

Optimal Scheduling of Data Center Virtual Power Plant in Electricity–Carbon Joint Market Under Uncertainty

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Abstract—As an emerging demand response (DR) resource, data centers (DCs) have garnered significant attention due to their ability to adapt to stochastic renewable energy fluctuations. To fully exploit the price signals from diverse markets and achieve the flexible complementarity between DCs and virtual power plant (VPP) resources, this paper proposes a coordinated framework for the data center virtual power plant (DCVPP) participating in the electricity–carbon joint market under uncertainty. Specifically, a refined model of power consumption for cooling system in DC is developed based on the second-order equivalent thermal parameter (ETP) theory, which enhances the accuracy of load modeling and maximizes the potential for DR. To address the penalty risks associated with forecast uncertainties in renewable energy generation and load demands, a risk-based reserve scheme is developed by integrating the Gaussian copula with two-sided superquantile theory. This scheme provides a coordinated mechanism for quantifying the correlations between forecast errors. On this basis, an optimal scheduling strategy of DCVPPs is formulated in the electricity–carbon joint market, which coordinates DC load flexibility with distributed energy resources to optimize economic performance and reduce carbon emissions. Case studies demonstrate that the proposed refined model achieves a root mean square error (RMSE) reduction ranging from 57.9% to 68.8%, and the risk-based reserve scheme reduces penalty costs by 24.4%. Furthermore, the integration of the carbon trading mechanism in the proposed optimal scheduling strategy results in an increase of \$259.9 in economic benefits and an average reduction of 14% in carbon emissions.

Index Terms—Data center (DC), electricity market, carbon market, virtual power plant (VPP), demand response, uncertainty, optimal scheduling, equivalent thermal parameter (ETP).

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I. INTRODUCTION

WITH the rapid advancement of information technology (IT) and the widespread adoption of Internet-based applications, the energy consumption of data centers (DCs) has attracted increasing attention [1]. Unlike conventional power loads, the DCs exhibit pronounced temporal and spatial flexibility, making them act as a novel class of large-capacity demand response (DR) resource when the real-time response capabilities and the flexible scheduling characteristics are fully considered [2]. Meanwhile, the increasing integration of renewable energy sources (RESs) introduces substantial operational uncertainty, and the coupling of electricity and carbon markets further increases system complexity. These challenges highlight the urgent need for advanced scheduling strategies that can enhance renewable energy utilization, reduce carbon emissions, and fully exploit the flexibility of DCs in future low-carbon energy systems.

Accurately modeling DC power consumption is essential for characterizing and exploiting its load flexibility. The total DC load consists of three primary components: IT equipment, cooling system, and other equipment. The IT equipment is responsible for processing user workloads, whereas the cooling system ensures effective heat dissipation to maintain the safe and reliable operation of the IT equipment. Typically, the power consumed by the IT equipment and cooling system accounts for 80%–90% of the total DC power consumption [3], [4]. Existing research on DC load modeling primarily focuses on the impact of operational conditions of IT equipment on overall DC energy consumption. The prevailing models include additive models [5], regression models [6], and linear models based on power usage effectiveness (PUE) [7]. To accurately characterize the strong coupling between the power consumption of the IT equipment and the cooling system, the effects of ambient temperature variations on DC load behavior and DR capability must be explicitly taken into account. Reference [8] proposes a DC load model based on the first-order equivalent thermal parameter (ETP) theory, but it fails to account for the indoor thermal mass differentiation, resulting in deviations between the simulated and actual load profiles under the dynamic operational conditions. Therefore, accurate DC load modeling requires an in-depth consideration of thermal environmental factors, which is essential for capturing load dynamics and

flexibility.

Unlike other flexible loads, DCs possess significant temporal load regulation potentials through batch workload scheduling mechanisms. Consequently, DC participation in DR programs has attracted increasing research interest, as it can enhance power system operation in a cost-effective and efficient way [9], [10]. Reference [11] proposes that DCs could minimize the carbon footprint and power cost by delaying the processing of flexible workloads. Reference [12] utilizes the scheduling flexibility of workloads and proposes a method for the DC workload scheduling, which effectively reduces the DC operational cost. Recently, as an effective solution to integrating distributed energy resources, data center virtual power plants (DCVPPs) have attracted rising attention in the DC energy management [13]. Reference [14] proposes an optimal power scheduling problem with a multisource virtual power plant (VPP) containing DC for maximizing the revenue. Considering the operational flexibility of the workloads and power supply devices, [15] builds a scheduling framework for DCVPPs. However, fully exploiting the operational flexibility of DCs and achieving coordinated optimization with internal flexible resources in DCVPPs to meet low-carbon economic objectives remain an open research challenge.

Participation in electricity markets under uncertainties arising from RESs and forecast errors introduces significant risks to the decision-making strategy of DCVPP. To hedge against the risks, the theory of quantile and superquantile, also known as the value at risk (VaR) and the conditional value at risk (CVaR), is employed to quantify the required reserve capacity and the expected value exceeding the reserve capacity [16]. In [17], the CVaR is employed in the stochastic model to manage the energy and reserve capacity, as well as to control the risk of VPP profit variability. By adopting the superquantile theory, [18] characterizes the economic penalties beyond the reserve capacity and optimizes the allocation of reserve capacity. It is found that the uncertainty is tackled by a confidence interval subjectively in the existing research, and therefore, the risks caused by the uncertainty beyond the confidence interval and the resulting economic penalties are not well quantified [19]. The temporal variability of penalties for the power deviations in electricity markets requires dynamic optimization of the upward and downward reserve capacity of such DCVPP. Furthermore, the forecast error parameters of different types of RESs and loads are mostly set independently in existing research, and the influence of the correlation between RESs and forecast errors on the reserve capacity is neglected [20]. Therefore, it is necessary to explicitly account for the correlation among forecast errors of RESs and loads in uncertainty modeling to investigate and analyze their interactive impacts on the day-ahead scheduling of DCVPP. A summary of existing literature is provided in Supplementary Material A Table SAI.

Accordingly, research on the optimal scheduling of DCVPP holds significant potential for effectively integrating the flexible regulation capabilities of DC loads with other distributed energy resources. Meanwhile, the evolution of electricity and carbon markets has led to increasingly com-

plex couplings among the energy, ancillary services, and carbon markets. This trend positions DCVPP as a pivotal participant in future electricity-carbon joint market transactions. To address the aforementioned research gaps, this paper proposes a coordinated framework for the DCVPP participating in electricity-carbon joint market under uncertainty. The power management framework of DCVPP is illustrated in Supplementary Material A Fig. SA1. The main contributions are summarized as follows.

1) To evaluate the DR potential of DC, a refined model of power consumption for cooling system in DC is developed based on the second-order ETP theory. This model improves the accuracy of load modeling, thus enabling more effective exploitation of load regulation potential and enhancing the operational flexibility of DCVPP.

2) To mitigate penalty risks arising from forecast uncertainties in RESs and loads, a risk-based reserve scheme is developed for DCVPP participating in the electricity market. By integrating the Gaussian copula with the two-sided superquantile theory, the scheme quantifies risks associated with both excess and insufficient power while accounting for forecast error correlations.

3) An optimal scheduling strategy of DCVPP participating in the electricity-carbon joint market is formulated. By coordinating the DR capability of DC load with the operational flexibility of distributed energy resources, the proposed strategy maximizes the DCVPP revenue in the electricity-carbon joint market while reducing carbon emissions.

The remainder of this paper is structured as follows. Section II presents the operational framework of DCVPP and the electricity-carbon joint market trading mechanisms. The DC modeling is formulated in Section III. Section IV introduces the optimal scheduling strategy of DCVPP participating in the electricity-carbon joint market. Section V focuses on the case studies. The conclusion is drawn in Section VI.

II. OPERATIONAL FRAMEWORK OF DCVPP AND ELECTRICITY-CARBON JOINT MARKET TRADING MECHANISMS

A. Operational Framework of DCVPP

This subsection presents the operational framework of a DCVPP participating in the electricity-carbon joint market, as illustrated in Fig. 1. The DCVPP dispatching center is assumed to manage a diversified portfolio of resources within a defined region, including DC, gas turbine (GT), wind turbine (WT), photovoltaic (PV) generator, energy storage (ES), and rigid load (RL). The DCVPP realizes the dispatching operation of energy equipment and implementation of the DR program at the DC side through the DCVPP dispatching center, thereby meeting the power demand of all users within the system.

Furthermore, the DCVPP is modeled as a price-taker player during the decision-making process of day-ahead optimal energy management [21]. Based on day-ahead forecasts, the DCVPP can purchase or sell electricity in the DAM and provide ancillary services to obtain the corresponding revenues. Meanwhile, it can also participate in the CET market to promote renewable energy consumption.

