

Transformer-LSTM-Attention Deep Learning Prediction and Multi-Time-Scale Error-Compensation Optimization for Hydro-Wind-PV-Storage Clean Energy Bases Using Cascade-Hydropower Reserve

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Abstract

High wind and photovoltaic (PV) penetration propagates forecast errors across day-ahead, intraday and real-time dispatch and increases short-term regulation demand. This paper proposes a Transformer-LSTM-attention deep learning prediction and multi-time-scale error-compensation optimization strategy for a hydro-wind-PV-storage clean energy base. The prediction module generates load, wind, PV and runoff forecasts at 1 h, 15 min and 1 min resolutions by combining temporal feature extraction, sequence modeling and attention weighting. The dispatch model represents residual load, wind and PV errors as a net-load deviation and converts quantile-based, or source-wise conservative, error margins into day-ahead and intraday cascade-hydropower reserve requirements. In real-time operation, the configured hydropower reserve compensates minute-level deviations, with storage and thermal units providing supplementary regulation under ramping, operating and network constraints. A case study is conducted on a Southwest China cascade-basin hydro-wind-PV-storage base with four cascade hydropower stations and a modified 30-bus equivalent local-grid system. The day-ahead MAPE values are 5.79%, 0.79% and 0.52% for wind, PV and load. Compared with fixed reserve, the proposed strategy reduces day-ahead-to-intraday hydropower fluctuation errors from 8.42% to 4.81% and from 7.48% to 6.02%; intraday-to-real-time errors decrease from 8.27% to 6.84% and from 8.44% to 8.09%. The power-supply guarantee rate remains 100.00%, while the required storage power capacity decreases by 34.00% and 32.11%. These results show improved cross-stage dispatch consistency and lower short-term storage regulation demand under the tested high-renewable operating conditions.

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1. Introduction

Driven by the global "dual-carbon" agenda, renewable

energy has been deployed rapidly worldwide. Recent renewable-capacity statistics and industry reports show

that China continues to lead global wind and PV deployment, with installed and under-construction capacities growing rapidly [1, 2]. However, the intermittency, volatility and limited predictability of wind and PV generation weaken the deliverability and controllability of the power supply, and as their penetration grows the available system flexibility becomes increasingly strained. More fundamentally, the discrepancy between forecasted and actual renewable outputs across different time scales is translated into scheduling deviations that propagate from day-ahead planning through intraday to real-time operation, forcing conventional units into frequent and deep ramping and raising the demand for short-term regulation resources. Against this background, artificial intelligence (AI), deep learning prediction and computer-aided optimization have become enabling technologies for converting multi-source operational data, meteorological information and forecast-error distributions into dispatchable reserve and regulation decisions.

To accommodate renewables on a large scale while improving the utilization of transmission corridors, large-scale clean energy bases that integrate hydro, wind, PV and storage and deliver power in a bundled manner have become an important development pattern [3]. Compared with a single wind or solar plant, such a base exploits the spatiotemporal complementarity among multiple resources and, in particular, the fast and flexible regulation of cascade hydropower to smooth renewable fluctuations and shape the delivered-power curve [4, 5]. Nevertheless, the benefit of a clean energy base ultimately depends on how effectively the scheduling layer copes with the forecast errors that accompany high renewable penetration.

Because forecast error is the root cause of scheduling deviation, accurate multi-source forecasting has been studied intensively, and AI-based data-driven deep-learning models now dominate the computer-technology layer of renewable forecasting. Hybrid architectures that combine Transformer encoders, LSTM recurrent units and attention mechanisms have improved wind and PV forecasting [6–8]. To serve dispatch at different resolutions, multi-time-scale wind forecasting [9] and attention-LSTM PV forecasting with online error correction [10] have also been proposed, while recent non-EAI studies further improve ultra-short-term wind and PV forecasting through decomposition, feature extraction and attention mechanisms [11, 12]. In this study, the Transformer-LSTM-attention forecasting module is therefore positioned as the AI input generator for dispatch optimization rather than as an isolated prediction exercise. However, regardless of the model, forecasting cannot eliminate the residual errors that inevitably remain at execution time; these errors grow with the renewable share and differ across time scales, so improving forecasting alone

still leaves the dispatch layer exposed to uncompensated deviations.

At the dispatch layer, multi-time-scale and uncertainty-aware scheduling has been developed to absorb such residual errors. Rolling day-ahead-intraday-real-time frameworks progressively revise unit outputs and reserves as fresher forecasts arrive [13, 14], while multi-source, multi-timescale cooperative dispatch coordinates heterogeneous resources across stages [15]. Capacity configuration and storage-allocation studies have also addressed hydro-wind-solar-storage bundling systems and nested multi-time-scale storage allocation under transmission, storage and operational constraints [16, 17]. Nevertheless, these studies generally represent forecast uncertainty through fixed reserve margins or scenario/robust sets that are not explicitly transformed into a deployable hydropower reserve across the day-ahead, intraday and real-time stages.

In parallel, ancillary-service mechanisms and reserve-allocation methods have been investigated to supply the regulation that high-penetration systems require. Studies of ancillary-service market design have identified both the value and the barriers of renewable participation as synchronous generation is displaced [18], and reserve-allocation models have been formulated to maintain frequency security in high-penetration grids using multiple types of resources [19]. Hydropower and energy storage, in particular, are increasingly coordinated to provide frequency-regulation reserve, and their substitution relationship and reserve sizing have been quantified [20, 21]. These works confirm that cascade hydropower and storage are high-value regulation resources, yet they mostly target frequency security or regulation cost and seldom configure hydropower reserve specifically to compensate the multi-time-scale forecast errors of load, wind and PV within a clean energy base. Multi-time-scale storage studies further indicate that large-capacity hydropower or pumped-storage resources are more suitable for longer and larger deviations, whereas electrochemical storage is more effective for shorter and high-frequency fluctuations [20, 21]. This motivates the operating hierarchy adopted in this paper: cascade hydropower provides the primary error-compensation reserve, while storage acts as a supplementary real-time regulator.

In summary, forecasting research reduces but cannot remove prediction errors, whereas dispatch research copes with uncertainty but rarely converts forecast-error characteristics into a stage-specific and deployable hydropower reserve. A unified strategy is therefore needed to link net-load forecast-error quantification, cascade-hydropower reserve sizing, real-time reserve deployment and the resulting storage requirement in a clean energy base with high renewable penetration.

To bridge this gap, this study proposes a Transformer-LSTM-attention deep learning prediction and multi-time-scale error-compensation optimization strategy for large-scale clean energy bases providing ancillary-service regulation. An AI prediction layer first produces multi-resolution forecasts of load, wind power, PV power and runoff, and the dispatch optimization layer then converts residual forecast-error characteristics into stage-specific cascade-hydropower reserve. The methodological core is a net-load-error-oriented reserve-sizing method for hydro-wind-PV-storage dispatch. It formulates reserve sizing from the combined effect of load, wind and PV forecast errors expressed as a net-load deviation. In the case study, because the available historical error records are source-wise, the net-load reserve requirement is approximated by a conservative source-wise aggregated margin. This approximation is explicitly distinguished from a model based on synchronized signed net-load error samples.

On this basis, a reserve-configuration and reserve-deployment dispatch framework is established for cascade hydropower. The day-ahead and intraday stages configure bidirectional hydropower reserve subject to headroom, ramping and reservoir constraints, while the real-time stage deploys the configured reserve to compensate minute-level net-load deviations with storage and thermal units as supplementary resources.

The ancillary-service compensation formulation further distinguishes reserve capacity from actual regulation energy. This avoids mixing MW reserve capacity with MWh regulation energy and allows the economic effect of hydropower error-compensation reserve to be evaluated as a comparative revenue indicator rather than as a complete market-settlement result. The strategy is examined on a representative transition day with four cascade hydropower stations and two wind-PV penetration levels, and is compared with a fixed-reserve baseline in terms of cross-stage dispatch deviation, power-supply guarantee rate, reserve usage and required storage power capacity.

The remainder of this paper is organized as follows. Section 2 presents the framework of the proposed strategy. Section 3 formulates the forecasting, error-compensation and multi-time-scale dispatch models. Section 4 describes the solution procedure. Section 5 reports the case study on a hydro-wind-PV-storage clean energy base in a cascade hydropower basin in Southwest China, and Section 6 concludes the paper.

2. Framework of the Proposed Strategy

The overall framework is shown in Figure 1. The proposed strategy couples a Transformer-LSTM-attention multi-resolution deep learning prediction module with a three-stage rolling dispatch optimization model. The forecasting module provides load, wind, PV

and runoff forecasts at the hourly, 15 min and 1 min resolutions. The forecasting model forms the AI-based predictive layer of the proposed framework, while the dispatch model converts the residual forecast errors into reserve-configuration and reserve-deployment decisions. The methodological focus of this paper is how forecast errors are translated into hydropower reserve requirements and how the configured reserve is deployed in real time.

The framework distinguishes reserve configuration from reserve deployment. The day-ahead and intraday stages use the empirical distribution of net-load forecast errors to determine the hydropower reserve capacity required for error compensation. In the case study, where the available historical error records are source-wise rather than synchronized net-load error samples, a conservative source-wise aggregated margin is used to approximate the time-varying reserve requirement. The real-time stage does not introduce an additional reserve-sizing parameter; instead, the minute-level net-load deviation is used to deploy the reserve already configured in the upper stages, subject to hydropower headroom, ramping, storage and network constraints. This distinction prevents the real-time layer from being misinterpreted as a separate sizing step.

Day-ahead stage. Using the hourly forecasts and the historical day-ahead net-load error distribution, or the conservative source-wise aggregated margin used in the case study, the day-ahead model configures upward and downward hydropower reserve for the next 24 h. The dispatch decisions include hydro, wind-PV, thermal and storage outputs, together with the reservoir release trajectory and the reserve capacity passed to the intraday stage.

Intraday stage. Rolling on the day-ahead commitment and reservoir boundary conditions, the intraday model updates the reserve requirement using the 15 min forecasts and the intraday net-load error distribution or its source-wise aggregated approximation. The purpose of this stage is not merely to correct the day-ahead schedule, but to leave sufficient hydropower headroom and ramping margin for the real-time deployment layer.

Real-time stage. The real-time model tracks the 1 min net-load deviation relative to the intraday schedule. The configured hydropower reserve is deployed first within its upward/downward reserve and ramping limits; storage and thermal units then provide supplementary correction, and load shortage is recorded only when the deviation cannot be fully compensated. Thus, the 1 min resolution is used for reserve deployment and performance evaluation, not for another round of reserve sizing.

The rolling intervals follow the forecast horizons used in the case study: the day-ahead plan is fixed at 0:00, the intraday plan is updated every 4 h, and

Technical Roadmap of the Proposed Multi-Time-Scale Error-Compensation Dispatch Strategy

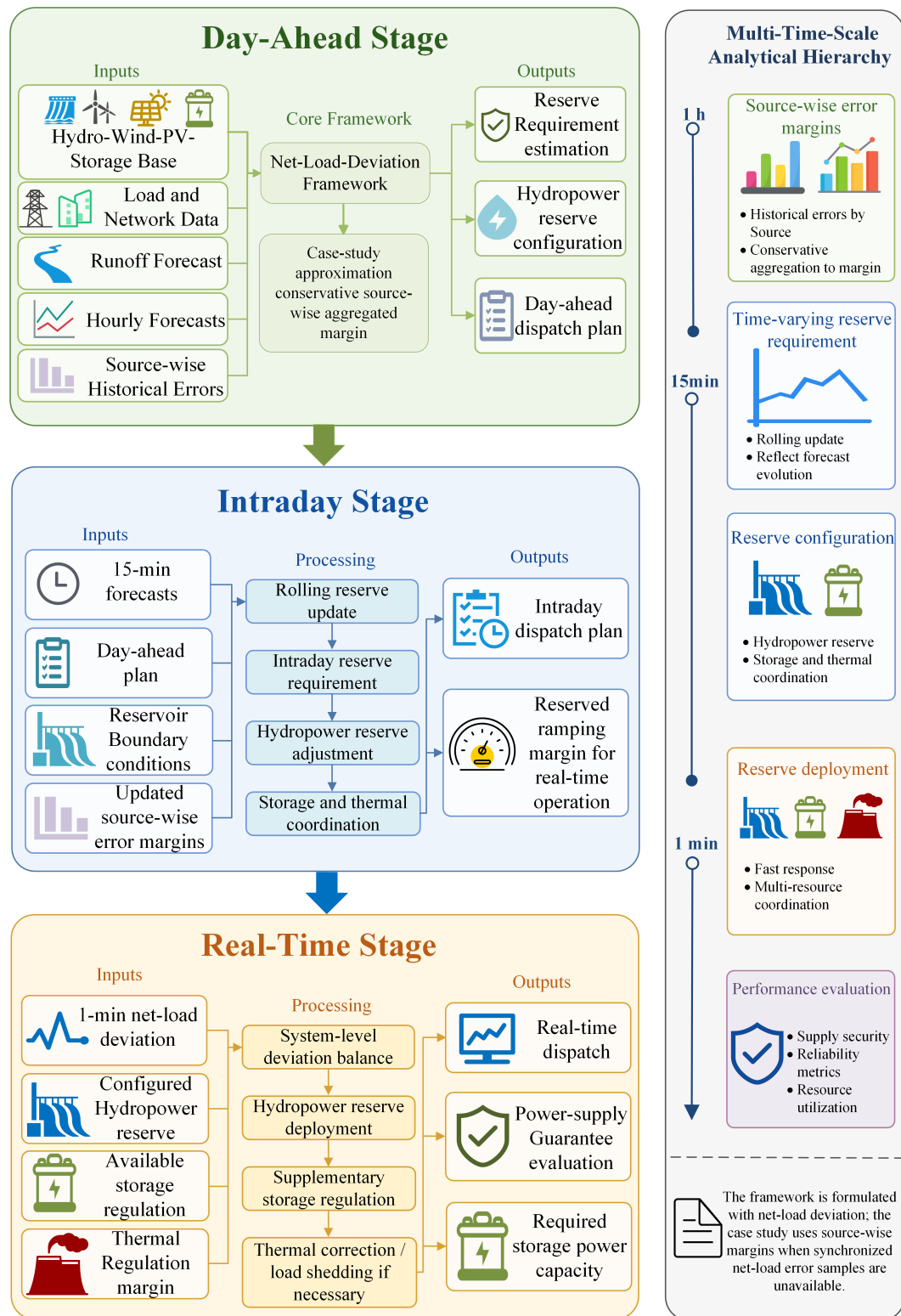


Figure 1. Technical roadmap of the proposed multi-time-scale error-compensation dispatch strategy

the real-time plan is updated every 0.5 h within each intraday window. The resulting dispatch chain is therefore: forecast update → error-margin evaluation → day-ahead/intraday reserve configuration → real-time reserve deployment → guarantee-rate evaluation and required-storage-power-capacity calculation.

