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Research Article

Evaluating CCS Investment of China by a Novel Real Option-Based Model

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Carbon capture and storage (CCS) technology is an effective method to mitigate CO_2 emission pressure; however it is hard to be evaluated due to uncertainties. This paper establishes a real options analysis (ROA) model to evaluate CCS investment from the perspective of the existing thermal power plant by considering the fluctuations of electricity price, carbon price, and thermal coal price. The model is solved by the proposed robust Least Squares Monte Carlo method and China is taken as a case study to assess power plant's CCS investment revenue. In the case study, robust ROA and ROA are compared under some CCS incentive factors. The results indicate that the proposed robust ROA is more realistic and suitable for CCS evaluation than common ROA to some extent. Finally, a policy schema to promote CCS investment is derived.

1. Introduction

Global greenhouse gas (GHG) emissions exacerbate global warming and make major contribution to climate change. International Panel on Climate Change has reported that approximately 35% of total anthropogenic GHG emissions were attributed to energy supply sector in 2010 [1]. Currently, the mitigation efforts of GHG emissions, especially CO_2, have focused on innovations of energy sector, such as renewable energy sources and Clean Development Mechanism [2]. Although those ways can reduce GHG emissions significantly, they are not able to completely replace fossil energy to meet future energy needs. In 2013, 41.3% world electricity is generated by coal. Most countries of the world will still use fossil fuels as their primary energy resource in the future.

Great attention has been paid to carbon capture and storage (CCS) technology which would significantly reduce CO_2 emission, especially for developing countries which take coal as the primary energy resource. China has become the biggest coal consumer and ranks the first place in terms of CO_2 emissions due to the rapid development, great pressure of air pollution, and energy security which has been posed to China. According to statistics released by the National Bureau of Statistics [3], China's coal consumption is about 70% of total energy consumption and more than 75% of electricity is generated by coal combustion. CCS technology is deemed as an important approach to significantly reduce CO_2 emissions with the purpose of maintaining fossil fuels usage in China power industry. In order to establish a nationwide carbon market and achieve the emission target in 2020, China has launched seven regional pilot carbon trading systems during 2013 to 2014 and drafted the regulations for national CO_2 market in 2016. Although regional carbon exchanges have been operating for a certain time, trading activities are depressed and companies have little incentive to buy carbon credits.

An integrated CCS system has three distinct components involving capture, transportation, and storage which need large-scale facility investments [4]. However, high operation costs and future revenue uncertainties place power plants in a dilemma to implement CCS retrofit under the stringent CO_2 emission restrain [5]. In this context, an in-depth cost-benefit analysis of CCS retrofitting is required, and effective economic incentives should be implemented to trigger CCS deployment of electric plants.

There are numerous uncertainties in CCS investment, such as climate policy, CCS cost, fossil energy price, power plant lifetime, and technological feasibility. Those

uncertainties are conspicuous obstacle to deployment of CCS technology, particularly in developing country like China. As to climate policy, Australian parliament repealed carbon tax after two years' fierce debate in 2014; Canada became the first country who announced withdrawing from the Kyoto Protocol in 2011. Therefore, the trend of future climate policy is unpredictable, and it affects the implementation of carbon tax system directly. On the other hand, CCS uses a combination of processes and technologies; some of them have not been proven at large scale or still in the research and development (R&D) stage, so it is hard to predict CCS investment cost. In addition, coal price has ridden a roller coaster of booms and busts around 2009 and has been falling since 2014; it brings a significant effect on generating cost of thermal electric plant. Furthermore, CCS deployment will decrease energy conservation and efficiency of power plant, in turn consume 10–40% more energy, and increase 10–60% more generating cost than the same power plant without CCS [6]. Therefore, it is difficult for power plants to implement CCS investment, and CCS cost is a vital economic challenge that must be overcome.

This paper integrates real options theory with robust technology and then applies it to evaluate the CCS investment from the perspective of electric plants. The uncertainties of electricity output price, fuel input price, and carbon price are taken into consideration in the model establishment; then the investments value of CCS can be evaluated in the simulation period which will help electric plants make a decision of whether to adopt CCS technology. With taking China's energy plant as a case study, the effects of initial carbon price, operations management cost, generating subsidy, and investment subsidy are analyzed. The proposed model can help electric plants to make investment decision and can also help government trigger energy plants' CCS investment in current China energy situation.

2. Literature Review

Although CCS technology has not been applied extensively, many researches have paid attention to CCS technology development and CCS policies. For technoeconomic analysis of CCS project, the conventional approach is discounted cash flow method (DCF) with the criterion of net present value (NPV). For example, Sekar et al. [7] performed an NPV analysis to determine the carbon price levels and growth rates which would be used to justify whether to build a baseline IGCC plant. Bohm et al. [8] estimated the lifetime NPV costs of power plants with different carbon capture preinvestment levels; they showed that a baseline PC plant is the most economical choice under low carbon prices while IGCC plant is preferable at higher carbon prices. NPV criteria decision is predicted based on current information and does not have the capabilities to deal with the future uncertainties. However, CCS technologies have not been driven to mature stage; power plants with CCS investment will be influenced by many factors; along with irreversible CCS investment cost, it is clear that NPV is not suitable for CCS investment evaluation.

