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A copula-based whole system model to understand the environmental and economic impacts of grid-scale energy storage

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HIGHLIGHTS

- Developed a novel model integrates optimisation, IO model, and copula function.
- Analysed the whole system's economic and carbon emission impacts of energy storage.
- Investigated the impact of grid-level energy storage in different power systems.
- The Copula function was adopted to deal with uncertainty in sector disaggregation.

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ABSTRACT

Energy storage is important in future power systems. However, the role of grid-scale energy storage in the power system and in the whole socio-economic system is unclear. A copula-based whole system model is developed to explore the economic and environmental effects of grid-scale energy storage, thus supporting the decision-making at micro and macro levels. A power system optimisation model is linked with an input-output model, and the copula function is embedded in the model to reflect the multiple and interactive uncertainties from electricity demand, emission constraints, and sector disaggregation. We conducted case studies on China and the UK in 2025 considering different storage technologies (Pumped hydro, Battery, Flywheels storage) to show the differences related with power systems and economic structures. We find that increasing energy storage capacity leads to increase in renewable generation capacity (solar generation in China and wind generation in the UK). Thus, it can reduce their total economy-wide carbon emissions. Uncertainty in sector disaggregation will have a large impact on carbon emissions in some extreme cases, especially in those sectors closely linked to the power sector and with high emission intensity.

1. Introduction

The CO_2 emissions from the power sector account for around 48 % of China's total CO_2 emissions and 16 % of the UK's emissions [1,2]. Decarbonisation of power system is therefore essential for meeting net-zero carbon objectives but is increasingly challenging as future electricity demand increases [3]. To achieve this, cleaner power generation will be required by gradually shifting from relying mainly on traditional fossil fuels to relying more on renewable energy sources such as wind and solar power. Electricity is central to many parts of life in modern societies. The decarbonisation of power system will inevitably affect other sectors as well, such as the heating, transport, and industrial sectors. Therefore, a whole system perspective is needed to investigate the impacts of decarbonisation of power systems. Due to energy storage playing a vital role in managing the intermittency of renewable energy generation, the whole system's economic and environmental impacts of energy storage incorporated into power systems with renewable energy generation need to be studied.

There is a high demand for energy storage in future power systems [4]. Among the current mainstreaming energy storage technologies, pumped hydro storage (PHS) is the most widely used storage technology globally, and battery energy storage (BES) is the most scalable and for which the market has seen strong growth in recent years, especially in China [5]. Other storage technologies account for a relatively small

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share of current energy storage systems, where flywheel energy storage (FES) may play a major role in frequency regulation as a very short-term storage type [6]. Hydrogen is considered an emerging technology with potential for the seasonal energy storage of variable renewable energy (VRE) [7]. Different types of energy storage thus need to be considered in power systems.

1.1. Literature review

In terms of grid-level energy storage, much emphasis of existing papers are placed on studying the optimal capacity of different types of energy storage incorporated in power systems with renewable power generation. Cárdenas et al. used an iterative method to explore how much energy storage capacity would be required as the penetration of renewables increases, but only compressed air energy storage (CAES) was considered [8]. Based on this, they investigated how to combine different energy storage technologies to minimise the total cost of electricity in a 100 % renewable-based grid [9]. Ziegler et al. explored the optimal combination of wind and solar power with storage to meet various electricity demands for four states of the US based on a self-developed optimisation model [10]. Li et al. developed an electricity system optimisation model to explore how to combine energy storage and renewable energy generation to achieve the UK electricity system's decarbonisation [11]. Cebulla et al. used an energy system model to analyse the required storage capacity for energy scenarios in Europe with high penetration of renewables [12].

Energy storage affects the operation of power systems, thus leading to changes in the whole system's economic and environmental performance. Studies on the economic impact of energy storage mainly focus on the impact on power system costs [13–16], and studies on the environmental impact focus mainly on the impact on power systems' carbon emissions [13,17–23]. Some of these studies revealed that the carbon emissions impact of energy storage on power systems is uncertain and can be positive, neutral, or negative [17–19]. There are some research explored the environmental and economic effects of the deployment strategies of energy storage. Peng et al. designed three battery deployment strategies to evaluate the effects on carbon emissions and system costs of China's provincial power sector [13]. Beuse et al. investigated the impact of different application scenarios of energy storage systems on carbon emissions of power systems in seven European countries [21]. McKenna et al. used an estimated marginal emission factor to analyse the impact of different energy storage operating scenarios on carbon emissions of power systems with high penetration of wind power [20]. Similarly, Pimm et al. calculated the regional marginal emissions factors of the UK's power system in 2019 to explore the carbon emissions impacts of storage operations [22]. Tang et al. studied the carbon emission reduction benefits of three energy storage strategies for twenty-eight European countries in 2019 by considering embodied emissions from cross-grid electricity transfer [23].

An integrated model that links bottom-up and top-down models has been widely used to evaluate the economy-wide impact. Siala et al. linked the outputs of the power system optimisation model to an extended Multi-Regional Input-Output (MRIO) model for evaluating the environmental and socio-economic impacts derived from the new power system [24]. Rocco et al. integrated an IO model and the OSeMOSYS model to analyse the economic and environmental impacts under the future energy generation mix [25]. Taliotis et al. constructed a model that integrates an optimisation model and IO model to assess the economic impact of policy pathways for energy transition in Cyprus [26].

In summary, many studies have focused on the alignment of renewable energy with optimal energy storage capacity, however, the reverse question has not yet been addressed (how to match the operational dynamics of energy storage systems with the optimal renewable generation and capacity mix). Moreover, existing studies have only analysed the economic and environmental effects of energy storage across the electricity system (i.e., direct effects). The whole system's economic and environmental effects (including direct and indirect effects) of energy storage have not been explored. In most cases, the use of an integrated model including the IO model requires sector aggregation and disaggregation of IO tables as appropriate. In conducting sector disaggregation, different disaggregation coefficients adopted may lead to different results. However, most present studies didn't take into account this uncertainty.

1.2. Motivation and contributions

Few studies have compared the whole system's impacts of energy storage in different national contexts, including different power systems and different economic structures. China is a manufacturing powerhouse and strongly relies on coal-fired power plants, whereas the UK is dominated by services industries and has a high gas-fired power plant capacity. Additionally, wind power dominates UK renewable energy generation, and solar power generation in China has seen a fast increase in recent years [27,28]. These distinct case studies offer valuable insights that can be extended to other economies with similar power systems and economic profiles. Specifically, in some economies with power systems similar to China's, developing solar power is a good option; in some economies with power systems similar to the UK's, developing wind power may be better. In industrially advanced countries similar to China, emission reduction strategies could focus on sectors with high carbon intensity, such as the non-metal and construction industries. Conversely, in economies with structures similar to that of the UK, emission reduction efforts might be more effectively directed toward electricity-intensive sectors, such as the steel industry.

To fill the above-mentioned gaps, a copula-based whole system model is developed to evaluate the economic and carbon emissions effects at the economy-wide level of changes in grid-scale energy storage for China and the UK in 2025. The contributions of this study are as follows: First, answered the question of how to match their operation of energy storage systems with the optimal renewable generation and capacity mix for two countries that have different power systems; Second, the whole system's effect is considered to better reveal the economic and carbon emissions impacts of energy storage; Third, the copula function is embedded into the model to provide a new perspective to consider uncertainties in disaggregating IO tables. Fourth, the model developed in this study can also be used for other economies, which is a useful tool for their policymakers in developing policies to decarbonise their power systems.

The rest of this paper is organized as follows. Section 2 describes the copula-based whole system model and presents the scenario setting and data sources for two cases. Section 3 shows the results and discussion. Section 4 summarises the conclusions, policy implications, and future research direction.

2. Methodology

The copula-based whole system model is developed shown in Fig. 1. The optimal installed capacity mix obtained from power system optimisation is used as input of the copula function and the optimal generation mix obtained from power system optimisation is used as the input of IO model to generate the sectoral final demand after sector disaggregation. Then shares of installed capacity at different confidence levels (used as disaggregation coefficients) obtained from using the copula function are used to generate IO tables at different confidence levels. Finally, the IO model can be used to analyse the whole system's economic and environmental impacts. The details of each part of this model are described as follows. The data source of this model is mentioned below. Other information, like the parameters of the power optimisation model, can be found in Supplementary Material.

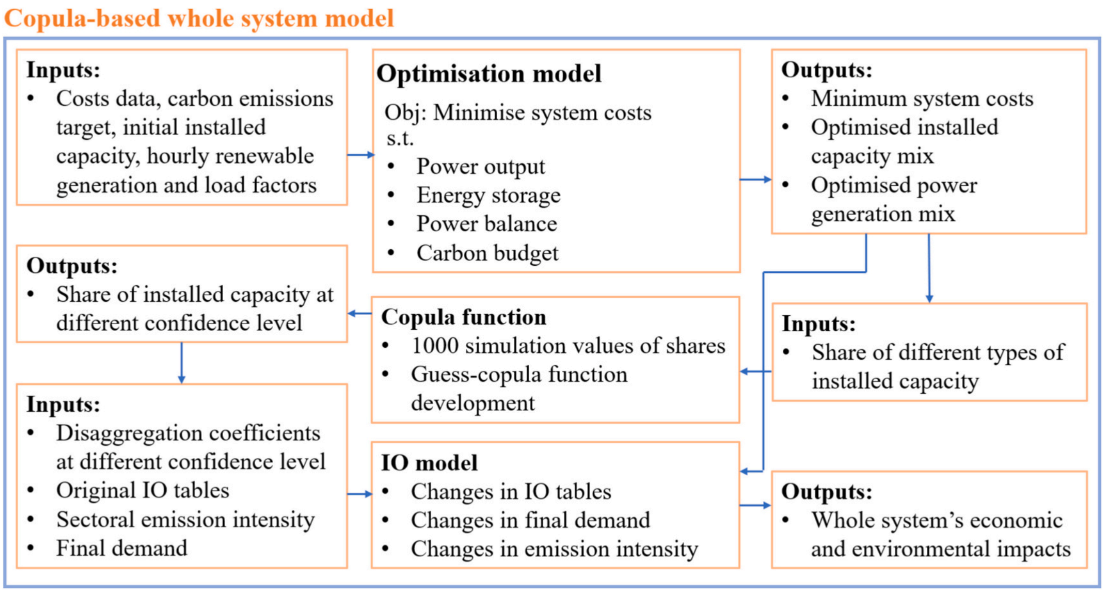

Fig. 1. The diagram of copula-based whole system model.

