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Design flexible renewable energy penetrated power system to address long-run and short-run interactive inference

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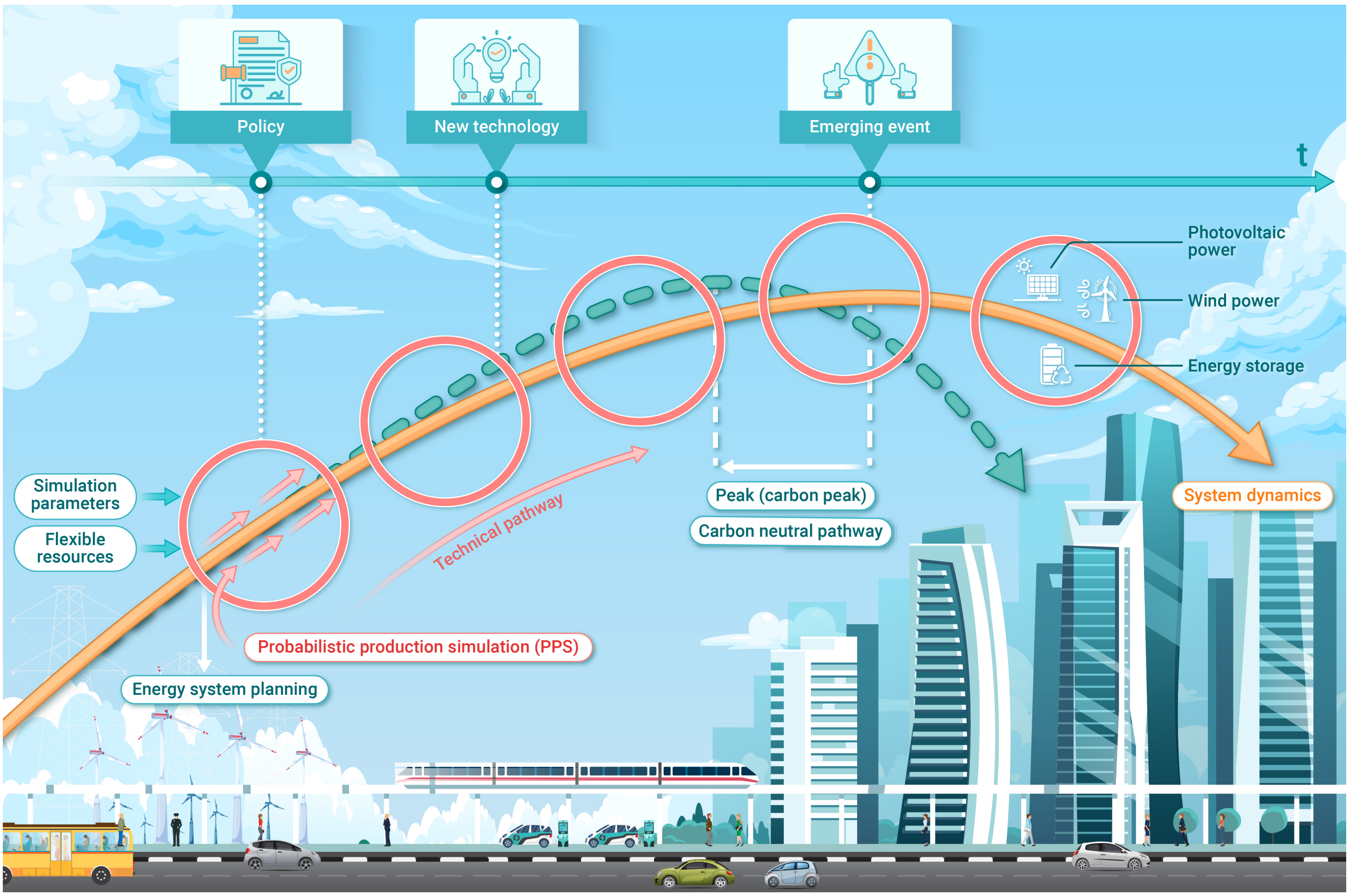
GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- A hybrid simulation method is proposed to couple the long-run and short-run interactive inference in the evolution of power systems.
- The economy, low carbon and flexibility are addressed in designing renewable energy penetrated power systems.
- Different evolution pathways can be simulated with various flexible resources under selected societal factors.

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For power systems with a high penetration of renewable energy, sufficient flexible resources such as energy storage must be combined to achieve sustainable energy development. However, in the planning of flexible resources, external societal factors can significantly change the evolution pathways of these resources. A simulation framework is urgently needed to integrate long-run development factors represented by societal influences, with the short-run operational characteristics within the physical energy framework. We provide technical support for the sustainable development of power systems, making the simulation results more accurate for future energy system planning. To address the lack of data for modeling external societal factors, a long-run modeling method based on system dynamics is proposed, alongside a short-run modeling method considering flexibility assessment and optimization. Long-run external societal factors necessitate a low-carbon system, while short-run concerns involve the actual topology of the power system to investigate high flexibility. We found that the sensitivity of various flexibility resource investments to both flexibility and low carbon in the power system is key to resolve this contradiction. An empirical calculation of the power system is conducted in the 213-bus flexibility test system including real data at 15-minute and 1-minute resolutions. Battery storage becomes the largest flexibility investment about a decade after the introduction of carbon reduction policies. While other flexibility resources particularly demand-side response due to unsaturated flexibility, also become major temporary investment assets. Considering the proposed interactive inference framework, there was a significant reduction in marginal abatement cost, and carbon trading continuously reduces the abatement cost.

INTRODUCTION

Future power systems are expected to be closely linked with societal changes.[1] China's commitment at the 75th United Nations General Assembly on September 22, 2020, to peak carbon emissions by 2030 and achieve carbon neutrality by 2060, represents a sustainable development shift.[2] This necessitates updating traditional energy planning models to include new carbon emission goals.[3-4] The implementation of carbon policies can provide a powerful impetus to the transformation of the power system. Countries have widely implemented carbon trading policies as an effective method in the low-carbon pathway.[5] The government encourages enterprises to participate in emission reduction efforts through market-oriented approaches. Currently, the carbon emission trading mechanism has emerged as an effective strategy for managing carbon dioxide emissions and has gained significant traction in many countries, including China, the United States, and the European Union. Meanwhile, implementing subsidy policies has effectively increased the motivation of enterprises within the power supply chain to reduce emissions.[6] The subsidy policy allows energy producers to receive government price support for using renewable energy sources in power generation. However, long-term and substantial financial subsidies may strain the government's financial resources. Additionally, the COVID-19 pandemic has led to varied government responses, like lockdowns and travel bans,[7] which have greatly impacted electricity demand.[8] For instance, during urban lockdowns, China and the United States saw significant reductions in industrial electricity use, by 12% and 20% respectively in 2020.[9-10] Conversely, residential electricity use has increased, with some European countries reporting nearly 40% increases.[9] On the supply side, renewable energy's share has grown despite a decrease in total power generation. The International Energy Agency noted a global power generation drop of 2.6% in early 2020, but a 3% increase in renewable energy generation, raising its share from 26% to 28%.[9] Meanwhile, coal and natural gas generation fell by 8% and 3%, respectively.[10] These trends highlight how macro-social factors can significantly affect power systems, especially those with substantial renewable energy component. Social science research may help improve our ability to manage this process of change towards more sustainable energy production and use. Of particular relevance is an approach that builds on the deep entanglement of technology and innovation with socio-cultural, political and economic factors, thus framing energy transition issues as socio-technological challenges. This interrelationship has long been at the heart of social research on technology, as well as more economically oriented research on innovation.

