

Article

Driving Mechanisms and Scenario-Based Simulation of Renewable Energy Penetration Evolution in China

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Abstract

Enhancing renewable energy penetration (REP) is essential for accelerating the low-carbon transition of the power system. The evolution of REP is driven by the interaction of multiple factors, including policy, technology, market demand, and environmental constraints. Based on the system dynamics (SD) method, this study constructs a model to simulate the evolution of REP in China during 2012–2060 under business-as-usual (BAU), single-factor, and synergistic scenarios. The results show that, by 2060, REP reaches 77.17% under the BAU scenario. REP improvement is most pronounced under the policy support scenario, reaching 80.71%, while REP increases by 4.58%, 1.94%, 2.36%, and 1.30% relative to BAU under the policy support, technological innovation, market demand expansion, and environmental constraint scenarios, respectively. After 2030, the effect of market demand expansion gradually strengthens and surpasses environmental constraints and technological innovation, with the crossover points corresponding to REP levels of 41.69% and 57.19%, respectively. The synergistic scenario analysis further shows that policy–market synergy is the most effective pathway, with REP reaching 81.21% by 2060, followed by policy–technology synergy at 80.89%. In contrast, policy–environment synergy (80.48%) does not outperform the single policy support scenario. This suggests that environmental constraints need to be coordinated with market-based consumption and technological support to effectively promote REP.

Keywords: renewable energy penetration; system dynamics; driving mechanisms; scenario simulation; BAU



Academic Editor: Francesco Nocera

Received: 20 June 2026

Revised: 12 July 2026

Accepted: 14 July 2026

Published: 20 July 2026

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1. Introduction

Climate change and energy security have become major challenges to global sustainable development [1]. Accelerating the low-carbon energy transition and increasing REP are important pathways for reducing carbon emissions and optimizing the energy structure [2]. As the world's largest energy consumer [3–5] and carbon dioxide (CO₂) emitter [6], China has proposed its carbon peaking and carbon neutrality goals, hereafter referred to as the dual-carbon goals. These goals reflect not only China's strategic commitment to addressing global climate change but also its internal need for high-quality development. The power sector is a major source of energy consumption and carbon emissions [6,7], as well as a key field for replacing fossil fuels with renewable energy [8]. According to IEA data cited by

Xiang et al. [9], CO₂ emissions from China's power sector accounted for approximately 43% of the country's total carbon emissions in 2020, making the sector's low-carbon transition directly relevant to achieving the dual-carbon goals [10]. In 2023, the share of non-fossil energy in China's installed power generation capacity exceeded 50% for the first time, reaching 53.9% [11]. Although renewable energy development has made significant progress, the rapid expansion of installed capacity has not yet been fully translated into effective substitution within the power structure, and a gap remains between current progress and the requirements of deep low-carbon transformation under the dual-carbon goals. Therefore, how to promote the penetration of renewable energy into the power supply structure has become an important issue requiring further investigation.

REP is a core indicator that reflects the contribution of renewable energy to the power supply structure [12,13]. Its improvement is not driven by a single factor but by the combined effects of policy, technology, market, and environmental factors [14,15]. These factors interact with and constrain one another through changes in power supply and demand, investment decision-making, price feedback, and thermal power substitution. Therefore, a single-factor or static perspective is insufficient to explain the long-term evolution of REP. Since these interactions involve feedback loops, time delays, and nonlinear responses, a system dynamics (SD) approach is suitable for identifying the driving mechanisms of REP from the perspective of system feedback and dynamic evolution.

Existing studies have provided useful insights into the influencing factors, policy mechanisms, and dynamic evolution of renewable energy development, but further research is still needed. First, REP is a structural transformation process shaped by policy guidance, technological progress, market response, and environmental constraints, yet the coupling and transmission mechanisms among multiple drivers have not been fully characterized. Second, REP improvement is long-term and stage-dependent, and the intensity and relative importance of different drivers may change across development stages; however, current research provides limited explanation of such dynamic differences. Third, existing scenario simulations mainly focus on single-policy reinforcement or partial parameter adjustment, while lacking a systematic comparison of the synergistic pathways formed by different driver combinations and their relative effects.

Against this background, this study aims to incorporate policy support, technological innovation, market demand, and environmental constraints into a unified analytical framework. It develops an SD model for the evolution of REP in China and uses multi-scenario simulations to compare the effects of different drivers and their combinations on REP and thermal power substitution. Different from official energy outlooks and studies that mainly provide target-oriented forecasts or examine individual policy and technology pathways, this study focuses on the feedback mechanisms, stage-specific effects, and synergistic interactions that shape REP evolution. In doing so, this study provides a mechanism-based analytical framework for scenario comparison, policy evaluation, and low-carbon power system transition analysis in China.

The novel contributions of this study are as follows. First, it constructs a REP-centered SD framework that integrates policy support, technological innovation, market demand, and environmental constraints, interpreting REP improvement as the result of coupled transmission among multiple drivers and thereby extending the mechanism-based perspective of REP research beyond single-policy or single-technology analyses. Second, based on long-term dynamic simulation, it reveals the stage-specific effects of different drivers on renewable power expansion, thermal power substitution, and REP improvement, thereby enhancing the explanation of the long-term evolutionary pattern of REP. Third, by comparing single-factor scenarios with synergistic scenarios, it identifies the relative performance and differential effects of different driver combinations, providing evidence for the design

of more coordinated renewable energy development policies and low-carbon power system transition strategies.

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 introduces the research method, model structure, and scenario settings. Section 4 presents and discusses the simulation results. Section 5 concludes the study and proposes policy implications.

2. Literature Review

2.1. Driving Factors of Renewable Energy Penetration

The improvement of REP is influenced by multiple factors. Existing studies have mainly examined the effects of policy institutions, technological innovation, market demand, and environmental constraints on renewable energy development.

(1) Policy institutions

Policy support plays a key role in promoting renewable energy development. Given that the renewable energy industry is capital-intensive, involves long investment cycles, and is characterized by high technological uncertainty, its development often requires institutional safeguards such as government subsidies, environmental regulations, R&D support, and industrial policies [16–19]. Policy absence [20], as well as policy uncertainty and discontinuity [21], can hinder the expansion of the renewable energy industry, whereas stable policy support helps attract capital investment and promote industrial growth. Bersalli et al. [22] and Zhang [23] have verified this point from the perspectives of cross-national comparisons and new energy industry clusters, respectively. Some studies indicate that government intervention can positively influence renewable energy development by altering energy consumption preferences [24], guiding resource allocation, and attracting corporate investment [25]. However, policy effectiveness varies with the stage of industrial development [26], policy costs [27], and regional differences [28], suggesting that policy instruments should be adjusted flexibly.

(2) Technological progress

Technological progress provides an important basis for enhancing the competitiveness of renewable energy. Existing studies have shown that advances in renewable energy technologies can significantly increase renewable power generation [29,30] and strengthen the substitution of renewable energy for conventional energy sources such as coal [31]. In terms of mechanisms, technological innovation can promote the long-term development of renewable energy by reducing costs, improving efficiency, and lowering risks [32,33]. Yan et al. [34] and Cheng and Yao [35] further confirmed the positive role of renewable energy technological innovation from the perspectives of environmental performance and sustainable development. However, lagging energy storage technologies, insufficient grid transmission capacity [36], and limited breakthroughs in key technologies [37] may still constrain the large-scale expansion of renewable energy.

(3) Market demand

Market demand is an important driver of the continuous expansion of renewable energy. Evidence from different countries and regions has confirmed the positive effect of demand-side factors on renewable energy development, including evidence from China [38], the United States [39], Denmark [40], and Europe [41]. Related studies suggest that the diffusion of low-carbon awareness, purchasing behavior, public acceptance, willingness to pay, and final consumption demand can all affect REP. However, the role of market demand is not unlimited. Wüstenhagen and Bilharz [42] argued that relying solely on demand pull is insufficient to achieve large-scale substitution of fossil energy and that demand-side forces should be combined with government policies and institutional arrangements. He et al. [43] reached a similar conclusion.

(4) Environmental constraints

Environmental constraints serve as important external pressures driving the low-carbon transition of the power system. In the power sector, they mainly operate through carbon emission regulation, carbon trading, and the internalization of carbon costs. Zhou and Zhao [44] showed that carbon price signals can change the cost–benefit structure of power generation enterprises, thereby influencing their generation behavior, carbon trading demand, and trading prices. Against the background of parallel renewable energy policies and carbon trading mechanisms, renewable portfolio standards on the consumption side, green certificate trading, and carbon emissions trading jointly affect green electricity expansion, power structure optimization, and CO₂ emission reduction [45,46]. Meanwhile, the effect of carbon pricing is not simply linear; rather, it depends on the coordination of policy instruments such as subsidies and market mechanisms [47].

2.2. Comprehensive Driving Mechanisms of REP

In addition to studies of individual factors, some scholars have examined the multiple driving mechanisms of REP from an integrated perspective. Existing research suggests that economic growth [48,49], R&D investment [50], outward foreign direct investment [51], unemployment [52], carbon emissions [53], population size [54], and financial development [55] may all affect renewable energy development. Wang et al. [56] found that supply structure, energy security, and carbon emissions are important factors influencing renewable energy development in China. Cross-country and regional studies further show that renewable energy development in different economies is jointly shaped by multiple factors. Przychodzen and Przychodzen [52] argued that economic growth, unemployment, and government debt expansion influence renewable electricity generation in transition economies. Vural [53] found that per capita gross domestic product (GDP), technological innovation, and trade have positive effects on renewable energy output in Latin American countries. Islam et al. [57] and Bamati and Raoofi [58] further revealed the complex drivers of renewable energy development in terms of income growth, investment, urbanization, infrastructure, institutional quality, and differences in national development levels.

2.3. Application of SD in Energy Transition Research

In research on renewable energy development and energy transition, existing studies have used structural equation models [59,60], econometric regression models [61,62], principal component analysis [63], and Divisia index decomposition methods [56] to identify influencing factors and their directions of effect. However, these methods have limitations in capturing multi-factor feedback, time delays, and long-term dynamic evolution. SD can reveal dynamic relationships among internal variables in complex systems and has therefore been widely applied to power system modeling and low-carbon energy transition research.

Existing SD studies have mainly focused on three aspects. First, SD has been used for policy evaluation in the power sector, generation capacity expansion, and demand-side management [64]. Second, it has been applied to identify the influencing factors of energy-related CO₂ emissions and simulate emission reduction scenarios [65]. Third, it has been used to analyze renewable energy development pathways, investment behavior, and policy effects. For example, Xu et al. [66] and Peng et al. [67] examined photovoltaic (PV) and wind power development, respectively, from the perspective of renewable energy industry evolution. Dianat et al. [68] combined SD with agent-based modeling and game theory to analyze market competition, investor responses, and the effects of support policies in renewable electricity development. In addition, some studies have applied

SD to sustainability assessments of power supply–demand systems, revealing dynamic interactions between power systems and economic, social, and environmental systems [69].

Overall, existing studies provide a useful foundation for understanding the drivers of REP, but several gaps remain. First, most studies focus on individual factors or parallel multi-factor analysis, paying limited attention to feedback relationships and synergistic effects among policy, technology, market, and environmental drivers. Second, they provide insufficient explanation of how the effects of different drivers vary across long-term evolutionary stages. Third, existing SD studies mainly examine single technologies, specific policy tools, or partial components of the power system, leaving REP, as a structural indicator, insufficiently explored. To address these gaps, this study develops an SD model that integrates policy support, technological innovation, market demand, and environmental constraints, and simulates the evolution of REP in China under different scenarios.