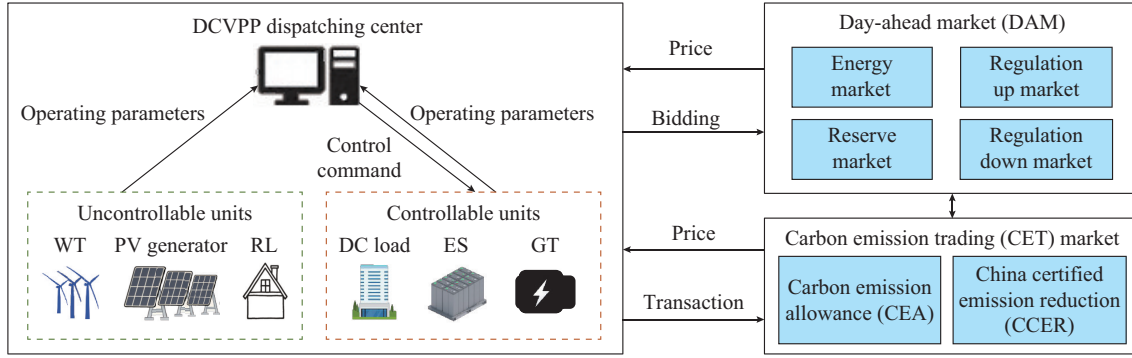


Fig. 1. Operational framework of DCVPP in electricity-carbon joint market.

Considering the coupling between the DAM and the CET market, the period in the cycle of carbon allowances and carbon clearance is assumed to be one day, which is aligned with the time scale of the DAM [22].

B. DAM

By participating in the DAM as a flexible power plant, the DCVPP can benefit from strategically selling electricity or providing ancillary services in response to fluctuating market prices. The proposed framework in this paper follows the product settings of the electricity market in Texas, USA, including the energy, reserve, and regulation up and down markets [18].

C. CET Market

The CET market treats the carbon emission rights as tradable commodities among emitters. When actual carbon emissions exceed the allocated allowances, emitters must either purchase additional allowances or incur penalty charges. In the CET market, the two primary trading products are CEA and CCER [23].

Under the CEA trading mechanism, regulators first set an overall cap on total carbon allowances, which are then allocated to individual emitters for subsequent spot trading at prevailing market prices [24]. The CEAs of the DCVPP are calculated as:

$$Q_t^{\text{CEA}} = \eta P_t^{\text{GT}} \quad (1)$$

where Q_t^{CEA} is the total amount of CEAs for the GT in DCVPP during time interval t ; η is the CEA factor per unit electricity for the GT; and P_t^{GT} is the generating power of GT.

The CCERs obtained from RESs in the DCVPP can be traded in the CET market, which is calculated as [25]:

$$Q_t^{\text{CC}} = \sum_{g \in \{\text{WT, PV}\}} (\varepsilon^{\text{OM}} \phi_g^{\text{OM}} + \varepsilon^{\text{BM}} \phi_g^{\text{BM}}) P_t^g \quad (2)$$

where Q_t^{CC} is the obtained CCER of DCVPP; ε^{OM} and ε^{BM} are the weights of the operating margin and build margin emission factors, respectively; ϕ_g^{OM} and ϕ_g^{BM} are the operating margin and build margin emission factors, respectively; and P_t^g is the generating power of RES g .

Carbon emissions within the DCVPP can be calculated as:

$$Q_t^{\text{CE}} = \chi P_t^{\text{GT}} + \kappa (P_t^{\text{chpur}} + P_t^{\text{Lpur}}) \quad (3)$$

where Q_t^{CE} is the actual carbon emission of DCVPP; χ is the

carbon emission factor of GT; κ is the carbon emission factor of thermal power unit; and P_t^{chpur} and P_t^{Lpur} are the charging power of ES and the power of loads through purchasing from the retail market, respectively.

III. DC MODELING

A. Workload Model

Figure 2 presents the practical architecture of DC operation. The workloads arriving at the IT equipment of DC can be classified into three categories: interactive, batch, and rigid workloads [16]. Interactive workloads require immediate processing. Batch workloads allow for flexible service time and can be delayed by hours, whereas the rigid workloads impose stringent requirements on either processing time or quality of service.

$$E_t^{\text{org}} = \lambda_t^{\text{org}} + \omega_t^{\text{org}} + \zeta_t^{\text{org}} \quad (4)$$

where E_t^{org} , λ_t^{org} , ω_t^{org} , and ζ_t^{org} are the original amounts of total workloads, interactive workloads, batch workloads, and rigid workloads arriving in DC, respectively.

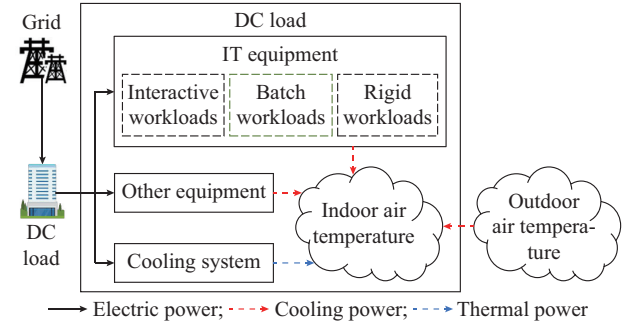


Fig. 2. Practical architecture of DC operation.

Batch workloads can be scheduled for execution within a specified time window, and hence their temporal shifting characteristics can be described as:

$$\begin{cases} \omega_t^{\text{flex}} = \omega_t^{\text{org}} + \sum_{t'=1}^{t-1} \omega_{t'} - \sum_{t''=t+1}^T \omega_{t''} \\ \sum_{t''=t+1}^T \omega_{t''} \leq \omega_t^{\text{org}} \end{cases} \quad (5)$$

where $\omega_{t'}$ is the batch workload migrated from time t' to t ; $\omega_{t''}$ is the batch workload transferred out from time t to t'' ;

and ω_t^{flex} is the amount of batch workloads processed after flexible shifting.

B. Modeling of DC Load Based on Second-order ETP Theory

The total power demand of DC, denoted as P_t^{DC} , can be decomposed into three components: the power consumption of IT equipment P_t^{IT} , the power consumption of cooling system P_t^{cool} , and the power consumption of other equipment P_t^{others} , which can be expressed as:

$$P_t^{\text{DC}} = P_t^{\text{IT}} + P_t^{\text{cool}} + P_t^{\text{others}} \quad (6)$$

P_t^{IT} is determined by the number of active servers and the corresponding workloads, with all servers assumed identical and the workloads evenly distributed. Thus, P_t^{IT} is given by [26]:

$$P_t^{\text{IT}} = n_t^{\text{on}} P_{\text{idle}} + (P_{\text{peak}} - P_{\text{idle}}) u_t n_t^{\text{on}} \quad (7)$$

$$u_t = \frac{E_t}{n_t^{\text{on}} \zeta} \quad (8)$$

where n_t^{on} is the number of active servers; E_t is the actual processed workload; u_t is the central processing unit (CPU) utilization rate of active servers; ζ , P_{idle} , and P_{peak} are the average service rate, idle power, and peak power of each active server, respectively.

To maintain the internal ambient temperature of DC, the cooling system supplies cooling power to eliminate the heat generated by IT equipment and other equipment, as well as that transferred from the outdoor environment [8]. Based on the second-order ETP theory [27], the relations among indoor and outdoor temperatures, cooling power, and the power consumption of IT equipment and other equipment are modeled as:

$$\begin{cases} \frac{d\text{Tem}_t^{\text{a}}}{dt} = -\frac{R_{\text{a}} + R_{\text{s}}}{C_{\text{a}} R_{\text{a}} R_{\text{s}}} \text{Tem}_t^{\text{a}} + \frac{\text{Tem}_t^{\text{s}}}{C_{\text{a}} R_{\text{s}}} + \frac{\text{Tem}_t^{\text{o}} + R_{\text{a}} Q_t^{\text{DC}}}{C_{\text{a}} R_{\text{a}}} \\ \frac{d\text{Tem}_t^{\text{s}}}{dt} = \frac{\text{Tem}_t^{\text{a}} - \text{Tem}_t^{\text{s}}}{C_{\text{s}} R_{\text{s}}} \end{cases} \quad (9)$$

$$Q_t^{\text{DC}} = k^{\text{IT}} P_t^{\text{IT}} + P_t^{\text{others}} - k^{\text{cop}} P_t^{\text{cool}} \quad (10)$$