Modeling these societal factors is a long-run simulation process. In the field of energy planning, there are many researches that can be used to study energy consumption and greenhouse gas emission paths, which can be generally divided into "top-down" models based on macroeconomic indicators, such as computable general equilibrium model (CGE), and "bottom-up" models based on technology selection and sectoral energy demand, such as long-term alternative energy planning system model (LEAP).[11-12] So far, the researches of energy pathway inference about macro social environment are long-run scale simulation process without short-run simulation including specific energy resources, such as topology of power grid and various kinds of flexible resources.

Accurately modeling the complex interactions between different time dimensions, including socio-cultural, political-economic factors and the physical makeup of a given region is a key research challenge (Figure 1). Security, reliability, flexibility, and economy constitute the four key performance indicators to the assessment of power systems. While security, reliability, and economy have been quantitatively well-established in existing research frameworks, flexibility has predominantly been addressed at a qualitative level.[13] In addition to being reliable to low-impact and high-probability outages, power system should also have high level of flexibility to withstand high-impact and low-probability events.[14] Looking ahead to a future energy landscape characterized by a substantial increase in renewable energy integration, wind power and PV generation are anticipated to become the main resource of the power supply.[15] The inherent randomness and variability of these renewable energy sources will instigate fundamental alterations in the intrinsic characteristics of the power system.[16] Consequently, the role of base load power plants is expected to diminish significantly, with conventional thermal power units adapting to rapid start-stop cycles within a single day. This shift necessitates compensatory measures through flexible resources such as demand-side response and energy storage systems to counterbal-

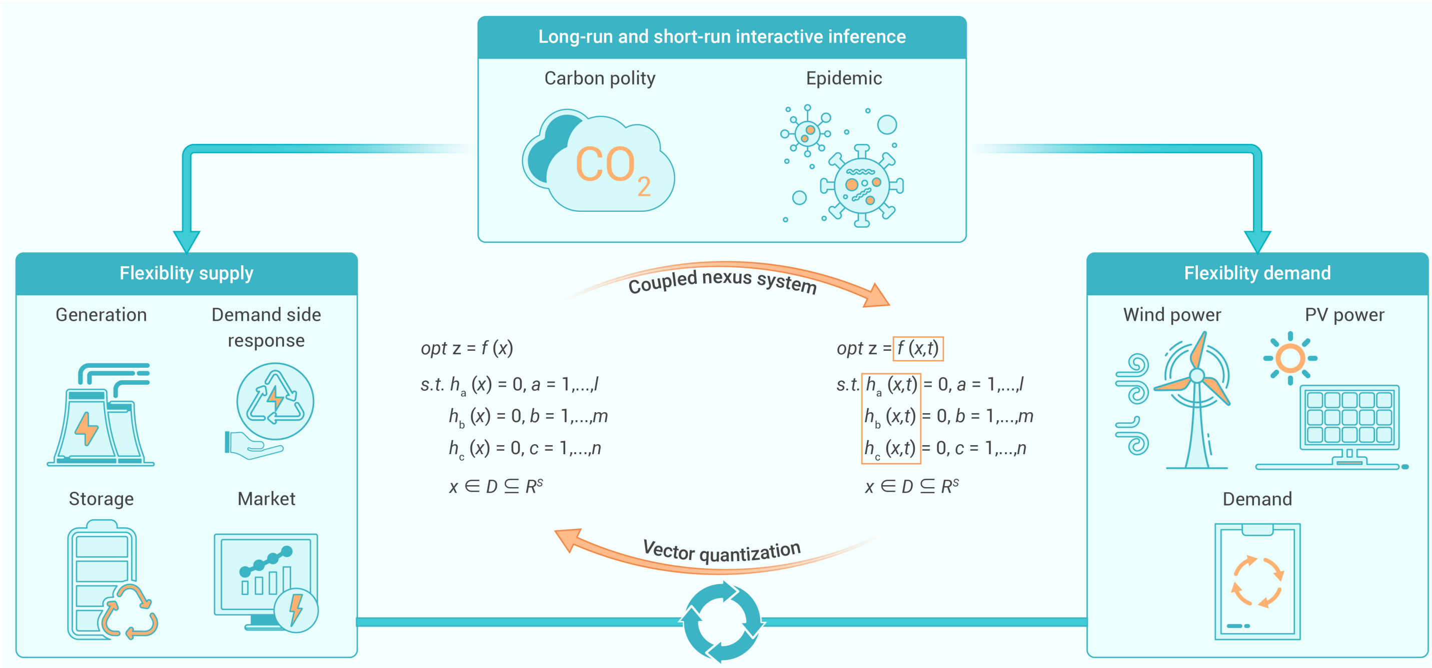

Figure 1. Coupled nexus framework of long-run and short-run interactive inference.

ance the unpredictable fluctuations inherent in renewable energy sources.[17-18] In this emerging paradigm, the high penetration of renewable energy will shift the focus of the existing key performance indicators, propelling the capability for flexible balancing to the forefront as a critical element for the safe and stable operation of the system.[19-20] Moreover, system flexibility can be used as an indicator that is more easily controlled by the external society, and as a bridge between the external society and internal resources, policy factors are transferred into the power system to change inner parameters.[21]

The traditional optimization methods in operations research encompass mathematical theories and methodologies that aim to optimize resource allocation under a set of objective or subjective constraints. This optimization typically seeks to maximize or minimize one or more specific indicators. In the realm of traditional power system planning, both the objective function and the constraint conditions are scalar in nature.[22-23] However, when variables such as GDP, population, economic development factors, policy incentives, and other macro factors are incorporated into the power system, the dynamics change significantly. These additional variables transform the traditional scalar objective functions and constraints into vectors and time-varying entities.[24] This shift underscores the critical need for a novel evolution framework capable of addressing the coupling of these macro indicators into current micro model.

Contemporary research predominantly employs system dynamics as the methodology for modeling social factors, such as policy implications in energy-related studies. System dynamics is a methodology designed to comprehend the behavior of intricate systems, which is fundamentally determined by their constituent elements.[25] Essentially, this implies that alterations in any individual component can influence the overall behavior of a complex system.[26] Predominantly recognized as a management concept pertinent to social systems, system dynamics has been extensively explored in areas like electricity price analysis, the economics of energy investment, and load forecasting.[27] However, its application in energy planning, particularly concerning the reform of the energy supply side, lack a framework approach that considers the coupling relationships within long-run and short-run interactive inference. Additionally, the utility of system dynamics in addressing specific engineering challenges is somewhat constrained. For instance, it struggles to integrate economic considerations of optimal flexible resource costs and to delineate the evolution pathways of multi-period resources essential for low-carbon planning.[28]

This research presents a new hybrid vector quantization framework that combines the benefits of system dynamics and optimization operations research. This unique approach brings together both detailed (micro) and big-picture (macro) views for a thorough modeling of external social factors. By integrating these aspects into the power system, it allows for a detailed understanding of energy dynamics. This method doesn't just look at the complex interactions within the power system; it also takes into account wider societal influences, leading to a comprehensive analysis. The framework proposed in this research can be incorporated into the external policy environment before carbon peaking is achieved, and the decarbonization goals of different societies and the power systems of different regions will affect their evolution pathways.

MATERIALS AND METHODS

Coupled nexus framework of long-run and short-run interactive inference

We propose a coupled nexus framework of interactive inference. A system dynamics approach is used to construct a model which is capable of simulating long-run variations in renewable energy capacity, the maximum annual investment capacity of flexible resources, and government subsidies, and other relevant indicators in response to various social indicators.[29] To facilitate a comprehensive understanding, an overall causal feedback diagram of the system is developed, which incorporates key levels and auxiliary parameters (Figure 2).