3. Methodology and Model

REP is a dynamic process shaped by multiple factors, including policy, technology, market demand, and environmental constraints. The relationships among these drivers are not simply linear; rather, they form complex feedback loops through investment decisions, cost changes, electricity supply and demand, electricity price fluctuations, and carbon emission constraints. SD method can capture the nonlinear relationships, feedback structures, and time-delay effects within complex systems, making it suitable for analyzing the long-term dynamic evolution of REP under varying external conditions. Therefore, this study employs SD to construct a model of REP evolution and uses scenario simulations to compare the effects of different drivers and their combinations on REP.

3.1. Model Framework

As shown in Figure 1, this study follows the logical framework of “drivers–mechanisms–system modules–evolutionary outcomes,” and incorporates policy support, technological innovation, market demand, and environmental constraints into a unified analytical framework.

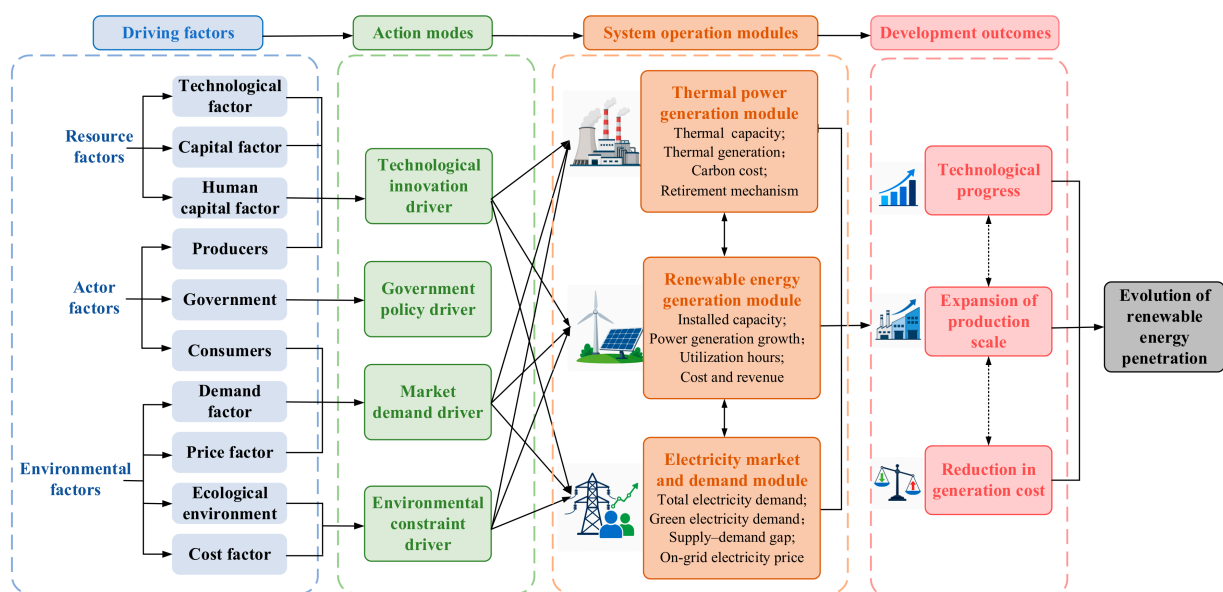


Figure 1. Integrated framework of the driving mechanism of renewable energy penetration.

Specifically, REP is jointly influenced by resource, market, and environmental conditions, which are further reflected in technological innovation, policy support, market

demand, and environmental constraints. These drivers affect REP by influencing renewable energy investment, thermal power development, electricity demand, on-grid electricity price, and carbon emissions.

At the system operation level, the model consists of three interrelated modules: the renewable power generation module, the thermal power generation module, and the electricity market and demand module. Together, these modules characterize the dynamic relationships among installed capacity, power generation, electricity demand, generation costs, investment coefficients, carbon costs, and electricity price feedback. The simulation results are used to analyze the evolution of REP under different scenarios.

3.2. Model Assumptions

To ensure a reasonable model structure and interpretable simulation results, this study makes the following assumptions when constructing the SD model.

(1) This study focuses on China's power system and characterizes the structural substitution relationship between renewable energy and thermal power. The model focuses on average evolution trends at the national level; it does not separately address differences among regions in terms of resource endowments, grid conditions, and levels of economic development, nor does it give special consideration to the unique circumstances of specific regions.

(2) In this study, "renewable energy" primarily refers to non-hydro renewable energy, including wind power and PV power generation; "thermal power" primarily refers to fossil-fuel-based power generation, especially coal-fired power generation. Both renewable and thermal power enter the electricity market as sources of electricity supply.

(3) Although renewable electricity and thermal electricity have the same physical properties and basic commodity functions, they exhibit different characteristics in terms of the volatility and flexibility of electricity supply. This study does not explicitly model renewable power variability or thermal power flexibility.

(4) It is assumed that electricity producers trade directly with the grid, while end users purchase electricity from the grid [70]. Direct transactions between electricity producers and end consumers are not considered. Both types of electricity are assumed to share the same on-grid electricity price in the electricity market.

(5) It is assumed that economic and social development proceeds smoothly; unexpected shocks and their impacts on economic development are not considered.

(6) Policy support, technological innovation, market demand expansion, and environmental constraints are represented by dimensionless adjustment coefficients in the model to characterize the relative strengthening or weakening of different driving mechanisms.

(7) The model focuses on the core feedback relationships among policy, technology, market demand, environmental constraints, renewable power generation, thermal power generation, electricity demand, and REP. Other factors not explicitly included in the model are not treated as independent driving variables in the scenario simulations.

3.3. Causal Loop and Stock–Flow Model

Based on the above model framework and assumptions, a causal loop diagram was first constructed to describe the main feedback relationships in China's REP evolution system, as shown in Figure 2.

As shown in Figure 3, a stock–flow diagram of China's REP evolution system was constructed using Vensim to illustrate the evolutionary processes, system structure, and interactions among variables.

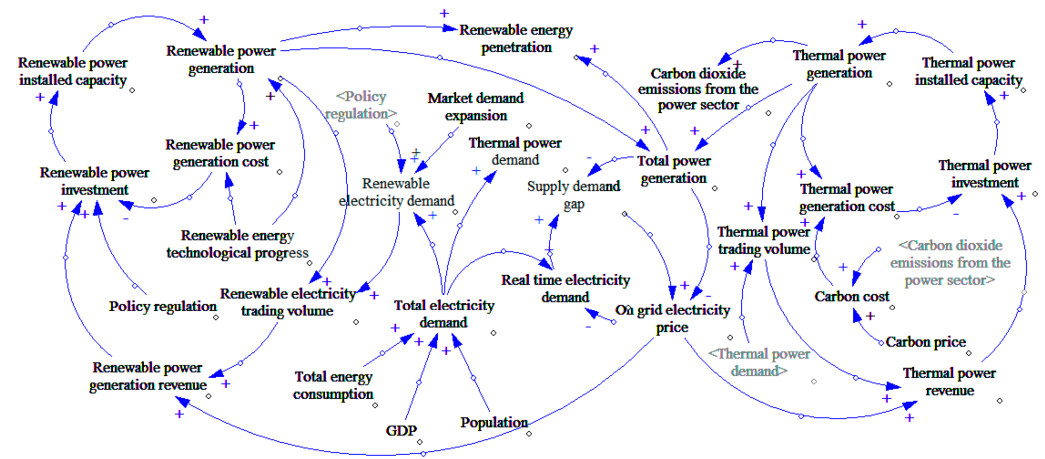


Figure 2. Causal loop diagram of renewable energy penetration evolution.

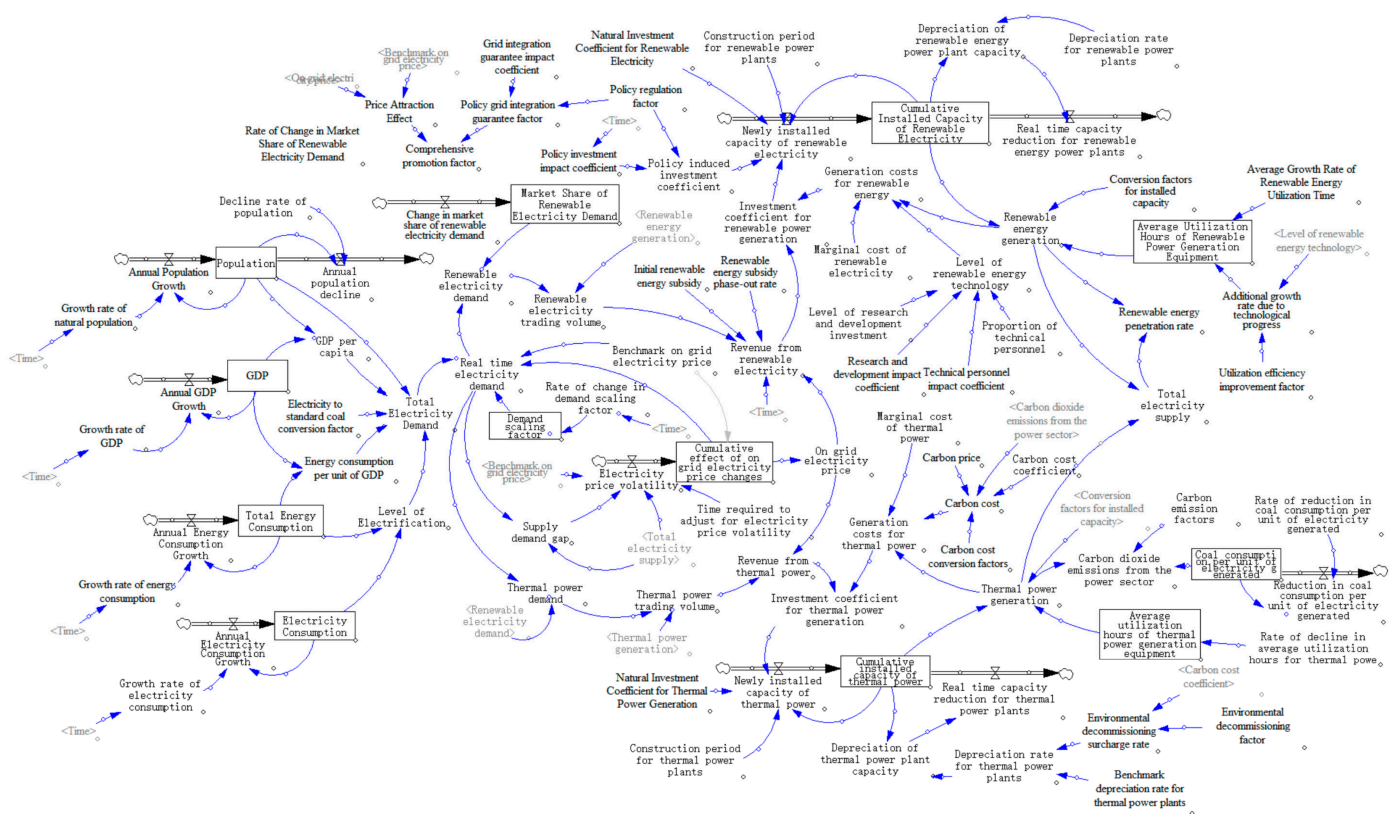


Figure 3. Stock–flow diagram of the SD model for REP evolution.

3.4. Modeling

The key equations characterizing the main feedback mechanisms of the SD model are presented in this section, while the complete set of model equations, variable definitions, and units is provided in Appendix A.

In the SD model of REP evolution developed in this study, total electricity demand is jointly determined by population size, economic income levels, energy efficiency levels, and the degree of end-use electrification [2].

$$D = PE \times EE \times TE \times EL \quad (1)$$

where D denotes total electricity demand, PE denotes population effect, EE denotes economic effect, TE denotes technological effect, and EL denotes electrification level.

Real-time electricity demand is further adjusted through price elasticity mechanisms.

$$D_r = \beta \times D \times \left(\frac{P}{P_0} \right)^e \quad (2)$$

where D_r denotes real-time electricity demand, β denotes the power demand scaling ratio, P denotes the on-grid electricity price, and e denotes the price elasticity of electricity demand.