3. Mathematical Model

3.1. Forecasting and Multi-Time-Scale Error-Compensation Models

3.1.1. Hybrid Forecasting Model

The hybrid Transformer-LSTM-attention model serves as the AI-based predictive layer of the proposed multi-time-scale optimization framework. It provides synchronized forecasts of load, wind power, PV power and runoff at the resolutions required by day-ahead, intraday and real-time dispatch. In this predictive layer, the Transformer encoder captures global temporal dependencies, the LSTM layer represents sequential nonlinear dynamics, and the attention mechanism reweights key time steps and influential features. Therefore, this section focuses on the data flow, architecture and forecasting accuracy of the adopted Transformer-LSTM-attention module, which provides the predictive basis for subsequent net-load error quantification and error-compensation dispatch.

The scheme takes the historical power series of hydro, wind, PV and load together with public meteorological data (wind speed, temperature and irradiance) as input. The Transformer encoder extracts global temporal features through positional encoding and multi-head self-attention; the LSTM layer captures sequential dynamics and nonlinear dependencies [22]; the attention layer re-weights the time steps and features that contribute most to the prediction; an information-fusion layer exploits cross-correlations among hydro, wind, PV and load; and a fully connected layer outputs the four power forecasts. The four sources are predicted jointly under a multi-task paradigm in which the encoder is shared and a separate output head is assigned to each source, so that complementary information is exploited while source-specific patterns are preserved [23, 24]. The same architecture is trained and executed at three temporal resolutions—hourly over a 24 h horizon for day-ahead dispatch, 15 min over a 4 h window for intraday dispatch, and 1 min over a 0.5 h window for real-time dispatch—yielding the multi-time-scale forecasts used by the dispatch model. The use of stage-dependent temporal resolutions follows the general idea of matching dispatch periods to time characteristics in multi-time-scale operation [25].

The input is a multi-dimensional time series $X \in \mathbb{R}^{n \times k \times t}$, where n is the number of samples, k the feature

dimension and t the number of time steps; $X_t \in \mathbb{R}^k$ denotes the feature vector at step t . The following equations summarize the standard formulations used to define the data flow; they are not the methodological contribution of this paper.

The LSTM cell updates its hidden state h_t and cell state c_t as in Eq. (1).

$$\begin{cases} \begin{bmatrix} f_t \\ i_t \\ o_t \end{bmatrix} = \sigma(W_{[f,i,o]}[h_{t-1}, X_t] + b_{[f,i,o]}) \\ c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c[h_{t-1}, X_t] + b_c) \\ h_t = o_t \odot \tanh(c_t) \end{cases} \quad (1)$$

where f_t , i_t and o_t are the forget, input and output gates; $\sigma(\cdot)$ is the sigmoid function; $\odot$ is the Hadamard product; and $W_\bullet$ and $b_\bullet$ are weight matrices and bias vectors.

The attention layer re-weights the hidden states and produces a context vector z , as in Eq. (2).

$$\begin{cases} \alpha_t = \frac{\exp(h_t^\top W_a q)}{\sum_{\tau=1}^T \exp(h_\tau^\top W_a q)} \\ z = \sum_{t=1}^T \alpha_t h_t \end{cases} \quad (2)$$

where α_t is the normalized attention weight, q the query vector, and W_a a learnable matrix.

The Transformer encoder captures global temporal dependencies through multi-head self-attention, as in Eq. (3) [26].

$$\begin{cases} \text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V \\ \text{MHA} = \text{Concat}(\text{head}_1, \dots, \text{head}_H) W_O \end{cases} \quad (3)$$

where $Q = XW_Q$, $K = XW_K$ and $V = XW_V$ are the query, key and value matrices; d_k is the per-head dimension; H the number of heads; and W_O the output projection. Sinusoidal positional encoding is added to the input embedding, and each sub-layer is followed by a position-wise feed-forward network with a residual connection and layer normalization, as in [26].

3.1.2. Net-Load Error Model for Multi-Time-Scale Reserve Sizing

The dispatch layer is driven by the residual error of the net load rather than by the forecasting error of a single source. For dispatch stage $k \in \{\text{DA}, \text{ID}, \text{RT}\}$, the system net load and its forecast are defined as

$$\begin{cases} p_t^{\text{net},k} = p_t^{\text{L},k} - \sum_{m=1}^M p_{t,m}^{\text{W},k} - \sum_{m=1}^M p_{t,m}^{\text{PV},k} \\ \hat{p}_t^{\text{net},k} = \hat{p}_t^{\text{L},k} - \sum_{m=1}^M \hat{p}_{t,m}^{\text{W},k} - \sum_{m=1}^M \hat{p}_{t,m}^{\text{PV},k} \end{cases} \quad (4)$$

The corresponding net-load forecast error is

$$\begin{cases} e_t^{\text{net},k} = p_t^{\text{net},k} - \hat{p}_t^{\text{net},k} \\ e_t^{\text{net},k} = \left(p_t^{\text{L},k} - \hat{p}_t^{\text{L},k} \right) - \sum_{m=1}^M \left(p_{t,m}^{\text{W},k} - \hat{p}_{t,m}^{\text{W},k} \right) \\ \quad - \sum_{m=1}^M \left(p_{t,m}^{\text{PV},k} - \hat{p}_{t,m}^{\text{PV},k} \right) \end{cases} \quad (5)$$

A positive $e_t^{\text{net},k}$ indicates that the realized net load is higher than forecasted and upward regulation is required. A negative value indicates lower-than-expected net load and requires downward regulation, storage charging or renewable curtailment.

For the day-ahead and intraday stages, the required reserve is determined from the empirical distribution of $e_t^{\text{net},k}$. Upward and downward reserve requirements are sized by the ξ -quantiles of the positive and negative net-load errors:

$$\begin{cases} R_t^{\text{up},\text{req},k} = \text{Quantile}_{\xi} \left(\max(e_t^{\text{net},k}, 0) \mid \tau \in \Omega_t^k \right) \\ R_t^{\text{dn},\text{req},k} = \text{Quantile}_{\xi} \left(\max(-e_t^{\text{net},k}, 0) \mid \tau \in \Omega_t^k \right) \\ k \in \{\text{DA}, \text{ID}\} \end{cases} \quad (6)$$

Here, Ω_t^k is the historical sample set used to characterize the error distribution of period t at stage k , and ξ is the confidence level. In the case study, $\xi = 0.90$ is used so that the configured reserve covers approximately 90% of historical deviations represented by the available error samples.

If synchronized source-level historical errors are not available to reconstruct $e_t^{\text{net},k}$ directly, the reserve requirement can be approximated by a conservative source-wise aggregated error margin:

$$\bar{R}_t^{\text{req},k} = \sum_{m=1}^M \left(\delta_m^{\text{L},k} \hat{p}_{t,m}^{\text{L},k} + \delta_m^{\text{W},k} \hat{p}_{t,m}^{\text{W},k} + \delta_m^{\text{PV},k} \hat{p}_{t,m}^{\text{PV},k} \right) \quad (7)$$

$k \in \{\text{DA}, \text{ID}\}$

The source-wise margin $\delta_m^{\text{s},k}$ is obtained from the empirical distribution of the normalized absolute error of source s :

$$\begin{cases} \delta_m^{\text{s},k} = \min\{\delta \geq 0 : \Pr(|e_{t,m}^{\text{s},k}| \leq \delta) \geq \xi\} \\ \epsilon_{t,m}^{\text{s},k} = \frac{\hat{p}_{t,m}^{\text{s},k,\text{his}} - p_{t,m}^{\text{s},k}}{\max(\hat{p}_{t,m}^{\text{s},k,\text{his}}, p_m^{\text{s},\text{rated}} \epsilon_0)} \end{cases} \quad (8)$$

The small threshold ϵ_0 avoids an ill-defined ratio when the forecast approaches zero, such as PV output at night or wind power below the cut-in speed. Eq. (7) should be interpreted as a conservative source-wise aggregated error margin, not as a probabilistic joint model, because it does not model correlation, compensation or cancellation among source errors. Under this source-wise approximation, the time-varying aggregated absolute margin is used as a conservative bidirectional reserve envelope, i.e., $R_t^{\text{up},\text{req},k} = R_t^{\text{dn},\text{req},k} = \bar{R}_t^{\text{req},k}$, unless synchronized signed net-load error samples are

available. In the present case study, the source-wise margins are used for day-ahead and intraday reserve sizing, while the real-time layer uses the 1 min deviation only for reserve deployment and performance evaluation.

3.2. Multi-Time-Scale Dispatching Model with Error Compensation

3.2.1. Day-Ahead Dispatching Model

The three stages use a lexicographic multi-objective structure in which power-supply adequacy is secured first. After load shortage is minimized, renewable curtailment, storage power capacity requirement, storage cycling, cross-stage tracking deviation, thermal backstop cost and energy revenue are optimized through a composite dispatch objective. This implementation keeps the power-supply-guarantee priority explicit while retaining the economic and renewable-accommodation terms in one lower-priority objective. The economic objective separates energy revenue, reserve-capacity compensation and regulation-energy compensation so that MW reserve capacity is not mixed with MWh regulation energy. This composite formulation is consistent with integrated multi-energy scheduling practices that coordinate flexibility and balance uncertainty [27]. For a generic dispatch horizon, the objective components are written as

$$\begin{aligned} \max F &= F_{\text{energy}} + F_{\text{AS}} + F_{\text{ES}} - C_{\text{sh}} - C_{\text{cur}} - C_{\text{ES}} \\ F_{\text{energy}} &= \sum_{t=1}^T \left[\sum_{m=1}^M \left(p_{t,m}^{\text{H}} r_t^{\text{H}} + p_{t,m}^{\text{WV}} r_t^{\text{WV}} \right) + \sum_{c=1}^C p_{t,c}^{\text{T}} r_t^{\text{T}} \right] \Delta T_t \\ F_{\text{AS}} &= \sum_{t=1}^T \sum_{m=1}^M \left[\pi_t^{\text{cap}} (R_{t,m}^{\text{up}} + R_{t,m}^{\text{dn}}) \Delta T_t + \pi_t^{\text{reg}} |\Delta p_{t,m}^{\text{H}}| \Delta T_t \right] \\ F_{\text{ES}} &= \sum_{t=1}^T \sum_{m=1}^M p_{t,m}^{\text{dis}} r_t^{\text{ES,dis}} \Delta T_t \\ \min f_q &= \sum_{t=1}^T \sum_{m=1}^M \left(p_{t,m}^{\text{H,cur}} + p_{t,m}^{\text{PV,cur}} + p_{t,m}^{\text{W,cur}} \right) \end{aligned} \quad (9)$$

where C_{sh} , C_{cur} and C_{ES} are the load-shortage, curtailment and storage-use costs, respectively.

The reserve-capacity term compensates available upward/downward reserve capacity, whereas the regulation-energy term compensates the actually deployed hydropower adjustment. In stages where reserve is configured but not yet deployed, the regulation-energy term is evaluated as zero or as an expected deployment term; in the real-time stage, it is evaluated from the realized $|\Delta p_{t,m}^{\text{H}}| \Delta T_t$. Since actual ancillary-service settlement data are unavailable in the case study, π_t^{cap} and π_t^{reg} are treated as exogenous compensation parameters rather than clearing prices from an actual trading platform. Thus, the model represents a comparative ancillary-service

compensation mechanism, not a complete market-settlement model.

The reserve configured in the day-ahead and intraday stages must cover the reserve requirement derived from the net-load error distribution or its source-wise approximation and remain feasible under hydropower headroom and ramping constraints:

$$\begin{cases} \sum_{m=1}^M R_{t,m}^{\text{up},k} \geq R_t^{\text{up,req},k} \\ \sum_{m=1}^M R_{t,m}^{\text{dn},k} \geq R_t^{\text{dn,req},k} \\ 0 \leq R_{t,m}^{\text{up},k} \leq P_{m,\text{max}}^H - P_{t,m}^H \\ 0 \leq R_{t,m}^{\text{dn},k} \leq P_{t,m}^H - P_{m,\text{min}}^H \\ R_{t,m}^{\text{up},k} \leq RU_m^H \Delta T_k \\ R_{t,m}^{\text{dn},k} \leq RD_m^H \Delta T_k \\ R_{t,m}^{\text{ac},k} = R_{t,m}^{\text{up},k} + R_{t,m}^{\text{dn},k} \\ k \in \{\text{DA}, \text{ID}\} \end{cases} \quad (10)$$

Here, RU_m^H and RD_m^H are expressed in MW/h, and ΔT_k converts the ramping rates into reachable reserve capacity within dispatch stage k . The scheduled hydropower output and the configured reserve must jointly satisfy the hydro output bounds, which prevents reserve from being counted when no physical headroom is available. In the case-study implementation, the time-varying reserve $R_{t,m}^{\text{ac},k}$ is calculated from the source-wise margins in Eq. (7) and imposed as hydropower headroom, ramping and storage-adequacy boundary conditions. Thus, the reserve-capacity sizing is auditable from the error margins and the forecast profiles, rather than being a separate market-bidding variable optimized inside the upper-stage MILP.

