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A Stochastic Process-Based Approach for Power System Modeling and Simulation: A Case Study on China's Long-Term Coal-Fired Power Phaseout

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Abstract: Power systems hold huge potential for emission reduction, which has made the modeling and pathway simulations of their decarbonizing development a subject of widespread interest. However, current studies have not yet provided a useful modeling method that can deliver analytical probabilistic information about future system behaviors by considering various uncertainty factors. Therefore, this paper proposes a stochastic process-based approach that can provide analytical solutions for the uncertainty ranges, as well as their changing momentum, accumulation, and probabilistic distributions. Quantitative probabilities of certain incidents in power systems can be deduced accordingly, without massive Monte Carlo simulations. A case study on China's long-term coal-fired power phaseout was conducted to demonstrate the practical use of the proposed approach. By modeling the coal-fired power system at the unit level based on stochastic processes, phaseout pathways are probabilistically simulated with consideration of national power security. Simulations span from 2025 to 2060, presenting results and accumulated uncertainties for annual power amounts, full-process emissions, and carbon efficiencies. Through this modeling and simulation, the probabilities of China's coal-fired power system achieving carbon peaking by 2030 and carbon neutrality by 2060 are 91.15% and 42.13%, respectively. It is expected that there will remain 442 GW of capacity with 0.18 Gt of carbon emissions in 2060.

Keywords: environmental modeling; power system; stochastic process; uncertainty analysis; environmental management

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1. Introduction

The power system has long been one of the major sources of carbon emissions. In China, the most industrially productive and carbon-emitting country, about half of the carbon emissions originate from its power system [1]. With legally binding international treaties such as the Paris Agreement [2] and increased global awareness of the importance of environmental protection, carbon reduction in power systems is receiving widespread attention and investment. China, for example, has made plans for a 2030 carbon peak and 2060 carbon neutrality [3], enacting a series of regulations regarding power systems [4–7]. The European Union is also promoting deep transformations to reduce power emissions despite geopolitical pressures [8]. Consequently, more studies are focusing on the impacts of clean development of the power system and potential low-carbon development pathways

for the future. Transition trends of the global power system were investigated in [9] and the annual development situations of power systems worldwide were monitored and analyzed in [10]. Reference [11] performed modeling and simulation of the global power system with spatial resolution. Some smaller-scale works have also been published. The photovoltaic–wind hybrid trend in the U.S. power system was modeled at the site level [12] and a short-term stochastic production simulation method was adopted to plan and evaluate new energy development [13]. Moreover, many studies project the decarbonization pathways until 2060 in China [14,15]. Specifically, China has an astonishingly massive coal-fired power system that occupies the major carbon budget of the nation, and the phaseout of coal-fired power will have an effective impact on China's long-term decarbonization plan [16]. Using a dynamic model, the socioeconomic influences of the phaseout are assessed as acceptable [17], and the huge investment in new energies is expected to compensate for the reduction in coal-fired power quitting [18]. However, some studies [19,20] indicate that the quick drop in coal-fired power could challenge national power security and independence, due to the ongoing growth in power demand and the current reliance on coal-fired power in China.

When studying the development of power systems, especially for long-term modeling and simulations, simulated results as well as their uncertainties are important. Clear and sensible uncertainty ranges are necessary for complete pathway evaluations, as there are too many discrepancies between actual conditions and simulation scenarios. A common uncertainty analysis tool is sensitivity analysis, for example, as seen in [18,20–22]. It can draw the upper and lower bounds of pathway results by systematically changing input parameters while providing limited probabilistic information. In addition, some studies focus on probabilistic uncertainty evaluations in forecasting electricity load [23,24] and wind power [25], by training some non-interpretable neutral networks. Other studies [26,27] attempt to interpolate the uncertainty range through random sampling and extensive Monte Carlo simulations; the stochastic programming approach can be used to reduce scenario numbers in a simulation [28]. Probabilistically modeling the uncertainties in studies on power system development pathways is becoming a cutting-edge trend.

Therefore, some research gaps still exist in current studies on power system modeling. Most studies conduct simulations in deterministic forms, generating typical simulation pathways in given scenarios. These results offer much less information compared to stochastic modeling. However, as mentioned above, current stochastic modeling methods highly rely on massive Monte Carlo simulations, which can be very computationally exhausting. So, to meet these gaps, a stochastic process-based modeling and simulation approach is proposed in this paper to facilitate studies on behavioral assessments and probabilistic pathways in power systems. The stochastic process is a powerful mathematical tool that models the probability distribution of random variables as functions dependent on a real parameter, which is usually time-dependent [29]. It is used in modeling the behaviors of many kinds of systems [30–32] and can expand beyond common deterministic values, e.g., fixed statistical numbers, to include variables with probabilistic features, as well as describe their time-dependent changing behaviors. So, applied to model uncertainties in power systems, stochastic process-based approaches can provide quantitative and analytical results of the uncertainty distribution range, the accumulation of uncertainties in system models, the probabilities of certain incidents, and uncertainty changes among different simulated pathways [33,34]. Stochastic processes have been employed in various types of power system studies. For example, a stochastic model is used for integrated electric and gas systems [35]. Studies on renewable power with stochastic processes from time and frequency domains were reviewed in [36]. A general method was proposed to model several stochastic processes in different power system stability analyses [37], and

stochastic modeling frameworks from financial sights have also been studied for coal-fired applications [38].

Exploiting the practicability of stochastic process-based modeling, a unit-level modeling and simulation approach is discussed in this paper, together with a case study on China's long-term coal-fired power phaseout. As previously mentioned, the coal-fired power system is a major source of emissions, posing a burden on the clean development of the entire power system. However, in China, the coal-fired power system currently plays a fundamental role in power supply, and hastily cutting down its size may lead to serious power security problems [39]. So, faced with this dilemma, potential pathways for the phaseout of coal-fired power have garnered special attention. By working on the case study, this paper not only demonstrates and analyzes the advantage of the stochastic process-based approach but also offers references for the development of coal-fired power in China from a probabilistic perspective. Compared to other simulations in studies of China's coal-fired power systems, this work offers further quantitative probabilistic information and clearer insights into the momentum of changing uncertainty ranges, without relying on extensive Monte Carlo calculations.

The rest of this paper is structured as follows: Section 2 introduces the proposed method and the simulation model settings. Section 3 presents the simulation results. Section 4 provides further discussions and related policy recommendations. Section 5 concludes the paper.

2. Methods and Materials

This section presents the analytical modeling of China's coal-fired power system units based on stochastic processes. As mentioned, stochastic processes are highly effective mathematical tools for analyzing uncertainties within the system model. It is important to note that we adopt the normal distribution assumption since the uncertainty is affected by multiple, complex, and non-analytical factors. The normal distribution can suitably approximate these uncertainties. The stochastic process-based modeling of the behaviors of coal-fired units is first presented in Section 2.1. Section 2.2 introduces the unit-level system model, which is constructed based on the presented modeling.

Then, carbon reduction pathways can be simulated. To fully discuss the potential for transitioning away from coal-fired power, simulations are based on the assumption that the nation will minimize coal-fired emissions as long as the national power demand is met; this involves the shutdown and upgrade of coal-fired units based on their technical levels, even if some choices may not be economically optimal. Detailed discussions are presented in Section 2.3. Moreover, the coal-fired power demand is another important constraint in the simulation. It is annually estimated based on public national power demand and new energy growth, as presented in Section 2.4. Detailed parameter settings, especially different uncertainty ranges, are presented in Section 2.5 for perspicuity.

2.1. Stochastic Process-Based Modeling

Considering the uncertainties in the working status of power systems, related parameters are modeled as stochastic processes rather than statistical or predicted numbers. Then, the current condition and simulated developing paths of a system can be depicted in a probabilistic way. To demonstrate the methodology of stochastic process-based modeling, detailed descriptions of how the annual behavior of coal-fired power units is modeled are presented in this subsection.

Technically, the annual power output of a coal-fired unit is calculated as shown in (1), while the emission amounts at the unit level and throughout the full power generation process are presented in (2) and (3), respectively, as follows:

$$g_{i,t} = c_{i,t} h_{i,t}, \tag{1}$$

$$e_{i,t} = c_{i,t} h_{i,t} r_{i,t} f_{i,t}, \tag{2}$$

$$\tilde{e}_{i,t} = c_{i,t} h_{i,t} r_{i,t} f_{i,t} a_{i,t}. \tag{3}$$

$g_{i,t}$ denotes the power generated by unit i at year t, $e_{i,t}$ denotes the unit-level emission of unit i at year t, and $\tilde{e}_{i,t}$ denotes the full process emission (with emissions related to mining, transportation, management, etc.) of unit i at year t. Related unit parameters include the installed capacity, $c_{i,t}$, the heat rate, $r_{i,t}$, the emission factor, $f_{i,t}$, the annual utilization hour, $h_{i,t}$, and the implicit carbon emission factor, $a_{i,t}$. Please refer to [40–42] for detailed explanations of the definition of utilization hours and the calculation regulations for unit-level emissions.

