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Capacity Optimization for Minimizing the Carbon Footprint of Power Systems

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Abstract

The carbon footprint of electricity supply is strongly influenced by power system capacity configuration and operational flexibility under uncertainty. This paper proposes a carbon-footprint-oriented capacity optimization framework for integrated power systems comprising thermal power, wind power, photovoltaic generation, and energy storage. A dispatch model is developed to represent coordinated system operation under uncertain load and renewable generation, which are modeled using information gap decision theory and Monte Carlo simulation. The carbon footprint of electricity supply is evaluated on a life-cycle basis as carbon emissions per unit of delivered electricity, together with electricity cost and power fluctuation rate as performance indicators. A multi-objective capacity optimization problem is solved using the non-dominated sorting genetic algorithm II (NSGA-II), and a practical optimal solution is selected from the Pareto front using the technique for order preference by similarity to an ideal solution (TOPSIS). Case studies show that the optimized capacity configuration reduces the carbon footprint of electricity supply by approximately 28%, while electricity cost and power fluctuation rate decrease by about 7% and 27%, respectively. Meanwhile, renewable energy utilization increases from 71.4% to 86.8%, and the renewable energy share rises from 42.0% to 55.6%, demonstrating that coordinated deployment of renewable energy and energy storage is essential for achieving carbon-efficient electricity supply under uncertainty.

Keywords: Power system, Carbon footprint, Capacity optimization, Renewable energy, Energy storage.

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1. Introduction

The power sector is one of the largest contributors to global carbon emissions and plays a decisive role in achieving climate mitigation targets [1]. As electricity demand continues to grow, driven by electrification in transportation, industry, and residential sectors, reducing the environmental impact of electricity supply has become a central challenge for modern power systems [2]. In recent years, large-scale integration of renewable energy sources such as wind and photovoltaic (PV) generation has been widely recognized as a key pathway toward lowering the carbon intensity of power generation [3]. However, increasing renewable penetration alone does not necessarily lead to the minimization of the carbon footprint of electricity supply at the system level.

The carbon footprint of electricity supply reflects the life-cycle-based carbon emissions associated with delivering one unit of electrical energy to end users [4]. From a system perspective, this footprint is jointly determined by generation technologies, capacity configuration, dispatch strategies, and the ability of the power system to cope with uncertainty. Although renewable energy sources exhibit significantly lower life-cycle carbon emissions than fossil-fuel-based generation, their inherent intermittency and variability introduce operational challenges that may offset part of the environmental benefits. In particular, insufficient system flexibility can lead to renewable curtailment, increased reliance on thermal units for balancing, and elevated power fluctuations, all of which adversely affect the effective carbon

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footprint of electricity supply [5,6]. Therefore, minimizing the carbon footprint of power systems requires coordinated capacity planning and operational strategies rather than a simple increase in renewable energy capacity.

A substantial body of literature has investigated capacity planning and operational optimization of power systems with high renewable penetration. Existing studies have focused on renewable energy expansion planning, energy storage sizing, and multi-objective optimization considering economic cost, reliability, and emissions. Various optimization techniques, including mixed-integer programming, stochastic optimization, and evolutionary algorithms, have been employed to address the complexity of capacity planning problems [7-9]. Energy storage systems (ESS) have been widely recognized as a critical enabler for renewable integration by providing peak shaving, frequency regulation, and balancing services. However, most existing studies evaluate environmental performance primarily through total or average carbon emissions, while the concept of system-level carbon footprint—defined as life-cycle carbon emissions per unit of delivered electricity—has received comparatively limited attention in capacity optimization frameworks.

Moreover, uncertainties associated with renewable energy generation and user load demand are often simplified or insufficiently represented in capacity planning models. In practice, wind speed variations, solar irradiance fluctuations, and load forecasting errors significantly affect dispatch outcomes and, consequently, the realized carbon footprint of electricity supply [10]. Ignoring these uncertainties may lead to capacity configurations that perform well under deterministic assumptions but exhibit suboptimal environmental and operational performance in real-world conditions. In addition, the interaction between renewable capacity, energy storage capacity, and thermal generation under uncertainty introduces complex trade-offs among economic cost, system stability, and carbon footprint, which cannot be adequately captured by single-objective optimization approaches [11].

To address these challenges, this paper proposes a carbon-footprint-oriented capacity optimization framework for integrated power systems comprising thermal power units, wind power, photovoltaic generation, and energy storage systems. The framework explicitly accounts for uncertainties in renewable generation and user load by combining information gap decision theory with Monte Carlo simulation. A detailed power system dispatch model is developed to reflect the operational interactions among different components under uncertain conditions. Based on this model, a set of performance indicators is established, including the cost of electricity, the power fluctuation rate, and, most importantly, the system-level carbon footprint of electricity supply measured on a life-cycle basis per unit of delivered electricity.

A multi-objective capacity optimization problem is formulated with the objectives of minimizing electricity cost, minimizing the carbon footprint of electricity supply, and minimizing power fluctuations. The non-dominated sorting genetic algorithm II (NSGA-II) is employed to obtain the Pareto-optimal capacity configurations, and the technique for order preference by similarity to an ideal solution (TOPSIS) is applied to select practical optimal solutions from the Pareto front. The proposed framework is validated using multiple regional power system case studies, allowing for a comparative assessment of optimal capacity configurations under different load characteristics and resource endowments.

The main contributions of this paper can be summarized as follows. First, a system-level carbon footprint metric is explicitly integrated into the capacity optimization of power systems, shifting the focus from renewable penetration or emission reduction to carbon footprint minimization per unit of electricity supply. Second, a unified dispatch and capacity optimization framework is developed that captures the coordinated effects of thermal power, renewable generation, and energy storage under uncertainty. Third, the trade-offs among economic cost, system stability, and carbon footprint are quantitatively analyzed through multi-objective optimization and sensitivity analysis. Finally, the proposed approach provides engineering insights into capacity planning strategies for achieving low-carbon-footprint electricity supply in power systems with high renewable penetration.

2. System Description and Modelling

Figure 1 illustrates the overall framework of the integrated power system considered in this study, including thermal power, wind power, photovoltaic generation, energy storage systems, and user-side electricity demand.

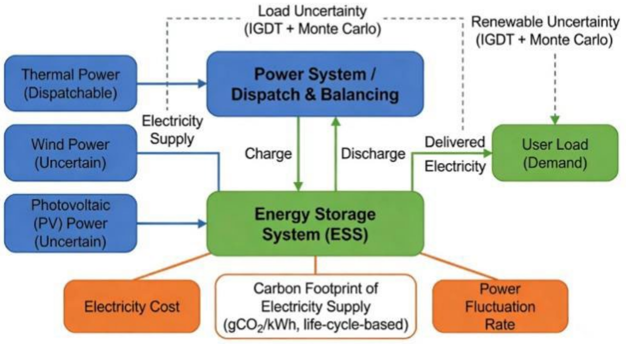

Figure 1. Overall framework of the integrated power system with renewable energy and energy storage

2.1. Overall Power System Framework

The power system considered in this study consists of four major supply-side components—thermal power units, wind power units, photovoltaic (PV) generation units, and energy storage systems (ESS)—as well as the electricity demand on the user side. These components interact dynamically through system dispatch to ensure a continuous balance between electricity supply and demand under uncertain operating conditions. The overall framework is designed to capture the operational interactions among different technologies and their combined impact on the system-level carbon footprint of electricity supply.

Wind power and PV generation are treated as non-dispatchable renewable energy sources whose power outputs are primarily determined by meteorological conditions. Although their life-cycle carbon emissions per unit of electricity are significantly lower than those of thermal power, their inherent intermittency and variability introduce uncertainty into system operation [12]. In contrast, thermal power units and energy storage systems are modeled as dispatchable and controllable resources. Thermal units provide stable base-load generation and peak regulation capability, while ESS offers fast-response balancing services that compensate for short-term fluctuations in renewable generation and load demand [13,14].

The operational objective of the power system is to satisfy electricity demand at all times while maintaining system stability and minimizing the environmental and economic costs associated with electricity supply. From a carbon-footprint-oriented perspective, the realized carbon footprint is not solely determined by the installed capacity of low-emission technologies but is jointly influenced by capacity configuration, dispatch decisions, renewable curtailment, and the extent to which flexible resources are utilized. For example, insufficient flexibility may lead to renewable energy curtailment and increased reliance on thermal power for balancing, thereby increasing the carbon footprint per unit of delivered electricity despite high renewable penetration [15].

