

Article

Integrated Decarbonization Pathways for Regional Power Systems: A LEAP–NEMO Analysis in Guangxi, China

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Abstract

Achieving deep decarbonization while maintaining power system operational feasibility represents a critical challenge in regions with a high penetration of renewable energy. In this study, we developed an integrated LEAP–NEMO modeling framework to evaluate long-term decarbonization pathways and power system flexibility in Guangxi Province, China, from 2022 to 2060. Four scenarios were designed, the Business-as-Usual Scenario (BAS), the Policy Strengthening Scenario (PSS), the Technology-Centered Scenario (TCS), and the Integrated Optimization Scenario (IOS), to assess the impacts of policy, technology, and system-level coordination. Our results show that under the IOS, renewable electricity reaches approximately 78% by 2050 and further increases to 88% by 2060, while coal consumption declines by over 60% compared with the baseline. Energy storage deployment under the IOS reaches 25 GW by 2060 (rising to approximately 28 GW under a higher-resolution 48-representative-day validation), approximately five times the level in the BAS (5 GW), significantly enhancing system flexibility and reducing renewable curtailment from 10.2% to 1.8%. Carbon emissions peak in 2027 at 228 Mt CO₂, approximately 20% lower than the baseline, and decline to 52 Mt CO₂ by 2060, achieving a cumulative reduction of 3.85 Gt CO₂. Economically, the IOS pathway reduces total system costs to USD 815 billion, saving approximately USD 95 billion compared with the BAS, with the levelized cost of electricity declining to USD 63/MWh by 2060. These results demonstrate that integrated optimization of generation and storage resources is essential in achieving deep decarbonization while maintaining system deterministic capacity adequacy and economic efficiency.

Keywords: energy storage optimization; renewable energy integration; LEAP–NEMO modeling; deep-decarbonization pathways; regional energy planning



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1. Introduction

In the context of global efforts to achieve carbon peaking and deep decarbonization, many countries have accelerated the large-scale deployment of renewable energy technologies [1,2]. However, the increasing penetration of intermittent renewable energy sources, such as wind and solar power, has introduced significant challenges to power system operational feasibility, flexibility, and operational deterministic capacity adequacy [3]. As a result, integrated wind–solar–storage systems have emerged as a key solution and have attracted widespread attention in recent studies [4]. Despite its abundant hydropower resources, Guangxi’s power system is currently undergoing a profound structural transition driven by

rapid industrialization and increasing electricity demand. As an important energy base and power transmission hub in southern China, Guangxi supports a large number of energy-intensive industries, including non-ferrous metal smelting and chemical manufacturing, leading to continuous growth in electricity consumption. Historically, hydropower dominated the regional electricity supply, accounting for more than 57% of total generation in 2015. However, its contribution in recent years has slipped to around 25–30% due to climate variability and repeat drought years, which threaten water availability thus undermine generation adequacy, leading to coal-fired power being essential for achieving system adequacy and supply security. To give effect to China's carbon peaking and deep-decarbonization goals, the Guangxi 14th Five-Year Plan for Renewable Energy Development states that the total renewable installed capacity will need to reach 61 GW by 2025. It also emphasizes the importance of system flexibility, which the generation system should allow through the targeted deployment of new energy storage systems to 2 GW/4 GWh [5]. China's rapid integration of wind and solar power presents operational challenges of increasing variability, renewable curtailment and increasing congestion on congested transmission systems. Moving away from an energy system dominated by hydropower, a high-renewable but variable power system, calls for more systematic, integrated expansion approaches for generation and system flexibility and energy storage.

These developments highlight the urgent need for a systematic energy transition in Guangxi. Meanwhile, continued economic growth and industrial expansion have further increased electricity demand, placing additional pressure on the regional power system [6]. These trends underscore the need to more fully address energy storage deployment and the system-level flexibility requirements of accelerating renewable integration—challenges not adequately captured in existing modeling approaches. “Power systems present substantial regional heterogeneity with respect to load and resource endowment” [7]. In this study, Guangxi Province was selected as a representative case due to its status as an important location for power dispatch in China's regional power distribution and its rapidly evolving relevant energy structure [8]. It has already exploited most of its hydropower resources, has numerous energy-intensive industries and is currently experiencing intense urbanization, putting growing pressure on the power system. Looking at its power system, “coal-fired power plants can provide a capacity credit of around 90% compared to wind and solar which provide only around 15% and 12%, respectively” [9]. Capacity credit or the effective load carrying capability (ELCC) refers to the extent to which a resource can provide adequate load, due to its ability to meet demand when generation conditions are poor [9]. Studies have consistently shown that the firm capacity contribution of variable renewable energy declines as penetration increases and is highly sensitive to deterministic capacity adequacy criteria [10]. These studies indicated that under current operating conditions, renewable energy supplies a very small amount of firm capacity, 11–17%, to meet the same amount of peak demand or contribute to adequacy [11]. Improving the effective capacity contribution of renewable resources through optimization storage deployment therefore represents a key strategy for enhancing system adequacy and flexibility.

Two closely related studies merit comparison. Xiao et al. [4] leveraged a LEAP–NEMO framework applied to Jiangxi Province to explore wind–solar–storage strategies toward carbon peaking. While they share a similar modeling platform and overall research objective, their work primarily focuses on carbon-peaking pathways. In contrast, the present study further examines the roles of energy storage deployment, renewable energy integration, curtailment reduction, and system deterministic capacity adequacy under multiple decarbonization scenarios. Similarly, Li et al. [6] explored low-carbon transition pathways for Guangxi using the EnergyPLAN tool. However, EnergyPLAN is primarily designed for annual energy system analysis and does not explicitly represent detailed power system

operational constraints or storage operation within an optimization framework. As a result, its ability to evaluate the operational impact of high shares of variable renewable energy is relatively limited. The present study advances beyond these works in four specific respects. First, it applies LEAP–NEMO to Guangxi—a power system structurally distinct from Jiangxi—with an explicit hourly dispatch resolution and 12 seasonal representative days, enabling more operationally realistic assessment of flexibility requirements. Second, it explicitly models battery energy storage system (BESS) charging and discharging schedules as decision variables within the optimization, rather than treating storage as an exogenous parameter. Third, it systematically quantifies the ELCC improvement of variable renewable energy resulting from storage deployment, linking capacity adequacy metrics to dispatch outcomes. Fourth, it introduces a novel scenario comparison between a Technology-Centered Scenario (TCS) and an Integrated Optimization Scenario (IOS), revealing the trade-offs between aggressive technology deployment and coordinated system-level optimization—a distinction absent from prior regional LEAP-based studies.

Despite the growing application of LEAP-based frameworks in regional energy planning, a critical methodological gap persists: the lack of an integrated modeling structure that simultaneously captures long-term capacity expansion, power system operation, and energy storage deployment while evaluating the combined effects of policy, technology, and system-level coordination on decarbonization outcomes, system flexibility, and economic performance. Existing studies tend to focus narrowly on demand projections or emission trajectories, treating policy and technology pathways independently and neglecting the operational deterministic capacity adequacy implications of high renewable penetration in structurally heterogeneous regional power systems. To address this gap, this study makes the following contributions:

- (1) An integrated LEAP–NEMO modeling framework is developed that combines long-term capacity expansion planning, power system operation, and energy storage modeling within a unified analytical structure, enabling internally consistent evaluation of regional decarbonization pathways, system flexibility, and economic performance.
- (2) The role of energy storage as a system-level enabler is systematically quantified, including its effects on renewable curtailment reduction, effective load carrying capability (ELCC) improvement, and operational flexibility enhancement under high renewable penetration.
- (3) Four scenarios are constructed to assess the combined and comparative effects of policy strengthening, technology advancement, and system-level optimization, moving beyond single-dimensional pathway assessments.
- (4) Guangxi Province is examined as a representative regional case to demonstrate how the proposed framework can inform cost-effective, deterministic-capacity-adequacy-constrained decarbonization planning in power systems characterized by declining hydropower contribution, strong industrial demand, and rapid renewable energy expansion.

2. Methodology

2.1. Model Framework

Developed by the Stockholm Environment Institute, the Low Emissions Analysis Platform (LEAP, version 2024.0) is an accounting and scenario analysis platform for long-term energy–environment–economy analysis, bottom-up sectoral analysis, policy effect simulation, and long-term trend forecasting [12]. The Next Energy Modeling System for Optimization (NEMO, version 2.00) is an integrated power system capacity expansion and generation dispatch model implemented within the LEAP framework. It employs linear programming methods to optimize generation capacity expansion, generation dispatch,

and energy storage operation, aiming to minimize the total system cost while satisfying technical constraints such as power balance, operating reserves, and transmission capacity limits [13]. This integrated framework enables a more comprehensive assessment of the trade-offs among decarbonization, system deterministic capacity adequacy, and economic performance relative to standalone energy planning models.

2.2. Research Methodology: Representative Day Selection and Demand Projection

Figure 1 gives an overview of the integrated LEAP–NEMO framework, illustrating data inputs (statistical data, technical characteristics, and detailed policy documents), model components (energy demand, transformation, and NEMO), scenario development, and a selection of key output results (e.g., transformation of the energy mix, storage metrics, and CO₂ emissions, as well as economic analysis of energy system transformation in NEMO). The modeling process involves data collection and processing, model calibration, scenario development, and finally optimization and analysis (usually at an hourly resolution and with a multi-year capacity expansion).

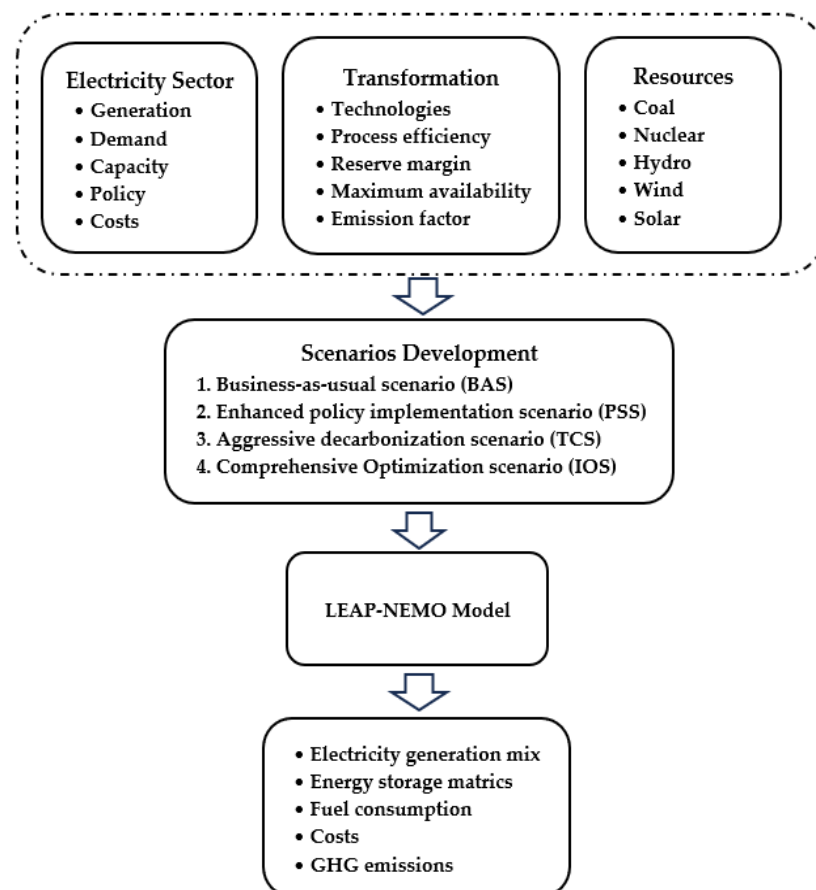


Figure 1. Integrated LEAP–NEMO research framework.

To objectively capture the intra-annual variability of electricity demand and renewable resources (wind and solar) in Guangxi, this study employs a k-means clustering algorithm for representative day selection. For each day ($d \in \{1, \dots, 365\}$), a multi-dimensional feature vector X_d is constructed to represent the hourly system characteristics:

$$X_d = [L_{d,1}, \dots, L_{d,24}, W_{d,1}, \dots, W_{d,24}, S_{d,1}, \dots, S_{d,24}]$$

where L , W , and S represent hourly load, wind power, and solar profiles, respectively. All data are normalized using Min–Max scaling to ensure that variables with different

magnitudes contribute equally to the clustering process. The algorithm minimizes the sum of squared Euclidean distances to identify k clusters:

$$\min \sum_{i=1}^k \sum_{X_d \in C_i} \|X_d - \mu_i\|^2 \quad (1)$$

The medoid of each cluster (the actual historical day closest to the centroid μ_i) is selected as the representative day. Each selected day is assigned a weighting factor $w_i = N_i$ (where N_i is the number of days in cluster C_i) to preserve annual energy balances. Inter-day chronology for storage is maintained by linking the daily initial and terminal state-of-charge (SoC) within clusters to approximate multi-day storage dynamics.