Total electricity supply encompasses both renewable and thermal power generation.

$$S = Q_{RE} + Q_T \quad (3)$$

where S denotes total electricity supply, Q_{RE} denotes renewable power generation, and Q_T denotes thermal power generation.

The supply-demand gap further exerts a feedback effect on electricity prices, maintaining a dynamic equilibrium in the electricity market.

$$P = P_0 + \int_0^{t_{end}} \Delta P \times dt \quad (4)$$

$$\Delta P = \frac{SD_{gap}}{S} \times \frac{P_0}{T_p} \quad (5)$$

$$SD_{gap} = D_r - S \quad (6)$$

where ΔP denotes the fluctuation in the on-grid electricity price, SD_{gap} denotes the supply-demand gap, and T_p denotes the adjustment time for electricity price fluctuations.

Renewable power generation is determined by the cumulative installed capacity of renewable energy and the average annual operating hours of power generation units.

$$Q_{RE} = K_{RE} \times H_{RE} \quad (7)$$

where Q_{RE} denotes renewable power generation, K_{RE} denotes the cumulative installed capacity of renewable energy, and H_{RE} denotes the average annual operating hours of renewable power generation units.

Cumulative installed capacity depends on the cumulative difference between new installations and depreciation. The depreciation rate of installed capacity can be calculated using the average-life depreciation method [71]. The investment appeal of new installed capacity stems not only from the intrinsic driver of increased power plant profits but is also divided into two types: natural investment and induced investment, with induced investment arising from government policy incentives aimed at increasing REP [72]. Given the objective existence of project construction cycles, a time lag effect is introduced to account for the impact of newly installed capacity on existing capacity.

$$K_{RE} = K_{RE,0} + \int_0^{t_{end}} (I_{RE} - D_{RE}^{dep}) \times dt \quad (8)$$

$$I_{RE} = K_{RE} \times n_{RE} \times \phi \times DELAY1(V_{RE}, T_{RE}) \quad (9)$$

where I_{RE} denotes newly installed renewable energy capacity, D_{RE}^{dep} denotes depreciation of renewable energy installed capacity, n_{RE} denotes the natural investment coefficient of renewable energy, ϕ denotes the policy promotion factor, V_{RE} denotes the renewable energy investment coefficient, and T_{RE} denotes the construction period of renewable power plants.

Revenue from renewable power generation is determined by the actual traded electricity volume, the on-grid electricity price, and the subsidy level. This model incorporates renewable power subsidies into the revenue function until 2021 and assumes a phase-out

of subsidies after 2021 to reflect the transition of renewable energy development from subsidy-driven to market-driven.

$$R_{RE} = [P + B] \times X_{RE} \quad (10)$$

$$B = IF \ THEN \ ELSE(t < 2021, B_0 \times EXP[r_b(t - 2012)], 0) \quad (11)$$

where R_{RE} denotes revenue from renewable power generation, B denotes the renewable power subsidy, X_{RE} denotes the trading volume of renewable electricity, B_0 denotes the initial renewable power subsidy, and r_b denotes the decline rate of renewable power subsidy.

At the same time, technological progress further enhances the market competitiveness of renewable energy by reducing costs and improving utilization efficiency.

$$H_{RE} = H_{RE,0} + \int_0^{t_{end}} H_{RE} \times (g_H + g_{tech}) dt \quad (12)$$

$$C_{RE} = Q_{RE} \times c_{RE} \times (1 - T \times \alpha) \quad (13)$$

where $H_{RE,0}$ denotes the initial average utilization hours of renewable power generation units, g_H denotes the growth rate of average utilization hours, g_{tech} denotes the additional growth rate induced by technological progress, C_{RE} denotes the cost of renewable power generation, c_{RE} denotes the marginal cost of renewable power generation, T denotes renewable energy technological progress, and α denotes the influence coefficient of technological progress.

Demand for renewable electricity is determined by real-time electricity demand and the market share of renewable electricity demand; its evolution exhibits path dependence and self-reinforcing characteristics, thereby reflecting a typical nonlinear expansion process.

$$D_{RE} = D_r \times M_{RE} \quad (14)$$

where D_{RE} denotes renewable electricity demand, and M_{RE} denotes the market share of renewable electricity demand.

As the regulating and backup power source for the power system, the demand for thermal power is determined by the residual portion of real-time electricity demand after subtracting renewable electricity demand.

$$D_T = \text{MAX}(0, D_r - D_{RE}) \quad (15)$$

where D_T denotes thermal power demand.

Thermal power generation is determined by cumulative thermal power installed capacity and average utilization hours. Thermal power capacity also follows the “new additions–depreciation” logic of stock evolution, but its investment behavior is constrained by both declining profit expectations and rising carbon costs.

$$Q_T = K_T \times H_T \quad (16)$$

$$K_T = K_{T,0} + \int_0^{t_{end}} (I_T - D_T^{dep}) \times dt \quad (17)$$

where K_T denotes cumulative installed capacity of thermal power, H_T denotes the average utilization hours of thermal power units, I_T denotes newly installed thermal power capacity, and D_T^{dep} denotes depreciation of thermal power installed capacity.

Total revenue from thermal power generation is determined by the volume of thermal power traded and the on-grid electricity price. Unlike the gradually increasing utilization hours of renewable power, the utilization hours of thermal power gradually decline.

$$R_T = P \times X_T \quad (18)$$

$$H_T = H_{T,0} - \int_0^{t_{end}} r_{H,T} \times dt \quad (19)$$

where R_T denotes revenue from thermal power generation, X_T denotes the trading volume of thermal electricity, and $r_{H,T}$ denotes the decline rate of average utilization hours of thermal power units.

The cost of carbon emissions enters the thermal power cost function through power-sector CO₂ emissions and the carbon pricing mechanism, not only increasing operating costs but also intensifying pressure to retire units through profit compression, thereby raising the depreciation rate of thermal power plants.

$$C_T = c_T \times Q_T + C_C \quad (20)$$

$$C_C = CO_2 \times P_C \times \theta_C \quad (21)$$

$$d_T = d_{T0} + d_E \quad (22)$$

where C_T denotes the cost of thermal power generation, c_T denotes the marginal cost of thermal power generation, Q_T denotes thermal power generation, C_C denotes carbon cost, CO_2 denotes power-sector CO₂ emissions, P_C denotes carbon price, θ_C denotes the carbon cost coefficient, d_T denotes the depreciation rate of thermal power capacity, d_{T0} denotes the benchmark depreciation rate of thermal power capacity, and d_E denotes the additional retirement rate induced by environmental constraints.

Finally, REP, as a core system indicator, is determined by the proportion of renewable power generation in total electricity supply and serves as a concentrated reflection of the system's overall evolution.

$$\rho_{RE} = \frac{Q_{RE}}{S} \quad (23)$$

where ρ_{RE} denotes REP.

3.5. Data Description and Scenario Design

3.5.1. Data Sources and Parameter Setting

To examine the dynamic evolution of REP under different driving mechanisms, this paper focuses on China's electricity sector and conducts simulation analyses based on a unified SD model. Taking into account the availability of historical data and the long-term goals of China's energy transition, the model's base year is set to 2012, the time step is set to one year, and the simulation period is set to 2012–2060. Specifically, statistical data from 2012 to 2023 are used for parameter calibration and model validation, while the period from 2024 to 2060 serves as the policy scenario simulation period to analyze the long-term evolution trends of REP under different scenarios.

Regarding model initialization, the initial values of the main stock variables were set based on actual 2012 data from China's electricity sector, while the key exogenous parameters and constant variables in the model were determined primarily based on statistical data, policy targets, existing literature, and model calibration results. Specifically, historical variables and initial stock values were mainly obtained from official statistical sources, while parameters such as demand elasticity, investment coefficients, technological progress coefficients, construction periods, and carbon-related parameters were determined

according to previous studies and model calibration. For parameters that cannot be directly obtained from statistical sources, their baseline values were further adjusted through iterative calibration against historical data from 2012 to 2023, so that the simulated trends of total electricity demand, renewable power generation, and thermal power generation could generally reproduce the historical evolution of China's electricity sector. The relevant data were primarily sourced from the China Statistical Yearbook, the China Energy Statistical Yearbook, the China Electric Power Yearbook, the National Energy Administration, the National Bureau of Statistics, the China Electricity Council, and relevant research literature. Key parameters and their initial values are shown in Table 1.

Table 1. Initial values of key variables.

Key Parameter	Initial Value	Unit	Source
GDP growth rate	0.0790	—	China Statistical Yearbook
GDP at constant 2012 prices	519,470	10 ⁸ yuan	China Statistical Yearbook
Natural population growth rate	0.0146	—	China Statistical Yearbook
Population	13.5922	10 ⁸ persons	China Statistical Yearbook
Total energy consumption	402,138	10 ⁴ tce ¹	China Statistical Yearbook
Growth rate of energy consumption	0.039	—	China Statistical Yearbook
Electricity consumption	61,158.28	10 ⁴ tce	China Electric Power Statistical Yearbook
Market share of renewable electricity demand	0.08	—	National Energy Administration; National Renewable Energy Power Development Monitoring and Evaluation Report
Change rate of the market share of renewable electricity demand	0.015	—	National Energy Administration, 2013–2023
Benchmark on-grid electricity price	0.38	yuan/kWh	National Energy Administration
Price elasticity of electricity demand	−0.25	—	Reference [73]
Cumulative installed capacity of renewable energy	0.6411	10 ⁸ kW	China Electric Power Statistical Yearbook
Average utilization hours of renewable power generation	1676	hour	China Electric Power Statistical Yearbook
Growth rate of average utilization hours of renewable energy	0.00217	—	China Electric Power Statistical Yearbook
Expansion rate of renewable energy installed capacity	0.1105	—	Reference [72]
Construction period of renewable power plants	1	year	Reference [74]
Depreciation rate of renewable power plants	0.0097	—	China Electric Power Statistical Yearbook
Marginal cost of renewable electricity	0.5	yuan/kWh	Reference [44]
Decline rate of renewable energy subsidy	0.2	—	Annual Development Report of China's Electric Power Industry
Influence coefficient of technology R&D	0.6	—	References [64,75]
Influence coefficient of technical talent	0.4	—	References [64,75]
Average utilization hours of thermal power plants	4982	hour	China Electric Power Statistical Yearbook
Decline rate of average utilization hours of thermal power	0.00895	—	China Electric Power Statistical Yearbook
Cumulative installed capacity of thermal power	7.87	10 ⁸ kW	China Electric Power Statistical Yearbook

Table 1. Cont.

Key Parameter	Initial Value	Unit	Source
Expansion rate of thermal power installed capacity	0.41	—	Reference [72]
Construction period of thermal power plants	2	year	Reference [46]
Depreciation rate of thermal power plants	0.0097	—	China Electric Power Statistical Yearbook
Marginal cost of thermal power	0.27	yuan/kWh	Reference [44]
Carbon price	50	yuan/t CO ₂	Carbon market data
Coal consumption for power supply	0.000325	tce/kWh	Annual Development Report of China's Electric Power Industry
Carbon emission coefficient	2.6	t CO ₂ /tce	Statistical data from the National Center for Climate Change Strategy and International Cooperation

¹ Note: tce denotes ton of coal equivalent.

3.5.2. Scenario Design

To examine the impact of different drivers on the evolution of REP, this paper constructs seven scenarios and compares them both individually and in combination. Among these, the baseline scenario (BAU) is based on current trends in China's power sector and the model's baseline parameters; scenarios S1–S4 are single-factor scenarios corresponding to policy support, technological innovation, market demand expansion, and increased environmental constraints, respectively; and scenarios S5–S7 are combined scenarios, as detailed in Table 2. These scenarios are designed as controlled scenario experiments to isolate and compare the relative effects of different driving mechanisms, rather than to provide comprehensive forecasts of multiple future uncertainties. The 10% adjustment is used as a standardized perturbation for comparability, rather than as a deterministic policy target.