The dispatch process follows a hierarchical coordination mechanism. First, day-ahead forecasts of wind power, PV generation, and user load are used to generate an initial dispatch plan. Due to forecast errors and real-time uncertainties, deviations between predicted and actual conditions inevitably occur [16]. These deviations are mitigated through real-time adjustments provided by thermal power units and ESS within their respective operational constraints [17]. When balancing capacity is insufficient, renewable energy curtailment may occur to preserve system stability [18]. This dispatch mechanism enables the framework to realistically represent the operational pathways through which capacity configurations affect both system stability and carbon footprint outcomes.

From a planning perspective, the proposed framework links long-term capacity configuration decisions with short-term operational performance. Installed capacities of thermal power, renewable generation, and energy storage determine the feasible space of dispatch strategies under uncertainty, which in turn influences electricity cost, power fluctuation rate, and the system-level carbon footprint. By explicitly modeling these interactions, the framework provides a basis for evaluating how different capacity configurations perform in terms of carbon footprint minimization rather than merely renewable capacity expansion.

2.2. User Load Uncertainty Model

Electricity demand on the user side is a critical factor influencing power system operation and capacity planning. Although typical load curves can represent the average temporal characteristics of electricity consumption, actual user load inevitably deviates from forecast values due to variations in weather conditions, economic activity, and consumer behavior [19-21]. These deviations introduce uncertainty into system dispatch and directly affect the utilization of generation resources, balancing requirements, and the resulting carbon footprint of electricity supply.

In this study, the baseline electricity demand is represented by typical daily load curves corresponding to working days in different regional power systems. These curves reflect the general diurnal pattern of electricity consumption and provide a reference for system planning and dispatch. However, relying solely on deterministic load profiles may lead to misleading assessments of system performance, particularly under high penetration of renewable energy sources where flexibility requirements are amplified.

To characterize load uncertainty without assuming a specific probabilistic distribution, **information gap decision theory (IGDT)** is employed. IGDT describes uncertainty in terms of deviation bounds around a nominal forecast value, allowing the model to capture a range of plausible load realizations. Let $P_{U,0,t}$denote the forecasted user load at time t, and $P_{U,t}$represent the actual load. The actual user load is assumed to lie within an uncertainty set defined as:

$$\mathcal{U}_U(\alpha) = \left\{P_{U,t} : \left| \frac{P_{U,t}-P_{U,0,t}}{P_{U,0,t}} \right| \le \alpha\right\} \tag{1}$$

where αdenotes the uncertainty horizon parameter in IGDT, representing the maximum relative deviation of actual load from its forecast value. This formulation allows the model to account for both upward and downward deviations from the predicted load curve in a unified and distribution-free manner.

The uncertainty horizon parameter α represents the maximum relative deviation from forecast values and is selected based on typical short-term forecasting error ranges reported in the literature for load and renewable generation. Since the objective of this study is to assess the robustness of capacity configurations rather than to calibrate forecasting accuracy, α is treated as a scenario-based uncertainty parameter rather than being benchmarked against specific historical error datasets.

The IGDT-based load uncertainty model is integrated with **Monte Carlo simulation** to generate a large number of possible load scenarios. For each simulation run, actual load curves are randomly sampled within the defined uncertainty bounds, reflecting different realizations of demand fluctuation. These scenarios are then used as inputs to the power system dispatch model, ensuring that the evaluation of capacity configurations considers a wide range of operating conditions rather than a single deterministic case.

From a carbon-footprint-oriented perspective, load uncertainty plays a crucial role in shaping system performance. Unexpected increases in load may require rapid ramping of thermal power units or intensified use of energy storage systems, potentially increasing the carbon footprint per unit of delivered electricity. Conversely, lower-than-expected demand may lead to renewable energy curtailment if insufficient flexibility is available, reducing the effective utilization of low-carbon generation. By explicitly modeling load uncertainty through IGDT and Monte Carlo simulation, the proposed framework captures these mechanisms and enables a more realistic assessment of how capacity configurations influence the carbon footprint of electricity supply under real-world operating conditions.

2.3. Wind and Photovoltaic Power Generation Models

Wind power and photovoltaic (PV) generation are key low-carbon energy sources in modern power systems and play a crucial role in reducing the carbon footprint of electricity supply. Due to their near-zero life-cycle carbon emissions during operation, increasing wind and PV generation is generally beneficial from an environmental perspective. However, their power outputs are inherently intermittent and highly dependent on meteorological conditions, which introduces significant uncertainty into system operation and dispatch [22].

In this study, the forecasted power outputs of wind power and PV generation are represented by typical daily generation profiles derived from historical data and short-term forecasting methods. These profiles reflect the expected availability of renewable energy and are used to construct day-ahead dispatch plans. Nevertheless, actual wind speed and solar irradiance may deviate from forecast values due to weather variability, resulting in discrepancies between predicted and realized renewable generation.

To describe renewable generation uncertainty without assuming specific probability distributions, **information gap decision theory (IGDT)** is employed, consistent with the load uncertainty modeling approach presented in Section 2.2. Let $P_{W,0,t}$ and $P_{P,0,t}$ denote the forecasted wind power and photovoltaic power outputs at time t, respectively, and let $P_{W,t}$ and $P_{P,t}$ represent their actual outputs. The uncertainties of wind and PV generation are modeled using the following uncertainty sets:

$$\mathcal{U}_W(\alpha) = \left\{P_{W,t}: \left|\frac{P_{W,t}-P_{W,0,t}}{P_{W,0,t}}\right| \leq \alpha\right\} \tag{2}$$

$$\mathcal{U}_P(\alpha) = \left\{P_{P,t}: \left|\frac{P_{P,t}-P_{P,0,t}}{P_{P,0,t}}\right| \leq \alpha\right\} \tag{3}$$

where α denotes the uncertainty horizon parameter, representing the maximum relative deviation of actual renewable generation from its forecast value. This formulation allows both overestimation and underestimation of renewable power outputs to be considered in a unified and distribution-free manner.

The IGDT-based renewable generation uncertainty model is integrated with **Monte Carlo simulation** to generate a large number of wind and PV generation scenarios. For each simulation run, actual renewable generation profiles are randomly sampled within the defined uncertainty bounds and combined with load scenarios to form realistic operating conditions. These scenarios are then used as inputs to the power system dispatch model, enabling robust evaluation of capacity configurations under combined supply-side and demand-side uncertainties.

From a carbon-footprint-oriented perspective, uncertainty in wind and PV generation directly affects system dispatch and carbon performance. Lower-than-expected renewable output increases reliance on thermal power units for balancing, thereby raising the carbon footprint per unit of delivered electricity. Conversely, higher-than-expected renewable output may lead to curtailment if system flexibility is insufficient, reducing the effective utilization of low-carbon generation. By explicitly modeling renewable generation uncertainty through IGDT and Monte Carlo simulation, the proposed framework captures these mechanisms and provides a realistic basis for assessing how capacity configurations influence the carbon footprint of electricity supply under real-world operating conditions.

In this study, information gap decision theory (IGDT) is employed to define bounded uncertainty sets for load demand and renewable generation without assuming specific probability distributions. Monte Carlo simulation is then used to randomly sample operating scenarios within these IGDT-defined uncertainty horizons. In this way, IGDT characterizes the robustness range of forecast deviations, while Monte Carlo simulation captures stochastic variability within the prescribed bounds, forming a complementary uncertainty representation framework.

2.4. Thermal Power Generation Model

Thermal power units are modeled as the primary dispatchable generation resources in the power system and play a critical role in maintaining supply–demand balance under uncertain operating conditions [23]. Despite their relatively high life-cycle carbon emission intensity compared with renewable energy sources, thermal units provide essential flexibility services, including base-load supply, peak regulation, and frequency control [24]. As a result, thermal power generation remains a key determinant of the system-level carbon footprint of electricity supply.

In the proposed framework, the total output power of thermal generation at each time step is composed of scheduled generation and regulation output. The scheduled generation is responsible for meeting the baseline electricity demand, while the regulation component compensates for real-time deviations caused by fluctuations in renewable generation and user load. The total output of thermal power units is constrained by their installed capacity, ensuring that generation levels remain within physically feasible limits.