2.1. Copula-based whole system model

2.1.1. Power system optimisation model

A linear power system optimisation model with hourly time resolution is developed to minimise the annual operation cost and capacity expansion costs of power systems at the national level in 2025. This model follows the following assumptions. 1) the total electricity demand in the economy can be jointly met by various types of domestic generation technologies and storage technologies and there are no losses related to transmission and distribution; 2) the electricity import from other countries and export to other countries is not considered; 3) the decommissioning of existing installed capacity is not considered due to the model being only used for short-term planning; 4) new types and small shares of installed capacity of power generation technologies and energy storage technologies are also not considered. The objective function can be expressed as eq. (1).

$$minC=\sum_{t\in T}\sum_{i\in I}c_i^{op}P_{i,t}+\sum_{t\in T}\sum_{s\in S}c_s^{op}\left(P_{s,t}^{charge}\eta_s^{charge}+P_{s,t}^{disch}\Big/\eta_s^{disch}\right)+\sum_{i\in I}c_i^{inv}\left(P_i^{instal}-P_i^{ex}\right)+\sum_{s\in S}c_s^{energy}\left(E_s^{instal}-E_s^{ex}\right)+\sum_{s\in S}c_s^{power}\left(P_s^{instal}-P_s^{ex}\right) \quad (1)$$

where.

t is the index describing a specific time interval;

i is the index describing a specific electricity generation technology;

s is the index describing a specific energy storage technology;

T is a set of 8760 h over a year, $t \in T$;

I is a set of generation technologies (VRE: wind and solar; other technologies in the UK: hydro, coal, gas, bioenergy, nuclear; other technologies in China: hydro, coal, gas, nuclear), $i \in I$;

S is a set of storage technologies (PHS, BES, and FES for the UK; PHS and BES for China), $s \in S$;

c_i^{op} is a parameter for the unit operating cost of generation technology i, including fuel cost ($/MWh);

c_s^{op} is a parameter for the unit operating cost of storage technology s ($/MWh);

c_i^{inv} is a parameter for the unit capital investment cost of generation technology i ($/MW);

c_s^{energy} is a parameter for the unit energy-related capital investment cost of storage technology s ($/MWh);

c_s^{power} is a parameter for the unit power-related capital investment cost of storage technology s ($/MW);

η_s^{charge} and η_s^{disch} are parameters for charging and discharging efficiency of storage technology s, respectively;

P_i^{ex} is a parameter for the initial existing power capacity of generation technology i (MW);

P_s^{ex} is a parameter for the initial existing power capacity of storage technology s (MW);

E_s^{ex} is a parameter for the initial existing energy capacity of storage technology s (MWh);

$P_{i,t}$ is a variable for power output of generation technology i at time t (MW);

$P_{s,t}^{charge}$ and $P_{s,t}^{disch}$ are variables for charging and discharging power of storage technology s at time t, respectively (MW);

P_i^{instal} is a variable for the installed capacity of generation technology i (MW);

P_s^{instal} is a variable for the installed power capacity of storage technology s (MW);

E_s^{instal} is a variable for the installed energy capacity of storage technology s (MWh).

In eq. (1), The first term represents the operating costs of all generation technologies; the second term indicates the charging and discharging costs of all energy storage technologies; the third term represents the capacity expansion capital costs of all generation technologies. The last two terms represent capital costs of all storage technologies of energy installed capacity and power installed capacity expansion, respectively. Different types of generation and storage considered in our model are listed above. Note that the lithium-ion battery is considered a representative battery storage technology because more than 90 % of current battery energy storage systems use lithium-ion battery technology which will continue to play an important role in the foreseeable future [5]. According to Mongird et al. [29] and public data, the E/P ratio of BES, PHS, and FES is 2 h, 8 h, and 0.4 h, respectively. The E/P ratio refers to the energy-to-power ratio, often expressed in hours, which represents the rate of maximum storage in MWh or kWh to the power rating in MW or kW.

The following constraints are required for the model. Eqs. (2)–(4) represent the constraints of power output of each generation type. Eqs. (2) and (3) are for non-VRE and VRE, respectively. The constraints of energy storage capacity can be formulated by eqs. (5)–(12). The power balance constraint is formulated by eq. (13). The carbon emissions limit is formulated by eq. (14). Eq. (15) states that all variables are non-negative.

$$P_{i,t} \le P_i^{instal} * CF_i \text{ for } i \in \{I, i = non\_VRE\} \tag{2}$$

$$P_{i,t} = A_{i,t} P_i^{instal} \text{ for } i \in \{I, i = VRE\} \tag{3}$$

$$\mathrm{P}_i^{ex} \le \mathrm{P}_i^{instal} \le \mathrm{P}_i^{max} \forall i \tag{4}$$

$$\mathrm{P}_{s,t}^{charge} \le \mathrm{P}_s^{instal} \forall s \tag{5}$$

$$\mathrm{P}_{s,t}^{disch} \le \mathrm{P}_s^{instal} \forall s \tag{6}$$

$$\mathrm{P}_s^{ex} \le \mathrm{P}_s^{instal} \forall s \tag{7}$$

$$\mathrm{E}_s^{ex} \le \mathrm{E}_s^{instal} \forall s \tag{8}$$

$$\mathrm{E}_s^{instal} \le \mu_s \mathrm{P}_s^{instal} \forall s \tag{9}$$

$$\mathrm{E}_{s,t} = \mathrm{E}_{s,t-1} + \mathrm{P}_{s,t}^{charge} \eta_s^{charge} - \mathrm{P}_{s,t}^{disch} \Big/ \eta_s^{disch} \forall s, t\ (t \ne 0) \tag{10}$$

$$\mathrm{E}_{s,t} = \mathrm{P}_{s,t}^{charge} \eta_s^{charge} - \mathrm{P}_{s,t}^{disch} \Big/ \eta_s^{disch} \forall s, t\ (t = 0) \tag{11}$$

$$\mathrm{E}_{s,t} \le \mathrm{E}_s^{instal} \forall s \tag{12}$$

$$\sum_{i \in I} \mathrm{P}_{i,t} - \sum_{s \in S} \left(\mathrm{P}_{s,t}^{charge} - \mathrm{P}_{s,t}^{disch} \right) = \mathrm{A}_t^d * \mathrm{P}^{load\_yr} \tag{13}$$

$$\sum_{t \in T} \sum_{i \in I} \mathrm{EF}_i * \mathrm{P}_{i,t} \le \mathrm{Q} \tag{14}$$

$$\mathrm{P}_{i,t}, \mathrm{P}_{s,t}^{charge}, \mathrm{P}_{s,t}^{disch}, \mathrm{P}_i^{instal}, \mathrm{P}_s^{instal}, \mathrm{E}_s^{instal}, \mathrm{E}_{s,t} \ge 0 \forall i, s, t \tag{15}$$

where.

CF_i is a parameter for the capacity factor of generation technology i;

$A_{i,t}$ is a parameter for the hourly generation factor of solar or wind power at time t;

P_i^{max} is a parameter for the upper bound of the capacity of generation technology i (MW);

μ_s is a parameter for E/P ratio of storage technology s;

A_t^d is a parameter for electricity load factor at time t;

P^{load_yr} is a parameter for the peak load in yr year (MW);

EF_i is a parameter for the emission factor of generation technology i (t CO_2/MWh);

Q is a parameter for the carbon emissions limit of the power sector (t CO_2);

$E_{s,t}$ is a variable for electricity stored by storage technology s at time t (MWh).

The optimisation model is a linear programme solved using Gurobi [30], with the output fed to the IO model.

2.1.2. Input-output model

The IO model developed by Leontief [31] is used to analyse the economic and carbon emissions impacts. The economic effects after power system optimisation can be indicated by the total output matrix $\mathbf{X_b}$, see eq. (16).

$$\mathrm{X_b} = (\mathrm{I} - \mathrm{A_b})^{-1} \mathrm{F_b} \tag{16}$$

where $\mathbf{I}$ is the identity matrix; $\mathbf{A_b}$ is the matrix of direct input coefficients of domestic products after power system optimisation; $(\mathbf{I} - \mathbf{A_b})^{-1}$ is the Leontief inverse matrix; $\mathbf{F_b}$ represents the final demand matrix after power system optimisation. Where

$$\mathrm{A_b} = \begin{pmatrix} \mathrm{A^N} & \mathrm{A^{Ne}} \\ \mathrm{A^{eN^*}} & \mathrm{A^{e^*}} \end{pmatrix}; \mathrm{F_b} = \begin{pmatrix} \mathrm{F^N} \\ \mathrm{F^{e^*}} \end{pmatrix} \tag{17}$$

where the matrix $\mathbf{F^{e^*}}$ represents the final demand of power subsectors after power system optimisation; matrix $\mathbf{F^N}$ represents the final demand of common sectors, which is from the disaggregated 2025 IO tables. The matrices $\mathbf{A^{eN^*}}$ and $\mathbf{A^{e^*}}$ represent the direct consumption coefficients of the power subsectors to the common sectors and the power subsectors to themselves after power system optimisation, respectively; matrices $\mathbf{A^N}$ and $\mathbf{A^{Ne}}$ represent the unchanged direct consumption coefficients of the common sectors to the common sectors and the common sectors to the power subsectors; which can be also derived from the disaggregated 2025 IO tables.

The eq. (16) can be extended as eq. (18) to analyse the carbon emissions effects after power system optimisation.

$$\mathrm{TE} = \mathrm{e}(\mathrm{I} - \mathrm{A_b})^{-1} \widehat{\mathrm{X_b}} \tag{18}$$

where $\mathbf{TE}$ is a row vector representing the total carbon emissions in 2025 by sector; $\mathbf{e}$ is a row vector with the elements representing the carbon emissions per unit of total output of each sector, which can be calculated by eq. (19); $\widehat{\mathbf{X_b}}$ is a diagonal matrix of $\mathbf{X_b}$. A detailed description of this model can be found in Miller & Blair [32].

$$e_i = \begin{cases} e_i^o, i = 1, \dots, N \\ CF_i * \sum_{t \in T} P_{i,t}, i = n, \dots, n+k \end{cases} \tag{19}$$

where e_i is the elements in the row vector $\mathbf{e}$, e_i^o is the carbon emissions intensity of common sector i, which is assumed to be equal to the carbon emissions per unit of total output of sector i in 2020 in China and in 2019 in the UK. For emission intensity of the power subsectors, it is equal to multiplying the carbon factor of generation technology CF_i by power generation $\sum_{t \in T} P_{i,t}$ obtained after power system optimisation.

The direct and indirect emissions can be written by eqs. (20) and (21).

$$\mathrm{DE} = \mathrm{e}\widehat{\mathrm{X_b}} \tag{20}$$

$$\mathrm{IE} = \mathrm{TE} - \mathrm{DE} = \mathrm{e}(\mathrm{I} - \mathrm{A_b})^{-1} \left(\widehat{\mathrm{X_b}} - \widehat{\mathrm{F_b}} \right) \tag{21}$$

where $\mathbf{DE}$ and $\mathbf{IE}$ represent direct and indirect emissions matrix, respectively; $\widehat{\mathbf{F_b}}$ is a diagonal matrix of $\mathbf{F_b}$. In this study, the sectoral direct and indirect carbon emissions refer to emissions generated within the sector and emissions generated by the sector as a result of the use of products or services from other sectors, respectively, which constitute the sectoral total carbon emissions.

2.1.3. Copula function

The copula function is a good tool to solve joint distribution problems between multiple correlated variables. It is widely used in financial risk analysis and hydrological modelling. With reference to Fan et al. [33], this study takes a step further from Lindner et al. [34] and uses it for sectoral disaggregation of IO tables. Due to the uncertainty of sector disaggregation, a Monte Carlo simulation is used to obtain 1000 simulation values for the disaggregation coefficients based on the future installed capacity mix under different scenarios in disaggregating the power sector. Then, the joint distribution can be expressed in eq. (22).

$$\mathrm{H}(\mathrm{v}_1, \ldots, \mathrm{v}_k) = \mathrm{C}(\mathrm{F}_1(\mathrm{v}_1), \ldots, \mathrm{F}_k(\mathrm{v}_k)) \tag{22}$$

where $F_k(v_k)$ represents the marginal distribution for the kth variable v_k, which is obtained based on 1000 simulation values of the corresponding disaggregation coefficients. $C(x)$ is a copula function. According to the inverse transformation of cumulative distribution functions, expressed in eq. (23), the copula function can be rewritten as eq. (24).

$$\mathrm{v}_i = \mathrm{F}_i^{-1}(\mathrm{u}_i)\ (i = 1, 2, \ldots, k) \tag{23}$$

$$\mathrm{C}(\mathrm{u}_1, \ldots, \mathrm{u}_k) = \mathrm{H}\left(\mathrm{F}_1^{-1}(\mathrm{u}_1), \ldots, \mathrm{F}_k^{-1}(\mathrm{u}_k)\right) \tag{24}$$

where F_i^{-1} is the inverse cumulative distribution function of the standard normal distribution; $H(x)$ is the joint cumulative distribution function of the multivariate normal distribution.