Equations (1)–(3) are in common fixed-value forms; so, to transform them into probabilistic forms, unit parameters are first treated as random variables. For example, the unit heat rate can be modeled as $R_{i,t} \sim \mathcal{N}(r_{i,t}, \sigma_{R,i,t})$ by assuming that the statistical discrepancy follows a normal distribution, denoted by $\mathcal{N}()$, with a standard deviation of $\sigma_{R,i,t}$. The mathematical expectation of this parameter is its statistical value in the dataset. The normal assumption regarding coal-fired unit parameters has been verified in other published works, i.e., [43–45].

Furthermore, to study the potential development paths of the unit, the changing of annual unit parameters should be included. The statistical values of different power units are commonly updated annually. For example, considering improvements in power techniques, the unit heat rate should decrease year by year. Thus, its distribution factors, i.e., expectations and standard deviations, can be modeled as functions related to the year, as $r_i(t)$ and $\sigma_{R,i}(t)$. Then the annually changing heat rate is modeled as a stochastic process, $R_i(t) \sim \mathcal{N}(r_i(t), \sigma_{R,i}(t))$. $R_i(t)$ describes the probability distributions of the heat rate year by year, and it is a typical discrete-time process. Therefore, its successive variation pattern can be analyzed by modeling the process as a Markov process in (4):

$$R_i(t) = \Phi(R_i(t-1), K(t)), \tag{4}$$

where $\Phi()$ denotes the state transform function between consecutive years. The discrete-time Markov process is memory-less, i.e., the current state is determined by its previous state and current external factors, $K(t)$. For different simulation preferences, the external factors can include technical development levels, operating profitability, power demand, climate influences, etc.

Thus, other parameters can be modeled as $C_i(t)$, $H_i(t)$, $F_i(t)$, and $A_i(t)$. So, the power and emission models of unit i are transformed into (5)–(7):

$$G_i(t) = C_i(t) H_i(t), \tag{5}$$

$$E_i(t) = C_i(t) H_i(t) R_i(t) F_i(t), \tag{6}$$

$$\tilde{E}_i(t) = C_i(t) H_i(t) R_i(t) F_i(t) A_i(t), \tag{7}$$

where $G_i(t)$, $E_i(t)$, and $\tilde{E}_i(t)$ represent the stochastic process forms of the annual power output, the unit level, and the full-process carbon emissions of the unit, respectively.

Based on modeling all coal-fired power units following (5)–(7), the total annual power, $G(t)$, and emission amounts, $E(t)$ and $\tilde{E}(t)$, of the national coal-fired power system can be deduced annually, as shown in (8)–(10):

$$G(t) = \sum_{i \in U_t} C_i(t) H_i(t), \tag{8}$$

$$E(t) = \sum_{i \in U_t} C_i(t) H_i(t) R_i(t) F_i(t), \tag{9}$$

$$\tilde{E}_i(t) = \sum_{i \in U_t} C_i(t) H_i(t) R_i(t) F_i(t) A_i(t). \tag{10}$$

Set U_t denotes all active units at year t.

As current studies do not provide widely recognized probability distribution models for coal-fired parameters, one compromise is to assume that unit parameters follow independent normal distributions. Here, independence refers only to the uncertainty range of different parameters, not their expectations, as different parameters have different statistical uncertainties. Therefore, $G(t)$, $E(t)$, and $\tilde{E}(t)$ are normal-production processes [46], and their distribution factors can be calculated following the expectation production law, as shown in (11):

$$\mathbb{E}(X_1 X_2) = \mathbb{E}(X_1)\mathbb{E}(X_2), \tag{11}$$

and the standard deviation production law, as shown in (12):

$$\mathbb{D}(X_1 X_2) = \sqrt{\mathbb{D}^2(X_1)\mathbb{D}^2(X_2) + \mathbb{E}^2(X_1)\mathbb{D}^2(X_2) + \mathbb{D}^2(X_1)\mathbb{E}^2(X_2)}, \tag{12}$$

where $\mathbb{E}(\cdot)$ and $\mathbb{D}(\cdot)$ denote the expectation and standard deviation of the process, and X_1 and X_2 denote any two independent processes.

Additionally, to model the national coal-fired power and emission amounts, different units have independent statistical uncertainties. So, according to the Lyapunov central limit theorem [47], the summations of a large number of independent stochastic processes can be approximately treated as normal stochastic processes, as shown in (13)–(15):

$$G(t) \sim \mathcal{N}(g(t), \sigma_G(t)), \tag{13}$$

$$E(t) \sim \mathcal{N}(e(t), \sigma_E(t)), \tag{14}$$

$$\tilde{E}(t) \sim \mathcal{N}(\tilde{e}(t), \sigma_{\tilde{E}}(t)). \tag{15}$$

$g(t)$ denotes the expectation of the annual power amount at year t, $e(t)$ denotes the expectation of the annual unit-level emission amount, and $\tilde{e}(t)$ denotes the expectation of the annual full process emission amount. $\sigma_G(t)$, $\sigma_E(t)$, and $\sigma_{\tilde{E}}(t)$ denote the corresponding standard derivations.

The Lyapunov–Theorem-based approximation fits most regular random distributions, including the normal assumption adopted in (5)–(7) at the unit level, which leads to the subsequent mathematical derivation. Other than the normal assumption, there are other parameter distributions that fit the central limit theorem. However, the normal assumption can approximate true conditions well and reduce computational complexities [43–45].

2.2. Unit-Level System Model

Following the proposed stochastic process-based modeling approach, a model of the unit-level coal-fired power system in China is constructed. The unit directory is based on the global coal plant tracker (GCPT) released in July 2024 [40]. Unit parameters, including installed capacities, locations, start years, and coal-type-based emission factors provided

in the GCPT, are adopted after being confirmed and fixed according to the China Electric Power Statistical Yearbooks [48,49]. However, the provided heat rate statistics are not accepted. Reliable heat rates are generated using a category mapping method based on unit technical levels and ages [50,51]. Moreover, unit utilization hours and implicit emission factors are determined according to unit locations by province, referring to [52,53] and provincial statistical yearbooks. The impact of load regulation with new energies has been taken into account when calculating the average utilization hours [52]. Moreover, further transformation of the coal-fired power system into a deep load regulation system will result in lower utilization hours [54] and lower heat rates [55]. These influences are considered by setting reasonable annual dropping rates.

Based on previous data sources, an up-to-date unit-level coal-fired power and emission system model was constructed. Even if multiple data sources are considered, unit-level parameters cannot be absolutely accurate. Parameter uncertainties must be included in the study to establish reasonable development pathways—and their uncertainty ranges—for the coal-fired power system. This issue will be discussed in Section 2.5.

Some preliminary calculations are performed to validate the unit-level model. China's national average heat rate in 2024 was around 303 gce/kWh, as announced by the State Council [56], but the calculated average heat rate based on GCPT was 346.10 gce/kWh, and the calculated average heat rate in 2024 was 303.93 gce/kWh after data modification. Moreover, the announced coal-fired power system capacity was 1.16 trillion watts in 2024, with a 4685-hour average utilization and a total power supply of 548 million kWh throughout 2023 [57]. The calculated results based on the unit-level model are 1.1266 trillion watts, 4528.3 h, and 517.2 million kWh, respectively, with biases around 5%. These biases are acceptable and will guide the settings of parameter uncertainty ranges in later simulations.

Furthermore, this paper focuses on the potential phaseout paths of coal-fired power from the perspective of national power security. The main driving force behind the phaseout is the development of new and clean energy sources, which alleviate the pressure on coal-fired power in supplying electricity for China, which has long been a huge manufacturing powerhouse and requires energy independence.

2.3. Phaseout Path of Coal-Fired Power

A common recognition of China's long-term energy system is that new energies will gradually take the major role, while coal-fired power techniques are also being upgraded to be more carbon-efficient. Therefore, the phaseout path of the coal-fired power system includes reducing units and decarbonizing. In this study, the full potential for coal-fired emission reduction is assessed. So, the phaseout paths of the system in simulations are derived from technical considerations, i.e., eliminating old and small units while supporting advanced and highly efficient units to operate as long as needed. Some of the simulated actions may not be the best from an economic perspective, yet in this way, the potential impact of China's resolute carbon reduction plan can be sufficiently assessed.