In practice, companies usually postpone a project instead of making decision immediately to avoid huge sunk costs [9]. Real options analysis (ROA) is a proved effective method to evaluate projects with uncertain future revenue; it gives decision-maker the opportunity to postpone judgment. So ROA is more suitable for large-scale investment project evaluation and received great attention to assess green and sustainable development projects recently. Although investment ROA strategy in the power sector has developed in less than twenty years, there are many excellent research findings. At the earliest, Kaminski [10] pointed out the growing importance and usefulness of real options and risk management in power plant operations and project valuation. Then Hsu [11] first used spark-spread options technique to tackle power plant valuation problem. After that, ROA was widely applied to evaluate power investment, including short-term power plant valuation [12] and Clean Development Mechanism (CDM) project valuation [13].

In order to capture specific characteristics, some researchers have applied ROA to evaluate CCS investment. Classified by real options solving techniques, Abadie and Chamorro [14] used binomial lattice method to assess CCS options value of a coal-fired power plant in a carbon-constrained environment. Fuss et al. [15] used Monte Carlo simulation to solve a real options CCS investment model. And Zhang et al. [16] developed a trinomial tree modeling-based real options approach to analyze the investment of CCS technology. Classified by uncertainties involved in models, both Abadie and Chamorro [14] and Fuss et al. [15] supposed that the carbon emission price and the electricity output price are uncertain. Szolgayová et al. [17] presented a real options model with stochastic electricity and CO_2 prices; they also analyzed the effect of price gaps. Zhang et al. [16] considered multiple uncertainties such as carbon price and government subsidy. There are also some researchers focusing on types of power plants and CCS technologies, such as Zhou et al. [9] who adopted a real options analysis to estimate the value of the CCS technology application to three kinds of power plants by considering the uncertainties of electricity price, fuel price, and emission allowances price. Heydari et al. [18] developed an analytical real options model for a coal-fired power plant to evaluate the choice between two available emissions-reduction technologies, full CCS technology and partial CCS technology.

Previous researches usually evaluated CCS investment by innovative real options solving methods or considering specified conditions. For CCS technology investment can be seriously affected by the above-mentioned uncertainties, which leads CCS investment options value to change largely; in order to handle this problem, a robust optimization method is used for CCS evaluation in this paper. It is widely recognized that optimal solution is highly sensitive to the perturbation of input data and may even be infeasible in some worse cases, so many approaches are proposed based on parameter uncertainty. One popular approach is robust optimization which assumes that parameters exist in a given "uncertainty set." After Soyster [19] first studied explicit approaches to solve robust optimization problems, the robust approaches have been extensively studied and extended (see

[20, 21]). For robust least squares problems, El Ghaoui and Lebret [22] disposed them by minimizing the worst-case residual error using second-order cone programming, and Chandrasekaran et al. [23] solved total least squares with bounded uncertainty by a Min-Min Model. In this paper, we use robust least squares to improve Least Squares Monte Carlo approach.

This paper adopts robust optimization theory to reform Least Squares Monte Carlo technique for evaluating real options value of power plant's CCS retrofit. Based on collected data and previous research, CCS investment of China's electric plants is evaluated in a given observation period. This study attempts to analyze CCS investment in a novel approach which is different from previous studies. At first, this paper considers three uncertainties of CCS investment, fuel price, electricity price, and carbon price, and simulates electricity price by a mean-reverting process which has been verified but rarely used in previous related research. Secondly, we collect historical data of China's energy sector from reliable institutions and then calculate regression parameters based on the processed data which can ensure the reliability of case study. Thirdly, the proposed robust ROA method presents different results compared with common ROA. And we illustrate that robust ROA is more realistic and suitable for CCS evaluation than ROA to some extent. Then the effects of carbon price, cost reductions, and subsidies for CCS investment are analyzed by three scenarios which provide implications for electric plants and government. At last, a policy approach to trigger CCS investment is proposed for launching an effective national carbon market.

3. Modeling Description

We assume that it should be decided whether a coal-fired power plant be retrofitted with CCS technology when government implements carbon tax system. Based on available research framework, we evaluate CCS cost saving value from the view of power plant. The CCS profit comes mainly from certified emission reduction; the cost refers to investment cost and efficiency penalty. Three sources of uncertainty, electricity output price, fuel input price, and carbon price, are taken into consideration for CCS investment valuation. We take fuel input price as uncertainty instead of generating cost because fuel is the most uncertain factor to generate electricity, and generating cost is usually stable once the power plant is fixed. Price series models of carbon, electricity, and fuel are given in the following before calculating CCS investment options value.