Thus, the joint cumulative distribution function of these correlated disaggregation coefficients can be obtained. A representative set of coefficients (the most likely value) is selected for updating the new intermediate matrix. Then IO tables at the most likely and original cases are used to conduct IO simulation.

2.2. Scenario design

In this study, we consider the impacts of three factors—electricity demand, carbon emissions constraints, and energy storage capacity. Peak load is chosen as an indicator of the electricity demand. Specifically, three peak loads (Base, Low, and High-Demand), two carbon emissions constraints (Loose, Strict), and three sets of storage capacity (No energy storage, Optimal level, Capacity doubles based on optimal level) (Table 1).

It is noted that the hourly load in our model is obtained by multiplying the peak load level set in scenarios by the hourly load factor. The peak loads of China and the UK in 2022 are 1,290,000 MW and 46,000 MW, respectively [35,36]. Thus, the values of peak load under three scenarios are shown in Table 1. The growth rate of 5.5 % and 1.5 % is estimated based on the average economic growth rate forecast referred to by the World Bank [37]. The change rate of 5 % in electricity demand is a random estimate based on the reality. As China announced carbon peak by 2030 and the UK announced net-zero emissions for the energy system by 2035, two scenarios (CP30/NZE35) are set accordingly, with more ambitious carbon emission targets (CP25/NZE30) are set. The carbon emissions of China under two scenarios are from Shu et al. [38], the values of carbon emissions under these two scenarios in the UK are calculated based on the UK's power sector's carbon emissions in 2022 (around 54 million tonnes) [2]. The decline rates of emissions under two scenarios in the UK are derived by summing up the average annual rate of decline in total carbon emissions. We then combine these three factors to set up eighteen scenarios (Table 2).

Table 1
The explanation of different levels of each factor.

	Description	Peak load in 2025 (MW)
China	Base: an average annual growth of 5.5 % based on 2022 level	1,500,000
	Low-demand (LD): 5 % lower than the Base scenario	1,425,000
	High-demand (HD): 5 % higher than the Base scenario	1,575,000
UK	Base: an average annual growth of 1.5 % based on 2022 level	48,000
	Low-demand (LD): 5 % lower than the Base scenario	45,600
	High-demand (HD): 5 higher than the Base scenario	50,400
	Description	Carbon constraints in 2025 (Mt)
China	Carbon peak by 2030 (CP30)	4700
	Carbon peak by 2025 (CP25)	4100
UK	Net-zero emissions (NZE) by 2035 (NZE35): a decline of 24.1 % by 2025 from 2022 level	41
	NZE by 2030 (NZE30): a decline of 37.5 % by 2025 from 2022 level	34
	Description	Storage capacity in 2025 (MW)
China	Opt: storage capacity obtained from results of optimisation model ES2: capacity doubles based on optimal level ES0: no storage capacity available	See Table S3
UK	Opt: storage capacity obtained from results of optimisation model ES2: capacity doubles based on optimal level ES0: no storage capacity available	See Table S4

2.3. Data source and processing

The UK and China IO tables are from the Office for National Statistics (ONS) and the National Bureau of Statistics of China (NBSC), respectively. The 2020 CO_2 emissions inventory of China is from China Emission Accounts and Datasets (CEADs) and the 2019 carbon emissions intensities inventory of the UK is from ONS. For the optimisation model, the hourly generation factors of solar, wind, and hourly electricity load data are from Tong et al. [39]. Hourly load factors are obtained from hourly load divided by peak load. Other data, like costs and installed capacity of different generation and storage types, can be found in Tables S1 and S2 in Supplementary Material.

In processing the IO tables, the 105 sectors of the UK IO table in 2019 are first aggregated into 20 sectors to fit our research focus, considering those with higher contributions to GDP, energy consumption, and CO_2 emissions. The classification of China's IO table in 2020, with 42 sectors, remains unchanged since it is highly aggregated. It is assumed that the structure of production and final demand remain unchanged in the short term. 2025 is the simulation year selected for our study, thus the final demand by sector in 2025 can be forecasted by eq. (25), which can be calculated by multiplying the total final demand F' in 2025 by the structure of final demand in the original IO tables **f**.

$$\mathrm{F}' = \mathrm{f}^* F' = \mathrm{f}^*(1+g)^* F \tag{25}$$

where $\mathbf{F}'$ represents the matrix of final demand by sector in the 2025 IO tables, F is the total final demand derived from the original IO tables, g is the change rate of total final demand, which is the same as the change rate of GDP due to the relationship between GDP and the total final demand in IO tables. The change rate is based on the International Monetary Fund forecast report on future economic development [40].

Table 2
Scenarios of electricity demand, carbon constraint and storage capacity in 2025.

Scenarios	Energy storage	Electricity demand	Carbon constraints
S1	Opt	Base	CP30 (or NZE35)
S2	Opt	LD	CP30 (or NZE35)
S3	Opt	HD	CP30 (or NZE35)
S4	Opt	Base	CP25 (or NZE30)
S5	Opt	LD	CP25 (or NZE30)
S6	Opt	HD	CP25 (or NZE30)
S7	ES2	Base	CP30 (or NZE35)
S8	ES2	LD	CP30 (or NZE35)
S9	ES2	HD	CP30 (or NZE35)
S10	ES2	Base	CP25 (or NZE30)
S11	ES2	LD	CP25 (or NZE30)
S12	ES2	HD	CP25 (or NZE30)
S13	ES0	Base	CP30 (or NZE35)
S14	ES0	LD	CP30 (or NZE35)
S15	ES0	HD	CP30 (or NZE35)
S16	ES0	Base	CP25 (or NZE30)
S17	ES0	LD	CP25 (or NZE30)
S18	ES0	HD	CP25 (or NZE30)

According to the balance relationship of IO tables, the total output by sector, intermediate demand, primary input and total input in the 2025 IO tables can be obtained.

On the basis of the IO tables in 2025, the power sector in both China and the UK is disaggregated, which follows the approach of Lindner et al. [34]. The IO table is originally composed of N + 1 sectors (N common sectors and 1 power sector), and it has N common sectors and k power subsectors after disaggregation. The intermediate input matrix is divided into four parts: the intermediate input matrix of unchanged common sectors; the matrix of input of common sectors to new sectors; the matrix of input of new sectors to common sectors; and the matrix of input of new sectors to new sectors. The matrices of final demand, primary input; as well as total input and output are divided into two parts.

In this study, the transmission and distribution (T&D) of electricity is first split from the power sector in 2025 China IO table according to the proportion of revenues in 2020 of China's three major grid operators in the total output of electricity sector in 2020. The new power sector excluding the T&D sector is then disaggregated into nine subsectors for China based on the shares of installed capacity by technology (six power generation sectors: hydroelectricity, coal-fired generation, gas-fired generation, nuclear power, wind power, solar power; and two storage sectors: pumped hydro, battery; and the other sector). Finally, the other sector combined with the T&D sector to form a new sector (i.e., the Other sector).

The T&D sector in the UK's 2025 IO table is not split due to a lack of data support. Similarly, the power sector is directly disaggregated into eleven subsectors for the UK (seven power generation sectors: hydroelectricity, coal-fired generation, gas-fired generation, bioenergy, nuclear power, wind power, solar power; and three storage sectors: pumped hydro, battery, flywheels; and the other sector). The difference between the UK and China is due to the differences in their power systems and storage systems, with the UK having a non-negligible share of bioenergy power generation and flywheel storage. Other generation and storage technologies with a relatively small share of installed capacity, such as CAES, are not considered separately for both China and the UK.

In order to correspond to the sector classification of disaggregated 2025 IO tables (50 sectors for China; 30 sectors for the UK), which can be found in Tables S5 and S6, the carbon emissions intensities by sector are adjusted.

3. Results and discussion

3.1. Optimal generation installed capacity

Fig. 2 shows the optimal installed capacity (in 2025) of each generation type compared to the existing capacity (in 2022) in China and the UK. The optimal capacity of power generation and energy storage under S1-S6 can be obtained by running the optimisation model; doubling the storage capacity on these respective basis gives the optimal generation capacity under S7-S12, and the optimal generation capacity under S13-S18 is obtained when the storage capacity is zero (shown in Tables S3 and S4). Figs. S1-S6 and Tables S1-S6 can be found in Supplementary Material.

In general, renewable energy capacity is expanded more when storage capacity is abundant, China tends to expand solar power generation, while the UK tends to expand wind power generation; when storage capacity is insufficient, renewable energy capacity is expanded less, and other types of energy are needed to meet the electricity demand. The capacity expansion of solar power generation increases in China while wind power generation expands in the UK as electricity demand increases and carbon constraints become stricter. The order of capacity expansion is mainly related to the investment cost and average capacity factor. In China, gas-fired generation is the first to expand capacity due to it having the lowest investment cost, and solar power

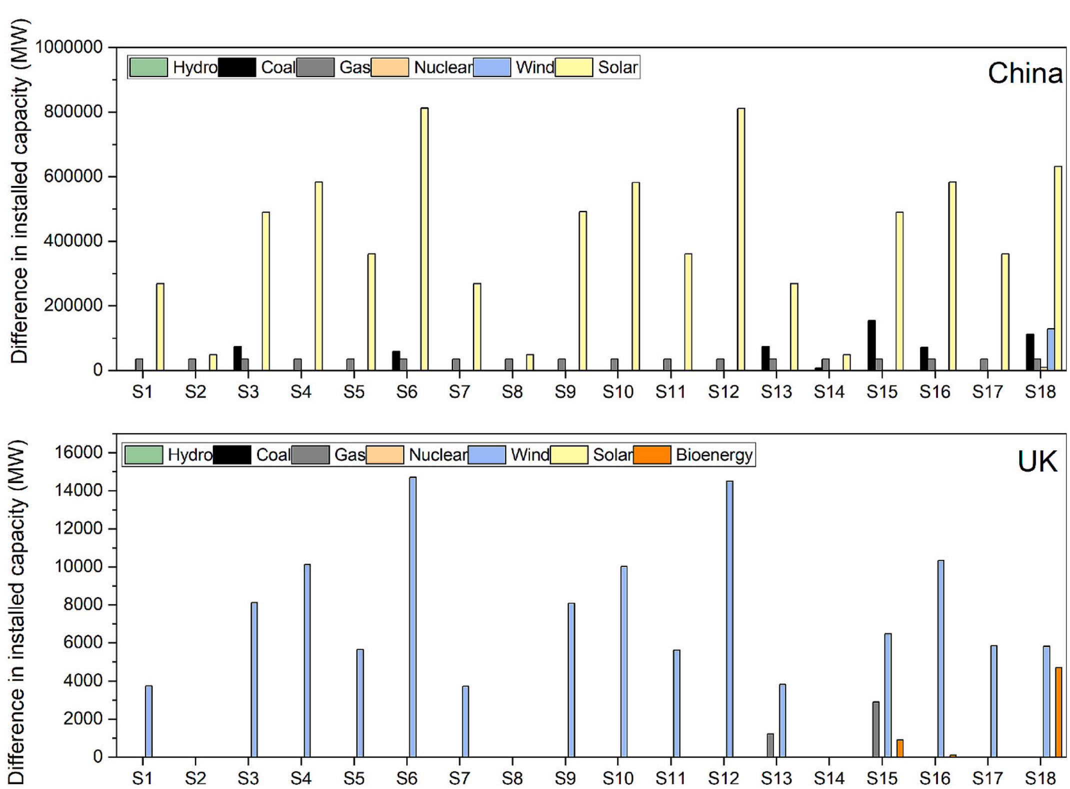

Fig. 2. The difference in optimal planning installed capacity of each generation type in China and the UK in 2025 under each scenario compared to existing capacity in 2022.
Note: The installed capacity of those generation types that will not be expanded remains at the 2022 levels since power plant decommissioning is not considered in our model.

generation is expanded due to its lower investment cost compared to other clean energy power generation. In the UK, the investment cost of wind power generation is lower than solar power generation considering the capacity factor, thus it is expanded. Other generation types, like coal-fired generation in China and gas-fired generation in the UK, are required to be expanded if the current generation capacity is insufficient to meet peak loads, as shown in S15. However, they cannot expand freely due to carbon emission constraints. Wind power generation in China and bioenergy power generation in the UK can be complementary generation types and thus are expanded in the context of high electricity demand and the absence of energy storage, as shown in S18.