2.3.1. Unit Reducing

When the demand for coal-fired power decreases, some coal-fired units may be directly shut down or regulated to work less. Shutting down a unit can be modeled as $H_i(t) = 0$. So, the utilization hour changes of different units under pressure will be crucial for modeling unit reduction. Some studies use the average utilization hours for all units [16] and some differentiate units by type [19]; moreover, a plant-by-plant strategy is proposed under two scenarios: maintaining constant utilization hours for all units year by year or allowing all units to reach a planned lifetime [22]. However, in this paper, a flexible and technique-level-based strategy is used.

First, all units are sorted according to their technical levels, as referenced in [22]. The sorting criteria are summarized in Table 1.

It is believed that the more outdated a unit is, the more its utilization hours will drop, and when dropping to 0, the unit is shut. A sectional sigmoid function, $\gamma()$, is adopted to model this dropping utilization behavior, as shown in (16):

$$\gamma(u_i) = \begin{cases} 0 & u_i < u_w \\ (1+\exp(-\tau(u_i-u_w)/u_l))^{-1} & u_w < u_i < u_w + u_l \\ 1 & u_w + u_l < u_i \end{cases}, \quad (16)$$

where u_i denotes the sorting order of unit i, and u_w denotes the turning point. A sketch of $\gamma()$ is in Figure 1. The turning point can be determined by solving the optimization problem in (17):

$$\text{minimize } u_w \quad \text{s.t.} \sum_{i \in U_t} \mathbb{E}\big(C_i(t)H_i(t)\gamma(u_i)\big) \geq \mathbb{F}\big(D_c(t+1)\big), \quad (17)$$

i.e., choose the smallest turning point that can guarantee that the generated coal-fired power meets the designed power demand scenario, which is modeled based on $D_c(t+1)$, and $\mathbb{F}()$ denotes the demand-scenario modeling function.

Table 1. The scoring metrics for unit sorting based on technique levels.

Attribute	Scoring Type	Scoring for Unit Sorting
Start year	Quantitative	age $<$ 1985→0; age $\in$ [1985,2025]→[0,1]; age $>$ 2025→1
Installed capacity	Quantitative	$C_i(t)/300$MW
CCUS	Categorical	Yes→10; No→0
Combustion Type	Categorical	Ultra-Super→4; Supercritical→3; Subcritical→2; Others→1

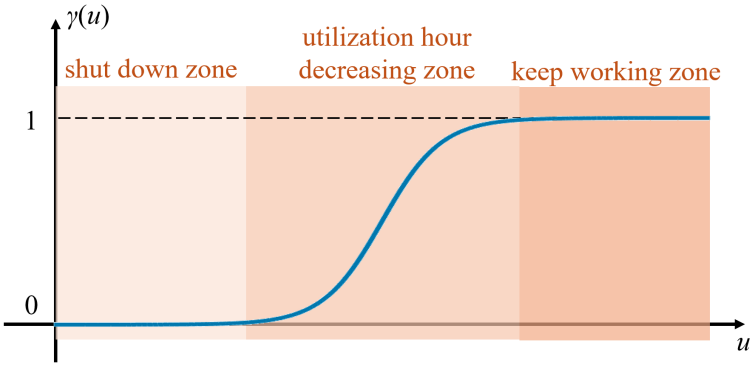

Figure 1. The sectional sigmoid function divides units into 3 groups, namely, shutting down, reducing working, and continuing to work. The parameters adopted are $\tau = 5$ and u_l, equal to 50% of the total unit amount.

Then, based on the unit order, the transition function of utilization hours from year t to $t+1$ is modeled as follows (18):

$$H_i(t+1) = \gamma(u_i)H_i(t) + X_{H,i}(t), \quad (18)$$

where $X_{H,i}(t)$ is the uncertainty growth.

2.3.2. Decarbonizing

Accompanying the technique advancement, the overall carbon efficiency of all coal-fired units will slowly yet continuously drop. The gradual decarbonization of a unit is modeled as shown in (19)–(21):

$$R_i(t+1) = \beta_{R,i}(t)R_i(t) + X_{R,i}(t), \tag{19}$$

$$F_i(t+1) = \beta_{F,i}(t)F_i(t) + X_{F,i}(t), \tag{20}$$

$$A_i(t+1) = \beta_{A,i}(t)A_i(t) + X_{A,i}(t), \tag{21}$$

where heat rates, emission factors, and implicit factors are expected to drop annually. $\beta_{R/F/A,i}(t)$ is the dropping rate [58] and $X_{R/F/A,i}(t)$ models the additional uncertainty.

On the other hand, the deployment of carbon capture, utilization, and storage (CCUS) will significantly reduce the emission of target units. Related projects will fully start in 2025 [6], and most CCUS units will become operational by 2030–2035 [59]. After that, considering the phaseout of coal-fired power, the progress of CCUS installation will slow down, until reaching 335 GW by 2060 [60]. Accordingly, the annual CCUS implementation amount is interpolated based on the following key statistics: 0 GW by 2025, 67 GW by 2030, 268 GW by 2035, and 335 GW by 2060.

CCUS equipment is more likely to be preferentially installed on advanced units. So, each year, units with higher technique level-based orders will be considered for new CCUS units within the annual CCUS amount. The installation mainly changes the heat rate and emission factor of a unit, as follows (22):

$$R_i(t+1) = \lambda_{R,i}(t)R_i(t) + \Lambda_{R,i}(t), \tag{22}$$

and (23):

$$F_i(t+1) = \lambda_{F,i}(t)F_i(t) + \Lambda_{F,i}(t), \tag{23}$$

where $\lambda_{R/F,i}(t)$ and $\Lambda_{R,i}(t)$ are the changing rate and the additional uncertainty related to CCUS-installation.

2.4. Long-Term Remaining Demands

Coal-fired power will shrink in China, only if new energies can take the place of supplying power to meet the country's demand. So, these factors should also be firmly considered in the simulation of the coal-fired power system.

Although China is investing a huge amount of resources in new energy development, there is still a long-term gap remaining between the new energy power amount and the nation's demand. Coal-fired power will still play an indispensable role in the near future. So, from the perspective of national power security, assessments of the phaseout of coal-fired power require an estimation of the remaining demand it has taken. Moreover, in addition to common renewable energies, nuclear power and gas are also included as new energy sources. This is because they are energy sources that use newer technologies and materials compared to coal-fired power, especially in China.

Two key aspects on the demand side are the nation's annual power demand and the upward trend of various new energy types. In this paper, future power demand and new energy development trends are modeled by interpolating key statistics from government documents and public research. Related statistics are summarized in Table 2. Note that some data are missing as reliable sources have not presented related predictions for some years, and these future data cannot be fully accurate. So uncertainties are considered in the

model, and with suitably large uncertainty ranges, the actual numbers in the future will have a considerably high probability of falling within the settled range.

The interpolation calculates growing rates, and the demands and developing trends are also modeled as stochastic processes in the following (24):

$$D_{T/N,j}(t+1) = \beta_{T/N,j}(t) D_{T/N,j}(t) + X_{T/N,j}(t), \tag{24}$$

where footnote T represents the nation's total demand, and footnote N, j represents the growth of new energy j (indexes are in Table 2). $X_{T/N,j}(t)$ models the additional uncertainty between two years, and $\beta_{T/N,j}(t)$ denotes the interpolated growing rates.

Then, by subtracting all other energy power from the total demand, the annual demand for coal-fired power is modeled as $D_C(t)$ in the following (25):

$$D_C(t) = D_T(t) - \sum_{j=1}^{7} D_{N,j}(t). \tag{25}$$

Table 2. Key statistics for interpolating national power demand and new energy growth.

	Index	2025	2030	2040	2050	2060	Ref. [3]
National Power demand	/	10.0 [1]	13.0	15.0	16.5	17.5	[61–63]
Wind	1	0.93	1.65	/ [2]	/	6.07	[64,65]
Photovoltaic	2	0.52	1.47	/	/	3.39	[64,65]
Hydro	3	1.50	1.88	/	2.51	2.58	[57,61]
Nuclear	4	0.54	0.94	/	2.55	3.00	[66]
Biomass	5	0.24	0.33	/	/	0.66	[67]
Gas	6	0.39	0.48	/	0.85	0.83	[61,68]
Other Energy [4]	7	0.05	/	/	/	0.05	/

[1] Unit: PWh, 1 PWh = 1×10^{12} kWh. [2] / means that data are not considered in interpolation. [3] Key referred contents: Wind and photovoltaic power are considered the main drivers of new energy growth, with their power output expected to double by 2025 [64] and grow 13-times by 2060 [65] compared to their levels in 2020. Hydropower has unstable utilization hours due to the climate [57], and the use of gas is also being [68], so their power amount is predicted by their capacity predictions in [61]. Nuclear and biomass power output predictions are directly quoted from corresponding references. [4] Assumed to be unchanged, since the amount is relatively very small.