Table 2. Scenarios setting scheme.

Scenario	Policy Driver	Technology Driver	Market Driver	Environmental Driver
BAU Baseline scenario	Baseline	Baseline	Baseline	Baseline
S1 Policy support	+10%	Baseline	Baseline	Baseline
S2 Technological innovation	Baseline	+10%	Baseline	Baseline
S3 Market demand expansion	Baseline	Baseline	+10%	Baseline
S4 Environmental constraint	Baseline	Baseline	Baseline	+10%
S5 Policy–technology synergy	+10%	Baseline	+10%	Baseline
S6 Policy–market synergy	+10%	+10%	Baseline	Baseline
S7 Policy–environment synergy	+10%	Baseline	Baseline	+10%

3.5.3. Model Validation

To verify the model's validity, this study conducted a historical validation using total electricity demand, renewable power generation, and thermal power generation. In addition to annual relative errors, root mean square error (RMSE) and mean absolute percentage error (MAPE) were used to quantify the model's fitting accuracy. RMSE and MAPE were calculated as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (S_t - A_t)^2} \quad (24)$$

$$MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{S_t - A_t}{A_t} \right| \times 100\% \quad (25)$$

where S_t denotes the simulated value in year t , A_t denotes the actual value in year t , and n denotes the number of historical observations. The historical validation results are shown in Tables 3–5.

The corresponding MAPE values are 1.58%, 3.50%, and 4.26%, respectively, and the annual relative errors are generally within 10%. These results indicate that the model can reasonably reflect the main characteristics of China's electricity sector and is suitable for subsequent scenario-based simulation.

To further examine model robustness and structural validity, sensitivity analysis and extreme-condition testing were conducted. Following the control variable method, four key parameters related to policy support, technological innovation, market demand expansion, and environmental constraints were adjusted by $\pm 5\%$ under the baseline scenario, while other parameters remained unchanged. Table 6 shows that the changes in REP are consistent with theoretical expectations under both moderate parameter perturbations and representative extreme conditions, suggesting good stability and robustness. Among the tested parameters, policy support and technological innovation show relatively larger effects on REP.

Table 3. Historical validation results for total electricity demand.

Year	Total Electricity Demand		
	Simulated Value (10^4 tce)	Actual Value (10^4 tce)	Relative Error (%)
2012	49,662.7	49,762.64	0.20%
2013	52,718.6	54,203.41	2.74%
2014	55,850	57,829.69	3.42%
2015	59,167.5	58,019.98	1.98%
2016	62,682.1	61,205.09	2.41%
2017	66,405.4	65,913.97	0.75%
2018	70,349.9	71,508.2	1.62%
2019	74,528.7	74,866.12	0.45%
2020	78,955.7	77,620.17	1.72%
2021	83,645.6	85,200.1	1.82%
2022	88,614.2	88,357.62	1.36%
2023	90,819.4	92,238	1.54%
RMSE	1211.32	—	—
MAPE	—	—	1.58%

Table 4. Historical validation results for renewable power generation.

Year	Renewable Power Generation		
	Simulated Value (10^8 kWh)	Actual Value (10^8 kWh)	Relative Error (%)
2012	1074.48	1066.4	0.76%
2013	1420.3	1495.13	5.00%
2014	1877.41	1834.12	2.36%
2015	2440.32	2245.48	8.68%
2016	3129.72	2986.59	4.79%
2017	3971.87	4035.7	1.58%
2018	5000.29	5434.9	8.00%
2019	6257.66	6304.6	0.74%
2020	7798.17	7273.31	7.22%
2021	9690.14	9818.58	1.31%
2022	12,019.3	11,899.47	1.01%
2023	14,616	14,692	0.52%
RMSE	218.57	—	—
MAPE	—	—	3.50%

Table 5. Historical validation results for thermal power generation.

Year	Thermal Power Generation		
	Simulated Value (10 ⁸ kWh)	Actual Value (10 ⁸ kWh)	Relative Error (%)
2012	39,208.3	39,255	0.12%
2013	40,279.2	42,216	4.59%
2014	41,379.3	43,030	3.84%
2015	42,533.1	42,307	0.53%
2016	43,759.5	43,273	1.12%
2017	45,074.7	45,877	1.75%
2018	46,493.5	49,249	5.60%
2019	48,030.3	50,465	4.82%
2020	49,699.1	51,770	4.00%
2021	51,513.8	56,655	9.07%
2022	53,487.5	57,450	6.90%
2023	55,632.6	60,984	8.78%
RMSE	2828.27	—	—
MAPE	—	—	4.26%

Table 6. Sensitivity analysis and extreme-condition test results.

Test type	Parameter/ Condition	Setting	Change from BAU	Result
Sensitivity analysis	Policy support coefficient	+5%	+2.40%	Passed
		−5%	−0.86%	Passed
	Technological progress coefficient	+5%	+1.80%	Passed
		−5%	−0.15%	Passed
	Market demand expansion coefficient	+5%	+0.37%	Passed
		−5%	−0.37%	Passed
	Carbon cost coefficient	+5%	+0.66%	Passed
		−5%	−0.13%	Passed
Extreme-condition test	Strong policy support	+50%	+13.75%	Passed
	Weak market demand	−50%	−3.87%	Passed

4. Results and Discussion

4.1. Evolution of Renewable Energy Penetration Under Single-Factor Scenarios

The simulation results shown in Figure 4 indicate that renewable power generation follows a sustained upward trend from 2012 to 2060 under all scenarios, although the magnitude of the driving effects varies across mechanisms. Under the current parameter settings, S1 produces the highest renewable power generation among the four single-factor scenarios. By 2060, renewable power generation under S1 reaches 16,522.2 billion kWh, representing an increase of 1399.0 billion kWh relative to BAU, or 9.25% (Table 7). This finding suggests that policy support plays an important role in promoting renewable energy development in the simulated scenarios.

S2 has a positive effect on renewable power generation in the early stage, while S3 shows an increasingly pronounced driving effect in the middle and later stages. Specifically, S3 surpasses S4 during 2029–2030 and exceeds S2 during 2038–2039. By 2060, renewable power generation under S3 increases by 726.0 billion kWh relative to BAU, corresponding to a growth rate of 4.80%, which is higher than the 2.88% observed under S2. This result suggests that demand-side factors become increasingly important in the middle and later stages of the simulation. Although technological innovation improves the economic fea-

sibility of renewable energy, its marginal effect becomes weaker over the long term and is gradually surpassed by market demand expansion. S4 produces the smallest increase in renewable power generation, only 1.16% above BAU by 2060, indicating a relatively limited direct contribution under the current model settings.

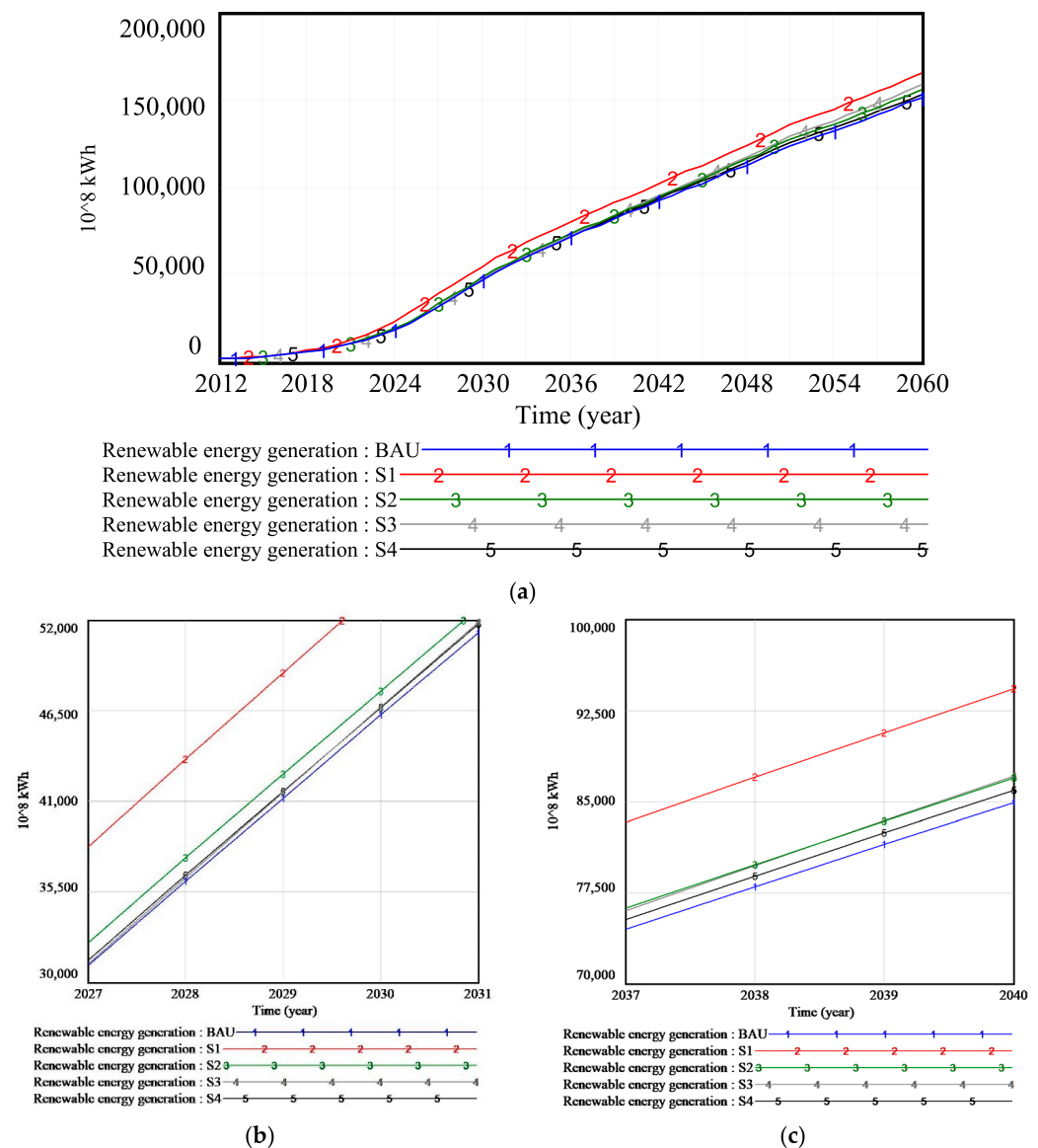


Figure 4. Evolution of renewable power generation under BAU and single-factor scenarios. (a) Overall evolution from 2012 to 2060; (b) enlarged view from 2027 to 2031; (c) enlarged view from 2037 to 2040.

Table 7. Scenario comparison of renewable power generation.

Year	BAU	S1		S2		S3		S4	
		Δ	Change Rate	Δ	Change Rate	Δ	Change Rate	Δ	Change Rate
2025	21,520.9	6193.0	28.78%	1040.5	4.83%	2.7	0.01%	172.1	0.80%
2030	46,223.2	7798.3	16.87%	1477.9	3.20%	503.9	1.09%	463.1	1.00%
2035	67,143.7	8507.2	12.67%	1621.7	2.42%	1187.4	1.77%	721.7	1.07%
2040	84,909.1	9360.5	11.02%	2011.3	2.37%	2193.0	2.58%	996.1	1.17%
2045	101,808	10,383	10.20%	2611	2.56%	3491	3.43%	1278	1.26%
2050	119,524	11,617	9.72%	3324	2.78%	4969	4.16%	1537	1.29%
2055	134,900	12,751	9.45%	3902	2.89%	6172	4.58%	1689	1.25%
2060	151,232	13,990	9.25%	4351	2.88%	7260	4.80%	1761	1.16%

Figure 5 shows that thermal power generation under all scenarios follows an inverted U-shaped trajectory, increasing initially and then declining after peaking around 2030. This pattern reflects the gradual substitution of thermal power by renewable energy. Under the simulated scenarios, thermal power continues to play a supporting role in the power system in the short term, whereas its long-term generation space gradually shrinks with the expansion of renewable energy.