Thermal power units are further subject to ramping constraints, which limit the rate at which their output power can increase or decrease between consecutive time intervals. These constraints reflect the physical and operational characteristics of thermal plants, such as boiler dynamics and turbine inertia, and are essential for realistically modeling system flexibility. Limited ramping capability implies that thermal units cannot instantaneously respond to large or rapid fluctuations, increasing the reliance on energy storage systems or renewable curtailment to preserve system stability.

From a carbon-footprint-oriented perspective, the operation of thermal power units represents a trade-off between system stability and environmental performance. On the one hand, sufficient thermal capacity and ramping capability are necessary to accommodate uncertainty and prevent excessive power fluctuations. On the other hand, increased utilization of thermal generation directly raises the life-cycle carbon emissions associated with electricity supply, thereby increasing the carbon footprint per unit of delivered electricity. Consequently, the installed capacity and operational role of thermal power units must be carefully balanced against renewable and storage capacities to achieve low-carbon-footprint outcomes.

In the dispatch process, thermal power units act as the final balancing resource when renewable generation and energy storage are insufficient to fully compensate for supply–demand mismatches. This hierarchical role ensures reliable system operation but also highlights the importance of capacity planning decisions. Excessive dependence on thermal power for balancing indicates insufficient system flexibility, while insufficient thermal capacity may compromise reliability. By explicitly modeling thermal generation constraints and their interaction with renewable energy and storage, the framework captures the fundamental mechanisms through which thermal power influences both system stability and carbon footprint.

2.5. Thermal Power Generation Model

Energy storage systems (ESS) are modeled as highly flexible resources that provide rapid response capability for balancing short-term power fluctuations in the power system. Unlike thermal power units, ESS does not serve as a primary energy source but functions as a regulation and buffering mechanism that absorbs excess electricity and releases it when required. As renewable energy penetration increases, the role of ESS becomes increasingly critical in shaping both system stability and the carbon footprint of electricity supply [25].

In the proposed framework, the output power of ESS is constrained by its installed capacity and operational limits. ESS can operate in both charging and discharging modes, enabling it to store surplus renewable generation during periods of low demand or high renewable output and to supply electricity during peak demand or renewable shortages. The rate of change in ESS output is limited by power ramping constraints, reflecting the physical charging and discharging characteristics of storage technologies. Compared with thermal power units, ESS typically exhibits much faster response capability, making it particularly effective for mitigating short-term imbalances caused by renewable variability and load uncertainty.

For tractability in capacity planning, the charging and discharging efficiency of energy storage systems is assumed to be constant, and the state of charge (SOC) is implicitly constrained within a safe operating range. Degradation and lifetime effects of energy storage are not explicitly modeled. This simplification is adopted because the focus of this study is on system-level capacity configuration and carbon footprint assessment rather than detailed electrochemical behavior of storage technologies.

From a carbon-footprint-oriented perspective, ESS influences system performance through multiple interacting mechanisms. By increasing the effective utilization of low-carbon renewable energy and reducing renewable curtailment, ESS can significantly lower the carbon footprint per unit of delivered electricity. In addition, ESS can reduce the need for frequent ramping and part-load operation of thermal power units, thereby limiting the reliance on high-emission generation for balancing purposes [26]. These effects highlight the potential of ESS to amplify the carbon footprint benefits of renewable energy integration.

However, the impact of ESS on carbon footprint is not unconditionally positive. When renewable utilization is low or when ESS capacity is oversized relative to system needs, increased cycling of ESS may lead to higher operational complexity and increased power fluctuations. Moreover, the carbon footprint associated with ESS operation depends on the carbon intensity of the electricity used for charging. If charging predominantly occurs during periods of high thermal generation, the environmental benefits of ESS may be diminished. Therefore, the effectiveness of ESS in reducing system-level carbon footprint is closely linked to its capacity configuration and coordination with renewable generation and thermal power units.

Within the dispatch hierarchy, ESS operates as a first-response balancing resource that addresses rapid and short-duration deviations between electricity supply and demand [27]. When ESS capacity and ramping capability are insufficient, thermal power units provide secondary balancing support, and renewable curtailment may occur as a last resort to maintain system stability. This coordinated interaction determines the realized dispatch outcomes and, ultimately, the carbon footprint of electricity supply under uncertainty.

By explicitly modeling ESS capacity and operational constraints, the proposed framework captures the essential role of energy storage in enabling low-carbon-footprint electricity supply. The ESS model completes the system representation and provides the necessary foundation for subsequent sensitivity analysis and multi-objective capacity optimization, where the trade-offs among storage capacity, renewable integration, system stability, and carbon footprint are quantitatively evaluated. The key system parameters and capacity ranges considered in this study are listed in Table 1.

Table 1. Key parameters and bounds of the power system

Parameter	Description	Value/Range	Unit
C_F	Installed capacity of thermal power	20-60	GW
C_W	Installed capacity of wind power	0-50	GW
C_P	Installed capacity of photovoltaic generation	0-50	GW
C_S	Installed capacity of energy storage systems	0-50	GW
α	IGDT uncertainty horizon parameter	0-0.30	-
T	Dispatch time horizon	24	H
Δt	Dispatch time interval	1	H
N	Number of Monte Carlo scenarios	1000	-

***Note:* The capacity bounds are determined based on technical feasibility, planning constraints, and regional system characteristics. The range of α reflects typical engineering uncertainty levels reported in the literature and is used for robustness-oriented scenario analysis.**

3. Performance Indicators

3.1. Cost of Electricity

The cost of electricity is a fundamental performance indicator for evaluating the economic feasibility of power system capacity configurations. While minimizing the carbon footprint of electricity supply is the primary objective of this study, economic performance remains a critical constraint in practical power system planning. Capacity configurations that achieve low carbon footprints but incur excessively high electricity costs are unlikely to be adopted in real-world applications. Therefore, electricity cost is incorporated as a key indicator to ensure a balanced assessment of environmental and economic performance.

Different power generation technologies exhibit distinct cost characteristics over their life cycles. Thermal power generation is primarily affected by fuel consumption and operation costs, whereas renewable energy technologies such as wind power and photovoltaic (PV) generation involve higher initial investment but lower operating expenses. Energy storage systems (ESS) introduce additional capital and operation costs but provide flexibility services that can reduce overall system cost by improving renewable energy utilization and reducing reliance on thermal power for balancing.

To enable a consistent comparison across different technologies, the **levelized cost of electricity (LCOE)** is adopted to represent the average cost of electricity generation over the entire life cycle of each component. The LCOE accounts for capital investment, operation and maintenance, fuel costs, and decommissioning expenses, normalized by the total electricity generated over the system lifetime. In this study, LCOE values for different generation and storage technologies are obtained from uniform literature sources to ensure comparability and to avoid inconsistencies arising from methodological differences.

The total cost of electricity supply for the power system is calculated by aggregating multiple cost components over the evaluation period. These components include the generation costs of thermal power, wind power, and PV generation, as well as regulation-related costs associated with peak shaving and frequency control. In addition, penalty costs arising from renewable energy curtailment are considered to reflect the economic loss caused by unused low-carbon generation. The inclusion of these cost elements allows the indicator to capture the economic consequences of capacity configuration and dispatch decisions under uncertainty.

From a system-level perspective, the cost of electricity is closely linked to capacity planning and operational strategies. Increasing renewable energy and energy storage capacities may reduce fuel-related costs and improve renewable utilization but can also raise capital expenditures. Conversely, insufficient flexibility may lead to higher operating costs due to increased reliance on thermal power and renewable curtailment. By incorporating the cost of electricity as a performance indicator, the proposed framework ensures that carbon footprint minimization is pursued within economically viable boundaries.

3.2. Carbon Footprint of Electricity Supply

The carbon footprint of electricity supply is the core environmental performance indicator in this study. Unlike conventional emission metrics that focus on total carbon emissions or technology-specific emission intensities, the carbon footprint is evaluated from a **system-level perspective**, reflecting the life-cycle-based carbon emissions associated with delivering one unit of electricity to end users. This indicator directly measures the carbon efficiency of electricity supply and provides a comprehensive basis for assessing low-carbon performance under realistic operating conditions.