2.5. Simulation Settings

Based on previous modeling, phaseout paths can be simulated by calculating the annual state transition of coal-fired power units. In the previous content of this section, the unit-level system model is set based on unit parameters, and the remaining coal-fired power demand is calculated based on some given data. Moreover, uncertainties, including initial uncertainties and annual growing trends, are necessary for stochastic modeling. These detailed settings of the simulation are as follows:

Stochastic processes, including the initial and transferring states of coal-fired parameters and new energies, are approximately modeled as normal processes. The empirical rule [69] is adopted to settle the quantitative uncertainty value. The empirical rule can provide a standard deviation for a statistical variable when the accuracy is determined. For example, if the statistic is believed to have 15% accuracy, following the empirical rule, the relative statistical discrepancy is assumed to have a 99.74% probability of being less than 15%. So, the corresponding standard deviation is 5% of the statistical value, as shown in Figure 2.

The specific settings of initial uncertainties and additional uncertainties during annual changes of related parameters are summarized in Table 3. Table 4 presents the annual changing rates for coal-fired units used in the simulation. Specifically, referring to [40], when a unit is transformed to a CCUS unit, its emission factor drops by 90% yet its heat

rate increases by 20%. The simulation period is from 2025 to 2060, aligning with the year of China's planned carbon neutrality. So, the initial uncertainties are those in 2025.

Table 3. The settings of uncertainty ranges in the simulations.

Parameter	I.U. [1]	A.U. [2]	Parameter	I.U.	A.U.
$D_T(t)$	15%	5%	$D_{N,j}(t)$	15%	5%
$C_i(t)$	30%	0%	$R_i(t)$	30%	20%
$F_i(t)$	30%	20%	$H_i(t)$	30%	20%
$A_i(t)$	30%	20%	CCUS	0%	20%

[1] I.U., initial uncertainty. [2] A.U., annual additional uncertainty.

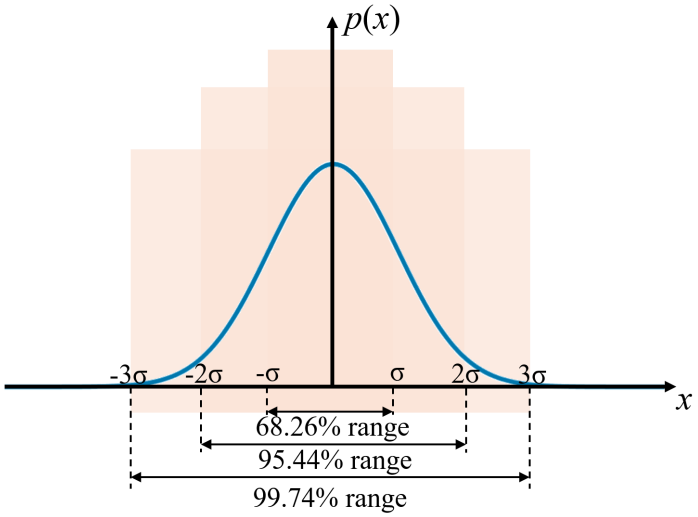

Figure 2. The empirical rule for a random variable following $\mathcal{N}(0,\sigma)$. In actual modeling, the statistical value is regarded as the distribution expectation.

Table 4. The settings of the annual changing rates of coal-fired units.

Parameter	Value	Parameter	Value	Parameter	Value
$\beta_{R,i}(t)$	0.99	$\beta_{F,i}(t)$	0.995	$\beta_{A,i}(t)$	0.99
$\lambda_{R,i}(t)$	1.2	$\lambda_{F,i}(t)$	0.1		

3. Results

3.1. Demand-Side Results

This subsection presents the simulation results related to the long-term remaining demand for coal-fired power.

Figure 3 presents the growth of the national annual demand via the normalized probability density function of $D_T(t)$, and Figure 4 presents the growth of the total power amount of new energies. Normalized probability density functions in different years are calculated separately, so the annual mathematical expectations, with the highest probability in each year, are normalized to 1. Via normalizing, the range and the annual changing momentum of uncertainties of the results can be straightforwardly recognized. The simulation results of other stochastic processes are also presented in the normalized probability density function forms later in this paper.

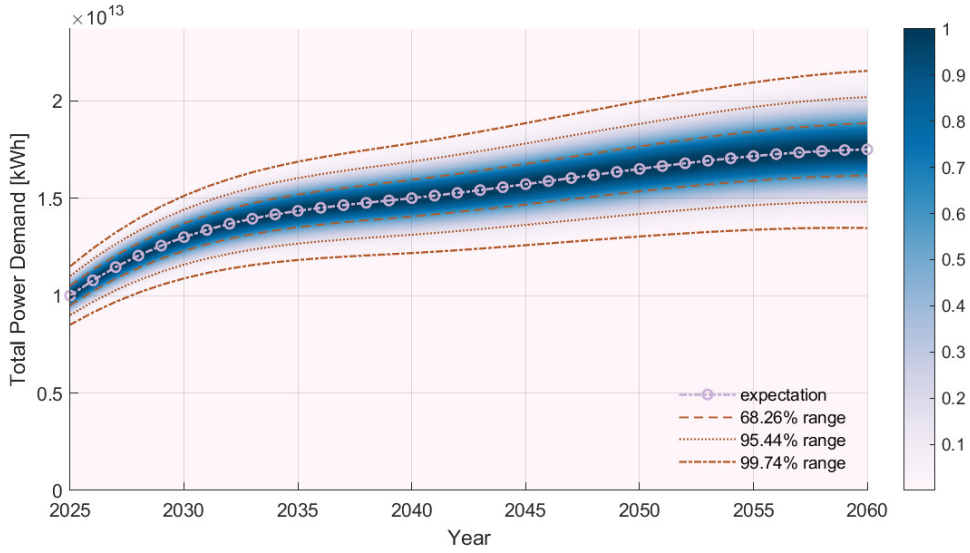

Figure 3. The annual normalized probability density function of the simulation results of the national power demand, i.e., $D_T(t)$.

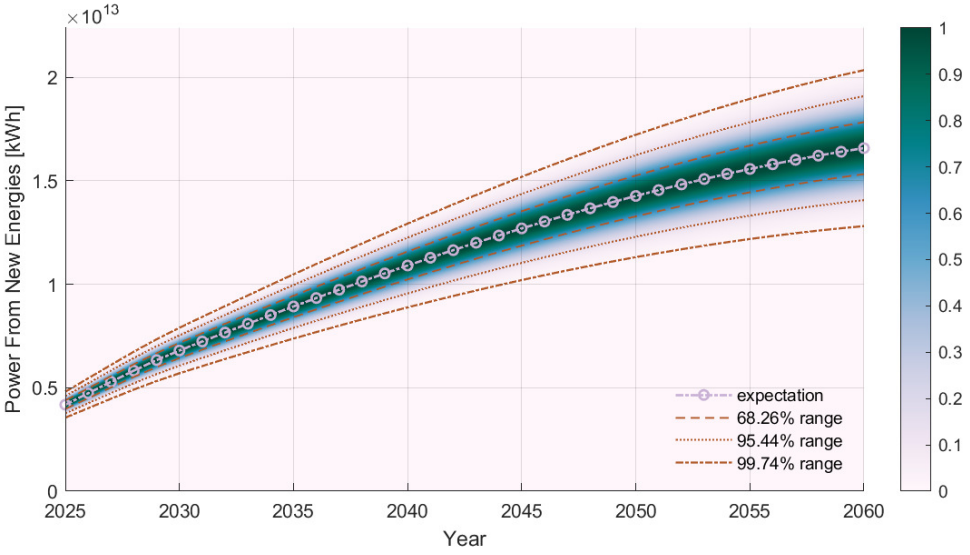

Figure 4. The annual normalized probability density function of the simulation results of the new energy power amount, i.e., $\sum_{j=1}^{7} D_{N,j}(t)$.

In Figure 3, national power demand continues to grow rapidly during the 15th five-year plan (2025–2030), but then the growth slows annually, mainly due to the industrial structure changes and population drop in China [61]. Meanwhile, Figure 4 shows that new energy development can maintain a much longer fast-growing momentum. The confidence in the country's huge investment in various new energy industries is a major strength for China in cutting down on coal-fired power.

The simulated remaining demand for coal-fired power is presented in Figure 5. The uncertainty range is much larger since it is calculated using $D_T(t)$ and $D_{N,j}(t)$, and the uncertainty of $D_C(t)$ is the summation of their individual uncertainties. The momentum of the process reaches a peak before 2030, indicating that the size of the coal-fired power system will be effectively restricted by then, attributed to China's 2030 carbon peak plan. But by 2060, there remains a 69.78% probability that coal-fired power will be needed to support the security and independence of the national power supply.