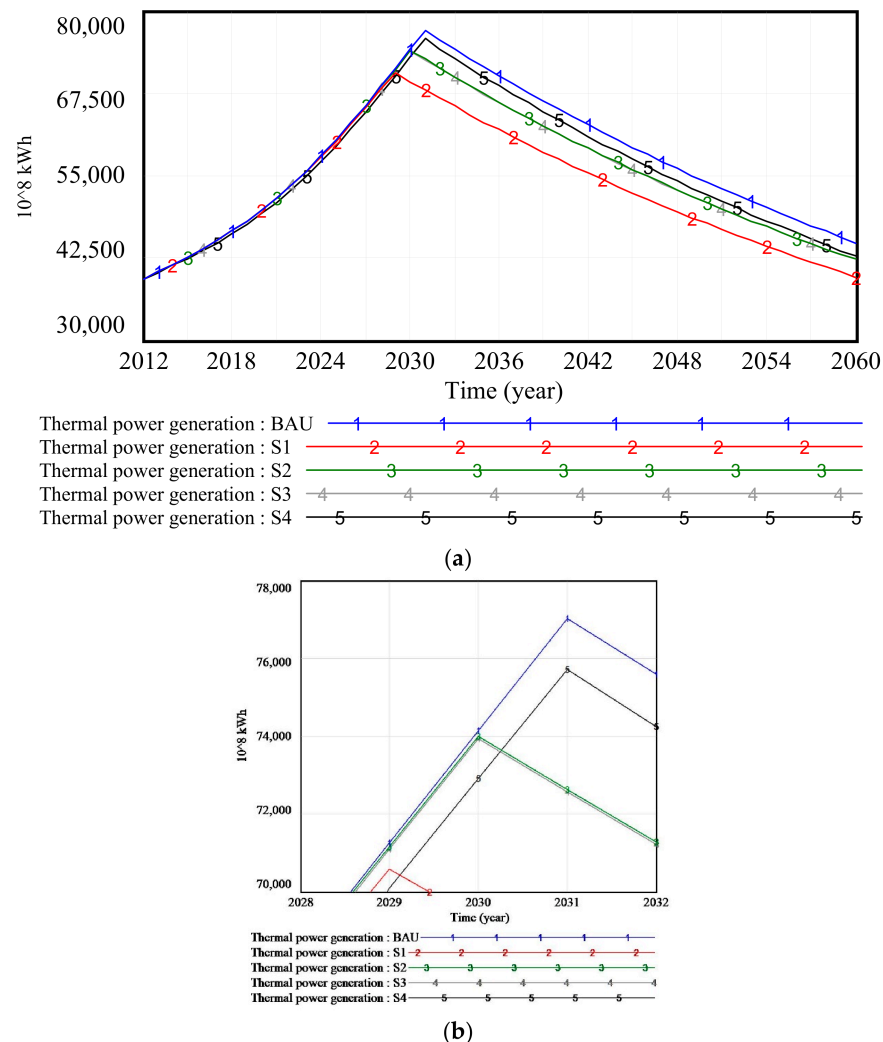


Figure 5. Evolution of thermal power generation under BAU and single-factor scenarios. (a) Overall evolution from 2012 to 2060; (b) enlarged view around the peak period from 2028 to 2032.

In terms of peak reduction, as summarized in Table 8, S1 shows the strongest restraining effect on thermal power generation under the current parameter settings, reducing the peak value by 8.35% relative to BAU and advancing the peak year from 2031 to 2029. This suggests that policy support contributes not only to renewable energy development but also to thermal power substitution in the simulated scenarios. S2 and S3 also contribute to reductions in the peak value of thermal power generation, with decreases of 3.92% and 4.00%, respectively, and both advance the peak year to 2030. Their effects are smaller than that of S1 but stronger than that of S4.

Notably, under S4, the peak value of thermal power generation decreases by only 1.68%, while the peak year remains unchanged at 2031. Its effect is therefore weaker than those of S2 and S3. This result suggests that, under the current model settings, increasing carbon costs alone does not necessarily lead to the rapid phase-out of thermal power. Environmental constraints therefore appear to function more as an indirect driving

mechanism and need to be combined with policy, market, and technological factors to promote thermal power substitution.

Table 8. Scenario comparison of thermal power generation peaks.

Scenario	Peak Value	Peak Year	Reduction	Change Rate
BAU	77,022.3	2031	—	—
S1	70,591.3	2029	6431.0	8.35%
S2	74,005.8	2030	3016.5	3.92%
S3	73,938.5	2030	3083.8	4.00%
S4	75,728.6	2031	1293.7	1.68%

Figure 6 presents the evolution of REP under different single-factor scenarios, reflecting structural adjustment in the power system. The main panel shows that REP increases substantially under all scenarios, indicating that renewable energy expands not only in generation scale but also in its relative share within the power supply structure in the simulated scenarios.

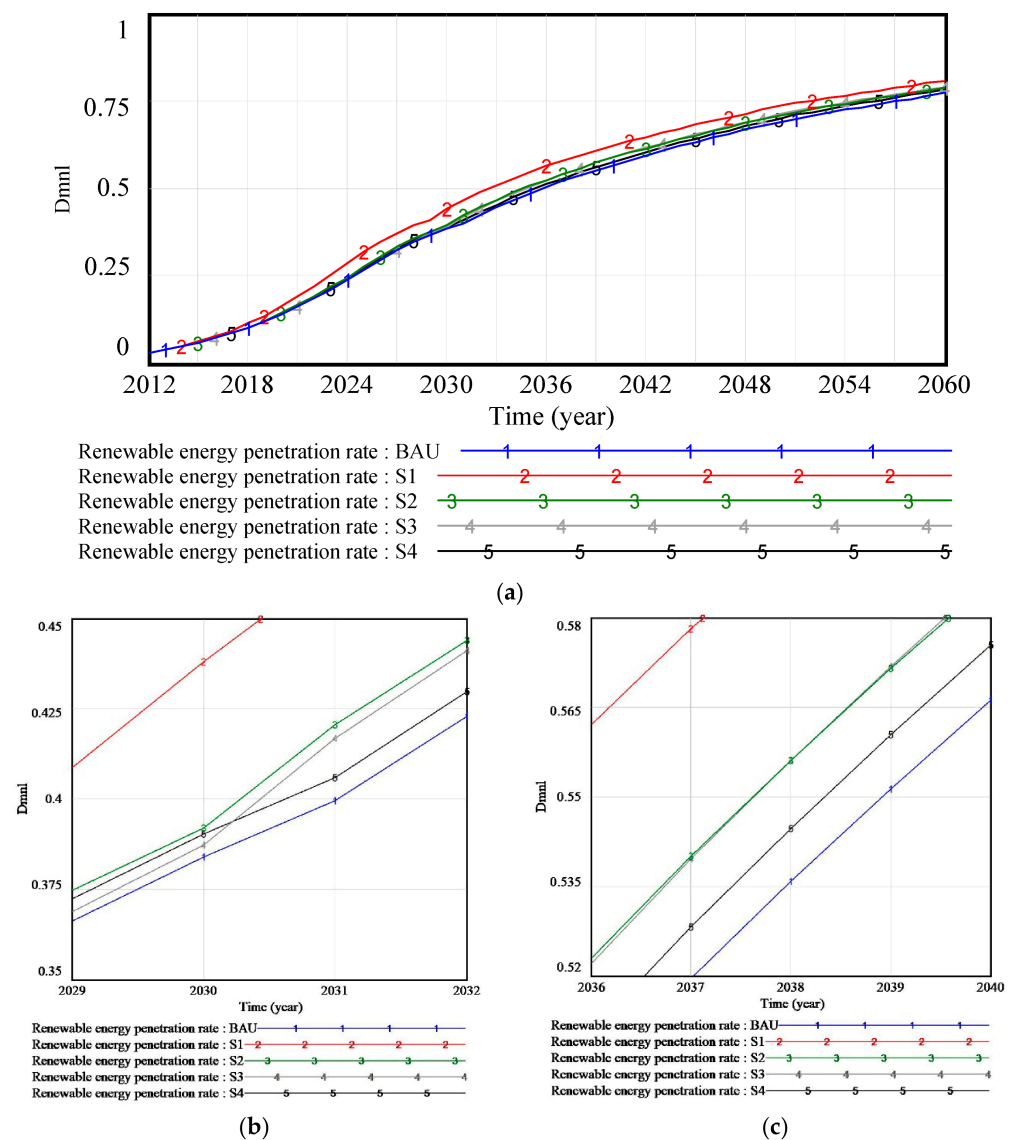


Figure 6. Evolution of REP under BAU and single-factor scenarios. (a) Overall evolution from 2012 to 2060; (b) enlarged view from 2029 to 2032; (c) enlarged view from 2036 to 2040.

In terms of scenario differences, as shown in Table 9, S1 reaches the highest REP level under the current parameter settings, with REP reaching 80.71% by 2060, 4.58% higher than the BAU level. In contrast, S4 increases REP by only 1.30% relative to BAU, representing the smallest improvement among the four scenarios. This suggests that relying solely on environmental constraints is insufficient to generate a significant structural substitution effect under the current model settings. The effect of S3 gradually strengthens in the later stage. Its REP level exceeds that under S4 during 2030–2031 and surpasses that under S2 during 2038–2039. Notably, the crossover points of REP are not fully consistent with those of renewable power generation. This indicates that REP improvement in the model depends on a coordinated structural transition between renewable power growth and the orderly withdrawal of thermal power.

Table 9. Scenario comparison of REP.

Year	BAU	S1		S2		S3		S4	
		Δ	Change Rate	Δ	Change Rate	Δ	Change Rate	Δ	Change Rate
2025	0.2628	0.0525	19.97%	0.0093	3.55%	0.0003	0.10%	0.0045	1.73%
2030	0.3840	0.0541	14.09%	0.0079	2.06%	0.0032	0.84%	0.0064	1.65%
2035	0.4844	0.0609	12.56%	0.0206	4.26%	0.0193	3.98%	0.0079	1.63%
2040	0.5661	0.0552	9.76%	0.0200	3.54%	0.0208	3.67%	0.0092	1.63%
2045	0.6321	0.0499	7.89%	0.0193	3.05%	0.0214	3.39%	0.0101	1.59%
2050	0.6890	0.0446	6.47%	0.0181	2.63%	0.0211	3.06%	0.0104	1.51%
2055	0.7330	0.0399	5.45%	0.0167	2.28%	0.0199	2.72%	0.0104	1.41%
2060	0.7717	0.0354	4.58%	0.0150	1.94%	0.0182	2.36%	0.0100	1.30%

Table 10 shows that, under the current scenario settings, the improvement effect of REP under the single-factor scenarios follows the order of S1 > S3 > S2 > S4. Further observation shows that although REP continues to rise under all scenarios, its annual increment narrows in the later stage. This implies that, within the simulated system, as the share of renewable energy increases, the marginal difficulty of further optimizing the power structure gradually increases.

Table 10. Comparison of REP enhancement capacity under different scenarios.