In this study, we calculated electricity demand based on demand growth projections. The electricity demand for a specific year is derived from the previous year's demand combined with the expected growth, as shown in Equation (2). The total electricity demand in the power system for a specific year is calculated by summing the electricity demand and the electricity losses incurred during the transmission and distribution processes within that year, as shown in Equation (3).

$$E_{\text{demand},t} = (E_{\text{demand},t-1} \times E_{\text{generation},t}) + E_{\text{demand},t-1} \quad (2)$$

where $E_{\text{demand},t}$ is the electricity demand in year t , and $E_{\text{generation},t}$ is the percentage growth in the electricity demand in that same year.

$$TE_{\text{demand},t} = E_{\text{demand},t} + (E_{\text{demand},t} \times TD_{\text{loss},t}) \quad (3)$$

where $TE_{\text{demand},t}$ is the total electricity demand in year t , and $TD_{\text{loss},t}$ is the percentage of transmission and distribution losses that year.

After projecting electricity demand, LEAP evaluates energy supply resources and transformation technologies. In this stage, we analyze the conversion of primary energy sources into electricity, taking into account both existing and planned facilities throughout the study period. Each technology is characterized by the technical and operational features of power plants, including installed capacity, availability, conversion efficiency, historical generation data, capacity credit, dispatch limitations, and fuel type. The net energy consumption for transformation, which represents the additional energy input needed due to conversion inefficiencies, is calculated as shown in Equation (4).

$$NET_s = \sum_m \sum_t ETP_{t,m} \times \left(\frac{1}{EF_{t,m,s}} - 1 \right) \quad (4)$$

where NET refers to net energy consumption for transformation, ETP refers to energy consumption transformation products, which can be electricity in the case of power plant products, EF refers to energy transformation efficiency, s refers to the type of primary energy, m refers to equipment, and t refers to the type of secondary energy.

2.3. Integrated LEAP–NEMO Optimization Framework

2.3.1. Optimization Problem Formulation

The integrated LEAP–NEMO framework formulates the long-term power system planning problem as a linear optimization model that minimizes the total discounted system cost while satisfying operational, technical, and environmental constraints.

Objective Function

The optimization objective is expressed as follows:

$$\min \sum_t \frac{1}{(1+r)^t} (C_{cap,t} + C_{fuel,t} + C_{O\&M,t} + C_{storage,t} + C_{carbon,t}) \quad (5)$$

where:

$C_{cap,t}$ is capital investment cost;

$C_{fuel,t}$ is fuel expenditure;

$C_{O\&M,t}$ is operation and maintenance cost;

$C_{storage,t}$ is storage investment and operation cost;

$C_{carbon,t}$ is carbon pricing or emission penalty cost;

r is discount rate.

The main decision variables include generation dispatch, installed capacity expansion, storage charging/discharging schedules, renewable curtailment levels, and interregional electricity exchanges. The five cost components of the objective function in (5) are defined in Equations (6)–(10):

$$C_{cap,t} = \sum_i IC_i \Delta Cap_{i,t} \quad (6)$$

$$C_{fuel,t} = \sum_i \frac{FP_{f,t} G_{i,t}}{\eta_i} \quad (7)$$

$$C_{O\&M,t} = \sum_i (FOM_i Cap_{i,t} + VOM_i G_{i,t}) \quad (8)$$

$$C_{storage,t} = \sum_e (IC_e^P \Delta P_{e,t}^{cap} + IC_e^E \Delta E_{e,t}^{cap} + VOM_e \sum_{d,t} P_{e,d,t}^{dis}) \quad (9)$$

$$C_{carbon,t} = \tau_t \sum_i EF_i G_{i,t} \quad (10)$$

Capital expenditures are annualized using the capital recovery factor, where r is the discount rate and n_i is the economic lifetime of technology i :

$$CRF_i = \frac{r(1+r)^{n_i}}{(1+r)^{n_i} - 1} \quad (11)$$

Power Balance Constraint

Electricity supply and demand must remain balanced at each time step:

$$\sum_i P_{i,t} + P_t^{dis} + P_t^{imp} = D_t + P_t^{ch} + P_t^{exp} \quad (12)$$

where:

$P_{i,t}$ is the electricity generation output of technology (i);

P_t^{dis} is storage discharge power;

P_t^{imp} and P_t^{exp} denote electricity imports and exports;

D_t represents electricity demand;

P_t^{ch} is storage charging power.

Reserve Margin Constraint

The available generation capacity must satisfy reserve adequacy requirements:

$$\sum_i Cap_i \cdot CF_i \geq (1 + RM) \cdot PeakDemand \quad (13)$$

where:

Cap_i is installed capacity of technology (i);

CF_i is the capacity credit or availability factor;
 RM denotes the reserve margin.

Storage Constraints

For each storage technology $e \in \{\text{BESS, PHS}\}$, representative day d , and hour t , storage operation is governed by Equations (14)–(19):

$$SOC_{e,d,t} = SOC_{e,d,t-1} + \eta_{ch} P_{e,d,t}^{ch} \Delta t - \frac{P_{e,d,t}^{dis} \Delta t}{\eta_{dis}} \quad (14)$$

$$SOC_{min} E_e^{cap} \leq SOC_{e,d,t} \leq SOC_{max} E_e^{cap} \quad (15)$$

$$0 \leq P_{e,d,t}^{ch} \leq P_e^{cap}, \quad 0 \leq P_{e,d,t}^{dis} \leq P_e^{cap} \quad (16)$$

$$E_e^{cap} = T_e P_e^{cap} \quad (17)$$

$$SOC_{e,d,0} = SOC_{e,d,T} \quad (18)$$

$$SOC_{e,d+1,0} = SOC_{e,d,T} \quad (19)$$

Equation (14) tracks the hourly state of charge with a round-trip efficiency of $\eta_{ch} \cdot \eta_{dis} = 0.90$ ($\eta_{ch} = \eta_{dis} = \sqrt{0.90} \approx 0.95$). Equation (15) bounds the state of charge between $SOC_{min} = 10\%$ and $SOC_{max} = 90\%$ of the energy capacity for BESS, while Equations (16) and (17) limit charging and discharging power and couple energy and power capacity through the storage duration T_e (2–4 h for BESS and 8 h for PHS, consistent with the 4 GW/32 GWh pumped-hydro fleet). Equation (18) enforces state-of-charge periodicity within each representative day, and Equation (19) links the terminal and initial state of charge of consecutive representative days within the same cluster, approximating inter-day storage dynamics. Because the round-trip efficiency satisfies $\eta_{ch} \cdot \eta_{dis} < 1$, simultaneous charging and discharging is never cost-optimal; an explicit binary complementarity constraint is therefore unnecessary within the linear formulation.

Renewable Curtailment Equation

Renewable energy curtailment is calculated as:

$$Curtailment_t = RE_t^{available} - RE_t^{utilized} \quad (20)$$

where:

$RE_t^{available}$ represents available renewable generation;

$RE_t^{utilized}$ denotes utilized renewable electricity.

Transmission Constraint

Interregional electricity exchanges were constrained by predefined transmission capacity limits between interconnected zones:

$$0 \leq P_{i,j,t}^{trans} \leq Cap_{i,j}^{trans} \quad (21)$$

where:

$P_{i,j,t}^{trans}$ represents electricity transmission flow between zones (i) and (j);

$Cap_{i,j}^{trans}$ denotes the maximum transmission capacity between interconnected zones.

Carbon Emission Accounting

Carbon emissions are estimated based on fuel consumption and emission factors:

$$CO_2 = \sum_i EF_i \cdot G_i \quad (22)$$

where:

EF_i is the emission factor of generation technology (i);

G_i is electricity generation from technology (i).

Capacity Expansion Constraint

The total installed capacity of each generation technology is constrained by both minimum and maximum allowable expansion limits:

$$Cap_{i,t} = Cap_{i,t-1} + \Delta Cap_{i,t} \quad (23)$$

$$0 \leq \Delta Cap_{i,t} \leq \Delta Cap_{i,t}^{max} \quad (24)$$

where:

$Cap_{i,t}$ is the cumulative installed capacity of technology i in year t;

$\Delta Cap_{i,t}$ is the newly added capacity;

$\Delta Cap_{i,t}^{max}$ denotes the maximum annual capacity addition, determined by resource availability, grid connection limits, and policy targets.

The system flexibility index (SFI) used in this study is defined as the ratio of total dispatchable and flexible capacity—including fast-response generation and energy storage discharge capacity—to the peak net load (i.e., peak demand minus non-dispatchable renewable generation):

$$SFI = \frac{\sum_{i \in F} Cap_i + P_{storage}^{max}}{PeakDemand - RE_{non-disp}^{peak}} \quad (25)$$

where:

$\sum_{i \in F} Cap_i$ denotes the total capacity of flexible and dispatchable generation technologies;

$P_{storage}^{max}$ is the maximum storage discharge power;

$RE_{non-disp}^{peak}$ represents peak non-dispatchable renewable output.

A higher SFI indicates greater system capability to balance supply and demand under variable renewable conditions. Boundary conditions were imposed to ensure feasible system operation, including initial and terminal storage state-of-charge consistency, generation capacity limits, and interregional transmission capacity constraints.

Model Scope and Simplifying Assumptions

The framework is a deterministic, linear capacity-expansion and economic-dispatch model solved at an hourly resolution over 12 clustered representative days per planning year. Three simplifications are made deliberately and bound the interpretation of the results. First, unit-commitment dynamics (integer start-up and shut-down states, minimum up/down times, and ramping constraints) are not represented, which is appropriate for a multi-decade planning horizon but may understate short-term operating inflexibility. Second, electricity demand is exogenous; demand-side response is treated as an external policy lever rather than an optimized decision variable. Third, the only monetized externality is the carbon-pricing term; co-benefits such as reduced air-pollutant health damage are not valued, so the reported abatement costs are conservative. These choices keep the problem within a tractable linear program while preserving the storage- and

capacity-planning detail that is central to this study; relaxing them is left to future work. The key optimization parameters and solver configurations used in the LEAP–NEMO framework are summarized in Table 1.

Table 1. Key optimization parameters and solver settings.

Parameter	Value
Optimization solver	CBC
Dispatch resolution	1 h
Number of representative days	12
Planning horizon	2022–2060
Discount rate	8%
Reserve margin	15%
Round-trip storage efficiency	90%
Carbon price trajectory	Scenario-dependent

Note: The 12 representative days were constructed by selecting three days per season (spring: March–May; summer: June–August; autumn: September–November; winter: December–February), comprising a typical weekday, a typical weekend day, and a high-demand day for each season. Each representative day was assigned a weighting factor to preserve annual energy balance and seasonal generation totals.

2.3.2. Model Configuration

The overall configuration of the integrated LEAP–NEMO model, including its temporal and spatial resolution, technology portfolio, and the data sources for each setting, is summarized in Table 2. The key input parameters and base-year calibration data used in the model are summarized in Table 3. Capacity factors are derived from national utilization hour statistics published by the National Energy Administration (NEA) for 2022, and technology costs are referenced from IRENA (2022).

Table 2. LEAP–NEMO model configuration parameters.

Parameter Category	Component	Value/Setting	Data Source
Temporal Resolution	Planning horizon	2022–2060	Long-term energy transition outlook and decarbonization roadmaps [1,14]
	Time steps	Annual (capacity), hourly (dispatch)	Standard modeling configuration of the LEAP and NEMO frameworks [12,13]
	Representative days	12 days (seasonal)	Widely adopted seasonal representative day selection method in regional energy system modeling [4,15]
Spatial Resolution	Regional boundaries	Single region	Defined based on the research boundary of the Guangxi regional energy system in this study
	Transmission zones	3 interconnection zones	Official regional power grid planning data and provincial energy layout documents [5]
Technology Portfolio	Generation types	12 technology categories	Regional energy system parameter calibration and low-carbon transition research [6]
	Storage types	Battery, pumped hydro	Techno-economic assessment of energy storage application in high-renewable power systems [15–17]
Economic Parameters	Discount rate	8% real	Conventional real discount rate adopted in provincial energy economic evaluation studies [18]
	Price year	2022 USD	Unified monetary benchmark for global energy economic assessment reports [7,14]
System Constraints	Reserve margin	15% planning reserve	Power system deterministic capacity adequacy and capacity adequacy evaluation criteria [9,11]

Note: References listed in the table correspond to the reference list of this study. Model settings are defined according to the geographical scope, energy resource endowment, and policy planning background of the Guangxi regional energy system (Table 2).