3.2. Optimal generation mix

The optimal generation mix of the power systems in China and the UK under each scenario is shown in Fig. 3. In China, coal-fired generation dominates power generation across all scenarios, accounting for more than 40 % of the total power generation. The share of solar power generation ranges from around 11 % when electricity demand is low and the carbon constraint is loose, to 26 % when demand is high and carbon constraint is strict. In the UK, gas-fired generation is the dominant type of power generation. As carbon constraints become stricter and electricity demand higher, this leads to a decline in gas-fired generation share from 44 % to 33 %, with it largely replaced by wind power generation, whose share rose from 15 % to 30 %. The shares of other generation types do not vary much in comparison to scenarios with no energy storage, where the shares of wind power generation in China and bioenergy power generation in the UK under S18 reach 12 % and 26 %, respectively. Additionally, the shares of coal-fired generation in the UK across all scenarios are almost zero, which coincides with the UK's target to phase out coal-fired power generation by 2025 [41].

In many cases, the expanded capacity will only be used to generate electricity during the peak load periods. To understand the utilisation efficiency of different power generation under each scenario, we compare the ratios obtained by using the annual electricity generation shares of each generation type divided by their corresponding capacity shares, which are shown in Fig. 4.

The utilisation rate of solar power generation in China increases as electricity demand increases and carbon constraints become tighter. This indicates that although solar power generation operates at the maximum available power, the share of annual electricity generation changes more than the share of capacity of solar power generation. With no energy storage, coal-fired power generation in China is utilised less on average due to the expansion of coal-fired power generation only to meet peak loads. In the UK, wind and gas-fired power generation utilisation rates are mainly influenced by carbon emission constraints. The stricter the carbon constraints, the higher the utilisation rate of wind generation but the lower the utilisation rate of gas-fired generation. This is because when carbon constraints are stricter, electricity generation from coal-fired generation will be reduced and replaced by wind generation. Also, the ratio of nuclear generation is highest in both China and the UK across all scenarios, which indicates that nuclear power generation is the most consistently utilised of these types of power generation to meet base load. In China, the utilisation efficiencies of gas and coal-

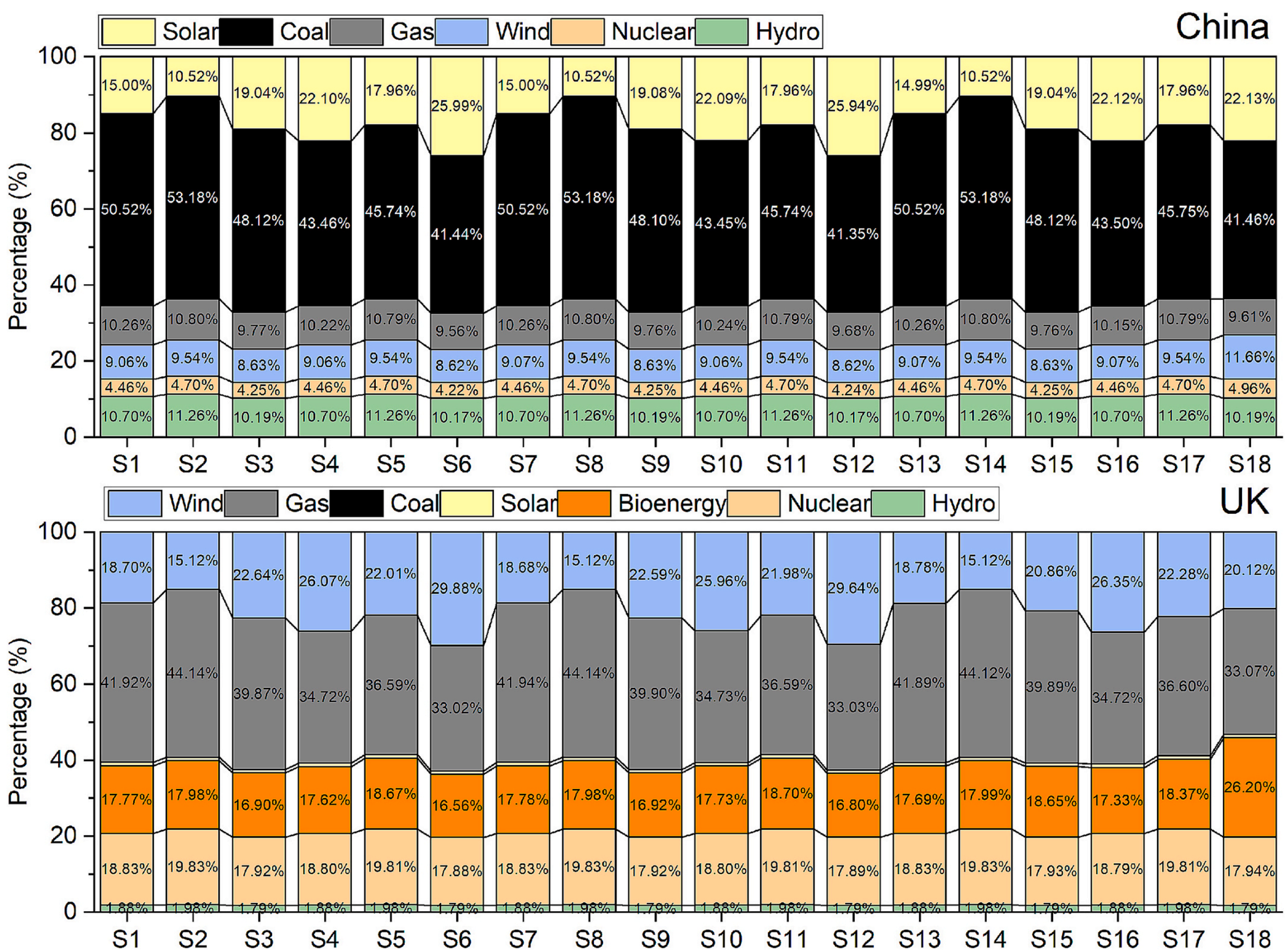

Fig. 3. The optimal generation mix in China and the UK in 2025 under each scenario.

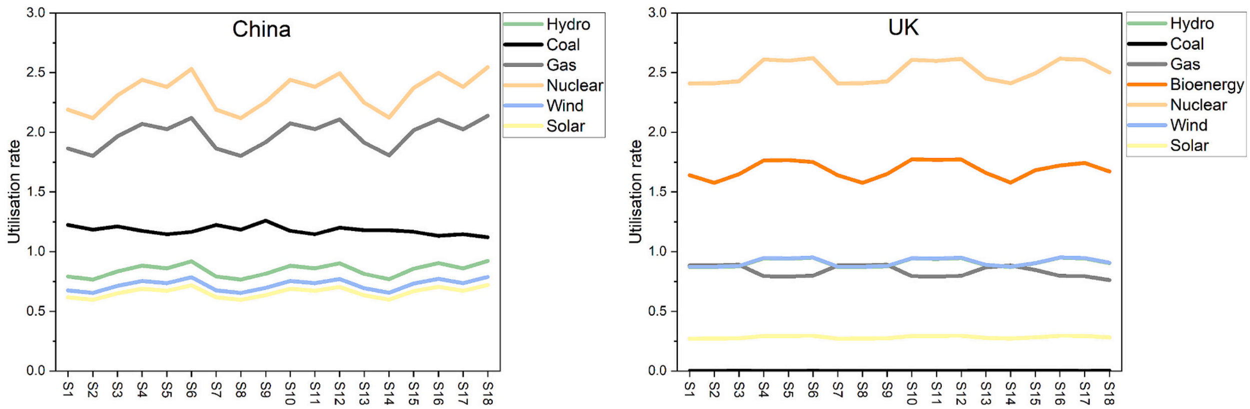

Fig. 4. Utilisation of different generation types in China and the UK under each scenario.

fired generation are relatively high, while the utilisation efficiencies of bioenergy and wind power generation are high in the UK.

Compared to scenarios with doubling storage capacity and without storage, the total power system costs are lower under the optimal storage capacity cases, with the minimised cost when with low electricity demand and loose carbon constraint, i.e., S2 (Opt, LD, CP30/NZE35). The impact of increased energy storage capacity on system costs in the UK is greater than the impact of reduced capacity, while the opposite is true in China (Fig. S5). This is because the UK's electricity supply has more capacity than China's relative to their respective electricity demand, and energy storage has a greater role to play in balancing China's electricity supply and demand.

3.3. Hourly operation of the power systems

The energy storage system must be charged when electricity demand is low to store excess electricity and then discharged when demand is high. Hourly charge and discharge by different storage types under different scenarios in China and the UK are shown in Figs. S1 and S2; hourly operation of different power generation technologies across all scenarios in China and the UK are shown in Figs. S3 and S4. With base electricity demand and a loose carbon constraint in China, increasing storage capacity leads to a shift in the use of storage (from PHS to BES) due to the higher efficiency of BES. To better show the results, we chose one month's results for comparison. Fig. 5 shows the results under S1 (Opt, Base, CP30) and S7 (ES2, Base, CP30), it can be seen that BES is more frequently used when there is more storage capacity. Compared to S1, S7 has slightly less solar power generation capacity but more BES capacity. To discharge the same amount of electricity, PHS requires more excess electricity for charging because of its lower efficiency compared to BES, which increases the total costs. Thus, BES is used more to store electricity under S7.

With high demand and a loose carbon constraint, increasing storage capacity leads to a shift from different energy storage types working separately to working together in China because of a reduction in coal-fired generation capacity, and results in a shift in the use of storage (mainly from PHS to BES) in the UK since BES has a higher efficiency. In Fig. 6, compared to S3 (Opt, HD, CP30) in China, BES is used more frequently under S9 (ES2, HD, CP30) because more BES capacity and less coal-fired generation capacity can be used under S9. Also, BES can be used separately under S3 while working together with PHS to be charged under S9 at some time in the second half-year because it is not

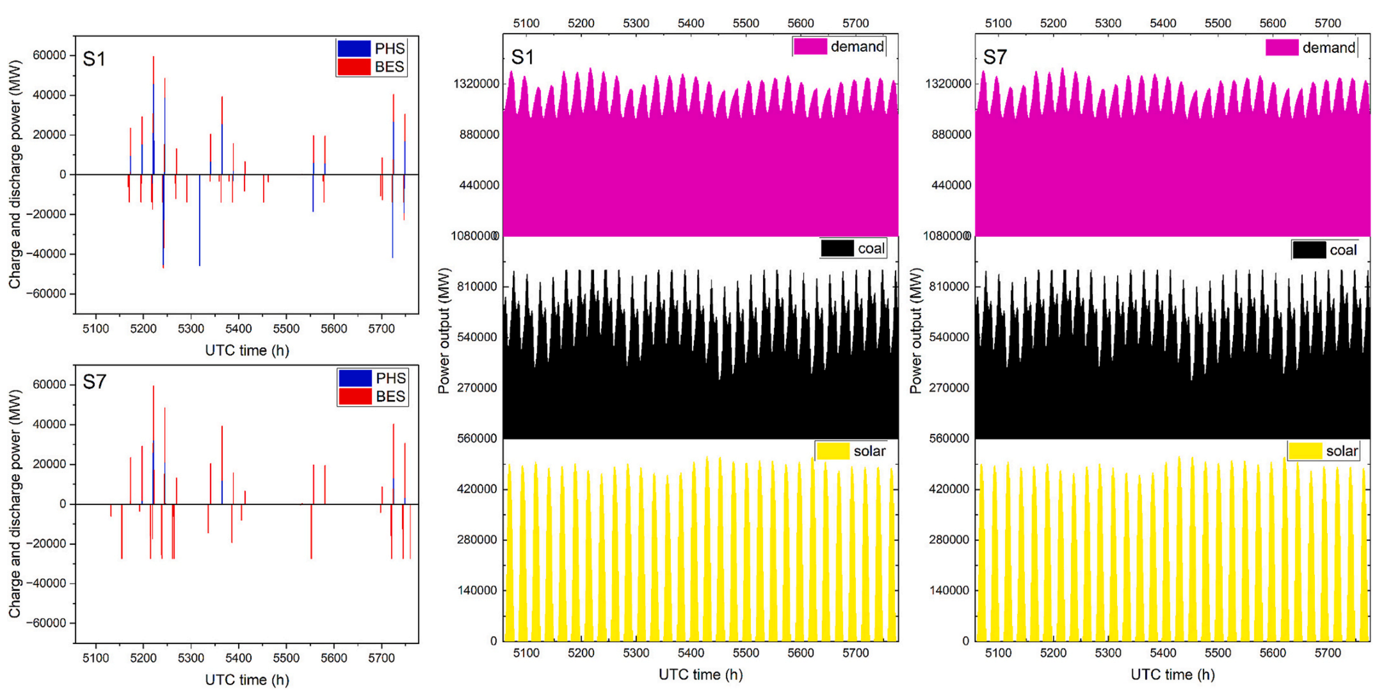

Fig. 5. Hourly charge (negative) and discharge (positive) of energy storage and power generation under S1 and S7 in China.