where Tem_t^{a} and Tem_t^{s} are the indoor air temperature and indoor solid temperature, respectively; Tem_t^{o} is the outdoor air temperature; C_{a} and C_{s} are the heat capacities of indoor air and indoor solid, respectively; R_{a} is the thermal resistance between the indoor air and the external environment; R_{s} is the thermal resistance between the indoor solid and indoor air; Q_t^{DC} is the total thermal power of DC; k^{IT} is the heat factor of IT equipment; and k^{cop} is the coefficient of performance of the cooling system. The analytical recursive form of (9) can be expressed as [27]:

$$\begin{bmatrix} \text{Tem}_t^{\text{a}} \\ \text{Tem}_t^{\text{s}} \end{bmatrix} = \mathbf{A} \begin{bmatrix} \text{Tem}_{t-1}^{\text{a}} \\ \text{Tem}_{t-1}^{\text{s}} \end{bmatrix} + \mathbf{B} (\text{Tem}_t^{\text{o}} + Q_t^{\text{DC}} R_{\text{a}}) \quad (11)$$

$$\begin{cases} \mathbf{A} = \begin{bmatrix} M - \frac{b}{2} Z + (C_{\text{s}} R_{\text{s}})^{-1} Z & (C_{\text{a}} R_{\text{s}})^{-1} Z \\ (C_{\text{s}} R_{\text{s}})^{-1} Z & M + \frac{b}{2} Z - (C_{\text{s}} R_{\text{s}})^{-1} Z \end{bmatrix} \\ \mathbf{B} = \begin{bmatrix} 1 - M - \frac{b}{2} Z + (C_{\text{a}} R_{\text{a}})^{-1} Z & 1 - M - \frac{b}{2} Z \end{bmatrix}^{\text{T}} \end{cases} \quad (12)$$

$$\begin{cases} Z = \frac{e^{\frac{1}{2}(-b + \sqrt{b^2 - 4c})\Delta t} - e^{\frac{1}{2}(-b - \sqrt{b^2 - 4c})\Delta t}}{\sqrt{b^2 - 4c}} \\ M = \frac{e^{\frac{1}{2}(-b + \sqrt{b^2 - 4c})\Delta t} + e^{\frac{1}{2}(-b - \sqrt{b^2 - 4c})\Delta t}}{2} \\ b = (C_{\text{a}} R_{\text{a}})^{-1} + (C_{\text{a}} R_{\text{s}})^{-1} + (C_{\text{s}} R_{\text{s}})^{-1} \\ c = (C_{\text{a}} C_{\text{s}} R_{\text{a}} R_{\text{s}})^{-1} \end{cases} \quad (13)$$

where $\mathbf{A}$ and $\mathbf{B}$ are the parameter matrices in recursive form; and b , c , Z , and M are the auxiliary variables introduced for notational convenience, which are used solely to simplify the expressions of $\mathbf{A}$ and $\mathbf{B}$.

Based on the combination of (10)-(13), the power consumption of cooling system is derived through the second-order ETP theory as:

$$\begin{cases} Q_t^{\text{DC}} = \frac{\text{Tem}_t^{\text{a}} - A_{11} \cdot \text{Tem}_{t-1}^{\text{a}} - A_{12} \cdot \text{Tem}_{t-1}^{\text{s}}}{B_{11} R_{\text{a}}} - \frac{\text{Tem}_t^{\text{o}}}{R_{\text{a}}} \\ P_t^{\text{cool}} = \frac{k^{\text{IT}} P_t^{\text{IT}} + P_t^{\text{others}} - Q_t^{\text{DC}}}{k^{\text{cop}}} \end{cases} \quad (14)$$

where A_{11} and A_{12} are the (1, 1) and (1, 2) elements of matrix $\mathbf{A}$, respectively; and B_{11} is the (1, 1) element of matrix $\mathbf{B}$.

The power consumption of other equipment typically constitutes only a small proportion of the total DC load. Therefore, it is assumed to be 10% of the combined power consumption of IT equipment and cooling system.

IV. OPTIMAL SCHEDULING STRATEGY OF DCVPP PARTICIPATING IN ELECTRICITY-CARBON JOINT MARKET

The overall structure of the proposed strategy is illustrated in Fig. 3, which comprises uncertainty modeling, electricity-carbon market participation, and DAM scheduling optimization. In practical DCVPP operations, the forecast errors in loads and RESs introduce substantial uncertainty into system operation. To mitigate the associated deviation risks, quantiles and superquantiles are adopted to estimate reserve capacity requirements and penalty risks, respectively. Meanwhile, the electricity and carbon markets provide market signals for the day-ahead optimal scheduling strategy. Based on these inputs, the optimization model maximizes the net profit of the DCVPP by coordinating purchase or sale of electricity, DR plan of DC, charging/discharging strategy for ES, and reserve allocation under uncertainties.

A. Uncertainty Modeling of Forecast Errors

Numerous studies have been undertaken to investigate the modeling of the forecast errors of loads and RESs [20], [28]. Without loss of generality, it is assumed that the probability distributions of WT, PV, DC load, and RL forecasts are Gaussian, with the mean values equal to the forecast values and the standard deviations equal to 30%, 20%, 15%, and 20% of the mean values, respectively. The correlation coefficient between RL and DC load is 0.65. The correlation coefficients between loads and PV output, as well as WT output, are 0.43 and -0.57, respectively. The correlation coefficient between PV output and WT output is assumed to be -0.31.

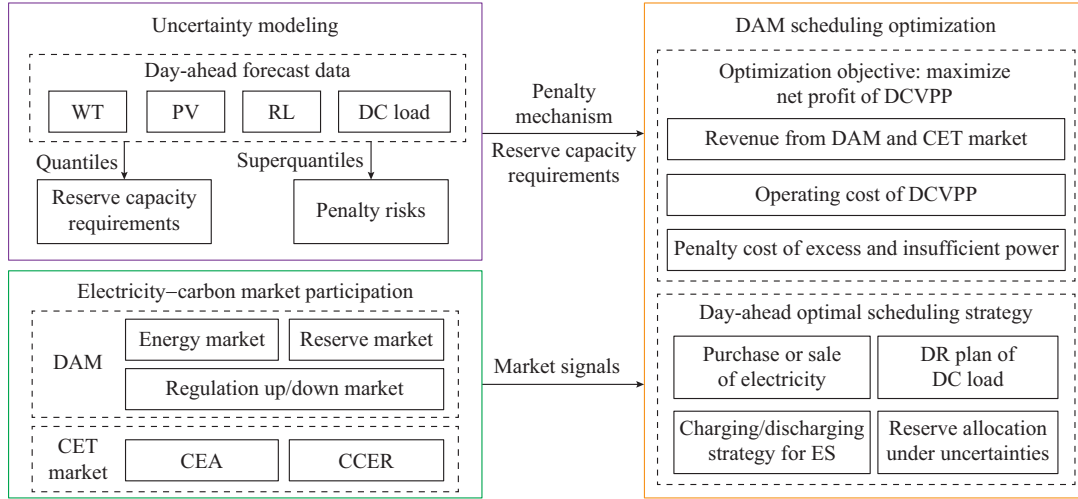


Fig. 3. Overall structure of proposed strategy for DCVPP.

The forecast errors are modeled by their related probability density functions (PDFs) $f(x)$ and cumulative distribution functions (CDFs) $F(x)$, which can be expressed as:

$$f(x) = (2\pi\sigma^2)^{-0.5} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \quad (15)$$

$$F(x) = \int_{-\infty}^x f(t) dt \quad (16)$$

where x is the uncertain parameter; σ is the standard deviation parameter; and μ is the mean value of the uncertain parameter.

To address the issue of estimation bias in the reserve capacity of DCVPP arising from the correlation, the Gaussian copula is used to accurately deal with the correlation among random variables [29]. Suppose the forecast errors in DCVPP during the same period as an m -dimensional random input matrix $X = [X_1, X_2, \dots, X_i, \dots, X_m]^T$ with Spearman correlation matrix ρ_X , where X_i is the i^{th} row vector of random variables.

Firstly, the quasi-Monte Carlo simulation (QMCS) method [30] is employed to generate the sample points $V = [V_1, V_2, \dots, V_i, \dots, V_m]^T$ efficiently from the unified and independent standard normal distributions, where V_i is the standard normal sample sequence corresponding to the i^{th} random variable.