The cascade hydropower model is given in Eq. (11).

$$\begin{cases} P_{t,m}^H = k_m^H Q_{t,m}^{\text{out}} H_{t,m} \\ H_{t,m} = Z_{t,m}^{\text{up}} - Z_{t,m}^{\text{tail}} - \Delta H_{t,m} \\ Z_{t,m}^{\text{up}} = f_m^{\text{ZV}}(V_{t,m}) \\ Z_{t,m}^{\text{tail}} = f_m^{\text{ZQ}}(Q_{t,m}^{\text{out}}) \\ V_{t,m} = V_{t-1,m} + (Q_{t,m}^{\text{in}} - Q_{t,m}^{\text{out}}) \Delta T_t \\ Q_{t,m}^{\text{in}} = Q_{t,m}^{\text{nat}} + \sum_{g \in \text{Up}(m)} Q_{t-\tau_{g,m},g}^{\text{out}} \end{cases} \quad (11)$$

where k_m^H is the comprehensive output coefficient; $Q_{t,m}^{\text{out}}$ the turbine release; $H_{t,m}$ the net head; $Z_{t,m}^{\text{up}}$ and $Z_{t,m}^{\text{tail}}$ the reservoir and tailwater levels; $\Delta H_{t,m}$ the head loss; $V_{t,m}$ the reservoir storage; $Q_{t,m}^{\text{in}}$ the inflow; $Q_{t,m}^{\text{nat}}$ the natural local inflow between cascade stations; $\text{Up}(m)$ the set of upstream stations affecting station m ; and $\tau_{g,m}$ the water travel time from upstream station g to station m . If the case data provide only processed inflow forecasts, the travel-time effect is interpreted as already embedded in $Q_{t,m}^{\text{in}}$.

The available wind output is given in Eq. (12).

$$P_{t,m}^{\text{W,av}} = \begin{cases} 0 & 0 \leq v_{t,m} \leq v_{m,\text{ci}} \\ \frac{v_{t,m}^3 - v_{m,\text{ci}}^3}{v_{m,\text{r}}^3 - v_{m,\text{ci}}^3} P_{m,\text{r}} & v_{m,\text{ci}} \leq v_{t,m} \leq v_{m,\text{r}} \\ P_{m,\text{r}} & v_{m,\text{r}} \leq v_{t,m} \leq v_{m,\text{co}} \\ 0 & v_{m,\text{co}} \leq v_{t,m} \end{cases} \quad (12)$$

The available PV output and cell temperature are given in Eq. (13).

$$\begin{aligned} P_{t,m}^{\text{PV,av}} &= f_{m,\text{pv}} P_{m,\text{E}} \frac{S_{t,m}}{S_{m,\text{ref}}} \\ &\times [1 + k_m (T_{t,m}^c - T_{m,\text{ref}})] \\ T_{t,m}^c &= T_{t,m}^i + \frac{S_{t,m}}{S_{m,\text{ref}}} (T_{m,\text{noc}} - T_{m,\text{ref}}) \end{aligned} \quad (13)$$

The power-delivery and power-balance constraints are given in Eq. (14).

$$\begin{cases} P_{t,m}^{\text{WV}} + P_{t,m}^H + P_{t,m}^{\text{dis}} \leq \bar{P}_m^{\text{tr}} \\ \sum_{m=1}^M (P_{t,m}^{\text{WV}} + P_{t,m}^H + P_{t,m}^{\text{dis}}) + \sum_{c=1}^C P_{t,c}^T + P_t^{\text{sh}} = P_t^L \end{cases} \quad (14)$$

The energy-storage operation constraints are written in Eq. (15).

$$\begin{cases} 0 \leq p_{t,m}^{\text{ch}} \leq u_{t,m}^{\text{ch}} \bar{p}_m^{\text{ES}} \\ 0 \leq p_{t,m}^{\text{dis}} \leq u_{t,m}^{\text{dis}} \bar{p}_m^{\text{ES}} \\ u_{t,m}^{\text{ch}} + u_{t,m}^{\text{dis}} \leq 1 \\ E_{t,m}^{\text{ES}} = E_{t-1,m}^{\text{ES}} + (\eta^{\text{ch}} p_{t,m}^{\text{ch}} - p_{t,m}^{\text{dis}} / \eta^{\text{dis}}) \Delta T_t \\ \underline{E}_m^{\text{ES}} \leq E_{t,m}^{\text{ES}} \leq \bar{E}_m^{\text{ES}} \end{cases} \quad (15)$$

The binary variables $u_{t,m}^{\text{ch}}$ and $u_{t,m}^{\text{dis}}$ are enforced in the day-ahead and intraday planning stages to prevent simultaneous charging and discharging. In the real-time minute-level correction, the storage power schedule committed by the upper stage is inherited and only limited downward when required for feasibility; the state-of-charge balance and capacity bounds in Eq. (15) are still retained.

The ramping constraint, applied at every stage, is given in Eq. (16).

$$\begin{cases} -RD_m^H \Delta T_t \leq P_{t,m}^H - P_{t-1,m}^H \leq RU_m^H \Delta T_t \\ -RD_c^T \Delta T_t \leq P_{t,c}^T - P_{t-1,c}^T \leq RU_c^T \Delta T_t \end{cases} \quad (16)$$

where RU and RD are the up and down ramping limits of the cascade hydropower (superscript H) and thermal units (superscript T), expressed in MW/h. The remaining output and resource constraints are given in Eq. (17).

$$\begin{aligned} P_{c,\text{min}}^T &\leq P_{t,c}^T \leq P_{c,\text{max}}^T \\ P_{t,m}^{\text{W,av}} + P_{t,m}^{\text{PV,av}} &= P_{t,m}^{\text{W}} + P_{t,m}^{\text{PV}} + P_{t,m}^{\text{W,cur}} \\ &\quad + P_{t,m}^{\text{PV,cur}} + P_{t,m}^{\text{ch}} \\ P_{t,m}^{\text{WV}} &= P_{t,m}^{\text{W}} + P_{t,m}^{\text{PV}} \\ P_{m,\text{min}}^H &\leq P_{t,m}^H - R_{t,m}^{\text{dn}} \\ P_{t,m}^H + R_{t,m}^{\text{up}} &\leq P_{m,\text{max}}^H \\ Q_{m,\text{min}}^{\text{out}} &\leq Q_{t,m}^{\text{out}} \leq Q_{m,\text{max}}^{\text{out}} \\ V_{m,\text{min}} &\leq V_{t,m} \leq V_{m,\text{max}} \end{aligned} \quad (17)$$

3.2.2. Intraday Dispatching Model

The intraday and real-time stages express the highest-priority power-supply-guarantee objective explicitly as the power-supply guarantee rate ER over the current rolling evaluation window $\mathcal{T}_{\text{win}}$. This definition is equivalent to minimizing the accumulated load shortage over the same window; the renewable-accommodation and revenue objectives retain the same priority order as in the day-ahead stage. The intraday stage rolls on the day-ahead schedule under this objective.

$$ER = \frac{\sum_{t \in \mathcal{T}_{\text{win}}} [\sum_{m=1}^M (P_{t,m}^{\text{WV}} + P_{t,m}^{\text{H}} + P_{t,m}^{\text{dis}}) + \sum_{c=1}^C P_{t,c}^{\text{T}}]}{\sum_{t \in \mathcal{T}_{\text{win}}} P_t^{\text{L}}} \quad (18)$$

$$ER = 1 - \frac{\sum_{t \in \mathcal{T}_{\text{win}}} P_t^{\text{sh}}}{\sum_{t \in \mathcal{T}_{\text{win}}} P_t^{\text{L}}}$$

where ER is the rolling-window power-supply guarantee rate. To keep the units safe during multi-time-scale rolling, the output oscillation and window-end boundary constraints are written in Eq. (19).

$$\begin{cases} o_{m,\min}^{\text{H}} \leq P_{t,m,\text{d}}^{\text{H}} - P_{t,m,\text{n}}^{\text{H}} \leq o_{m,\max}^{\text{H}} \\ o_{c,\min}^{\text{T}} \leq P_{t,c,\text{d}}^{\text{T}} - P_{t,c,\text{n}}^{\text{T}} \leq o_{c,\max}^{\text{T}} \\ E_{m,\text{n},\text{end}}^{\text{ES}} \geq E_{m,\text{d},\text{end}}^{\text{ES}} \\ V_{m,\text{n},\text{end}} \geq V_{m,\text{d},\text{end}} \end{cases} \quad (19)$$

where subscripts d and n denote the day-ahead plan and the intraday value rolled from it; $o_{m,\bullet}^{\text{H}}$ and $o_{c,\bullet}^{\text{T}}$ are the oscillation bounds of the hydro and thermal units; and the subscript "end" denotes the end of the rolling window. The intraday model also obeys the ramping constraint in Eq. (16), the storage constraint in Eq. (15) and the resource constraints in Eq. (17).

3.2.3. Real-Time Dispatching Model

The real-time stage corrects the minute-scale net-load deviation between the realized value and the intraday schedule. The correction is formulated at the system level, so the thermal adjustment is indexed by thermal unit c rather than by sub-base m . The real-time deviation balance is

$$\begin{aligned} \sum_{m=1}^M \Delta P_{t,m}^{\text{H}} + \sum_{m=1}^M \Delta P_{t,m}^{\text{ES}} + \sum_{c=1}^C \Delta P_{t,c}^{\text{T}} + P_t^{\text{sh}} = \\ \Delta P_t^{\text{L}} - \sum_{m=1}^M \Delta P_{t,m}^{\text{W}} - \sum_{m=1}^M \Delta P_{t,m}^{\text{PV}} \end{aligned} \quad (20)$$

$$\begin{aligned} \Delta P_t^{\text{L}} &= P_t^{\text{L,RT}} - P_t^{\text{L,ID}} \\ \Delta P_{t,m}^{\text{W}} &= P_{t,m}^{\text{W,RT}} - P_{t,m}^{\text{W,ID}} \\ \Delta P_{t,m}^{\text{PV}} &= P_{t,m}^{\text{PV,RT}} - P_{t,m}^{\text{PV,ID}} \end{aligned}$$

The corrective resources are bounded by the configured reserve, ramping capability and operating limits:

$$\begin{cases} -R_{t,m}^{\text{dn}} \leq \Delta P_{t,m}^{\text{H}} \leq R_{t,m}^{\text{up}} \\ -RD_m^{\text{H}} \Delta T_{\text{RT}} \leq \Delta P_{t,m}^{\text{H}} \leq RU_m^{\text{H}} \Delta T_{\text{RT}} \\ P_{m,\min}^{\text{H}} \leq P_{t,m}^{\text{H,ID}} + \Delta P_{t,m}^{\text{H}} \leq P_{m,\max}^{\text{H}} \\ -\bar{P}_m^{\text{ch}} \leq \Delta P_{t,m}^{\text{ES}} \leq \bar{P}_m^{\text{dis}} \\ -RD_c^{\text{T}} \Delta T_{\text{RT}} \leq \Delta P_{t,c}^{\text{T}} \leq RU_c^{\text{T}} \Delta T_{\text{RT}} \\ P_{c,\min}^{\text{T}} \leq P_{t,c}^{\text{T,ID}} + \Delta P_{t,c}^{\text{T}} \leq P_{c,\max}^{\text{T}} \\ P_t^{\text{sh}} \geq 0 \end{cases} \quad (21)$$

In the real-time objective, hydropower reserve deployment is assigned the lowest regulation penalty, storage and thermal corrections are penalized more heavily, and load shortage has the highest penalty. This priority reflects the intended operating logic: the minute-level deviation is first absorbed by the configured hydropower reserve, then by storage, then by thermal correction, and finally by load shedding only when necessary.

After the real-time dispatch is obtained, the network security of the bundled delivery is evaluated through a DC power-flow check over the modified 30-bus equivalent system of the local power grid, as in Eq. (22). The network topology used for the case study is introduced later in Section 5.1.

$$E_l \leq \sum_{i=1}^N G_{l,i} P_{t,i} - \sum_{j=1}^{N_l} G_{l,j} P_{t,j}^{\text{L}} \leq \bar{F}_l \quad (22)$$

$$l = 1, \dots, L$$

where l indexes the L network branches; i and j index the buses; N is the number of buses with power injection and N_l the number of buses carrying load demand; $G_{l,i}$ and $G_{l,j}$ are the power-transfer distribution factors of the injection at bus i and of the load at bus j on branch l ; $P_{t,i}$ is the power injected at bus i at time t ; $P_{t,j}^{\text{L}}$ is the load demand at bus j ; and E_l and $\bar{F}_l$ are the lower and upper power-flow limits of branch l . The bus injection $P_{t,i}$ aggregates the outputs of the hydro, wind-PV, storage and thermal units connected at bus i according to the bus-equipment mapping introduced in Appendix A, so that Eq. (22) links the dispatch result to the branch-flow check. The optimization itself enforces the bundled transmission-corridor capacity (Eq. (14)), the boundary condition (Eq. (19)), the ramping constraint (Eq. (16)) and the storage constraint (Eq. (15)); Eq. (22) is used as a post-dispatch network-security evaluation for the reported case-study trajectory.