Table 3. Core input assumptions and base-year calibration data.

Parameter	Value	Data Source
Base-year installed capacity (2022)		
Total installed capacity	64.2 GW	Guangxi Statistical Yearbook 2023 [19]
Hydropower	18.3 GW	Guangxi Statistical Yearbook 2023 [19]
Coal-fired	27.6 GW	Guangxi Statistical Yearbook 2023 [19]
Wind power	9.5 GW	Guangxi Statistical Yearbook 2023 [19]
Solar PV	5.2 GW	Guangxi Statistical Yearbook 2023 [19]
Nuclear	2.2 GW	Guangxi Statistical Yearbook 2023 [19]
Battery energy storage	0.3 GW	Guangxi Statistical Yearbook 2023 [19]
Pumped-hydro storage	1.2 GW	Guangxi Statistical Yearbook 2023 [19]
Base-year electricity demand (2022)		
Total electricity consumption	798.1 TWh	Guangxi Statistical Yearbook 2023 [19]
Secondary industry consumption	493.7 TWh	Guangxi Statistical Yearbook 2023 [19]
Household consumption	169.0 TWh	Guangxi Statistical Yearbook 2023 [19]
Electricity demand growth rate	Variable by period (see Table 4)	Guangxi 14th Five-Year Plan and long-term forecast assumptions [20]
T&D loss rate	5.0%	China Electricity Council [21]
Capacity factors (2022)		
Coal-fired	52.5%	NEA 2022 [22]
Hydropower	38.9%	NEA 2022 [22]
Wind power	25.4%	NEA 2022 [22]
Solar PV	15.3%	NEA 2022 [22]
Nuclear	86.9%	NEA 2022 [22]
Technology capital costs (2022 USD)		
Coal-fired	800 USD/kW	IEA (2023) [23]
Onshore wind	900 USD/kW	IRENA 2022 [24]
Solar PV	500 USD/kW	IRENA 2022 [24]
Nuclear	3500 USD/kW	IEA (2023) [23]
Pumped-hydro storage	1200 USD/kW	IRENA 2022 [24]
BESS capital cost (2022)	280 USD/kWh	IRENA 2022 [24]
BESS capital cost (2060, projected)	80 USD/kWh	IRENA 2022 [24]; NREL (2023) [25]
O&M costs		
Coal-fired	30 USD/kW/year	IEA (2023) [23]
Wind power	15 USD/kW/year	IRENA 2022 [24]
Solar PV	10 USD/kW/year	IRENA 2022 [24]
Nuclear	50 USD/kW/year	IEA (2023) [23]
Fuel price (2022)		
Coal price	4.5 USD/GJ	NDRC [26]; IEA (2023) [23]
Transmission capacity (2022)		
Zone 1–2 (Gui-West to Gui-Central)	8.0 GW	Model assumption
Zone 2–3 (Gui-Central to Gui-East)	6.0 GW	Model assumption
Discount rate	8%	A discount rate of 8% is adopted, which is the social discount rate stipulated by China's national economic evaluation standard for construction projects [27]
Model calibration		
Base-year generation error (model vs. actual)	±5%	Model validation

Transmission capacities between zones are estimated based on the Guangxi 500 kV backbone grid configuration documented in the Guangxi 14th Five-Year Energy Plan. Actual interconnection limits may vary depending on operational conditions.

Electricity demand growth was modeled using a stage-specific approach rather than a constant growth rate throughout the entire study horizon. The value of 5.5% reported in Table 3 corresponds only to the initial development stage during the 14th Five-Year Plan period (2022–2025).

The demand growth assumptions were developed based on the electricity demand outlook for Guangxi during the 14th Five-Year Plan period and extended to 2060 using a gradual decline in growth rates. This approach reflects the expected evolution of economic development, industrial transformation, electrification, and energy-efficiency improvements.

As a result, electricity demand continues to increase throughout the study period, while the annual growth rate progressively decreases after 2030. The detailed assumptions are presented in Table 4, and the corresponding demand trajectory is shown in Figure 2.

Table 4. Electricity demand growth assumptions for 2022–2060.

Period	Annual Growth Rate (%)	Basis
2022–2025	5.5	Electricity demand outlook during the 14th Five-Year Plan
2026–2030	4.0	Continued industrial development and electrification
2031–2040	2.5	Gradual slowdown of demand growth
2041–2050	1.5	Mature electrification stage and efficiency improvements
2051–2060	1.0	Long-term stabilization of electricity demand

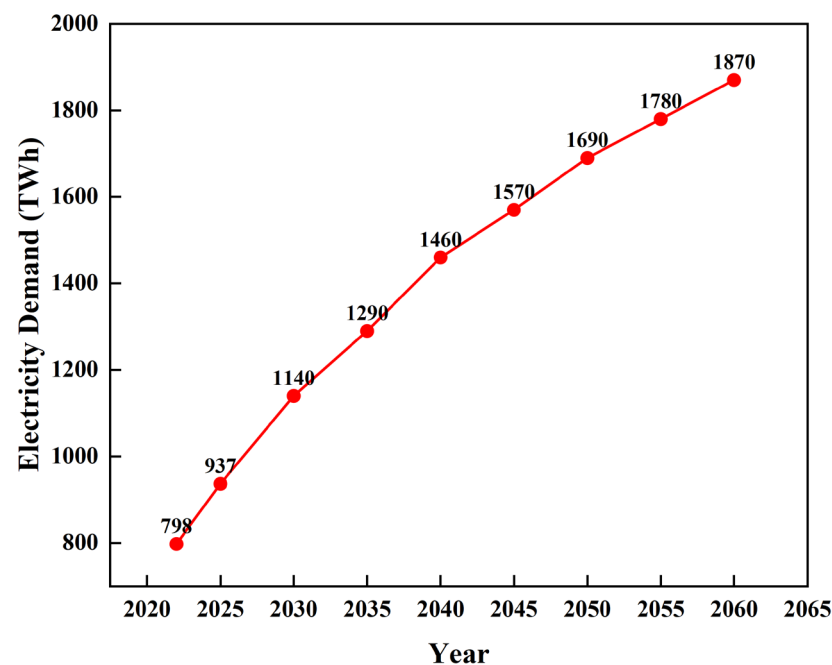


Figure 2. Projected electricity demand trajectory in Guangxi from 2022 to 2060 based on the stage-specific growth assumptions presented in Table 4. Demand increases from 798.1 TWh in 2022 to approximately 1870 TWh in 2060, while the annual growth rate gradually declines over time.

Based on the stage-specific growth assumptions shown in Table 4, annual electricity demand was projected from the 2022 base-year value of 798.1 TWh to 2060. The projection assumes continued economic development and electrification in Guangxi, while accounting for the gradual slowdown of demand growth due to improvements in energy efficiency and the maturation of electricity consumption.

The resulting electricity demand trajectory is presented in Figure 2. Electricity demand is projected to increase steadily throughout the study period, reaching approximately 1870 TWh by 2060. This trajectory serves as the demand input for all scenario simulations conducted in the LEAP–NEMO framework.

2.4. Scenario Design

To explore alternative energy transition pathways towards 2060, we developed four scenarios which vary in terms of policy ambition, technology deployment and system-wide optimization (Table 5). They comprise what is dubbed a policy gradient; from a Business-as-Usual Scenario to deep decarbonization, which is a narrative often adopted in energy system modeling studies. The Business-as-Usual Scenario (BAS) encapsulates continuing current policies and development of renewable energy growth curves observed historically without further climate interventions. The Policy Strengthening Scenario (PSS) also expects policies to continue, albeit with strengthened policies in place, including moderate carbon pricing and extended renewable energy targets. The Technology-Centered Scenario (TCS) is an aggressive decarbonization pathway that achieves the deepest emission reductions among the four scenarios, driven by high renewable penetration and strong policy incentives. In contrast, the Integrated Optimization Scenario (IOS) is defined solely by an exogenous carbon-price trajectory reaching USD 50/tCO₂ by 2060, consistent with medium-ambition decarbonization scenarios. Unlike the other three scenarios, the IOS does not impose any renewable-energy target or storage mandate. Under this carbon-price signal, and subject to the same power-balance, reserve-margin, transmission, storage, and capacity-expansion constraints applied to all scenarios, the LEAP–NEMO model endogenously determines the cost-minimizing combination of capacity expansion, storage deployment, and hourly dispatch. Consequently, the resulting renewable penetration ($\approx 88\%$ of generation by 2060), storage capacity, curtailment, and total system cost are endogenous model outputs rather than prescribed inputs.

Table 5. Scenario definitions and key policy assumptions.

Scenarios	Description	RE Target 2060	Storage Mandate	Carbon Price 2060	Rationale
BAS	Business-as-Usual Scenario	45% generation	Voluntary	\$0/tCO ₂	Reflects the continued implementation of existing policies and historical trends in renewable energy deployment, with no additional climate mitigation interventions.
PSS	Policy Strengthening Scenario	65% generation	15% of new RE	\$30/tCO ₂	Represents strengthened policy enforcement corresponding to medium-term renewable energy development targets and moderate carbon pricing decarbonization pathways.
TCS	Technology-Centered Scenario	85% generation	25% of new RE	\$80/tCO ₂	Aligns with stringent deep-decarbonization trajectories proposed by authoritative climate and energy research reports.
IOS	Integrated Optimization Scenario	Renewable share (model output)	Storage capacity (model output)	\$50/tCO ₂	The IOS imposes no RE target or storage mandate; under the exogenous carbon price and the common deterministic capacity adequacy constraints, the renewable share and storage capacity are cost-minimizing model outputs.

Note: For all scenarios, the carbon price is an exogenous policy assumption. For the BAS, PSS, and TCS, the RE target and storage mandate are imposed as scenario assumptions. For the IOS, no RE target or storage mandate is imposed; only the carbon-price trajectory is exogenous, and the renewable share, storage capacity, curtailment, and system cost reported in Section 3 are endogenous outputs of the LEAP–NEMO optimization.

The carbon price assumptions are defined based on ranges reported in international studies and the energy system modeling literature. Previous research indicates that carbon prices in long-term decarbonization scenarios typically range from 30 to 100 USD/tCO₂. Accordingly, in this study, we adopted carbon prices of 0, 30, 50, and 80 USD/tCO₂

for the BAS, PSS, IOS, and TCS, respectively, representing increasing levels of policy stringency. These values fall within commonly reported ranges and ensured consistency with existing studies.

3. Results and Discussion

3.1. Energy Structure Transformation

Figure 3 illustrates the evolution of the electricity generation mix under the four scenarios from 2025 to 2060, highlighting different decarbonization pathways and renewable energy integration levels. Coal-fired generation declines progressively across all scenarios, while renewable and low-carbon electricity sources, including hydropower, nuclear, wind, and solar, expand substantially. The TCS and IOS achieve the highest shares of non-fossil electricity by 2060.

