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The feasibility and policy engagements in achieving net zero emission in China's power sector by 2050: A LEAP-REP model analysis

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A R T I C L E I N F O

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A B S T R A C T

The low-carbon transition in China's power sector plays a crucial role in the mitigation of climate change worldwide, and increasing renewable energy penetration rate is widely recognized as the key approach to decarbonize this sector. This paper proposes a renewable energy penetration model to examine the feasibility for net zero emission by 2050 in China's power sector taking into account of economic and social development. It also evaluates the impacts of carbon pricing and financial incentives on renewable energy penetration and carbon emissions. The results indicate that along with economic development, China's electricity demand will continue to grow, but at a gradually slowing rate. It is possible for the power sector to achieve net zero emission by 2050 while meeting this growing electricity demand, with a renewable energy penetration rate of 75%. To ensure the achievement of the goal, we recommend setting the carbon price with the current market price as the baseline and increasing it annually by a relative increment index of 10%. Furthermore, given the high initial cost and late start of offshore wind power, we suggest incorporating associated grid connection cost into the transmission and distribution price to ensure the comprehensive and healthy development of renewable energy.

1. Introduction

To limit the extent of global temperature rise and reduce the adverse effects of climate change, the Paris Agreement requires countries to update their nationally determined contributions based on their respective national circumstances and to strive for maximum emission reductions [1]. In 2021, China's energy consumption and carbon dioxide emissions accounted for 26.5 % and 27 % of the world total, respectively [2,3]. As the world's largest energy consumer and carbon emitter, the Chinese government updated its climate goals during the 75th session of the United Nations General Assembly, aiming to peak carbon emissions before 2030 and achieve carbon neutrality by 2060 [4]. Due to the increasing role of electricity in China's energy use, the power sector accounts for nearly half of carbon emissions in the country's total, with an annual CO2 emissions of 4.5 billion tons [5]. Considering the challenges of achieving net zero emission in other industrial sectors, it is imperative for China's power sector to achieve net zero emission by 2050 in order to support the entire energy system in achieving carbon neutrality by 2060. It is evident that deep decarbonization of the power sector is crucial for China and the global energy system to reduce emissions [6].

Promoting the development of renewable energy is the most effective way for the power industry to decarbonize [7]. Countries around the world have implemented various policies and measures with regard to renewable energy [8]. Three major tools are employed including the feed-in tariff (FIT), renewable portfolio standard, and the carbon emissions trading scheme (ETS) [9]. In comparison, existing researches generally consider FIT and ETS to be more effective [10,11]. Through the FIT policy, subsidies for renewable energy production increase, directly expanding the supply of renewable energy. The ETS internalizes the environmental cost of fossil fuels, indirectly enhancing the competitiveness of renewable energy prices. China initiated FIT policy for renewable energy in 2006, and thanks to the subsidy in the policy, the renewable energy installation in the country has witnessed dramatic growth over the past decade. As of 2022, the cumulative installed capacity of renewable energy in the country reached 1,213 GW [12]. In addition, China has implemented the ETS and, in July 2021, launched a nationwide carbon emissions trading market, with the power sector

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being the sole participating sector [13].

It's worth noting that despite having the world largest renewable energy generation capacity, in 2022, only 31.3 % of China's electricity supply came from renewable sources, and 58.4 % of electricity supply still coming from coal-fired units [12]. To achieve the net zero emission goal, profound transformations are required in the power system over the coming decades, with a continuous increase in the penetration of renewable energy. However, due to the growing pressure on subsidy payments, the central government discontinued national subsidies for new energy generation starting in 2021 [14]. Moreover, in 2022, the average carbon price in the national carbon market was only RMB¥55 (about US$8) per ton, significantly less effective in incentivizing renewable energy compared to the discontinued electricity subsidies. Despite the substantial decrease in the cost of renewable energy generation [15], it remains unclear whether renewable energy is competitive compared to traditional fossil fuels under current policies, given its unstable output and lower utilization hours. If the lower carbon price level results in inadequate penetration of renewable energy, it may pose a threat to the carbon reduction targets of the power sector. This paper seeks to develop a renewable energy penetration model, to explore the pathway for China's power sector towards net zero emission and assess the policy efforts required for the development of renewable energy.

Regarding the low-carbon transformation pathway in the power sector, there is a substantial amount of research that can be categorized into two main modeling approaches: top-down and bottom-up models [16]. Top-down models primarily focus on macroeconomic factors and study low-carbon transformation pathways based on certain economic assumptions, with an emphasis on the power sector. For instance, Hübler and Loschel [17] analyzed the low-carbon development roadmap of the European Union using a computable general equilibrium (CGE) model at both macroeconomic and sectoral levels. Kai [18] conducted regression analysis and Monte Carlo simulations to study potential emission pathways at the sectoral level by calculating emissions from China's economic sectors over the past 23 years. Tan [19] established a research framework using LMDI (logarithmic mean Divisia index) and STIRPAT (stochastic impacts by regression on population, affluence and technology) models to predict Chongqing's carbon reduction potential, providing a comprehensive analysis of the current state, key influencing factors, and potential pathways for low-carbon transformation. Top-down models offer a distinct advantage in analyzing policy orientations related to macroeconomic operations but may somewhat weaken the role of technology as a driving force for policies and underestimate the market potential brought about by advancements in energy technology. In contrast, bottom-up models start from a micro perspective, considering specific technical, economic, and environmental parameters to analyze energy supply and utilization. Some scholars have investigated the impact of certain key technologies on the low-carbon transformation of the power sector. Pina et al. [20] utilized the TIMES (The Integrated Markal-Efom System) model to simulate the role of demand response technology in the power system, indicating that demand-side management can significantly reduce investments in renewable energy capacity and improve the operation of existing installed capacity. Huang et al. [21] proposed an integrated optimal power flow and multi-criteria decision model, thoroughly exploring the economic characteristics of energy storage system technology on the integration of renewable energy and energy transition. Jakob et al. [22], using the EnergyPLAN tool, studied the impact of the coupling of waste heat utilization technology in the electricity, industrial, transportation, and other sectors on the efficiency and benefits of Europe's energy transition. Some scholars have also modeled the entire power system, with HE et al. [6] developing the SWITCH-China model to study how the Chinese power system will evolve under carbon constraints as the cost of renewable energy accelerates its decline. Zheng et al. [23] used the GREAN (Global Renewable-energy Exploitation ANalysis) platform to establish a power system planning model with a high share of renewable energy capacity to evaluate the impact of power supply cost related to China's transition to carbon neutrality. Kamia et al. [24] assessed power sector pathways to net zero emission by 2050 for the Association of Southeast Asia Nations using the Low Emissions Analysis Platform (LEAP). In the realm of low-carbon transformation in the power sector, bottom-up models can provide a more comprehensive description of energy substitution-related technologies and their environmental and economic impacts.

Among the bottom-up models, the LEAP model developed by the Stockholm Environment Institute has been widely adopted by thousands of organizations in over 190 countries and regions due to its advantages in alternative predictions, quantitative dynamics, and policy settings [25]. It is extensively used for long-term forecasting and scenario analysis of energy demand and related environmental issues in integrated resource planning. Nnaemeka et al. [26] explored energy demand, supply, and related greenhouse gas emissions in Nigeria from 2010 to 2040 based on scenario analysis; Nieves et al. [27] analyzed energy demand and greenhouse gas emissions generated in Colombia for the years 2030 and 2050; Nayyar et al. [28] conducted energy planning for Pakistan from 2015 to 2050, considering resource potential, techno-economic parameters, and carbon dioxide emissions. Recently, the LEAP platform has introduced energy storage modeling and the NEMO (the Next Energy Modeling System for Optimization) optimization framework, shifting the research focus from energy utilization on the demand side to energy planning on the supply side and its environmental and economic benefits. It is particularly worthy noting that despite its widespread use, there is still limited publication on utilizing the latest functionalities to simulate supply-side energy planning, especially in the context of China's power system planning and optimization [29,30].

While the aforementioned studies have contributed to understanding the low-carbon transformation pathways in the power sector, they have not conducted a quantitative analysis of the impacts of different policies on the transformation. A few models [31–34] have begun to assess policies, such as Lin et al. [31] which used an improved dynamic recursive CGE model to investigate the effects of different carbon price levels on energy, the environment, and the economy, and recommended maintaining the carbon price at $10/t, gradually increasing it to $20/t. However, these evaluations have been primarily based on top-down CGE models, with very few bottom-up electricity system models. Such research takes a macroeconomic perspective on energy issues and may not effectively provide policy guidance specific to the power sector. In the EU where carbon and electricity markets are more mature than China, carbon price has reached €80/t. It is worth discussing whether the carbon prices obtained from top-down models can promote a high penetration of renewable energy in China. Additionally, some renewable energy sources in China currently have relatively high costs, and phasing-out FIT due to fiscal pressures does not imply that renewable energy no longer requires support. The question of how to achieve effective development after subsidy removal has not been addressed in the aforementioned research.

To fill the literature gaps, we develop a new research framework that integrates a comprehensive quantitative assessment, employing a bottom-up modeling approach, of the carbon pricing policies and financial incentive measures required for achieving net zero emission in the Chinese power sector. This framework takes into account both the demand and supply sides of electricity, serving as a comprehensive, data-intensive dynamic model with functionalities such as electricity demand forecasting, power generation mix optimization, carbon emissions analysis and policy effectiveness assessment. In comparison to previous bottom-up studies exploring net-zero emission pathways, our framework adds a quantitative assessment of the required policy stringency. Unlike top-down studies, this framework allows for a comprehensive analysis of specific supply, conversion, and utilization technologies in the power sector and their economic and environmental benefits, thus providing more tailored support policies for the power sector.

In summary, the primary contributions of this paper are as follows:

(1) Based on environmental and techno-economic optimization analysis, we develop a model for the penetration of renewable energy sources in China using the LEAP platform and its NEMO framework. We also set a high carbon price policy scenario, under which two carbon pricing mechanisms are designed. Taking the advantages of the LEAP model in policy research and its latest supply-side energy planning capabilities, we provide a design framework for other modelers to evaluate policy effectiveness required for achieving net zero emission in the power sector using a bottom-up approach; (2) To discuss the goal of achieving net zero emission in the power sector, we quantify the environmental and economic impacts of different carbon pricing mechanisms, as well as the influence of subsidies and preferential policies on the penetration of high-cost renewable energy sources. This addresses the shortcomings of current top-down models that analyze energy issues across multiple sectors, rather than focusing on the power sector. It helps gain a comprehensive understanding of the costs associated with renewable energy policies, aiding policymakers in formulating more cost-effective and socially attractive transformation policies.