Then, the standard normally distributed samples $Z = [Z_1, Z_2, \dots, Z_i, \dots, Z_m]^T$ with Spearman correlation matrix L_Z are generated by using the Cholesky decomposition, where Z_i is the correlated standard normal sample sequence corresponding to the i^{th} random variable after the correlation transformation.

$$\begin{cases} Z = L_Z V \\ 2\sin(\pi\rho_X/6) = L_Z L_Z^T \end{cases} \quad (17)$$

Based on the principle of equal probability transformation, Z is converted into the original probability spaces and the correlated samples following different distributions $X = [X_1, X_2, \dots, X_i, \dots, X_m]^T$ are obtained using inverse transfor-

mation as:

$$X_i = F_i^{-1}(\Phi(Z_i)) \quad (18)$$

where $\Phi(\cdot)$ is the standard normal CDF; and $F_i^{-1}(\cdot)$ is the inverse function of CDF for the i^{th} random variable.

B. Risk-based Reserve Scheme for DCVPP

Two-sided quantiles and superquantiles are employed to characterize the tail behavior of forecast errors. For a given confidence level β , α_1 and α_2 denote the probabilities of insufficient power and excess power, respectively. The lower and upper quantiles of the random variables are denoted by q_{α_1} and q_{α_2} , and the corresponding superquantiles, representing the expected deviations in the lower and upper tail regions beyond q_{α_1} and q_{α_2} , are denoted by sq_{α_1} and sq_{α_2} , respectively. This subsection presents the mechanism of two-sided quantiles and superquantiles, as illustrated in Fig. 4, with its calculation for random variables expressed as [31]:

$$\begin{cases} q_{\alpha_1} = F^{-1}(\alpha_1) \\ q_{\alpha_2} = F^{-1}(1 - \alpha_2) \end{cases} \quad (19)$$

$$\begin{cases} sq_{\alpha_1} = \alpha_1^{-1} \int_{-\infty}^{q_{\alpha_1}} tf(t) dt \\ sq_{\alpha_2} = \alpha_2^{-1} \int_{q_{\alpha_2}}^{+\infty} tf(t) dt \end{cases} \quad (20)$$

$$\alpha_1 + \alpha_2 + \beta = 1 \quad (21)$$

Typically, to facilitate the calculation of q_{α_1} , q_{α_2} , sq_{α_1} , and sq_{α_2} , QMCS method is employed to sample from the PDF of continuous random variables. This allows for the direct determination of approximate values based on the correlated QMCS samples obtained from the Gaussian copula.

For the row vector $X_i = [x_1, x_2, \dots, x_n]^T$ in the generated correlated sample matrix X , the sample values are sorted in ascending order to obtain the ordered result $x_{(1)} \leq x_{(2)} \leq \dots \leq x_{(n)}$, where $x_{(i)}$ is the i^{th} order statistic of X_i , namely the i^{th} smallest value among the sample points after sorting. The quantiles and the superquantiles can be calculated as:

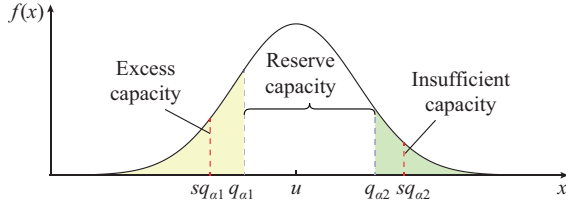


Fig. 4. Mechanism of two-sided quantiles and superquantiles.

$$\begin{cases} q_{a_1} = x_{(\lfloor a_1 n \rfloor)} \\ q_{a_2} = x_{(\lfloor (1-a_2)n \rfloor)} \end{cases} \quad (22)$$

$$\begin{cases} sq_{a_1} = (a_1 n)^{-1} \sum_{i=k+1}^n x_{(i)} & k = \lfloor a_1 n \rfloor \\ sq_{a_2} = [(1-a_2)n]^{-1} \sum_{i=k+1}^n x_{(i)} & k = \lfloor (1-a_2)n \rfloor \end{cases} \quad (23)$$

where $\lfloor \cdot \rfloor$ represents the floor function, which rounds a number down to the closest integer; and k is the cutoff index in the ordered sample set, determined by the sample size and the tail probability. The differences between the two-sided superquantiles and quantiles are used to determine the penalty capacity as:

$$\begin{cases} P_{\mathcal{R},t}^+ = q_{\mathcal{R},a_1}(t) - sq_{\mathcal{R},a_1}(t) & \mathcal{R} \in \{\text{WT, PV, DC, RL}\} \\ P_{\mathcal{R},t}^- = sq_{\mathcal{R},a_2}(t) - q_{\mathcal{R},a_2}(t) & \mathcal{R} \in \{\text{WT, PV, DC, RL}\} \end{cases} \quad (24)$$

where $P_{\mathcal{R},t}^+$ and $P_{\mathcal{R},t}^-$ are the excess capacity and insufficient capacity of the random power source $\mathcal{R}$, respectively; $q_{\mathcal{R},a_1}$ and $q_{\mathcal{R},a_2}$ are the lower and upper quantiles of $\mathcal{R}$, respectively; and $sq_{\mathcal{R},a_1}$ and $sq_{\mathcal{R},a_2}$ are the expected deviations in the lower and upper tail regions of $\mathcal{R}$, respectively. Note that these reserve capacities are introduced as explicit decision variables, rather than quantities derived from a fixed confidence level.

C. Objective Function

The objective of the proposed strategy is to maximize the net profit of DCVPP in the electricity-carbon joint market, which is defined as the gross profit Y_{DCVPP} minus the associated costs C_{DCVPP} , and can be expressed as:

$$\max(Y_{\text{DCVPP}} - C_{\text{DCVPP}}) \quad (25)$$

$$Y_{\text{DCVPP}} = Y^E + Y^{\text{RS}} + Y^{\text{RU}} + Y^{\text{RD}} + Y^{\text{CET}} = \sum_{t=1}^{24} \left(\sum_i p_t^i P_t^i + Y_t^{\text{CET}} \right) \quad (26)$$

$$C_{\text{DCVPP}} = \sum_j C_j + C_L + C_{\text{CO}_2} + C^+ + C^- \quad (27)$$

where Y^E , Y^{RS} , Y^{RU} , Y^{RD} , and Y^{CET} are the daily gross profits from the energy, reserve, regulation up, regulation down, and CET markets, respectively; p_t^i and P_t^i are the market price and bidding capacity of DCVPP in market i including energy, reserve, regulation up, and regulation down (denoted by superscripts E, RS, RU, and RD), respectively; Y_t^{CET} is the hourly gross profit of DCVPP in the CET market; and C_j , C_L , C_{CO_2} , C^+ , and C^- are the daily costs of power source

j including wind power and PV, loads, carbon emissions, excess penalty capacity, and insufficient penalty capacity, respectively.

1) Gross Profit of CET Market and Carbon Emission Cost

Under the regulations of CET market, the offset ratio of CCERs to CEAs is capped at 5% of the total allowances being offset. Carbon emissions are initially covered using CEAs. When carbon emissions exceed the allocated CEAs, CCERs may partially cover the excess carbon emissions, while any remaining deficit must be compensated through allowance purchases in the CET market [25]. Furthermore, surplus CEAs and CCERs can be traded to generate additional revenue. Accordingly, the gross profit from CET market participation and the associated carbon emission costs are calculated as:

$$\Delta Q_t = Q_t^{\text{CE}} - Q_t^{\text{CEA}} \quad (28)$$

$$C_{\text{CO}_2} = \sum_{t=1}^{24} C_t^{\text{CET}} \quad (29)$$

$$C_t^{\text{CET}} = \begin{cases} 0 & \Delta Q_t \leq r^{\text{CC}} Q_t^{\text{CEA}} \\ [Q_t^{\text{CE}} - (1+r^{\text{CC}})Q_t^{\text{CEA}}] p^{\text{CEA}} & \Delta Q_t > r^{\text{CC}} Q_t^{\text{CEA}} \end{cases} \quad (30)$$

$$Y_t^{\text{CET}} = \begin{cases} Q_t^{\text{CC}} p^{\text{CC}} - \Delta Q_t p^{\text{CEA}} & \Delta Q_t \leq 0 \\ (Q_t^{\text{CC}} - \Delta Q_t) p^{\text{CC}} & 0 < \Delta Q_t \leq r^{\text{CC}} Q_t^{\text{CEA}} \\ (Q_t^{\text{CC}} - r^{\text{CC}} Q_t^{\text{CEA}}) p^{\text{CC}} & \Delta Q_t > r^{\text{CC}} Q_t^{\text{CEA}} \end{cases} \quad (31)$$

where ΔQ_t is the deviation of actual carbon emissions from the total amount of CEAs; C_t^{CET} is the hourly cost of DCVPP in the CET market; r^{CC} is the CCER offset ratio; and p^{CEA} and p^{CC} are the trading prices of CEA and CCER in the CET market, respectively.

