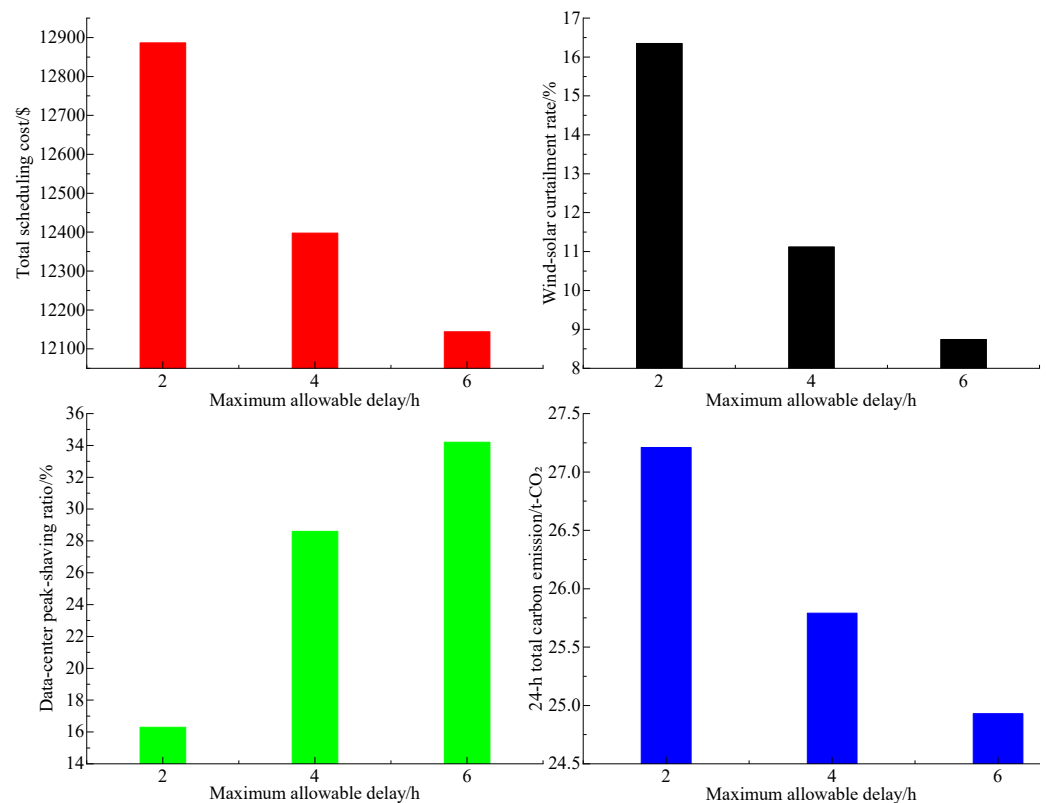


Figure 10. Sensitivity analysis results for the maximum delay of batch-processing tasks.

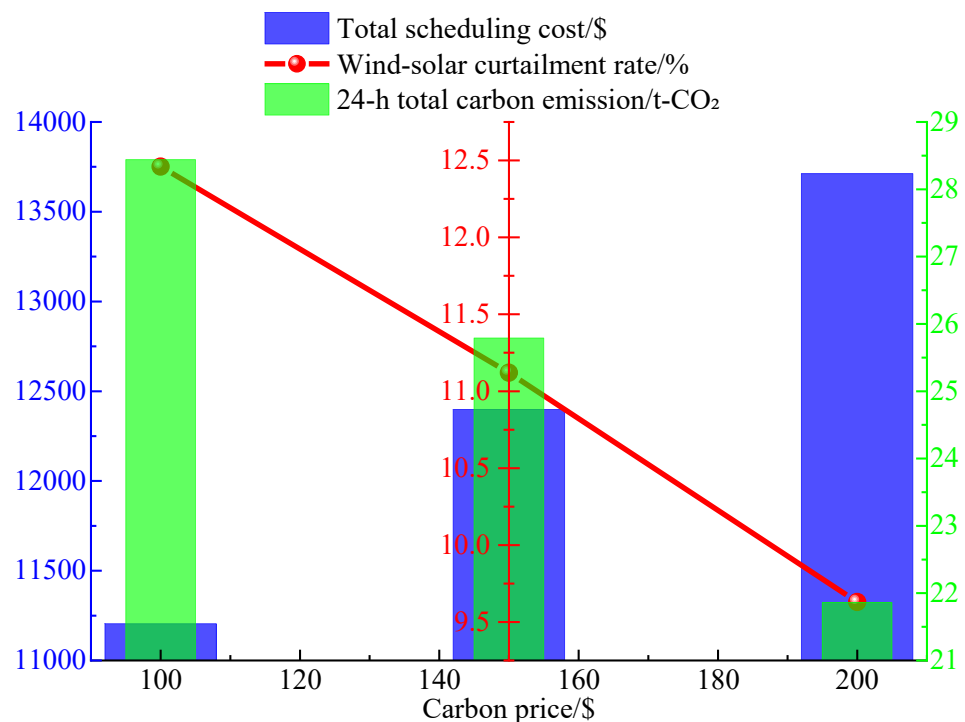


Figure 11. Sensitivity analysis results for carbon price variation.