The rest of this manuscript is organized as follows. In Section 2, the research methodology is provided, including the research framework,

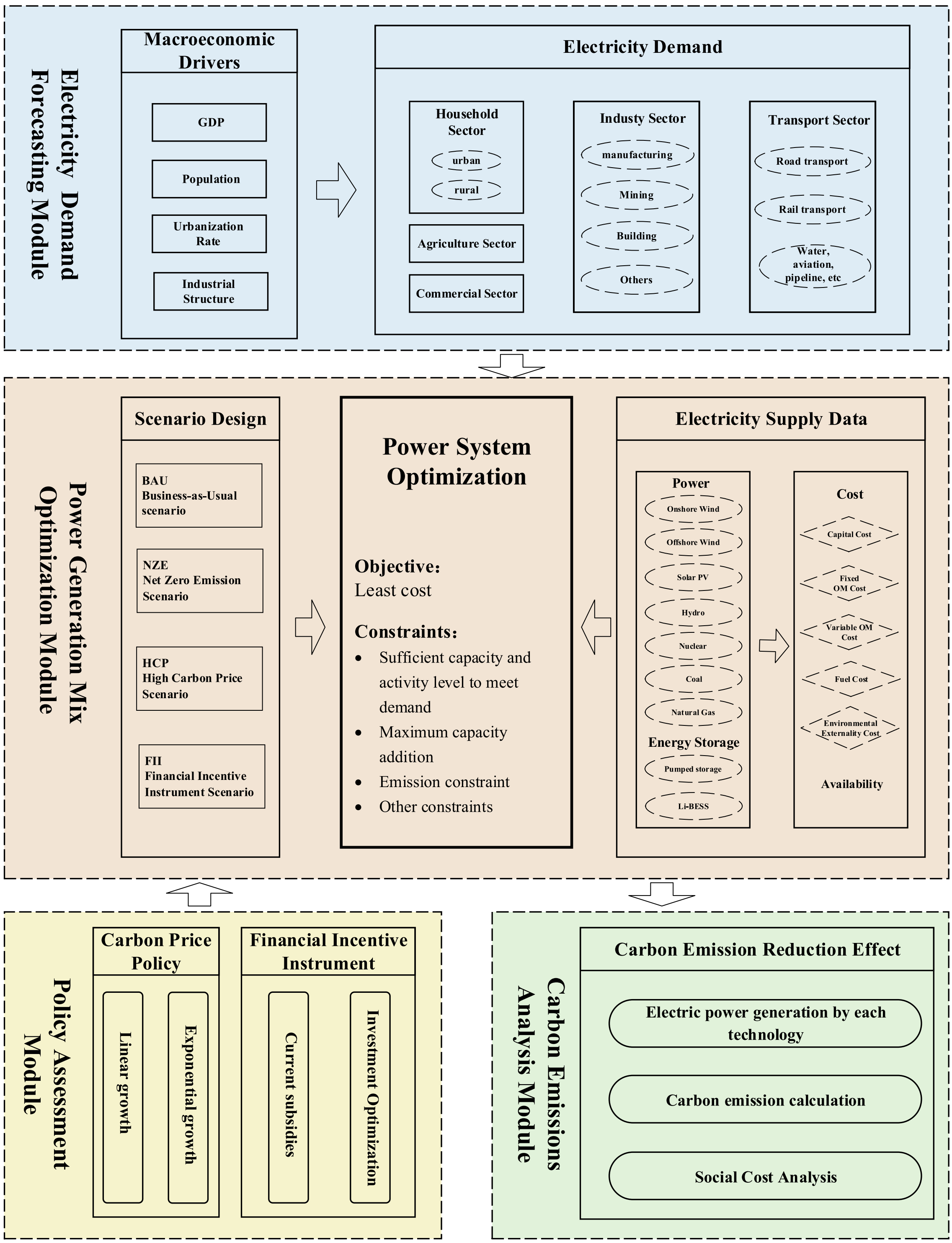

Fig. 1. Modelling framework for renewable energy penetration.

model used, data sources, and scenario design. Section 3 presents the results, including electricity demand, capacity and cost of individual power source and optimization in each scenario. Section 4 discusses the findings, while Section 5 presents the conclusions and policy implications.

2. Research methodology

2.1. Research framework

The research framework of this paper is shown in Fig. 1. For a comprehensive assessment of renewable energy penetration and emissions reduction in the future power system under the goal of net zero emission in the power sector, we develop the Renewable Energy Penetration (LEAP-REP) model based on the LEAP platform. The model consists of four modules: the electricity demand forecasting module, the power generation mix optimization module, the carbon emissions analysis module, and the policy assessment module. The electricity demand forecasting module predicts changes in China's electricity demand by industry based on macroeconomic driving factors such as gross domestic product (GDP), population, urbanization level, and industrial structure. The power generation mix optimization module evaluates the environmental and techno-economic performance of different generation technology categories based on their costs and efficiencies, and simulates the optimal power generation mix considering seasonal and daily variations in demand and supply. The carbon emissions analysis module calculates and compares the carbon emissions of the power system under different scenarios, and analyzes the cost of emissions reduction. The policy assessment module evaluates the impact of carbon pricing policies and financial incentive instruments on the development of renewable energy and carbon emissions reduction through scenario analysis.

To examine the feasibility of achieving net zero emission in the power sector by 2050 and the required policy stringency, we establish four scenarios: the business-as-usual scenario (BAU), net zero emission scenario (NZE), high carbon price scenario (HCP), and financial incentive instrument scenario (FII). By simulating the BAU and NZE, we investigate the feasibility of achieving net zero emission by 2050 in the power sector while meeting the development needs of China. Through simulating the HCP and FII, we assess the impacts of policy stringency on achieving net zero emission in the power sector. Furthermore, considering the challenge of implementing carbon prices significantly higher than the current market price, in the HCP we design two carbon pricing mechanisms: linear growth and exponential growth. We assess the impact of different carbon price levels under each of these mechanisms on carbon emissions in the power sector. Since this study focuses on the penetration of renewable energy, the electricity demand mainly reflects the economic and social development needs. Therefore, the scenario design starts from the power generation mix optimization module, meaning that the electricity demand forecasting results under different scenarios are consistent. The following sub-sections elaborate the LEAP-REP model, scenario design, and basic data sources respectively.

2.2. LEAP-REP model

2.2.1. Electricity demand forecasting module

Electricity demand is driven by two high level exogenous variables: population and GDP, and is predicted through LEAP [35]. The LEAP model is a bottom-up end-use energy consumption model, including sectors such as household, agriculture, commerce, industry, and transportation in society. The LEAP model can simulate in detail the development paths of all these sectors. Therefore, it is widely used in energy policy analysis and climate change mitigation assessments [36].

In the household sector, electricity demand is divided into urban and rural residents' electricity demand for living, mainly including lighting, home appliances, and heating. The electricity demand in agricultural sector is mainly based on the value-added agricultural production. The electricity demand in industrial sector accounts for the electricity demand of manufacturing, mining, construction, and other industries. The commercial sector takes into account of the electricity demand in tertiary industry such as wholesale, retail, accommodation, catering, finance, and real estate. The transportation sector considers the electricity demand of railways, roads, and other transportation modes, based on the turnover or electric vehicle mileage conversion.

When calculating with the LEAP model, the terminal electricity demand is mainly determined by the product of activity level and electricity consumption intensity. The activity level is closely related to the strength of electricity consumption activities in each sector, and can fully reflect the dynamic changes in energy consumption of energy-using objects. electricity consumption intensity is the amount of electricity consumption generated by a unit activity level, reflecting the efficiency of energy use. The specific calculation formula of terminal electricity demand is as follows:

$$E = \sum_{a}\sum_{b} A_{b,a} \times I_{b,a} \tag{1}$$

Where, E represents the total electricity demand; $A_{b,a}$ represents the activity level of each sector; $I_{b,a}$ represents the electricity consumption intensity; a represents different sectors; b represents end-use devices.

In addition, considering the impact of climate change, we use the Representative Concentration Pathways (RCP) scenario proposed by the Intergovernmental Panel on Climate Change (IPCC) to estimate changes in China's electricity demand. Given the assumption of proactive emission reduction measures in this paper, the prediction is based on the RCP2.6 scenario. According to Fan's research [37], there is a significant correlation between climate and electricity demand. Under the RCP2.6 scenario, the growth in China's electricity demand due to climate factors is estimated to be approximately 7.72 TWh/decade. Following Kamia's approach [38], the impact of climate change is integrated into the electricity demand forecasting module of the LEAP model.

2.2.2. Power generation mix optimization module

The power generation mix optimization module first calculates the annual electricity generation of the power system based on the predicted power demand results, taking into account of the losses in the transmission and distribution process. Then, by comparing the generation costs of different fuel types, the module determines the minimum cost expansion and power dispatching of the power system for each year within the research timeframe. Based on China's resource endowment and the historical generation of various power sources, the power sources considered in this study consist of onshore wind, offshore wind, solar photovoltaic (PV), hydro, nuclear, natural gas, coal, natural gas carbon capture and storage (CCS) and coal CCS. In addition, as energy storage technology can transfer electricity and facilitate supply–demand balance, this study also considers two types of energy storage: traditional pumped hydro storage and new types of Li-ion battery energy storage system (Li-BESS), with the optimization process only considering daily carryover.

Optimization covers all modelled time periods. Due to the significant impact of climate conditions on power generation, especially for hydropower, this study divides each year into two seasons, wet and dry. For each season, a detailed hourly system load curve and various power generation curves are further established to simulate the optimization process of annual electricity supply and demand. This approach ensures that the power generation mix optimization meets not only the total electricity demand but also the demand at each time.

Optimization is solved by NEMO, a high-performance, open-source energy system optimization tool designed under the project of the Energy Modeling Program at the Stockholm Environment Institute. NEMO simulates an energy system through least-cost optimization with perfect foresight. Essentially, this means it seeks to meet energy and power demands over time at the lowest possible cost. The cost minimization function operates on discounted costs (all costs are discounted to the beginning of the simulation). The costs include investment cost, fixed operating cost, variable operating cost, fuel cost, environmentally-related carbon emission cost and subsidy. The dynamic accounting model for electricity generation of various power sources can be expressed as follows:

$$C_j^T = \sum_{i=1}^{n}\left(CA_{i,j}^{new} \times C_{i,j}^{I} + CA_{i,j}^{T} \times C_{i,j}^{FO}\right) \times \frac{1}{(1+r)^i}$$
$$+\sum\nolimits_i^n \sum\nolimits_{k=1}^2 \sum\nolimits_{t=1}^{24}\left(C_{i,j}^{VO} + C_{i,j}^{F} + C_{i,j}^{E} - I_{i,j}^{F}\right) \times GE_{i,j,k,t} \times D_k \times \frac{1}{(1+r)^i} \quad (2)$$

$$CA_{i,j}^T = CA_j^{history} + \sum_{i-1} CA_{i,j}^{new} \quad (3)$$

Where, j represents different types of power sources, including onshore wind, offshore wind, solar PV, hydro, nuclear, natural gas, coal, CCS, pumped hydro storage and Li-BESS; C_j^T represents the total cost of electricity generation for a given power source; $CA_j^{history}$, $CA_{i,j}^T$, $CA_{i,j}^{new}$ represent the historical installed capacity, cumulative installed capacity in year i, and newly added installed capacity in year i for power source j; $C_{i,j}^I$, $C_{i,j}^{FO}$, $C_{i,j}^{VO}$, $C_{i,j}^F$, $C_{i,j}^E$, $I_{i,j}^F$ represent the unit investment cost, fixed operating cost, variable operating cost, fuel cost, carbon emissions-related environmental cost and subsidy income of power source j in year i, respectively. Whilst the investment cost and fixed operating cost are associated with the capacity, other costs are associated with the electricity generation; k represents the season, with this paper being divided into two seasons: wet and dry; D_k is the number of days in each season within a year; t represents hours; $GE_{i,j,k,t}$ represents the electricity generation of power source j in the i-th year, k season, and t hour; r is the discount rate; n is the calculation period.

The optimization objective of the model is to minimize the discounted total cost of the power system, which includes investment costs and operational costs for various types of power sources, among other factors. The objective function can be expressed as:

$$\min TC = \min \sum_{j=1}^{J} C_j^T \quad (4)$$

Where, TC represents the present value of total cost of the power system; J is the number of types of power sources. The optimization process takes into account the following important constraints.

First, the constraint of power system balance. This ensures that the electricity generated by each source in each hour can meet the demand for various types of electricity. The constraint conditions are expressed as:

$$\sum_{j=1}^{J} GE_{i,j,k,t} \times (1 - loss) = \sum_a \sum_b E_{b,a,t} \quad (5)$$

$$GE_{i,j,k,t} \leqslant CA_{i,j}^T \times MA_k \quad (6)$$

Where, $loss$ represents the line loss rate for transmission and distribution; $E_{b,a,t}$ represents the electricity demand for end-use devices in the t-th hour; MA_k represents the maximum utilization hours for season k.

Second, the constraints on power source capacity expansion. In response to the expected termination of subsidies for non-hydropower renewable energy in 2021, there was a rush of new energy installations in 2020. From the perspective of the rush of new installations, due to the constraints of materials, equipment, and other production capacities, the capacity addition of power sources each year is limited. Therefore, based on the capacity addition of each type of power source in the rush year and the historical capacity addition, the maximum capacity addition constraint is set for each power source. In that case, the following constraints exist:

$$CA_{i,j}^{new} \leqslant CA_j^{\max} \quad (7)$$

Where, $CA_j^{\max}$ is the maximum annual additional capacity for power source j.