2) Generation Costs of WT, PV, ES, and GT in DCVPP

The generation costs of WT and PV are adopted from [32], while the detailed cost formulations and parameters for ES and GT are available in [18] and [33].

3) Costs of Loads (DC and RL) in DCVPP

$$C_L = C_{\text{pur}} + C_{\text{DR}} \quad (32)$$

$$\begin{cases} C_{\text{pur}} = \sum_{t=1}^{24} P_t^{\text{Lpur}} \kappa^E p_t^E \\ C_{\text{DR}} = \delta_\omega \sum_{t=1}^{24} \sum_{t'=t+1}^{24} \omega_{t'}(t'-t) \end{cases} \quad (33)$$

where C_{pur} is the cost of power purchased from the retail market; C_{DR} is the cost of the DR program; δ_ω is the cost of migrating per unit batch workload over the time domain; κ^E is the ratio of the retail market price to the energy market price, which is set to be 1.45; and p_t^E is the market price in the energy market [18].

4) Penalty Costs of Excess and Insufficient Power

$$C^+ = \sum_{t=1}^{24} \varphi^+ p_t^E \sum_{\mathcal{R}} \alpha_{\mathcal{R},t} P_{\mathcal{R},t}^+ \quad (34)$$

$$C^- = \sum_{t=1}^{24} \varphi^- p_t^E \sum_{\mathcal{R}} \alpha_{\mathcal{R},t} P_{\mathcal{R},t}^- \quad (35)$$

where φ^+ and φ^- are the deviation penalty coefficients of ex-

cess and insufficient power, respectively; and $\alpha_{\mathcal{R}1,t}$ and $\alpha_{\mathcal{R}2,t}$ are the probabilities corresponding to the occurrence of the excess and insufficient power scenarios, respectively.

D. Problem Constraints

1) Constraints of Bidding Capacity of DCVPP

$$P_t^E = P_t^{\text{WT}} + P_t^{\text{PV}} + P_t^{\text{disch}} + P_t^{\text{GT}} - P_t^{\text{LVPP}} - P_t^{\text{chVPP}} \quad (36)$$

$$P_t^\tau = P_{\text{ES},t}^\tau + P_{\text{GT},t}^\tau \quad \tau \in \{\text{RS}, \text{RU}, \text{RD}\} \quad (37)$$

where P_t^{disch} and P_t^{chVPP} are the discharging and charging capacities of ES, respectively; P_t^{LVPP} is the total load power supplied by the sources in DCVPP; and P_t^τ , $P_{\text{ES},t}^\tau$ and $P_{\text{GT},t}^\tau$ are the bidding capacities of DCVPP, ES, and GT in the ancillary market τ , respectively.

2) Constraints of DC Participating in DR Program

Transmission and queuing delays for workloads must adhere to the constraints defined by the M/M/1 queuing theory and not exceed the maximum delay specified in the service-level agreement [16]. The related constraints can be described as:

$$0 \leq n_t^{\text{on}} \leq n^{\text{IT}} \quad (38)$$

$$0 \leq u_t \leq u_{\max} \quad (39)$$

$$0 \leq (\mu - E_t/n_t^{\text{on}})^{-1} \leq T^{\text{delay}} \quad (40)$$

where n^{IT} is the number of servers in DC; $u_{\max}$ is the maximum CPU utilization for a single server; and T^{delay} is the tolerant service delay of workloads.

The internal ambient temperatures of the DC are within acceptable ranges, which can be expressed as:

$$Tem_{\min}^a \leq Tem_t^a \leq Tem_{\max}^a \quad (41)$$

$$|Tem_t^a - Tem_{t-1}^a| \leq \Delta Tem_{\max}^a \quad (42)$$

where $Tem_{\min}^a$ and $Tem_{\max}^a$ are the minimum and maximum indoor air temperatures in the DC, respectively; and $\Delta Tem_{\max}^a$ is the maximum variation of indoor air temperature.

Constraints (43) and (44) represent the load-power balance requirements of the DCVPP. Constraint (45) indicates that the DCVPP cannot simultaneously sell and buy electricity in the energy market.

$$P_t^{\text{DC}} + P_t^{\text{RL}} = P_t^{\text{Lpur}} + P_t^{\text{LVPP}} \quad (43)$$

$$\begin{cases} P_t^{\text{Lpur}} \geq 0 \\ P_t^{\text{LVPP}} \geq 0 \end{cases} \quad (44)$$

$$\text{sgn}[P_t^{\text{Lpur}}] + \text{sgn}[P_t^E] \leq 1 \quad (45)$$

where P_t^{RL} is the power demand of RL; and $\text{sgn}[\cdot]$ is the signum function.

3) Constraints of Reserve Capacity

The related constraints of the reserve capacity balance of DCVPP can be described as:

$$\sum_{\mathcal{R}} P_{\mathcal{R},t}^{\text{resup}} = P_{\text{ES},t}^{\text{resup}} + P_{\text{GT},t}^{\text{resup}} \quad (46)$$

$$-\sum_{\mathcal{R}} P_{\mathcal{R},t}^{\text{resdown}} = P_{\text{ES},t}^{\text{resdown}} + P_{\text{GT},t}^{\text{resdown}} \quad (47)$$

$$0 \leq P_{\mathcal{R},t}^{\text{resup}}(t) \leq P_{\mathcal{R}}^{\text{max}} \quad (48)$$

$$P_t^{\mathcal{R}} - P_{\mathcal{R},t}^{\text{max}} \leq P_{\mathcal{R},t}^{\text{resdown}} \leq 0 \quad (49)$$

where $P_{\text{ES},t}^{\text{resup}}$ and $P_{\text{GT},t}^{\text{resup}}$ are the upward reserve capacities provided by ES and GT, respectively; $P_{\text{ES},t}^{\text{resdown}}$ and $P_{\text{GT},t}^{\text{resdown}}$ are the downward reserve capacities provided by ES and GT, respectively; $P_{\mathcal{R},t}^{\text{resup}}$ and $P_{\mathcal{R},t}^{\text{resdown}}$ are the upward and downward reserve capacities received by the random power source $\mathcal{R}$, respectively; $P_t^{\mathcal{R}}$ is the forecast power of $\mathcal{R}$; and $P_{\mathcal{R}}^{\text{max}}$ is the maximum power of $\mathcal{R}$.

4) Constraints of ES and GT

The constraints and parameters for ES and GT are available in [18] and [34].

V. CASE STUDY

To validate the effectiveness and superiority of the proposed model and strategy, a series of case studies based on practical data is conducted. The composition of the diversified power units within the DCVPP is introduced, followed by the presentation and discussion of the simulation results. In particular, the analysis focuses on several key aspects, including the modeling of power consumption for cooling system in DC, uncertainty modeling using the probability distribution of forecast error, and the optimal scheduling strategy for DCVPP in the electricity-carbon joint market. The problem is coded with the YALMIP toolbox [35] in MATLAB environment and solved by the use of commercial optimization software GUROBI [36].

A. Basic Data

The typical DCVPP shown in Fig. 1 is selected as the test system. The maximum power demands of the DC load and RL are 4 MW and 1.5 MW, respectively, while the installed capacity of GT is 6 MW. The maximum day-ahead forecast power outputs of WT and PV are 4 MW and 4.5 MW, respectively. The maximum power capacity and rated capacity of ES are 6 MW and 15 MWh, respectively. The parameters of the generating units and ES are adopted from [18]. Without loss of generality, it is assumed that 30% of the total arriving workloads are the interactive workloads, 50% are batch workloads, and the remaining 20% are rigid workloads. The detailed parameters of the DC and CET market are presented in Supplementary Material A Table SAII and Table SAIII, respectively [37], [38]. The data of WT and PV power generation, load profiles, and market prices from the Electric Reliability Council of Texas (ERCOT) for four typical days are shown in Supplementary Material A Fig. SA2, where the time step of the sampling point is 1 hour [39].

B. Accuracy and DR Capability of DC Load Model

In this subsection, three different DC load models are compared to demonstrate the accuracy and superiority of the proposed model of power consumption for cooling system in DC. To ensure the validity of the evaluation results, real operational data collected from a DC in China are used for model accuracy verification. Hourly energy consumption and temperature data are employed as inputs to the second-order ETP model (denoted as Model 1) to estimate the corresponding parameters of the power consumption of cooling system in DC. For comparison, two existing models are also adopt-

ed to calculate the power consumption of cooling system in DC using the same input data [7], [8]. The first benchmark model (denoted as Model 2) is a PUE model [7], in which regression analysis is conducted to obtain a static PUE metric representing the ratio of total DC power consumption to the power consumption of IT equipment. The second benchmark model (denoted as Model 3) is a first-order ETP model to characterize the coupling relationship between power consumption of IT equipment and the cooling system [8].