5.3. Effectiveness Analysis of the Solution Algorithm

The model proposed in this paper is a stochastic-robust optimization model for the coupled data center–grid–energy storage system. It simultaneously involves 0–1 binary variables for batch-processing tasks, mutual-exclusivity constraints for UPS/energy-storage charge-discharge, nonlinear energy-consumption characteristics of HVAC, and non-convex

power-flow constraints. Therefore, it belongs to a nonlinear, non-convex, mixed-variable optimization problem. Common solution approaches include commercial convex solvers (Gurobi), standard PSO, Genetic Algorithm (GA), and Differential Evolution (DE). The hardware configuration for comparative experiments is an Intel i7-12700H processor with 16 GB of RAM, and the simulation platform is MATLAB R2023b. The performance of different solution algorithms is presented in Table 3 below.

Table 3. The performance of different solution algorithms.

Solution Algorithm	Total Scheduling Cost/\$	Number of Convergence Iterations	Single-Run Solving Time (2 Data Centers)/s	Single-Run Solving Time (6 Data Centers)/s
Gurobi	12,482.6	-	11.2	24.7
PSO	12,613.7	72	22.4	47.3
GA	12,573.8	96	30.1	63.5
DE	12,481.3	84	28.5	58.2
The proposed method	12,397.4	58	26.8	52.1

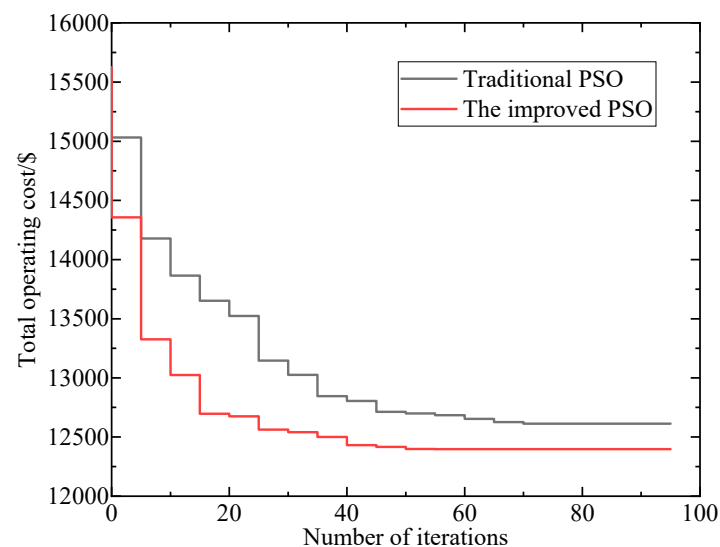
Gurobi is the fastest commercial solver in terms of computation speed. Nevertheless, strong nonlinearities exist in the energy consumption of IT equipment and HVAC cooling loads within the proposed model, which necessitates the introduction of convex approximation and relaxation. Although it yields the low objective-function value, some individual solutions may violate the original nonlinear constraints (e.g., air-conditioner COP constraints and the nonlinear relationship of server power), producing pseudo-optimal solutions that cannot be directly deployed in practical engineering. Accordingly, Gurobi is not suitable for directly solving the original mechanistic model without simplifications in this paper. Standard PSO adopts a fixed inertia weight. In the later iteration stage, population diversity diminishes rapidly, leading to premature convergence. It finally achieves a total scheduling cost of \$12,613.7, which is markedly inferior to that of the improved PSO. Despite acceptable solving speed, standard PSO tends to get stuck in local optima with unstable solution quality and large fluctuations across multiple simulation runs. GA explores the solution space via crossover and mutation operations and exhibits decent global search capability; however, multiple hyper-parameters such as crossover probability and mutation probability require tuning. The population converges slowly in late iterations and demands more iteration steps, hence resulting in the largest number of iterations and considerably increased computational time. DE generates new individuals through differential mutation and performs well for low-to-medium-dimensional problems. As the model dimension rises (i.e., more data centers and sharply increased task-scheduling variables), population diversity decays rapidly and the search efficiency degrades. Its computation time is higher than that of standard PSO. The improved PSO proposed in this paper adopts an adaptive inertia-weight strategy based on a premature-convergence indicator: a larger inertia weight is employed in early iterations to enhance global search, whereas a smaller weight is adopted in later iterations to strengthen local exploitation. Distinct update rules are applied for elite individuals and ordinary particles. The number of convergence iterations drops to 58, outperforming standard PSO, GA and DE. Premature convergence is avoided and a high-quality feasible solution of \$12,397.4 is obtained. Compared with GA and DE, the improved PSO requires fewer hyper-parameters and facilitates easy engineering implementation. Its computation time for small-scale cases is 26.8 s, slightly higher than standard PSO, yet the solution quality is substantially improved. When extended to large-scale scenarios, its computation time rises to 52.1 s.