Third, the constraint on carbon emissions. Since different scenarios imply different carbon emissions reduction targets, different carbon emission constraints are thus set to simulate the optimization process to study the impact of different incentives and policies on the development of renewable energy under carbon emission constraints. The carbon emission constraint can be expressed as:

$$CE_i^T \leqslant CE_i^{\max} \quad (8)$$

Where, CE_i^T is the carbon emissions of the electricity system in year i; $CE_i^{\max}$ is the carbon emissions limit for year i.

Additionally, the optimization process also considers constraints related to the reliability of the power system, energy storage charge and discharge constraints, among others.

The model developed in this study can utilize various solvers such as Cbc, GLPK, HIGHS, CPLEX, Mosek, and more through NEMO. Given the complexity of the simulations in this research, the high-performance mathematical optimization solver software CPLEX Optimizer developed by IBM is employed for solving.

2.2.3. Carbon emissions analysis module

The carbon emissions in the power system mainly come from the combustion of fossil fuels. Among the power sources studied in this paper, only coal-fired and gas-fired power plants emit carbon due to the combustion of fossil fuels, while other power sources are clean energy sources and have negligible carbon emissions. Therefore, after determining the amount of energy generated by fossil fuel power generation within the research time frame, the carbon emissions of the power system can be calculated based on the emission factors of different energy sources (carbon emissions per unit of energy), as shown in the following formula:

$$CE_i^T = \sum_{j=1}^{J}\sum_{k=1}^{2}\sum_{t=1}^{24}\frac{1}{f_j} \times CF_j \times GE_{i,j,k,t} \times D_k \quad (9)$$

$$CF_j = CC_j \times OF_j \times 44/12 \quad (10)$$

Where, f_j is the energy efficiency of power source; CF_j represents the energy conversion carbon emission coefficient of power source j; CC_j、OF_j respectively represent the carbon content and carbon oxidation rate of the unit heat value of fossil fuels consumed by the power source j; 44/12 is the ratio of the relative molecular weight of carbon dioxide to carbon.

2.3. Data sources

The data used in this study mainly come from national statistics. The data that cannot be obtained from national statistics are obtained through investigation, literature review, and the reports of various research institutions as shown in Table 1, and specific data values are provided in Appendices A and B. Based on the description of the model in Section 2.2, this subsection describes the basic data required for the three modules.

The most basic parameters for the electricity demand forecasting module are GDP and population, the historical data of which are sourced from the National Bureau of Statistics [39], and the change trend of which is based on Goldman Sachs' China 2023 Outlook [40] and the United Nations World Population Prospects 2022 [41]. As noted in Section 2.2.1, the terminal electricity demand is determined by the activity level and energy intensity. The data required for calculating the activity level, such as the urban population, rural population, value-added of various industries, converted turnover data, and the electric vehicle driving mileage, are from the National Bureau of Statistics, the

Table 1
Summary of model basic data.

Demand data	Source	Supply data	Source
GDP	National data [39], China 2023 Outlook [40]	Historical installed capacity and power generation, maximum capacity addition	China Electric Power Yearbook [43]
Population	National data [39], World Population Prospects 2022 [41]	Investment cost, operation cost, and fuel cost	Investigation, 2022 ATB Cost Data for Electricity Generation Technologies, Technology Data – Generation of Electricity and District heating [44,45]
Value-added of various industries	National data [39]	Carbon emission cost	National carbon emissions trading market
Converted turnover	2021 Railway Statistical Yearbook [42]	Discount rate	Loan Prime Rate from the People's Bank of China
Electric vehicle driving mileage	he Ministry of Public Security of the People's Republic of China	System load curves and power generation curves	Investigation
Power consumption intensity	China Electric Power Yearbook [43]		

National Railway Administration of the People's Republic of China [42], and the Ministry of Public Security of the People's Republic of China, respectively. In addition, the power consumption intensity data required for calculating the energy intensity is collected from the *China Electric Power Yearbook* [43].

The data required for the power generation mix optimization module include, but is not limited to, historical installed capacity and power generation for different types of power sources, various costs, discount rate, system load curves, different power source generation curves, and maximum annual new installed capacity. Among them, historical installed capacity and power generation data, as well as annual maximum new installed capacity, are collected from the *China Electric Power Yearbook* [43]. Investment cost, operating cost, and fuel cost are obtained through investigation, and cost trends are based on the "2022 Annual Technology Baseline (ATB) Cost and Performance Data for Electricity Generation Technologies" [44] published by National Renewable Energy Laboratory in the USA and "Technology Data – Generation of Electricity and District heating" [45] published by Danish Energy Agency. Carbon emission cost is based on the average carbon price in China's national carbon market in 2022, which was about RMB 55/t. The discount rate is represented by the prime loan rate from the People's Bank of China, which is 4.99 %. In this study, we take 5 %, very close to 4.99 %. System load curves and power generation curves are obtained through investigation.

The carbon emission analysis module uses technology and environmental databases embedded in LEAP as environmental parameters which provide IPCC Tier 1 emission factors for different fuels.

2.4. Scenarios design

To achieve the net zero goal in the power sector, four scenarios (BAU, NZE, HCP and FII) are designed for simulation with 2015 as the base year, 2022 as the start year, and 2050 as the end year, to study the effects of different policies on renewable energy penetration and carbon emissions. The key assumptions of these scenarios are summarized in Table 2.

(1) Business-as-usual scenario (BAU). BAU assumes a continuation of current policies and a downward trend in the cost of renewable energy worldwide. Carbon emissions constraints are not set, and power supply is optimized based solely on the cost of each power source.

Table 2
Key assumptions of scenarios.

Scenario	Binding carbon emissions targets	Carbon price increase	Financial incentives
BAU	No	No	No
NZE	Zero carbon emissions by 2050	No	No
HCP	No	Yes	No
FII	No	Yes	Provide certain financial incentives to renewable energy sources that have an important development status and are relatively expensive

(2) Net zero emission scenario (NZE). NZE examines the feasibility of achieving net zero emission in the power sector by 2050 while ensuring the developmental needs of China. Based on BAU, this scenario sets the net zero emission target for the power sector as a hard constraint in the power generation mix optimization. This allows for the calculation of the required penetration of renewable energy to achieve net zero.

(3) High carbon price scenario (HCP). HCP assesses the impact of carbon pricing on the optimization results. Building upon the design of NZE noted above, this scenario removes the hard constraint on carbon emissions and instead optimizes the power generation mix by increasing carbon emission prices. This approach determines a reasonable carbon price required to achieve the net zero emission by 2050 in the power sector.

In practice, setting a carbon price that is several times the current market price is not very feasible for any economy. Therefore, we design two incremental carbon pricing mechanisms: a linear growth mechanism and an exponential growth mechanism with the current carbon market price as the baseline, as illustrated in Fig. 2.

Both carbon pricing mechanisms use the current carbon market price as the base price. The key difference between the two is that in the linear growth mechanism the carbon price increases each year by a constant absolute increment, while in the exponential growth mechanism the carbon price increases each year by a constant relative increment. The expressions for the carbon price in the two growth system are as follows:

$$P_l = P_0 + a \times (n - 2021) \tag{11}$$

$$P_e = P_0 \times (1 + b)^{n-2021} \tag{12}$$

Where, P_e and P_l represent the carbon prices for the linear growth

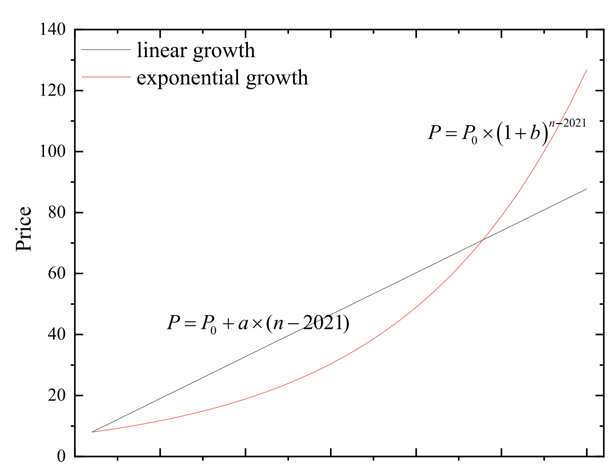

Fig. 2. Carbon price growth mechanism illustration.

mechanism and the exponential growth mechanism, respectively; P_0 is the initial carbon price; n is the calculating year; a, b represent absolute increment and relative increment respectively.

(4) Financial incentive instrument scenario (FII). FII evaluates the influence of financial incentives for renewable energy on the optimization results. Building upon the design of HCP, this scenario maintains the high carbon price setting while providing certain incentives for important but high-cost renewable energy sources for the purpose of enhancing the penetration of such renewable energy sources and promote the comprehensive development of renewable energy.

Since 2021, China has discontinued national subsidies for new energy generation. However, due to the later development and higher costs associated with offshore wind power in China, certain coastal provinces are planning to provide local subsidies to promote the development of new offshore wind power projects. For example, the Guangdong provincial government is offering subsidies for offshore wind power projects that are fully connected to the grid from 2022 to 2024. The standards for these subsidies are 1,500, 1,000 and 500 RMB/kWh [46]. Additionally, the Shandong provincial government has proposed subsidies for floating offshore wind projects that are built and connected to the grid from 2022 to 2025. The subsidy rates for these projects are 1,000, 800, 600 and 400 RMB/kWh [47].

Given the financial tightness faced by local governments due to the pandemic, raising subsidy would impose considerable pressure on them. Therefore, we suggest adopting a model similar to the European offshore wind power investment model, where offshore wind power projects are categorized into main projects and grid-connected supporting projects. The investments in grid-connected supporting projects include funding for offshore substations, offshore converter stations, onshore control centers, among others. These costs, constituting approximately 25 % of the total investment, are borne by the grid company and are incorporated into the transmission and distribution tariff. Essentially, this shifts the cost from the power generation companies to the consumers.

Building on the analysis provided, the FII will be structured to include two sub-scenarios: the local subsidies scenario and the investment pattern optimization scenario. This study aims to investigate financial incentive policies that facilitate the holistic development of renewable energy.

3. Results

3.1. Electricity demand

First, the electricity demand forecasting module was executed to obtain the electricity demand in China from 2015 to 2050, as shown in Fig. 3. The data for 2015–2021 represent historical data, while the data for 2022–2050 are the forecast results. Among them, the predicted total electricity demand for the year 2022 is 8,513 TWh. According to the latest results from the *China Electric Power Yearbook*, the total electricity consumption for the entire society in China in 2022 was 8,637 TWh. The difference between the two number is only 1.43 %, demonstrating a high level of predictive accuracy.

From the perspective of total electricity demand, whilst it will continue to grow, its growth rate will gradually slow down. By 2030, 2040, and 2050, the electricity demand will reach 10,405 TWh, 12,561 TWh, and 14,096 TWh respectively. The per capita electricity demand will increase from 7,712 kWh in 2021 to 10,752 kWh in 2050, which falls between the current levels of highly energy-efficient countries like Japan and Germany and high-energy-consuming countries like the United States and Canada. The forecast results are close to the "China Generation Development Analysis Report" [48] by the State Grid Energy Research Institute.