3.1. The Model for Electricity Output Price. Unlike common commodity, whose market prices are compelled by the supply and demand relationship, traded electricity cannot be stockpiled in electricity market. The feature of grid electricity makes its price curve exhibit high frequency, mean reversion, and multiple seasonality effect. There are numerous methods that have been developed for forecasting electricity spot price, and a brief survey given by Geman [24] found that electricity price displays the trends of mean reversion, seasonality, and stochastic volatility which are also recognized in other literatures. Therefore, we assume that the electricity price follows a mean-reverting process:

$$dp_t^e = \kappa\left(\alpha_e - \ln p_t^e\right) p_t^e dt + \sigma_e p_t^e dz_t^e, \tag{1}$$

where p_t^e is electricity price at time t, α_e is drift parameter that denotes the long-run equilibrium value, κ is the speed of mean reversion, and σ_e stands for instantaneous volatility. dz_t^e represents the increment of a Wiener process, $dz_t^e = \varepsilon_t^e \sqrt{dt}$, where ε_t^e is a random variable of standard normal distribution. Here we ignore the correlation between thermal power price and CCS electricity price.

3.2. The Model for Carbon Price. Carbon credit price is the most important component in carbon trading system and the biggest factor to CCS technology investment; to investigate the effect of carbon price volatility, accurate forecasting model is needed. Geometric Brownian Motion has been employed in most previous CCS investment researches to depict carbon price series; the model can be described by the following equation:

$$dp_t^c = \alpha_c p_t^c dt + \sigma_c p_t^c dz_t^c, \tag{2}$$

where p_t^c is carbon allowance price at time t, α_c stands for the expected growth rate, and σ_c represents the instantaneous volatility of the carbon price. dz_t^c is independent increments of the Wiener process, $dz_t^c = \varepsilon_t^c \sqrt{dt}$, where ε_t^c denotes a standard normal variable.

3.3. The Model for Fuel Input Price. The costs of power generation mainly contain operational cost and fuel cost. In general, fuel cost has a greater impact on power plant's revenue than operational cost. Pindyck [25] found that fuel prices have significant mean-reverting effect by examining the prices of oil, coal, and natural gas in the United States. According to Pindyck's recommendation, Geometric Brownian Motion model is widely accepted to formulate fuel prices in investment analysis (see [18]). In this paper, we also assume that fuel price follows a Geometric Brownian Motion:

$$dp_t^F = \alpha_F p_t^F dt + \sigma_F p_t^F dz_t^F, \tag{3}$$

where p_t^F is the fuel price for thermal power, dz_t^F is independent increments of the Wiener process, $dz_t^F = \varepsilon_t^F \sqrt{dt}$, where ε_t^F is a standard normal random variable, and α_F and σ_F represent the drift and variance parameters, respectively.

3.4. Valuation of CCS Cost Saving. The problem of evaluating power plant's cost saving after retrofitting with CCS technology is usually solved by maximizing the total discounted expected profits over the planning horizon. The electric plant's annual profit V is total revenues minus total costs, the revenues are derived from selling electricity and carbon credit, the costs refer to fuel cost, CCS operational and maintenance cost, and CCS implementation cost. Let s_t denote whether the CCS module is running at time t; a_t is

the executed action at time t. So the profit of power plant at time t can be expressed as

$$V\left(s_t, p_t^E, p_t^C, p_t^F, a_t, t\right) = PV_E + PV_C - PV_F - \mathrm{OMC}\left(s_t\right) - C\left(a_t\right) \tag{4}$$

with

$$\begin{aligned} PV_E &= q\left(s_t\right) \cdot p_t^E \\ PV_C &= \eta \cdot q\left(s_t\right) \cdot p_t^C \\ PV_F &= \gamma \cdot q\left(s_t\right) \cdot p_t^F, \end{aligned} \tag{5}$$

where $q(s_t)$ is electricity generation capacity, η represents CCS carbon emission rate, and γ is fuel conversion efficiency in CCS power plant. p_t^E, p_t^C, and p_t^F represent electricity output price, carbon price, and fuel input price, respectively. OMC refers to operations management cost of CCS; C denotes the CCS module deployment cost if CCS technology is adopted; otherwise it equals zero.

3.5. Robust Model for Least Squares Monte Carlo Simulation. The least squares method is a standard approach to estimate parameters in regression analysis by minimizing the mean-squared error over all estimators. For a linear least squares problem, a solution x should be found to fit the equation $y = Ax +$ noise with the given matrices $A \in R^{n\times m}$, $y \in R^n$. The least squares method minimizes residual $\|\Delta y\|$ subject to $y = Ax+\Delta y$; $\|\cdot\|$ is 2-norm. However, the elements of matrix A are usually subject to errors since they are measurements. The total least squares solution finds the smallest error $\|\Delta A \Delta y\|_F$ subject to the consistency equation $(A + \Delta A)x = y + \Delta y$ and provides Maximum Likelihood estimate for x when the errors in A and y are independent and identically distributed Gaussian noise [26]; $\|\cdot\|_F$ is Frobenius norm. Then El Ghaoui and Lebret [22] presented a robust least squares (RLS) by Min-Max techniques to the following optimization problem:

$$\min_x \quad r\left(A, y, \rho\right) \triangleq \min_x \max_{\|\Delta A \Delta y\|_F \le \rho} \left\|(A + \Delta A)\, x - \left(y + \Delta y\right)\right\|. \tag{6}$$