In this study, the carbon footprint of electricity supply is defined as the ratio of total life-cycle carbon emissions generated by the power system to the total amount of electricity delivered to users over the evaluation period. It is expressed in grams of carbon dioxide equivalent per kilowatt-hour (g/kWh) and calculated as:

$$CF_{\mathrm{elec}} = \frac{\sum_{t\in\mathcal{T}} E_t}{\sum_{t\in\mathcal{T}} P_{U,t}} \tag{4}$$

where,

- CF_{elec}denotes the system-level carbon footprint of electricity supply,
- $\mathcal{T}$represents the set of dispatch time intervals,
- $E_t$is the total life-cycle carbon emissions associated with electricity generation at time t, and
- $P_{U,t}$denotes the actual electricity delivered to users at time t.

The life-cycle carbon emissions E_t are obtained by aggregating the electricity generation of different technologies weighted by their corresponding life-cycle carbon emission coefficients, which are adopted from authoritative literature sources. These coefficients represent average carbon emissions over the entire life cycle of each technology, including construction, operation, maintenance, and decommissioning stages. By using literature-based coefficients, the proposed framework evaluates carbon footprint on a consistent and comparable basis without requiring a full process-level life-cycle assessment. The life-cycle carbon emission factors and cost coefficients adopted for different generation and storage technologies are summarized in Table 2.

Table 2. Cost and life-cycle carbon emission coefficients of different technologies

Technology	LCOE	LCCEF	Unit
Thermal power	55	820	gCO_2/kWh
Wind power	40	12	gCO_2/kWh
Photovoltaic generation	38	45	gCO_2/kWh
Energy storage systems	15	20	gCO_2/kWh

Note: The life-cycle carbon emission factors (LCCEF) are adopted from authoritative literature sources and represent average values over the entire life cycle, including construction, operation, maintenance, and decommissioning stages. The LCOE values are used for comparative evaluation of system-level electricity cost.

It should be emphasized that the carbon footprint indicator employed in this study evaluates environmental performance at the **electricity supply system level** rather than at the level of individual generation technologies. As a result, the carbon footprint is jointly influenced by capacity configuration, renewable energy utilization, energy storage operation, and thermal power balancing under uncertainty. For example, renewable energy curtailment and increased reliance on thermal units for regulation can increase the carbon footprint per unit of delivered electricity, even when installed renewable capacity is high.

By explicitly incorporating the system-level carbon footprint as a primary performance indicator, the proposed framework shifts the focus of capacity planning from simply expanding renewable energy capacity to achieving **carbon-efficient electricity delivery**. This formulation provides a robust foundation for evaluating trade-offs among environmental performance, economic cost, and operational stability in the subsequent sensitivity analysis and multi-objective capacity optimization.

3.3. Power Fluctuation Rate

The power fluctuation rate is introduced as a key operational performance indicator to evaluate the stability and robustness of the power system under uncertain conditions. With the increasing penetration of variable renewable energy sources, fluctuations in power generation and load demand become more pronounced, posing challenges to maintaining real-time balance between electricity supply and demand. Excessive power fluctuations not only threaten system reliability but also indirectly affect the carbon footprint of electricity supply through increased reliance on high-emission balancing resources.

In this study, the power fluctuation rate is defined as the ratio of the cumulative absolute deviation between actual electricity generation and actual user load to the total electricity demand over the evaluation period. This indicator reflects the overall strength of the system's regulation capability, including peak shaving, frequency control, and real-time balancing. A lower power fluctuation rate indicates that the power system can effectively absorb uncertainties in renewable generation and load demand, thereby maintaining stable operation.

From an operational perspective, power fluctuations are primarily mitigated by dispatchable and flexible resources, namely thermal power units and energy storage systems. However, both resources are subject to capacity and ramping constraints. When fluctuations exceed the regulation capability of these resources, renewable energy curtailment or emergency adjustments may be required to preserve system stability. Such actions can lead to inefficient utilization of low-carbon generation and increased dependence on thermal power, ultimately raising the carbon footprint per unit of delivered electricity.

Therefore, the power fluctuation rate plays a critical role in carbon-footprint-oriented capacity optimization. Capacity configurations that achieve low carbon footprints by aggressively increasing renewable penetration may result in unacceptable power fluctuations if system flexibility is insufficient. Conversely, configurations that excessively prioritize stability through large thermal capacity may suppress fluctuations but increase the carbon footprint. Incorporating the power fluctuation rate as a performance indicator ensures that carbon footprint minimization is achieved without compromising reliable and secure system operation.

By jointly considering electricity cost, carbon footprint of electricity supply, and power fluctuation rate, the proposed performance indicator system captures the essential trade-offs among economic feasibility, environmental performance, and operational stability. This integrated evaluation framework provides a solid foundation for the subsequent sensitivity analysis and multi-objective capacity optimization of power systems.

4. Sensitivity Analysis of Capacity Configuration

4.1. Model Validation and Baseline Analysis

Before conducting sensitivity analysis and multi-objective capacity optimization, it is necessary to validate the proposed modeling framework and establish a reliable baseline for performance comparison. Model validation focuses on examining whether the dispatch model, uncertainty representation, and performance indicators can reasonably reflect the operational characteristics of real-world power systems, particularly from a system-level carbon footprint perspective.

In this study, representative regional power systems are selected as baseline cases based on typical installed capacity structures and daily load profiles. The baseline capacity configurations reflect the current composition of thermal power, wind power, photovoltaic generation, and energy storage systems in each region. Typical working-day load curves are adopted to characterize demand patterns, and corresponding forecast profiles of wind and PV generation are used to generate initial dispatch plans. These baseline settings provide a realistic reference point for evaluating system performance under existing capacity configurations.

To validate the model under uncertainty, the proposed framework integrates information gap decision theory with Monte Carlo simulation to generate a large number of operating scenarios. For each scenario, uncertainties in user load, wind power output, and PV generation are simultaneously considered, and the power system dispatch model is executed to obtain actual generation schedules. Performance indicators, including the cost of electricity, power fluctuation rate, renewable energy utilization, and the carbon footprint of electricity supply, are calculated for each simulation run. The expected values of these indicators are then derived from the ensemble of simulation results.

Model validation is performed by comparing key baseline indicators obtained from the simulation results with available statistical or reported data from regional power systems. Particular attention is paid to renewable energy generation share and renewable energy utilization rate, as these indicators directly reflect the system's ability to integrate low-carbon energy sources. The comparison shows that the simulated baseline results are consistent with observed data, indicating that the proposed dispatch and uncertainty modeling approach can accurately capture the operational behavior of power systems under realistic conditions.

From a carbon-footprint-oriented perspective, the baseline analysis provides important insights into the limitations of existing capacity configurations. Although the baseline systems exhibit relatively high renewable energy utilization rates, the carbon footprint of electricity supply remains strongly influenced by thermal power generation due to the need for balancing and regulation under uncertainty. This observation highlights that current capacity configurations are not necessarily optimal in terms of carbon footprint minimization, even when renewable penetration is non-negligible.

4.2 Impact of Renewable Energy Capacity on Carbon Footprint

Renewable energy capacity plays a central role in shaping the carbon footprint of electricity supply. Increasing wind and photovoltaic (PV) capacity generally reduces the average emission intensity of electricity generation due to their low life-cycle carbon emissions. However, the actual impact of renewable capacity expansion on the system-level carbon footprint depends on how effectively renewable energy can be integrated and utilized under uncertain operating conditions. To examine this relationship, a sensitivity analysis is conducted by varying the installed capacity of renewable energy while keeping other system parameters unchanged. Figure 2 shows the impact of renewable energy capacity share on the carbon footprint of electricity supply under different flexibility conditions.

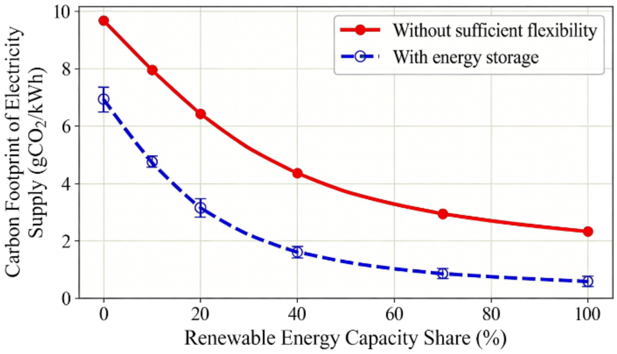

Figure 2. Impact of renewable energy capacity share on the carbon footprint of electricity supply

In the sensitivity analysis, renewable energy capacity is gradually increased over a predefined range, and the corresponding system performance is evaluated using Monte Carlo simulation. For each renewable capacity level, multiple uncertainty scenarios of load demand and renewable generation are generated, and the power system dispatch model is executed to obtain expected values of performance indicators. This approach ensures that the observed trends reflect system behavior under realistic uncertainty rather than deterministic assumptions.