The practical fitting effects of different DC load models are illustrated in Fig. 5, which compares the actual and estimated hourly DC load over 480 hours. The estimation results obtained through Model 1 closely align with the real value, effectively capturing the dynamic characteristics of DC load behavior. This high level of accuracy demonstrates the capability of Model 1 to characterize the coupled electrical-thermal dynamics of the DC load. The comparison of the accuracy of different DC load models is illustrated in Fig. 6, which presents the root mean square errors (RMSEs), mean absolute errors (MAEs), and mean absolute percentage errors (MAPEs) of the DC load estimates obtained from the three models. Compared with that of Models 2 and 3, the RMSE of Model 1 is reduced by 68.80% and 57.91%, respectively. Similarly, the MAE is reduced by 69.68% and 64.27%, respectively, while the MAPE results further confirm the superior estimation accuracy of Model 1. Collectively, these results validate the superior performance of the proposed model in accurately capturing the dynamic characteristics of the DC load.

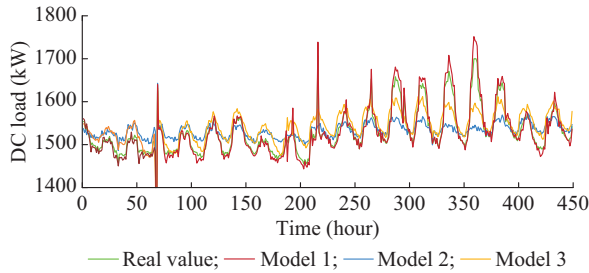


Fig. 5. Practical fitting effects of different DC load models.

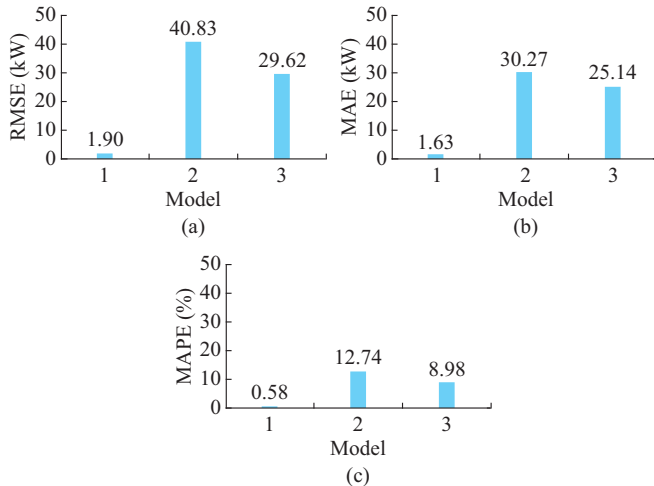


Fig. 6. Comparison of accuracy of different DC load models. (a) RMSE. (b) MAE. (c) MAPE.

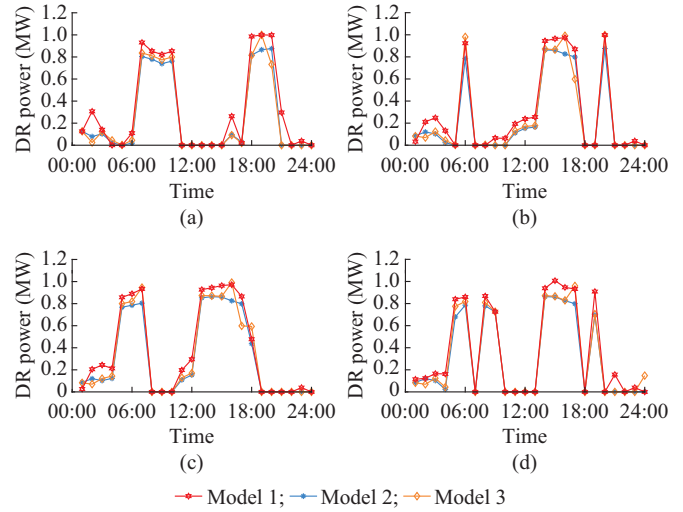


Fig. 7. DR capability comparison of different DC load models across typical days in four seasons. (a) Spring. (b) Summer. (c) Autumn. (d) Winter.

To illustrate the practical applicability of the proposed model, three different DC load models are incorporated into the optimal scheduling strategy for the DCVPP described in Section IV, corresponding to scenarios S1-S3, respectively. The DR capability comparison of different DC load models across typical days in four seasons is illustrated in Fig. 7. To provide a benchmark, a scenario without demand response (denoted as without DR) is also evaluated, where the DC load remains at its nominal level without any flexibility.

Table I presents the optimization results in different scenarios. As the typical scenario, S3 shows an average increase of 21.6% and 15.9% in total DR capability compared with S1 and S2, respectively. Consequently, the average net profit of DCVPP in S3 is 29.7% and 24.9% higher than that of S1 and S2, respectively. These results can be attributed to two primary factors. First, characterizing the relationship between the DC load and the power consumption of IT equipment solely through a static PUE value overlooks its potential for dynamic adjustments in response to actual power demand, thereby constraining the flexibility of DC load demand management. Second, Model 3 neglects the effects of temperature variations in the solid materials within the DC, resulting in inaccuracy in representing thermodynamic characteristics and consequently limiting the DR capability of the DC.

C. Analysis of Reserve Capacity in DCVPP

To evaluate the impact of reserve capacity on DCVPP operations, a comparative analysis is conducted across three operational scenarios: S4 (without reserve capacity), S5 (with reserve capacity but without considering forecast error correlations), and S6 (with reserve capacity considering forecast error correlations). Table II presents the impact of reserve capacity on DCVPP operations on a typical spring day.

A comparison of net profits with and without reserve capacity shows that the reserve capacity in S5 and S6 enables the DCVPP to shift from losses to profitable operation, thus substantially improving its economic performance.

TABLE I
OPTIMIZATION RESULTS IN DIFFERENT SCENARIOS

Scenario	Spring		Summer		Autumn		Winter	
	DR capability (MW)	Net profit (\$)	DR capability (MW)	Net profit (\$)	DR capability (MW)	Net profit (\$)	DR capability (MW)	Net profit (\$)
Without DR	0	439	0	97	0	251	0	153
S1	6.12	457	5.77	139	7.69	354	7.34	182
S2	6.24	467	6.11	149	8.07	365	7.82	194
S3	7.74	541	7.15	216	9.05	444	8.79	267

TABLE II
IMPACT OF RESERVE CAPACITY ON DCVPP OPERATIONS ON A TYPICAL SPRING DAY

Scenario	Reserve capacity (MW)		Penalty cost (\$)		Net profit (\$)
	Excess	Insufficient	Excess	Insufficient	
S4	0	0	645.3	1290.6	-887
S5	17.2	-28.1	53.8	212.3	528
S6	20.1	-32.2	35.6	165.5	541

This comparison demonstrates the effectiveness of the proposed risk-based reserve scheme. When forecast error correlations are considered, the total penalty cost in S6 is reduced by 24.41%, and the net profit increases by 2.36% compared with that in S5. The results across different reserve capacity configurations show that the consideration of forecast error correlations improves the estimation accuracy of power deviations and reserve adequacy, leading to lower penalty costs and higher net profits across multiple markets. Furthermore, the higher net profit in S6 demonstrates the advantage of considering forecast error correlations. Compared with S5, S6 allocates more appropriate reserve capacity to cope with correlated uncertainties, which reduces the penalty cost from \$266.1 to \$201.1 and increases the net profit from \$528 to \$541. This indicates that the proposed scheme achieves a better balance between reserve allocation and market bidding.

Figure 8 shows the impact of forecast error correlations on reserve capacity allocation in the DCVPP on a typical spring day. Due to the strong negative correlation coefficient between WT and load (-0.57), during the period 19:00-06:00, a positive forecast error in WT output (i.e., WT generation being overestimated) is more likely to coincide with a negative forecast error in load demand (i.e., load being underestimated). Consequently, DCVPP in S6 requires a larger upward reserve capacity than that in S5 to mitigate the penalty costs associated with power shortages. Conversely, due to the strong positive correlation coefficient between PV and load (0.43), during the period 10:00-17:00, DCVPP requires a larger downward reserve capacity to reduce the penalty costs arising from power surplus. Notably, the downward reserve capacity significantly exceeds the upward reserve capacity. This is because allocating reserve capacity constrains the bidding capacity of DCVPP in the energy, reserve, and regulation up market. Accordingly, the DCVPP optimizes its reserve allocation by balancing revenues of multiple markets against penalty costs.