The robust least squares minimizes worst-case residual $r(A, y, \rho)$ over a set of perturbations, and the obtained solutions deviate more from the least squares solution when the bound ρ gets larger. If $\rho = 0$, it recovers the standard least squares problem. For every $\rho > 0$, $r(A, y, \rho)$ can be represented as $\rho r(A/\rho, y/\rho, 1)$. El Ghaoui and Lebret [22] proved that when $\rho = 1$, the worst-case residual can be given by

$$r\left(A, y\right) = \left\|Ax - y\right\| + \sqrt{\|x\|^2 + 1}, \tag{7}$$

which can result in a unique solution by minimizing over $x \in R^m$ and can be formulated as a second-order cone programming (SOCP):

$$\begin{aligned} \min \quad & \lambda \\ \text{s.t.} \quad & \left\|Ax - y\right\| \le \lambda - \tau \\ & \left\|\begin{bmatrix} x \\ 1 \end{bmatrix}\right\| \le \tau. \end{aligned} \tag{8}$$

Using duality theorem, the optimal solution x_{RLS} of problem (8) is

$$x_{\mathrm{RLS}} = \begin{cases} \left(\mu I + A^T A\right)^{-1} A^T y, & \text{if } \mu \triangleq \dfrac{(\lambda - \tau)}{\tau} > 0, \\ A^\dagger y, & \text{otherwise}, \end{cases} \tag{9}$$

where (λ, τ) is the unique optimal point for the problem. $A^\dagger$ denotes the Moore-Penrose pseudoinverse of A:

$$\mu = \begin{cases} \dfrac{\left\|Ax - y\right\|}{\sqrt{\|x\|^2 + 1}}, & \text{if } Ax \ne y, \\ \text{any unit - norm vector}, & \text{otherwise}. \end{cases} \tag{10}$$

This paper uses robust technique to improve the Least Squares Monte Carlo method for options evaluation, the robust least squares will be embedded for the uncertainty revenue of CCS power plant, and SOCP model (8) is used to calculate options values instead of common least square regression for Least Squares Monte Carlo method.

Before giving the case study, we take a comparison of LSM method and robust LSM method by a simple options pricing example. Considering American style call options, we assume that the asset price $S = 100$, the exercise price $K = 120$, the risk-free interest $r = 0.05$, and the asset volatility $\sigma = 0.2$. During period $T = 10$, the holder can exercise the option at time $t = 1, 2, \ldots, 10$. We calculate the option price with 10,000 paths and duplicate the experiment ten times. The results indicate that robust LSM has higher options value than LSM method under the given parameter setting, in which LSM option price is 36.8683 and robust LSM option price is 38.7645.

4. Assumptions and Data Collection for Case Study

China is taken as a case study to evaluate CCS investment by the models established in Section 3. In Chinese power sector, most electricity is generated by the conventional thermal power plants which confront big challenges from increasingly strict environmental policies. CCS technology could ensure the normal production of thermal power plants without emitting lots of greenhouse gases, but it should be well evaluated before installation for high cost. Before taking the case study, some assumptions are given first.

We choose a conventional coal power plant to evaluate CCS cost saving from 2015 to 2035. We assume that a national

Table 1: Parameters description of the case study.

Parameter	Coal-fired plant	PC + CSS
Electricity output (MWh)	3×10^6	3×10^6
Capital cost (yuan)	2.6×10^9	4.8×10^9
O&M cost (yuan/year)	3×10^8	3.6×10^8
Coal consumption (ton)	325 g/kWh $* 3 \times 10^6$ MWh = 975,000 tons	1170,000 tons (CCS efficiency loss rate is 20%)
Emission factor (g CO_2/kWh)	893 g/kWh	893 g/kWh
Emission quantity (ton)	893 $* 3 \times 10^6$ MWh = 2,679,000 tons	267,900 tons (CCS capture rate is 90%)
Electricity price (yuan/MWh)	316	428
Risk-free rate	4%	

carbon market will be launched in 2017 and ignore the deployment time of CCS module. At present, carbon credit is the most common carbon emission mitigation policy; this policy gives enterprises carbon emission limit; each enterprise must buy the credit from carbon market if its carbon emission beyond the threshold, and enterprises also can benefit from selling carbon credits by implementing low carbon technologies. We suppose that carbon credit system with volatile price mechanism will be adopted for carbon market and ignore the effects of other climate policies.

Relevant data is collected from China Energy Statistical Yearbook [3] and China Electric Power Yearbook 2014 [27]. And some other parameters are investigated or estimated based on previous related literatures [9, 28]. Table 1 shows the assumptions of parameters.