From the perspective of each sector, the proportion of electricity demand in each sector is shown in Fig. 4, of which the industrial sector has the largest share, followed by residential and commercial sectors. Nevertheless, the proportion of the industrial sector will gradually decrease from 73 % in 2015 to 46 % in 2050, mainly due to the decrease in the proportion of industrial value-added and the gradual reduction in energy consumption resulting from industrial restructuring, whilst the proportion of residential and commercial electricity demand will respectively increase from 13 % and 11 % in 2015 to 26 % and 18 % in 2050, due to the increase of residential electrification level and the value-added in the tertiary industry. The transportation sector has the fourth highest share of electricity demand. Given the increase of electric

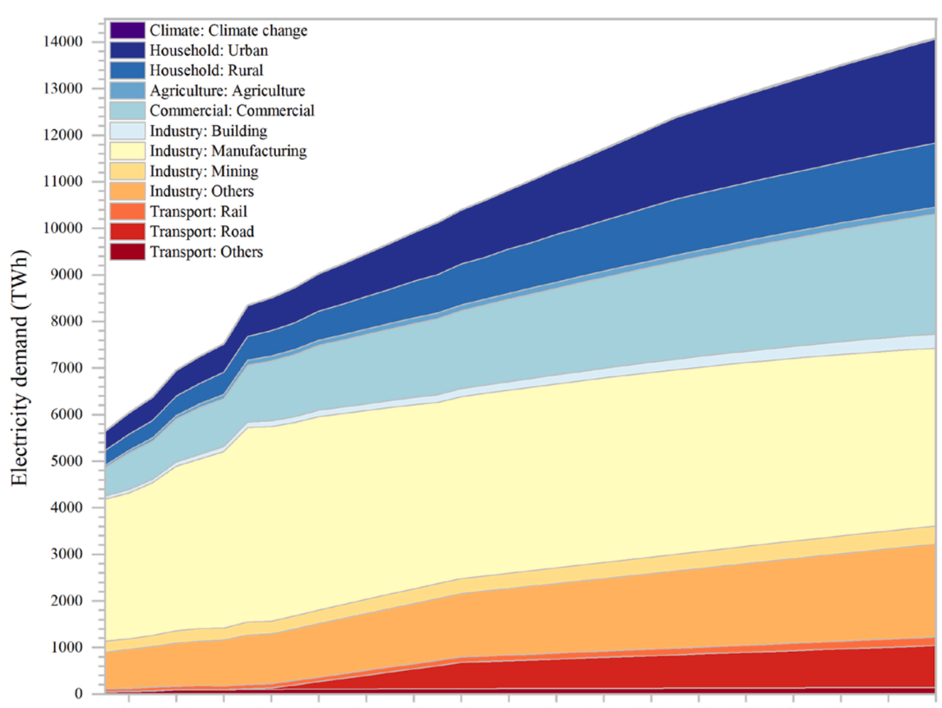

Fig. 3. Forecast results of electricity demand in the whole society.

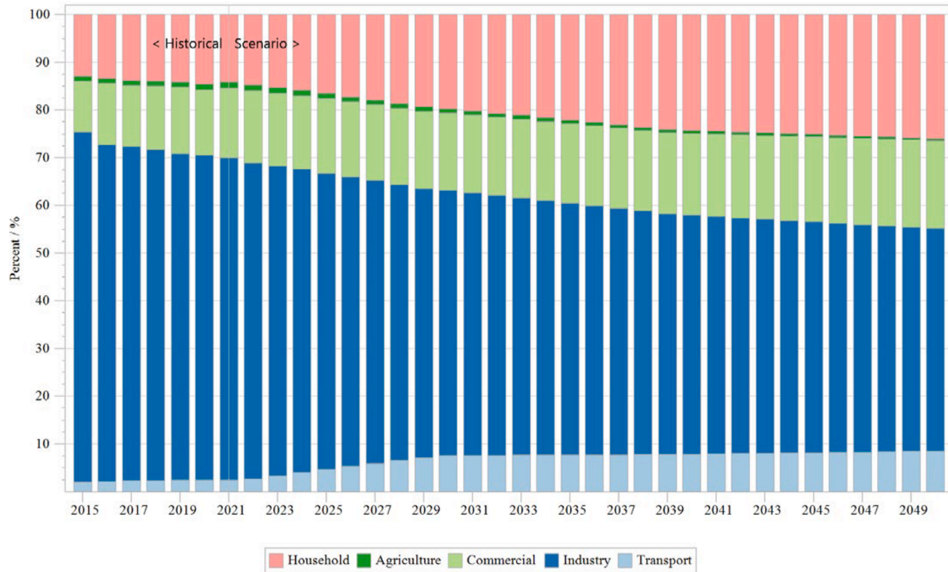

Fig. 4. Proportion of electricity demand by industry.

vehicles and the electrification rate of railways, the proportion is expected to increase from 2.00 % in 2015 to 8.67 % in 2050. The agricultural sector has the smallest share of electricity demand. Although its electrification level will increase, its proportion in the country's total electricity demand will remain basically unchanged due to the decrease of its proportion in the value-added.

3.2. Power generation techno-economic characteristics

In the power generation mix optimization module, the number of operating hours and generation costs are the most important factors determining the expansion of power capacity. The capacity and costs required for adding a single fuel-type power source are calculated and compared with the power source mix optimization to analyze the techno-economic characteristics of different fuel-type power sources, laying the foundation for optimizing the power generation mix in various scenarios.

The estimation of the capacity and cost of individual power source proceeds as follows: First, input the lifecycle and yearly cost data of different power sources, then import the load change curve and renewable energy generation curve in typical wet and dry seasons, respectively. Finally, calculate the capacity and cost required to meet the annual electricity demand for individual and combined power source. The required installed capacity and cumulative cost results by 2050 are shown in Figs. 5 and 6 respectively. In these figures, "Combination" represents the optimization results of power source combination, including all the power sources mentioned in Section 2.2.2, namely onshore wind, offshore wind, PV, hydro, nuclear, natural gas, coal, natural gas CCS and coal CCS, while "Coal only", "Hydro only", and others represent the optimization results of individual power sources. Furthermore, given that solar PV does not generate power at night, and relying solely on it cannot fulfil the electricity demand, optimization becomes unfeasible. Therefore, this section does not analyze solar PV.

The capacity calculation results show that, due to different operating hours, the necessary installed capacity of nuclear is the smallest based on the combined optimization capacity. It is followed by coal and natural gas power (including CCS), while the accumulated capacity required for onshore wind power, hydropower, and offshore wind power is relatively large. This is primarily attributed to the impact of weather conditions on renewable energy generation, leading to lower annual

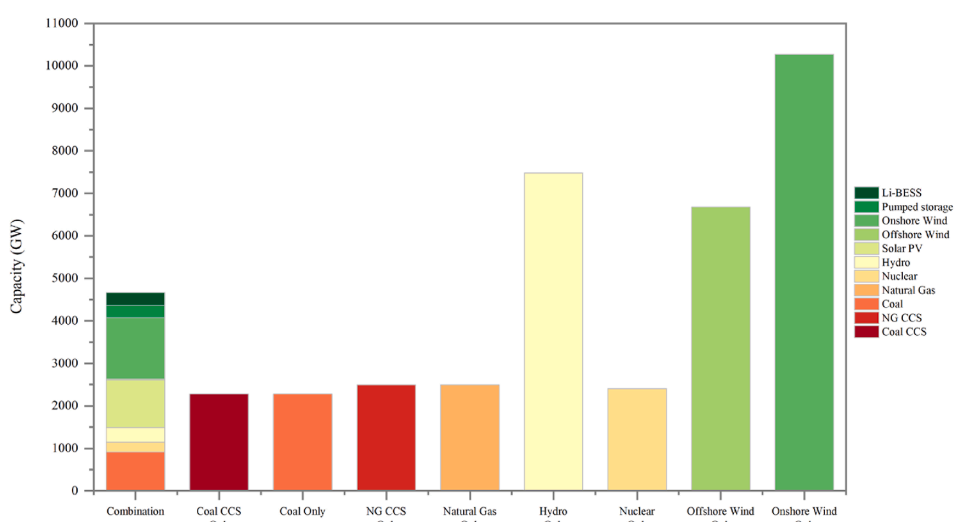

Fig. 5. Results of the installed capacity for individual power source and combination.

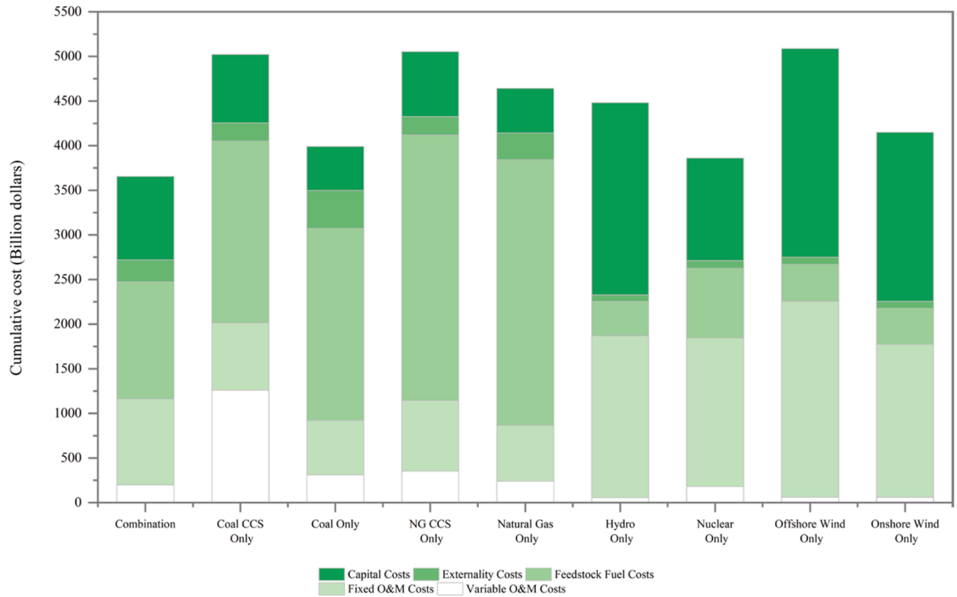

Fig. 6. Results of the cumulative generation cost for individual power source and combination. Including the generation costs of historical installed capacity prior to 2021.

operating hours. Consequently, more installed capacity is needed to meet the same electricity demand. In addition, despite hydropower has slightly higher annual average utilization hours than offshore wind power, the reduced low hydropower generation during the dry season necessitates a higher total installed capacity to meet the electricity demand. This can partially explain the power shortage in China's southwest Sichuan Province in 2022.

Further analysis of the cost calculation results reveals that by 2050, the scenarios with the lowest to highest cumulative costs are ranked in the following order: the power generation mix, nuclear power, coal power, onshore wind power, hydropower, natural gas power, coal CCS, natural gas CCS, and offshore wind power. In this ranking, the power generation mix has the lowest cost because it optimizes various power source combinations, validating the model's effectiveness. Although nuclear power has a high per-unit investment cost, it has lower total investment cost resulting from its smaller required capacity, as well as