Policies aimed at fostering renewable energy usage in power generation can be broadly categorized into two types: those designed to actively encourage public adoption of renewable energy sources, and those that impose restrictions on alternative power generation technologies, thereby creating a niche for renewable energy to fulfill unmet power demands. The policies under consideration in this study fall into the former category. Consequently, the pivotal factor in this context is augmenting the public's inclination towards installing renewable energy capacity. An increase in public willingness to adopt renewable energy correlates with an expansion in the capacity of renewable energy installations. This escalation, in turn, stimulates manufacturers to enhance the production of renewable power systems, which is likely to result in a decrease in the costs associated with these systems. This cost reduction, coupled with an increase in the return on investment, further fuels public interest and willingness to utilize renewable power systems. This cycle constitutes the principal causal feedback loop within the system model. Additionally, if there is an increase in annual output—indicative of augmented power generation capacity—independent producers are poised to reap higher profits and realize an improved return

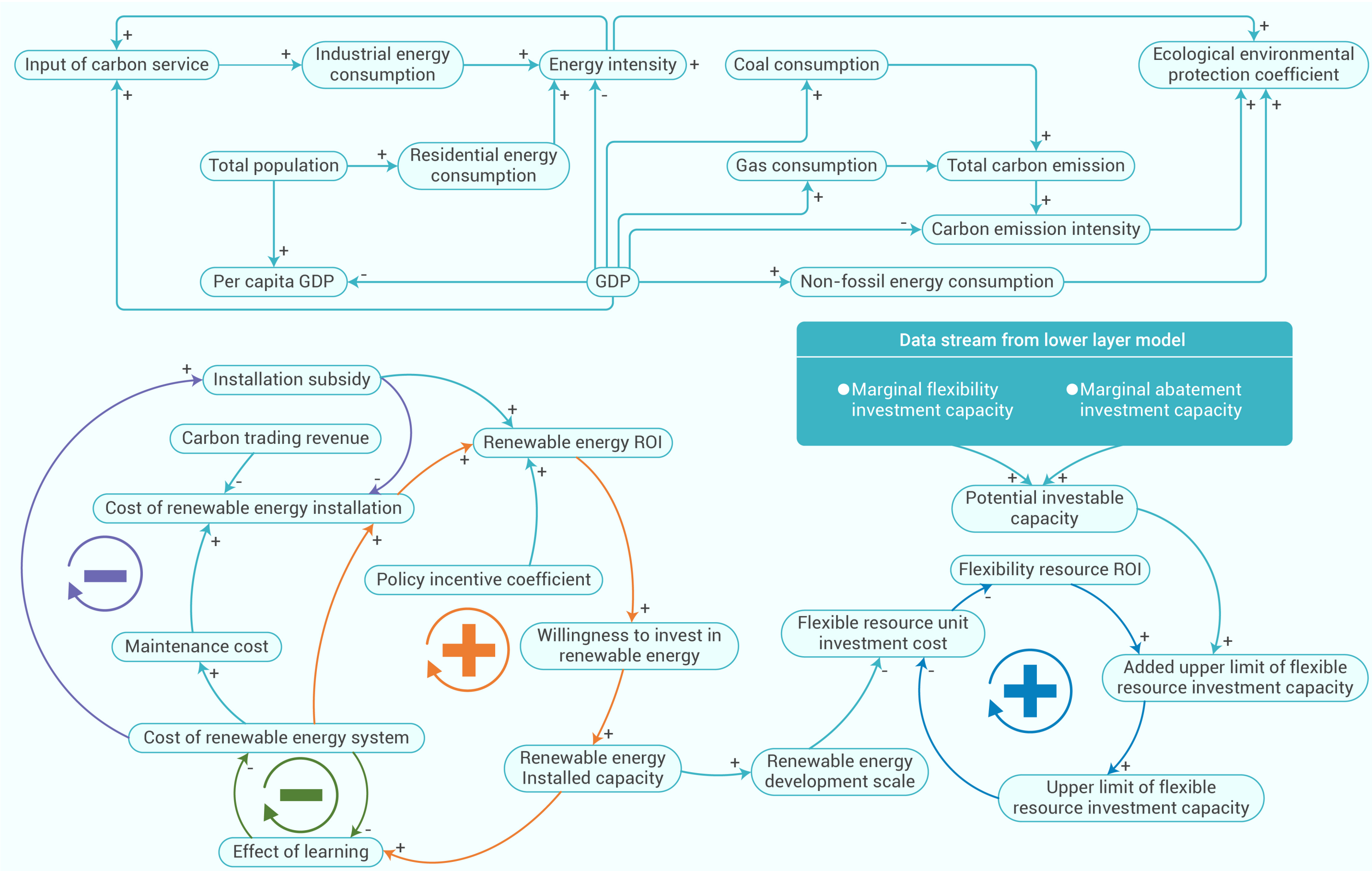

Figure 2. Vector quantified causal loop diagram based on system dynamics.

on investment.

Above is the social module, showing the causal relationship such as GDP, total population and energy consumption. Below is the energy module, showing the causal relationship such as ROI, government subsidies, and energy cost. The box shows the lower data flow.

Conversely, if the society benefits from subsidies for installing renewable power systems, this would lower the overall installation costs, thereby enhancing the ROI for users. As the investment intent reaches a certain magnitude, it is expected that renewable energy subsidies will be scaled back. This dynamic interplay between ROI, government subsidies, and the rate of new installations forms a critical component of the system's economic sustainability and is pivotal in understanding the long-term viability of renewable energy initiatives (Figure S1).

In the causal loop diagram, ROI is the driving force behind the continued growth of renewable power system installations. With the continuous decline of renewable energy costs, if the subsidies provided by the government remain unchanged, renewable energy return on investment will continue to increase, forming a positive feedback path. This will lead to an increase in the total number of renewable energy installations, which will ultimately increase policy costs to levels that the government cannot afford. More practically, when the return on investment reaches a certain level, the government will try to reduce the return on investment by reducing the installation subsidy. This will also reduce the growth in the number of renewable energy installations each year. If the society provides subsidies for the installation of renewable energy, this will reduce the total cost of installing system. This will also improve the return on investment for users. When the investment intention increases to a certain value, renewable energy subsidies will decrease.

In the system dynamics model dedicated to flexible resources, the ROI of these resources is influenced by a combination of factors, not limited to the unit investment cost. It also encompasses the marginal abatement factor and the marginal flexibility factor, both derived from the subordinate level of flexible resources planning. Collectively, these can be considered as a single, composite impact factor.[30] If the results from the lower-tier analysis indicate that a particular flexible resource has the highest marginal abatement factor, it implies that achieving a unit reduction in carbon dioxide emissions necessitates a higher investment in this specific resource. Consequently, within the chosen analytical year, the potential for investment in this flexible resource is at its zenith. This relationship can be mathematically expressed as Equation (1):

$$\begin{cases} PIC_{i,t}^{Fle} = ROI\int_{t-1}^{t}[\varepsilon_f\frac{dP_{i,\tau}}{df},\varepsilon_c\frac{dP_{i,\tau}}{dc}][f_\tau - f_{\tau-1}, c_\tau - c_{\tau-1}]^T d\tau \\ \varepsilon_f + \varepsilon_c = 1 \end{cases} \tag{1}$$

where $PIC_{i,t}^{Fle}$ denotes the annual investment capacity of the i^{th} flexible resource. ROI indicates to the return on investment. $P_{i,\tau}$ represents to the cumulative investment capacity. f and c refer to flexibility and carbon emission.