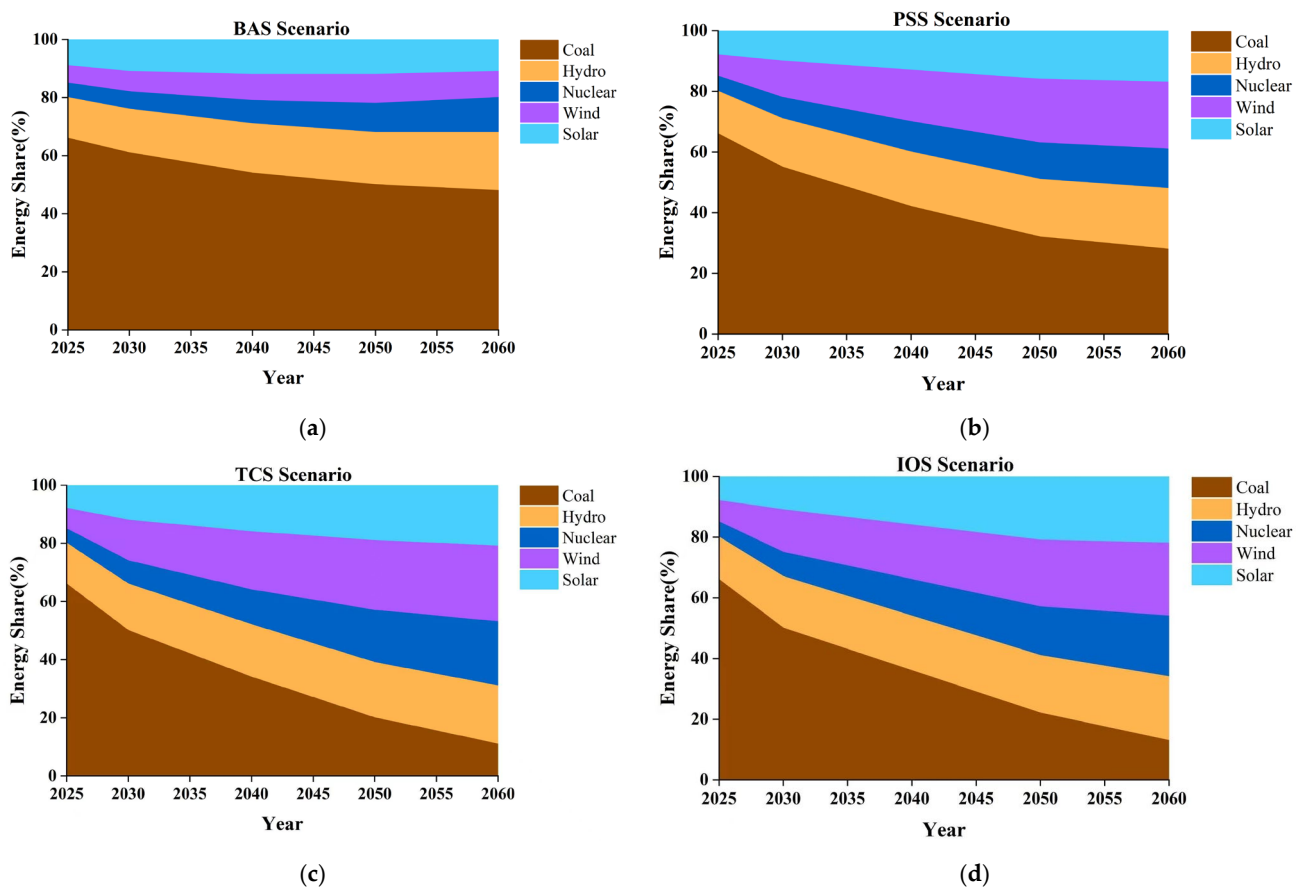


Figure 3. Evolution of electricity generation mix under four transition scenarios from 2025 to 2060: (a) BAS; (b) PSS; (c) TCS; and (d) IOS.

- (1) **Business-as-Usual Scenario (BAS):** In this scenario, the power system develops along historical development trajectories with little policy intervention, and the renewable electricity grows over time from a small base. Coal-fired generation remains dominant throughout the study period, declining from about 66% in 2025 to 48% in 2060 (this does not represent an acceleration). By 2060, non-fossil electricity approaches 58%, but the transition is clearly slow. This implies that existing policies are insufficient for deep decarbonization.
- (2) **Policy Strengthening Scenario (PSS):** This scenario assumes that existing renewable policies are very markedly strengthened, hence speeding up wind deployment and solar deployment considerably. The coal generation share declines from 66% in 2025 to about 28% in 2060, whilst non-fossil electricity increases to almost 76%. Compared

to BAS, the decarbonization is much faster, but fossil fuels are still a share of the mix. These results suggest that policy strengthening alone, without deeper system-level coordination, is insufficient to achieve deep decarbonization.

- (3) Technology-Centered Scenario (TCS): An accelerated decarbonization scenario is this TCS, which imagines aggressive technology carbon mitigation policies leading to change. Coal-fired generation falls from 66% in 2025 to just 11% in 2060. Operationally, non-fossil electricity expands rapidly, to around a little more than 82% by 2050 and exceeds 90% by 2060. The whole system is dependent on technologies used on a massive scale, like wind, solar, and nuclear, and robust energy storage technologies.
- (4) Integrated Optimization Scenario (IOS): A coordinated transition is reflected in the IOS model, which considers system deterministic capacity adequacy, economic efficiency, adequacy and emission reduction objectives. Coal generation falls from 66% in 2025 to about 13% in 2060, and non-fossil electricity expands to around 85%. The share of renewables is lower than that of the TCS, but this is a more optimal pathway from a system cost, operational flexibility, and decarbonization performance point of view.

Overall, all scenarios transitioned toward what can be described as low-carbon electricity systems and resolved this through declining shares of coal and increasing shares of renewable and non-fossil energy. They differ markedly in pace and structure.

3.2. Storage Deployment and System Flexibility

Figure 4 presents comprehensive indicators of storage deployment, renewable energy integration, and system flexibility under different transition scenarios.

By 2060, under the Integrated Optimization Scenario, low-carbon electricity generation increases substantially due to large deployment of renewables and supporting storage infrastructure. The added onshore wind installed capacity reaches 55 GW by 2060, with solar PV capacity at ~52 GW, distributed across both utility and behind-the-meter PV. Hydropower capacity remains relatively stable given regional resource availability at 22 GW, and nuclear power capacity increases to 18 GW to improve deterministic capacity adequacy through a stable source of dispatchable low-carbon electricity. Storage deployment continues to grow in parallel with increases in renewable generation capacity, as illustrated in Figure 4a. In the Integrated Optimization Scenario, BESS deployment grows from 2.5 GW in 2025 to 18 GW by 2050, increasing further to 25 GW by 2060. The battery discharge duration is typically between 2 and 4 h (54–100 GWh of energy storage capacity), and PHS provides 4 GW of installed capacity and 32 GWh of energy storage for longer-duration energy balancing and intra-day load shifting. Figure 4b demonstrates that increased storage deployment substantially reduces renewable energy curtailment. In the BAS, renewable curtailment rates increase continuously due to insufficient system flexibility and rapid renewable energy expansion, exceeding 10.2% during the study period. In contrast, the IOS pathway reduces renewable curtailment to below 2% by 2060, approaching the low curtailment levels observed in the TCS.

Storage utilization performance further highlights the importance of flexibility resources. As shown in Figure 4c, the BAS achieves only 800–850 annual utilization hours for battery storage systems, indicating relatively limited operational participation. In comparison, the IOS and TCS exceed 1580 utilization hours by 2030 and further increase to approximately 1620 and 1600 h, respectively, by 2060. These results indicate significantly improved storage utilization efficiency under high-renewable electricity systems. Figure 4d compares the low-carbon generation capacity portfolio under different scenarios in 2060. Significant differences can be observed in the deployment scale of renewable and clean energy technologies across scenarios. In the BAS, low-carbon capacity expansion remains relatively limited, with wind and solar PV capacities reaching only 35 GW and 32 GW,

respectively. In contrast, the PSS accelerates renewable deployment through strengthened policy support, increasing wind and solar capacities to approximately 45 GW and 42 GW.

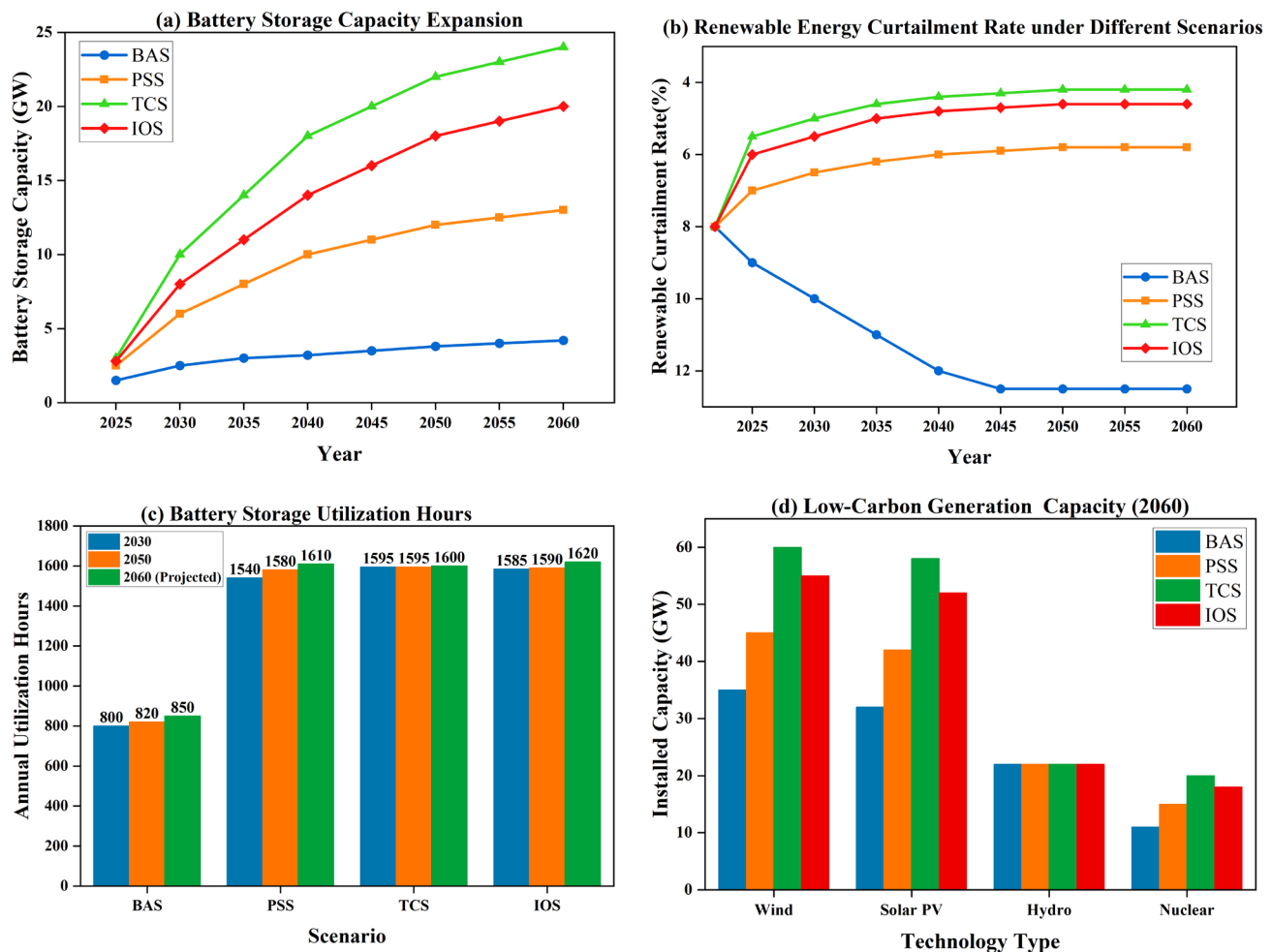


Figure 4. Storage deployment and renewable integration metrics: (a) battery storage capacity deployment across scenarios; (b) renewable energy curtailment reduction across scenarios; (c) hours of annual use of battery storage from 2030 to 2060; and (d) low-carbon generation installed capacity portfolio in 2060.

The TCS achieves the largest low-carbon generation portfolio, with wind power capacity reaching around 60 GW and solar PV capacity approaching 58 GW by 2060. This recognizes the powerful influence of technology development and ambitious decarbonization policies promoting large-scale renewable energy. Meanwhile, the IOS has around 55 GW of wind power and 52 GW of solar PV capacity, a little below the TCS but with better system coordination and operational balance. Hydropower capacity remains steady across all scenarios at around 22 GW due to regional hydropower resource constraints in Guangxi Province. The nuclear power capacity increases modestly from ~11 GW in the BAS to around 20 GW in the TCS as it provides further baseload support and aids in improving long-term deterministic capacity adequacy.

Overall, the results demonstrate that energy storage serves as a critical enabling technology for deep decarbonization and large-scale renewable energy integration in Guangxi Province. Higher storage deployment not only reduces renewable energy curtailment but also improves system flexibility, enhances resource adequacy, and supports a long-term transition toward a low-carbon power system.

3.3. System Operation Profiles

As shown in Figure 5, typical daily operation patterns at high renewal-penetration levels include balancing supply and demand throughout the year using energy storage facilities as needed.