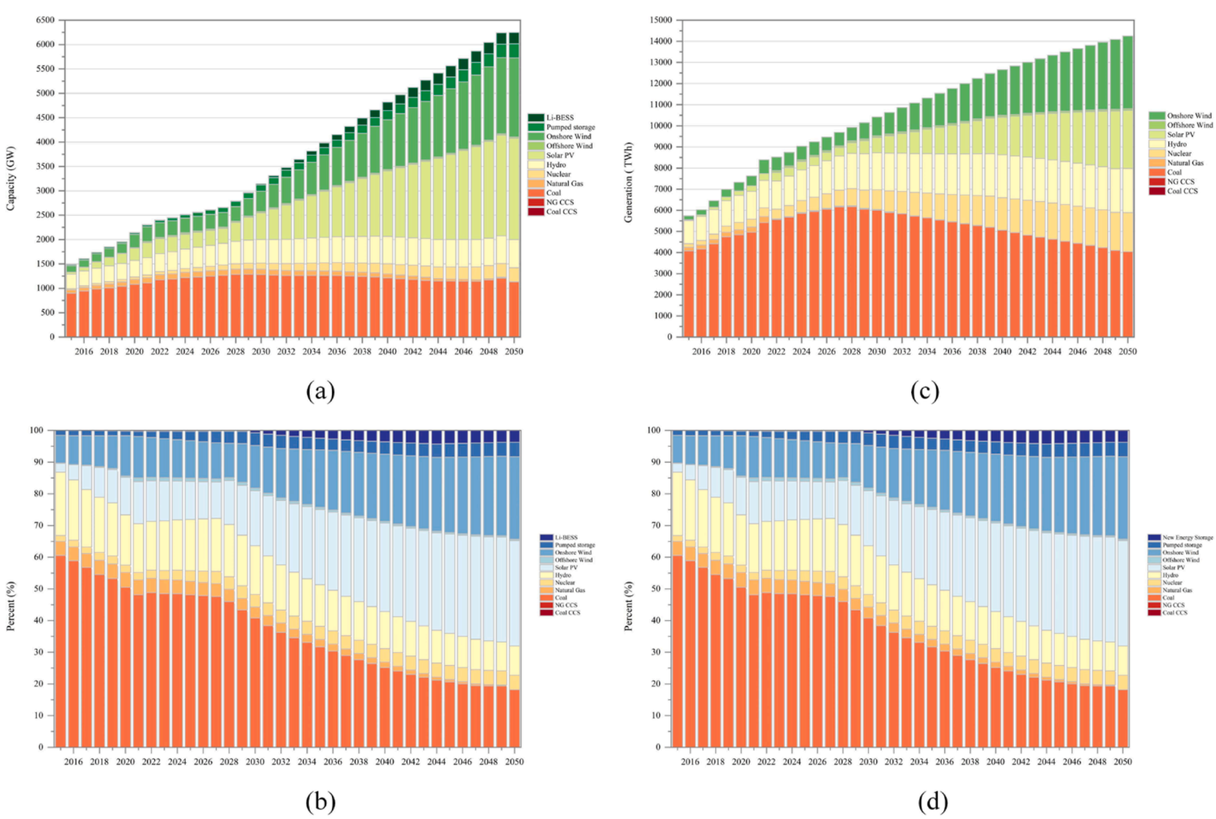

Fig. 7. Optimization results of capacity and power generation for BAU. (a) Absolute values of capacity; (b) Percent shares of capacity; (**c)** Absolute values of power generation; **(d)** Percent shares of power generation.

its lower fuel costs compared to coal and natural gas power generation. Natural gas power, despite having a low investment cost, faces higher fuel cost due to China's resource constraints, marked by "shortage in natural gas and oil but abundance in coal" [49]. These fuel costs constitute over 70 % of the total power generation cost, resulting in a higher cumulative cost. Coal CCS and NG CCS have higher cumulative costs due to the substantial investment cost of CCS technology and variable cost associated with carbon capture. They are ranked just after offshore wind power, which has the highest investment and fixed cost.

The costs of three renewable energy sources, namely, offshore wind, onshore wind, and hydro, are also compared. Although offshore wind requiring the least cumulative installed capacity, its high unit investment and operation costs result in the highest overall cost. Conversely, although onshore wind requires the highest cumulative installed capacity, its low unit investment and operation costs lead to the lowest overall cost.

3.3. Business-as-usual (BAU) scenario

In the BAU scenario, the optimized results for installed capacity and the capacity proportions for various power sources are shown in Fig. 7 (a) and (b). These results align with the cost analysis in Section 3.2. From 2022 to 2027, the majority of newly added power sources are low-cost coal power, reflecting the cost-effective option during that period. As the cost of renewable energy generation decreases, starting in 2028, onshore wind power and PV gradually replace coal power as the main sources of development. By 2050, their installed capacity would grow to 1,622 GW and 2,067 GW, representing 26 % and 33 % of the total installed capacity, respectively. Among other power sources, nuclear power and hydropower will see steady growth, with installed capacity reaching 285 GW and 579 GW, respectively, by 2050. Natural gas power, offshore wind power, and CCS, constrained by high generation costs, will experience limited growth. In terms of energy storage, pumped hydro storage is prioritized from 2022 to 2029. During this period, although the cost of pumped hydro storage is slightly higher than that of Li-BESS, it has a lifespan of over 40 years, far exceeding the 15-year lifespan of Li-BESS technologies, giving it a competitive advantage. However, given that the cost of Li-BESS will continue to decline due to technology advancement, and pumped hydro storage is limited by factors like site resources, leading to increasing costs, it is evident that starting from 2030, the cost of Li-BESS will become more competitive than pumped hydro storage, even though they have lifespan disadvantage. By 2033, Li-BESS would outperform pumped hydro storage in terms of cost-effectiveness.

The optimized results for the annual electricity generation and the proportions for different power sources are shown in Fig. 7(c) and (d). Over the research period, renewable energy has an average annual electricity generation of 4,439 TWh, accounting for 41 % of the total electricity generation. By 2050, this figure will increase to 8,363 TWh, representing 59 % of the total electricity generation. Among these, onshore wind power generates 3,438 TWh, PV generates 2,747 TWh, and hydropower generates 2,099 TWh, accounting for 24 %, 19 %, and 15 %, respectively. Coal power has an average annual electricity generation of 5,164 TWh, making up 48 % of the total electricity generation. By 2050, its electricity generation decreases to 4,041 TWh, constituting 28 % of the total electricity generation.

The carbon emissions in the BAU scenario are calculated based on the optimized results for power generation mix and various energy sources emission factors, as shown in Fig. 11(a). Over time, carbon emissions in the baseline scenario will increase from 3,572.6 Mt in 2015 to a peak of 5,328.4 Mt in 2028, and will gradually decline to 3,476.1 Mt in 2050, reaching a level similar to the year 2015. However, it remains far from achieving the goal of net zero emission in the power sector.

3.4. Net zero emission (NZE) scenario

In the NZE scenario, the optimized results for the capacity and the proportion of various types of power sources are shown in Fig. 8(a) and (b). In this scenario, coal power will be phased out, with only 164 GW remained by 2050, accounting for 2 % of the total installed capacity. Renewable energy sources such as wind and solar will see further expansion. Both onshore wind and PV power will witness rapid growth starting from 2022, with installed capacities reaching 2,042 GW and 2,227 GW, respectively, by 2050. Offshore wind power will also see significant development, with an installed capacity of 477 GW by 2050. Due to the increased share of renewable energy sources with lower capacity factors, the cumulative installed capacity of the power system in this scenario will grow by 17 % compared to the baseline scenario. Nuclear power and hydroelectric power maintain stable growth in this scenario, with increased installed capacities compared to the baseline scenario, reaching 285 GW and 687 GW by 2050, respectively. Additionally, due to cost factors, CCS, which was not developed in the baseline scenario, will begin to expand in 2033. By 2050, the installed capacities of coal CCS and natural gas CCS will reach 728 GW and 97 GW, respectively. The development of energy storage will be consistent with the baseline scenario, as it is influenced by the increasing capacity of renewable energy sources.

Concerning electricity generation, as shown in Fig. 8(c) and (d), by 2050, the electricity generation from coal and natural gas without carbon capture technology will be reduced to zero. The electricity generation from coal CCS and natural gas CCS will reach 1,955 TWh and 47 TWh, respectively, combined accounting for 14 % of the total electricity generation. Renewable energy sources will contribute 10,734 TWh of electricity, representing 75 % of the total electricity generation. This result aligns with our expectations and reinforces the idea that decarbonizing the power system hinges on reducing fossil fuel consumption and significantly increasing the use of renewable energy. However, as the share of large-scale renewable energy generation continues to grow, the power system will face significant challenges in matching supply and demand, necessitating substantial energy storage capacity. From the typical daily load dispatch curve for 2050 (Fig. 9), it is evident that energy storage will become a critical dispatch resource in the future. It will play a pivotal role in balancing the power system, ensuring stability, and accommodating the increased use of renewable energy.

In terms of carbon emissions, under the NZE scenario, there is a significant reduction in carbon emissions from the power system, ultimately achieving zero emissions by 2050. When considering the total carbon emissions, from 2022 (the first year of the modeling period) to 2050, the cumulative carbon emissions in the NZE scenario amounts to 71,780.66 Mt (Fig. 11a), a reduction of 60,233.16 Mt carbon emissions from 132,013.82 Mt which is approximately 46 % of the total emissions in the BAU scenario.

3.5. High carbon price (HCP) scenario

In the HCP scenario, the carbon emissions of the power system are calculated under the linear growth mechanism and the exponential growth mechanism, as designed in Section 2.3 (3). The results are shown in Fig. 10. Evidently, carbon emissions from the power system will gradually decrease as the carbon price increment increases under both mechanisms. However, when power system carbon emissions drop to below 100Mt by 2050, further increasing the carbon price increment will have a less significant effect on reducing emissions. For instance, under the linear growth mechanism, when the absolute increment is \$2.75 per year, power system carbon emissions in 2050 will be 52.93 Mt. If the absolute increment is raised to \$3 per ton per year, the emissions will be reduced to 36.49 Mt, a decrease of only 16.44 Mt. More convincingly, under the exponential growth mechanism, when the relative increment is 10 % per year, carbon emissions in 2050 will be 64.37 Mt. If the relative increment increases to 10.5 % per year, the

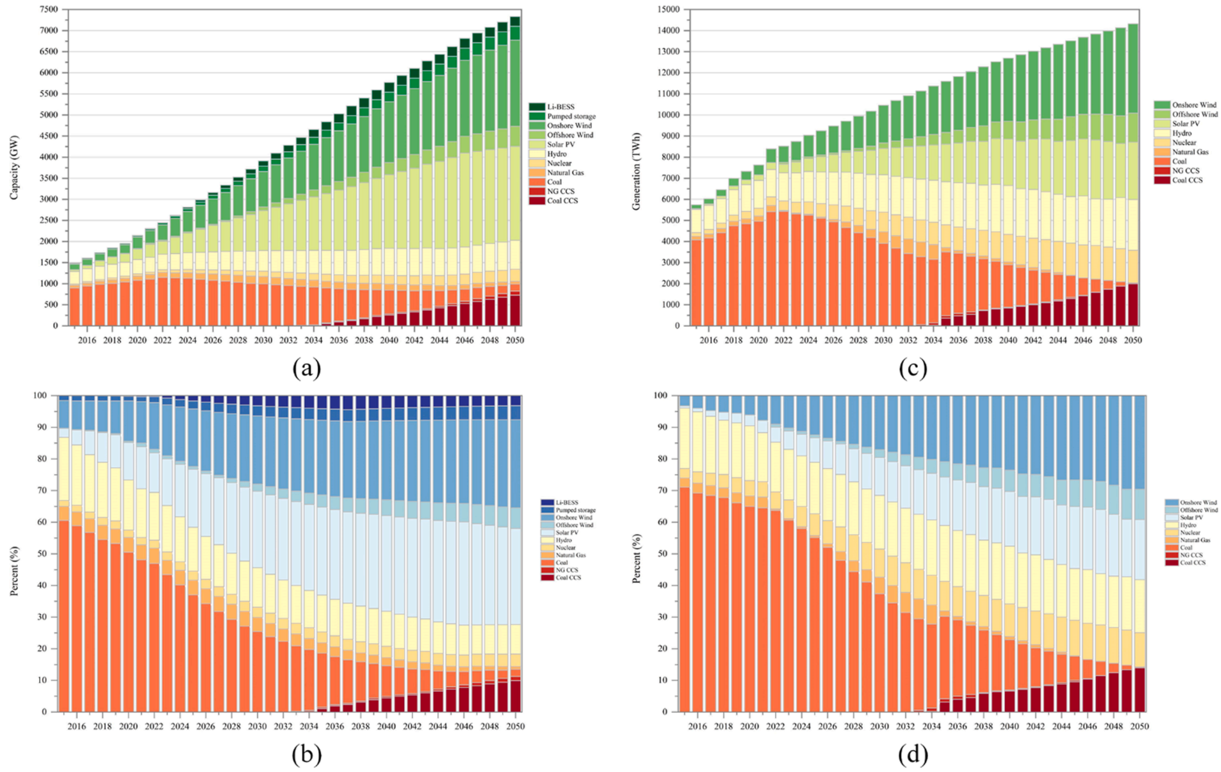

Fig. 8. Optimization results of capacity and power generation for NZE. (a) Absolute values of capacity; (b) Percent shares of capacity; **(c)** Absolute values of power generation; **(d)** Percent shares of power generation.