Hybrid simulation

System dynamics encounters challenges in yielding optimal solutions for specific engineering problems while adept at modeling complex systems, A notable difficulty arises in accounting for the economic aspects of optimal flexible resource costs and tracing the evolution path of future multi-period source-charge-storage systems within low-carbon planning frameworks, particularly those aiming for minimal carbon emission intensity. Conversely, although operational research excels in detailing specific energy grid structures and utilizing solvers to identify optimal solutions, it often falls short in integrating social and environmental factors that extend beyond the physical parameters of the grid. To surmount these limitations inherent in singular methodologies, this study proposes a hybrid co-simulation method. This innovative approach amalgamates the strengths of both system dynamics and operational research. It uniquely captures the intersection of energy

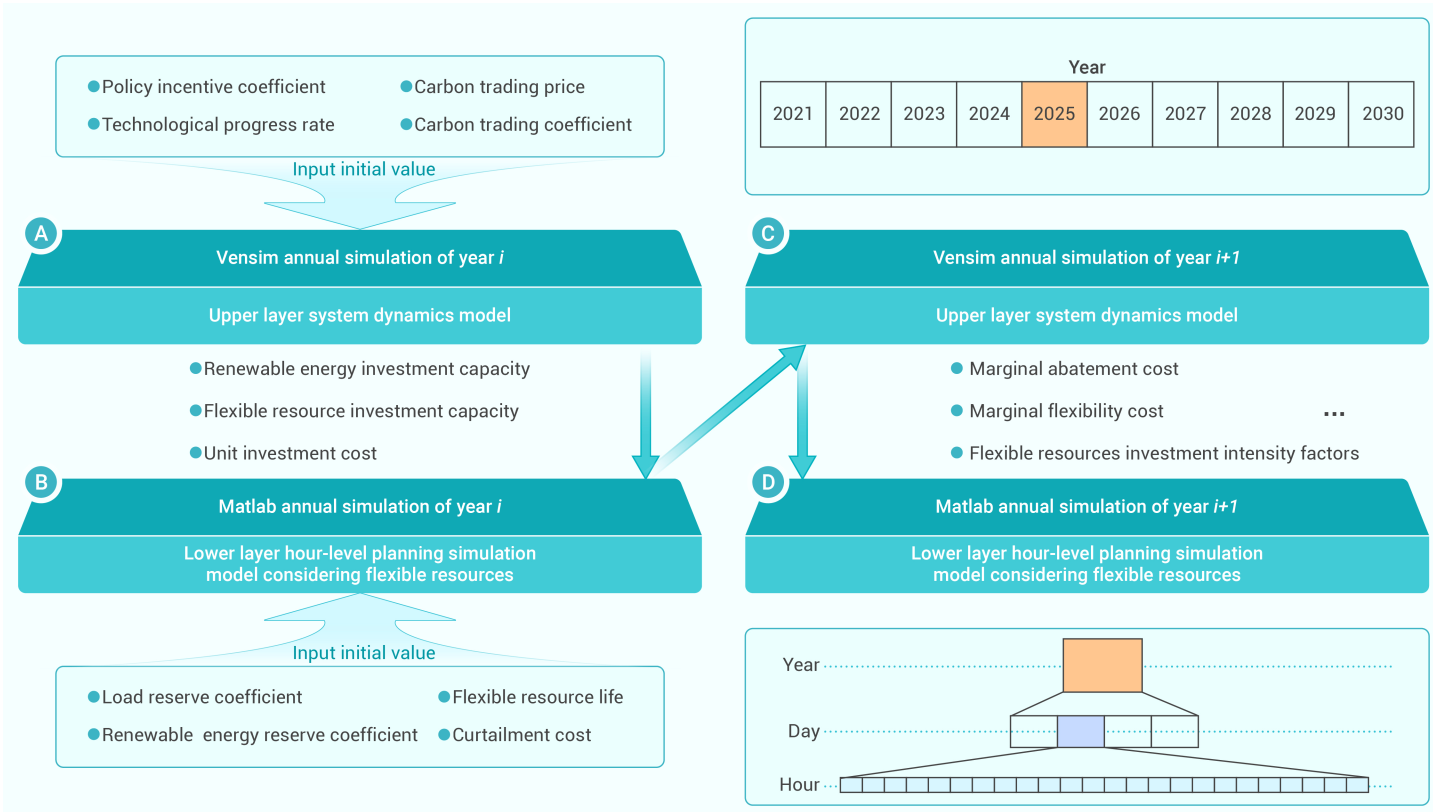

Figure 3. Hybrid simulation flow of data interaction.

structures with social and environmental factors, thereby offering a comprehensive model. This method is designed to synthesize both micro and macro perspectives, enabling a multifaceted analysis of the energy structure from various vantage points.

The hybrid simulation flow elucidates the intricate data interaction mechanism among three pivotal simulation tools —Vensim(Vensim Personal Learning Edition), Python, and Matlab—utilized in the co-simulation process (Figure 3).[31] This process is integral to coupling the economic aspects, low-carbon objectives, and flexibility characteristics of the power system under study. At the outset of the simulation, which commences in the first year, both the upper and lower models undergo simultaneous data initialization. Subsequently, the upper model computes and relays key parameters to the lower model. These parameters include the calculated renewable energy investment capacity, the maximal investible capacity for flexible resources, and the associated costs of each resource, which serve as boundary conditions for the lower model. Conversely, the lower model contributes to this interactive process by transferring critical data back to the upper model. This data comprises the marginal abatement cost, marginal flexibility cost, and the flexibility resource investment intensity factor, which are derived from hour-level stochastic production simulations. These simulations reflect the evolving investable potential of each flexibility resource, capturing the transition dynamics from year 1 to year 2. This bidirectional data flow between the models ensures a comprehensive and dynamic understanding of the system' s behavior over time.

Flexibility supply and demand

The generation of flexibility demand scenarios is a key step for power system flexibility evaluation . In a distribution system with a high proportion of new energy access, the output of distributed new energy units occupies a major position, so compared with a system with a low proportion of new energy access, high randomness is the main constraint for the generation of flexible demand scenarios. To solve this problem, this chapter models the uncertainty of new energy output and load, and then generates a flexible demand scenario.

From the definition of flexibility demand, the change of net load value is a direct factor affecting flexibility demand. There are two main factors affecting the net load $L^{P}_{n,t,d}$, one is the predicted value of load and renewable energy output, and the other is the forecast error of load and renewable energy. Consider the definition of flexibility requirements and net load. The value of flexibility supply $F_{n,t,d}$ can be calculated by Equations (2) - (3).

$$L^{P}_{n,t,d} = P^{Load}_{n,t,d} - P^{W}_{n,t,d} - P^{V}_{n,t,d} \tag{2}$$

$$F_{n,t,d} = L^{P}_{n,t+1,d} - L^{P}_{n,t,d} \tag{3}$$

The state of flexibility supply is determined by the flexible resources running state under constraints of economic scheduling and the static characteristics of flexible resources. When the static characteristics are determined, the flexible resources running state will become the decisive factor of flexibility supply. The main flexibility resources are thermal unit flexibility retrofit, energy storage and demand-side response. Define flexibility supply adequacy indicators $\Delta u(t)$ and $\Delta d(t)$ as Equations (4) - (5) :

$$\Delta u(t) = \sum_{i=1}^{I} S^{U}_{i,t,d} - \sum_{j=1}^{J} F^{U}_{j,t,d} \tag{4}$$

$$\Delta d(t) = \sum_{i=1}^{I} S^{D}_{i,t,d} - \sum_{j=1}^{J} F^{D}_{j,t,d} \tag{5}$$

where $S^{U}_{i,t,d}$ and $S^{D}_{i,t,d}$ respectively represent the upward and downward flexibility supply of the i^{th} flexible resource. $F^{U}_{i,t,d}$ and $F^{D}_{i,t,d}$ respectively represent the upward and downward flexibility demand of the i^{th} flexible resource.