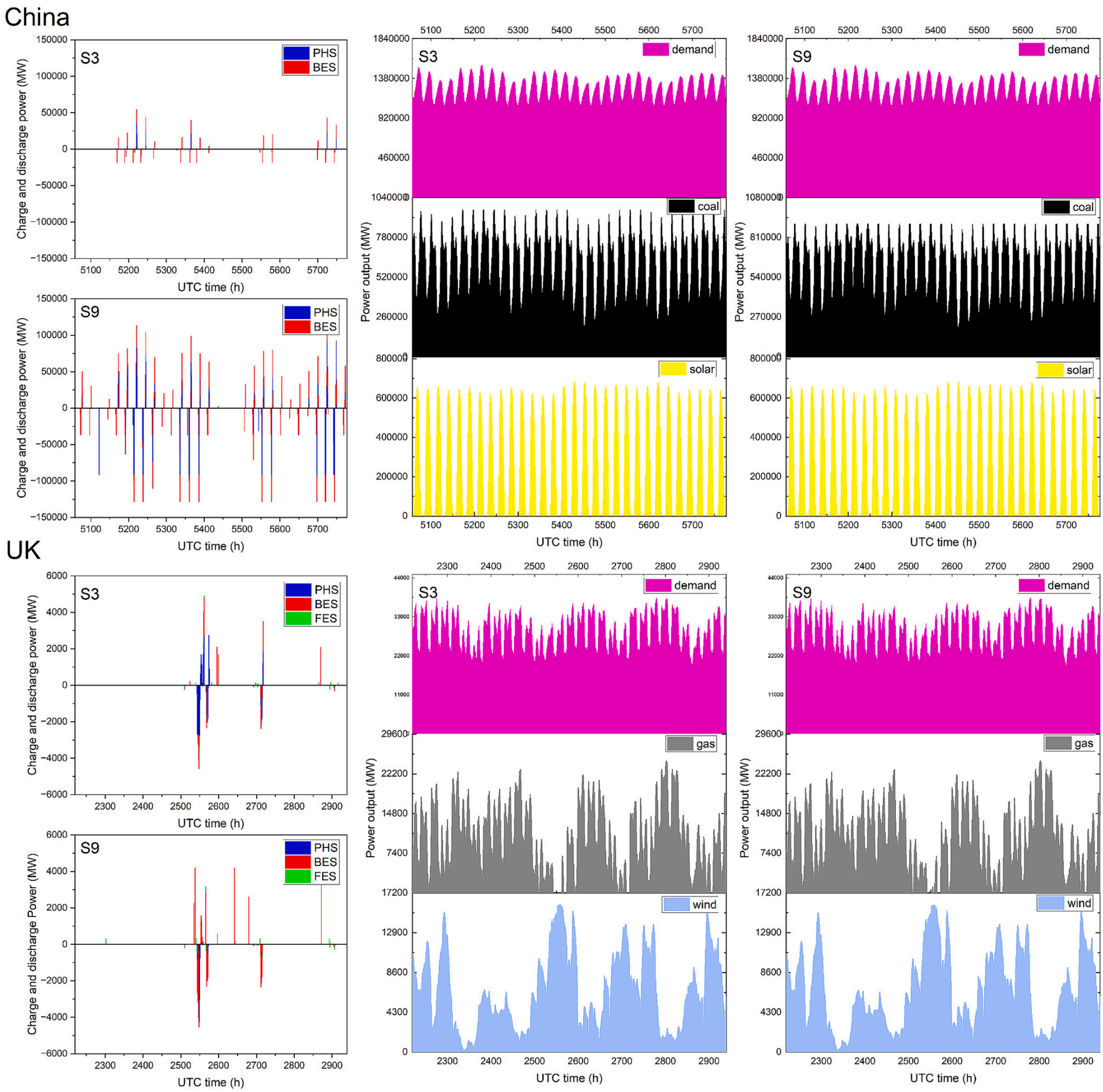

Fig. 6. Hourly charge (negative) and discharge (positive) of energy storage and power generation under S3 and S9 in China and the UK.

enough to meet the residual electricity demand by using BES alone due to less coal-fired generation capacity under S9. In the UK, due to the higher efficiency of BES, it is used less under S3 (Opt, HD, NZE35) compared to S9 (ES2, HD, NZE35) at some time in summer because using BES to store excess electricity can reduce the use of electricity generation from gas-fired generation, thus can reduce the total costs. Additionally, since coal-fired generation has a higher carbon intensity, it will be used in the UK only when gas-fired generation cannot meet the residual electricity demand at peak load times, although it has a lower operation cost.

With base electricity demand and a strict carbon constraint, increasing storage capacity leads to a shift from working together to working separately on different energy storage types in both China and the UK. In Fig. 7, under S4 (Opt, Base, CP25/NZE30) and S10 (ES2, Base, CP25/NZE30), since electricity generation in China from coal-fired generation in the first half-year is reduced and solar power generation is expanded, energy storage needs to be used more in the first half-year. Also, energy storage capacity is less under S4 compared to S10, thus BES and PHS need to complement each other to store excess electricity and meet the remaining electricity demand under S4, while they can be used separately at some time under S10 to meet these two objectives. Similarly, PHS, BES, and FES need to discharge together to meet the residual electricity demand and charge together to store the excess power from wind and gas-fired generation under S4 in the UK.

3.4. Economy-wide effects

The total economic output is not affected by the change in storage

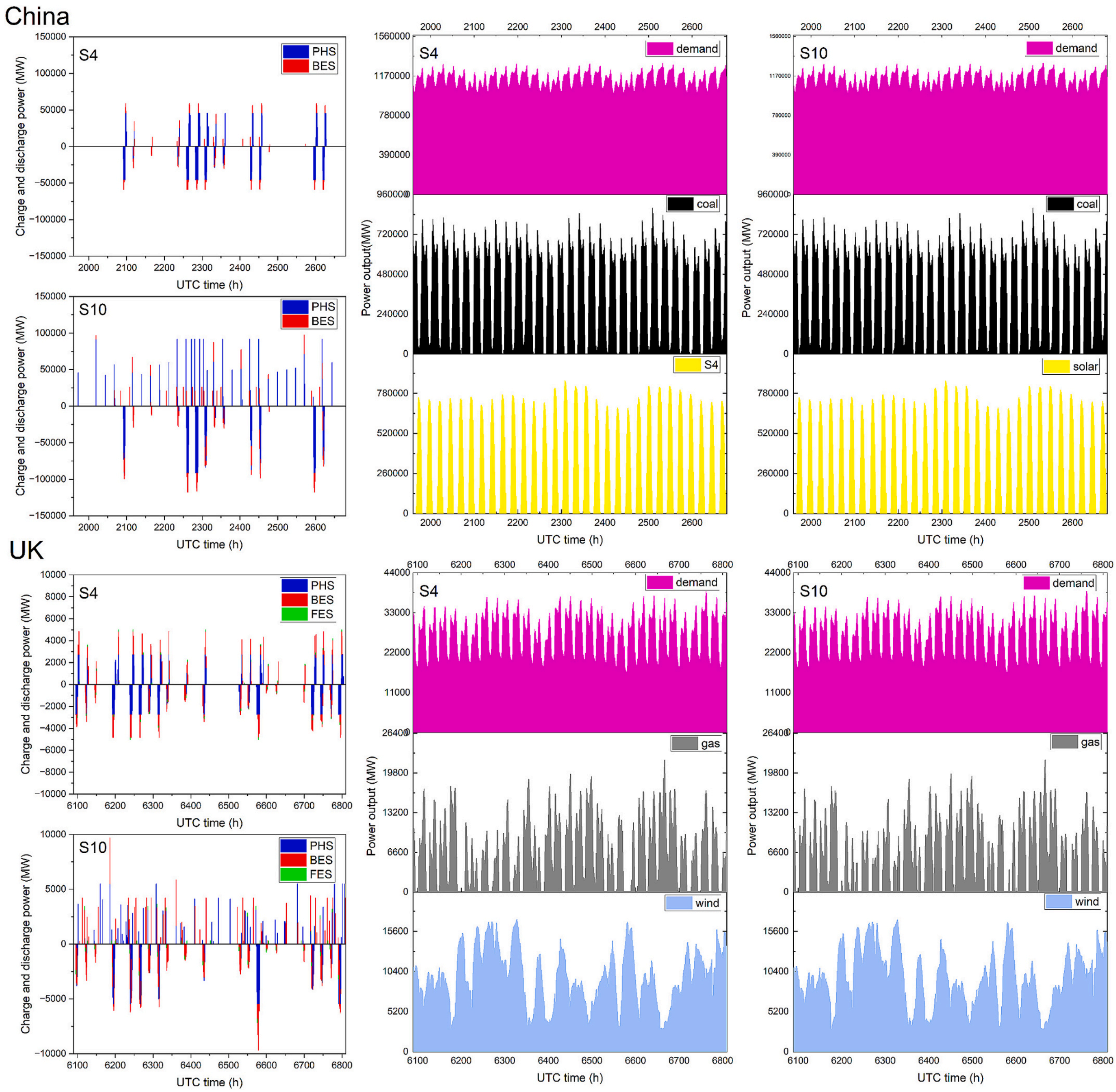

Fig. 7. Hourly charge (negative) and discharge (positive) of energy storage and power generation under S4 and S10 in China and the UK

capacity but is only related to electricity demand. An increase in electricity demand will lead to an increase in the power sector's final demand, which will increase the total economic output (Fig. S5). Fig. 8 compares the total carbon emissions of China and the UK under different energy storage capacity scenarios. For both China and the UK, the total carbon emissions decrease when energy storage capacity doubles but increase when there is no storage compared to those scenarios with optimal storage capacity. This suggests that increasing energy storage has a positive effect on the whole system's carbon emissions reduction.

Moreover, changes in storage capacity will lead to indirect emissions changes in all sectors but only lead to changes in direct carbon emissions of coal and gas-fired generation sectors for China and the UK. This is because only the emission intensities of coal- and gas-fired are changed after optimising the power system, which is based on the assumption that in the optimisation model, the carbon factors for each power generation and energy storage type except for coal- and gas-fired electricity generation are zero. Generally speaking, bioenergy power is considered carbon neutral, and other types of power generation and storage do not directly emit CO_2. The direct emissions of coal- and gas-fired generation can be obtained by multiplying the annual electricity generation by their corresponding carbon factors.