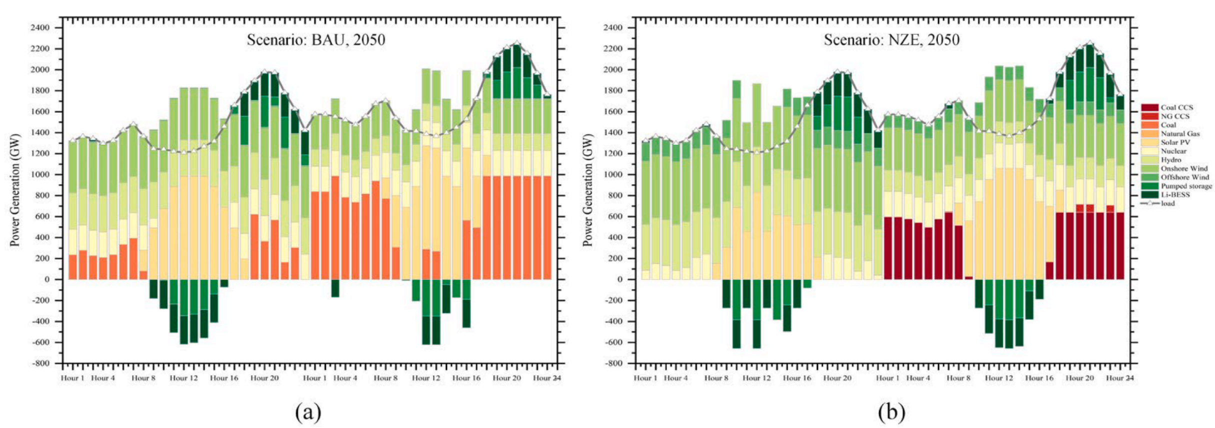

Fig. 9. Typical daily load dispatch curve for BAU and NZE in 2050.

emissions will amount to 61.21 Mt, a decrease of only 3.16 Mt. At this point, we believe the carbon pricing mechanism is one at which net zero emission can be achieved, and any remaining emissions can be eliminated through administrative measures. The carbon price mechanism under these conditions is as follows: the linear growth mechanism starts with a base price of \$8/t in 2021 and increases by \$2.75/t each year, reaching \$87.75/t by 2050. The exponential growth mechanism starts with a base price of \$8/t in 2021 and increases by 10 % each year, reaching \$127/t by 2050.

Continuing the comparison of the total cost of power system under the two carbon pricing mechanisms, as shown in Fig. 11(b). It can be seen that in the initial years of implementing high carbon pricing policies, the cost incurred in the exponential growth mechanism are much lower than those in the linear growth mechanism and are close to the net zero emission scenario. However, in the subsequent years, the cost in the exponential growth mechanism gradually exceed those in the net zero emission scenario, reaching a point of convergence around 2040, and then surpassing the linear growth mechanism. This is because the exponential growth mechanism initially has a slower rate of carbon price increase in the early years of policy implementation and then accelerates at a faster rate than the linear growth mechanism. With both mechanisms achieving the same net zero emission goal, the carbon price under the exponential growth mechanism is 45 % higher than the linear growth mechanism by 2050. However, over the entire calculation period, \$371 billion is saved in power system cost, which accounts for 5.22 % of the total cost. Such a carbon pricing mechanism aligns better with the development context of developing countries like China, promoting economic growth while providing a favorable environment for phasing out fossil fuel-based power generation.

The capacity and generation optimization results under the exponential growth carbon pricing mechanism are shown in Fig. 12, and the results are similar to the net zero emission scenario. In 2050, the

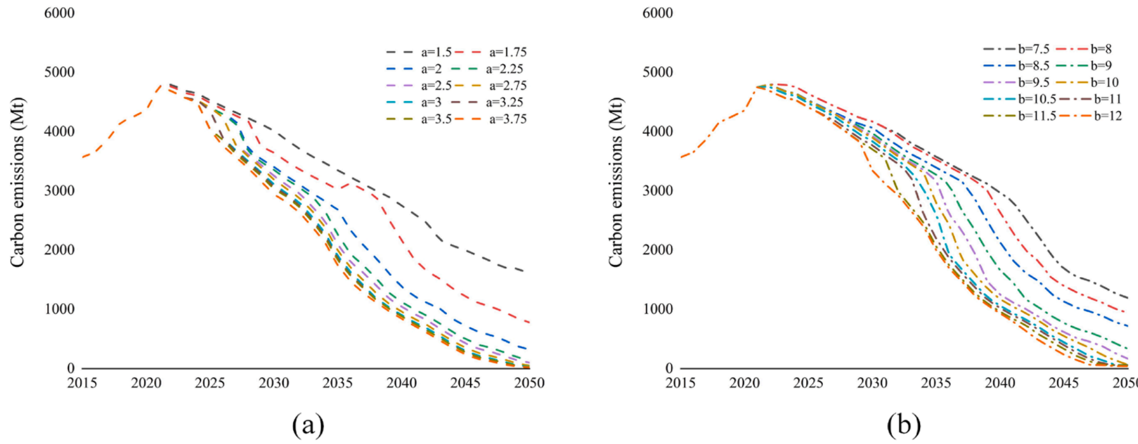

Fig. 10. Carbon emissions results under different carbon pricing mechanisms. (a) carbon emissions in the linear growth mechanism; (b) carbon emissions in the exponential growth mechanism.

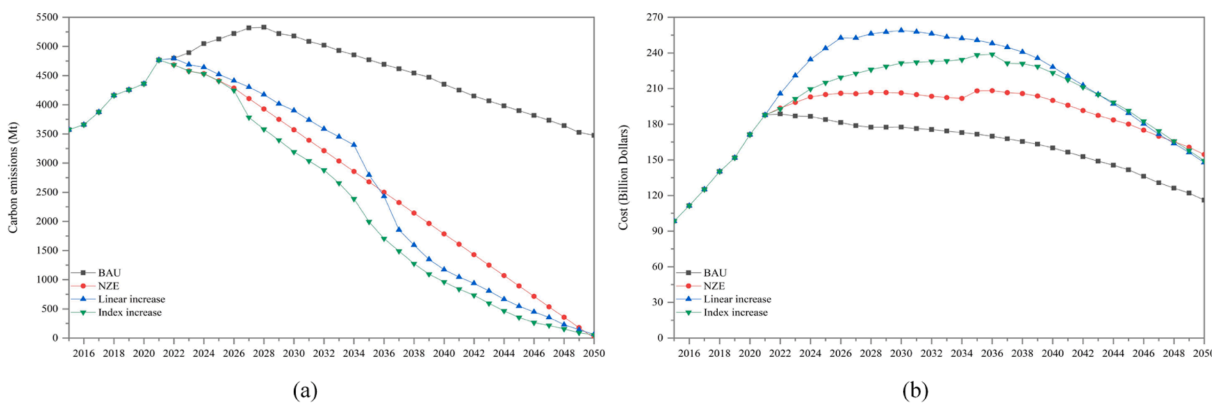

Fig. 11. Comparison of carbon emissions and cost results in different scenarios. (a) Carbon emissions in different scenarios; (b) Cost in different scenarios.

installed renewable energy capacity will be 5,336 GW, accounting for 75 % of the total installed capacity, with a generation of 103,738 TWh, equivalent to 73 % of the total generation. The difference is that, guided by the carbon price, natural gas power generation, being cleaner than coal due to lower emissions, serves as a transitional power source until the cost of CCS decreases. It will see stable growth until 2030, reaching a peak capacity of 208 GW. However, in the case of being driven by the net zero emission target, its capacity begins to decrease after 2035, to 114 GW by 2050.

3.6. Financial incentive scenario

Based on the optimal power generation mix, renewable energy sources such as onshore wind, solar and hydro gradually gain competitive advantages and will be fully developed due to cost reductions and carbon emission constraints. However, offshore wind, which started later and has higher cost, cannot achieve comprehensive development within a decade under the subsidy reduction policy, whether in the BAU, NZE or HCP. Given that China's eastern region has huge offshore wind energy resources and is close to the load centers, we argue that it is necessary to put in place certain financial incentives to stimulate the development of offshore wind power.

Combining the scenario design from Section 2.3 (4), the optimization is carried out for the two financial incentive scenarios, local subsidies and investment pattern optimization. This results in the additional capacity for each power source as shown in Fig. 13. In the local subsidy scenario (Fig. 13(a)), the comprehensive subsidy policy is based on the average value of subsidies announced by various provincial governments for offshore wind power, set at RMB 1000/kW, with a subsidy duration of 5 years (2022–2026). It can be seen that the effect of local subsidy is less remarkable in incentivizing the development of offshore wind power except the years 2024 and 2025, and stagnation expected after the subsidy is discontinued. In contrast, in the investment pattern optimization scenario (Fig. 13(b)), offshore wind power becomes competitive as early as 2023, and various types of renewable energy can achieve sustainable development.

3.7. Sensitivity analysis

Decarbonization in the power sector is a dynamic process influenced by various factors, including both the supply and demand sides. On the supply side, renewable energy generation, particularly sensitive to meteorological conditions, may be impacted by future climate change, and we choose to conduct sensitivity analysis on hydroelectric generation, which is most affected by climate change. Due to conflicting findings in existing research on whether climate change will increase or decrease China's hydroelectric capacity, we refer to the predictions of Wang [50] and Fan [51], considering two sensitivity scenarios for hydroelectric generation: H + 10 %, assuming a linear growth of 10 % by 2050; H-10 %, assuming a linear decrease of 10 % by 2050. Additionally, potential new clean energy generation technologies, such as geothermal, biomass, and ocean energy, may play a role in achieving net zero emission in the power sector. We design a sensitivity scenario for new generation technologies: N, incorporating geothermal, biomass, and ocean energy into the generation mix optimization module. On the demand side, the potential with flexible loads is a crucial aspect of a

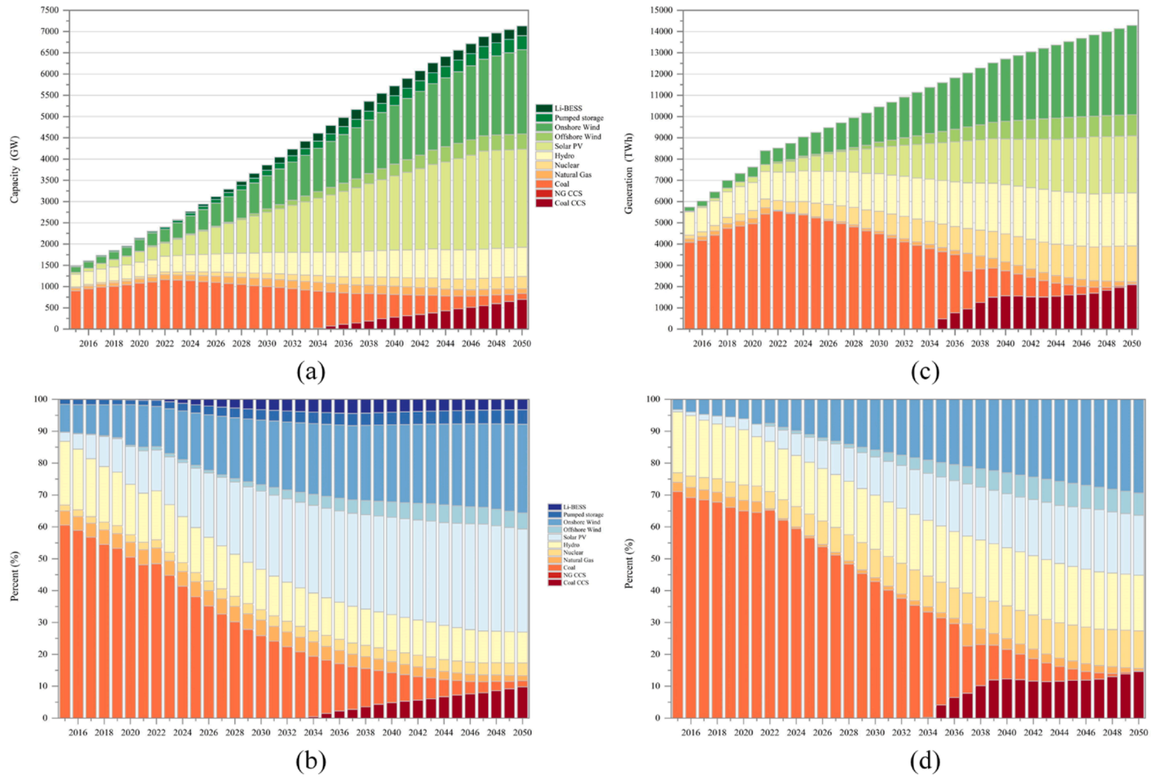

Fig. 12. Optimization results of capacity and power generation for HCP. (a) Absolute values of capacity; (b) Percent shares of capacity; (c) Absolute values of power generation; (d) Percent shares of power generation.