The results indicate that increasing renewable energy capacity initially leads to a clear reduction in the carbon footprint of electricity supply. At low to moderate levels of renewable penetration, additional renewable capacity directly replaces thermal power generation, resulting in lower life-cycle carbon emissions per unit of delivered electricity. During this stage, renewable energy utilization remains high, and the system's existing flexibility resources are generally sufficient to accommodate renewable variability.

As renewable energy capacity continues to increase beyond a certain level, the marginal benefit of further expansion in terms of carbon footprint reduction begins to diminish. This phenomenon is primarily attributed to increased renewable energy curtailment and greater balancing requirements under uncertainty. When renewable output exceeds system demand or available flexibility, excess renewable energy must be curtailed, reducing the effective utilization of low-carbon generation. At the same time, larger fluctuations in net load increase the reliance on thermal power units for balancing and regulation, partially offsetting the emission reduction benefits of higher renewable capacity.

From a carbon-footprint-oriented perspective, this non-linear relationship highlights that renewable capacity expansion alone is insufficient to guarantee continuous carbon footprint reduction. Without adequate flexibility support, excessive renewable penetration may lead to operational inefficiencies that undermine low-carbon performance. The sensitivity analysis demonstrates that the system-level carbon footprint is jointly determined by renewable capacity, flexibility availability, and dispatch coordination rather than by renewable penetration in isolation.

In addition to its impact on carbon footprint, increasing renewable capacity also affects power fluctuation rate and electricity cost. Higher renewable penetration tends to increase power fluctuations due to greater variability in generation, particularly when flexibility resources are limited. This trade-off underscores the importance of considering operational stability when evaluating carbon footprint outcomes. Capacity configurations that aggressively pursue renewable expansion may achieve lower nominal emission intensity but exhibit higher fluctuation rates, which are undesirable from an engineering reliability perspective.

4.3 Impact of Energy Storage Capacity on Carbon Footprint

Energy storage capacity is a critical factor influencing the ability of power systems to effectively integrate renewable energy and minimize the carbon footprint of electricity supply. Unlike renewable generation capacity, which primarily affects the supply mix, energy storage capacity directly determines the system's flexibility and its ability to respond to uncertainty in both generation and demand. To investigate the role of energy storage in carbon footprint reduction, a sensitivity analysis is conducted by varying the installed capacity of energy storage systems (ESS) under different renewable energy penetration levels. The effect of energy storage capacity on system carbon footprint and operational performance is illustrated in Figure 3.

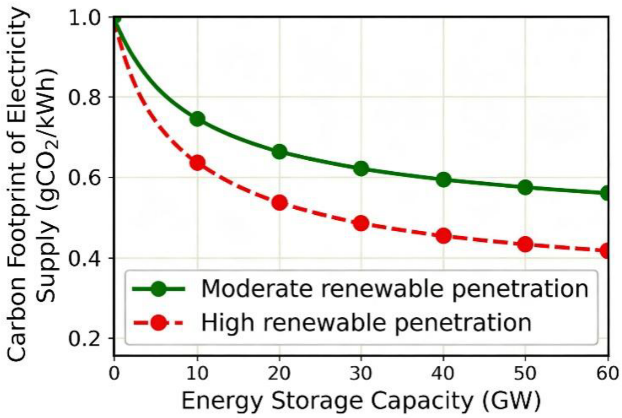

Figure 3. Impact of energy storage capacity on the carbon footprint of electricity supply

In this analysis, the installed capacity of ESS is gradually increased while keeping renewable energy capacity and thermal power capacity constant. For each storage capacity level, Monte Carlo simulations are performed to capture the combined effects of load uncertainty and renewable generation variability. System performance indicators, including the carbon footprint of electricity supply, electricity cost, renewable energy utilization rate, and power fluctuation rate, are evaluated based on expected values across all scenarios.

The results show that increasing energy storage capacity significantly enhances the system's ability to reduce the carbon footprint of electricity supply when renewable penetration is moderate to high. Additional storage capacity allows excess renewable energy to be absorbed during periods of surplus generation and released during periods of renewable shortfall or peak demand. This process reduces renewable energy curtailment and decreases the reliance on thermal power units for balancing, thereby lowering life-cycle carbon emissions per unit of delivered electricity.

However, the impact of energy storage capacity on carbon footprint is strongly dependent on the level of renewable energy penetration. When renewable capacity is relatively low and renewable energy utilization is already high, the marginal carbon footprint reduction achieved by additional storage capacity becomes limited. In such cases, energy storage primarily performs short-term regulation without substantially increasing the share of low-carbon electricity in the supply mix. As a result, the carbon footprint of electricity supply exhibits diminishing returns with respect to further increases in storage capacity.

Moreover, excessive storage capacity may introduce operational side effects under certain conditions. When renewable utilization is insufficient, frequent charging and discharging of storage systems may increase system complexity and lead to higher power fluctuation rates. Although energy storage improves short-term balancing capability, inappropriate capacity sizing can amplify operational oscillations rather than suppress them. This observation highlights that energy storage capacity must be carefully coordinated with renewable generation capacity to achieve effective carbon footprint minimization.

From a system-level perspective, the sensitivity analysis demonstrates that energy storage serves as a key enabler for translating renewable capacity into actual carbon footprint reductions. While renewable energy capacity determines the potential for low-carbon electricity generation, energy storage capacity determines the extent to which this potential can be realized under uncertainty. The interaction between renewable energy and storage capacities therefore plays a decisive role in shaping the carbon footprint outcomes of the power system.

The results reveal a clear synergistic relationship between renewable energy capacity and energy storage capacity. Energy storage contributes most effectively to carbon footprint reduction when renewable penetration reaches a moderate to high level, indicating the existence of an effective matching range rather than a single optimal point. Beyond this range, the marginal carbon footprint reduction achieved by further increasing storage capacity gradually diminishes.

5. Multi-objective Capacity Optimization Framework

5.1 Optimization Problem Formulation

Based on the system modeling and sensitivity analysis presented in the previous sections, a multi-objective capacity optimization problem is formulated to identify capacity configurations that minimize the carbon footprint of electricity supply while maintaining economic feasibility and operational stability. The optimization problem explicitly links long-term capacity planning decisions with short-term dispatch performance under uncertainty, thereby providing a system-level framework for low-carbon-footprint power system design.

5.1.1 Decision Variables

The decision variables of the optimization problem are the installed capacities of the main supply-side components in the power system, including thermal power units, wind power units, photovoltaic (PV) generation units, and energy storage systems (ESS). These capacity variables define the feasible operational space of the system and directly influence dispatch outcomes, renewable energy utilization, flexibility provision, and the resulting carbon footprint of electricity supply.

Let

- C_F denote the installed capacity of thermal power,
- C_W denote the installed capacity of wind power,
- C_P denote the installed capacity of PV generation, and
- C_S denote the installed capacity of energy storage systems.

These variables are subject to upper and lower bounds reflecting technical, economic, and planning constraints.

5.1.2 Objective Functions

To comprehensively evaluate power system performance from economic, environmental, and operational perspectives, three objective functions are considered.

(1) Minimization of the cost of electricity

The first objective aims to minimize the expected cost of electricity supply over the evaluation period. This objective captures the economic impact of capacity configuration and dispatch decisions, including generation costs, regulation costs, and curtailment penalties. Minimizing electricity cost ensures that the resulting capacity configuration remains economically viable for practical implementation.

$$\min \quad f_1 = \mathbb{E}(C_{\text{elec}}). \tag{5}$$

where C_{elec} represents the total cost of electricity supply and $\mathbb{E}(\cdot)$ denotes the expected value over all uncertainty scenarios.