4. Solution Procedure

The three-stage dispatch model formulated in Section 3 is a nonconvex mixed-integer nonlinear program (MINLP): it involves the binary unit-commitment and storage charge/discharge variables, and—most critically—the cascade-hydropower model (Eq. (11)) is nonlinear, because the forebay and tailwater levels are

nonlinear functions of the storage and release ($Z_{t,m}^{\text{up}} = f_m^{\text{ZV}}(V_{t,m})$, $Z_{t,m}^{\text{tail}} = f_m^{\text{ZQ}}(Q_{t,m}^{\text{out}})$) and the generated power $P_{t,m}^{\text{H}} = k_m^{\text{H}} Q_{t,m}^{\text{out}} H_{t,m}$ is a bilinear product of the release and the head. Such a model cannot be passed directly to a mixed-integer linear solver. This section therefore (i) linearizes the hydropower nonlinearities so that each stage becomes a mixed-integer linear program (MILP) or, for the real-time relaxation, an LP (Section 4.1), (ii) explains how the priority-ordered multi-objective is solved within the multi-time-scale rolling loop (Section 4.2), and (iii) summarizes the overall solution flow and implementation (Section 4.3). It should be noted that the available wind and PV outputs (Eqs. (12) and (13)) are evaluated from the exogenous wind-speed, irradiance and temperature forecasts and therefore enter the dispatch model as known parameters rather than as nonlinear terms in the decision variables; the only nonlinearity that must be treated inside the optimization is the cascade-hydropower model. The DC power-flow relation in Eq. (22) is used after dispatch to check the reported network operating trajectory.

4.1. Linearization of the Cascade-Hydropower Model

Piecewise linearization of the reservoir characteristic curves. The forebay-level-storage curve f_m^{ZV} and the tailwater-level-release curve f_m^{ZQ} in Eq. (11) are univariate nonlinear functions. They are represented by tabulated piecewise-linear (PWL) characteristic curves. Eq. (23) gives the equivalent convex-combination form of this interpolation.

$$\begin{cases} V_{t,m} = \sum_{p=1}^P \lambda_{t,m,p} V_{m,p} \\ Z_{t,m}^{\text{up}} = \sum_{p=1}^P \lambda_{t,m,p} f_m^{\text{ZV}}(V_{m,p}) \\ \sum_{p=1}^P \lambda_{t,m,p} = 1 & \lambda_{t,m,p} \geq 0 \\ \lambda_{t,m,p} = 0 & \text{outside the active segment} \end{cases} \quad (23)$$

where $V_{m,p}$ are the storage breakpoints and $\lambda_{t,m,p}$ are the convex-combination weights. The tailwater curve f_m^{ZQ} is represented in the same way over a set of release breakpoints. In the Python implementation, these PWL maps are evaluated by direct interpolation during the SLP head-update step rather than by explicitly adding the λ variables to each MILP; this gives the same tabulated head value for the solved storage and release trajectories while keeping the optimization model compact.

Successive linear programming for the bilinear production function. Once the head $H_{t,m} = Z_{t,m}^{\text{up}} - Z_{t,m}^{\text{tail}} - \Delta H_{t,m}$ is rendered piecewise-linear, the only remaining nonlinearity is the bilinear term $P_{t,m}^{\text{H}} =$

$k_m^{\text{H}} Q_{t,m}^{\text{out}} H_{t,m}$. It is resolved by successive linear programming (SLP): within each iteration ν the head is held at the value $H_{t,m}^{(\nu)}$ obtained from the previous solution, so the production function (Eq. (24)) becomes linear in the release; the head is then refreshed from the newly solved storage and release trajectories.

$$\begin{cases} P_{t,m}^{\text{H},(\nu)} = k_m^{\text{H}} H_{t,m}^{(\nu)} Q_{t,m}^{\text{out}} \\ H_{t,m}^{(\nu+1)} = f_m^{\text{ZV}}(V_{t,m}^{(\nu)}) - f_m^{\text{ZQ}}(Q_{t,m}^{\text{out},(\nu)}) - \Delta H_{t,m} \end{cases} \quad (24)$$

The iteration is initialized with the rated head, solves the resulting MILP, updates the head through Eq. (24), and repeats until the head converges, i.e. $\max_{t,m} |H_{t,m}^{(\nu+1)} - H_{t,m}^{(\nu)}| \leq \epsilon_H$; the converged solution then satisfies the original nonlinear output characteristic. A trust region $|Q_{t,m}^{\text{out}} - Q_{t,m}^{\text{out},(\nu)}| \leq \Delta Q_m$ is imposed in the early iterations to prevent the optimum from oscillating between extreme operating points. After this treatment, each dispatch stage is solved by GUROBI through the gurobipy interface in Python.

4.2. Lexicographic Multi-Objective Solution within the Rolling Loop

Each stage carries the priority-ordered objectives defined in Section 3.2: the power-supply guarantee objective has the highest priority, and the lower-priority composite dispatch objective contains renewable-curtailment, storage, tracking, thermal and revenue terms. They are solved lexicographically within each linearized SLP iteration: the highest-priority objective is optimized first; its optimal value is then fixed—within a small tolerance—as an additional constraint, and the next objective is optimized over the restricted feasible set, so that no higher-priority objective is degraded. The three stages are linked by the multi-time-scale rolling of Section 2: the day-ahead plan is fixed at 0:00, the intraday model rolls every 4 h on the day-ahead commitment and discharge-flow plan, and the real-time model rolls every 0.5 h within each intraday window. At the day-ahead and intraday rolls, the reserve is sized from net-load error quantiles or, in the case study, from conservative source-wise aggregated margins, following Eqs. (6)-(8) and (10). At the real-time roll, the reserve configured in the upper stages is deployed according to the realized minute-level net-load deviation in Eqs. (20) and (21). After the SLP loop converges, the boundary conditions produced by the upper stage—the commitment scale, the initial/terminal storage, and the reserve and ramping limits—are handed down as constraints to the lower stage.

4.3. Solution Flow and Implementation

The three-stage dispatch flowchart is shown in Figure 2. The data preprocessing, multi-resolution forecasting, dispatch optimization and figure generation are

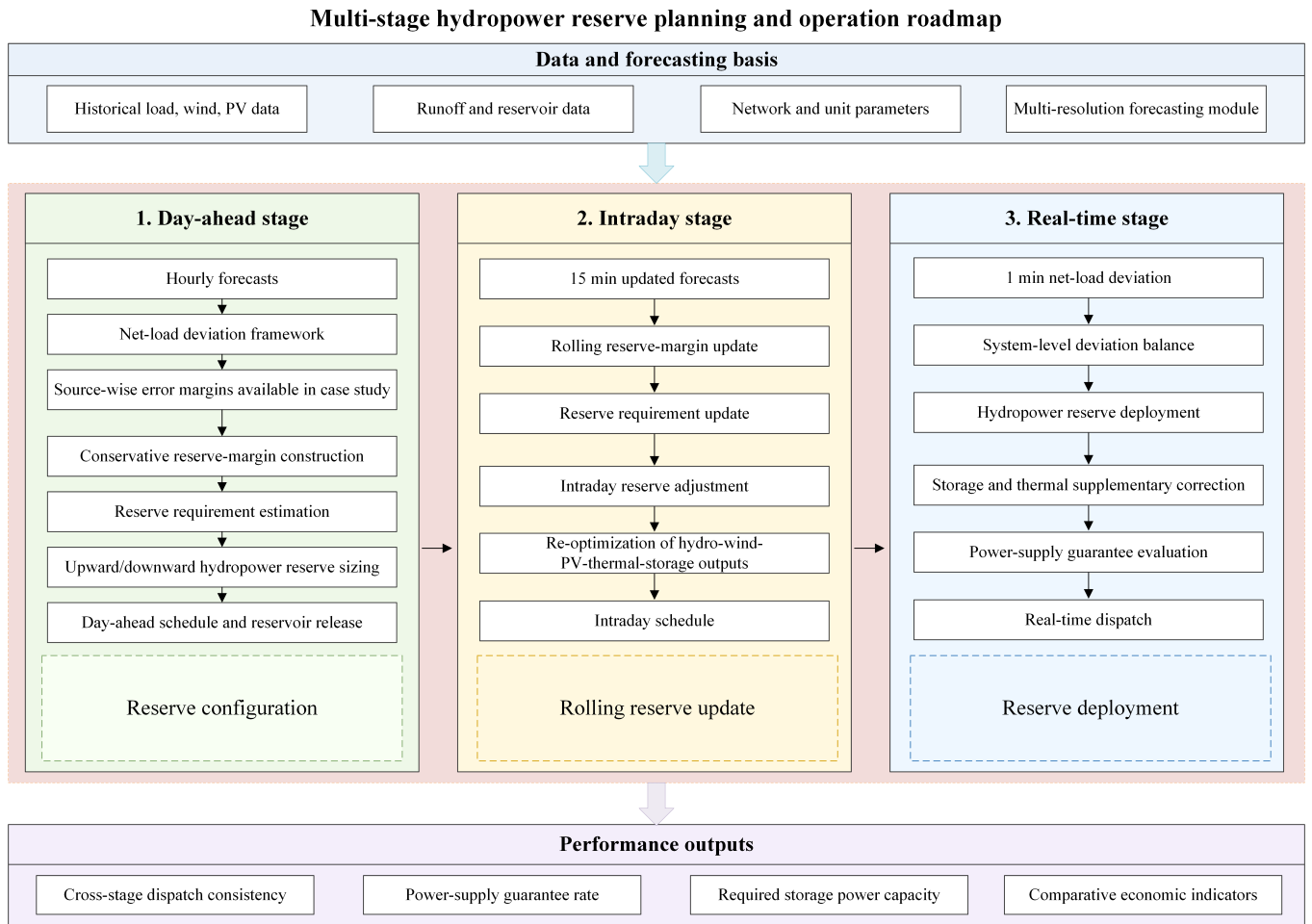


Figure 2. Flowchart of the three-stage error-compensation dispatch procedure

implemented in Python. The day-ahead, intraday and real-time dispatch models are formulated as MILP/LP problems and solved by GUROBI through the gurobipy interface. The reservoir characteristic curves are represented by tabulated PWL interpolation, and the bilinear hydropower production term is handled by the SLP head-update loop described in Section 4.1. At each rolling stage, the reserve requirement is derived from the net-load error formulation or, in the case study, from the conservative source-wise aggregated margin. The boundary conditions produced by the upper stage, including reservoir storage, hydropower output, reserve capacity and ramping margins, are passed to the lower stage.

The case-study computation is implemented in Python. The optimization models are solved by GUROBI through the gurobipy interface. Unless otherwise specified, the reported figures and tables are processed and visualized using the same Python case-study workflow to ensure consistency between the dispatch results and the plotted data. The MILP stages are solved to a relative optimality gap of 1%, and the SLP head iteration is terminated when the maximum

head change falls below $\epsilon_H = 0.1$ m or when the preset iteration limit is reached.

5. Case Study

5.1. Parameter Settings

A case study is carried out on a hydro–wind–PV–storage clean energy base in a cascade hydropower basin in Southwest China. The installed capacities, reservoir parameters, network topology and operating profiles used in the study are taken from the case data and processed in Python for dispatch optimization and result visualization. Four scenarios are set to evaluate the proposed dispatch strategy:

- **Scenario 1:** Wind–PV installed capacity equal to 1.5–2 times the hydropower installed capacity, using the conventional fixed-reserve regulation strategy.
- **Scenario 2:** Wind–PV installed capacity equal to 2–2.5 times the hydropower installed capacity, using the conventional fixed-reserve regulation strategy.

- **Scenario 3:** Wind-PV installed capacity equal to 1.5–2 times the hydropower installed capacity, using the proposed error-compensation strategy.
- **Scenario 4:** Wind-PV installed capacity equal to 2–2.5 times the hydropower installed capacity, using the proposed error-compensation strategy.

A representative transition day between spring and summer is selected as the dispatch object. Based on the forecasting scheme, the day-ahead, intraday and real-time input power profiles of wind generation, PV generation and load are obtained for each cascade clean-energy sub-base. The representative day-ahead and intraday forecast and realized profiles used for the main-case forecasting-accuracy calculation and rolling input check are shown in Figures A.1 and A.2 in Appendix A. The real-time profiles are used internally for rolling dispatch but are not separately plotted in the manuscript to keep the appendix compact. The runoff and reservoir data enter the hydropower constraints and SLP head update but are not separately plotted.

The basic parameters of the four sub-bases—each formed by a cascade hydropower station together with its co-located wind and PV plants (indexed by m in Section 3 and reported per sub-base in Table 1)—are listed in Table 1. Because the various energy sources play different roles in the clean energy base, a differentiated price is adopted for each supply source; the prices of hydropower, wind-PV, storage and thermal power are listed in Table 2. The power-flow network is represented by a modified 30-bus equivalent system of the local power grid. This wording is used deliberately: the case system preserves a 30-bus power-flow structure while mapping the hydro, wind-PV, storage, thermal and load devices to the corresponding buses listed in Appendix A. The one-line diagram is shown in Figure 3. The case-study workflow uses the same input data set for the fixed-reserve and error-compensation strategies so that the comparison isolates the effect of the reserve-sizing and reserve-deployment rule rather than differences in forecast inputs.

5.2. Analysis of Forecasting Absolute Errors

Based on the forecasting scheme and historical operating data, the source-wise forecast errors of wind power, PV power and load are obtained at different time scales and compared with the realized data. Figure 4 reports the source-wise error samples, while Figure 5 summarizes the corresponding empirical distributions. The day-ahead and intraday distributions are used for reserve-margin construction; the real-time distribution is shown only to characterize minute-level deviations used for reserve deployment and performance evaluation. These figures do not replace synchronized net-load error samples; rather, they

provide the source-wise margins used to approximate the reserve requirement when synchronized net-load error samples are unavailable. When synchronized source-level data are available, the same samples can be converted into net-load errors according to Eqs. (4)–(6) for direct reserve sizing.