Optimal planning and operation considering flexible resources

Based on the probabilistic production simulation, the flexibility of unit startup and shutdown is considered in the model. To improve computing efficiency, the unit commitment model with single binary variables is adopted, which only uses a set of binary variables to represent the unit state.[31] The total cost of all system C^{total} consists of the investment cost C^{inv}_{y}, the operation cost C^{ope} and the carbon tax C^{CO2}.[32] The objective function is expressed

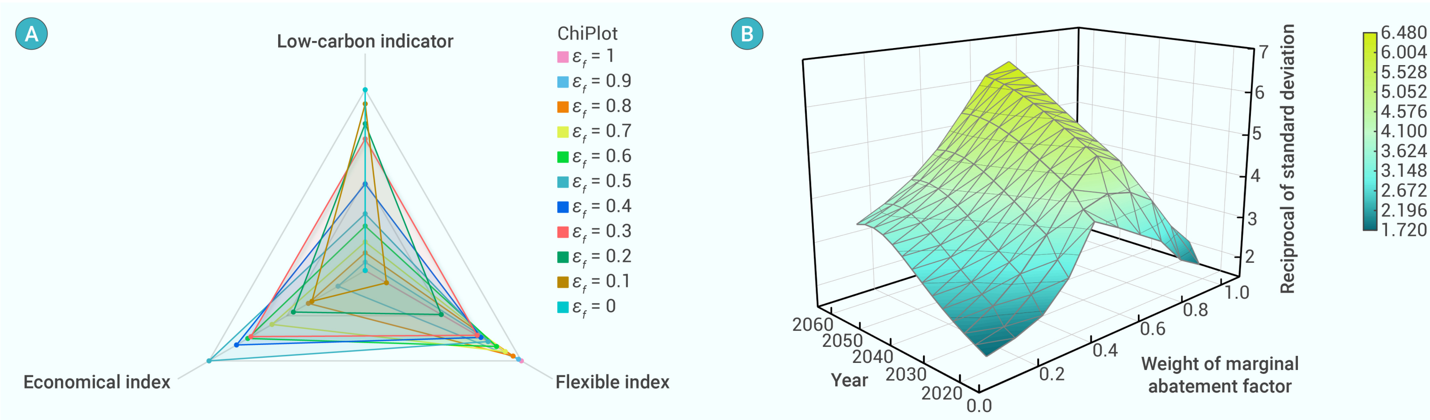

Figure 4. Comparative tests of marginal abatement factor and marginal flexibility factor in energy evolution (A) Three-dimensional radar map of evaluation indicators among economic indicator, low-carbon indicator and flexible indicator in 2060. (B) The inverse of the standard deviation of the three indicators in evolution pathway.

as Equations (6) - (8)

$$\min C^{total} = \frac{r(1+r)^N}{(1+r)^N-1}\sum_{y=0}^{N}\frac{C_y^{inv}}{(1+r)^N} + C^{ope} + C^{CO2} \tag{6}$$

$$C_y^{inv} = \sum_{i\in Fle}[c_i^{inv}P_i(y=0) + c_i^{rep}P_i(0<y<N) - c_i^{rep}P_i\frac{l_i^{whole}}{l_i^{rest}}(y=N)] \tag{7}$$

$$\begin{aligned} C^{ope} = \sum_{d=1}^{ND}\rho_d[&\sum_{t=1}^{T}\sum_{gc\in\Omega_G} c_{gc}^G P_{gc,t,d}^G + \sum_{t=2}^{T}\sum_{gc\in\Omega_G} c_{gc}^Q + \sum_{t=1}^{T}\sum_{n\in\Omega_N}\lambda^{LC}P_{n,t,d}^{LC} + \\ &\sum_{t=1}^{T}\sum_{gr\in\Omega_R} c_{gr}^R(P_{gr,t,d}^{Pre} - P_{gr,t,d}^R) + \sum_{t=1}^{T}\sum_{i\in\Omega_{DR}} c_i^{com}P_{i,t,d}^{com}] \end{aligned} \tag{8}$$

where r refers to the discount rate. c_i^{rep} denote the unit replacement cost; P_i denotes the capacity of the i^{th} flexible resource; l_i^{whole} indicates the whole lifespan of the i^{th} flexible resource, and l_i^{rest} represents the rest lifespan of the i^{th} flexible resource at the end of the project lifetime. ρ_d refers to the number of the selected representative day d. c_{gc}^G indicates the generation cost of the conventional units, and $P_{gc,t,d}^G$ refers to the output of the conventional units. c_{gc}^Q represents the startup cost of the conventional units. $P_{n,t,d}^L$ and λ^L denote the load shedding and its unit penalty. c_{gr}^R and $P_{gr,t,d}^R$ indicate the generation cost and output of renewable plants. c_i^{com} and $P_{i,t,d}^{com}$ denote the compensation cost and power of demand-side response.

The constraints mainly consider conventional unit operation, power balance, and other types of flexible resource operation constraints. The start-up cost constraint is expressed as Equations (9) - (10). Here $x_{gc,t,d}$ denotes the on/off status of a unit.

$$c_{gc,t,d}^Q = (x_{gc,t,d} - x_{gc,t-1,d})c_{gc}^Q \tag{9}$$

$$c_{gc,t,d}^Q \geqslant 0 \tag{10}$$

Given that the descriptions of operation constraints of conventional coal-fired units and gas-fired units are the same, these constraints are classified into one category in this study, and only their parameters are considered as Equations (11) - (12):

$$-\overline{R_{gc}^G} \leqslant P_{gc,t,d}^G - P_{gc,t-1,d}^G \leqslant \overline{R_{gc}^G} \tag{11}$$

$$0 \leqslant P_{n,t,d}^{LC} \leqslant \gamma^{LC}P_{n,t,d}^{Load} \tag{12}$$

where $\overline{R_{gc}^G}$ denotes the maximum climbing rate of conventional units. γ^{LC} represents the load shedding rate.

Unit flexibility generally reflects the ability to adapt to large fluctuations and respond to load changes, mainly including the minimum technical unit output, unit climbing rate, and unit start and stop time. Among them, reducing the minimum unit output, that is, increasing the peak-shaving capacity of the unit, is the most widely used target. Reducing the minimum output of a thermal power unit can make room for renewable energy to come online, thus achieving carbon reduction. Here Fle1, Fle2 and Fle3 represent thermal unit flexibility retrofit, Energy storage and demand-side response, respectively. The model of flexible transformation for reducing the minimum output of thermal power unit is as Equations (13) - (14):

$$0 \leqslant P_{gc,t,d}^{Fle1} \leqslant \overline{P_{gc}^G} - \gamma^{Fle1}\underline{P_{gc}^G} \tag{13}$$

$$\underline{P_{gc}^G} - P_{gc,t,d}^{Fle1} \leqslant P_{gc,t,d}^G \leqslant \overline{P_{gc}^G} \tag{14}$$

When the new energy proportion increases gradually, energy storage technology is increasingly widely used. On the power side, the uncertainty and volatility caused by high-proportion renewable energy are mitigated.[33] Energy storage power quantity constraints are shown as Equations (15) - (17):

$$P_{i,t,d}^{Fle2} = E_{i,t+1,d}^{Fle2} - E_{i,t,d}^{Fle2} \tag{15}$$

$$\underline{P_i^{Fle2}} \leqslant P_{i,t,d}^{Fle2} \leqslant \overline{P_i^{Fle2}} \tag{16}$$

$$0 \leqslant E_{i,t,d}^{Fle2} \leqslant T_i\overline{P_i^{Fle2}} \tag{17}$$

Demand-side response refers to the use of prices or incentive mechanisms to guide loads to actively change their electricity consumption plans or patterns within a specific period of time. The two types of demand-side response models are as Equations (18) - (21) :

$$P_{n,t,d}^L = P_{n,t,d}^{L0} - P_{n,t,d}^{Fle3^{SH}} - P_{n,t,d}^{Fle3^{RD}} \tag{18}$$

$$\underline{P_{n,t,d}^{Fle3^{SH}}} \leqslant P_{n,t,d}^{Fle3^{SH}} \leqslant \overline{P_n^{Fle3^{SH}}} \tag{19}$$

$$\sum\nolimits_{t=1}^{T} P_{n,t,d}^{Fle3^{SH}} = 0 \tag{20}$$

$$0 \leqslant P_{n,t,d}^{Fle3^{RD}} \leqslant \overline{P_n^{Fle3^{RD}}} \tag{21}$$