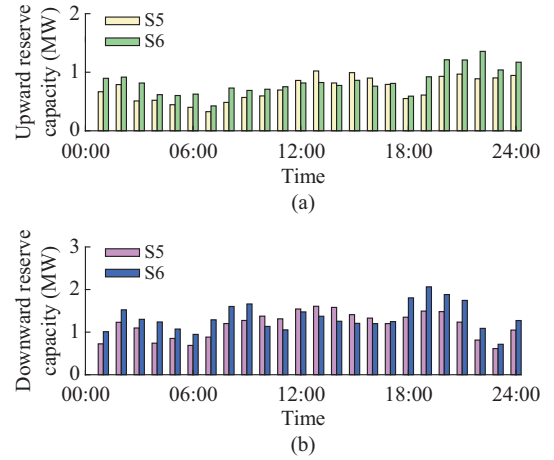


Fig. 8. Impact of forecast error correlations on reserve capacity allocation in DCVPP on typical spring day. (a) Upward reserve capacity. (b) Downward reserve capacity.

D. Motivational Analysis and Bidding Strategy Optimization for DC and VPP Aggregation

To interpret the economic motivation of DC and VPP aggregation, this paper designs distinct test scenarios. Table III compares the net profits under non-aggregated and aggregated operation with and without DR across typical days in four seasons. In these scenarios, this paper systematically evaluates how DC and VPP aggregation and DR implementation affect the economic performance of the DCVPP.

TABLE III
COMPARISON OF NET PROFITS UNDER NON-AGGREGATED AND AGGREGATED OPERATION WITH AND WITHOUT DR ACROSS TYPICAL DAYS IN FOUR SEASONS

Season	DR implementation	Net profit (\$)	
		Non-aggregated operation (DC and VPP)	Aggregated operation (DCVPP)
Spring	Without DR	-835	439
	With DR	-485	541
Summer	Without DR	-973	97
	With DR	-604	216
Autumn	Without DR	-819	251
	With DR	-400	444
Winter	Without DR	-927	153
	With DR	-562	267

As shown in Table III, the non-aggregated operation of

the DC and VPP leads to negative net profits in all typical days in four seasons, mainly due to the high cost of supplying the DC load through electricity procurement from the energy market. However, under the aggregated operation, the DC load can be partially supplied by the RESs and controllable resources within the VPP. Even without DR, this aggregation increases the net profit to \$439, \$97, \$251, and \$153 in typical days in four seasons, respectively. Thus, aggregating DC into the VPP yields substantial economic benefits. Moreover, the DC participation in the DR program has a significant impact on the net profit of DCVPP. Comparative results show an average profit increase of 74.4% for the scenario with DR implementation compared to that without DR implementation, primarily due to the strategic temporal shifting of batch workloads. These results indicate that DCVPP aggregation and DC-side DR jointly improve the economic viability of DCVPP operation.

The comparisons of the workload distribution patterns and load power of DCVPP with and without DR implementation in typical days in four seasons are presented in Supplementary Material A Fig. SA3 and Fig. SA4, respectively. Taking the typical spring day as an example, during the periods of peak electricity prices (07:00-10:00 and 17:00-19:00), the DCVPP strategically reallocates workloads to the low-price periods (12:00-15:00 and 21:00-24:00). This load-shifting mechanism serves dual purposes: reducing the operating costs and enhancing the bidding capacity of DCVPP in the DAM.

To validate the effectiveness of the proposed strategy for DCVPP participating in the electricity-carbon joint market, three comparative cases are designed in Table IV, with the corresponding optimization results detailed in the subsequent analysis.

TABLE IV
DESIGN OF DIFFERENT MARKET PORTFOLIO CASES

Case	DAM			CET market	
	Energy	Reserve	Regulation up/down	CEA	CCER
1	√				
2	√	√	√		
3	√	√	√	√	√

Note: √ represents participation of DCVPP in the corresponding market.

Table V presents the economic and emission comparison under different cases across typical days in four seasons. By comparing the net profits of Case 1 and Case 2, it can be observed that when the DCVPP participates only in the energy market without engaging in reserve and regulation up/down markets, its flexible regulation capability is not fully utilized, resulting in overall losses. In contrast, joint participation in the energy and ancillary service markets increases the net profit of DCVPP from -\$471, -\$750, -\$355, and -\$944 to \$279, -\$11, \$192, and -\$31, respectively, thus highlighting the significance of its participation in diversified DAM. In addition, Table V illustrates the impact of the CET mechanism on the profit and carbon emissions of DCVPP. Compared with Case 2, the daily carbon emissions in Case 3 are

reduced by 5.6%, 7.6%, 1.2%, and 41% in typical days in four seasons, while the net profit increases by \$261, \$226, \$252, and \$298, respectively. The improvements can be attributed to the synergistic effects of the electricity-carbon trading mechanism. Under this mechanism, DCVPP strategically reduces carbon emission costs by decreasing GT utilization, while obtaining additional carbon asset income from RES integration for CCER trading. Consequently, the incorporation of the CET mechanism effectively aligns the economic and environmental objectives of the DCVPP.

TABLE V
ECONOMIC AND EMISSION COMPARISON UNDER DIFFERENT CASES ACROSS
TYPICAL DAYS IN FOUR SEASONS

Season	Case	DAM revenue (\$)	CET revenue (\$)	Operating cost (\$)	Carbon emission (tCO ₂)	Net profit (\$)
Spring	1	4147		4618	114	-471
	2	4599		4320	93	279
	3	4472	269	4200	88	541
Summer	1	3336		4086	96	-750
	2	4028		4039	84	-11
	3	3866	240	3890	78	216
Autumn	1	3281		3636	80	-355
	2	3703		3511	68	192
	3	3612	265	3433	67	444
Winter	1	3055		3999	94	-944
	2	3796		3827	76	-31
	3	2926	350	2909	44	267

The results in Table V, together with the RES generation and market price profiles shown in the Supplementary Material A Fig. SA2, indicate that the typical spring day exhibits the highest overall revenue due to peak RES output, which maximizes the bidding capacity and profit of DCVPP through the diversified DAM. Compared with the typical spring day, the typical autumn day demonstrates marginally lower RES output and DAM prices, resulting in slightly reduced revenue. On typical summer day, heavy reliance on PV output creates significant diurnal volatility combined with peak power loads, necessitating frequent GT unit activation during RES output valleys, thereby elevating operating costs and restricting overall profitability of DCVPP. On typical winter day, constrained RES generation capacity limits DAM bidding participation and profit optimization shifts to maximize CET gains through strategic carbon emission reduction.

The bidding capacity of DCVPP in the DAM across typical days in four seasons is illustrated in Fig. 9, which details the bidding capacity allocation of DCVPP across various electricity markets. Due to variations in renewable energy availability and load demand, the bidding strategies differ markedly on these days. It is evident that the bidding strategy in the DAM dynamically matches the peak and valley time of the market price curves, as reflected in Supplementary Material A Fig. SA2. When market prices are relatively high (05:00-13:00 on typical spring day and 14:00-16:00 on

typical summer day), the DCVPP prefers to sell more electricity correspondingly. Conversely, during peak load periods (01:00-04:00 on both typical autumn and winter days), the DCVPP reduces its bidding capacity to avoid a shortage of internal power supply for load demand. In addition, when ancillary service market prices exceed those of the energy market (05:00-07:00 on typical winter day), the DCVPP strategically reallocates the bidding capacity toward ancillary service provision. As further evidenced in Supplementary Material A Fig. SA3, the DC workloads are shifted from the peak-price periods to the low-price periods, thereby enhancing the bidding capacity of DCVPP during peak-price periods. These results indicate that the proposed strategy effectively exploits the potential flexibility of DCVPP and enables a coordinated optimization across multiple markets, ultimately improving operational economic performance.