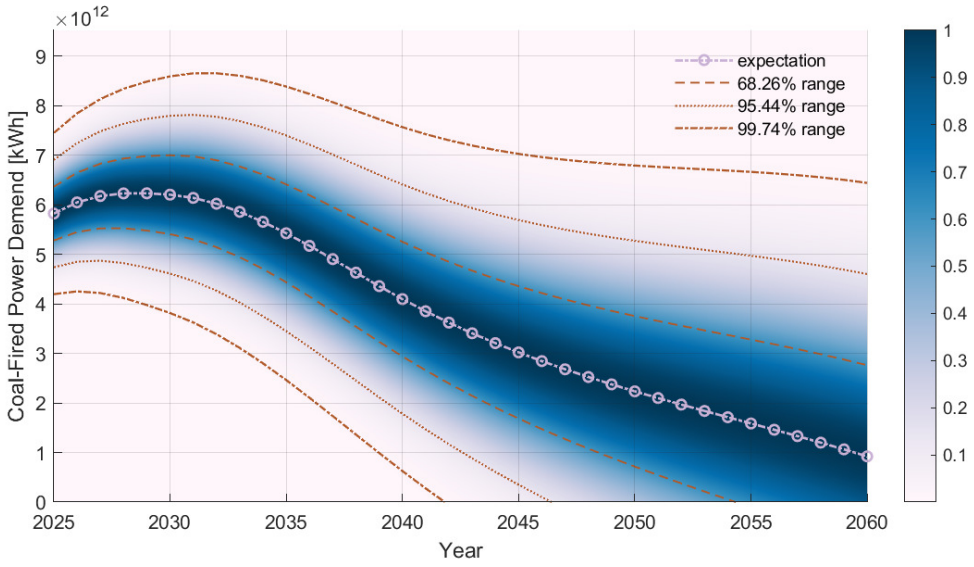

Figure 5. The annual normalized probability density function of the demand for coal-fired power, i.e., $D_C(t)$. Demand reaching 0 means that coal-fired power is unnecessary (may completely quit) since new energies can meet the national power demand.

3.2. Phaseout Paths upon Fixed-Value Demands

Annual emissions during the coal-fired power phaseout are presented in this subsection.

Fixed-value demands may describe the phaseout path in a rather certain scenario, e.g., $\mathbb{F}(D_C(T)) = \mathbb{E}(D_C(T))$, simulating that national power demands and new energy developments all grow as planned. Related results are shown in Figure 6. Emissions drop significantly after peaking in 2029, and the average unit carbon efficiency reaches 0.195 tonCO2/MWh (the mathematical expectation). Results show that when national power demand and new energies grow as planned, coal-fired power is expected to peak before 2030, meeting the government's request [3]. But by 2060, coal-power emissions still exist, with a probability larger than 99.74%.

Moreover, an over-demand scenario is simulated by $\mathbb{F}(D_C(T)) = \mathbb{E}(D_C(T)) + \mathbb{D}(D_C(T))$, i.e., the coal-fired power demand only has a 15.87% probability of exceeding this scenario. This can happen due to national power demand bursts or sluggish new energy developments. Corresponding results are shown in Figure 7; by 2060, the remaining annual coal-fired emissions range from 0.17 to 1.35 Gt (within a 99.74% probability range), about 2.9% to 22.9% of the 2025 levels. The average carbon efficiency is expected to be 183.8% of that shown in Figure 6d due to more units without CCUS still working.

As shown in Figure 8, an optimistic scenario is simulated, where $\mathbb{F}(D_C(T)) = \mathbb{E}(D_C(T)) - \mathbb{D}(D_C(T))$, and there is a 15.87% probability that coal-fired power demand will be less than this scenario. It simulates the bloom in new energy development that rapidly replaces coal-fired power. Consequently, coal-fired power will be completely phased out by 2055, which can be beneficial for China's 2060 carbon neutrality pledge. Also, due to the quick drop in the number of working units, the result uncertainties in this scenario are smaller than in previous results.

The simulation results of $D_C(t)$ were introduced previously, and coal-fired power phaseout path simulations can be conducted upon $\mathbb{F}(D_C(t))$ (see (17)) in either fixed values or stochastic process forms by designing $\mathbb{F}()$.

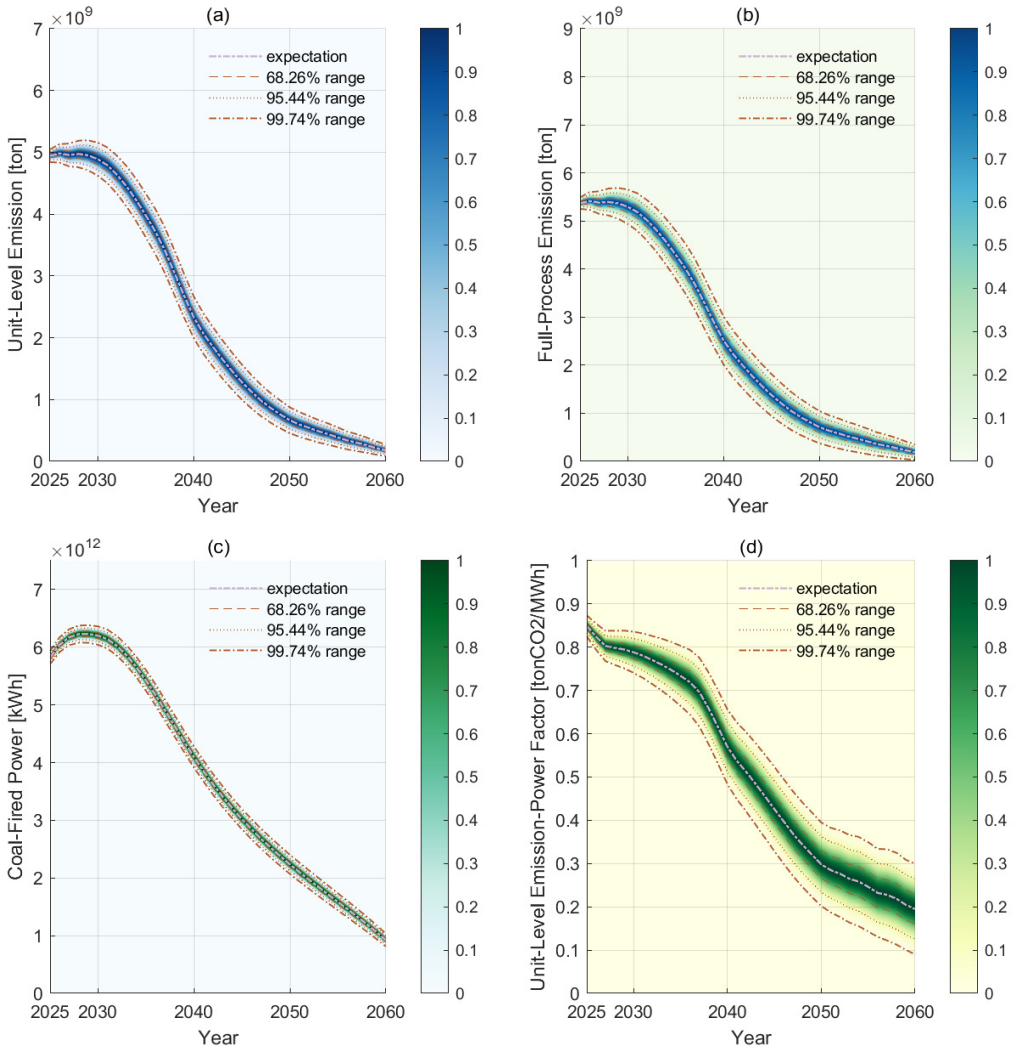

Figure 6. Phaseout path simulation results when the demand scenario is as planned, as $\mathbb{F}(D_C(T)) = \mathbb{E}(D_C(T))$, (**a**) annual unit-level emission, (**b**) annual full-process emission, (**c**) annual power amount, (**d**) emission-power factor, indicating the cleanliness level of coal-fired power.