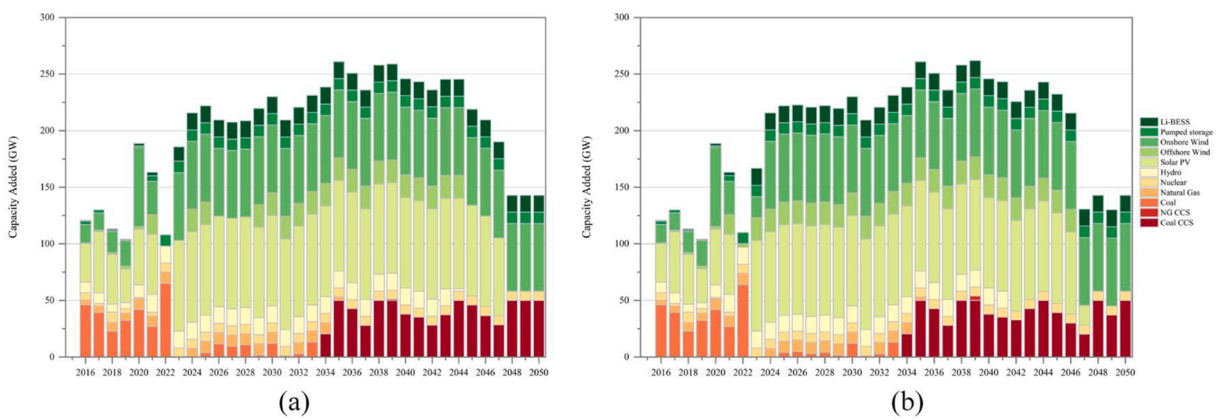

Fig. 13. Optimization results of capacity addition in FII. (a) Capacity addition in the local subsidy scenario; (b) Capacity addition in the investment pattern optimization scenario.

sustainable power system with large shares of variable renewable energy. According to the requirements of the ‘Measures for Demand-Side Management of Electricity’ [52] issued by the National Development and Reform Commission, we design a demand response sensitivity scenario: D-10 %, assuming a demand response capacity equivalent to 10 % of the maximum electricity load. Since the four scenarios designed in the research framework are progressive, we conduct a sensitivity analysis on the investment pattern optimization scenario in FII scenario, denoted as scenario F.

Sensitivity analysis results are presented in Fig. 14. Fig. 14(a) shows the capacity optimization results. By 2050, in the H-10 % scenario, the hydroelectric capacity is 68 GW less than the F scenario, while the total installed capacity is 128 GW more. In the H + 10 % scenario, the hydroelectric capacity is 10 GW more than the F scenario, while the total installed capacity is 84 GW less. This is because the decrease in hydroelectric generation makes it less economically viable, leading to its substitution by other renewable energy sources. Simultaneously, the decrease in generation requires more capacity from other sources. Conversely, the increase in hydroelectric generation enhances its techno-economic characteristics, but due to capacity constraints, it only contributes a small additional capacity. Additionally, the increase in generation reduces the total installed capacity needed to meet the same electricity demand. Fig. 14(b) presents the results of power system cost calculations. Due to differences in hydroelectric generation, the H-10 % scenario requires more investment and operating costs, resulting in a total cost of approximately $6,214 billion, 1.35 % higher than the F scenario. The H + 10 % scenario requires less investment and costs, with a total cost of approximately $6,034 billion, 1.59 % lower than the F scenario. Moreover, whether in the H-10 % or H + 10 % scenario, the optimal carbon price needed to achieve net-zero emissions remains

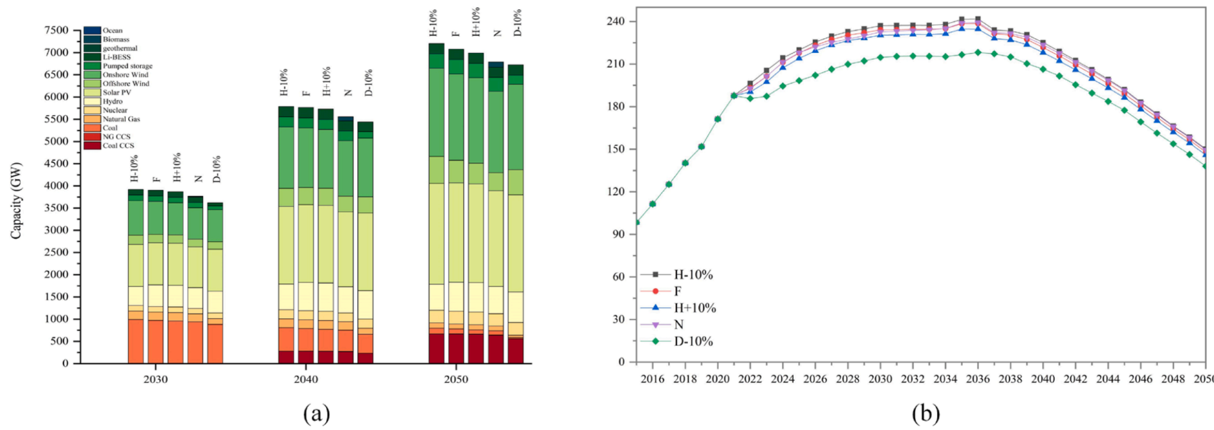

Fig. 14. Sensitivity analysis results of capacity and cost. (a) Absolute values of capacity mix; (b) Cost.

unchanged. Under the exponential growth carbon pricing mechanism, with a base price of $8/t and an annual increase of 10 %, the carbon emissions of the power sector in 2050 are 63.0 Mt and 65.4 Mt, respectively. This indicates that changes in hydroelectric generation have little impact on the policy requirements for decarbonization in the power sector.

Similarly, the sensitivity of new generation technologies is relatively low. By 2050, the N scenario has a total installed capacity 62 GW less than the F scenario. In this scenario, influenced by factors such as resource endowment and costs, only biomass power generation experiences some development, reaching an installed capacity of 121 GW by 2050. Compared to other renewable energy sources like wind and solar, biomass power generation has a higher utilization factor, resulting in a lower total installed capacity. In terms of costs, the total cost for the N scenario is approximately $61,464 billion over the calculation period, slightly higher than the F scenario. The optimal carbon price needed to achieve net zero emission in this scenario also remains unchanged.

In contrast, demand response shows higher sensitivity. By 2050, in the D-10 % scenario, the total installed capacity is 353 GW less than the F scenario. Although demand response does not lead to a decrease in the overall electricity demand, it helps match power supply and demand more efficiently, thereby reducing the required installed capacity of the power system. This is similar to the function of energy storage. Therefore, in the D-10 % scenario, the installed capacity of energy storage, especially pumped hydro storage, is lower. By 2050, the pumped hydro storage capacity is 206 GW, which is 120 GW less than the F scenario. In terms of costs, the total cost of the power system in the D-10 % scenario is $5674 billion, 7.47 % lower than the F scenario, significantly lower than other sensitivity analysis scenarios. Moreover, the optimal carbon price required to achieve net zero emissions is also lower in the D-10 % scenario, with the optimal carbon pricing mechanism starting at a base price of $8/t and increasing by 9.5 % annually, reaching $111/t by 2050.

4. Discussion

In the context of China's termination of national subsidies for new energy generation and the relatively low average carbon price in the national carbon market, we modeled the Chinese power system and its carbon emissions to explore the feasibility of achieving net zero emission in the Chinese power sector and the required policy measures. Simulation results indicate that, with stringent emission reduction constraints and considering resource and capacity limitations, the Chinese power sector can achieve net zero emission by 2050. Renewable energy installed capacity will increase to over 80 %, with wind and solar power accounting for over 70 %. This result aligns with findings in existing literature [53,54]. This suggests that a substantial increase in clean energy supply, particularly from wind and solar sources, coupled with the vigorous development of complementary energy storage technologies, can drive the low carbon transformation of the power sector and achieve net zero emission. However, according to the BAU results, under current policies and relying solely on market competition, the transformation of the power sector is insufficient, and carbon emissions are projected to remain high by 2050. This implies that market failures exist, preventing the automatic realization of a low carbon transformation in the power system, and policy intervention is required.

Carbon pricing is considered one of the most cost-effective public policy tools [55]. Our research indicates that the carbon pricing mechanism with exponential growth incurs much lower costs compared to the linear growth mechanism, aligning with the development realities of developing countries, including China. Moreover, as China has not yet reached its carbon peak and has more opportunities for carbon reduction compared to developed economies, the cost of emission reduction is lower. A lower carbon price at the current transitioning stage is more suitable under the exponential growth carbon pricing mechanism. From the perspective of carbon pricing levels, achieving net zero emission in the Chinese power sector by 2050 would require a carbon price of around $127/t. According to the "IPCC Special Report on Global Warming of 1.5 °C", achieving a 2 °C temperature control requires a global carbon price level of $15–220/t by 2030 and $45–1050/t by 2050. To achieve a 1.5 °C temperature control, global carbon price levels need to increase further to $135–6050/t by 2030 and $245–14300/t by 2050 [56]. Considering the varying development stages of different countries, we believe the calculated carbon pricing results for China fall within a reasonable range. In addition, appropriate financial incentives are also effective measures. After the termination of subsidies for new energy, if the carbon price is increased, China's onshore wind, photovoltaic, and other renewable energy sources will gradually gain a competitive advantage. However, due to higher costs, the development of offshore wind power may stagnate. Considering the financial constraints of local governments after the pandemic, China can refer to the European investment model of separating offshore wind power development and grid transmission. The grid-related projects for offshore wind power projects can be undertaken by the grid company. Under this investment model, the investment cost of offshore wind power will decrease, thereby promoting its development.

Finally, China's power sector is accelerating its transformation towards the net zero emission goal. Influenced by factors such as climate change, the decarbonization process in the future has significant uncertainty, and corresponding policies need constant adjustments. From the sensitivity analysis, it can be observed that the changes in electricity generation due to climate factors and new power generation technologies have minor impacts on the power sector's net zero emission, and it may not even affect carbon pricing policies. On the other hand, demand response will have a crucial impact on the power system by smoothing peaks and valleys, improving the operational efficiency of the power system, reducing investment and operating costs. Net zero emission can be achieved at relatively low carbon price levels. In the future, demand response should be a key focus along with renewable energy and energy storage in the low-carbon transformation of the power sector. As China's demand-side management capabilities improve, carbon pricing levels can be adjusted accordingly.

5. Conclusion and policy implications

The penetration of high renewable energy is the key pathway for decarbonizing the electricity sector. Despite having the world's largest renewable energy installed capacity, China's power supply is still dominated by coal-fired power. Under gradually stricter carbon emission targets, it is imperative that the penetration rate of renewable energy in China continues to increase. The development speed and scale of renewable energy will be influenced by market economics and government policies, and supportive policies are needed to guide the healthy development of various types of renewable energy to achieve the net zero goals of the electricity sector.