In recent years, China coal power plants widely adopt ultrasupercritical or supercritical steam generators for increasing energy efficiency and controlling pollution. And supercritical pulverized coal plants have a high share in China electricity generation market; those plants are mainly built from 2005 to 2008 and will be greatly influenced by the climate policy in the following decades. Therefore, we choose supercritical pulverized coal plants as the representative of conventional coal power plants for the case study; the average coal consumption quantity of supercritical pulverized plant is about 325 g/kWh according to China Electric Power Yearbook 2014 [27].

To formulate electricity price series, we collect historical data from two sources. The first source is the website of National Development and Reform Commission which takes charge of electricity pricing in China. The on-grid electricity prices are different by regions, so we select six regional on-grid prices data in northern China, including Beijing, Tianjin, Northern Hebei, Southern Hebei, Shanxi, and Shandong (the range is from 2005 to 2014) and then average them for parameters estimation. The second source is referred to in Zhou et al. [9]. It should be noted that collected prices are exclusive of pollution abatement subsidy which usually increases on-grid electricity price with 0.015 RMB/kWh or 0.02 RMB/kWh. The electricity price equation (1) can be transformed by Ito's lemma:

$$d \ln p_t^e = \left(\kappa\left(\alpha_e - \ln p_t^e\right) - \frac{\sigma_e^2}{2}\right) dt + \sigma_e dz_t^e; \qquad (11)$$

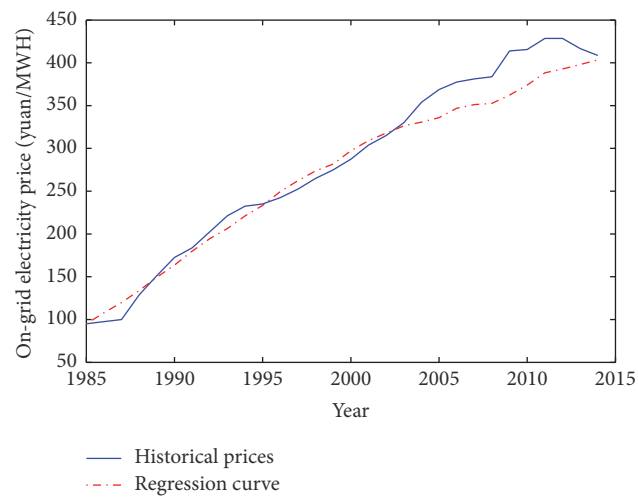

Figure 1: Historical on-grid electricity price.

then stochastic equation (11) can be discretized as follows:

$$\ln p_{t+1}^e - \ln p_t^e = \left(\kappa\left(\alpha_e - \ln p_t^e\right) - \frac{\sigma_e^2}{2}\right)\Delta t + \sigma_e \sqrt{\Delta t}\varepsilon_t, \qquad (12)$$

where $\varepsilon_t \sim N(0, 1)$.

We assume that equation (12) has the form $Y = \beta_1 + \beta_2 X + \mu$; then the values of parameter β_1 and β_2 can be estimated by Min-Max residuals with collected electricity prices data:

$$\begin{aligned} \widehat{\beta}_1 &= \kappa\alpha_e \Delta t = -1.6887, \\ \widehat{\beta}_2 &= -\kappa\Delta t = 3.1478, \\ \kappa &= 0.075, \\ \alpha_e &= 6.2067, \\ \sigma_e &= 0.0099. \end{aligned} \qquad (13)$$

Figure 1 displays historical on-grid prices by solid curve and regression prices by dotted curve. It is clear that regression model fits well to the historical data. Notice that we assume that the development tendency of China's power industry will continue in the coming decades and on-grid

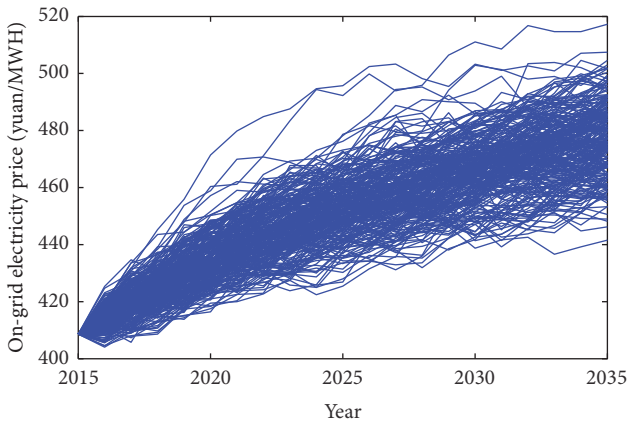

Figure 2: Trend of on-grid electricity price.