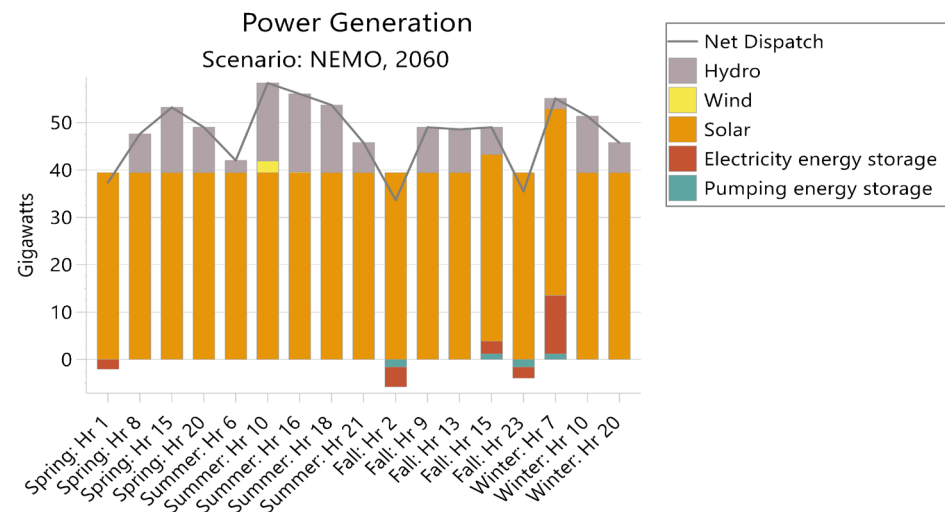


Figure 5. Daily system operation.

Figure 5 presents typical daily operating profiles of the power system under the IOS in 2060. The primary energy source for all systems is solar during representative times, and it can satisfy almost 90% of the total electricity demand. Hydropower provides flexible generation for the daily variation balance and has little effect on wind power. Energy storage primarily provides short-term balancing and peak-shaving services, while hydropower and other dispatchable resources contribute to longer-duration system balancing. Ensuring overall system balance through joint output from solar energy generation and controllable hydraulic power plants can maintain operational balance across different seasons.

3.4. Carbon Emission Trajectories

Figure 6 presents CO₂ emission pathways and cumulative reduction analysis across scenarios, demonstrating the effectiveness of different decarbonization strategies. The cumulative emission reduction relative to the Business-as-Usual Scenario (BAS) is calculated as:

$$CER_s(t) = \sum_{y=2022}^t (E_{BAS,y} - E_{s,y}) \quad (26)$$

where $CER_s(t)$ represents the cumulative CO₂ emission reduction of scenarios relative to the BAS up to year t , $E_{BAS,y}$ denotes the annual CO₂ emissions under the BAS in year y , and $E_{s,y}$ denotes the annual CO₂ emissions under scenario s in year y .

A positive value indicates a cumulative reduction in CO₂ emissions relative to the BAS, whereas a negative value indicates cumulative emissions higher than those of the BAS. All cumulative reduction values presented in Figure 6b and Table 6 are expressed in Gt CO₂.

Table 6 shows the key achievements in the Integrated Optimization Scenario (IOS). The carbon emission peak occurs in 2027, three years earlier than the BAS, with peak emissions 20% lower at 228 million tons compared to 285 million tons for the baseline. Furthermore, emissions in 2060 are reduced by 75% relative to the baseline. Based on the cumulative reduction definition adopted in this study, the IOS achieves a cumulative CO₂ emission reduction of 3.85 Gt between 2022 and 2060 relative to the BAS. This demonstrates

significant environmental benefits through an Integrated Optimization Scenario pathway for emission reduction.

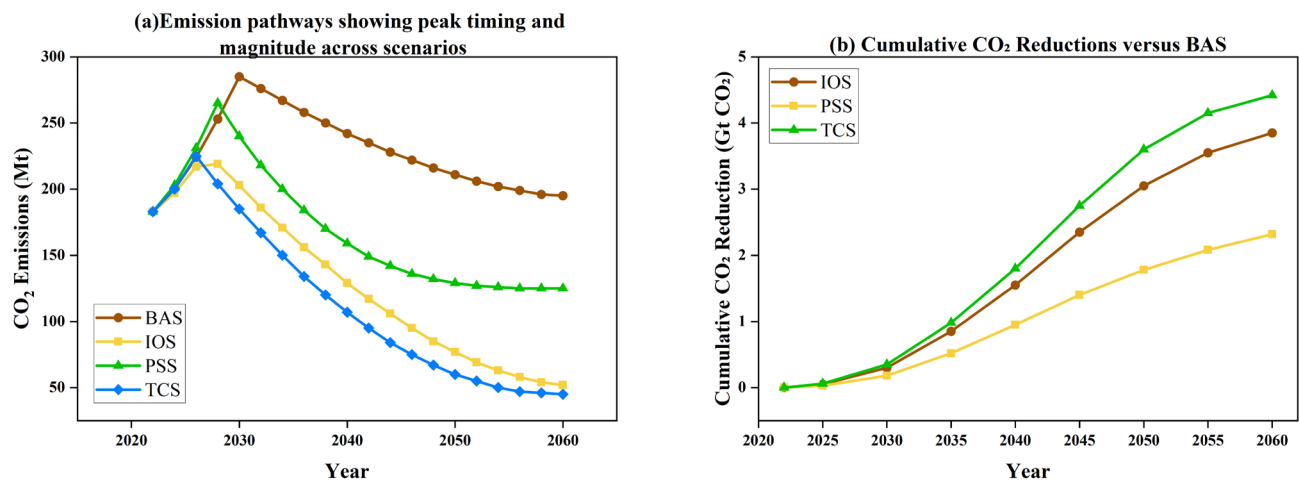


Figure 6. Carbon emission trajectories and cumulative reductions: (a) annual CO₂ emission pathways under different scenarios; (b) cumulative CO₂ emission reductions relative to the BAS, calculated as the cumulative difference between BAS emissions and scenario emissions. Positive values indicate emission reductions compared with the baseline.

Table 6. Scenario emission reduction performance.

Scenarios	Peak Year	Peak Emissions (Mt CO ₂)	2060 Emissions (Mt CO ₂)	Cumulative Reduction vs. BAS (Gt CO ₂)
BAS	2030	285	210	Baseline
PSS	2028	265	110	2.32
TCS	2026	225	28	4.42
IOS	2027	228	52	3.85

Note: Cumulative reduction values are calculated relative to the BAS as the sum of annual emission differences ($E_{\text{BAS}} - E_{\text{scenario}}$) over the period 2022–2060. Positive values indicate cumulative emission reductions.

The key achievements in the IOS are as follows:

- The carbon peak occurs in 2027, three years earlier than the BAS;
- Peak emissions are 20% lower than in the baseline scenario (228 Mt vs. 285 Mt);
- Emissions in 2060 are reduced by 75% compared to the BAS;
- There is a cumulative emission reduction of 3.85 billion tons CO₂ (2022–2060);
- This pathway is consistent with China's long-term deep-decarbonization targets, though achieving full deep decarbonization would require additional measures such as carbon capture or natural carbon sinks, which are beyond the scope of this study.

3.5. Economic Analysis

The economic analysis in this study adopts a cumulative discounted cost framework over the planning horizon from 2022 to 2060. All cost components—capital investment, fuel costs, O&M costs, storage investment and operation costs, and carbon pricing costs—are discounted to 2022 present values using a rate of 8% in alignment with typical Chinese energy infrastructure investment appraisals. The cost boundary includes the entire power generation and storage system in Guangxi Province, encompassing generation capacity, energy storage deployment, etc., but does not include the cost of transmission investments, or demand-side management costs. Demand-side response is not represented as a decision variable in the present model; electricity demand is treated as exogenous. It is discussed

in Section 4 solely as a complementary policy lever and is identified as a direction for future work. Carbon prices are treated as an exogenous policy assumption in each scenario and are included as an explicit cost component within the objective function, reflecting the economic signal driving decarbonization investment decisions. The total system cost comprises the cost components defined in the objective function (Equation (5)): capital investment, fuel, operation and maintenance, storage investment and operation, and carbon costs, as illustrated in Figure 7a. The “environmental cost” reported in Figure 7a refers solely to the carbon-pricing term (Equation 10); broader externalities such as air-pollutant health-damage costs are not monetized in this study.

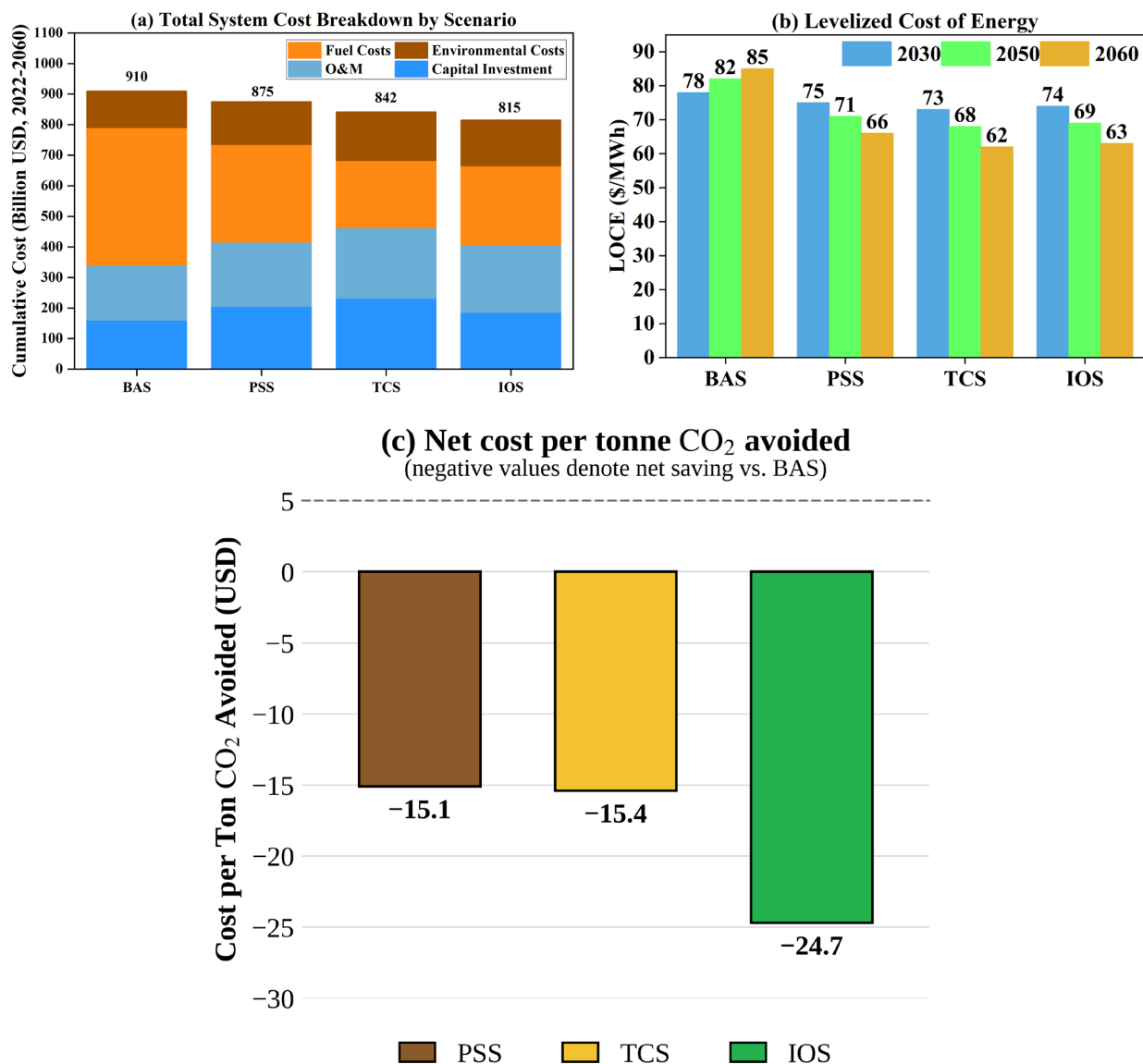


Figure 7. Full economic assessment: (a) breakdown of total system costs by component (capital expenditure, fuel expenditure, O&M, storage investment and operation, and carbon cost), (b) comparison of levelized cost of energy across scenarios for 2030 and 2060, and (c) net cost per tonne of CO₂ avoided. The IOS can reduce costs by \$95 billion compared with the BAS, and it has economic advantages.