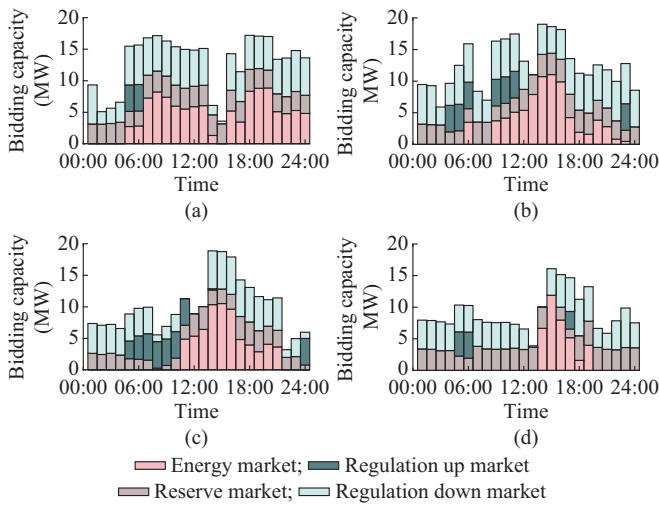


Fig. 9. Bidding capacity of DCVPP in DAM across typical days in four seasons. (a) Typical spring day. (b) Typical summer day. (c) Typical autumn day. (d) Typical winter day.

E. Sensitivity Analysis

To ensure both conciseness and representativeness, the sensitivity analysis is conducted on the typical spring day, which reflects moderate conditions of RES generation and DAM prices. The analysis quantifies the impacts of key parameters on operation results to evaluate the robustness of the proposed model and strategy.

To investigate the influence of the deviation penalty coefficient on the reserve capacity and net profit of DCVPP, a sensitivity analysis is conducted under different multiples of the baseline penalty coefficients $\varphi^+ = 1.0$ and $\varphi^- = 2.0$ [18].

Figure 10 presents the impact of penalty coefficient multiple on reserve capacity and net profit of DCVPP in different forecast error correlation scenarios on a typical spring day. As shown in Fig. 10, both the upward and downward reserve capacities consistently increase as the penalty coefficient multiples increase on the typical spring day. This indicates that as the DCVPP operator becomes more risk-averse, larger reserve capacities are required to hedge against uncertainty. Meanwhile, the net profit of DCVPP decreases since higher penalty coefficient multiples effectively increase the

weight of the penalty cost term in the objective function. Notably, with the increase of penalty coefficient multiples, the total reserve capacity considering the correlation increases more significantly, and the net profit decreases less compared to that when the forecast error correlation is ignored, thus verifying the applicability of the proposed scheme under different risk preferences.

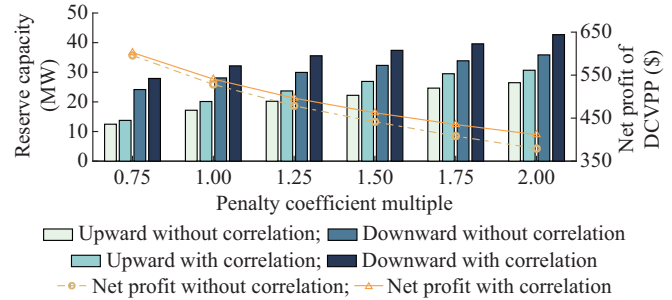


Fig. 10. Impact of penalty coefficient multiple on reserve capacity and net profit of DCVPP in different forecast error correlation scenarios on a typical spring day.

Supplementary Material A Fig. SA5 depicts how the daily net profit and total DR capacity change as the cost coefficient of migrating batch workloads increases for DCVPP on the typical spring day. As the cost coefficient of migrating batch workloads increases, both the DR capacity and net profit of the DCVPP decrease. This is because higher migration costs increase operating costs for a given workload shifting strategy. As a result, the bidding capacity and revenue of DCVPP in the DAM decrease correspondingly. These results indicate that the migration cost of batch workloads significantly affects the enthusiasm of DC to participate in the DR program and the profit of DCVPP in multiple markets.

To assess the impact of adjusting the CCER offset ratio on the net profit of DCVPP, the original baseline ratio of 5% is adjusted by ± 2 and ± 4 percentage points, resulting in ratios of 7%, 3%, 9%, and 1%, respectively. The resulting net profit of DCVPP and carbon emissions after implementing these offset ratio adjustments are presented in Supplementary Material A Fig. SA6. When the CCER offset ratio increases from 1% to 9%, the net profit of DCVPP demonstrates an upward trend. The minimum net profit of \$532.18 occurs at the offset ratio of 1%, while the maximum net profit of \$549.46 is achieved at the offset ratio of 9%, representing a variation of 3.25%. Carbon emissions exhibit an increasing trend with higher CCER offset ratios, reaching the minimum of 87.67 tCO₂ at 1% and the maximum of 87.72 tCO₂ at 9%. This phenomenon occurs because higher CCER offset ratios enable the DCVPP to purchase more low-cost CCER credits for compliance, thereby reducing its carbon emission costs and increasing net profits. Paradoxically, excessive reliance on the CCER offset mechanism may diminish the incentive of DCVPP to implement emission reduction measures, potentially undermining decarbonization efforts.

To quantify the impact of correlation among RESs and forecast errors, the baseline correlation matrix is scaled by 0.25, 0.50, 0.75, 1.00, and 1.25, while keeping all marginal distributions and model settings unchanged. All scaled matri-

ces remain positive semidefinite. For each scenario, the uncertainty model is regenerated and the DCVPP scheduling problem is solved. Figure 11 presents the impact of correlation coefficient multiple of forecast error on reserve capacity and net profit of DCVPP on a typical spring day. It shows that higher correlation coefficients consistently result in larger upward and downward reserve requirements, since a stronger correlation increases the likelihood of simultaneous forecast deviations, requiring more reserve capacity to hedge the joint risks. Consequently, less flexible capacity is available for market trading, leading to a decline in net profit of DCVPP as the correlation coefficient multiples increase. These results indicate that the proposed model and strategy respond appropriately to the changes in the correlation matrix and maintain robust performance across the considered correlation coefficient range.

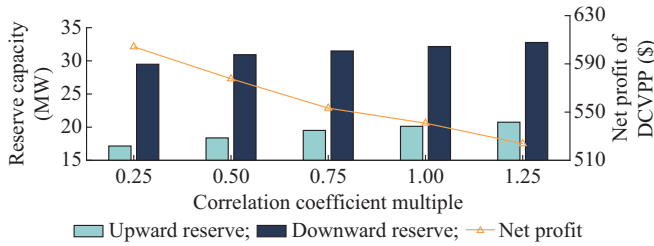


Fig. 11. Impact of correlation coefficient multiple of forecast error on reserve capacity and net profit of DCVPP on a typical spring day.

VI. CONCLUSION

This paper presents an operational framework for DCVPP that integrates DC with a VPP consisting of WT, PV, ES, GT, and RL. Furthermore, an optimal scheduling strategy is proposed for the DCVPP participating in the electricity-carbon joint market under uncertainty. From the theoretical models and case study results, the main conclusions are drawn as follows.

1) Compared with two existing DC load models, the proposed model achieves a substantially improved fitting accuracy, with a RMSE reduction ranging from 57.9% to 68.8%, and a MAE reduction ranging from 64.27% to 69.68%, respectively. For the cases adopting the proposed model, the net profit of DCVPP increases by an average of 36.5% and 30% across four seasonal typical days, respectively. The results illustrate that the proposed model can more accurately capture the load characteristics of DC and effectively exploit its DR potential.

2) Based on the proposed scheme incorporating forecast error correlations, the penalty cost of the DCVPP is reduced by 24.41%, while the net profit increases by 2.36% compared to the scheme that neglects these correlations. Test results verify that the proposed scheme can mitigate the penalty risk of excess and insufficient power caused by forecast errors of RESs and load, thereby enhancing the economic performance of DCVPP across multiple markets.

3) The proposed strategy for such aggregated DCVPP significantly increases overall profitability while reducing carbon emissions in the electricity-carbon joint market. Test results illustrate that the net profit of DCVPP is increased by

74.4% on average when the DR program is enabled. Moreover, coordinated participation in the diversified DAM increases the net profit of DCVPP by \$261, \$226, \$252, and \$298 for four seasonal typical days, respectively. In addition, the integration of the CET mechanism aligns the economic benefits with low-carbon objectives in the optimal scheduling of the DCVPP.

Overall, the results indicate that the proposed strategy is well-suited for the practical DCVPP operations in electricity-carbon joint markets. For DC operators, it systematically exploits workload flexibility to provide DR while maintaining service continuity and operational reliability. For VPP aggregators, it enables coordinated management of diverse resources, thus enhancing revenue robustness and reducing imbalance risks under forecast uncertainty. For policymakers and market designers, the proposed framework provides an implementable approach to integrating carbon trading with DR, supporting policy designs that jointly pursue economic efficiency and verifiable carbon emission reductions.

Future work will explore the extension to DCVPPs based on multiple DCs, enabling such spatial flexibility through the coordinated DR and workload migration across geographically distributed DCs. In addition, incorporating grid constraints and real-time carbon markets will further enhance the practical applicability and decarbonization effectiveness.

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