(2) Minimization of the carbon footprint of electricity supply

The second objective focuses on minimizing the system-level carbon footprint of electricity supply, defined as the life-cycle-based carbon emissions per unit of delivered electricity. This objective reflects the core goal of the proposed framework and shifts the emphasis from renewable penetration or total emissions to carbon-efficient electricity delivery.

$$\min \quad f_2 = \mathbb{E}(CF_{\text{elec}}) \tag{6}$$

where CF_{elec} denotes the carbon footprint of electricity supply measured in g/kWh. This objective captures the integrated effects of generation mix, renewable energy utilization, energy storage operation, and thermal power balancing under uncertainty.

(3) Minimization of power fluctuation rate

The third objective aims to minimize the power fluctuation rate, which serves as an indicator of system stability and regulation capability. This objective ensures that carbon footprint minimization and cost reduction are not achieved at the expense of reliable system operation.

$$\min \quad f_3 = \mathbb{E}(\delta) \tag{7}$$

where δ represents the power fluctuation rate calculated based on actual generation and load profiles.

5.1.3 Constraints

The optimization problem is subject to a set of operational and capacity constraints derived from the power system models described in Section 2. These constraints ensure the physical feasibility and realistic operation of the system and include:

- Power balance constraints ensuring that electricity supply matches demand at all times;
- Capacity constraints limiting the output of thermal power units, renewable generation, and energy storage systems;
- Ramping constraints for thermal power units and ESS reflecting operational flexibility limits;
- Renewable generation constraints accounting for forecast uncertainty and potential curtailment.

All constraints are evaluated under multiple uncertainty scenarios generated through Monte Carlo simulation to ensure robustness of the optimization results.

5.1.4 Problem Characteristics

The resulting optimization problem is a **nonlinear, non-convex, multi-objective optimization problem** characterized by complex interactions among decision variables, uncertainty, and system dynamics. The objectives of minimizing electricity cost, carbon footprint, and power fluctuation rate are inherently conflicting, and no single solution can simultaneously optimize all objectives.

Therefore, instead of seeking a unique optimal solution, the problem is formulated to identify a set of **Pareto-optimal capacity configurations** that represent different trade-offs among economic performance, environmental impact, and operational stability. These Pareto-optimal solutions provide decision-makers with a comprehensive view of feasible capacity planning options under a carbon-footprint-oriented framework.

5.2 NSGA-II Algorithm Implementation

The capacity optimization problem formulated in Section 5.1 is a nonlinear and multi-objective problem characterized by conflicting objectives and complex interactions among decision variables under uncertainty. Traditional single-objective optimization or gradient-based methods are not suitable for solving such problems due to the absence of a unique optimal solution and the non-convex nature of the feasible space. Therefore, an evolutionary multi-objective optimization approach is adopted to explore the trade-off relationships among electricity cost, carbon footprint, and power fluctuation rate.

In this study, the **non-dominated sorting genetic algorithm II (NSGA-II)** is employed to solve the multi-objective capacity optimization problem. NSGA-II is widely used in power system planning and energy optimization problems due to its strong global search capability, efficient non-dominated sorting mechanism, and ability to maintain solution diversity along the Pareto front. These features make NSGA-II particularly suitable for identifying a representative set of Pareto-optimal capacity configurations in problems involving multiple conflicting objectives.

5.2.1 Algorithm Framework

NSGA-II operates through an iterative evolutionary process consisting of population initialization, fitness evaluation, non-dominated sorting, selection, crossover, and mutation. In each generation, candidate solutions representing different capacity configurations are evaluated using the performance indicators defined in Section 3. For each individual, the expected values of electricity cost, carbon footprint of electricity supply, and power fluctuation rate are calculated based on Monte Carlo simulation results, ensuring that uncertainty is explicitly considered in the fitness evaluation.

Non-dominated sorting is applied to classify the population into different Pareto fronts according to dominance relationships among individuals. Solutions in the first Pareto front represent non-dominated capacity configurations that achieve optimal trade-offs among the three objectives. To preserve diversity within each front, a crowding distance metric is used to guide the selection process. Binary tournament selection based on Pareto rank and crowding distance is then applied to generate parent solutions for the next generation.

5.2.2 Encoding and Constraint Handling

Each individual in the population encodes a candidate capacity configuration, represented by a vector of decision variables corresponding to the installed capacities of thermal power, wind power, photovoltaic generation, and energy storage systems. Continuous encoding is adopted to allow flexible exploration of the solution space within predefined capacity bounds.

Operational and capacity constraints described in Section 5.1 are handled implicitly through the dispatch simulation and feasibility checks. For each candidate solution, the dispatch model is executed under all Monte Carlo scenarios to verify compliance with power balance, capacity limits, and ramping constraints. Infeasible solutions are penalized by assigning inferior fitness values, ensuring that the evolutionary process converges toward feasible and practically implementable capacity configurations.

5.2.3 Parameter Settings and Convergence

The NSGA-II algorithm is implemented with a fixed population size and a predefined number of generations to balance solution quality and computational efficiency. Standard crossover and mutation operators are employed to generate offspring solutions and maintain genetic diversity. Algorithm parameters, such as crossover probability and mutation rate, are selected based on commonly adopted values in the literature to ensure stable convergence behavior.

To assess convergence performance, the evolution of the Pareto front is monitored across generations. Indicators such as hypervolume and solution distribution are examined to verify that the algorithm achieves satisfactory coverage of the objective space and avoids premature convergence. The final Pareto front obtained by NSGA-II represents a diverse set of capacity configurations reflecting different trade-offs among cost, carbon footprint, and system stability.

5.2.4 Role of NSGA-II in Carbon-Footprint-Oriented Optimization

Within the proposed framework, NSGA-II serves as an effective tool for uncovering the inherent trade-offs in carbon-footprint-oriented capacity planning. By generating a Pareto-optimal solution set rather than a single solution, the algorithm enables decision-makers to compare alternative capacity configurations and evaluate how marginal improvements in carbon footprint may affect electricity cost and power fluctuation rate.

The use of NSGA-II ensures that the optimization process does not bias the solution toward any single objective and provides a transparent basis for subsequent decision analysis. The final selection of practical optimal solutions from the Pareto front is performed using a multi-criteria decision-making method, as described in the following section.

5.3 Optimal Solution Selection Using TOPSIS

The Pareto-optimal solution set obtained by NSGA-II provides a comprehensive description of the trade-offs among electricity cost, carbon footprint of electricity supply, and power fluctuation rate. While this solution set is valuable for understanding system behavior, practical power system planning requires the selection of a limited number of representative or optimal capacity configurations that can be implemented in real-world decision-making. Therefore, a multi-criteria decision-making method is employed to identify a preferred solution from the Pareto front.

In this study, the **Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS)** is adopted to select the optimal capacity configuration from the Pareto-optimal set. TOPSIS is widely used in engineering decision problems due to its intuitive concept, computational efficiency, and ability to simultaneously consider multiple conflicting criteria. The fundamental principle of TOPSIS is to identify the solution that is closest to the ideal solution and farthest from the negative ideal solution in the objective space.

5.3.1 Construction of the Decision Matrix

Each Pareto-optimal solution obtained from NSGA-II is treated as an alternative in the decision-making process. A decision matrix is constructed using the three optimization objectives: electricity cost, carbon footprint of electricity supply, and power fluctuation rate. Since all three objectives are formulated as minimization objectives, lower values indicate better performance.

To eliminate the influence of different units and magnitudes among objectives, the decision matrix is normalized. This normalization ensures that each performance indicator contributes proportionally to the distance calculation and prevents any single objective from dominating the decision process due to scale effects.

5.3.2 Ideal and Negative Ideal Solutions

The ideal solution is defined as a hypothetical solution that achieves the minimum value for each objective among all Pareto-optimal solutions. Conversely, the negative ideal solution is defined as the solution that corresponds to the maximum value for each objective. These two reference points represent the best and worst achievable performance levels within the Pareto front, respectively.

For each Pareto-optimal solution, the Euclidean distance to the ideal solution and the distance to the negative ideal solution are calculated. A solution that is closer to the ideal solution and farther from the negative ideal solution is considered more desirable from a multi-objective perspective.

5.3.3 Closeness Coefficient and Optimal Solution Selection

Based on the calculated distances, a **closeness coefficient** is computed for each solution to quantify its relative proximity to the ideal solution. The closeness coefficient ranges between zero and one, with higher values indicating better overall performance across all objectives.