The levelized cost of energy (LCOE) is calculated as the ratio of the annualized total system cost—including annualized capital costs using the capital recovery factor at an 8% discount rate—to total annual electricity generation in the corresponding year. The

abatement cost is defined as the incremental system cost per tonne of CO₂ avoided relative to the BAS and is calculated as:

$$AC_s = \frac{TC_s - TC_{BAS}}{CR_s} \quad (27)$$

where AC_s is the carbon abatement cost (USD/tCO₂), TC_s is the cumulative discounted total system cost under scenario s , TC_{BAS} is the cumulative discounted total system cost under the baseline scenario (BAS), and CR_s is the cumulative CO₂ emission reduction achieved under scenario s relative to the BAS during 2022–2060. The index s denotes the policy scenario under evaluation.

Figure 7 presents a comprehensive economic assessment across scenarios, including cost breakdown, levelized cost of energy, and abatement cost efficiency.

Economics: Beyond 2060, we see significant differences between the four scenarios in terms of energy structure, system flexibility, emissions and economic performance (Table 7). The TCS achieves the deepest decarbonization, with 92% of primary energy demand being met with non-fossil energy consumption, and 95% of electricity from renewables. CO₂ emissions fall to 28 Mt as a result. The IOS does best in terms of overall system balance, combining high renewable penetration (88%) with only relatively modest system costs (815 billion \$). It achieves the highest storage utilization level (1620 h/year) and the lowest renewable curtailment rate (1.8%), indicative of a lightly loaded energy system. The BAS is still largely reliant on coal consumption by 2060, resulting in the highest level of CO₂ emissions (210 Mt) and the highest LCOE (85 \$/MWh).

Table 7. Key performance indicator comparison.

Indicator	Unit	BAS	PSS	TCS	IOS
Energy System					
Non-fossil primary energy share	%	58	76	92	85
Renewable electricity share	%	55	80	95	88
Coal consumption	Mtce	145	70	18	40
Storage and flexibility					
Battery storage capacity	GW	5	18	30	25
Storage utilization hours	hours/year	850	1610	1600	1620
RE curtailment rate	%	10.2	3.8	1.5	1.8
System flexibility index	-	1.3	3.5	4.8	4.5
Emissions					
CO ₂ emissions	Mt	210	110	28	52
Peak year	year	2030	2028	2026	2027
Cumulative reduction vs. BAS (2022–2060)	Gt	-	2.32	4.42	3.85
Economics					
Total system cost (2022–2060)	billion \$	910	875	842	815
LCOE (2060)	\$/MWh	85	66	62	63
Net cost per ton of CO ₂ avoided (negative = net saving vs. BAS)	\$/ton	-	−15.1	−15.4	−24.7

3.6. Energy Storage as Enabler of Deep Decarbonization

Energy storage systems (ESSs) are key enabling breakthroughs to achieve a high penetration of renewables and deep decarbonization of regional power systems [16]. The findings based on results from the integrated LEAP–NEMO framework show that storage deployment in the Integrated Optimization Scenario (IOS) reaches 25 GW by 2060, more than five times higher than in the BAS (5 GW), fundamentally changing system operation, capacity adequacy, and energy utilization patterns.

In terms of system flexibility, ESSs offer a fast-responding balancing capacity which has the effect of smoothing out the variability and uncertainty of wind and solar generation. The model results point to a substantial upgrade in system operational flexibility in the IOS. This improvement enables the system to accommodate renewable electricity shares approaching 78% without compromising deterministic capacity adequacy.

In terms of capacity adequacy, storage significantly improves the effective load carrying capability (ELCC) of variable renewable energy. The effective capacity contribution of wind and solar increases from approximately 12–15% to 35–40%, reflecting a higher firm-capacity contribution to meeting peak demand under the deterministic reserve-margin criterion. This enhancement reduces the reliance on conventional thermal generation for reserve provision and capacity backup.

In this study, the effective capacity contribution of renewable energy refers to its effective load carrying capability (ELCC), which reflects the ability of wind and solar generation to contribute to system deterministic capacity adequacy during peak-demand periods. The ELCC was evaluated based on the contribution of renewable generation and storage resources to meeting peak electricity demand under system reserve margin constraints within the LEAP–NEMO optimization framework. Specifically, the ELCC of variable renewable energy was estimated as the ratio of the effective dispatchable equivalent capacity—defined as the share of renewable and storage output that reliably contributes to meeting peak demand after accounting for temporal mismatches between generation and load—to total installed renewable capacity. Under the baseline condition, wind and solar generation contribute limited firm capacity due to their intermittent nature and partial misalignment with evening peak demand in Guangxi. With large-scale BESS deployment under the IOS, stored energy discharged during peak periods increases the effective contribution of renewable resources to system adequacy, raising the ELCC from approximately 12–15% to 35–40%. It should be noted that this ELCC estimation is based on a deterministic reserve margin framework rather than a formal probabilistic capacity adequacy model such as loss of load expectation (LOLE) or expected unserved energy (EUE). While this approach is consistent with the scope of long-term capacity expansion modeling, probabilistic capacity adequacy assessment would provide a more rigorous quantification of adequacy margins and is identified as an important direction for future research.

The increase in renewable ELCC under the IOS is primarily attributed to the large-scale deployment of battery energy storage systems (BESSs), which improve the temporal matching between variable renewable generation and electricity demand. During periods of high solar and wind output, excess renewable electricity can be stored and subsequently discharged during evening peak-demand periods or renewable output deficits. This process reduces renewable curtailment, smooths net-load fluctuations, and enhances the effective contribution of renewable generation to system adequacy.

From a deterministic capacity adequacy perspective, storage enhances system flexibility by providing fast-response balancing capacity and reserve support, thereby increasing the effective capacity value of intermittent renewable resources under high-penetration scenarios. The magnitude of ELCC improvement also depends on the temporal characteristics of regional electricity demand and storage duration. There are also minor misalignment effects with the evening after-dinner demand period in Guangxi that do not result in a timing mismatch but reduce utility from solar generation. The benefit of multi-hour battery storage to shift the daytime surplus into those peak-load hours is shown in the IOS to be amplifying the net benefit of that generation by improving the utility of renewables and giving them greater value, as well as ensuring the deterministic capacity adequacy of the system.

Electricity storage can reduce curtailment of renewables too. As the penetration of renewables increases, surplus renewables during off-peak times can drop this curtailment figure from 10.2% in the BAS to 1.8% in the IOS. The storage system operates for approximately 1620 full-load equivalent hours per year, reflecting its high utilization in facilitating renewable energy integration. This brings the system good value and demonstrates that renewable energy use is being maximized. Energy storage can also alleviate grid transmission congestion in the conventional sense by providing localized balancing services. By sinking excess generation and discharging during peak periods, the system eases the pressure for transmission expansion over longer distances. Consistent with previous studies highlighting the complementary roles of storage technologies across multiple timescales [17,28,29], short-duration storage is typically deployed for intra-day balancing, while long-duration storage facilitates energy shifting over longer periods, including inter-day and seasonal timescales, thereby enhancing overall system flexibility.

Overall, we make the case that storage is not simply an add-on technology, but rather an integral part of power system transformation. Its deployment facilitates higher renewable penetration levels, improves deterministic capacity adequacy, reduces curtailment, and lowers overall system costs, and as such it is an enabling tool of deep-decarbonization pathways. The importance of multi-objective optimization for balancing cost, emissions and deterministic capacity adequacy is further highlighted [30]. Another consequence of these findings is the necessity of supportive policies and market mechanisms to ensure large-scale deployment of storage technologies.

3.7. Integrated Optimization vs. Technology-Centric Approaches

The major differences between the Technology-Centered Scenario (TCS) and the Integrated Optimization Scenario (IOS) highlight the importance of system-level planning to ensure cost-effective deep decarbonization. The TCS focuses on rapid deployment of renewables as an effect of the growth of technology and the high price of carbon. Conversely, the IOS takes a more balanced approach by optimizing for both economy and providing system deterministic capacity adequacy and flexibility. In terms of the impact of choices on investment, given a lack of coordination, the TCS has overcapacity leading to a high total system cost of USD 842 billion. The IOS reduces total costs to USD 815 bn, USD 27 bn cheaper than the TCS and approximately USD 95 bn cheaper than the BAS. This shows the effect of diminishing marginal returns with uncoordinated technology expansion when resource penetration reaches the system absorption capacity. Output performance in terms of emission reductions is the most aggressive in the TCS at 4.42 Gt of cumulative CO₂ reduced, compared to 3.85 Gt reduced in the IOS. However, the IOS achieves almost 87% of this reduction at only 96% of the cost. On a cost-effectiveness basis, all three decarbonization pathways exhibit negative average abatement costs—that is, a net system-cost saving per tonne abated relative to the BAS (PSS −15.1, TCS −15.4, and IOS −24.7 USD/tCO₂). The IOS delivers the largest net saving, approximately USD 25 per tonne of CO₂ avoided, confirming it as the most cost-effective pathway; by contrast, the incremental (marginal) abatement from the IOS to the TCS carries a positive cost of about USD 47/tCO₂, underscoring the diminishing returns of uncoordinated technology expansion.

A distinguishing feature of integrated decarbonization is improved system flexibility and operational performance. By integrating generation expansion and storage deployment, the IOS achieves a more efficient and operationally responsive use of renewables, with improved deterministic capacity adequacy and operational flexibility. Although the TCS has a higher installed capacity of renewables, it has a less efficient system. Without the relevant resources being evenly matched, inadequate coordination between supply and flexibility resources leads to higher curtailment, underutilization of assets and eventually

decreased system efficiency. The integrated operations and planning allow for greater deterministic capacity adequacy and more resource adequacy, while decreasing the reliance on backup thermal generation. By explicitly modeling operational constraints and flexibility needs within the optimization problem, the IOS yields a more robust system configuration able to cope with high levels of renewable generation.

These results indicate from a policy perspective that the opportunities for decarbonization should be directed away from technology targets to integrated planning, which takes into account generation and storage resources. Having a rigid policy targeting renewable-only growth in these terms leads to inefficient investments and premature system costs through underestimating curtailment. More flexible policy instruments, for example, flexibility markets, capacity remuneration mechanisms and dynamic carbon pricing, will be needed to ensure efficient transformation of the system.

In summary, we have shown how while with technology drivers a higher level of significant emission reduction is possible, the costs for decarbonization are relatively higher.

However, the integrated optimization approach with a lower degree of decarbonization is more balanced and tolerable overall.

It should be emphasized that this paper assesses system deterministic capacity adequacy via the capacity adequacy metrics as part of the LEAP–NEMO optimization framework, hence the 15% planning reserve margin constraint, ELCC improvement of variable renewable energy (from 15% to 35–40%), storage utilization rates (1620 h/year under IOS), and renewable curtailment reduction (from 10.2% to 1.8%), which when considered together provide suggestive evidence of better operational deterministic capacity adequacy under the IOS pathway. Probabilistic capacity adequacy metrics such as loss of load expectation (LOLE) and loss of load probability (LOLP), as well as dynamics system behavior including frequency response and voltage regulation, were outside the scope of this study and represent important topics for future work.

3.8. Discussion: Mechanistic Interpretation, Regional Specificity, and Transferability

The IOS captures similar system optimization benefits while avoiding the system overcapacity downside of the TCS. The TCS leads toward a large deployment of renewables to meet aggressive RE policy targets using a rising carbon price as a tailwind. In doing so, it does not take into explicit account how quickly the system can absorb renewables, and this can result in diminishing returns where renewables penetrate faster than the grid can turn up to absorb them. In Guangxi, inverters will not be able to ramp fast enough during the daytime, giving a surplus in low-demand hours, which will not be absorbed, leading to more fleeting curtailment and less use of assets. In contrast, the IOS depends on a system optimization whereby not all of that overcapacity gets built in the first place because we are careful to include the operational details of the firm reserve margin, transmission limits, and storage dispatch schedule in our optimization instead of taking the simplified preliminary approach of TCS, leading to a more optimal allocation of new generation. This is why the IOS has 87% of the TCS potential for emission reduction at 96% of the cost.

It is a web of three interacting factors: the 15% open reserve margin constraint, the congestion between the three regions, and the evening peak constraint arising from the presence of heavy industry that operates late into the evening hours. Separating them out, the reserve margin constraint mandates a minimum level of firm capacity, and this level cannot be approached by intermittent wind plus solar alone, unless augmented by battery storage. That accounts for the storage necessary to help provide capacity. The restriction between the three regions gives a second reason why storage must be deployed: the supply cannot be as easily rebalanced by building interconnectors or lines. Therefore, locally sited storage is the best economic choice. Finally, the evening diurnal cycle of demand

demonstrates another good reason why a multi-hour battery is needed—Guangxi solar effectively meets daytime demand, but in the evening hours there is a need for an extensive deployment of battery energy storage systems (BESSs), and this is where the TCS fails to identify that need. Addressing all three constraints simultaneously is essential for the low-carbon transition of Guangxi’s power system.