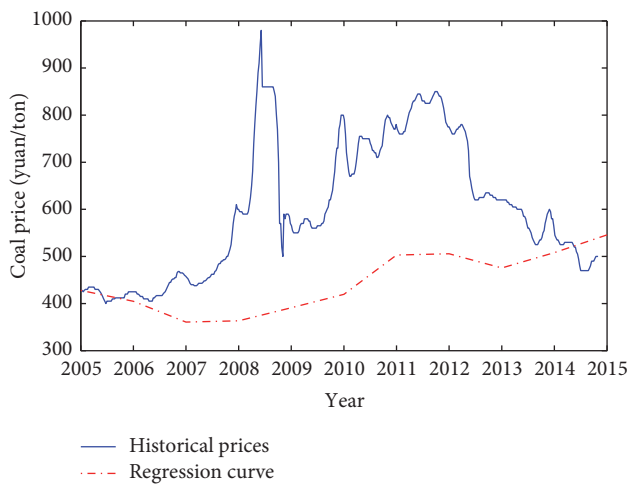

Figure 3: Historical thermal coal price.

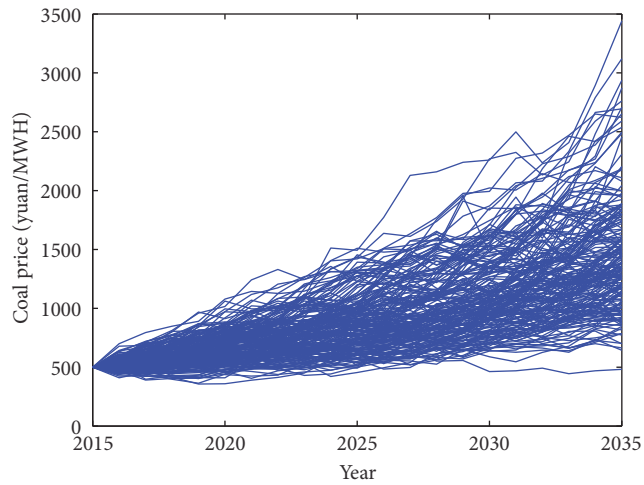

Figure 4: Simulation of thermal coal price.

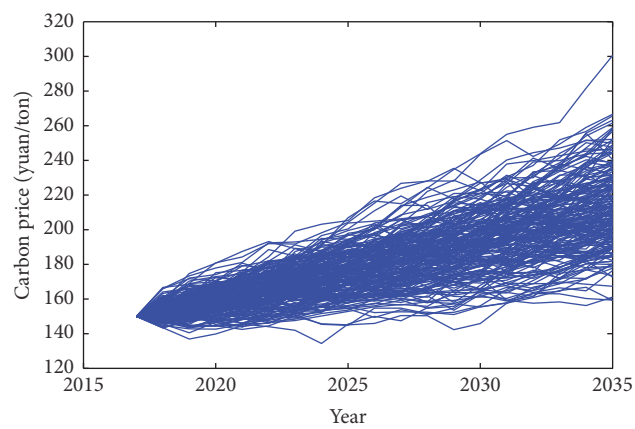

Figure 5: Simulation of carbon price.

prices follow a stochastic process with above parameters; this assumption is also used by Zhou et al. [9] and Heydari et al. [18]. Then the following process can be obtained by simulation, as shown in Figure 2.

Historical coal prices come from Qinhuangdao Coal Exchange Center; the horizon covers from January 2009 to November 2015. For the coal price depending on calorific values, six coal prices are averaged for parameter estimation in this paper, and the curve of average price is shown in Figure 3. Since China has not yet launched a nationwide carbon system, we cannot get the historical coal prices data, so parameters of carbon price process are supposed based on previous research. The drift parameter is 0.02 which has been studied and used by Zhou et al. [9] and the volatility parameter is 0.0287 in accordance with Szolgayová et al. [17].

Geometric Brownian Motion model is commonly employed to simulate coal and carbon prices as described in Section 3; its equation is

$$dS = S\mu\, dt + \sigma S\, dz. \tag{14}$$

According to Ito's lemma, equation (14) is rewritten as

$$d \ln S = \left(\mu - \frac{\sigma^2}{2}\right) dt + \sigma\, dz; \tag{15}$$

after discretization, we get

$$\ln S_t - \ln S_{t-1} = \left(\mu - \frac{\sigma^2}{2}\right) \Delta t + \sigma \sqrt{\Delta t} \cdot \varepsilon_t, \tag{16}$$

where ε_t is the standard normal variate.

Based on discretization equation (16) and collected data, coal price follows a stochastic process with parameters $\alpha_F = 0.0572$ and $\sigma_F = 0.0884$. We also assume that the development environment will continue and the parameters of price processes will not change in the coming decades. Figures 4 and 5 show the price trajectories of fuel input price P_F and carbon price P_C in 200 simulation paths, respectively.

Table 2: Scenarios setting and description.