A comparison between the main-case day-ahead MAPE of the adopted forecasting scheme and representative English-language benchmarks for wind, PV and load forecasting is given in Table 3. The comparison in Table 3 is intended only as a rough reference against representative reported MAPE values in the literature [28–30], rather than a strictly controlled benchmark, because the datasets, forecasting horizons and evaluation conditions are different. The reported values for the adopted forecasting scheme are computed from the same Scenario 4 proposed-strategy input profiles provided in Appendix A; near-zero wind and PV periods below 5% of installed capacity are excluded from the percentage calculation to avoid night-time or cut-in artifacts. These values indicate that the forecasting module provides sufficiently accurate multi-resolution inputs for the subsequent error-compensation dispatch analysis. The empirical distributions in Figure 5 are then used to obtain the source-wise error margins listed in Table 4.

The coefficients in Table 4 are dimensionless error-margin coefficients rather than reserve-capacity values. At each dispatch period, they are multiplied by the corresponding forecasts to form the time-varying aggregated absolute reserve requirement, as defined in Eq. (7).

Because the available case data provide unsigned source-wise error margins rather than synchronized signed net-load errors, $\hat{R}_t^{\text{req},k}$ is used as a conservative bidirectional reserve envelope in Eq. (10). Thus, the reserve requirement varies with the hourly or 15 min forecast trajectory, even though Table 4 reports only the error-margin coefficients.

5.3. Dispatching Result Analysis

This section analyzes the first multi-time-scale rolling dispatch of the selected representative transition day. The results are used to evaluate the dispatch mechanism under the tested operating condition. Scenarios 1 and 3 share the same lower wind-PV scale and Scenarios 2 and 4 the same higher wind-PV scale, so that within each pair the two scenarios differ only in the regulation strategy.

5.3.1. Multi-Time-Scale Unit Output Fluctuation Error Distribution under Different Scenarios

To quantify the cross-stage dispatch accuracy, the output fluctuation error of a unit type $x \in \{H, T\}$ between two adjacent stages is defined in Eq. (25)

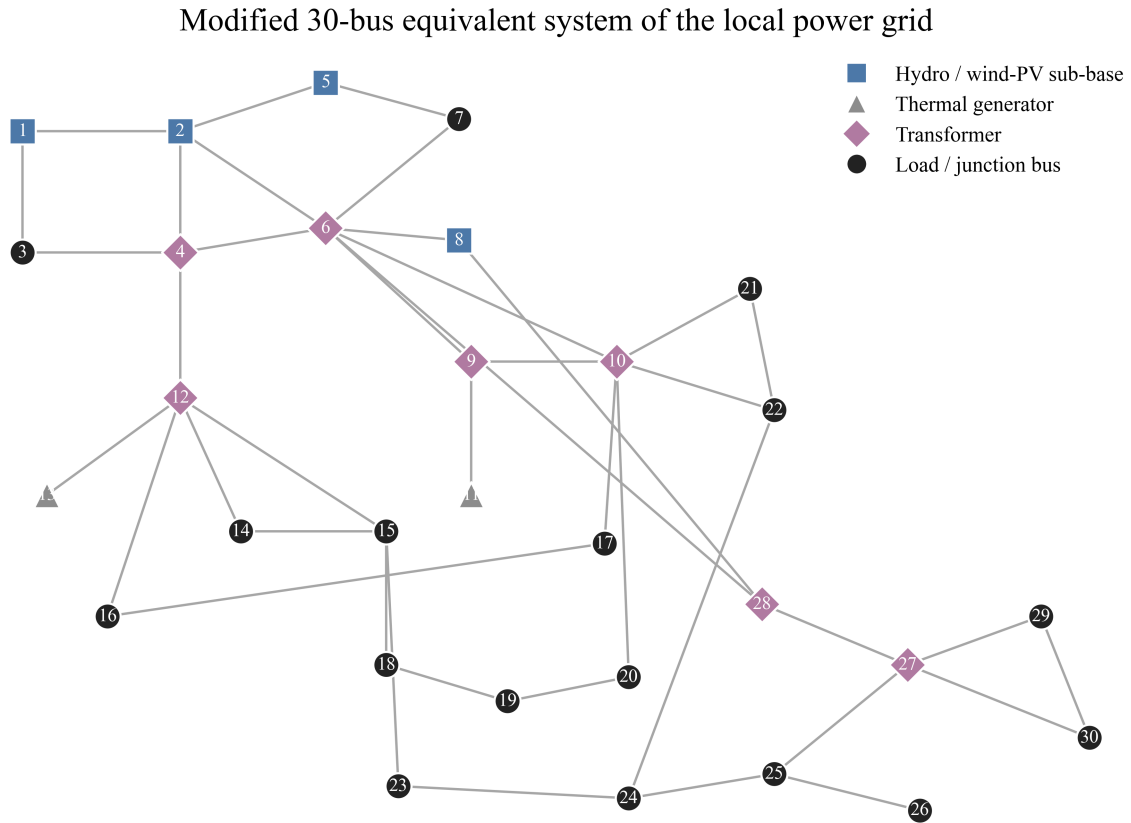


Figure 3. Topology of the modified 30-bus equivalent system of the local power grid

Table 1. Basic parameters of the cascade clean energy base

Item	Sub-base 1	Sub-base 2	Sub-base 3	Sub-base 4
Hydropower station	Station 1	Station 2	Station 3	Station 4
Hydropower capacity (MW)	600	695	600	1280
Wind capacity (MW)	317	212	300	1098
PV capacity (MW)	770	900	680	1155
Regulating storage (10^8 m^3)	42.14	4.83	0.55	10.88
Dead water level (m)	1076	950	835	736

as the window-averaged absolute revision from the coarser-stage plan to the finer-stage schedule. The finer-stage schedule is first aggregated to the coarser-stage resolution so that genuine higher-resolution refinement is not counted as an artificial fluctuation.

$$\beta_x = \frac{\frac{1}{T} \sum_{t=1}^T |\bar{p}_{t,x}^{\text{fine}} - p_{t,x}^{\text{coarse}}|}{\max\left(\frac{1}{T} \sum_{t=1}^T |p_{t,x}^{\text{coarse}}|, 1\right)} \times 100\% \quad (25)$$

where $p_{t,x}^{\text{coarse}}$ is the scheduled output of unit type x at the coarser stage, and $\bar{p}_{t,x}^{\text{fine}}$ is the finer-stage schedule averaged over the corresponding coarser-stage period. The denominator lower bound avoids an ill-conditioned percentage when the reference output is close to zero. Because thermal output is close to zero in several periods, the percentage-based thermal

fluctuation index is sensitive to the denominator and can become numerically large. Therefore, the thermal entries are interpreted only as supplementary indicators of thermal correction intensity, while cross-stage dispatch consistency is mainly evaluated using the hydropower fluctuation error and the power-supply guarantee rate.

The output fluctuation errors between adjacent time scales under each scenario are listed in Table 5. In the day-ahead-to-intraday transition, the proposed error-compensation strategy reduces the hydropower output fluctuation error from 8.42% to 4.81% at the lower wind-PV scale and from 7.48% to 6.02% at the higher wind-PV scale. In the intraday-to-real-time transition, the hydropower fluctuation error decreases from 8.27% to 6.84% at the lower scale

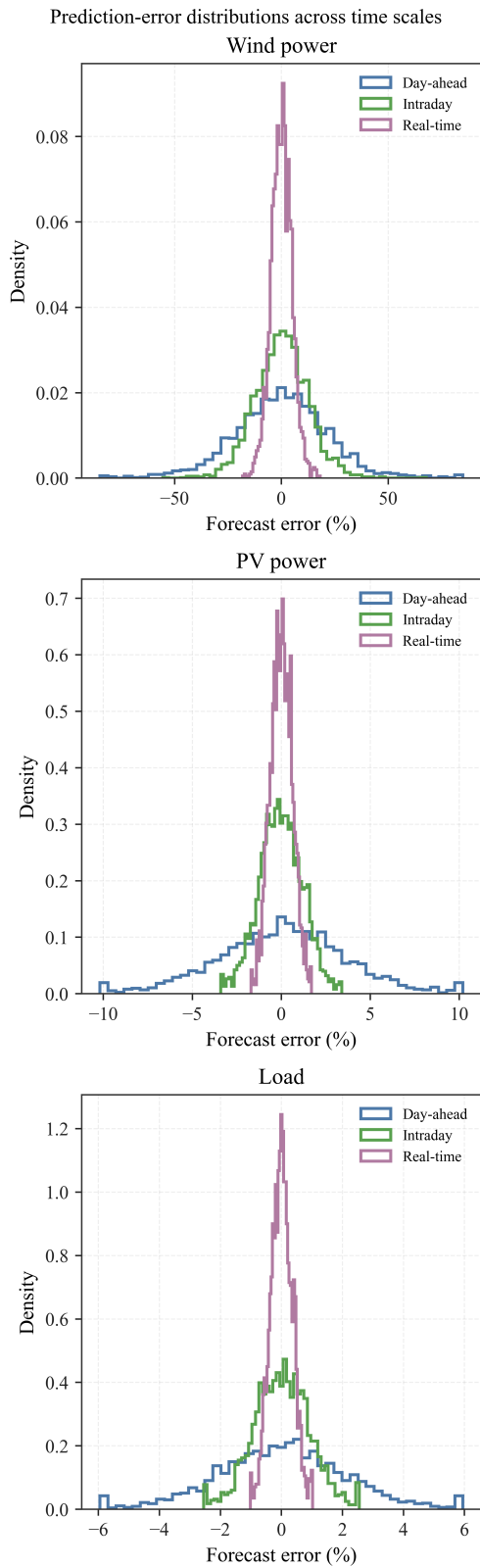


Figure 4. Source-wise forecast-error distributions used for conservative reserve-margin construction

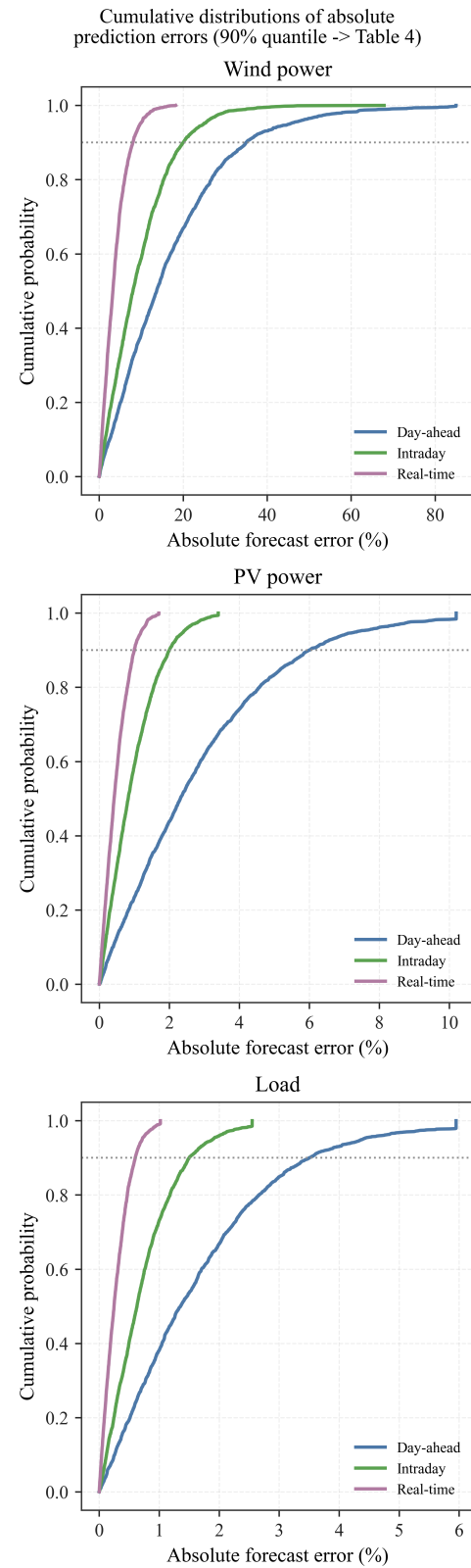


Figure 5. Probability distributions of source-wise forecast errors for day-ahead and intraday reserve-margin estimation

Table 2. Price and compensation settings of the cascade clean energy base

Source / Compensation item	Value
Wind and PV energy	1 CNY/kWh
Hydropower energy	1.1 CNY/kWh
Thermal generation	0.55 CNY/kWh
Storage discharge energy	1.2 CNY/kWh
Regulation-energy compensation parameter	1.2 CNY/kWh
Reserve-capacity compensation parameter	External parameter; not separately available in the original case data
Equivalent storage-power capacity penalty in the objective	1.55×10^3 CNY-equivalent/MW

Table 3. Forecasting MAPE of the Transformer-LSTM-Attention Deep Learning Module Compared with Representative Benchmarks

Category	Wind power	PV power	Load
Proposed forecast MAPE (%)	5.79	0.79	0.52
Representative benchmark MAPE (%)	10.50	2.89	2.39

and from 8.44% to 8.09% at the higher scale. The corresponding power-supply guarantee rate remains 100.00% in the reported adjacent-stage windows under all four scenarios. These comparisons show that the proposed strategy improves cross-stage hydropower dispatch consistency while maintaining short-term supply adequacy in the analyzed rolling window; under the higher wind–PV scale, the improvement is moderate because the system operates closer to the transmission and regulation limits.