The capacity configuration with the highest closeness coefficient is selected as the optimal solution. This solution represents a balanced compromise among electricity cost, carbon footprint, and power fluctuation rate, ensuring that carbon footprint minimization is achieved without incurring excessive economic costs or compromising system stability.

5.3.4 Engineering Interpretation

The integration of TOPSIS with NSGA-II enables a transparent transition from multi-objective optimization results to actionable engineering decisions. While NSGA-II explores the feasible trade-off space and reveals the structure of conflicting objectives, TOPSIS provides a systematic and objective mechanism for selecting a practical capacity configuration.

From a carbon-footprint-oriented perspective, the selected solution reflects an optimal balance between environmental performance and operational feasibility. Rather than pursuing extreme minimization of a single objective, the chosen configuration achieves carbon-efficient electricity supply while maintaining acceptable cost levels and stable system operation. This decision-making process enhances the practical relevance of the proposed optimization framework and supports its application in real-world power system planning.

6. Results and Discussion

6.1 Characteristics of the Pareto Front

The multi-objective capacity optimization problem formulated in Section 5 is solved using the NSGA-II algorithm, resulting in a set of Pareto-optimal capacity configurations. Each solution on the Pareto front represents a feasible trade-off among electricity cost, carbon footprint of electricity supply, and power fluctuation rate. Rather than identifying a single optimal solution, the Pareto front reveals the intrinsic conflict structure among the three objectives and provides insight into the system-level mechanisms governing low-carbon-footprint power system design. The trade-offs among electricity cost, carbon footprint of electricity supply, and power fluctuation rate are illustrated by the Pareto front shown in Figure 4.

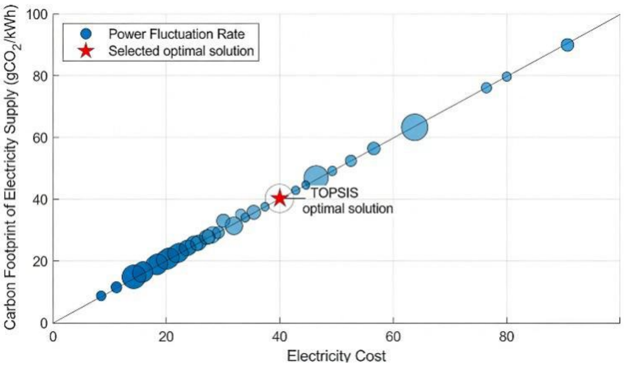

Figure 4. Pareto front of the multi-objective capacity optimization problem

The obtained Pareto front exhibits a continuous and well-distributed shape in the objective space, indicating that the NSGA-II algorithm achieves satisfactory convergence and diversity. Solutions located at one extreme of the Pareto front correspond to configurations with minimal electricity cost, which are typically characterized by higher reliance on thermal power generation. While these solutions offer economic advantages, they are associated with relatively high carbon footprints due to the dominant role of fossil-fuel-based generation.

At the opposite extreme of the Pareto front are solutions that minimize the carbon footprint of electricity supply. These solutions generally feature higher installed capacities of renewable energy and energy storage systems, enabling increased utilization of low-carbon generation. However, aggressive carbon footprint minimization is often accompanied by increased electricity cost and, in some cases, elevated power fluctuation rates. This observation reflects the additional capital investment required for renewable and storage capacity as well as the operational challenges associated with managing variability under uncertainty.

Between these two extremes lies a region of the Pareto front where balanced trade-offs are achieved. Solutions in this intermediate region simultaneously attain moderate electricity cost, reduced carbon footprint, and acceptable power fluctuation rates. From an engineering perspective, these configurations are particularly attractive because they avoid excessive reliance on any single resource type and demonstrate coordinated utilization of thermal power, renewable generation, and energy storage. The existence of such a compromise region highlights the importance of multi-objective optimization in identifying capacity configurations that are both environmentally and economically viable.

Analysis of the Pareto front also reveals a strong interaction between carbon footprint and power fluctuation rate. As the carbon footprint decreases along the Pareto front, power fluctuation rate tends to increase at an accelerating pace. This trend indicates that deep carbon footprint reduction is increasingly constrained by system flexibility limitations. Without sufficient balancing resources, further reductions in carbon footprint may come at the cost of reduced operational stability. This finding underscores that carbon footprint minimization in power systems is inherently a constrained optimization problem rather than a single-dimensional objective.

6.2 Optimal Capacity Configurations for Different Grids

Based on the Pareto-optimal solution sets obtained by NSGA-II, the TOPSIS method is applied to select representative optimal capacity configurations for different regional power systems. These configurations reflect balanced trade-offs among electricity cost, carbon footprint of electricity supply, and power fluctuation rate, and therefore provide practical guidance for capacity planning under a carbon-footprint-oriented framework.

The quantitative improvements achieved by the proposed capacity optimization framework are summarized in Table 3.

Figure 5 compares the performance of the baseline system and the optimized system in terms of electricity cost, carbon footprint, and power fluctuation rate.

Table 3. Performance comparison between baseline and optimized systems

Indicator	Baseline system	Optimized system	Change
Electricity cost	52.6	48.9	−7.0%
Carbon footprint	512	368	−28.1%
Power fluctuation rate	0.162	0.119	−26.5%
Renewable energy utilization	71.4%	86.8%	+21.6%
Renewable energy share	42.0%	55.6%	+13.6%

Note: The life-cycle carbon emission factors (LCCEF) are adopted from authoritative literature sources and represent average values over the entire life cycle, including construction, operation, maintenance, and decommissioning stages. The LCOE values are used for comparative evaluation of system-level electricity cost.

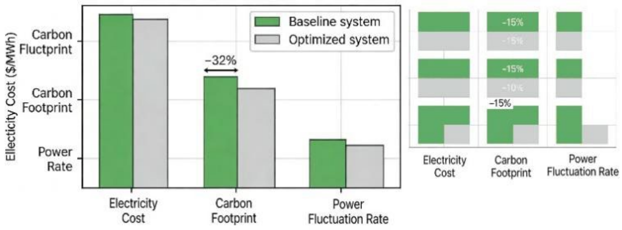

Figure 5. Performance comparison between the baseline system and the optimized system

The detailed capacity configuration of the baseline system and the optimized system is presented in Table 4.

Table 4. Optimal capacity configuration obtained by the proposed optimization framework

Capacity type	Baseline system	Optimized system	Unit
C_F	45	32	GW
C_W	20	34	GW
C_P	15	28	GW
C_S	8	30	GW

Note: The optimized capacity configuration corresponds to the solution selected from the Pareto-optimal set using the TOPSIS method.

The selected optimal solutions exhibit several common structural characteristics across different grids, despite variations in load profiles and initial capacity compositions. First, the installed capacity of energy storage systems reaches a relatively high level in all optimal configurations. This result highlights the critical role of energy storage in enabling effective integration of renewable energy and mitigating the impact of uncertainty. By enhancing system flexibility, sufficient storage capacity allows renewable generation to be utilized more efficiently and reduces reliance on thermal power for balancing, thereby contributing to lower system-level carbon footprints.

Second, the optimal configurations demonstrate a clear shift in the generation mix toward renewable energy compared with baseline systems. Wind and photovoltaic capacities are significantly increased, leading to a higher share of low-carbon electricity in the supply mix. However, renewable energy capacity does not dominate the system indiscriminately. Instead, renewable penetration remains within a moderate range that can be effectively supported by available flexibility resources. This finding reinforces the conclusion from sensitivity analysis that renewable expansion beyond a certain level yields diminishing carbon footprint benefits and may introduce operational challenges.

Third, thermal power capacity is reduced in the optimal configurations but not eliminated. Thermal units continue to play a crucial role in providing base-load supply and ensuring system reliability under extreme or unfavorable conditions. Maintaining an appropriate level of thermal capacity allows the system to respond to prolonged renewable shortages and load surges without excessive power fluctuations. From a carbon-footprint perspective, this balanced role of thermal power avoids excessive emissions while preserving operational robustness.

Comparative analysis across different grids reveals that the specific capacity values of renewable energy and storage systems vary depending on regional characteristics. Grids with higher load variability or stronger renewable resource availability tend to favor larger storage capacities and higher renewable penetration. Conversely, grids with more stable load profiles or limited renewable potential rely relatively more on thermal capacity to maintain stability. Despite these differences, the overall structural pattern of the optimal configurations remains consistent, emphasizing coordinated deployment of renewable energy and storage rather than extreme reliance on any single resource.