Scenarios unit	Configuration setup
Scenario 1: initial cases	Case 1.1: four initial carbon prices are considered with CO_2 price drift parameter $\alpha_C = 0.02$ and volatility parameter $\sigma_c = 0.0287$
	Case 1.2: CO_2 price drift parameter $\alpha_C = 0.05$ compared with Case 1.1
	Case 1.3: CO_2 price volatility parameter $\sigma_c = 0.0574$ compared with Case 1.1
Scenario 2: cost reductions cases	Case 2.1: initial CO_2 price is 100 yuan/ton, operations management cost process with exponential parameter $\lambda = -0.01$, and investment cost process is calculated by relevant setting, and other parameters are the same as Case 1.1
	Case 2.2: initial CO_2 price is 125 yuan/ton compared with Case 3.1
	Case 2.3: $\lambda = -0.01$ for operations management cost reduction compared with Case 2.2
Scenario 3: subsidies cases	Case 3.1: initial CO_2 price is 100 yuan/ton, generating subsidy is 30 yuan/MWh, and investment subsidy is calculated by relevant setting, and other parameters are the same as Case 1.1
	Case 3.2: initial CO_2 price is 125 yuan/ton compared with Case 3.1
	Case 3.3: generating subsidy is 15 yuan/MWh compared with Case 3.2

Table 3: CCS cost saving values in scenario 1.1.

Carbon price (yuan/ton)	NPV	ROV	Robust ROV	Percentage of gaps*
50	$-2.9759e+09$	0	0	—
100	$-8.8332e+08$	$3.4122e+07$	$3.5696E+07$	4.61%
125	$1.6075e+08$	$3.8025e+08$	$3.9416E+08$	3.66%
150	$1.2013e+09$	$1.1841e+09$	$1.2089E+09$	2.09%
200	$3.2965e+09$	$3.1520e+09$	$3.1865E+09$	1.10%

*(Robust ROV − ROV)/ROV × 100%.

5. Numerical Experiment and Scenarios Analysis

This section will calculate options valuation of power plant's CCS investment in China based on established model in Section 3 and collected data in Section 4. The options valuation is solved by improved Least Squares Monte Carlo method which includes a robust least squares problem in each iteration, and the robust problem is solved by the YALMIP toolbox of MATLAB. In general, the results will converge to a point when simulation paths are more than 1000. To get a more accurate result, we calculate a result based on 10000 paths of Monte Carlo simulation and replicate the simulation 10 times to generate a large sample of random routing in order to cover every possible result.

The initial scenario analyzes CCS investment under different carbon prices, drift parameters, and volatility parameters. As mentioned above, CCS investment has high cost and uncertainty; power plants in developing countries like China will not involve in CCS installation unless it is profitable. So some incentive methods should be used to promote power plants' CCS deployment. Undoubtedly, electric plants have motivation to implement CCS investment if operations management cost or investment cost decreases significantly with technological improvement. And government subsidy also has a significant effect on promoting new project investment. To analyze the effects of investment incentives on the CCS cost saving, cost reductions and government subsidies are analyzed in scenario 2 and scenario 3. The brief description of scenarios setting is listed in Table 2.

5.1. Initial Scenario. Based on related research about China carbon price [9, 29], we select initial carbon price to be 50, 100, 125, 150, and 200 yuan/ton to express different carbon initial policies; the 125 yuan/ton is a baseline price, and the others refer to lower carbon price and higher carbon price, respectively. In scenario 1.1, the parameters are valued according to Section 4. Taking scenario 1.1 as the baseline, a good development prospect of CCS policy with carbon price drift parameter $\alpha_C = 0.05$ is studied in scenario 1.2 and a more uncertain environment of CCS trading system with carbon price volatility parameter $\sigma_C = 0.0574$ is analyzed in scenario 1.3.

5.1.1. Scenario 1.1. Table 3 shows that CCS cost saving value increases greatly with the initial carbon price increases; both options' values of ROA and robust ROA increase more than 300% with carbon price increases from 125 yuan/ton to 150 yuan/ton. So the increases of initial carbon prices can encourage power plants to implement CCS investment, and the electric plants will not invest CCS unless carbon price is high enough. Table 4 shows that electric plants will install CCS module almost immediately when initial carbon price is high enough and postpone the investment when initial carbon prices are low; the optimal investment timing becomes much late with initial carbon price decreases. Both ROA and robust ROA present much higher CCS investment value than NPV method when carbon price is no more than 125 yuan/ton. It is remarkable that robust ROA value is higher than ROA value and the gap decreases with carbon

Table 4: Quantities of approved paths and CCS deployment timing in scenario 1.1.

Carbon price	ROV		Robust ROV	
	Implemented paths	Optimal timing	Implemented paths	Optimal timing
50	0	—	0	—
100	1148	17.02	1248	16.79
125	5987	7.64	6109	7.48
150	9221	3.82	9291	3.75
200	9936	3.12	9969	3.09

Table 5: CCS cost saving values in scenario 1.2.

Carbon price	NPV	ROV	Robust ROV	Percentage of gaps
50	$-2.2640e+09$	0	0	—
100	$5.4161E+08$	$6.4195E+08$	$6.5925E+08$	2.69%
125	$1.9480E+09$	$1.8442E+09$	$1.8859E+09$	2.26%
150	$3.3477E+09$	$3.1581E+09$	$3.2011E+09$	1.36%
200	$6.1560E+09$	$5.9059E+09$	$5.9598E+09$	0.91%

Table 6: Quantities of approved paths and CCS deployment timing in scenario 1.2.