5.3.2. Hydropower Reserve Usage for Error Compensation

The error-compensation reserve capacity is used to smooth the prediction errors of large-scale renewable energy at different time scales. Figures 6 and 7 report the hydropower reserve usage in the intraday and real-time stages, respectively.

Compared with the fixed-reserve scenarios, the error-compensation scenarios show a more targeted use of hydropower reserve, because the reserve is sized according to the error margin rather than assigned as a uniform fixed margin. In the real-time stage, the proposed strategy tracks the minute-level net-load deviation by deploying the reserve configured in the upper stages and by using storage as supplementary regulation when necessary. This reserve-usage pattern is consistent with the reduced cross-stage hydropower deviations and high real-time power-supply guarantee rate reported in Table 5.

The full-day aggregation of the reserve-usage trajectories further shows that the daily deployed hydropower reserve energy decreases from 3.96 GWh in Scenario 1 to 3.37 GWh in Scenario 3 at the lower wind–PV scale, and from 4.13 GWh in Scenario 2 to 3.84 GWh in Scenario 4 at the higher wind–PV scale. This indicates that the proposed error-compensation

strategy does not simply increase reserve deployment; instead, it reallocates hydropower reserve more selectively to periods with higher forecast-error exposure.

5.3.3. Dispatching Revenue Indicators and Required Storage Power Capacity

The multi-time-scale dispatching revenue indicators under each scenario are listed in Table 6. Because the available case data do not provide independent reserve-capacity and regulation-energy market settlements, Table 6 is used as a comparative revenue indicator processed within the same case-study workflow. It should not be interpreted as a complete market-settlement result of Eq. (9). In particular, the base-level total revenue indicator denotes the combined revenue of the clean energy base, including hydropower-and-ancillary revenue, wind–PV revenue, thermal revenue and storage-discharge revenue; therefore, it should not be added again to the other revenue components. Under this accounting interpretation, the error-compensation scenarios show slightly lower base-level revenue because less reserve and storage regulation energy is deployed, while the load-shortage cost remains zero in the reported windows. Thus, the revenue comparison is used to indicate the relative operating tendency under the same accounting assumptions, whereas the adequacy and storage-power-capacity conclusions are supported by the physical dispatch indicators in Tables 5 and 7.

The required storage power capacity under each scenario is listed in Table 7. The unit of Table 7 is MW, so the table reports storage power capacity rather than stored energy amount.

The stacked bars in Figure 8 use the same sub-base storage power capacity components as Table 7. At the lower wind–PV scale, the total required storage power capacity decreases from 921.52 MW in Scenario 1 to 608.17 MW in Scenario 3, a reduction of approximately 34.00%. At the higher wind–PV scale, the total required storage power capacity decreases from 1183.58 MW in Scenario 2 to 803.48 MW in Scenario 4, a reduction of approximately 32.11%. This comparison suggests that the proposed error-compensation strategy can reduce the dependence on short-term storage regulation

Table 4. Source-wise 90% absolute-error margins used in the case study

Stage	Rolling window in this case	Sampling interval	Wind margin	PV margin	Load margin	Application
Day-ahead	0:00-24:00	1 h	0.350	0.060	0.035	Reserve-capacity sizing
Intraday	0:00-4:00	15 min	0.200	0.020	0.015	Rolling reserve update
Real-time	0:00-0:30	1 min	0.080	0.010	0.006	Reserve deployment and guarantee-rate evaluation

Note: The real-time row reports the observed 1 min deviation level for reserve deployment and guarantee-rate evaluation only; it is not used to size an additional real-time reserve coefficient. Reserve capacity is configured only in the day-ahead and intraday stages.

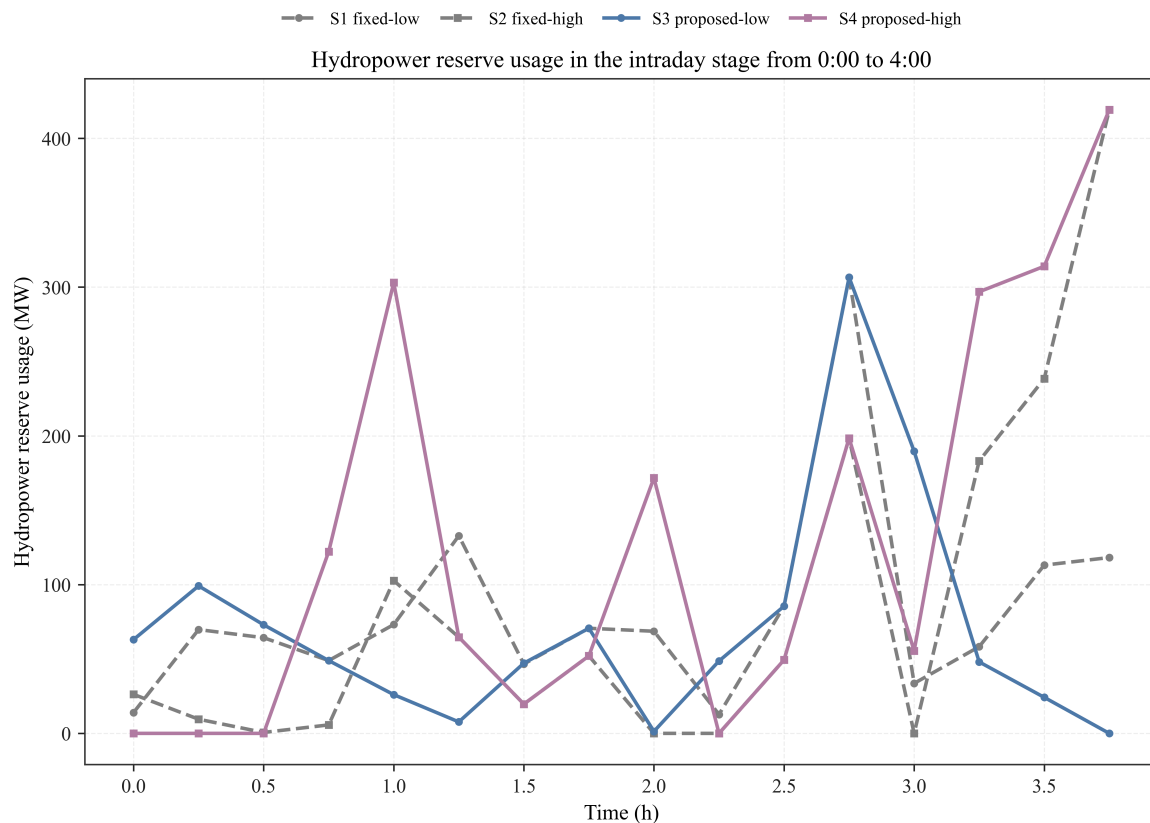

Figure 6. Hydropower reserve usage in the intraday stage from 0:00 to 4:00

Table 5. Multi-time-scale unit output fluctuation errors under different scenarios

Item	S1	S2	S3	S4
Hydropower fluctuation error, day-ahead → intraday	8.42%	7.48%	4.81%	6.02%
Thermal fluctuation error, day-ahead → intraday	120.22%	88.09%	32.19%	62.41%
Power supply guarantee rate, day-ahead → intraday	100.00%	100.00%	100.00%	100.00%
Hydropower fluctuation error, intraday → real-time	8.27%	8.44%	6.84%	8.09%
Thermal fluctuation error, intraday → real-time	83.25%	76.45%	75.07%	77.20%
Power supply guarantee rate, intraday → real-time	100.00%	100.00%	100.00%	100.00%

by making more effective use of cascade-hydropower reserve. This interpretation is based on the observed storage power requirement in the tested scenarios; detailed reserve-deployment statistics would further

quantify the substitution ratio between hydropower reserve and storage regulation.

5.3.4. Multi-Time-Scale Dispatching Results of Scenario 4

Scenario 4 is selected as the main high-renewable operating case because it combines the higher wind-PV installed scale with the proposed error-compensation strategy. Therefore, the key paired comparison should be made between Scenario 2 and Scenario 4, which have the same wind-PV capacity level but different reserve-sizing strategies.

Under this paired comparison, the required storage power capacity decreases from 1183.58 MW in Scenario 2 to 803.48 MW in Scenario 4, corresponding to a reduction of 32.11%, while the reported rolling-window power-supply guarantee rate remains 100.00%. This result indicates that the proposed strategy reduces the dependence on supplementary short-term storage

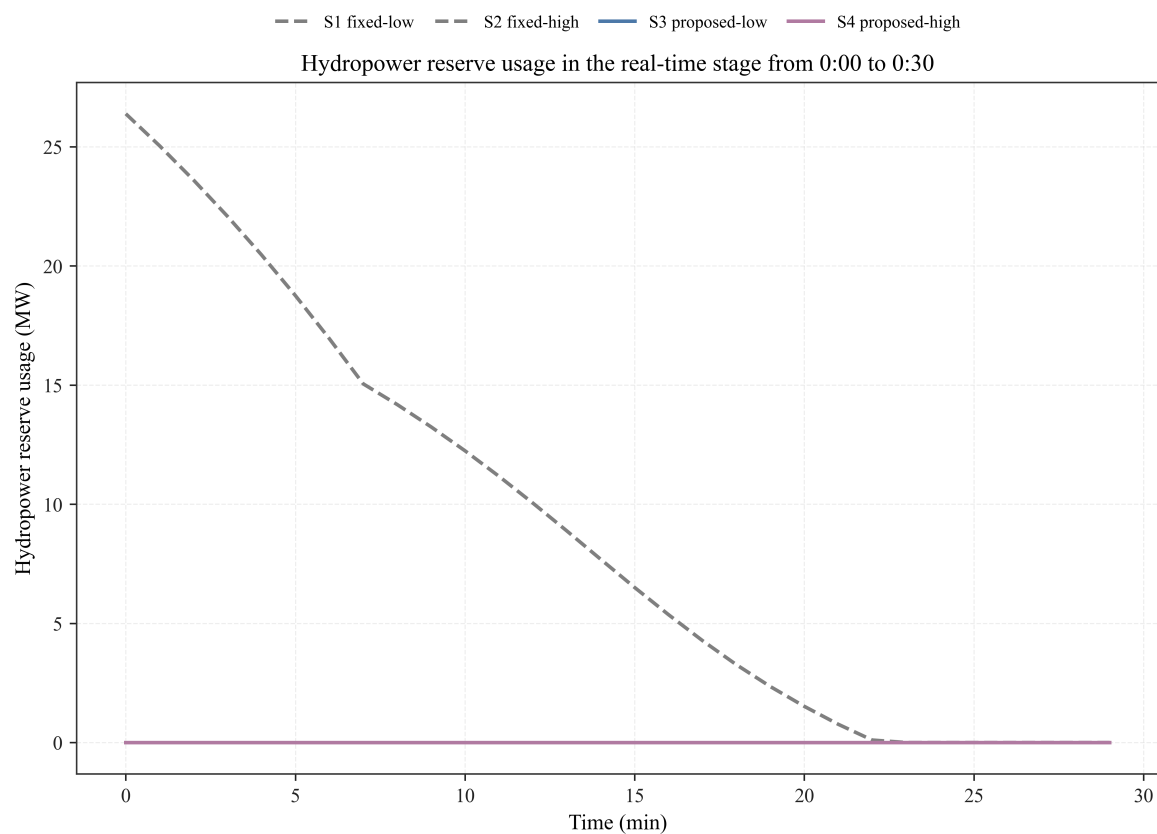


Figure 7. Hydropower reserve usage in the real-time stage from 0:00 to 0:30

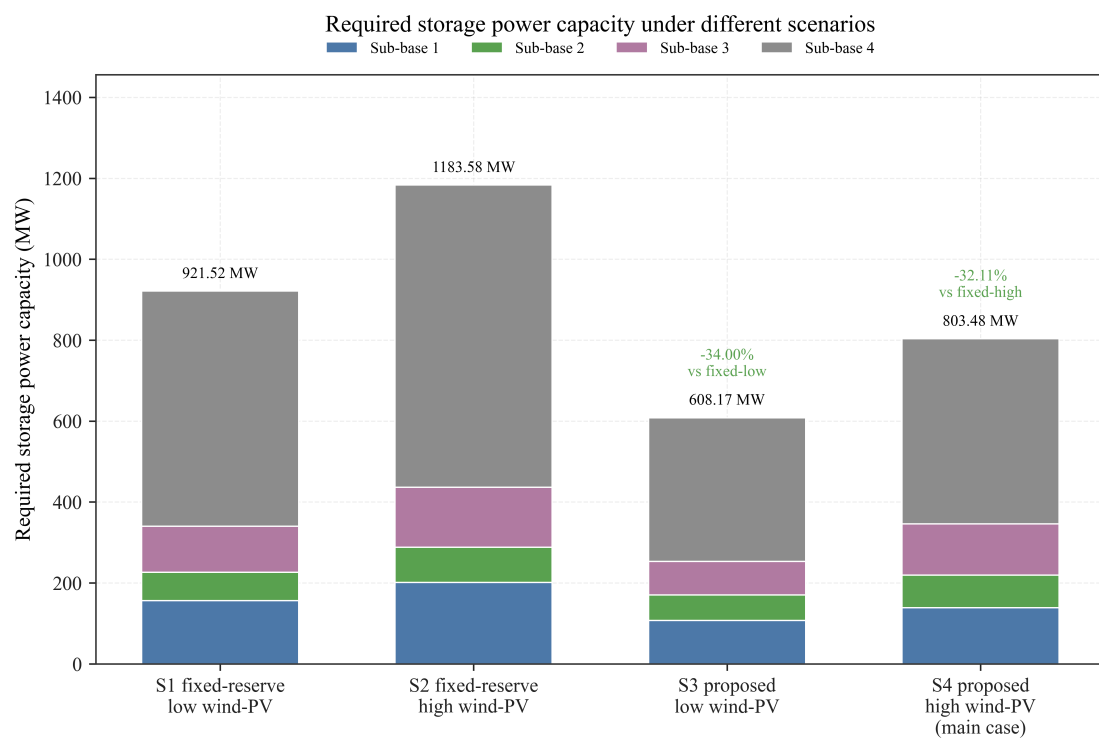


Figure 8. Required storage power capacity under different scenarios

Table 6. Multi-time-scale dispatching revenue indicators under different scenarios (10^7 CNY). Base-level total revenue indicator is not additive with hydropower-and-ancillary revenue