In Fig. 8, we can see that the total carbon emissions difference of "HD-CP30/NZE35" is greater than others, which means the difference between different energy storage capacity scenarios with high electricity demand and low carbon constraints is greater. Thus, S3 (Opt, HD, CP30/NZE35), S9 (ES2, HD, CP30/NZE35), and S15 (ES0, HD, CP30/NZE35), which belongs to the type of "HD-CP30/NZE35", are chosen to compare sectoral emissions distribution. The sector classification of China and the UK IO tables is shown in Tables S5 and S6.

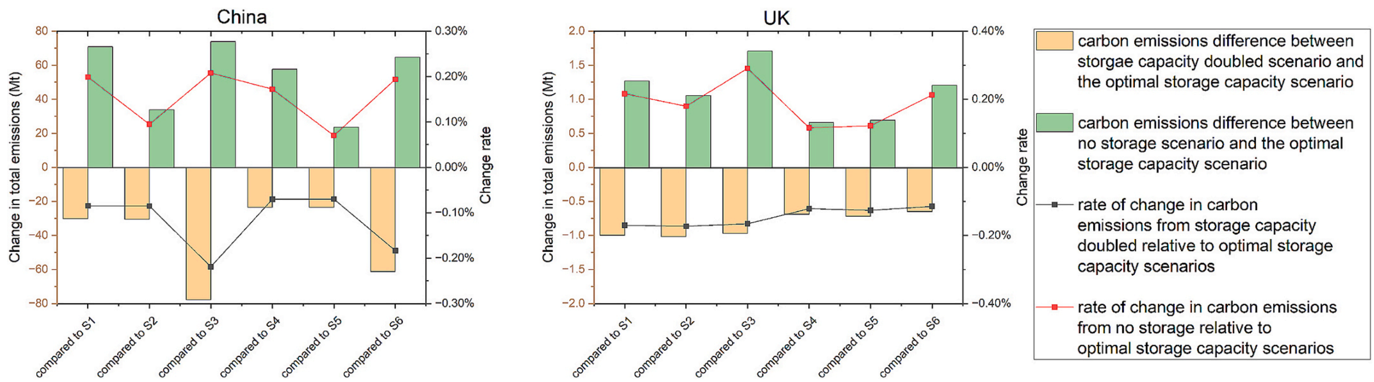

Fig. 8. The difference in total carbon emissions in China and the UK under no storage and doubling storage capacity compared to the optimal storage capacity scenarios with the same electricity demand and carbon constraints

Table 3
The difference in sectoral carbon emissions of power subsectors in China and the UK between S3, S9, and S15 (unit: Mt).

	Sec code	Difference between S9 and S3		Difference between S15 and S3	
		Direct emissions	Indirect emissions	Direct emissions	Indirect emissions
China	Sec42	0.00 (0.00 %)	−0.49 (−0.35 %)	0.00 (0.00 %)	0.11 (0.08 %)
	Sec43	−0.07 (−0.00 %)	−27.85 (−5.82 %)	0.14 (0.00 %)	28.82 (6.02 %)
	Sec44	0.07 (0.02 %)	−0.25 (−0.38 %)	−0.14 (−0.03 %)	0.08 (0.12 %)
	Sec45	0.00 (0.00 %)	−0.10 (−0.40 %)	0.00 (0.00 %)	0.03 (0.14 %)
	Sec46	0.00 (0.00 %)	−0.48 (−0.34 %)	0.00 (0.00 %)	0.10 (0.07 %)
	Sec47	0.00 (0.00 %)	−0.47 (−0.14 %)	0.00 (0.00 %)	0.18 (0.05 %)
	Sec48	0.00 (0.00 %)	16.13 (99.62 %)	0.00 (0.00 %)	−16.19 (−100.00 %)
	Sec49	0.00 (0.00 %)	6.54 (100.45 %)	0.00 (0.00 %)	−6.51 (−100.00 %)
	Sec50	0.00 (0.00 %)	−6.34 (−0.58 %)	0.00 (0.00 %)	6.01 (0.55 %)
UK	Sec20	0.00 (0.00 %)	−0.04 (−5.44 %)	0.00 (0.00 %)	0.03 (4.75 %)
	Sec21	−0.03 (−58.34 %)	−0.13 (−6.59 %)	0.01 (16.92 %)	0.11 (5.45 %)
	Sec22	0.03 (0.07 %)	−0.87 (−5.41 %)	−0.01 (−0.02 %)	1.87 (11.59 %)
	Sec23	0.00 (0.00 %)	−0.20 (−4.72 %)	0.00 (0.00 %)	0.68 (15.65 %)
	Sec24	0.00 (0.00 %)	−0.15 (−4.27 %)	0.00 (0.00 %)	0.14 (4.00 %)
	Sec25	0.00 (0.00 %)	−0.52 (−5.63 %)	0.00 (0.00 %)	−0.33 (−3.58 %)
	Sec26	0.00 (0.00 %)	−0.06 (−6.15 %)	0.00 (0.00 %)	0.05 (5.19 %)
	Sec27	0.00 (0.00 %)	0.87 (85.94 %)	0.00 (0.00 %)	−1.01 (−100.00 %)
	Sec28	0.00 (0.00 %)	0.67 (86.77 %)	0.00 (0.00 %)	−0.77 (−100.00 %)
	Sec29	0.00 (0.00 %)	0.13 (86.91 %)	0.00 (0.00 %)	−0.15 (−100.00 %)
	Sec30	0.00 (0.00 %)	−0.07 (−6.55 %)	0.00 (0.00%)	0.06 (5.44 %)

Note: The figures in the bracket represent the proportions of change in direct/indirect emissions of the corresponding sectors.

3.4.1. Effects on the power subsectors

The difference in direct and indirect emissions of the power subsectors in China and the UK under the three scenarios is shown in Table 3. When storage capacity doubles, the annual electricity generation from coal-fired power decreases while from gas-fired power increases, thus leading to direct emissions of coal-fired generation (Sec43 in China or Sec21 in the UK) decreasing, and direct emissions of gas-fired generation (Sec44 in China or Sec22 in the UK) increasing; when there is no storage, the opposite is true. Since the three scenarios are bound by the same carbon emissions constraint, there is no change in the sum of direct emissions of the two sectors.

The indirect emissions of power subsectors are affected by the capacity share of each generation and storage type, the share of annual electricity generation of each generation type and the total annual discharge power of each storage type, and the emission intensity of coal- and gas-fired generation. In China, the main factor that affects the indirect emissions of power generation subsectors is the capacity and annual electricity generation of coal-fired generation, and they are greater under S3 (Opt, HD, CP30) than those under S9 (ES2, HD, CP30) but less than those under S15 (ES0, HD, CP30). This is the reason that the indirect emissions of all power generation sectors decrease under S9 while increasing under S15 compared to S3.

In the UK, the indirect emissions of Sec23 (bioenergy power generation) increase significantly (15.65 %, 680 thousand tonnes) under S15 (ES0, HD, NZE35) compared to S3 (Opt, HD, NZE35) due to the positive effects of the increased shares of gas-fired generation capacity and annual electricity generation of bioenergy power generation on its indirect emissions. Although there is no difference in gas-fired generation capacity between S3 and S9 (ES2, HD, NZE35), the capacity share of gas-fired generation is reduced due to more storage capacity under S9. Thus, compared to S3, indirect emissions of Sec22 (gas-fired generation) decrease under S9. The changes in indirect emissions of other power generation sectors are mainly determined by the effect of changes in the share of gas-fired generation capacity. Moreover, the change in indirect emissions of Sec25 (wind power generation) is determined by changes in the capacity share of gas-fired generation and the annual electricity generation share of wind power generation. When storage capacity doubles, they are decreased, leading to a decrease in indirect emissions of Sec25; when there is no storage, the capacity share of gas-fired generation increases but the share of annual electricity generation of wind power generation decreases, resulting in indirect emissions of Sec25 decrease since the latter has a greater effect on indirect emissions than the former.

3.4.2. Effects on other sectors

The changes in other sectors' carbon emissions in China and the UK between these three scenarios are shown in Fig. 9. It mainly depends on the changes in capacity shares of coal-fired generation in China and gas-fired generation in the UK. As energy storage capacity doubles, the capacity shares of coal-fired generation in China and gas-fired generation in the UK decrease, leading to a decline in indirect emissions of other sectors. Although the carbon emission intensity of China's coal-fired generation and the UK's gas-fired generation sectors increases due to

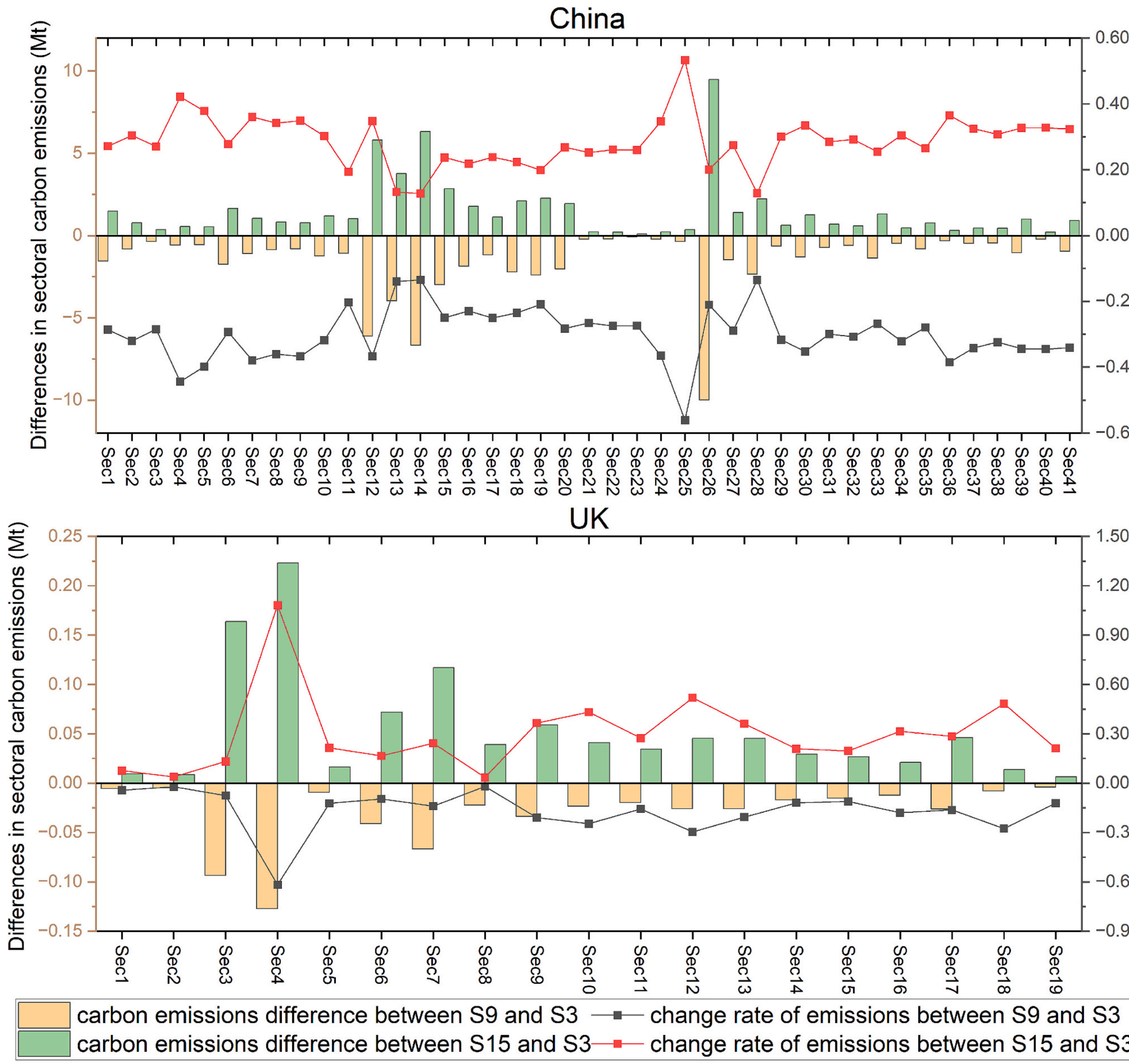

Fig. 9. The difference in sectoral carbon emissions of other sectors in China and the UK between S3, S9, and S15.

the decrease in their respective total economic output when storage capacity doubles, it is not enough to offset the reduction effect on indirect emissions of their reduced capacity shares. The opposite is true when there is no storage.