Table 4 gives the statistical results of multiple repeated simulations.

Table 4. The statistical results of multiple repeated simulations.

Algorithm	Optimal Total Scheduling Cost (\$)	Worst Total Scheduling Cost (\$)	Average Value Over 20 Runs (\$)	Standard Deviation	Average Convergence Iteration Number	Average Single-Run Computation Time (s)
Traditional PSO	12,613.7	13,172.5	12,846.1	142.3	72	22.4
The improved PSO	12,397.4	12,541.6	12,452.8	48.6	58	26.8

Due to the fixed inertia weight, the standard PSO suffers from premature convergence. Its standard deviation across 20 repeated simulations reaches 142.3, indicating large solution fluctuations and a significant gap between the optimal and worst-case solutions. The improved PSO proposed in this paper introduces a premature-judgment index, adaptive inertia weight and weight truncation strategy. Its standard deviation over 20 repeated simulations is only 48.6, which greatly improves solution stability. The average number of convergence iterations decreases from 72 to 58, achieving a faster convergence speed. However, the calculation logic for the premature-judgment index is added in each generation, and the average computation time increases from 22.4 s to 26.8 s. Even so, it still satisfies the engineering requirements for day-ahead scheduling. The average fitness decline curves of the two algorithms are plotted in Figure 12, intuitively demonstrating that the improved PSO converges faster and is less prone to falling into local optima.

**Figure 12.** Convergence curves of the standard and improved PSO algorithms.

To verify the applicability of the proposed solution algorithm under multiple scenarios, Table 5 presents the statistical results obtained from multiple independent Monte Carlo runs. A 95% confidence level is adopted for the confidence interval. A feasible solution is defined as the one that satisfies all constraints including voltage, power flow, SOC, and task delay.

Table 5. Statistical results obtained from multiple independent Monte Carlo runs.

Algorithm	Standard Deviation	95% Confidence Interval	Feasible-Solution Ratio
PSO	142.3	[12,779.4, 12,912.8]	70.0%
GA	97.5	[12,528.1, 12,619.5]	80.0%
DE	74.1	[12,446.5, 12,516.1]	85.0%
PSO	48.6	[12,429.9, 12,475.7]	95.0%

The standard PSO suffers from premature convergence. It yields a large standard deviation over 20 trials with a feasible-solution ratio of only 70%, and produces infeasible scheduling schemes that violate constraints after multiple iterations. Although GA and DE achieve a moderate improvement in the feasible-solution ratio, their standard deviations remain relatively large. In this paper, an adaptive inertia-weight strategy is introduced into the improved PSO to enhance population diversity. Combined with variable-clamping repair and penalty-function-based constraint handling, the feasible-solution ratio is increased to 95%, the standard deviation is markedly reduced, and the 95% confidence interval becomes narrower. Consequently, the proposed algorithm exhibits substantially better solution stability than the comparison algorithms. Meanwhile, the average number of convergence iterations is decreased, leading to faster convergence.

6. Conclusions

This paper addresses the conflict between high energy consumption of data centers and the accommodation of distributed renewable energy in distribution networks amid the rapid growth of computing-intensive services. It fully exploits multi-dimensional spatiotemporal flexible resources within data centers, including IT equipment, air-conditioning cooling, batch-processing tasks, and UPS energy storage. Combined with distributed wind-solar generation and grid-side energy storage in distribution networks, a stochastic-robust collaborative trading-scheduling model is established. An improved particle swarm optimization algorithm is adopted to solve the proposed model. Multiple groups of simulation comparisons are carried out on a modified IEEE 33-node system, and the main numerically validated conclusions are drawn as follows:

- (1) Integrated modeling can effectively characterize the multi-link flexible coupling relationships inside data centers. Cross-time-slot migration of batch-processing tasks under business-level SLA delay constraints can jointly alter IT loads, air-conditioning cooling power consumption, and UPS charge-discharge behaviors. When the above multi-dimensional resources are coordinately involved in scheduling, the load-side regulation potential can be significantly unleashed compared with schemes relying merely on energy storage or single demand-response measures. Simulation results demonstrate that the proposed strategy achieves a 28.6% peak-shaving ratio for data-center loads under the constraint of 4 h maximum task delay.
- (2) A multi-scenario clustering method is employed to characterize the uncertainty of wind-solar output, and a stochastic-robust collaborative trading model is constructed. A carbon-emission cost term is incorporated into the objective function to realize joint economic and low-carbon optimization. Numerical case studies reveal that compared with conventional demand-response schemes, the overall system scheduling cost decreases by 10.7%, and a carbon emission reduction of 3.47 t CO₂ is achieved over the 24 h simulation horizon. Meanwhile, the distribution-network power flow is well balanced; the maximum node voltage deviation is suppressed to 0.041 p.u., improving the voltage operation performance of the distribution network.
- (3) Targeting the nonlinear and non-convex characteristics of the model, an improved particle swarm optimization algorithm is developed, in which a premature-convergence indicator is introduced to adaptively adjust the inertia weight. Results from 20 repeated Monte Carlo trials show that the feasible-solution ratio of the proposed algorithm reaches 95%, and its solution stability outperforms meta-heuristic algorithms such as standard PSO, GA and DE. The average computation time for day-ahead scheduling scenarios is 26.8 s, which satisfies the engineering scheduling requirements of small-to-medium-sized data-center clusters.

Future research can be carried out in the following directions: (1) For large-scale multi-data-center clusters, investigate task clustering, problem decomposition and parallel-solving strategies to reduce the computational burden of meta-heuristic algorithms and realize minute-level scheduling for practical engineering applications. (2) Combine transient-simulation tools to verify the system operation stability of scheduling schemes under fault disturbances. Further research on market-bidding mechanisms can be conducted to refine the transaction procedures for data centers participating in electricity markets.

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Abbreviations/Nomenclature

Abbreviation	Full name
PSO	Particle Swarm Optimization
QoS	Quality of service
HVAC	Heating, ventilation and air conditioning
PUE	Power Usage Effectiveness
DS	Distribution system
GA	Genetic Algorithm
DE	Differential Evolution
Variables	Meaning
$\hat{E}_t^{IT}$ and E_t^{IT}	The IT energy consumption of the data center in time period t before and after demand response
$\hat{E}_t^{DC}$ and E_t^{DC}	The overall energy consumption of the data center in time period t before and after demand response
$\hat{\lambda}_t$ and λ_t	The workload demand of the data center in time period t before and after demand response
E^{idle} and E^{max}	The idle power and peak power of a single server
μ	The service rate of a single server
m_t	The number of active servers of the data center in time period t
M	The total number of servers deployed in the data center
γ_{PUE}	The energy efficiency level of the data center
η_t	The average service utilization of the data center during time period t
CPU^{max}	The upper limit of CPU utilization
L_t^{cool}	The cooling load of air conditioners during period t
L_t^{IT}	The heat generated by IT equipment in period t
L_{env}	Environmental heat
t_1	The heat transfer coefficient of the computer room environment