Adjusted Parameter	S1	S2	S3	S4
2025	0.0342	0.0294	0.0283	0.0290
2030	0.0294	0.0173	0.0184	0.0179
2035	0.0180	0.0190	0.0196	0.0195
2040	0.0137	0.0147	0.0150	0.0150
2045	0.0113	0.0121	0.0124	0.0124
2050	0.0098	0.0106	0.0107	0.0109
2055	0.0072	0.0078	0.0078	0.0081
2060	0.0066	0.0071	0.0071	0.0074
Cumulative	0.7804	0.7600	0.7633	0.7551

4.2. Evolution of Renewable Energy Penetration Under Synergistic Scenarios

Given the relatively strong effect of policy support in the single-factor scenarios, three policy-centered synergistic scenarios are further designed. The evolution of key power-system indicators under the synergistic scenarios is shown in Figure 7. By 2060, REP reaches 80.89% under S5, 81.21% under S6, and 80.48% under S7, all higher than the BAU level of 77.1%. Among them, S6 shows the strongest improvement, achieving both the highest renewable power generation and the highest penetration rate. This suggests that the promoting effect of policy support can be more fully released when combined

with demand expansion. Further comparison shows that S6 outperforms both S5 and S7. Without sufficient demand absorption, policy effects may not be fully translated into actual generation growth and structural substitution. In comparison, the effect of S5 is more dependent on long-term technological accumulation. S6, by contrast, combines supply expansion with demand absorption, thereby producing a stronger overall effect.

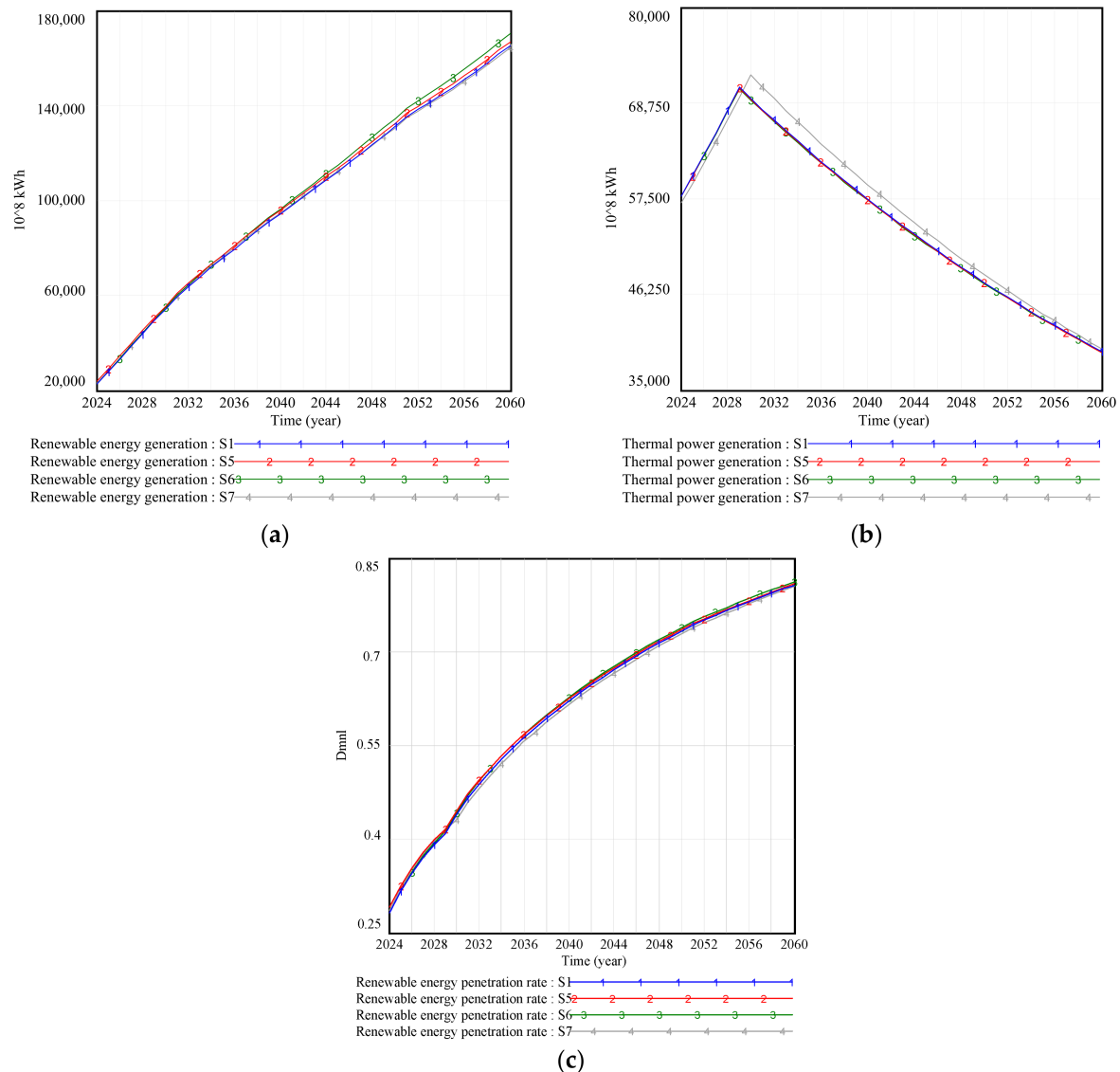


Figure 7. Evolution of key power-system indicators under synergistic scenarios. (a) Renewable power generation; (b) thermal power generation; (c) renewable energy penetration.

One noteworthy result is that S7 does not show a stronger effect than S1. Compared with S1, renewable power generation under S7 is lower by 97.4 billion kWh in 2060, and REP is lower by 0.23 percentage points. In terms of thermal power substitution, the peak value of thermal power generation under S7 is 1446.8 billion kWh higher than that under S1, and the peak year is delayed from 2029 to 2030. This suggests that environmental constraints and policy support do not necessarily form a simple linear superposition effect; instead, a possible offsetting effect may exist between them. One possible explanation is that an increase in the carbon cost coefficient mainly acts on the thermal power side and does not directly expand renewable energy supply or green electricity demand. Meanwhile, rising thermal power costs may affect the market attractiveness of renewable electricity through feedback effects related to electricity prices and the supply–demand gap. Therefore,

environmental constraints need to be coordinated with market, technology, and flexibility regulation to improve REP.

Compared with previous studies, these findings both support and extend existing conclusions. The positive effects of policy support and technological progress are generally consistent with previous studies showing that policy instruments promote renewable energy development [16,19], while technological innovation enhances renewable power generation and energy transition [29,31]. However, this study further finds that market demand becomes more influential in the middle and later stages of the simulation, and that policy–market synergy produces a stronger improvement in REP than single-factor scenarios. In addition, our finding on policy–environment synergy differs from studies emphasizing the positive coupling effects of renewable energy policy instruments and carbon market mechanisms [46], but is consistent with Wu et al. [45], who suggested that such mechanisms may involve overlapping or conflicting effects. Specifically, the policy–environment synergy scenario in this study does not outperform the single policy support scenario. Overall, the scenario results suggest that higher REP should not be directly interpreted as overall optimal system performance, and REP improvement should be understood together with renewable expansion, demand absorption, system flexibility, backup capacity, and supply security.

5. Conclusions and Policy Implications

Based on SD, this study constructs a model of REP evolution in China. Focusing on four driving mechanisms—policy support, technological innovation, market demand expansion, and environmental constraints—this study establishes BAU, single-factor, and synergistic scenarios to simulate renewable power generation, thermal power generation, and REP in China’s power system. The main conclusions are as follows.

(1) In all scenarios, renewable power generation and REP show sustained upward trends, while thermal power generation initially increases and then declines. This suggests a possible low-carbon transition pathway of China’s power structure under the model assumptions and scenario settings. Thermal power continues to play a system-supporting role in the short term in the simulation results, while its long-term generation space gradually shrinks.

(2) Under the current scenario settings and parameter assumptions, policy support shows the strongest effect on REP among the single-factor scenarios. By 2060, REP under S1 reaches 80.71%, representing a 4.58% increase relative to BAU, and S1 shows the strongest influence on both renewable power generation growth and peak thermal power reduction. This indicates that policy support plays a central role in promoting renewable energy expansion and structural substitution under the current model settings.

(3) Both market demand expansion and technological innovation are shown to promote REP, but their effects differ across stages. In the early and middle stages, technological innovation enhances the competitiveness of renewable energy by reducing costs and improving efficiency, whereas market demand expansion exerts a stronger influence in the middle and later stages. By 2060, REP under S3 reaches 78.99%, higher than the 78.67% under S2, suggesting the importance of demand-side green electricity consumption and electrification for long-term structural optimization.

(4) Among the synergistic scenarios, policy–market synergy shows the strongest improvement under the current scenario settings. Under S6, renewable power generation reaches 17,020.1 billion kWh by 2060, and REP reaches 81.21%, both of which are the highest among all scenarios. Notably, S7 does not outperform the single policy support scenario in the simulation results, suggesting that environmental constraints and policy support do not simply produce a linear additive effect. Without market-based consumption and

technological support, the carbon cost mechanism may not be fully translated into REP improvement.

(5) REP improvement is not a linear process driven by a single factor, but rather the result of systemic evolution driven by the combined effects of policy, market, technology, and environmental factors. Among these factors, policy support plays an important guiding role; market demand expansion is a key condition for releasing policy effects; technological innovation supports long-term competitiveness; and environmental constraints serve as a complementary mechanism for facilitating the orderly substitution of thermal power generation.

Based on these findings, this study proposes the following policy implications. First, stable and continuous policy support should be maintained. Renewable energy policies should focus on stabilizing investment expectations, improving policy coordination, and providing consistent institutional support for REP improvement. Second, green electricity demand should be further expanded. Policy efforts should encourage green electricity consumption, corporate green procurement, end-use electrification, and market-based renewable energy consumption. Third, technological innovation should be continuously promoted. Support for renewable power generation technologies, energy storage, smart grids, and flexibility regulation should be strengthened to improve cost competitiveness, generation efficiency, and system compatibility. Finally, environmental constraints should be strengthened prudently. Carbon-related policy instruments should be coordinated with electricity supply–demand balance, price stability, and system flexibility, rather than being implemented as isolated constraints. Overall, renewable energy penetration should be promoted through coordinated policy, market, technological, and environmental measures, while balancing system flexibility, supply security, and cost control.

This study also has some limitations. First, the national-level model does not fully capture regional heterogeneity in renewable resources, electricity demand, grid accommodation capacity, and policy implementation. Second, the deterministic scenario design cannot fully represent the simultaneous effects of technological progress, electricity demand growth, policy changes, carbon pricing, fuel prices, economic growth, and international energy markets on real-world electricity systems. Third, although this study considers REP, electricity prices, and supply–demand balance, broader system-level trade-offs related to system costs, storage, transmission, flexibility, renewable curtailment, backup generation, and energy security are not fully examined. Future research could extend the model to regional or provincial scales, incorporate compound scenarios or probabilistic uncertainty analysis, include broader power system performance indicators, and apply its general feedback structure to other national contexts after recalibrating country-specific parameters.

Author Contributions: Conceptualization, Y.Y. and W.W.; methodology, Y.Y.; software, Y.Y.; validation, Y.Y. and X.L.; formal analysis, Y.Y.; investigation, Y.Y.; resources, W.W.; data curation, Y.Y. and X.L.; writing—original draft preparation, Y.Y.; writing—review and editing, Y.Y., W.W. and X.L.; visualization, Y.Y.; supervision, W.W.; project administration, W.W.; funding acquisition, W.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Fund of China, grant number 23AGL033.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used in this study are derived from publicly available sources. Further details are available from the corresponding author upon reasonable request.

Acknowledgments: The authors gratefully acknowledge the support of their institutions.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

REP	Renewable energy penetration
SD	System dynamics
BAU	Business-as-usual
PV	Photovoltaic
R&D	Research and development
GDP	Gross domestic product
CO ₂	Carbon dioxide
tce	Ton of coal equivalent

Appendix A

Appendix A.1 Main Equations of the SD Model

The complete equations of the SD model are presented in this appendix. The equations are grouped into the electricity demand and market module, the renewable power generation module, and the thermal power generation module. The definitions and units of the variables used in the equations are provided in Appendix A.2.