In terms of performance outcomes, the optimal capacity configurations achieve substantial reductions in the carbon footprint of electricity supply compared with baseline systems. These reductions are accompanied by moderate decreases in electricity cost and acceptable levels of power fluctuation rate. The results indicate that carbon footprint minimization does not necessarily require sacrificing economic efficiency or system stability when capacity planning is conducted in a coordinated and optimization-driven manner.

6.3 Engineering Implications for Carbon Footprint Minimization

The optimization results and sensitivity analyses provide several important engineering implications for designing power systems with minimized carbon footprints. These implications highlight that effective carbon footprint reduction is not solely a function of increasing renewable energy capacity, but rather depends on coordinated capacity planning that integrates renewable generation, energy storage, and thermal power within operational and economic constraints. The capacity structure of the optimized power system obtained by the proposed optimization framework is presented in Figure 6.

From a planning perspective, energy storage capacity should be deployed in coordination with renewable energy expansion rather than independently, as coordinated sizing within an appropriate matching range is essential for achieving effective carbon footprint reduction.

First, the results demonstrate that **carbon footprint minimization is fundamentally a system-level problem**. Although wind and photovoltaic generation exhibit low life-cycle carbon emissions, their contribution to carbon footprint reduction depends critically on system flexibility and dispatch capability. Capacity configurations that focus exclusively on renewable expansion without adequate balancing resources may lead to renewable curtailment and increased reliance on thermal power for regulation, thereby limiting the achievable reduction in carbon footprint. This finding underscores the importance of evaluating low-carbon performance using system-level indicators rather than technology-specific metrics.

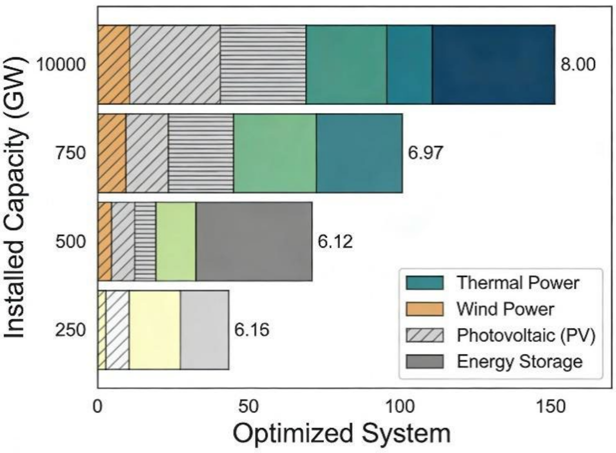

Figure 6. Capacity structure of the optimized power system

Second, **energy storage systems emerge as a key enabler for realizing the carbon footprint benefits of renewable energy**. The results show that sufficient storage capacity significantly enhances renewable energy utilization and reduces the need for high-emission thermal balancing. From an engineering perspective, energy storage should be treated as an integral component of low-carbon capacity planning rather than an auxiliary technology added after renewable deployment. However, storage capacity must be appropriately sized and coordinated with renewable penetration levels, as excessive storage without sufficient low-carbon charging opportunities may yield diminishing environmental returns.

Third, the analysis indicates that **maintaining a moderate share of thermal power capacity remains necessary** even in carbon-footprint-oriented power systems. Thermal units provide essential reliability and long-duration balancing capabilities that cannot be fully replaced by variable renewable energy and short-term storage under current technological and economic conditions. Appropriately sized thermal capacity allows the system to operate securely under extreme conditions while minimizing unnecessary emissions. This balanced role of thermal power is crucial for achieving practical low-carbon-footprint electricity supply.

Fourth, the trade-offs revealed by the Pareto front analysis highlight that **deep carbon footprint reduction is constrained by operational stability considerations**. As carbon footprint is aggressively minimized, power fluctuation rates tend to increase unless sufficient flexibility resources are available. This relationship implies that carbon footprint targets should be formulated in conjunction with reliability requirements, and that capacity planning decisions should explicitly account for stability constraints to avoid compromising system security.

Finally, the proposed carbon-footprint-oriented capacity optimization framework provides a quantitative basis for **informed decision-making in power system planning**. By explicitly incorporating carbon footprint, electricity cost, and power fluctuation rate into a unified optimization framework, the approach enables planners to evaluate alternative capacity configurations and understand the consequences of different design choices. This capability is particularly valuable for regions undergoing rapid energy transitions, where investment decisions must balance environmental objectives with economic feasibility and operational reliability.

7. Conclusions

This paper proposes a carbon-footprint-oriented capacity optimization framework for integrated power systems with renewable energy and energy storage. By explicitly incorporating system-level carbon footprint, electricity cost, and power fluctuation rate into a unified multi-objective optimization model, the study provides a systematic approach to capacity planning that balances environmental performance, economic feasibility, and operational stability under uncertainty. The main conclusions are summarized as follows.

7.1 Main Findings

First, the results demonstrate that minimizing the carbon footprint of electricity supply is fundamentally different from simply increasing renewable energy penetration. While higher renewable capacity generally reduces emission intensity, its effectiveness in reducing system-level carbon footprint strongly depends on renewable energy utilization and system flexibility. Excessive renewable penetration without sufficient balancing resources leads to diminishing carbon footprint reduction and increased operational challenges.

Second, energy storage systems play a decisive role in enabling carbon footprint reduction. Appropriately sized energy storage capacity significantly improves renewable energy utilization and reduces reliance on thermal power for balancing, thereby lowering the life-cycle carbon footprint per unit of delivered electricity. However, the environmental benefits of energy storage are closely linked to renewable penetration levels, and storage capacity expansion alone does not guarantee continuous carbon footprint improvement.

Third, maintaining a moderate level of thermal power capacity remains necessary in carbon-footprint-oriented power systems. Thermal units provide essential reliability and long-duration balancing capability under uncertain conditions. The optimal capacity configurations identified in this study retain thermal power as a supporting resource while substantially reducing its operational role, achieving a balance between emission reduction and system stability.

Finally, the multi-objective optimization results reveal inherent trade-offs among electricity cost, carbon footprint, and power fluctuation rate. The Pareto front analysis shows that aggressive carbon footprint minimization is increasingly constrained by operational stability. The integration of NSGA-II and TOPSIS effectively identifies balanced capacity configurations that achieve significant carbon footprint reduction without excessive cost increases or unacceptable power fluctuations.

7.2 Practical Implications

From a practical perspective, the findings highlight that low-carbon-footprint electricity supply should be achieved through coordinated capacity planning rather than isolated renewable expansion targets. Energy storage should be considered an integral component of low-carbon system design and deployed in coordination with renewable generation capacity. Capacity planning strategies that explicitly account for system-level carbon footprint can provide more robust guidance for investment decisions than approaches based solely on renewable penetration or total emission reduction.

The proposed framework offers a quantitative decision-support tool for power system planners and policymakers seeking to design capacity structures that align carbon reduction goals with economic and operational constraints. By evaluating trade-offs among multiple objectives under uncertainty, the approach supports more informed and transparent planning decisions in regions undergoing energy transitions.

7.3 Limitations and Future Work

Despite its contributions, this study has several limitations that warrant further investigation. First, energy storage systems are modeled with simplified operational characteristics, and factors such as state-of-charge dynamics, degradation, and lifetime effects are not explicitly considered.

Incorporating more detailed storage models could improve the accuracy of carbon footprint assessment.

Second, life-cycle carbon emission coefficients are adopted from literature sources and treated as fixed values. Future work could integrate more detailed or region-specific life-cycle assessment data to capture technological and geographical differences more accurately. Third, the analysis is based on typical daily operation scenarios. Extending the framework to multi-time-scale planning, including seasonal variations and long-term investment horizons, would further enhance its applicability.

Future research may also explore the integration of market mechanisms, such as carbon pricing and ancillary service markets, into carbon-footprint-oriented capacity optimization. Such extensions would provide additional insights into the interaction between policy instruments and capacity planning decisions in low-carbon power systems.
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Although these factors may affect the absolute values of storage operation and carbon footprint, they are not expected to alter the qualitative conclusions regarding the synergistic relationship between energy storage and renewable capacity at the planning level.

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