S	The heat transfer area inside the computer room
T_t^{out} and T_t^{in}	The outdoor and indoor temperature of the computer room
γ_t^{cop}	The ratio of cooling load to air conditioning energy consumption
$y_{k,t}$	The processing demand of type- k tasks arriving at time interval t
$E_{delay}^{task,k}$	The maximum allowable delay interval for type- k tasks
F_j^k	The 0–1 binary parameter
C_j^{proc}	The maximum available processing capacity for batch processing at interval j
S_t^u	The start interval of type- u tasks arriving at interval t
P_u	Required consecutive processing duration
η^{ch} and η^{dis}	The charging and discharging efficiencies of UPS energy storage
C_{max} and D_{max}	The maximum charging and discharging power
SOC_t	The state of charge of UPS energy storage at time t
c_t and d_t	Charging and discharging power of UPS
E_{UPS}^N	Rated energy storage capacity of UPS
ϕ_k	The power consumption corresponding to unit computation volume of type- k tasks
$y_{k,t}^{base}$	The baseline scheduling scheme
$\Delta y_{k,t}$	The transferable/reducible load volume in each interval relative to the baseline
P_t^{wt}	The wind turbine output power during time interval t
v	The current wind speed
v_{in}	The cut-in wind speed
v_{out}	The cut-out wind speed
v_r	The rated wind speed
P_N^{WT}	The rated power of the wind turbine
k_1 and k_2	The linear transformation coefficients for wind power output
k' and c	The shape parameter and scale parameter of the Weibull distribution for wind speed
P_t^{pv}	The photovoltaic output power during time interval t
G_t and G_N	The actual solar irradiance and rated solar irradiance at interval t
$T_t^{pv}, T_N^{pv}, T_t^{amb}$ and T^{noct}	The actual temperature of photovoltaic panels, reference temperature, ambient temperature at interval t and nominal operating temperature in sequence
P_N^{pv}	The rated power of photovoltaic equipment
β	The power temperature coefficient of photovoltaic cells
ξ and ψ	The shape parameters of the Beta distribution
P_{max}^{pv}	The maximum power generation of photovoltaic systems
a_1, a_2, a_3, a_4 and a_5	The daily output ratio, daily peak-valley difference ratio, peak output time, valley output time, and daily average output of renewable energy
P_{av}^{renew}	The daily average output of renewable energy
P_{max}^{renew} and P_{min}^{renew}	The maximum and minimum renewable energy output
$y_{s,m}^*$ and $y_{s,m}$	The standard value and indicator value of the m -th renewable energy output indicator under the s -th scenario
y_m	The dataset composed of the m -th renewable energy output indicator
π_s	The probability of scenario s
Ω_s	The scenario set
$C_t^{grid}, C_t^{loss}, C_t^p$ and C_t^{carbon}	The power purchase cost of the DS from the upper-level grid, network loss cost, renewable energy curtailment cost and carbon emission cost during time period t
C_t^{DC}	The total operation cost

λ_t^{grid}	The electricity price for the DS purchasing power from the upper-level grid in period t
P_t^{grid}	The power purchased by the DS from the upper-level grid during time period t
λ_t^{loss}	The network loss cost per unit transmission power
$a_{l,t}$	The square of the current flowing through branch l in period t
r_l	The resistance of branch l
λ_t^{wt} and λ_t^{pv}	The wind power curtailment cost and photovoltaic power curtailment cost
P_t^{wt} and P_t^{pv}	The active power output of wind turbine w and photovoltaic unit v in period t
P_{max}^{wt} and P_{max}^{pv}	The predicted maximum output of wind turbines and photovoltaics in period t
λ_{carbon}	The carbon price
e_{grid}	Carbon-emission factor for grid power purchase side
E_{total}	The total carbon-dioxide emissions
$P_{l,t}^{DN}$ and $P_{b,t}^{DN}$	The active power flowing through line b and line l at time t
Q_t^{grid}	The reactive power purchased by the distribution network from the upper-level grid at time t
$\tan \phi$	The power factor of data center loads
$Q_{b,t}^{DN}$ and $Q_{l,t}^{DN}$	The reactive power flowing through line b and line l at time t
x_l	The reactance of line l
$U_{n,t}$	The square of the voltage magnitude at node n at time t
$a_{l,max}$	The upper limit of the square of the current on branch l
$U_{n,max}$ and $U_{n,min}$	The upper and lower limits of the voltage magnitude at bus n
E_t^{ess}	The energy stored in the energy storage device during period t
E_{max}^{ess} and E_{min}^{ess}	The upper and lower limits of stored energy for the energy storage device
η^{char} and $\eta^{dischar}$	The charging and discharging efficiencies of the energy storage device
P_t^{char} and $P_t^{dischar}$	The charging and discharging power of the energy storage device in period t
E_0^{ess} and E_{24}^{ess}	The initial and final stored energy of the energy storage device
P_{rated}^{ess}	The rated charge-discharge power
$I_{t,char}$ and $I_{t,dischar}$	The binary variables corresponding to charging and discharging of the energy storage device in each period
w^t	The adaptive inertia weight of the t -th generation
r_1, r_2	Random numbers uniformly distributed in the interval $[0, 1]$
c_1, c_2	Learning factors
V_{im}^t	The velocity of particle i in the m -th dimension at the t -th iteration
X_{im}^t	The position of particle i in the m -th dimension at the t -th iteration
p_{im}^t	The personal best position of particle i up to the t -th iteration
p_{gm}^t	The global best position found by the swarm up to the t -th iteration
η	The premature-convergence index of the particle swarm
E_g	The optimal adaptive fitness value of particles
E_{avg}^*	The portion where the fitness value E_i outperforms its average adaptive fitness value E_{avg}
E_i^*	The historical personal best fitness value of particle i
t_{max}	The preset maximum iteration number of the algorithm
k_1	Constant greater than 1
Δ	The adjustment factor

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