Electricity market and demand module:

$$GI = G \times GR \quad (A1)$$

$$G = G_0 + \int_0^{t_{end}} GI dt \quad (A2)$$

$$PI = POP \times PIR \quad (A3)$$

$$POP = POP_0 + \int_0^{t_{end}} (PI - PD) dt \quad (A4)$$

$$PD = POP \times PDR \quad (A5)$$

$$ECONI = ECON \times ECONR \quad (A6)$$

$$ECON = ECON_0 + \int_0^{t_{end}} ECONI dt \quad (A7)$$

Renewable power generation module:

$$\phi = \phi_0 \times p \quad (A8)$$

$$V_{RE} = I_{RE} / C_{RE} \quad (A9)$$

$$T = a \times R + b \times L \quad (A10)$$

$$X_{RE} = \text{MIN}(Q_{RE}, D_{RE}) \quad (A11)$$

$$M_{RE} = M_{RE,0} + \int_0^{t_{end}} \Delta M_{RE} \times dt \quad (A12)$$

$$\Delta M_{RE} = r_M \times F \times M_{RE} \quad (A13)$$

$$F = A_P \times A_G \quad (A14)$$

Thermal power generation module:

$$Q_T = K_T \times H_T \quad (A15)$$

$$I_T = IFTHENELSE(V_T \geq \theta_T, K_T \times n_T \times DELAY1(V_T, T_T), 0) \quad (A16)$$

$$D_T^{dep} = K_T \times d_T \quad (A17)$$

$$V_T = R_T / C_T \quad (A18)$$

$$X_T = MIN(Q_T, D_T) \quad (A19)$$

$$CO_2 = Q_T \times q_c \times \varepsilon \quad (A20)$$

$$q_c = q_{c,0} - \int_0^{t_{end}} \Delta q_c \times dt \quad (A21)$$

Appendix A.2 Variable Definitions and Units

The definitions and units of the variables used in the SD model are summarized in Table A1.

Table A1. Definitions and units of model variables.

Variable	Definition	Unit
t_{end}	End time of the simulation	year
GI	Annual increment of GDP	10^8 yuan
GR	GDP growth rate	%
G	Gross domestic product	10^8 yuan
PI	Annual population increase	person
PIR	Population growth rate	%
POP	Population	person
PD	Annual population decrease	person
PDR	Population decline rate	%
$ECONI$	Annual increment of energy consumption	tce
$ECON$	Total energy consumption	tce
$ECONR$	Growth rate of energy consumption	%
D	Total electricity demand	10^8 kWh
PE	Population effect	person
EE	Economic effect	Yuan/person
TE	Technological effect	tce/yuan
EL	Electrification level	%
D_r	Real-time electricity demand	10^8 kWh
β	Power demand scaling ratio	%
P	On-grid electricity price	yuan/kWh
P_0	Benchmark on-grid electricity price	yuan/kWh
e	Price elasticity of electricity demand	—
ΔP	Fluctuation in on-grid electricity price	yuan/kWh
S	Total electricity supply	10^8 kWh
T_p	Adjustment time for electricity price fluctuations	times/year
SD_{gap}	Supply–demand gap	10^8 kWh
Q_{RE}	Renewable power generation	10^8 kWh
Q_T	Thermal power generation	10^8 kWh
H_{RE}	Average utilization hours of renewable energy units	hours
g_H	Growth rate of average utilization hours of renewable energy units	%
g_{tech}	Additional growth rate induced by technological progress	%
K_{RE}	Cumulative installed capacity of renewable energy	10^8 kW
$K_{RE,0}$	Initial cumulative installed capacity of renewable energy	10^8 kW
I_{RE}	Newly installed renewable energy capacity	10^8 kW
D_{RE}^{dep}	Depreciation of renewable energy installed capacity	10^8 kW
V_{RE}	Renewable energy investment coefficient	—
n_{RE}	Natural investment coefficient of renewable energy	—

Table A1. Cont.

Variable	Definition	Unit
ϕ	Induced investment coefficient	—
p	Policy regulation factor	—
T_{RE}	Construction period of renewable power plants	year
R_{RE}	Revenue from renewable power generation	10^8 yuan
C_{RE}	Cost of renewable power generation	10^8 yuan
X_{RE}	Trading volume of renewable electricity	10^8 kWh
D_{RE}	Renewable electricity demand	10^8 kWh
B	Renewable energy subsidy	yuan/kWh
M_{RE}	Market share of renewable electricity demand	%
r_M	Change rate of the market share of renewable electricity demand	%
F	Integrated promotion factor	—
A_P	Price attractiveness effect	—
A_G	Policy-driven consumption guarantee factor	—
c_{RE}	Marginal cost of renewable power generation	yuan/kWh
T	Renewable energy technological progress	%
α	Influence coefficient of technological progress	—
R	Technology R&D effort	—
L	Share of technical talent	%
K_T	Cumulative installed capacity of thermal power	10^8 kW
I_T	Newly installed thermal power capacity	10^8 kW
V_T	Thermal power investment coefficient	—
n_T	Natural investment coefficient of thermal power	—
θ_T	Investment activation threshold for thermal power	—
T_T	Construction period of thermal power plants	year
D_T^{dep}	Depreciation of thermal power installed capacity	10^8 kW
d_T	Depreciation rate of thermal power capacity	%
d_E	Additional retirement rate induced by environmental constraints	%
H_T	Average utilization hours of thermal power units	hour
$r_{H,T}$	Decline rate of average utilization hours of thermal power units	%
D_T	Thermal power demand	10^8 kWh
X_T	Trading volume of thermal electricity	10^8 kWh
R_T	Revenue from thermal power generation	10^8 yuan
C_T	Cost of thermal power generation	10^8 yuan
C_C	Carbon cost	10^8 yuan
q_c	Coal consumption for power supply	tce/kWh
ε	Carbon emission coefficient	t CO ₂ /tce
P_C	Carbon price	yuan/t CO ₂
θ_C	Carbon cost coefficient	—
ρ_{RE}	Renewable energy penetration	%

References

1. Sun, Y.; Zhu, S.; Wang, D.; Duan, J.; Lu, H.; Yin, H.; Tan, C.; Zhang, L.; Zhao, M.; Cai, W.; et al. Global supply chains amplify economic costs of future extreme heat risk. *Nature* **2024**, *627*, 797–804. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Yu, B.; Fang, D.; Xiao, K.; Pan, Y. Drivers of renewable energy penetration and its role in power sector's deep decarbonization towards carbon peak. *Renew. Sustain. Energy Rev.* **2023**, *178*, 113247. [\[CrossRef\]](#)
3. Bob, D. *BP Statistical Review of World Energy*; BP: London, UK, 2015.
4. Bob, D. *BP Statistical Review of World Energy*; BP: London, UK, 2023.
5. Bhattacharya, S.; Banerjee, R.; Ramadesigan, V.; Liebman, A.; Dargaville, R. The flexibility dilemma—managing cost and emissions in a fossil fuel-dominated power sector under increasing penetration of variable renewable energy sources. *Appl. Energy* **2026**, *405*, 127199. [\[CrossRef\]](#)
6. Guan, D.; Liu, Z.; Geng, Y.; Lindner, S.; Hubacek, K. The gigatonne gap in China's carbon dioxide inventories. *Nat. Clim. Change* **2012**, *2*, 672–675. [\[CrossRef\]](#)

7. Wang, Z.; Zhang, H.; Wang, B.; Ding, Y. Towards a synergistic future: The impact of power sector decarbonization on Sustainable Development Goals in China. *Sustain. Prod. Consum.* **2025**, *56*, 385–395. [\[CrossRef\]](#)
8. Wang, B.; Duan, M. Have China's emissions trading systems reduced carbon emissions? Firm-level evidence from the power sector. *Appl. Energy* **2025**, *378*, 124802. [\[CrossRef\]](#)
9. Xiang, C.; Zheng, X.; Xie, L. How can China's power sector reform reduce carbon emissions? A long-term competition perspective. *China Econ. Rev.* **2023**, *80*, 102000. [\[CrossRef\]](#)
10. Xing, Y.; Zhang, X.; Li, D.; Xue, J.; Cao, J.; Zhang, R. Carbon emission reduction responsibility allocation in China's power generation sector under the "dual carbon" target—Based on a two-stage shared responsibility approach. *J. Clean. Prod.* **2025**, *489*, 144699. [\[CrossRef\]](#)
11. China Electricity Council. *Annual Development Report of China's Power Industry 2024*; China Electricity Council: Beijing, China, 2024.
12. Painuly, J.P. Barriers to renewable energy penetration; a framework for analysis. *Renew. Energy* **2001**, *24*, 73–89. [\[CrossRef\]](#)
13. Ali, J.S.; Qiblawey, Y.; Alassi, A.; Massoud, A.M.; Muyeen, S.M.; Abu-Rub, H. *Power System Stability with High Penetration of Renewable Energy Sources: Challenges, Assessment, and Mitigation Strategies*; IEEE Access: New York, NY, USA, 2025.
14. Alyamani, T.; Damgacioglu, H.; Celik, N.; Asfour, S.; Feiock, R. A multiple perspective modeling and simulation approach for renewable energy policy evaluation. *Comput. Ind. Eng.* **2016**, *102*, 280–293. [\[CrossRef\]](#)
15. Wang, Q.; Kwan, M.P.; Fan, J.; Zhou, K.; Wang, Y.F. A study on the spatial distribution of the renewable energy industries in China and their driving factors. *Renew. Energy* **2019**, *139*, 161–175. [\[CrossRef\]](#)
16. Romano, A.A.; Scandurra, G.; Carfora, A.; Fodor, M. Renewable investments: The impact of green policies in developing and developed countries. *Renew. Sustain. Energy Rev.* **2017**, *68*, 738–747. [\[CrossRef\]](#)
17. Szendrei, T.; Eross, A.; Mohammed, M.; Ersoy, E. FiT for purpose? Investigating the effects of feed-in-tariffs on renewable energy penetration in Europe. *Appl. Energy* **2025**, *395*, 126102. [\[CrossRef\]](#)
18. Wang, Q.; Zhang, F. Free trade and renewable energy: A cross-income levels empirical investigation using two trade openness measures. *Renew. Energy* **2021**, *168*, 1027–1039. [\[CrossRef\]](#)
19. Lund, P.D. Effects of energy policies on industry expansion in renewable energy. *Renew. Energy* **2009**, *34*, 53–64. [\[CrossRef\]](#)
20. Fatima, N.; Li, Y.; Ahmad, M.; Jabeen, G.; Li, X. Factors influencing renewable energy generation development: A way to environmental sustainability. *Environ. Sci. Pollut. Res.* **2021**, *28*, 51714–51732. [\[CrossRef\]](#)
21. Aguirre, M.; Ibikunle, G. Determinants of renewable energy growth: A global sample analysis. *Energy Policy* **2014**, *69*, 374–384. [\[CrossRef\]](#)
22. Bersalli, G.; Menanteau, P.; El-Methni, J. Renewable energy policy effectiveness: A panel data analysis across Europe and Latin America. *Renew. Sustain. Energy Rev.* **2020**, *133*, 110351. [\[CrossRef\]](#)
23. Zhang, H. Analysis of the driving mechanism and evolutionary path of new energy industrial clusters under the background of low-carbon economy. *Ind. Technol. Econ.* **2016**, *35*, 155–160.
24. Li, C.; Yang, X.; Wang, L. The impact of renewable energy development on regional carbon emission reduction: Based on the spatio-temporal analysis of 30 provinces in China. *Environ. Manag.* **2024**, *74*, 439–460. [\[CrossRef\]](#)
25. Yang, Z.; Zhang, M.; Liu, L.; Zhou, D. Can renewable energy investment reduce carbon dioxide emissions? Evidence from scale and structure. *Energy Econ.* **2022**, *112*, 106181. [\[CrossRef\]](#)
26. Zhou, Y.; Pu, Y.; Chen, S.; Fang, F. Government support and emerging industry development: Evidence from the new energy industry. *Econ. Res. J.* **2015**, *50*, 147–161.
27. Tu, Q.; Mo, J.; Fan, Y. Evolution, effectiveness evaluation, and future prospects of China's renewable energy policies. *China Popul. Resour. Environ.* **2020**, *30*, 29–36.
28. Wang, B.; Wu, Y.; Liu, P.; Chen, S. Regional heterogeneity in influencing factors of renewable energy development: From the perspective of the production–transmission–consumption industrial chain. *J. Beijing Inst. Technol. (Soc. Sci. Ed.)* **2022**, *24*, 39–50.
29. Zheng, S.; Yang, J.; Yu, S. How renewable energy technological innovation promotes renewable power generation: Evidence from China's provincial panel data. *Renew. Energy* **2021**, *177*, 1394–1407. [\[CrossRef\]](#)
30. Xinyu, W.; Haoran, L.; Khan, K. Innovation in technology: A game changer for renewable energy in the European Union? *Nat. Resour. Forum* **2025**, *49*, 1462–1477.
31. Su, T.; Chen, Y.; Lin, B. Uncovering the role of renewable energy innovation in China's low carbon transition: Evidence from total-factor carbon productivity. *Environ. Impact Assess. Rev.* **2023**, *101*, 107128. [\[CrossRef\]](#)
32. Boudet, H.S. Public perceptions of and responses to new energy technologies. *Nat. Energy* **2019**, *4*, 446–455. [\[CrossRef\]](#)
33. Li, W.; Ullah, S. Research and development intensity and its influence on renewable energy consumption: Evidence from selected Asian economies. *Environ. Sci. Pollut. Res.* **2022**, *29*, 54448–54455. [\[CrossRef\]](#)
34. Yan, Z.; Zou, B.; Du, K.; Li, K. Do renewable energy technology innovations promote China's green productivity growth? Fresh evidence from partially linear functional-coefficient models. *Energy Econ.* **2020**, *90*, 104842. [\[CrossRef\]](#)