Stage / Item	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Day-ahead dispatch				
Base-level total revenue indicator	11.157	12.488	10.863	12.268
Hydropower generation and ancillary revenue	6.128	5.995	5.878	5.738
Thermal generation revenue	0.044	0.093	0.083	0.156
Storage generation revenue	0.784	0.719	0.516	0.592
Load shortage cost	0.000	0.000	0.000	0.000
Wind/PV curtailment cost	0.000	0.000	0.000	0.000
Intraday dispatch (0–4 h)				
Base-level total revenue indicator	1.597	1.780	1.600	1.762
Hydropower generation and ancillary revenue	1.167	1.194	1.216	1.198
Thermal generation revenue	0.004	0.017	0.001	0.036
Storage generation revenue	0.093	0.119	0.064	0.082
Load shortage cost	0.000	0.000	0.000	0.000
Wind/PV curtailment cost	0.000	0.000	0.000	0.000
Real-time dispatch (0–0.5 h)				
Base-level total revenue indicator	0.237	0.266	0.230	0.262
Hydropower generation and ancillary revenue	0.187	0.202	0.190	0.212
Thermal generation revenue	0.000	0.000	0.000	0.000
Storage generation revenue	0.024	0.032	0.015	0.018
Load shortage cost	0.000	0.000	0.000	0.000
Wind/PV curtailment cost	0.000	0.000	0.000	0.000

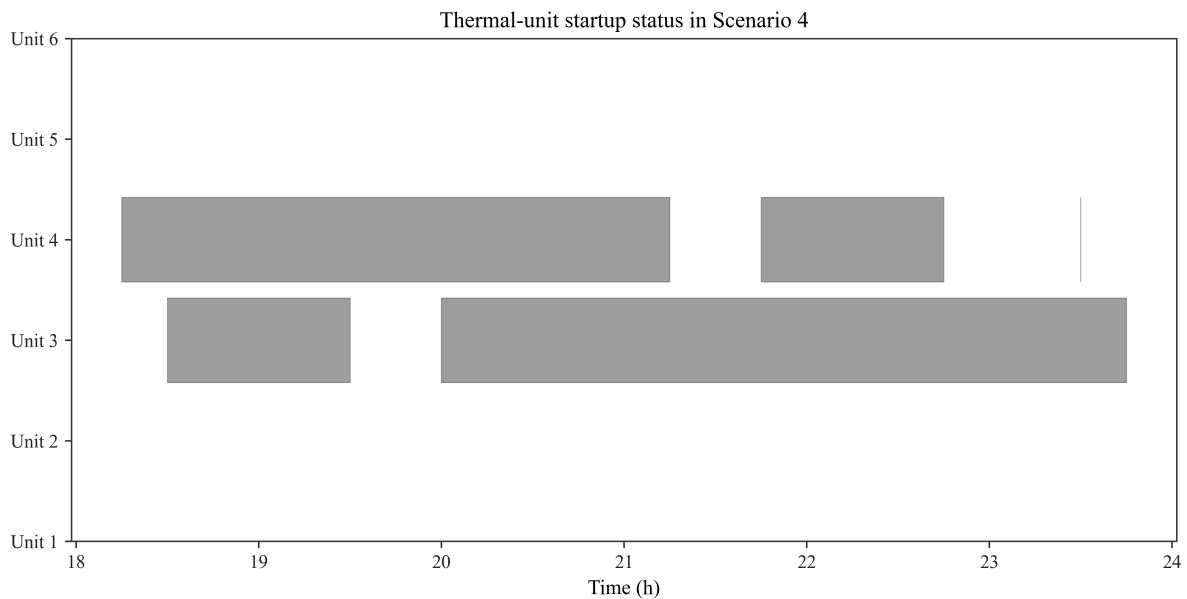


Figure 9. Thermal-unit startup status in Scenario 4

regulation under the tested high-renewable operating condition.

The on/off status of the thermal units in Scenario 4 is shown in Figure 9. Compared with the fixed-reserve scenarios, the error-compensation scenarios reduce the required storage power capacity and actual reserve deployment while the dispatch is mainly supplied by the clean-energy base. This result is consistent with the high real-time power-supply guarantee rate and lower storage power requirement observed in Scenarios 3 and 4.

The multi-time-scale dispatching output distribution of the main case, Scenario 4, is shown in Figures 10–12. The corresponding scenario-level comparisons have already been reported in the preceding comparison tables, so the non-main-case dispatch profiles are not repeated in the appendix. The results show that the clean-energy base provides the dominant share of scheduled power, while thermal units and storage act as supplementary regulation resources. The consistency among the day-ahead, intraday and real-time schedules indicates that the proposed strategy can coordinate

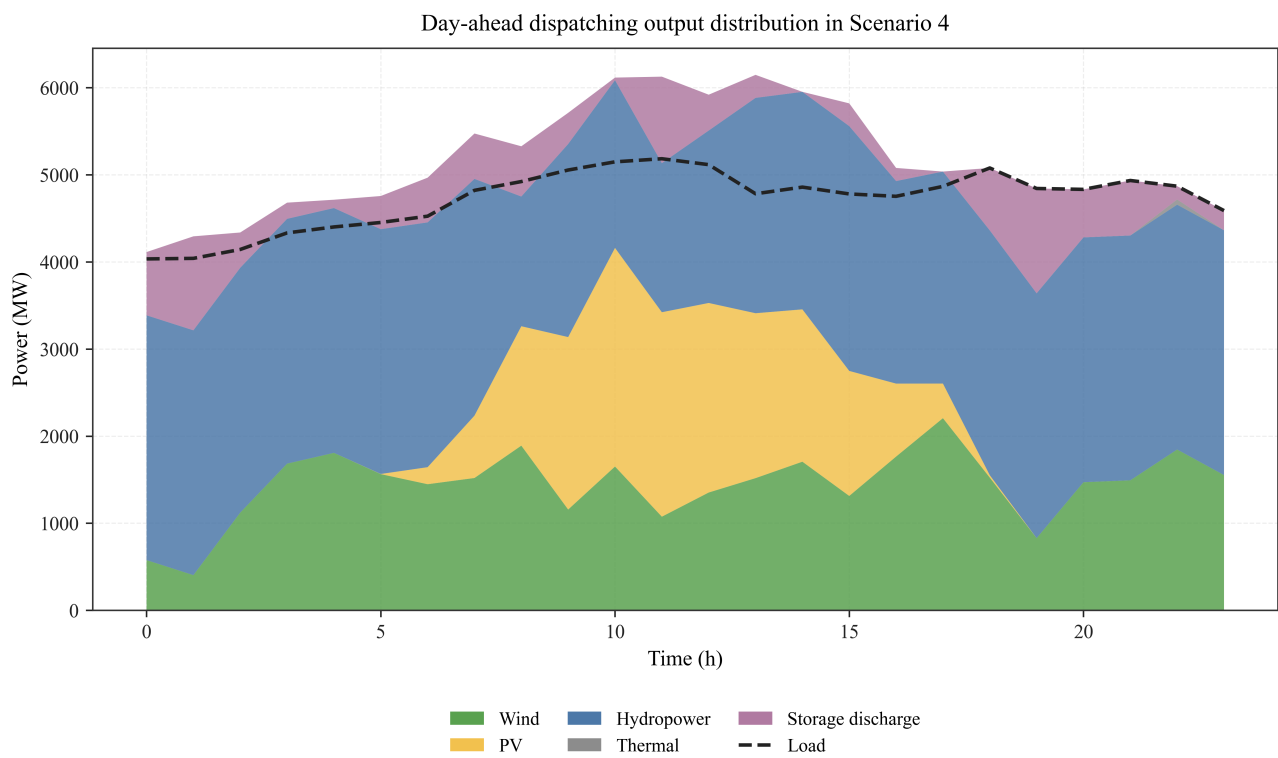


Figure 10. Day-ahead dispatching output distribution in Scenario 4

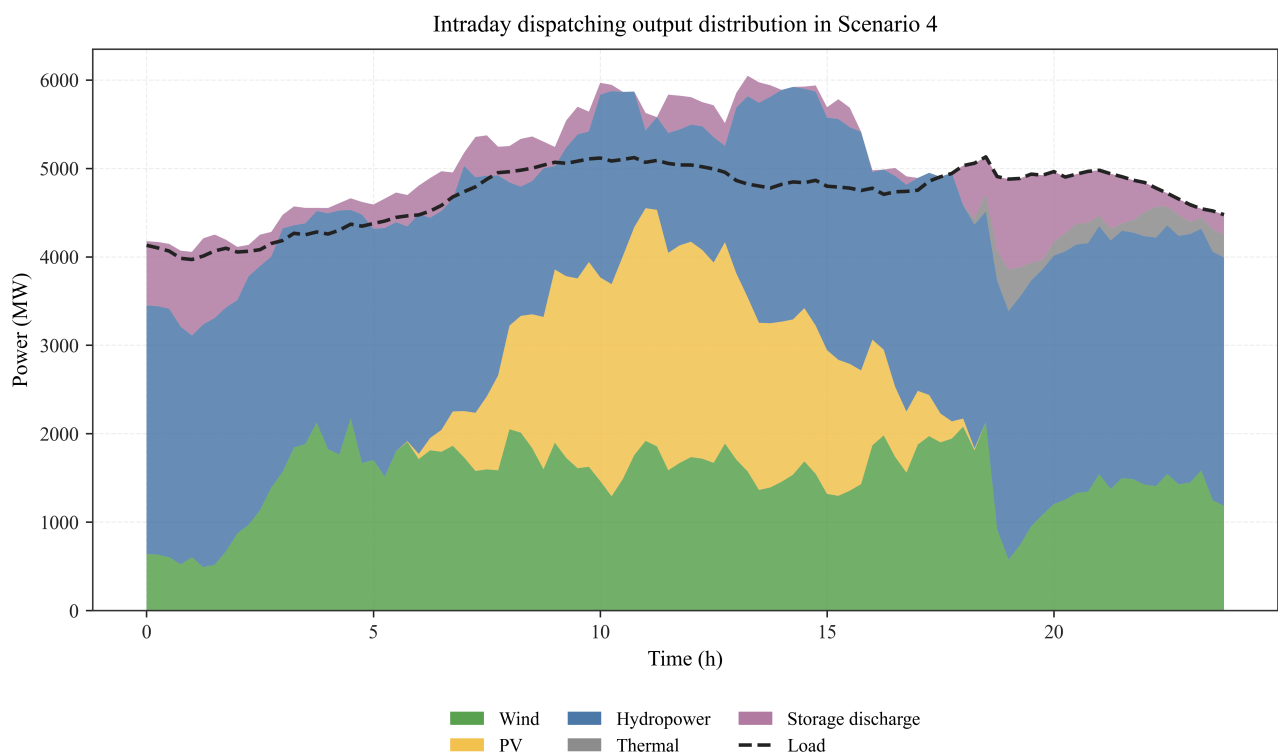


Figure 11. Intraday dispatching output distribution in Scenario 4

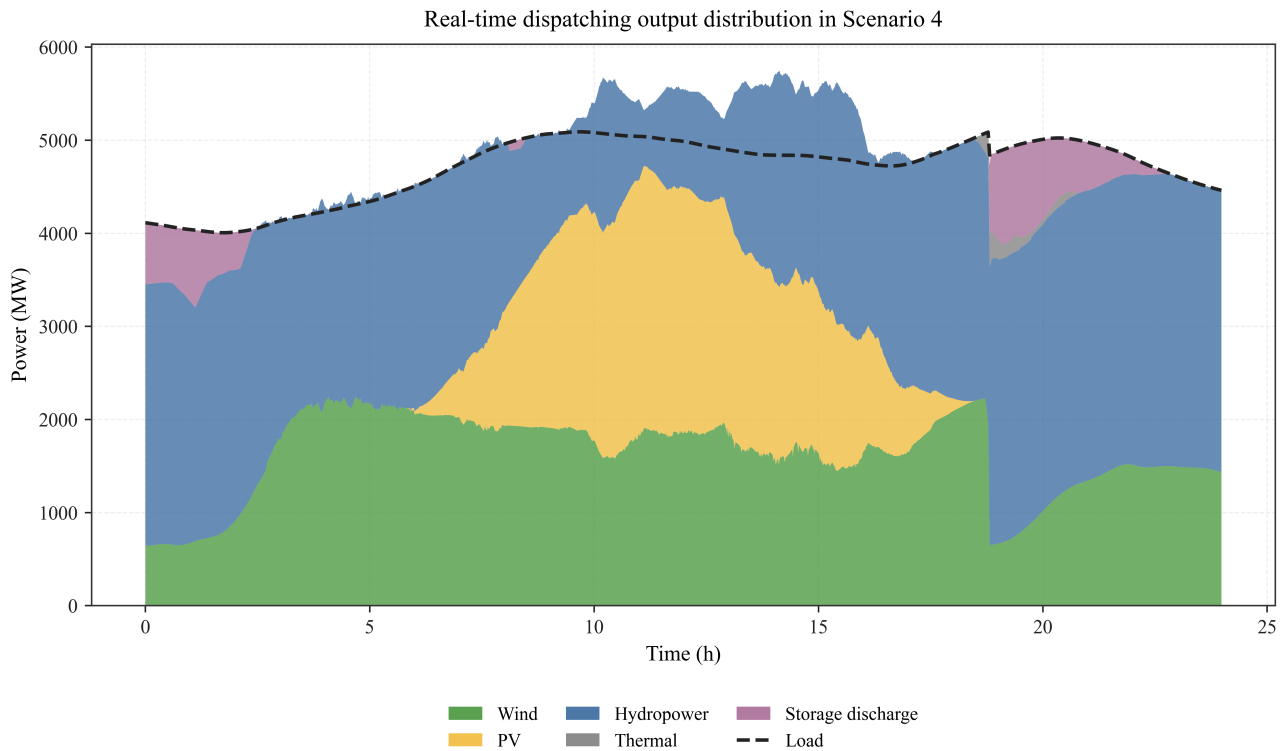


Figure 12. Real-time dispatching output distribution in Scenario 4

Table 7. Required storage power capacity under different scenarios (MW)

Item	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Sub-base 1	156.53	201.08	107.27	138.69
Sub-base 2	69.59	87.17	62.89	80.48
Sub-base 3	114.13	148.11	83.11	126.67
Sub-base 4	581.27	747.22	354.90	457.64
Total required storage power capacity	921.52	1183.58	608.17	803.48

Comparison: Scenario 3 = -34.00% vs Scenario 1;
Scenario 4 = -32.11% vs Scenario 2.

hydropower reserve deployment, storage operation and thermal correction within the analyzed rolling horizon. The selected-bus injection and load trajectories in Figure 13 are reported as a post-dispatch diagnostic, while the DC power-flow feasibility is checked through Eq. (22).