The power balance constraints are described by Equation (22).

$$P_{n,t,d}^G + P_{n,t,d}^R + P_{n,t,d}^{Fle2} - (P_{n,t,d}^{Load} - P_{n,t,d}^{LC} - P_{n,t,d}^{Fle3}) = P_{n,t,d}^{Brout} - P_{n,t,d}^{Brin} \tag{22}$$

RESULTS

In this research, a benchmarking system situated in Northwest China is employed, specifically designed for investigating power system flexibility (Figure S2). The parameters of the flexibility test system such as power flow constraints and investment costs of various resources are transparent.[34] This flexibility test system is notable for its high renewable energy penetration rate, exceeding 38%, and incorporates real data at time scales of 15 minutes and 1 hour. It comprehensively includes resources spanning power generation, grid

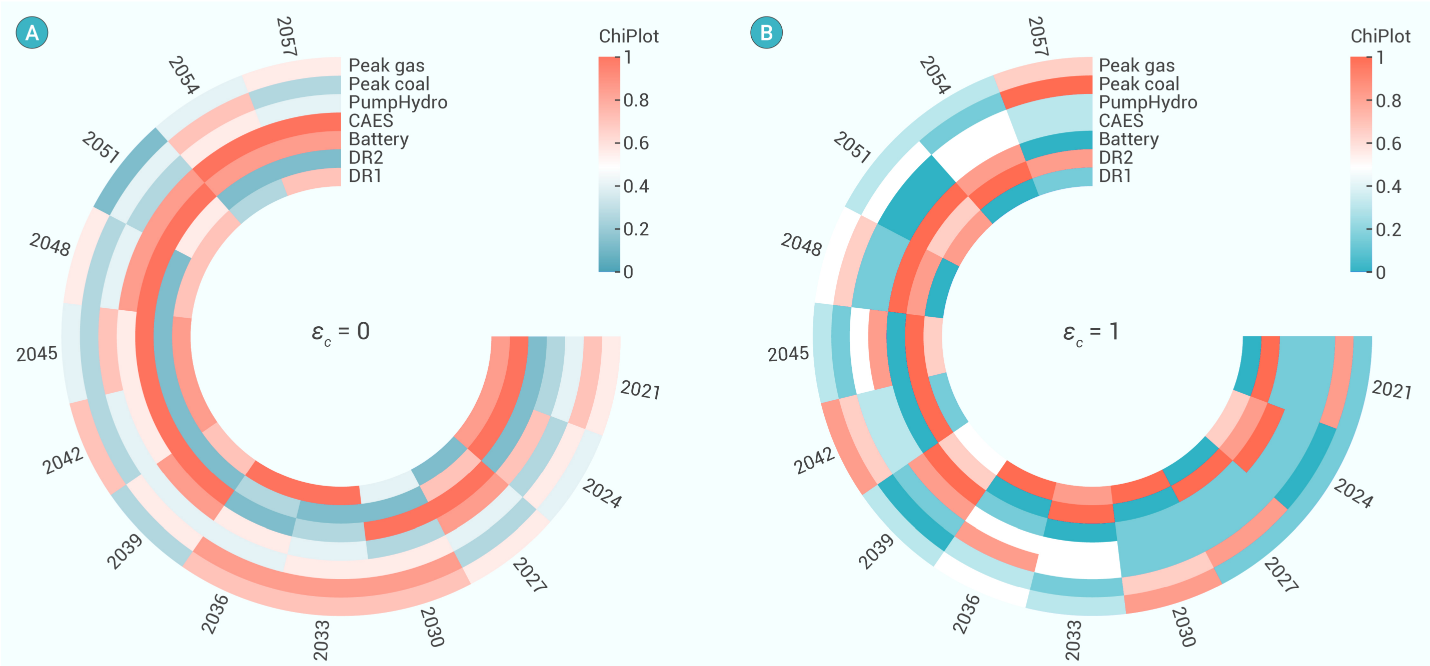

Figure 5. Various flexibility resources development investment intensity at each time node in the evolution process (A)$\varepsilon_c = 0$. (B)$\varepsilon_c = 1$.

infrastructure, demand, energy storage, market dynamics, and other pertinent aspects. These resources collectively represent the entire gamut of a large-scale power system's structure, transmission, and consumption processes, both within and across regions. The system is characterized by an abundance of renewable energy resources. The total initial power generation capacity is quantified at 303.96GW, with renewable energy sources contributing 38.04% to this capacity. The total load is measured at 124.23GW, with 22.45GW being transferred to external power systems. It encompasses a diverse array of generator sets including coal-fired thermal power, gas thermal power, hydropower, wind power, and PV (Figure S3).

Designed with a focus on flexibility studies, the test system is versatile enough to support both planning and operational business studies. It is modeled on China's 5-zone regional power system and innovatively incorporates features such as integrated power grids and direct current (DC) lines, drawn from real-world grid data. Consequently, research conducted using this system is poised to offer valuable insights into the impacts of new technologies and algorithms on the performance of contemporary power systems. Thermal power flexible retrofit, battery energy storage, compressed air energy storage and two types of demand-side response are considered in our study.[35-37]

The calculation of the ROI for flexible resources in macro and micro evolution is influenced by a confluence of factors: not only the unit investment cost of the flexible resources but also the marginal abatement factor and the marginal flexibility factor derived from more granular levels of flexible resource planning. These latter two can be aggregated into a singular impact factor. This part of the study concentrates on the weighting of these marginal factors, a critical aspect that directly affects the decision-making pathways in the coupled system inference process.

Predominantly, economic considerations of the system take precedence. However, given the increasing societal and policy pressures for a sustainable energy mix, the low-carbon characteristic of the system is equally pivotal. In the trajectory towards a low-carbon transformation, the role of various flexible resources is indispensable, thereby necessitating the inclusion of system flexibility as a key objective.

The comprehensive optimal result is represented by the red triangle (Figure 4A). This optimal state is achieved when the marginal flexible factor is weighted at 0.3 and the marginal abatement factor is around 0.7, leading to the simultaneous attainment of high values (approximately 0.75) across low-carbon, economic, and flexible indicators of the coupled system. This result suggests that the pursuit of low carbon emissions is integral to the system's flexibility. In essence, the flexible indicator is a function of the low-carbon indicator, when the flexible indicator is an independent variable and the low-carbon indicator is a dependent variable. Consequently, when a high weight is assigned to the marginal abatement factor, the system inherently gravitates towards more economically viable resources to achieve lower carbon emissions. We simultaneously test the reciprocal of standard deviation of the three indicators on the pathways, and the maximum value gradually approaches the point that the weight of marginal abatement factor is around 0.7 (Figure 4B).

Considering two extreme cases, the marginal flexibility factor equals to 1 and the marginal abatement factor equals to 0. Define the flexibility resource development factor $FD_{i,t}$ on the evolution path:

$$FD_{i,t} = \frac{dP_{i,t}/dt}{dP_{i,t-1}/dt}$$

where $dP_{i,t}/dt$refers to the derivative of flexible resource investment capacity.