In China, Sec12 (manufacture of chemical products), Sec13 (manufacture of non-metallic mineral products), Sec14 (smelting and processing of metals), and Sec26 (construction) are sectors that are most affected. Sec3 (manufacturing) and Sec4 (gas supply and distribution) experience relatively large changes in emissions among other sectors in the UK. The main sectors for UK manufacturing emissions are the coking, fertiliser, cement, and iron and steel production industries, which have relatively high emissions intensity. Among these sectors, relatively high emissions intensity and high demand for electricity lead to greater changes in their indirect emissions.

3.5. Discussion

In current power systems, the installed capacities of BES, and PHS in China are around 13 GW and 45.8 GW, respectively [5]; the capacities of BES, PHS, and FES in the UK are around 2.1 GW, 2.7 GW, and 0.4 GW, respectively [28,42,43]. In the optimal storage capacity scenarios, the results of this paper suggest that by 2025, energy storage capacity in China does not need to be expanded in most cases, except in the case with high demand and strict carbon constraint (S6). Under this scenario, the solar power generation capacity in 2025 (1205 GW) is four times the capacity installed in 2022 (393 GW) [27], and the capacity of BES and PHS will be expanded to about 18 GW and 58 GW (Table S3). In the UK, storage capacity will not be expanded; the capacity of wind power generation will remain at the 2022 level (12 GW) [28] when, with base electricity demand and loose carbon constraint, and will be expanded to 27 GW when demand is high and carbon constraint is strict (Table S4). Energy storage, especially BES, will see a rapid increase in installed capacity in the near future with the increasing installed capacity of renewable energy generation. The cost of BES will show a declining trend [44]. BES in the UK is expected to reach 18 GW of installed capacity by 2035, far higher than the potential of 10 GW of installed capacity of PHS [45]. By 2025, China is expected to reach 30 GW of installed BES capacity and 62 GW of PHS capacity [46,47]. Since the reality of the power system is difficult to represent completely through modelling and we have only modelled the power systems in the short term (the decommissioning and lifetime of power plants and energy storage systems are not considered), the results may have some deviation from the reality and other future planning. The uncertainty of electricity demand and sector disaggregation on carbon emissions are discussed as follows. The results of total emissions with different carbon constraints can be seen in Fig. S6.

3.5.1. Uncertainty analysis: electricity demand

Fig. 10 shows the comparison of total direct and indirect carbon emissions in China and the UK under different electricity demand scenarios. It can be seen that increasing demand reduces the whole system's carbon emissions, except for S18 of the UK (ES0, HD, NZE30). This is because increasing electricity demand makes a cleaner power system, leading to indirect emissions decreasing significantly, though direct emissions increase a small amount. The impact of electricity demand on total carbon emissions is greater in China than in the UK due to China having a higher carbon intensity of power generation. The proportion of changes in indirect emissions to changes in total emissions is significantly higher in China than it is in the UK, which indicates that emissions from the supply chain in China are more affected by electricity demand.

The changes in electricity demand lead to changes in power system optimisation results. In China, carbon emissions are mainly from coal-fired generation, and decreasing electricity demand leads to less solar power capacity expansion, resulting in increased shares of coal-fired capacity and generation, thus leading to an increase in total indirect emissions. In the UK, gas-fired generation is the largest carbon emitter, and the shares of its capacity and annual electricity generation increase due to less wind power capacity as electricity demand decreases, thus resulting in changes in total indirect emissions, which is opposite to changes in demand. The only exception occurs in the UK under S18. Under this scenario, the differences in the shares of annual electricity generation and capacity of gas-fired generation are less compared to S16 (ES0, Base, NZE30), and the effect on total indirect emissions of gas-fired generation will be offset by other factors that would lead to an increase in indirect emissions, like an increase in annual electricity generation share of bioenergy power generation. Thus, this leads to a slight increase in total indirect emissions under S18 compared to S16.

3.5.2. Uncertainty analysis: sector disaggregation

The difference in the whole system's carbon emissions (same as total indirect carbon emissions because of no difference in total direct emissions) between the original and most likely cases in China and the UK under eighteen scenarios are shown in Fig. 11. In general, sector disaggregation uncertainty leads to the greatest difference in total emissions in S5 (with optimal storage capacity, low demand, and strict carbon constraint) in China; while in the UK, the largest total emissions difference is in S8 (with storage capacity doubled, low demand, and loose carbon constraint). Although the difference in total emissions between the original and most likely cases for both China and the UK is not significant (less than 0.1 %), it will become significant in some extreme cases. Specifically, when there is great uncertainty in the disaggregation of coal-fired and gas-fired power generation sectors, the difference in total carbon emissions becomes larger. Moreover, carbon emissions of those sectors that are more closely linked to the power sector and with high emission intensity (as mentioned above) are more affected by sector disaggregation uncertainty than the other sectors. In some extreme cases, the uncertainties in disaggregation coefficients for China's coal-fired generation and the UK's gas-fired generation sectors could arrive at 2.8 % and 1.4 % respectively, which results in the

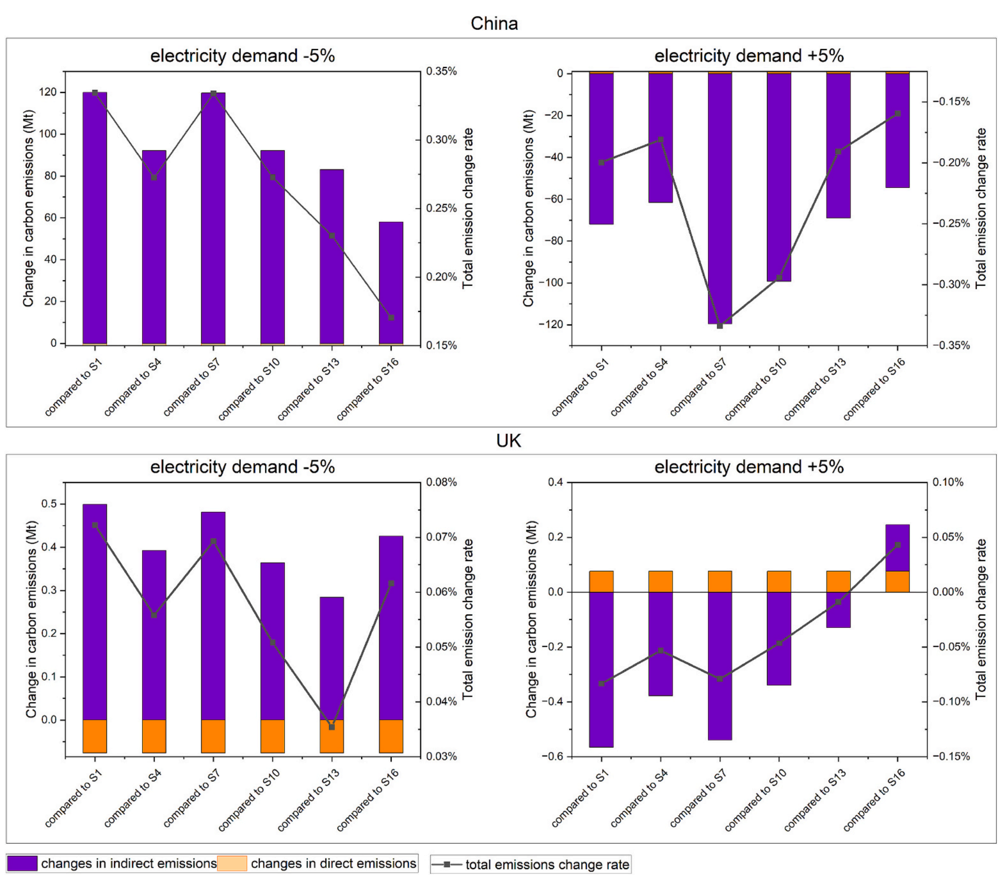

Fig. 10. The difference in carbon emissions in China and the UK under high and low demand compared to base demand scenarios with the same storage capacity and carbon constraints.

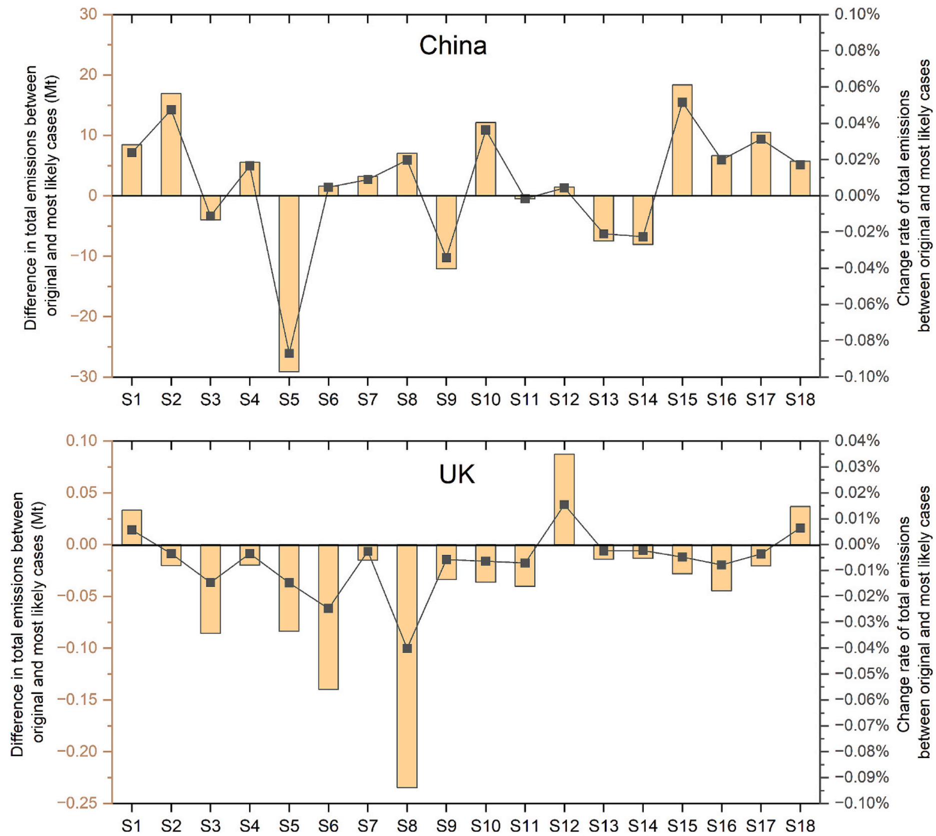

Fig. 11. The difference in total indirect carbon emissions under each scenario between the original and most likely cases in China and the UK.

differences in total carbon emissions of 1263 Mt (3.54 %) and 21 Mt (3.70 %). The total emissions difference in the UK is slightly greater than in China indicating the UK is more vulnerable to uncertainty in disaggregation of the power sector.