6. Conclusions

This paper proposes a Transformer-LSTM-attention-aided deep learning prediction and multi-time-scale error-compensation optimization strategy for a large-scale hydro-wind-PV-storage clean energy base providing ancillary-service regulation. The strategy separates reserve-capacity configuration from real-time reserve deployment: day-ahead and intraday forecast

errors are used to size hydropower reserve through quantile-based net-load error margins or, when only source-wise error distributions are available, through a conservative source-wise aggregated margin; minute-level real-time deviations are then compensated by deploying the configured reserve together with storage and thermal correction.

The results show that the proposed strategy improves cross-stage hydropower dispatch consistency in the analyzed rolling window. Compared with the fixed-reserve strategy, the day-ahead-to-intraday hydropower output fluctuation error is reduced from 8.42% to 4.81% at the lower wind-PV scale and from 7.48% to 6.02% at the higher wind-PV scale. In the intraday-to-real-time transition, the hydropower fluctuation error is reduced from 8.27% to 6.84% at the lower wind-PV scale and from 8.44% to 8.09% at the higher wind-PV scale.

Real-time power-supply adequacy is maintained under the tested scenarios while the actual hydropower reserve energy deployed is reduced. The reported adjacent-stage guarantee rate is 100.00% under all four scenarios; in the full-day aggregation, both the mean and minimum real-time guarantee rates remain 100.00%. Meanwhile, the daily deployed reserve energy decreases from 3.96 GWh to 3.37 GWh at the lower wind-PV scale and from 4.13 GWh to 3.84 GWh at the higher wind-PV scale. This result shows that reserve sizing based on forecast-error characteristics

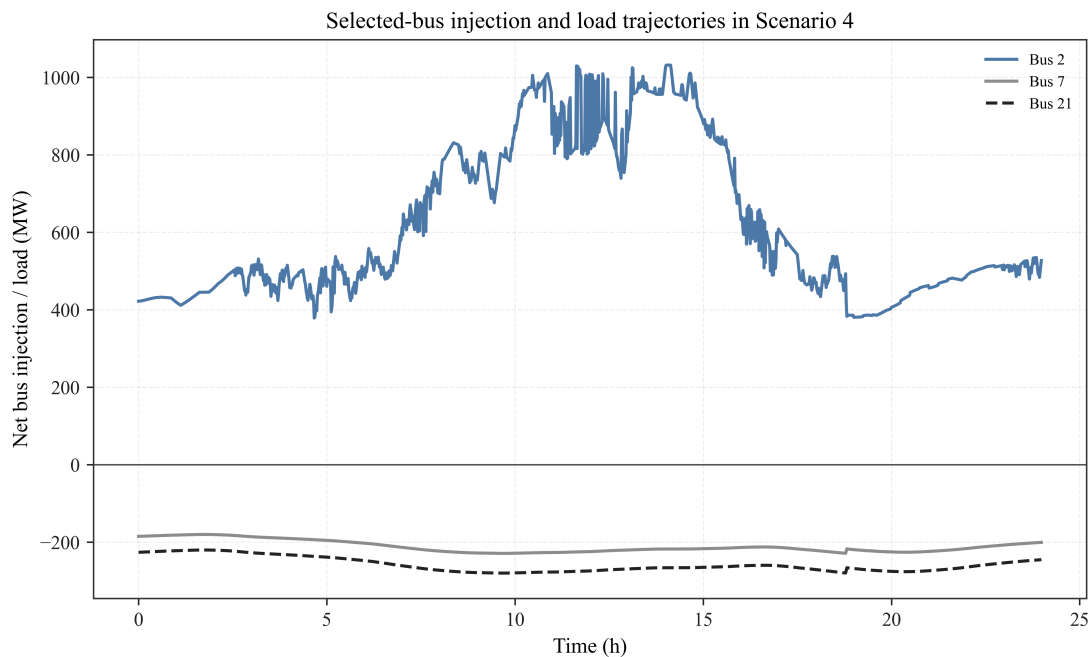


Figure 13. Selected-bus injection and load trajectories in Scenario 4

can reduce unnecessary real-time reserve deployment while preserving short-term supply adequacy in the tested setting.

The storage-sizing comparison further indicates a lower requirement for supplementary short-term regulation. The total required storage power capacity decreases from 921.52 MW to 608.17 MW at the lower wind–PV scale and from 1183.58 MW to 803.48 MW at the higher wind–PV scale, corresponding to reductions of about 34.00% and 32.11%, respectively. This result suggests that properly configured cascade-hydropower reserve can reduce the dependence on short-term storage regulation in the tested scenarios.

The findings should be interpreted within the tested representative transition day and reported rolling windows.

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A. Additional Data

The auxiliary data in this appendix provide the thermal-unit parameters, bus-equipment mapping, and representative forecast and realized profiles used for the case-study implementation. Table A.1 lists the thermal-unit parameters, Table A.2 gives the bus-equipment mapping, and Figure A.1 and Figure A.2 show the representative day-ahead and intraday forecast and actual profiles, respectively.

Table A.1. Basic parameters of thermal power units

Unit No.	Output upper limit (MW)	Output lower limit (MW)	Unit No.	Output upper limit (MW)	Output lower limit (MW)
1	320	40	2	140	20
3	600	60	4	600	60
5	320	40	6	140	20

Table A.2. Load and equipment conditions at the buses of the modified equivalent system of the local power grid

Bus	Type	Bus	Type	Bus	Type	Bus	Type	Bus	Type
1	Hydropower station 1	7	Load	13	Thermal generators 2, 4, 6	19	Load	25	—
2	Hydropower station 2, Load	8	Hydropower station 4, Load	14	Load	20	Load	26	Load
3	Load	9	Transformer 2	15	Load	21	Load	27	Transformer 4
4	Load, Transformer 1	10	Transformer 3, Load	16	Load	22	—	28	Transformer 4
5	Hydropower station 3	11	Thermal generators 1, 3, 5	17	Load	23	Load	29	Load
6	Transformers 2, 3	12	Transformer 1, Load	18	Load	24	Load	30	Load

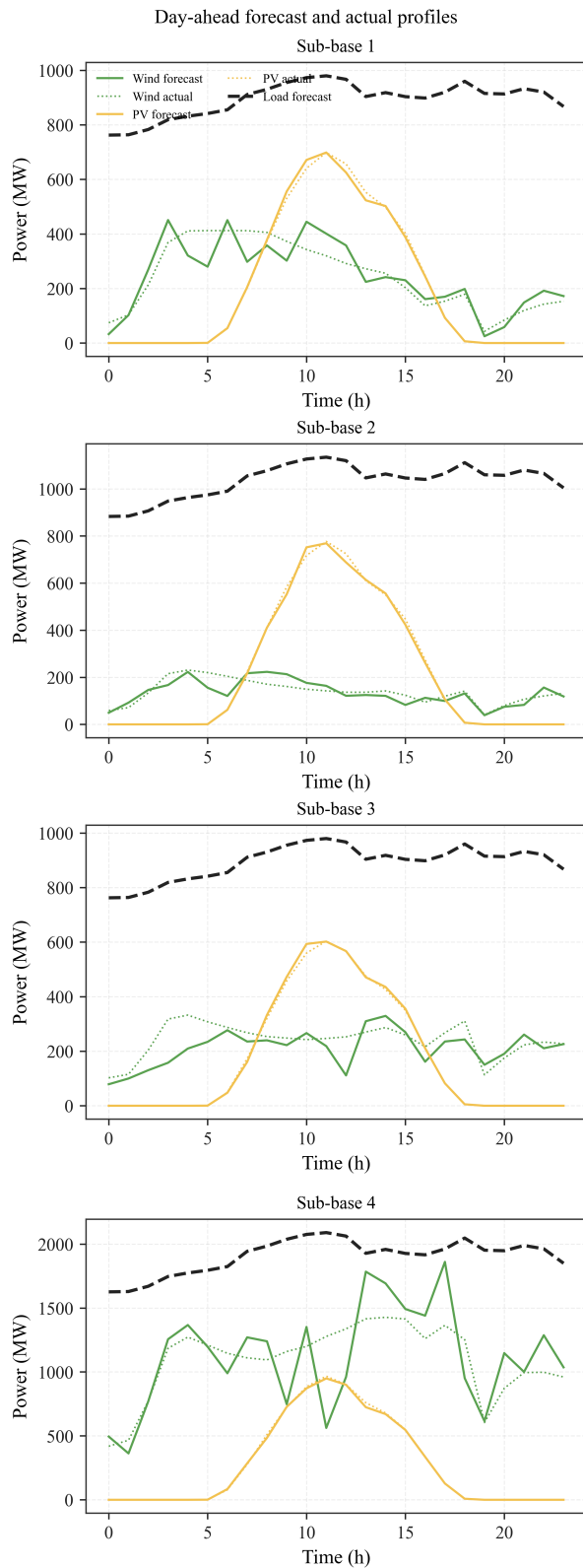


Figure A.1. Day-ahead forecast and actual profiles

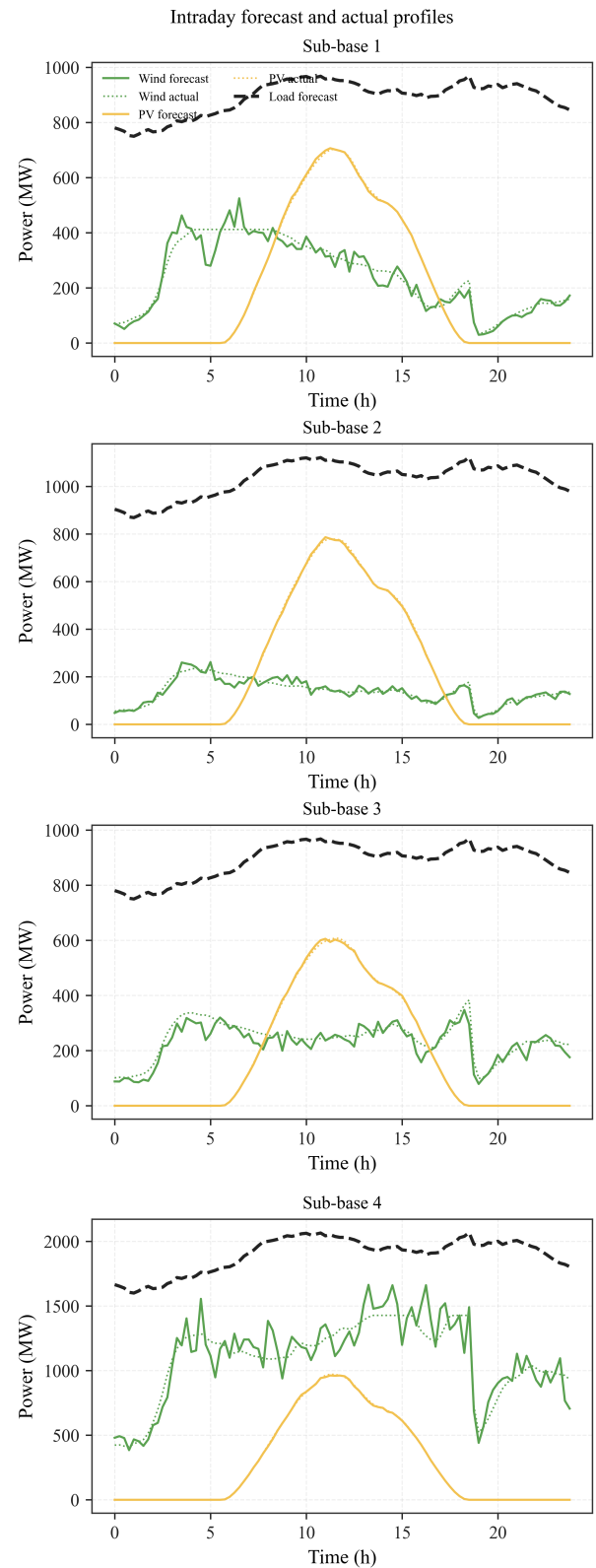


Figure A.2. Intraday forecast and actual profiles