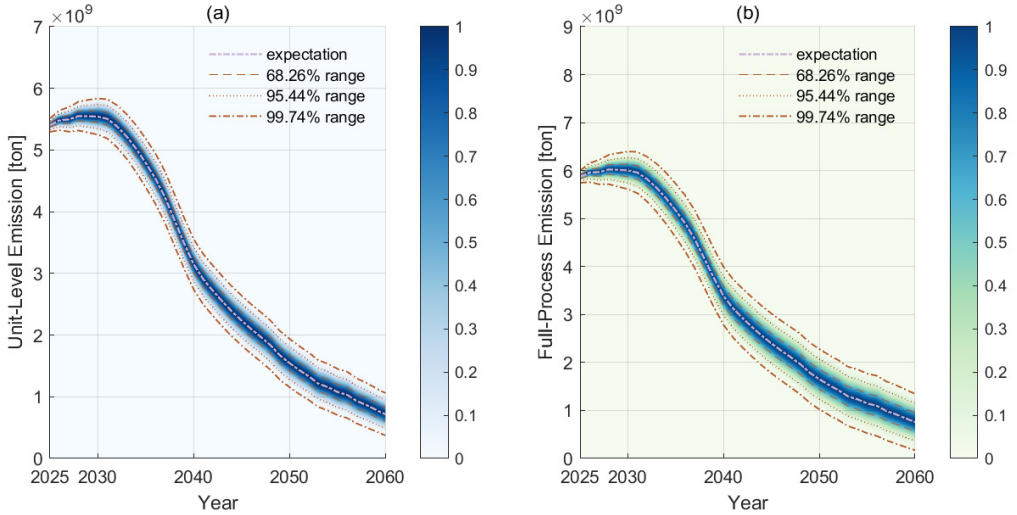

Figure 7. *Cont*.

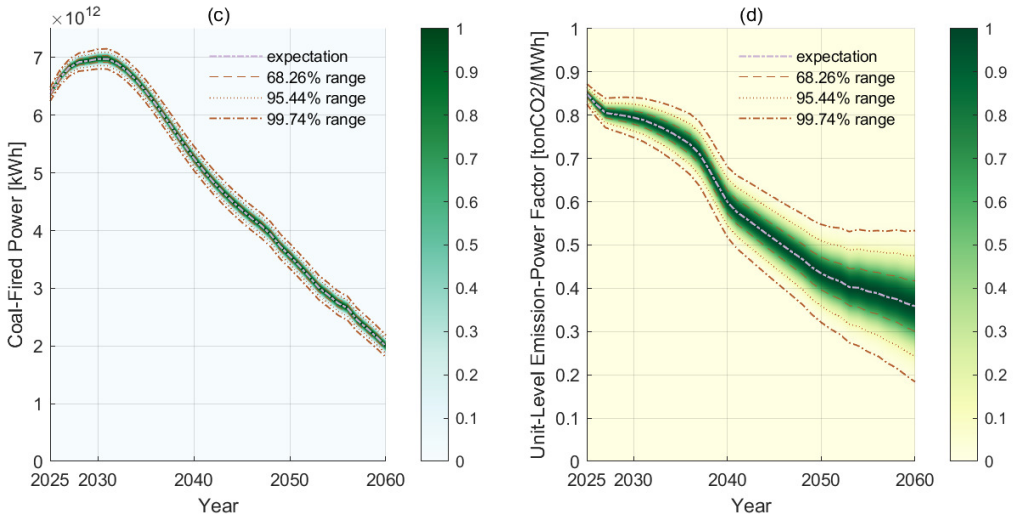

Figure 7. Phaseout path simulation results when the demand scenario is over-planned, with $\mathbb{F}(D_C(T)) = \mathbb{E}(D_C(T)) + \mathbb{D}(D_C(T))$, (**a**) annual unit-level emission, (**b**) annual full-process emission, (**c**) annual power amount, (**d**) emission-power factor.

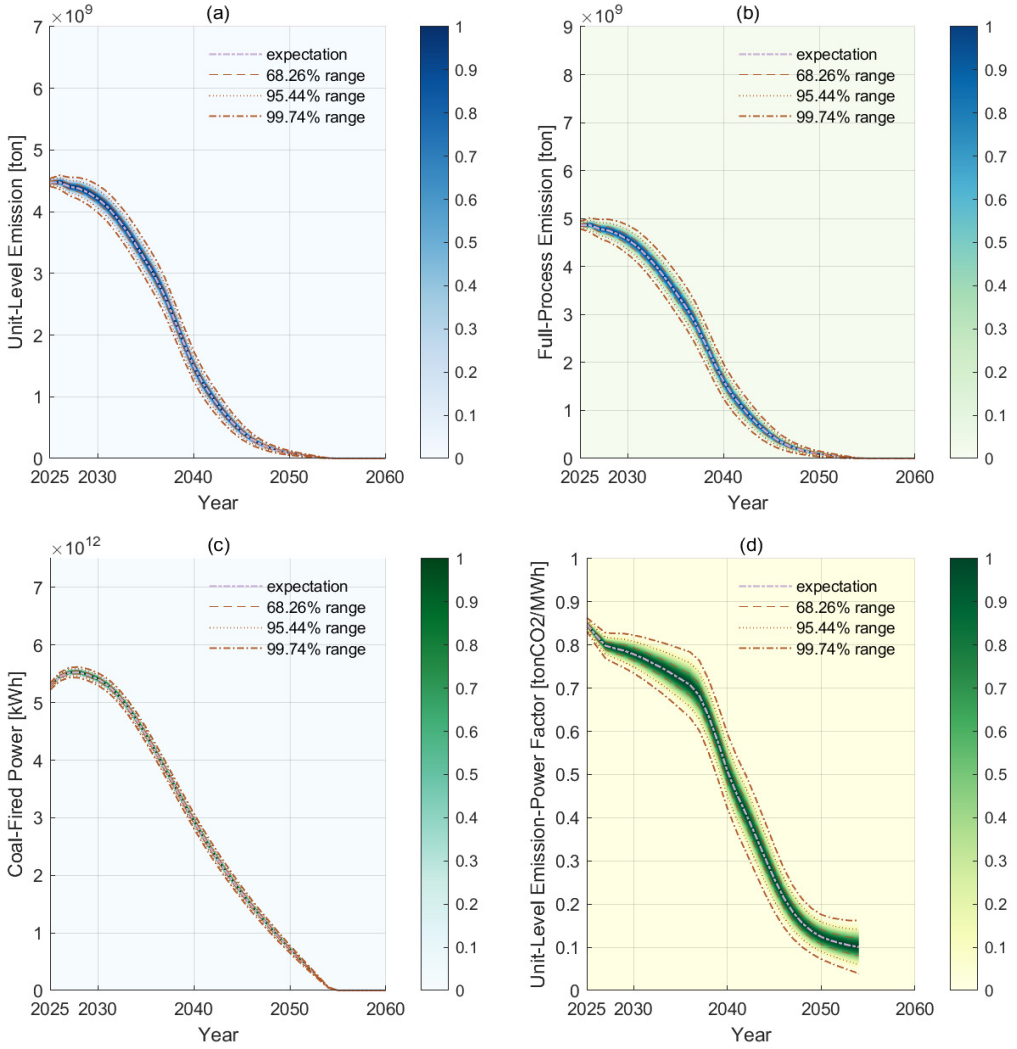

Figure 8. Phaseout path simulation results when the demand scenario is 'below planned', with $\mathbb{F}(D_C(T)) = \mathbb{E}(D_C(T)) - \mathbb{D}(D_C(T))$, (**a**) annual unit-level emission, (**b**) annual full-process emission, (**c**) annual power amount, (**d**) emission-power factor.

3.3. Phaseout Paths upon Stochastic Demands

Moreover, coal-fired power demands can also be modeled as stochastic processes; straightforwardly, $\mathbb{F}(D_C(T)) = D_C(T)$. Then, result uncertainties will apparently increase, providing more probabilistic information.

Unit-level emissions upon $\mathbb{F}(D_C(T)) = D_C(T)$ are presented in Figure 9. The uncertainty range expands, apparently. Most optimistically, coal-fired carbon can vanish by 2037 (a probability of less than 0.13%); however, in the worst cases, emissions will peak after 2032 and still maintain an amount of 2.90 Gt by 2060.

Full-process emissions are presented in Figure 10, where the annual emission distribution in 2060 ranges from 0 to 4.70 Gt, and the cumulative carbon emissions could reach between 64.18 and 116.12 Gt, accounting for 4.3% to 9.7% of the total carbon budget needed to limit the global temperature increment to under 2 °C (1200–1500 Gt [70,71]).