35. Cheng, Y.; Yao, X. Carbon intensity reduction assessment of renewable energy technology innovation in China: A panel data model with cross-section dependence and slope heterogeneity. *Renew. Sustain. Energy Rev.* **2021**, *135*, 110157. [\[CrossRef\]](#)
36. Ma, L.; Shi, D.; Pei, Q. National low-carbon energy transition and renewable energy development: Constraint factors, supply characteristics, and cost competitiveness comparison. *Comp. Econ. Soc. Syst.* **2018**, *5*, 70–79.
37. Zhang, S.; Ma, B. World energy development trends and China's future energy development direction. *Nat. Resour. Econ. China* **2019**, *32*, 20–27+33.
38. Ma, Y.; Zhang, Q. Research on the driving mechanism of new energy industry development. *J. Nantong Univ. (Soc. Sci. Ed.)* **2011**, *27*, 112–115.
39. Bird, L.A.; Holt, E.; Carroll, G.L. Implications of carbon cap-and-trade for US voluntary renewable energy markets. *Energy Policy* **2008**, *36*, 2063–2073. [\[CrossRef\]](#)
40. Hvelplund, F. Renewable energy and the need for local energy markets. *Energy* **2006**, *31*, 2293–2302. [\[CrossRef\]](#)
41. Dijk, A.V.; Beurskens, L.W.M.; Boots, M.G.; Kaal, M.B.T.; de Lange, T.J.; Sambeek, V.E.; Uytterlinde, M.A. *Renewable Energy Policies and Market Developments*; Energy Research Centre of the Netherlands ECN: Petten, The Netherlands, 2003.
42. Wüstenhagen, R.; Bilharz, M. Green energy market development in Germany: Effective public policy and emerging customer demand. *Energy Policy* **2006**, *34*, 1681–1696. [\[CrossRef\]](#)
43. He, Y.; Xu, Y.; Pang, Y.; Tian, H.; Wu, R. A regulatory policy to promote renewable energy consumption in China: Review and future evolutionary path. *Renew. Energy* **2016**, *89*, 695–705. [\[CrossRef\]](#)
44. Ying, Z.; Xin-Gang, Z. The impact of Renewable Portfolio Standards on carbon emission trading under the background of China's electricity marketization reform. *Energy* **2021**, *226*, 120322. [\[CrossRef\]](#)
45. Wu, J.; Chen, Y.; Yu, L.; Li, J. Coupling effects of consumption side renewable portfolio standards and carbon emission trading scheme on China's power sector: A system dynamic analysis. *J. Clean. Prod.* **2022**, *380*, 134931. [\[CrossRef\]](#)
46. Feng, T.T.; Yang, Y.S.; Yang, Y.H. What will happen to the power supply structure and CO₂ emissions reduction when TGC meets CET in the electricity market in China? *Renew. Sustain. Energy Rev.* **2018**, *92*, 121–132. [\[CrossRef\]](#)
47. Wang, Y.; Wang, B.; Cui, L. Voluntary or mandatory? Convergence and coexistence of “dual carbon” markets: A system dynamics analysis based on multi-agent evolutionary games. *J. Clean. Prod.* **2025**, *530*, 146841. [\[CrossRef\]](#)
48. Asiedu, B.A.; Hassan, A.A.; Bein, M.A. Renewable energy, non-renewable energy, and economic growth: Evidence from 26 European countries. *Environ. Sci. Pollut. Res.* **2021**, *28*, 11119–11128. [\[CrossRef\]](#)
49. Fang, D.; Li, X.; Yu, B.; Han, Z. Refined decomposition analysis of renewable energy penetration and its nexus with economic growth in emerging industrialized economies: Evidence from China. *J. Clean. Prod.* **2025**, *499*, 145252. [\[CrossRef\]](#)
50. Yu, B.; Fang, D.; Meng, J. Analysis of the generation efficiency of disaggregated renewable energy and its spatial heterogeneity influencing factors: A case study of China. *Energy* **2021**, *234*, 121295. [\[CrossRef\]](#)
51. Soto, G.H.; Martinez-Cobas, X. Does outward foreign direct investment and the green transition affect renewable energy penetration among European Union countries? *Renew. Energy* **2025**, *241*, 122306. [\[CrossRef\]](#)
52. Przychodzen, W.; Przychodzen, J. Determinants of renewable energy production in transition economies: A panel data approach. *Energy* **2020**, *191*, 116583. [\[CrossRef\]](#)
53. Vural, G. Analyzing the impacts of economic growth, pollution, technological innovation and trade on renewable energy production in selected Latin American countries. *Renew. Energy* **2021**, *171*, 210–216. [\[CrossRef\]](#)
54. Da Silva, P.P.; Cerqueira, P.A.; Ogbe, W. Determinants of renewable energy growth in Sub-Saharan Africa: Evidence from panel ARDL. *Energy* **2018**, *156*, 45–54. [\[CrossRef\]](#)
55. Wang, Y.; Wang, D.; Yu, L.; Mao, J. What really influences the development of renewable energy? A systematic review and meta-analysis. *Environ. Sci. Pollut. Res.* **2023**, *30*, 62213–62236. [\[CrossRef\]](#)
56. Wang, B.; Wang, Q.; Wei, Y.M.; Li, Z.P. Role of renewable energy in China's energy security and climate change mitigation: An index decomposition analysis. *Renew. Sustain. Energy Rev.* **2018**, *90*, 187–194. [\[CrossRef\]](#)
57. Islam, M.M.; Irfan, M.; Shahbaz, M.; Vo, X.V. Renewable and non-renewable energy consumption in Bangladesh: The relative influencing profiles of economic factors, urbanization, physical infrastructure and institutional quality. *Renew. Energy* **2022**, *184*, 1130–1149. [\[CrossRef\]](#)
58. Bamati, N.; Raoofi, A. Development level and the impact of technological factor on renewable energy production. *Renew. Energy* **2020**, *151*, 946–955. [\[CrossRef\]](#)
59. Chen, J.; Lü, R. An empirical study on the driving mechanism of energy service enterprises' growth. *Sci. Technol. Manag. Res.* **2015**, *35*, 109–113.
60. An, H. Mechanism and Effects of New Energy Replacing Fossil Energy. Doctoral Dissertation, China University of Mining and Technology-Beijing, Beijing, China, 2021.
61. Wang, Z.; Long, L. Research on the driving mechanism of tourism development promoting urbanization in ethnic regions: A case study of Fenghuang County, Hunan Province. *J. Minzu Univ. China (Philos. Soc. Sci. Ed.)* **2016**, *43*, 11–17.

62. Dai, Y. Driving mechanism of new drivers of economic growth and their consumption spillover effects. *Bus. Econ. Res.* **2021**, *1*, 189–192.
63. Zhao, L.; Tan, C. An empirical study on the driving mechanism of fiscal policy affecting technological innovation. *Sci. Manag. Res.* **2017**, *35*, 99–102. [[CrossRef](#)]
64. Ahmad, S.; Tahar, R.M.; Muhammad-Sukki, F.; Munir, A.B.; Rahim, R.A. Application of system dynamics approach in electricity sector modelling: A review. *Renew. Sustain. Energy Rev.* **2016**, *56*, 29–37. [[CrossRef](#)]
65. Yang, H.; Li, X.; Ma, L.; Li, Z. Using system dynamics to analyse key factors influencing China's energy-related CO₂ emissions and emission reduction scenarios. *J. Clean. Prod.* **2021**, *320*, 128811. [[CrossRef](#)]
66. Xu, L.; Wang, X.; Huang, L.; Hou, Y. Research on the driving mechanism of China's solar photovoltaic industry development. *Sci. Technol. Prog. Policy* **2010**, *27*, 91–95.
67. Peng, G.; Xiang, Y.; Chen, W.; Xu, B.; Liu, J. Dynamic deduction and analysis of wind power installation and investment development in power systems under the “dual carbon” goals. *Electr. Power Autom. Equip.* **2022**, *42*, 70–77.
68. Dianat, F.; Khodakarami, V.; Hosseini, S.-H.; Shakouri, G.H. Combining game theory concepts and system dynamics for evaluating renewable electricity development in fossil-fuel-rich countries in the Middle East and North Africa. *Renew. Energy* **2022**, *190*, 805–821. [[CrossRef](#)]
69. Liu, J.-p.; Tian, Y.; Zheng, H.; Yi, T. Research on dynamic evolution simulation and sustainability evaluation model of China's power supply and demand system. *Energies* **2019**, *12*, 2009. [[CrossRef](#)]
70. Ying, Z.; Xin-gang, Z.; Zhen, W. Demand side incentive under renewable portfolio standards: A system dynamics analysis. *Energy Policy* **2020**, *144*, 111652. [[CrossRef](#)]
71. Song, X.H.; Han, J.J.; Zhang, L.; Zhao, C.P.; Wang, P.; Liu, X.Y.; Li, Q.C. Impacts of renewable portfolio standards on multi-market coupling trading of renewable energy in China: A scenario-based system dynamics model. *Energy Policy* **2021**, *159*, 112647. [[CrossRef](#)]
72. Du, Z.; Xu, E.; Zhang, X.; Liu, D.; Shen, S. Research on evolution and development of power generation scale and cost under tradable green certificates market in China. *Electr. Power* **2019**, *52*, 168–176.
73. Wu, J.; Chen, Y.; Yu, L.; Li, G.; Li, J. Has the evolution of renewable energy policies facilitated the construction of a new power system for China? A system dynamics analysis. *Energy Policy* **2023**, *183*, 113798. [[CrossRef](#)]
74. Zhang, J.; Zhou, X. Impact analysis of market-oriented carbon emission reduction policies in power generation industry based on system dynamics. *Electr. Power* **2020**, *53*, 114.
75. Zhang, L. Research on the Driving Mechanism of China's New Energy Vehicle Battery Industry Development. Doctoral Dissertation, Beijing Jiaotong University, Beijing, China, 2022.

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