After normalization, it reveals that expediting investments in flexibility retrofits for thermal power units can substantially diminish the carbon emissions of the system (Figure 5). Concurrently, augmenting the demand side response is shown to significantly enhance the system's flexibility. Notably, in the latter stages of the system's evolution, battery energy storage emerges as the optimal resource for flexibility. Moreover, the results indicate that the optimal resource aligned with the objective of low-carbon emission is the reduction-type demand-side response. In addition, it is observed that the flexibility retrofit of coal-fired units, particularly in the later stages, contributes to the improvement of the system's low-carbon attributes. These findings underscore the multifaceted approach required to optimize both the flexibility and low-carbon properties of power systems.

To underscore the merits of our novel interactive inference model compared to traditional models, we conducted a comparative analysis centered on the implementation of carbon policies within the social environment. Our findings reveal a notable inflection point in the development curve of battery energy storage for the years 2036 and 2045. Hour-level simulations for these years indicate that in 2036, the reduction type of demand-side response constitutes the primary source of flexibility supply, reaching its saturation point. Subsequently, battery energy storage experiences a rapid development phase to compensate for the emerging flexibility supply deficit. By 2045, none of the flexibility resources have reached saturation, leading to a more gradual development trajectory for battery energy storage.

In examining the progression of energy development, we delineated four

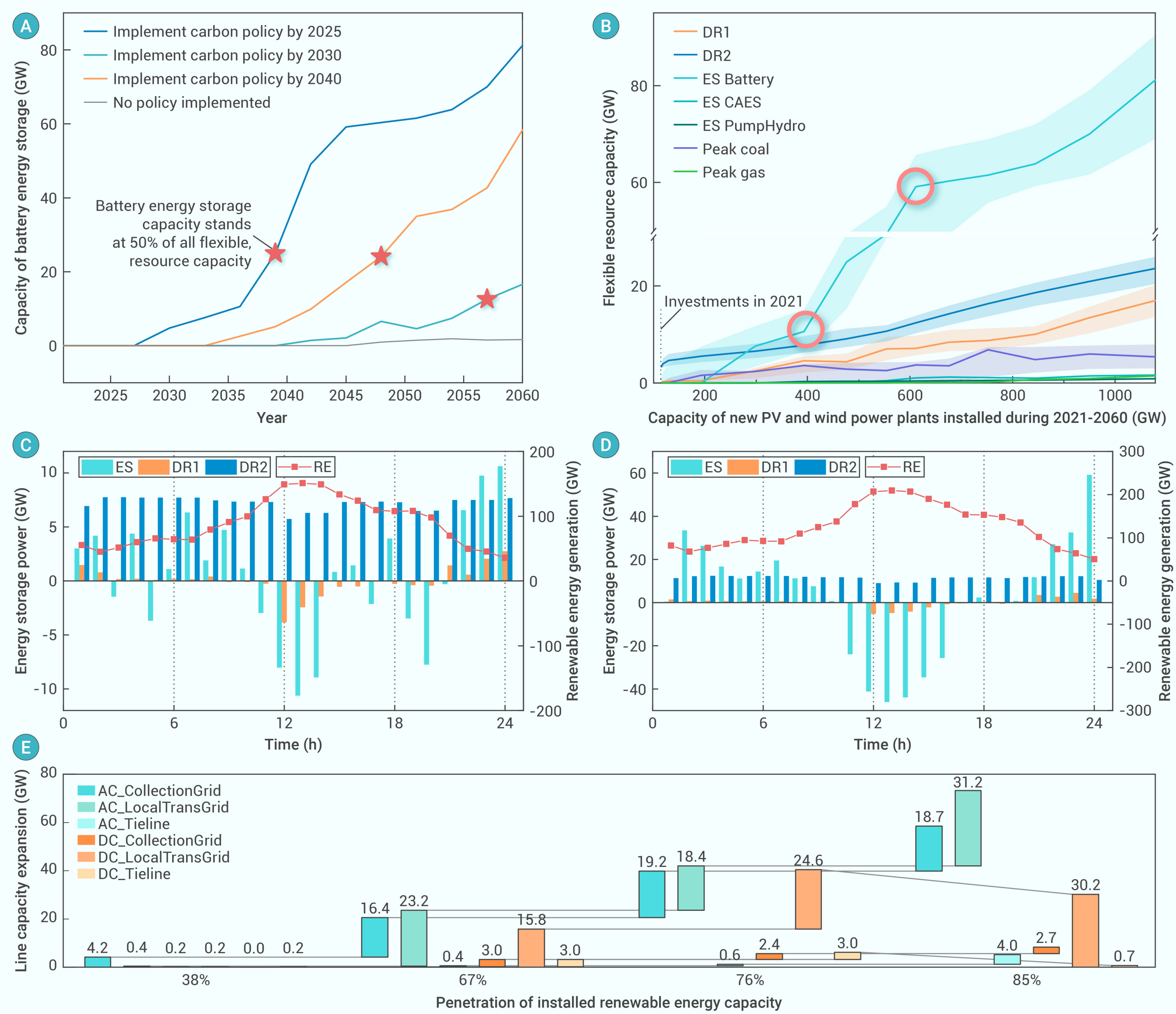

Figure 6. Evolution pathways of variable flexible resources and transmission lines (A) Evolution pathways of battery energy storage when implementing carbon policy at different time node. (B) Evolution pathways of 7 kinds of flexible resources as the capacity of new PV and wind power plants gradually increases. (C) Hourly output of various flexible resources in 2036. (D) Hourly output of various flexible resources in 2045. (E) Expansion of various types of power transmission lines at different renewable energy penetration.

distinct stages based on renewable energy penetration rates: 38%, 67%, 76%, and 85% (Figure 6). Accompanying these stages, the capacities of the AC collection grid and the AC regional transmission grid exhibit a linear increase. In contrast, the capacity of the DC regional transmission grid increases only up to the 76% penetration stage, after which it begins to decline. The DC Tie line emerges at a 67% penetration rate of installed renewable energy capacity, whereas the AC Tie line appears at an 85% penetration rate. In the initial stages with lower renewable energy penetration, demand-side response and thermal power unit flexibility retrofits serve as the main sources of flexibility. The AC collection grid is the primary focus of investment. However, as carbon policies take effect, new targets redirect the coupled system towards battery storage, resulting in a significant expansion of the AC local transmission grid in response to increased penetration rates.

We analyze the proposed framework's ability to decarbonize future power systems with a high proportion of renewable energy, and discuss marginal abatement costs under three scenarios (Figure 7). When considering the proposed nexus framework, the marginal abatement cost presents a negative cost for mild carbon reduction, ranging from -348M$ to 1574M$. After taking carbon trading into account, the marginal abatement cost increases from -455M$ to 1019M$. These two scenarios significantly reduce the cost of carbon abatement, especially for deep carbon abatement greater than 60%, than without using the proposed nexus framework. It is worth mentioning that in the mild carbon emission reduction before 10%, compressed air energy storage has almost no investment, and in the medium and deep carbon emission reduction, compressed air energy storage has rapidly increased investment and maintained at about $1600M. On the contrary, the investment in the transfer demand-side response and the two types of flexibility retrofit i gradually reduced, and the available resources are gradually tilted towards the shedding demand-side response and various storage.