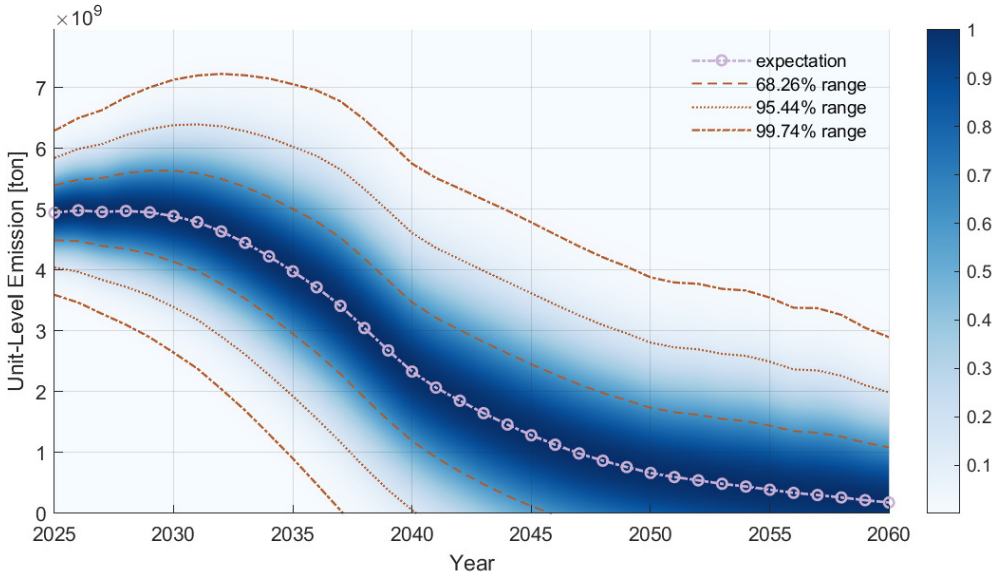

Figure 9. The annual unit-level emission results of simulated phaseout paths when the demand is in stochastic process forms, such as $\mathbb{F}(D_C(T)) = D_C(T)$.

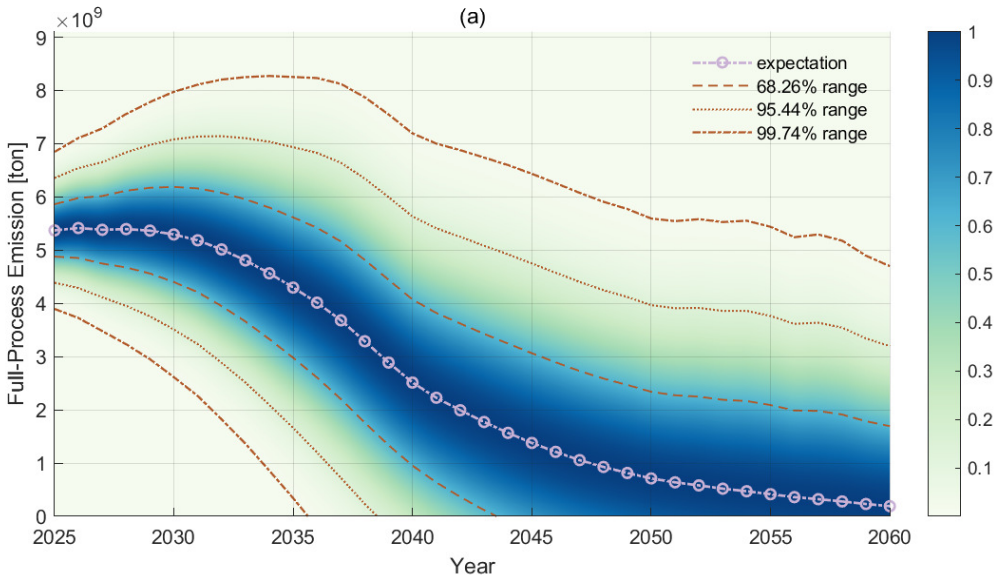

Figure 10. *Cont.*

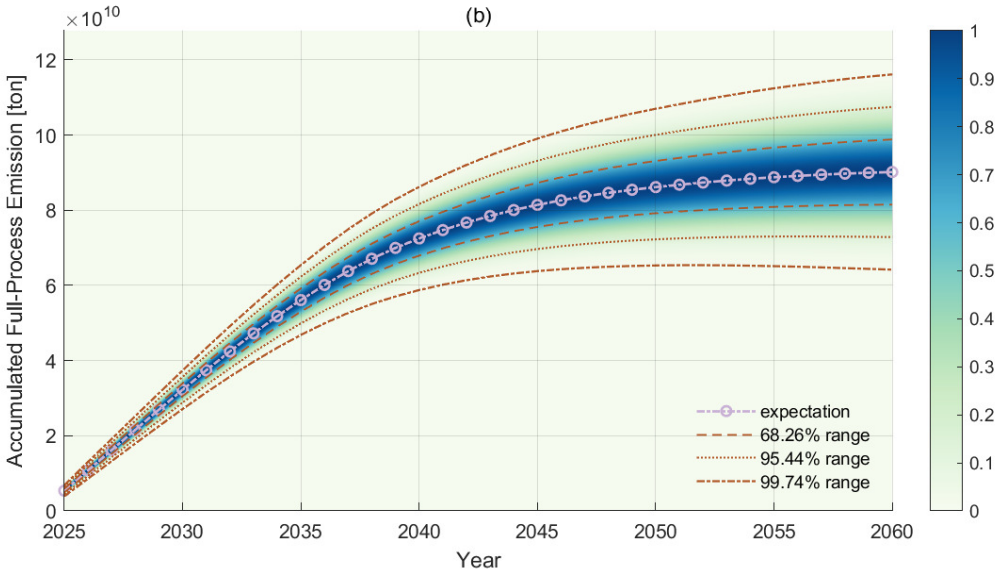

Figure 10. The full-process emission results of simulated phaseout paths when the demand is in stochastic process forms, as $\mathbb{F}(D_C(T)) = D_C(T)$, (**a**) annual amount, (**b**) accumulative amount since 2025.

4. Discussions

4.1. Probabilistic Information

The distinct advantage of stochastic process-based modeling is its ability to quantitatively assess uncertainty distributions, enabling deductions based on simulation results to have probabilistic features. Moreover, additional probabilistic information is presented in Section 3 as follows:

The probability of coal-fired emissions peaking can be calculated by integrating the probability density results in Figure 9. The carbon peak year can be mathematically modeled as t_p in (26):

$$t_p = \underset{2025 \le t \le 2060}{\arg\max} \; E(t), \tag{26}$$

then $P(t_p \le 2030) = \sum_{t=2025}^{2030} P(t_p = t)$, where $P()$ is the probability function. The calculated result of $P(t_p \le 2030)$ is 91.15%, indicating an optimistic short-term trend.

Additionally, the probability of coal-fired emission neutrality can be calculated annually; the results are shown in Figure 11. Specifically, when coal-fired units all shut down, the emissions, spontaneously, are zero. However, zero emissions can also occur when some units are still operating, as P_{null} is clearly bigger than P_{quit}. This is due to the extra uncertainty from unit parameters, including heat rate and emission factors.

In particular, the probability of coal-fired emission neutrality by 2060 is 42.13%; alarmingly, China's coal-fired power system will more likely still be necessary by then. So, to fulfill the carbon neutrality pledge, the use of carbon capture technologies could be another crucial investment direction.

Some published works have provided probabilities of carbon peaking in China's power system. For example, studies in [72] were published in 2018; they estimate that P_{quit} ranges over 71% when an optimal carbon market scheduling strategy is in operation, and is only 4–6% without government regulation. Simulations in [73] show that power sectors in some cities have less than a 20.08% probability of failing to reach carbon peaks by 2030. Our results indicate more optimistic forecasts using up-to-date data; this may imply that China's power system is on a positive developing trend. On the other hand, to the best of the authors' knowledge, this study is the first to assess the probability of carbon neutrality in coal-fired power systems. However, similar results can be found in

the deterministic phaseout path simulation results found in [16,22,59,74]; all show that current actions may not provide full confidence in achieving coal-fired emission neutrality by 2060. Some studies [19,75] on regional systems also support this concern. So, more powerful policies, further investments, and sure actions are necessary to fully achieve China's long-term carbon control target in its power system.