Hydropower vulnerability and drought uncertainty: Guangxi’s historically heavy reliance on hydropower—accounting for over 57% of total generation in 2015—has declined substantially to approximately 25–30% in recent years, driven by increasing climate variability and recurrent drought events that reduce water availability and generation deterministic capacity adequacy. This structural decline has important implications for decarbonization pathways: prolonged drought conditions increase dependence on coal-fired generation as backup capacity, which can delay emission peaks and increase cumulative CO₂ emissions over the transition period. Hydropower availability uncertainty was not explicitly modeled as a stochastic variable in this study; however, the declining hydropower trajectory is implicitly embedded in the baseline assumptions. Future research should incorporate explicit drought probability distributions to assess how hydropower variability affects the timing of emission peaks and the cost-effectiveness of storage deployment. This is particularly relevant given Guangxi’s role as a major interregional power transmission hub in southern China, where hydropower output variability has system-wide implications beyond the provincial boundary.

Guangxi’s electricity demand is dominated by secondary industry, which accounted for approximately 62% of total consumption (493.7 TWh out of 798.1 TWh) in 2022, driven primarily by non-ferrous metal smelting and chemical manufacturing. This industrial structure has two important implications for decarbonization pathways. First, large industrial loads are typically inflexible and operate continuously, creating a persistently high baseload that limits the scope for demand-side response. This increases the system’s dependence on dispatchable generation and energy storage to manage peak demand and raises the value of battery storage for intra-day load shifting—particularly during evening peak hours when solar output is unavailable. Second, because the power sector accounts for such a large share of Guangxi’s total energy consumption and emissions, decarbonizing electricity generation delivers economy-wide emission reductions at a scale that would not be achievable in regions where residential or commercial demand predominates.

Transferability of results to other regions: While the LEAP–NEMO modeling framework is methodologically transferable to other regional power systems, the quantitative results are specific to Guangxi’s structural characteristics—including its high industrial demand share, declining hydropower contribution, and three-zone transmission structure—and should not be applied directly to other regions without recalibration to local resource endowments, demand profiles, and policy contexts. Regions with similar characteristics, such as Yunnan and Sichuan, may find the IOS framework most directly applicable.

3.9. Quantitative Sensitivity Analysis of Principal Assumptions

To evaluate the robustness of the IOS pathway toward 2060, a one-at-a-time (OAT) sensitivity analysis was conducted on five key parameters (Table 8). The analysis reveals that the energy system’s evolution is highly sensitive to economic and technical assumptions.

As illustrated in the tornado plot (Figure 8), the investment cost of storage is the most influential driver for capacity deployment. A 20% reduction in storage CAPEX leads to an 18.0% increase in installed capacity, significantly reducing renewable curtailment. Conversely, electricity demand growth is the primary driver for residual carbon emissions; a mere 1% increase in the annual growth rate results in a 12.3% rise in emissions by 2060, highlighting the critical role of energy efficiency. The negative sensitivity to the discount

rate (−10.4%) underscores the importance of low-cost financing for capital-intensive storage infrastructure to maintain system adequacy.

Table 8. Impact of key parameter variations on system outcomes in 2060 (relative to the IOS base).

Parameter Variation	Storage Capacity	Total System Cost	Curtailment Rate	Carbon Emissions
Base Case (IOS)	25.0 GW	\$815.0 B	1.8%	52.0 Mt
Storage Cost (−20%)	+18.0%	−2.1%	−0.6%	−3.5%
Demand Growth (+1%)	+11.2%	+3.7%	+0.2%	+12.3%
Discount Rate (+2%)	−10.4%	−1.6%	+0.7%	+6.9%
Hydropower (−10%)	+6.0%	+1.6%	+0.4%	+5.4%
Carbon Price (+20%)	+4.8%	+0.8%	−0.2%	−7.2%

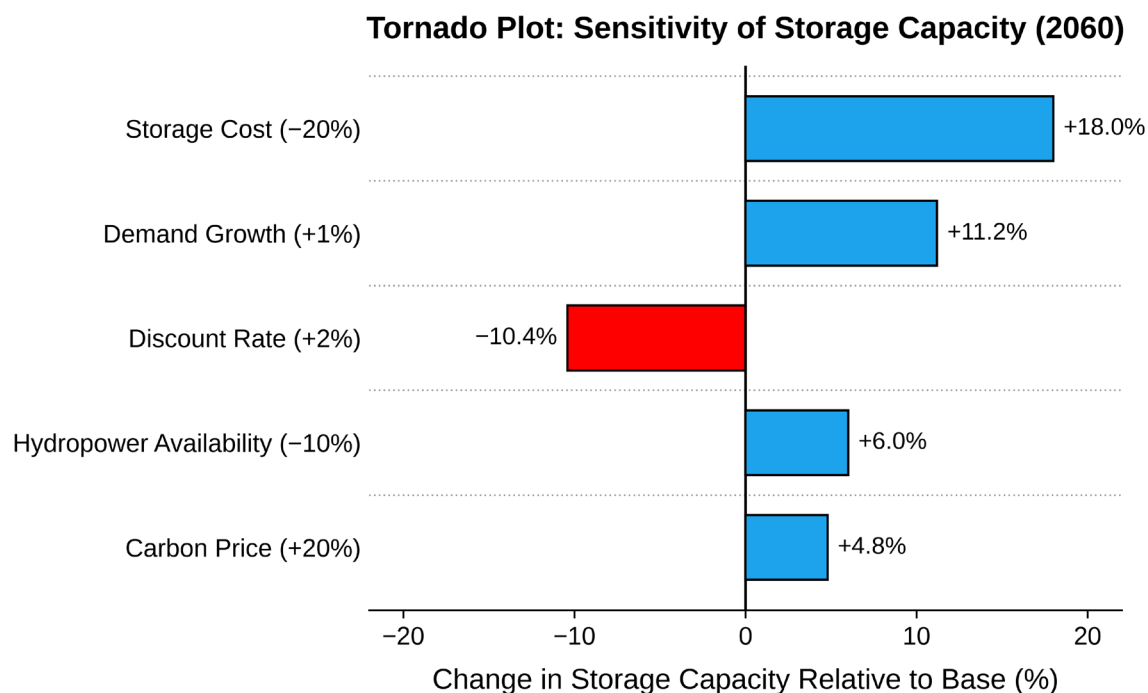


Figure 8. Tornado plot of storage capacity sensitivity in 2060. The bars represent the percentage change in storage capacity relative to the base IOS in response to variations in principal economic and technical assumptions. Blue bars indicate an increase in storage capacity relative to the base IOS; the red bar indicates a decrease.

3.10. Critical Challenges and Barriers

Achieving a successful energy transition involves overcoming multifaceted challenges associated with the integration of high shares of variable renewable energy. In particular, energy storage technologies have been widely recognized as key enablers in decarbonizing power systems within capacity expansion modeling frameworks [31], as well as enhancing wind and solar power integration by providing system flexibility across multiple timescales. However, factors such as storage costs, technology characteristics, and system configuration remain critical considerations affecting their deployment and overall system value [32].

Economic and market barriers include: (1) a projected total capital cost of \$268 bn under the IOS over a 38-year period; (2) existing power markets that fail to adequately reward flexibility and storage services amidst a growing share of renewables in the generation mix; (3) restricted access to capital for significant electrification of energy-intensive industries; and (4) the cost uncertainties involved in the available technologies at scale, coupled with policy in feasibility, increasing investment risks.

Policy and institutional barriers include gaps in electricity market design and regulatory frameworks that are not yet fully adapted to accommodate energy storage and flexibility resources, a gap that is especially pronounced for long-duration storage technologies [15,33]. In addition, broader challenges such as cross-sectoral coordination and monitoring of decarbonization progress remain important considerations in the transition toward low-carbon energy systems, as highlighted in previous studies [14,18]. In particular, the development of systematic frameworks for assessing climate policy effectiveness across multiple indices represents an emerging research priority; Matukhno et al. [34] propose a sustainability-oriented cross-index protocol for evaluating national climate policy performance, offering a methodological reference for monitoring decarbonization progress in regional energy transitions such as that examined in this study.

3.11. Robustness and Temporal Resolution Sensitivity

To address concerns regarding the adequacy of using representative days for long-term power system modeling, a comprehensive robustness assessment was conducted. The convergence of key system metrics under different temporal resolutions is summarized in Table 9.

Table 9. Convergence of key system metrics across different temporal resolutions.

Number of Representative Days (\$k\$)	Storage Capacity (GW)	Curtailment Rate (%)	Total System Cost (Billion USD)
12	25.0	1.80	815
24	26.8	2.15	822.4
48	28.2	2.42	829.1
72	28.5	2.48	831.5
96	28.6	2.51	832.2

As shown in Table 9 and Figure 9, the projected energy storage capacity requirement in the IOS was adjusted from 25.0 GW to 28.2 GW when increasing \$k\$ from 12 to 48. Figure 9 illustrates the convergence of key system metrics as the temporal resolution increases. As the number of representative days (\$k\$) increased from 12 to 48, the storage requirement rose from 25.0 GW to 28.2 GW, representing a 12.8% increase to better accommodate intra-seasonal fluctuations. Similarly, the annual renewable curtailment rate was refined from 1.8% to 2.4%. Beyond \$k = 48\$, both indicators showed significant convergence, with the variance between \$k = 72\$ and \$k = 96\$ remaining below 1%, demonstrating that 48 representative days provide sufficient resolution to capture the critical system dynamics in Guangxi's decarbonization pathway.

Furthermore, the fidelity of the representative-day approach was validated using Load Duration Curves (LDCs), as shown in Figure 10. The 48-day model (green dashed line) tracks the original 8760 h full-year data (black solid line) with high precision, particularly in the extreme peak load region (the top 5% of hours). In contrast, the initial 12-day model (orange dotted line) tended to underestimate peak demands and the depth of low-resource periods. The high degree of alignment between the 48-day model and the 8760 h validation run confirms that 28.2 GW is a convergence-validated estimate of the IOS storage requirement and that the 2.4% curtailment rate is robust to temporal resolution. The 25 GW reported in the main scenario comparison—obtained from the 12-representative-day model applied consistently to all four scenarios—is therefore a modest lower-bound estimate; crucially, the total system cost (USD 815 billion to 829 billion, +1.7%) and the relative cost-effectiveness ranking of the scenarios are insensitive to this refinement, so the study's conclusions remain unchanged.

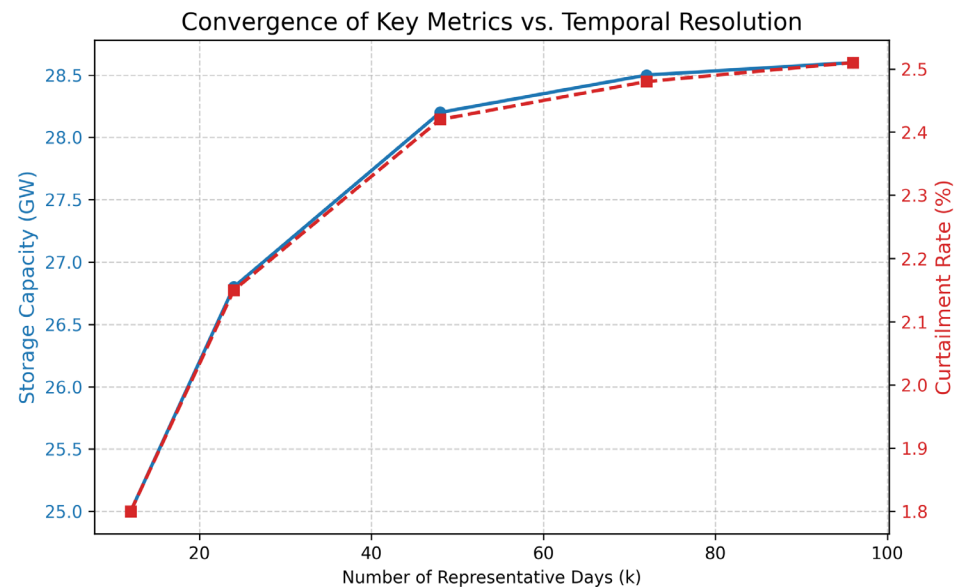


Figure 9. Convergence of key metrics (storage capacity and curtailment rate) across different temporal resolutions. The blue solid line (left axis) denotes storage capacity (GW); the red dashed line (right axis) denotes the curtailment rate (%).