DISCUSSION

Our study establishes a comprehensive framework of long-run and short-run interactive inference, elucidating the mechanisms by which policies, investments, and societal actions catalyze the evolution of the power systems. We developed an evaluation indicator system and simulated key indicators across different stages of power system development. Initially,

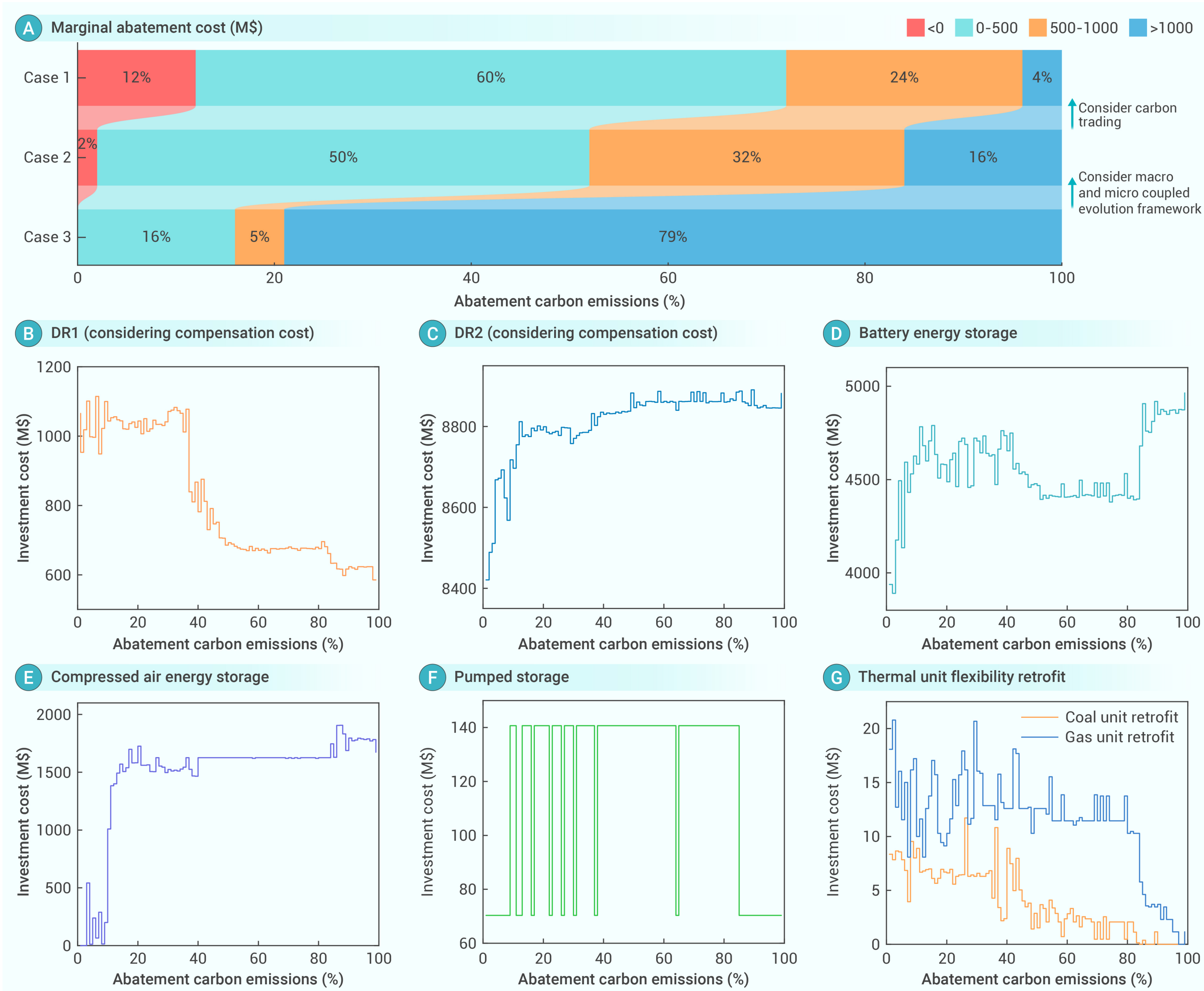

Figure 7. Costs of CO2 emissions abatement in 2060 by deploying various flexible resources (A) Marginal abatement costs in three cases. (B) Investment cost of shifting demand-side response. (C) Investment cost of shedding demand-side response. (D) Investment cost of battery energy storage. (E) Investment cost of compressed air energy storage. (F) Investment cost of pumped storage. (G) Investment cost of thermal unit flexibility retrofit.

economic considerations dominate the system's priorities. However, as external carbon policies are integrated, there is a notable shift in the system's focus: low-carbon and flexibility indicators emerge as primary objectives. In later stages, the system's emphasis transitions from flexibility to a low-carbon orientation, which is attributed to the early and middle stages being periods of resource investment accumulation, with the ultimate goal of flexibility being to counterbalance the uncertainties introduced by renewable energy and facilitate a low-carbon transition.

The framework, with its focus on economy, flexibility, and low-carbon objectives, provides a roadmap for the evolution of diverse resources within the interactive inference. The result reveals that battery energy storage and compressed air energy storage, with values around 0.8 of *FD*, are highly effective in enhancing system flexibility (Figure 3A). Interestingly, while compressed air storage does not attract substantial investment, battery energy storage remains a significant focus, affirming its integral role in the system's low-carbon transition (Figure 3B). Additionally, while demand-side response may not significantly contribute to system flexibility, it plays a crucial role in reducing carbon emissions.

We further analyzed the development trends of flexible resources under different carbon policy implementation timelines. Focusing on battery energy storage, recognized as a leading flexible resource, we observe that its dominance in the system's infrastructure typically emerges approximately five years post-policy introduction and constitutes over half of all flexible resources within two decades (Figure 4A). The evolutionary trajectory of the power system exhibits two critical nodes and three distinct stages, particularly when new PV and wind power capacities reach 400GW and 600GW, respectively, creating significant inflection points.

To offer a more granular and detailed hour-level simulation, we separately analyzed the two nodes in the energy evolution pathways. In the initial phase, with low renewable energy penetration, demand-side response serves as a vital flexibility provider, primarily driven by the economic imperatives of investors. As the scale of PV and wind power installations expands, and with changes in the coupled system indicators, battery energy storage progressively ascends as the leading flexibility resource.

Through a cost-sensitivity analysis of the depth of carbon abatement, we demonstrate that the proposed coupled nexus framework is economical in terms of carbon abatement. In case 2, there is 16% of the abatement carbon emissions are high-cost, 63% less than basic case. And introducing carbon trading into the framework further reduces marginal abatement costs. Meanwhile, the economics of deep carbon reduction cannot be achieved without significant investments in battery energy storage, compressed air energy storage, and shedding demand-side response, which points us to the best potential future investments in flexible resources. In the late stage of carbon reduction, the investment cost of battery energy storage reached 5000$ approximately.

Our work holds significant global implications. The interconnected nature of energy and social systems necessitates a modeling approach that can handle vector variables for objective functions and constraints. Our proposed framework, grounded in system dynamics and vector quantization, offers a robust method for navigating future energy transitions. However, the broad applicability of this framework across diverse global contexts underscores the need for a thorough understanding of local power systems and societal conditions. This requirement highlights the importance of tailoring the framework to specific regional nuances, ensuring its effectiveness in facilitating sustainable energy transitions worldwide.

Despite the demonstrated potential of our proposed interactive inference framework in addressing the coupled nexus, further research and development are imperative. Future iterations of the model should incorporate more detailed internal structures based on system dynamics and additional social factors to more accurately simulate future energy evolution pathways. Moreover, expanding the range of energy types and flexibility suppliers, including nuclear and biomass, is essential to enhance this promising approach in the context of ongoing energy transitions. In addition, hydrogen plants and electric vehicles can also serve as an excellent flexible resource in the evolution pathway of future energy systems. Our future system dynamics models and hour-level simulations will be more refined to this resource, and become the major flexible resources to achieve a more flexible and low-carbon evolution direction.

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AUTHOR CONTRIBUTIONS

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DECLARATION OF INTERESTS

The authors declare no competing interests.

ETHICAL STATEMENT AND PATIENT CONSENT

Not Applicable.

DATA AND CODE AVAILABILITY

Data are available from the corresponding author upon reasonable request.

SUPPLEMENTAL INFORMATION

It can be found online at https://doi.org/10.59717/j.xinn-energy.2024.100042

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