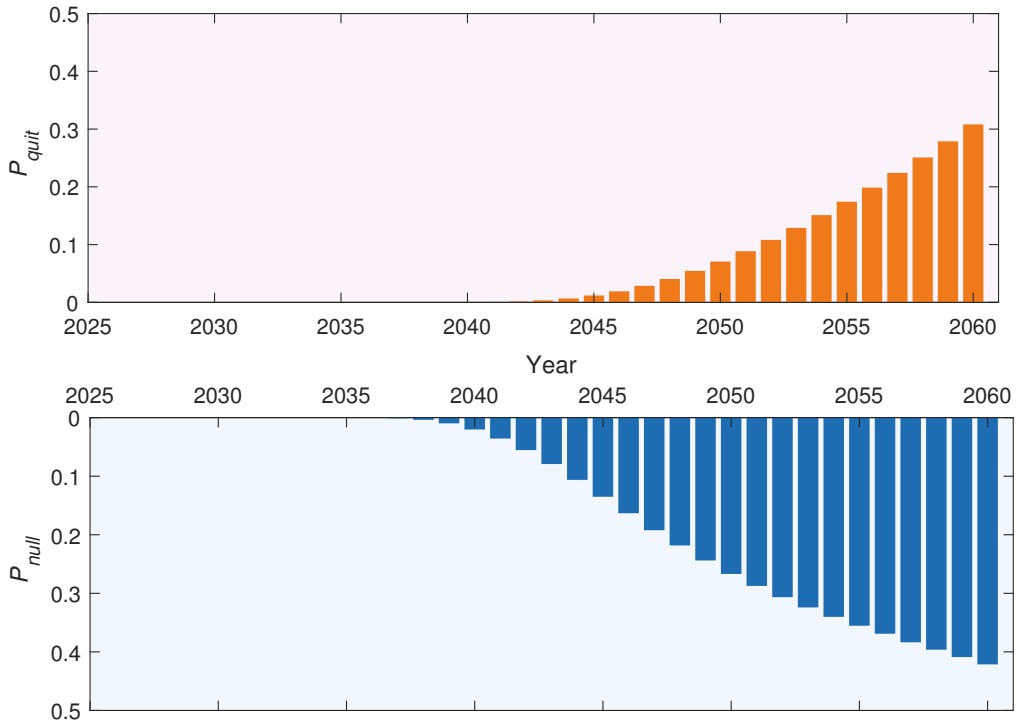

Figure 11. The annual probabilities of the coal-fired system completely shutting down, P_{quit}, and coal-fired emission neutrality, P_{null}.

4.2. Emission-Reduction Potential

Based on the stochastic process-based simulation case study on China's coal-fired power phaseout, the emission-reduction potential is revealed. Macroscopically, in the next few years, the coal-fired power system will still be one of the major carbon sources in China, due to compromises made for national power security [76]. However, from a long-term perspective, the development of a coal-fired power system will serve as an important impetus for reducing China's carbon emissions.

Future coal-fired power development is driven by two main forces. The first is internal. Cleaning technology upgrades can change the high-emission image of coal-fired power. As shown in Figure 6, carbon efficiency is expected to drop to 0.195 tonCO2/MWh, which is much lower than the average efficiency of China's entire power grid in 2022 (0.5703 tonCO2/MWh [77]). In particular, the deployment of CCUS can sharply reduce unit-level emissions [78,79]; the results in Figure 11 reveal the possibility of reaching net-zero or even negative emissions for coal-fired power units. For long-term development, revolutionary upgrades are possible and may save coal-fired power systems from completely vanishing. China is rich in coal, and it will be exceedingly appealing if coal-fired power can be clean and effective.

Nevertheless, considering the technological development and the costs associated with upgrades, shutting down will be the final fate of most coal-fired units. This is the development-driving force from the outside. However, from the perspective of national power security, coal-fired power can only be reduced if new energies are able to take the wheel. In the long-term future, new energies can support the nation's huge power

demands, leading to carbon neutrality, but this is practically impossible before 2030. The expected power structure in our simulation is presented in Figure 12. Even if new energies can develop unexpectedly fast, national power demand will also grow considerably in the next few years [62], due to China's status as the most industrially productive [80] (yet still developing) country [81]. So, new energy development is only one aspect of peaking emissions before 2030. Efficient production and energy conservation on the national level may be other essential points.

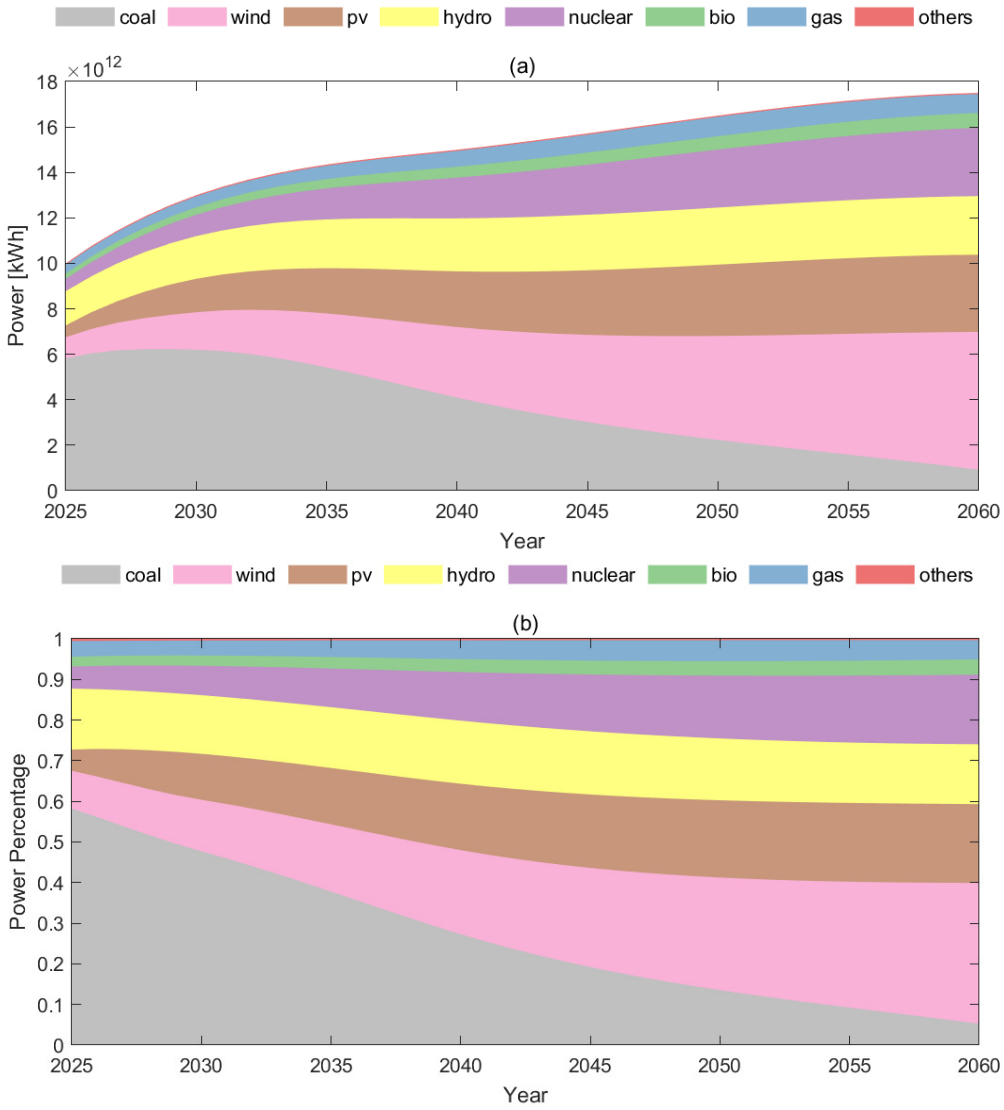

Figure 12. The long-term power structure in China, as projected by simulated expectations shown in Figure 4 (**a**) annual amounts and (**b**) annual percentages.

4.3. Policy Recommendations

Based on studies in this paper, some recommendations on policies and future studies will be discussed.

First, for China, developing new energy may be the only way to meet the requirements for both carbon reduction and national power security. Long-term and sustained investments in various new energy industries are obligatory for leading the country toward its 2060 carbon neutrality pledge.

Also, upgrading the carbon efficiency of coal-fired power units is important, especially for the long-term transformation of China's power grid. The potential of permanently reserving coal-fired power as a net-zero power source should not be abandoned. It meets

the country's rich coal resources and can deeply promote the resilience of the national power supply, both now and in the foreseeable future.

On the other hand, for power system studies—not only those focusing on coal-fired power phaseouts—the proposed stochastic process-based modeling and simulation approach can be adopted to obtain more probabilistic information. Studies and publications on practical probabilistic models for different sections of power systems are also encouraged.

5. Conclusions

This paper proposes a power system modeling and simulation approach based on the stochastic process. It describes the changing momentum and accumulation of different uncertainties during the simulation and provides useful probabilistic information on power system evolutions without relying on massive Monte Carlo simulations. To demonstrate the proposed method in practical application, it was applied in a case study, simulating China's long-term coal-fired power phaseout. Results include annual emissions, power amounts, carbon efficiencies, and the probability distributions of their uncertainties. By analyzing the uncertainty range, further probabilistic results are deduced, e.g., in the simulation model, China's coal-fired power emissions have a 91.15% probability of peaking before 2030, but only a 42.13% chance of achieving carbon neutrality by 2060. So, after realizing the 2030 carbon peak pledge, China will still need further investments in new energies and carbon-sinking technologies to fulfill its 2060 target. Moreover, China's accumulative coal-fired power emissions from 2025 to 2060 are expected to range from 64.18 to 116.12 Gt (with a 99.74% probability). This accounts for 4.3% to 9.7% of the global carbon budget of the 2 °C temperature rise limitation, highlighting the considerable carbon reduction potential in China's coal-fired power system.

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

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