This paper develops a renewable energy penetration model to fully consider both the demand and supply side of the electricity sector in China. The simulation results show that on the demand side, China's electricity demand will continue to grow along with economic development in the country, but its growth rate will gradually slow down, reaching 10405, 12,561 and 14,096 TWh by 2030, 2040, and 2050, respectively. On the supply side, in the BAU scenario, by 2050, renewable energy share of installed capacity will reach 75 %, supplying 59 % of the electricity demand. At this point, carbon emissions will stand at 3,476.06 Mt, equivalent to the 2015 level. Under the NZE scenario, with mandatory emission reduction constraints in place, China's power sector can achieve net zero carbon emissions by 2050, leveraging its abundant renewable energy potential within capacity constraints. In this scenario, the share of renewable energy in installed capacity and electricity generation will increase to 80 % and 75 % respectively.

The findings demonstrate the feasibility of China achieving net zero emission by 2050 in its power sector while ensuring economic growth. To actively strive towards this goal, we design scenarios involving high carbon price policy scenario and financial incentive scenario. These scenarios, while ensuring net zero emission by 2050, evaluate the impact of different policies on renewable energy penetration and power system cost. Building on the findings noted above, the main policy recommendations are as follows:

(1) Promote the concurrent development of renewable energy, energy storage and demand response technologies. Under market mechanisms, the competitiveness of renewable energy costs is a prerequisite for its high penetration. At the same time, addressing the supply–demand matching challenges resulting from the high penetration of renewable energy requires a reduction in the cost of complementary energy storage and an enhancement in demand-side management capabilities. This can significantly boost the penetration rate of renewable energy. Implementing policies such as promoting advanced standards for various renewable energy and energy storage technologies, using administrative and economic measures to encourage user participation in demand response, optimizing the investment environment to reduce unreasonable costs in renewable energy development, and establishing a green financial system to lower the financing costs for renewable energy investments by enterprises are essential measures. These actions will continuously drive the development of energy storage, demand response, and renewable energy technologies, forming the foundation for accelerating decarbonization in the power sector.

(2) Implement a carbon pricing mechanism with exponential growth to gradually increase carbon prices in the carbon market. According to the simulation results of the high carbon pricing policy scenario, while achieving net zero emission by 2050, the carbon pricing mechanism with exponential growth saves 5.35 % of cost compared to the linear growth carbon pricing mechanism. This indicates that a carbon pricing mechanism that starts with slow growth and accelerates later is better suited for China's development stage. Currently, China's carbon market is in its early stages of operation with relatively few trading entities and sufficient quota supply. The carbon market should gradually enrich the trading entities and continuously raise carbon prices through adjusting quota supply and allocation methods. To achieve net zero emission by 2050 in the power sector, the carbon price levels should be approximately $18/t in 2030, about $48/t in 2040, and approximately $127/t in 2050.

(3) Provide appropriate financial subsidies and preferential policies for offshore wind power. The onshore renewable energy resources in eastern China is underdeveloped. If we want to achieve localized clean energy supply, it is necessary to promote offshore wind power development. However, as offshore wind power is a late starter in China, it has no cost advantage. Terminating financial subsidies due to financial pressure may hinder its expansion. Considering the financial burden on the government, an advisable approach is to consider the investment model used in European offshore wind power, where the costs of grid connection infrastructure are borne by the grid companies. This approach can stimulate technological advancement and cost reduction in the offshore wind power industry, leading to a smooth transition towards grid parity, and ultimately promoting the comprehensive and healthy development of renewable energy sources.

Although there are significant findings in this study, there exist some limitations in it. Given that the model primarily optimizes capacity expansion and electricity supply with a focus on cost, it considers reliability in the power system to a lesser extent, particularly without accounting for the impact of extreme weather. As climate change leads to more frequent extreme weather events, we plan to incorporate additional reliability constraints into the model in the future.

CRediT authorship contribution statement

Zhongrui Ren: Conceptualization, Methodology, Software, Writing. **Sufang Zhang:** Supervision, Editing, Funding acquisition. **Huijuan Liu:** Validation. **Ren Huang:** Validation. **Huaqing Wang:** Investigation. **Lei Pu:** Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

A.1 Lists the main basic data values of the electricity demand forecasting module

Table A1
Major macroeconomic data.

year	GDP(Billion yuan)	Population(Million person)	urbanization rate (%)
2015	688858.2	1383.26	57.33
2016	746395.1	1392.32	58.84
2017	832035.9	1400.11	60.24
2018	919281.1	1405.41	61.50
2019	986515.2	1410.08	62.71
2020	1013567.0	1412.12	63.89
2021	1149237.0	1412.60	64.72

Table A2
Proportion of value-added by various sectors.

	Primary industry (%)	secondary industry (%)	Among them: mining(%)	manufacturing (%)	construction (%)	other industries (%)	tertiary industry (%)
2015	8.4	40.8	6.8	71.9	16.6	4.7	50.8
2016	8.1	39.6	6.2	72.5	16.8	4.5	52.4
2017	7.5	39.9	6.4	70.5	17.5	5.6	52.7
2018	7	39.7	6.2	70.2	18.0	5.7	53.3
2019	7.1	38.6	6.2	69.4	18.6	5.8	54.3
2020	7.7	37.8	5.7	69.5	18.9	5.9	54.5
2021	7.2	39.3	5.5	70.1	17.7	6.6	53.5

Table A3
Main data of the transportation sector.

	Number of electric vehicles (thousands of vehicles)	Driving mileage (billion kilometers).	Converted turnover (in billions of ton-kilometers).	Railway electrification rate (%)
2015	580		3350.37	61.2
2016	910		3380.11	64.5
2017	1530		3748.87	68.5
2018	2600		3986.50	60.2
2019	3090	41.6	4153.91	71.9
2020	4920	64.1	3565.59	74.9
2021	7840	100.94	3950.91	77

Appendix B

Lists the main basic data values of the power generation mix optimization module.

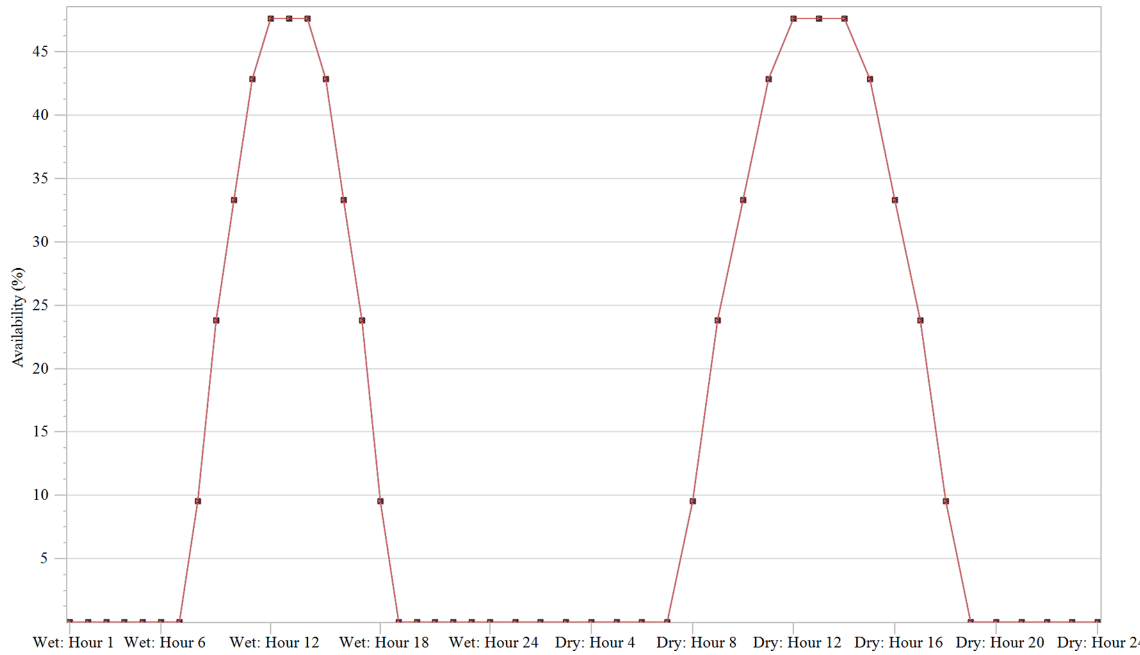

Fig. B1. Availability of solar PV.

Table B1
Historical capacity of various types of power sources (Thousand kW).

	2015	2016	2017	2018	2019	2020	2021
Pumped storage	23,050	26,090	28,690	29,990	30,290	31,490	36,390
New Energy Storage	0	600	210	1210	2110	4110	7050
Onshore Wind	129,716	145,844	161,210	179,825	202,310	272,650	302,320
Offshore Wind	1034	1626	2790	4445	6840	9000	26,390
Solar PV	42,180	76,310	130,420	174,330	204,290	253,560	306,540
Hydro	296,490	305,980	315,420	322,600	327,750	338,790	354,550
Nuclear	27,170	33,640	35,820	44,660	48,740	49,890	53,260
Coal	900,090	946,240	985,620	1,008,350	1,040,630	1,082,630	1,109,620
Natural Gas	66,030	70,110	75,800	83,750	90,240	99,730	108,940

Table B2
Historical electricity generation of various types of power sources (billion kwh) .

	2015	2016	2017	2018	2019	2020	2021
Onshore Wind	185.6	240.9	304.6	365.8	405.3	466.5	655.8
Solar PV	39.5	66.5	117.8	176.9	224	261.1	327
Hydro	1096.9	1144	1161.9	1199.2	1270.2	1321.8	1300.9
Nuclear	171.4	213.2	248.1	295	348.7	366.2	407.5
Coal	4079.6	4169.9	4417.3	4742.3	4846.2	4958.3	5417.6
Natural Gas	166.9	188.3	203.2	215.5	232.5	252.5	287.1

Table B3
Investment cost of various types of power sources (Only some years are listed) ($/kW).

	2022	2025	2030	2035	2040	2045	2050
Pumped storage	1499	1499	1508	1508	1508	1508	1508
New Energy Storage	1258	998	786	738	688	639	590
Onshore Wind	1111	985	776	737	698	660	621
Offshore Wind	1691	1526	1382	1293	1228	1177	1135
Solar PV	635	556	426	407	388	369	350
Hydro	1596	1596	1526	1456	1387	1387	1387
Nuclear	2205	2112	2090	2019	1949	1878	1808
Coal	1070	1053	1002	951	918	885	853
Natural Gas	926	909	890	870	851	833	814
Coal CCS	1729	1687	1563	1421	1275	1243	1211
NG CCS	1439	1382	1304	1222	1149	1109	1069

Table B4
Fixed OM Cost of various types of power sources (Only some years are listed) ($/kW).

	2022	2025	2030	2035	2040	2045	2050
Pumped storage	17.8	17.8	17.8	17.8	17.8	17.8	17.8
New Energy Storage	48.37	38.40	30.25	28.37	26.48	24.59	22.70
Onshore Wind	42.19	40.98	38.95	37.49	36.03	34.57	33.11
Offshore Wind	98.79	91.03	83.01	77.63	73.58	70.33	67.62
Solar PV	19.95	18.17	15.22	14.72	14.23	13.74	13.25
Hydro	54	54	54	54	54	54	54
Nuclear	146	146	146	146	146	146	146
Coal	22	22	22	22	22	22	22
Natural Gas	21.43	21.43	21.43	21.43	21.43	21.43	21.43
Coal CCS	42.5	42.5	42.5	42.5	42.5	42.5	42.5
NG CCS	35.4	35.4	35.4	35.4	35.4	35.4	35.4

Table B5
Other major parameters of power sources.

	Variable OM Cost ($/MWh)	Maximum Capacity Addition (MW)	Life-time	Availability (%)		energy efficiency (%)
				dry	wet	
Pumped storage	0.51	10,000	40	60	60	85
New Energy Storage	0	30,000	15	80	80	85
Onshore Wind	0	70,000	30	20	30	100
Offshore Wind	0	20,000	30	30	40	100
Solar PV	0	60,000	30	Fig. B1	Fig. B1	100
Hydro	0	20,000	50	28	60	100
Nuclear	2.31	10,000	40	90	90	32.62
Coal	5.03	100,000	30	85	85	38.77
Natural Gas	2.77	10,000	30	80	80	52.90
Coal CCS	50	50,000	30	85	85	38.77
NG CCS	15	10,000	30	80	80	52.90

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