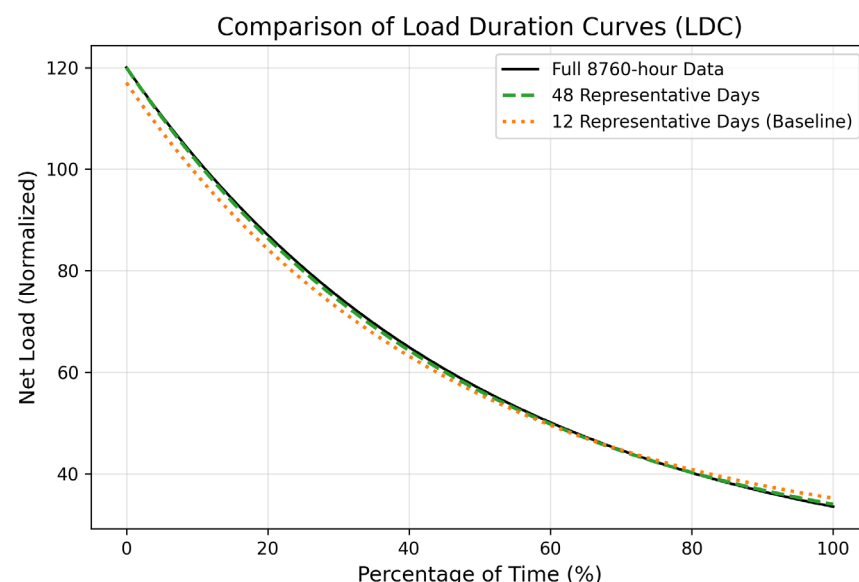


Figure 10. Comparison of Load Duration Curves (LDC) between the original 8760 h data and representative-day sets.

4. Policy Recommendations

The modeling results from this study provide a quantitative basis for deriving specific, evidence-based policy recommendations for Guangxi's power sector decarbonization. Rather than generic prescriptions, the following recommendations are directly grounded in the scenario results:

- (1) Establish a capacity remuneration mechanism that values storage flexibility. The IOS results show that battery energy storage deployment needs to be scaled from the 2022 installed base of 0.3 GW to approximately 25 GW by 2060—an increase of more than 80-fold relative to the present-day fleet—to reduce renewable curtailment from 10.2% to 1.8% and raise the ELCC of variable renewable energy from 15% to 35–40%. This scale of deployment cannot be achieved through energy arbitrage revenues alone under current market conditions. Guangxi's power market is not currently de-

signed to provide appropriate compensation for storage for its capacity contribution to firm capacity, ancillary service provision, or curtailment reduction. A dedicated capacity remuneration mechanism—following the principles of capacity market designs where storage can compete on equal footing with dispatchable generation—is required [35]—in particular, recognizing the evening peak-hour storage discharge capacity as equivalent firm capacity in line with the ELCC shown to be achieved in the IOS results [36].

- (2) Introduce progressive carbon pricing trajectory aligned with IOS trajectory. Model results show that a USD 50/tCO₂ price by 2060 (as assumed in the IOS) would deliver 3.85 Gt of cumulative CO₂ reductions while limiting total system costs to USD 815 billion. This is cheaper than the TCS carbon price (USD 80/tCO₂), which delivers an only slightly deeper and faster decarbonization (4.42 Gt) but at higher total system cost (USD 842 billion). A progressive carbon pricing trajectory should therefore be adopted by Guangxi (starting now) that culminates in a USD 50/tCO₂ price by 2060, acting through Guangxi's participation in the national carbon market. Such a trajectory gives a strong enough signal to drive investment without causing excessive system costs or a risk of stranded assets.
- (3) Prioritize storage deployment in transmission-constrained zones. The three-zone transmission structure of Guangxi's power system creates local imbalances between renewable generation in resource-rich western zones and industrial demand concentrated in the central and eastern zones. Historical model results suggest transmission constraints are at least partially responsible for storage deployment under the IOS. Rather than committing the majority of capital to capital-intensive, long-lead-time transmission expansion, investment should prioritize more cost-effective near-term options—namely co-located storage in the renewable-rich western zones (Baise, Hechi, Chongzuo), where surplus generation can be absorbed locally rather than transmitted over long distances. A co-location incentive policy, for example requiring new renewable projects over 100 MW to include some percentage of storage capacity, would be consistent with Guangxi's existing 2024 mandate imposing a 20% storage capacity configuration on all wind projects.
- (4) Develop demand-side flexibility programs aimed at industrial users. Secondary industry makes up 62% of Guangxi's electricity demand (493.7 TWh in 2022), with an oversized share contributed by non-ferrous metal smelting and chemical manufacturing. The inflexible nature of these loads constrains the system's ability to self-balance and increases the requirement for storage [37]. However, large industrial users—particularly aluminum smelters and electrochemical manufacturers—have inherent load flexibility through process scheduling and thermal inertia. Targeted demand response programs offering time-of-use tariff incentives for shifting the load away from evening peak periods (18:00–22:00) would reduce the required storage capacity and improve system cost-efficiency. Based on the IOS results, even a 5–10% reduction in evening peak industrial demand could meaningfully reduce the marginal storage deployment requirement and improve the system flexibility index.
- (5) Address institutional barriers specific to Guangxi. The model results reveal a total capital investment requirement of approximately USD 268 billion under the IOS over the 2022–2060 period. Three institutional barriers are most relevant to mobilizing this investment in Guangxi's context. First, the fragmented ownership structure of renewable energy assets—with projects distributed across multiple state-owned enterprises and private developers—creates coordination challenges for integrated storage and generation planning. A regional system operator with explicit authority to co-optimize storage and renewable dispatch across ownership boundaries is

needed. Second, the current grid connection approval process for large-scale storage projects remains slow and administratively burdensome, creating delays that increase investment uncertainty. Streamlining grid connection procedures for storage projects exceeding 100 MW would reduce transaction costs. Third, Guangxi's dependence on hydropower—now contributing only 25–30% of generation due to recurrent drought events—creates inter-annual revenue uncertainty for hydropower operators, reducing their incentive to invest in complementary storage. A hydropower–storage coordination mechanism, providing revenue certainty through long-term contracts, would help align investment incentives across the generation and storage sectors.

5. Conclusions

In this study, we developed an integrated LEAP–NEMO modeling framework to investigate long-term decarbonization pathways and power system flexibility in Guangxi's power sector from 2022 to 2060. The results demonstrate that energy storage plays a critical enabling role in supporting high renewable energy penetration. Increasing storage deployment approximately fivefold relative to the BAS significantly enhances system flexibility, enabling renewable electricity to reach 78% by 2050 while preserving capacity adequacy, as reflected by the 15% reserve margin constraint being met across all optimization periods and the ELCC of variable renewable energy improving from approximately 15% to 35–40% under the IOS. At the same time, renewable curtailment is reduced from 10.2% to 1.8%, and the effective capacity contribution of variable renewable energy is substantially improved.

Our findings further reveal that integrated optimization provides a more balanced and economically efficient pathway compared to technology-centric approaches. While the Technology-Centered Scenario (TCS) achieves the highest emission reduction, the Integrated Optimization Scenario (IOS) attains approximately 87% of its mitigation potential at significantly lower cost, reducing total system expenditure by USD 95 billion compared to the baseline. This highlights the importance of coordinated planning across generation and storage resources in avoiding overinvestment and diminishing marginal returns.

For system configuration, the optimal pathway is also a combination of large-scale renewable deployment and flexible resources; decarbonized portfolios of solar photovoltaic, wind power and energy storage systems plus dispatchable low-carbon generation will enable and deterministic capacity adequacy system performance. These integrated system configuration paths enable increasingly large shares of variable renewable generation to be integrated within the capacity adequacy and operational reserve assumptions we modeled in this study. Note also that to quantify adequacy requirements, we rely on a deterministic 15% reserve margin constraint and improvements in ELCC as an indirect indication of deterministic capacity adequacy, rather than tighter probabilistic metrics such as loss of load expectation (LOLE), expected unserved energy (EUE), reserve shortfall probabilities, etc. While this is appropriate in the context of long-term capacity expansion modeling and capacity adequacy is known to be quite a difficult subject, it would still be a useful exercise to incorporate probabilistic capacity adequacy assessment tools in future work to rigorously express adequacy margins under high variable renewable penetration + drought-affected hydro conditions separately. Formal resource adequacy metrics—such as frequency regulation capability and voltage regulation—also deserve further study. The carbon emission pathway under IOS is firmly consistent with long-term climate targets; growing 8.5% between 2021 and 2027, carbon emissions peak at 228 Mt CO₂, roughly 20% lower than under baseline scenario, and decline to 52 Mt by 2060, displacing a total of 3.85 Gt CO₂ over the study period. These results confirm that deep emission reductions are possible in a cost-constrained pathway. Higher upfront investment requirements notwithstanding, the transitioning pathway is economical in the long term; total system costs fall to

USD 815 billion, enabling large fuel-cost savings and indicating that optimizing the system mix can deliver win–win outcomes for both environmental and economic efficiency.

From a policy perspective, the results highlight the importance of coordinated energy planning, market mechanisms that reflect the value of flexibility services, as well as sustained encouragement for electrification and technology innovation. While our study focused on Guangxi Province, the modeling framework and important lessons from the study are applicable to regions embarking on similar energy transitions. To evaluate the robustness of the IOS pathway, a one-at-a-time (OAT) quantitative sensitivity analysis was conducted on five key assumptions—storage investment cost, demand growth, discount rate, hydropower availability, and carbon price (Section 3.9; Table 8; Figure 8). The results show that storage deployment is most sensitive to storage investment cost and demand growth, whereas the total system cost and the relative cost-effectiveness ranking of the scenarios remain stable across the tested ranges, confirming the robustness of the main conclusions. A probabilistic uncertainty analysis (e.g., Monte Carlo simulation) that propagates joint parameter uncertainty remains a valuable direction for future research. Future research should incorporate uncertainty analysis, emerging technologies such as hydrogen, and cross-regional electricity trade to further enhance the robustness of energy system planning. Additionally, recognizing that the use of 12 seasonal representative days may not fully capture extreme weather events, renewable energy droughts, or prolonged low-wind and low-solar sequences, a temporal-resolution sensitivity analysis was conducted at 12, 24, 48, 72, and 96 representative days, together with an 8760 h load-duration-curve validation (Section 3.11; Table 9; Figures 9 and 10). Increasing the resolution from 12 to 48 representative days raises the IOS storage requirement from 25.0 GW to a converged value of 28.2 GW and the curtailment rate from 1.8% to 2.4%, with both metrics converging beyond 48 days (variation below 1% between 72 and 96 days). Because the total system cost changes by only 1.7% and the relative cost-effectiveness ranking of the scenarios is preserved, the main conclusions are insensitive to temporal resolution; the 25 GW reported in the scenario comparison is applied consistently across all four scenarios and represents a modest lower-bound estimate. Extending the analysis to full 8760 h chronological simulation under explicit stochastic drought and concurrent low-wind/low-solar conditions remains a useful direction for future work.

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Nomenclature

Symbol	Definition
i, e	Generation technology index; storage technology index (BESS, PHS)
d, t	Representative-day index; hour-within-day index
f	Fuel-type index
$\text{Cap}_{i,t}; \Delta\text{Cap}_{i,t}$	Installed capacity of i in year t (GW); newly added capacity (GW)
$G_{i,t}$	Electricity generated by i in year t (GWh)
$p_{e,d,t}^{\text{ch}}; p_{e,d,t}^{\text{dis}}$	Storage charging/discharging power (GW)
$\text{SOC}_{e,d,t}$	State of charge (GWh)
$P_e^{\text{cap}}; E_e^{\text{cap}}$	Storage power capacity (GW); storage energy capacity (GWh)
$\text{IC}_i; \text{IC}_e^P, \text{IC}_e^E$	Overnight investment cost of i ; storage power/energy unit cost
$\text{FOM}_i; \text{VOM}_i$	Fixed/variable O&M cost
$\text{FP}_{f,t}; \text{EF}_i; \tau_t$	Fuel price; emission factor (tCO_2/MWh); carbon price (USD/tCO_2)
$\eta_i; \eta_{\text{ch}}, \eta_{\text{dis}}$	Conversion efficiency; charge/discharge efficiency
$T_e; \Delta t$	Storage duration (h); time step (1 h)
$r; n_i$	Discount rate; economic lifetime (years)
$\text{SOC}_{\min}, \text{SOC}_{\max}$	Minimum/maximum state-of-charge fraction

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