4. Conclusions

Our results indicate that increasing energy storage capacity can increase renewable generation capacity, thus leading to reduction in total economy-wide carbon emissions for both China and the UK. The impact of changes in energy storage capacity on power subsectors' carbon emissions is mainly associated with their respective installed capacity and annual generation shares. From the sector perspective, carbon emissions of Sec12 (manufacture of chemical products), Sec13 (manufacture of non-metallic mineral products), Sec14 (smelting and processing of metals), and Sec26 (construction) in China and Sec3 (manufacturing) and Sec4 (gas supply and distribution) in the UK that are closely linked to the power sector and have high emissions intensity are more likely to be affected. The dynamic operation of energy storage mainly affects solar power generation in China, while in the UK it mainly affects wind power generation. In some extreme cases, uncertainty in sector disaggregation will have a large impact on carbon emissions, especially in those sectors closely linked to the power sector and with high emission intensity.

Some recommendations can be put forward for the consideration of policymakers based on the results. First, governments should prioritise investment in and deployment of energy storage technologies, as increasing storage capacity can enhance renewable generation capacity and significantly reduce economy-wide carbon emissions. Second, policy measures should be tailored to optimise the renewable energy mix; in China, greater emphasis should be placed on supporting solar power, whereas in the UK, wind energy should be the focus. Third, targeted decarbonisation strategies should be developed for sectors closely linked to the power industry and characterised by high emission intensities. Fourth, inter-sectoral coordination and planning should be strengthened to ensure that the decarbonisation of the power sector drives emissions reductions in other high-emission sectors.

There are some limitations to this study. First, the decommissioning and lifetime of power generation and energy storage systems are not considered in the optimisation model since only a short-term planning (2025 as the simulation year) is conducted. Second, the model simplifies energy storage by not considering the integration of short-, medium-, and long-term storage deployment and integration of the deployment strategy of these types of storage. Third, uncertainties of parameters, like generation and storage costs and VRE generation availability are not considered. These limitations will be addressed in future studies.

CRediT authorship contribution statement

Fan He: Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Matthew Leach:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Michael Short:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Yurui Fan:** Methodology. **Lirong Liu:** Writing – review & editing, Supervision, Methodology, Conceptualization.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2024.124935.

Data availability

Data will be made available on request.

References

[1] Guan Y, Shan Y, Huang Q, Chen H, Wang D, Hubacek K. Assessment to China's recent emission pattern shifts. Earths Future 2021:9. https://doi.org/10.1029/2021EF002241.
[2] ONS. Provisional UK greenhouse gas emissions national statistics 2022. 2023.
[3] IEA.. Tracking clean energy progress 2023. 2023.
[4] Mostafa MH, Abdel Aleem SHE, Ali SG, Ali ZM, Abdelaziz AY. Techno-economic assessment of energy storage systems using annualized life cycle cost of storage (LCCOS) and levelized cost of energy (LCOE) metrics. J Energy Storage 2020;29:101345. https://doi.org/10.1016/J.EST.2020.101345.
[5] CNESA. Energy storage industry research white paper 2023. 2023.
[6] Xu K, Guo Y, Lei G, Zhu J. A review of flywheel energy storage system technologies. Energies (Basel) 2023;16:6462. https://doi.org/10.3390/en16186462.
[7] He G, Mallapragada DS, Bose A, Heuberger-Austin CF, Gençer E. Sector coupling: via hydrogen to lower the cost of energy system decarbonization. Energy Environ Sci 2021;14:4635–46. https://doi.org/10.1039/d1ee00627d.
[8] Cárdenas B, Swinfen-Styles L, Rouse J, Hoskin A, Xu W, Garvey SD. Energy storage capacity vs. renewable penetration: a study for the UK. Renew Energy 2021;171:849–67. https://doi.org/10.1016/j.renene.2021.02.149.
[9] Cárdenas B, Swinfen-styles L, Rouse J, Garvey SD. Short-, medium-, and long-duration energy storage in a 100% renewable electricity grid: a UK case study. Energies (Basel) 2021:14. https://doi.org/10.3390/en14248524.
[10] Ziegler MS, Mueller JM, Pereira GD, Song J, Ferrara M, Chiang YM, et al. Storage requirements and costs of shaping renewable energy toward grid decarbonization. Joule 2019;3:2134–53. https://doi.org/10.1016/j.joule.2019.06.012.
[11] Li C, Chen D, Li Y, Li F, Li R, Wu Q, et al. Exploring the interaction between renewables and energy storage for zero-carbon electricity systems. Energy 2022:261. https://doi.org/10.1016/j.energy.2022.125247.
[12] Cebulla F, Naegler T, Pohl M. Electrical energy storage in highly renewable European energy systems: capacity requirements, spatial distribution, and storage dispatch. J Energy Storage 2017;14:211–23. https://doi.org/10.1016/j.est.2017.10.004.
[13] Peng L, Mauzerall DL, Zhong YD, He G. Heterogeneous effects of battery storage deployment strategies on decarbonization of provincial power systems in China. Nat Commun 2023:14. https://doi.org/10.1038/s41467-023-40337-3.
[14] Li R, Tang BJ, Yu B, Liao H, Zhang C, Wei YM. Cost-optimal operation strategy for integrating large scale of renewable energy in China's power system: from a multi-regional perspective. Appl Energy 2022;325:119780. https://doi.org/10.1016/J.APENERGY.2022.119780.
[15] Hou H, Xu T, Wu X, Wang H, Tang A, Chen Y. Optimal capacity configuration of the wind-photovoltaic-storage hybrid power system based on gravity energy storage system. Appl Energy 2020;271:115052. https://doi.org/10.1016/J.APENERGY.2020.115052.
[16] Lv Q, Zhou M, Zheng B, Zhang C, Wei W. Impact of short-term and long-term energy storage units on power system operation economy: a parametric linear programming method. J Phys Conf Ser 2023;2522:012001. https://doi.org/10.1088/1742-6596/2522/1/012001.
[17] Lin Y, Johnson JX, Mathieu JL. Emissions impacts of using energy storage for power system reserves. Appl Energy 2016;168:444–56. https://doi.org/10.1016/j.apenergy.2016.01.061.
[18] Hittinger EMLS, Azevedo I. Bulk energy storage increases United States electricity system emissions. Environ Sci & Amp; Technol 2015;49:3203–10. https://doi.org/10.1021/es505027p.
[19] Li M, Shan R, Virguez E, Patiño-Echeverri D, Gao S, Ma H. Energy storage reduces costs and emissions even without large penetration of renewable energy: the case of China southern power grid. Energy Policy 2022:161. https://doi.org/10.1016/j.enpol.2021.112711.
[20] McKenna E, Barton J, Thomson M. Short-run impact of electricity storage on CO2 emissions in power systems with high penetrations of wind power: a case-study of Ireland. Proc Inst Mech Eng Part A: J Power Energy 2017;231:590–603. https://doi.org/10.1177/0957650916671432.
[21] Beuse M, Steffen B, Dirksmeier M, Schmidt TS. Comparing CO2 emissions impacts of electricity storage across applications and energy systems. Joule 2021;5:1501–20. https://doi.org/10.1016/j.joule.2021.04.010.
[22] Pimm AJ, Palczewski J, Barbour ER, Cockerill TT. Using electricity storage to reduce greenhouse gas emissions. Appl Energy 2021:282. https://doi.org/10.1016/j.apenergy.2020.116199.
[23] Tang Y, Li Y, Yuan X, Pimm A, Cockerill TT, Wang Q, et al. Estimation of emission factors from purchased electricity for European countries: impacts on emission reduction of electricity storage. Environ Sci Technol 2022;56:5111–22. https://doi.org/10.1021/acs.est.1c06490.
[24] Siala K, de la Rúa C, Lechón Y, Hamacher T. Towards a sustainable European energy system: linking optimization models with multi-regional input-output analysis. Energ Strat Rev 2019:26. https://doi.org/10.1016/j.esr.2019.100391.
[25] Rocco MV, Rady Y, Colombo E. Soft-linking bottom-up energy models with top-down input-output models to assess the environmental impact of future energy scenarios. Modelling, Measurement and Control C 2018;79(3):103–10. https://doi.org/10.18280/mmc_c.790307.
[26] Taliotis C, Giannakis E, Karmellos M, Fylaktos N, Zachariadis T. Estimating the economy-wide impacts of energy policies in Cyprus. Energ Strat Rev 2020;29:100495. https://doi.org/10.1016/J.ESR.2020.100495.
[27] China Electricity Council.. China electric power statistical yearbook 2022. Beijing: China Statistics Press; 2023.
[28] BEIS. Digest of UK energy statistics (DUKES) 2023. 2023. https://www.gov.uk/government/statistics/digest-of-uk-energy-statistics-dukes-2023.
[29] Mongird K, Viswanathan V, Balducci P, Alam J, Fotedar V, Koritarov V, et al. An evaluation of energy storage cost and performance characteristics. Energies (Basel) 2020;13:3307. https://doi.org/10.3390/en13133307.
[30] Gurobi Optimization.. Gurobi optimizer reference manual. 2023.
[31] Leontief W. Environmental repercussions and the economic structure: an input-output approach. Rev Econ Stat 1970;52:262–71. https://doi.org/10.2307/1926294.
[32] Miller RE, Blair PD. Input-output analysis. Cambridge University Press; 2009. https://doi.org/10.1017/CBO9780511626982.
[33] Fan M, Li Z, Ding T, Huang L, Dong F, Ren Z, et al. Uncertainty evaluation algorithm in power system dynamic analysis with correlated renewable energy sources. IEEE Trans Power Syst 2021;36:5602–11. https://doi.org/10.1109/TPWRS.2021.3075181.
[34] Lindner S, Legault J, Guan D. Disaggregating input-output models with incomplete information. Econ Syst Res 2012;24:329–47. https://doi.org/10.1080/09535314.2012.689954.
[35] China Electricity Council. The annual report on development of china's power industry 2022. 2022. https://english.cec.org.cn/#/newsdetails?id=1550040674299142145.
[36] National Grid ESO. Britain's electricity explained: 2022 Review. 2023. https://www.nationalgrideso.com/news/britains-electricity-explained-2022-review.
[37] World Bank. World development indicators.. 2024. https://databank.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG/1ff4a498/Popular-Indicators.
[38] Shu Y, Zhang L, Zhang Y, Wang Y, Lu G, Yuan B, et al. Carbon peak and carbon neutrality path for China's power industry. Chin J Eng Sci 2021;23:1. https://doi.org/10.15302/J-SSCAE-2021.06.001.
[39] Tong D, Farnham DJ, Duan L, Zhang Q, Lewis NS, Caldeira K, et al. Geophysical constraints on the reliability of solar and wind power worldwide. Nat Commun 2021;12:6146. https://doi.org/10.1038/s41467-021-26355-z.
[40] IMF. World economic outlook database.. 2023. https://www.imf.org/en/Publications/WEO/weo-database/2023/October/download-entire-database.
[41] IEA.. Electricity market report 2023. 2023.
[42] Directorate-General For Energy. Database of the European energy storage technologies and facilities. 2020.. http://data.europa.eu/88u/dataset/database-of-the-european-energy-storage-technologies-and-facilities.
[43] Rystad Energy. Rystad energy predicts UK battery energy storage market to grow to 24GW by 2030. 2023. https://www.solarpowerportal.co.uk/rystad_energy_predicts_uk_battery_energy_storage_market_to_grow_to_24gw_by/.
[44] NREL. Electricity annual technology baseline (ATB) data.. https://atb.nrel.gov/electricity/2022/data.
[45] CCC.. The sixth carbon budget electricity generation. 2020.
[46] National Development and Reform Commission of China.. Guidance on accelerating the development of new types of energy storage. 2021.
[47] China National Energy Administration.. Medium- and long-term development plan for pumped hydro storage (2021–2035). 2021.