Carbon price	ROA		Robust ROA	
	Implemented paths	Optimal timing	Implemented paths	Optimal timing
50	0	—	0	—
100	7585	5.60	7650	5.52
125	9606	3.44	9670	3.38
150	9850	3.21	9906	3.15
200	9978	3.09	9989	3.08

Table 7: CCS cost saving values in scenario 1.3.

Carbon price	NPV	ROV	Robust ROV	Percentage of gaps
50	$-2.9722E+09$	0	0	
100	$-8.9079E+08$	$1.2613E+08$	$1.2371E+08$	−1.96%
125	$1.4869E+08$	$5.4167E+08$	$5.3340E+08$	−1.55%
150	$1.1921E+09$	$1.2617E+09$	$1.2487E+09$	−1.04%
200	$3.1363E+09$	$3.1216E+09$	$3.1012E+09$	−0.66%

price increasing; this finding is consistent with implemented paths of two models. The optimal investment year of robust ROA is earlier than that of ROA under different carbon prices. So robust ROA is more optimistic than ROA; the reason might be that the simulation environment is stationary relatively, and the options values of robust ROA are regressed by considering volatility of revenue, so robust ROA can get greater options value with lower volatility.

5.1.2. Scenario 1.2. Carbon price is the expression of carbon policy and the most important factor in CCS investment. This scenario analyzes the impact of a positive development prospect of carbon policy. The drift parameter is 0.05 which makes carbon price grow faster than scenario 1.1. The results are shown in Tables 5 and 6, which include the following findings: with the faster growth of carbon price, CCS presents higher investment value, more implemented paths, and earlier investment timing than scenario 1.1. The options value in scenario 1.2 is tenfold greater than that of scenario 1.1 when carbon price is 100 yuan/ton, and the magnification decreases with the carbon price increasing.

Table 6 also shows that electric plants have motivation to invest CCS with low carbon prices which would not happen in scenario 1.1. So a good development prospect of CCS policy will accelerate CCS investment. But extremely low carbon price, 50 yuan/ton, also cannot trigger CCS investment in scenario 1.2. We also get that the robust real options value is greater than common real options value which is consistent with implemented paths of two models, and the optimal timing of robust ROA to invest in CCS is a little earlier than that of ROA under different carbon prices.

5.1.3. Scenario 1.3. Scenario 1.3 investigates the impact of carbon price volatility which is set to be double that of scenario 1.1; the results are shown in Tables 7 and 8. The values of NPV in scenario 1.3 are lower than that of scenario 1.1,

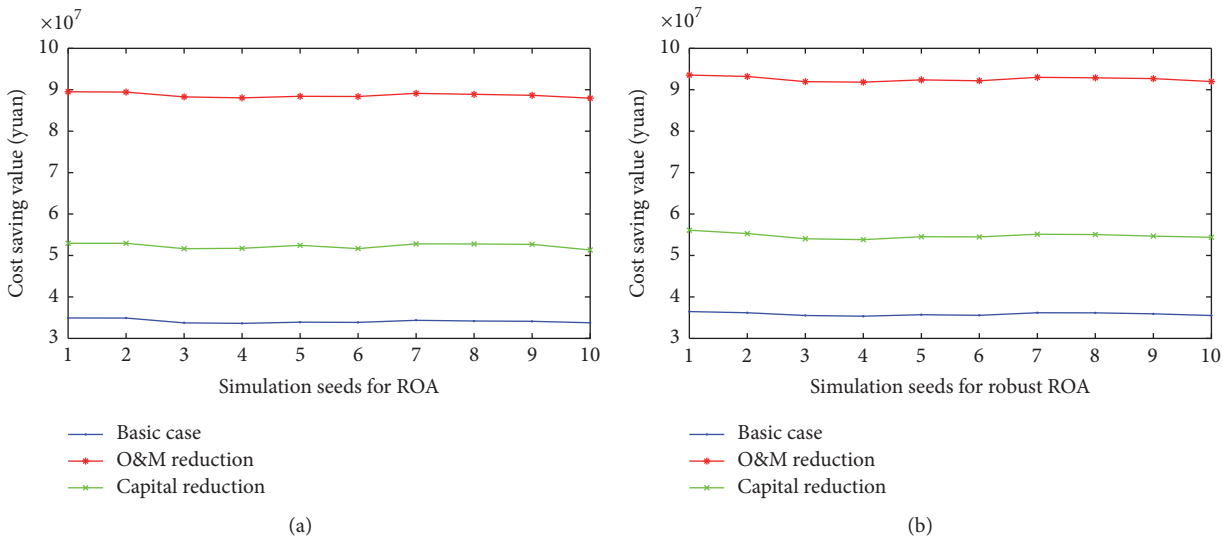

Figure 6: CCS cost saving values of two methods in scenario 2.1.

Table 8: Quantities of approved paths and CCS deployment timing in scenario 1.3.

Carbon price	ROA		Robust ROA	
	Implemented paths	Optimal timing	Implemented paths	Optimal timing
50	0	—	0	—
100	1967	15.20	2037	15.05
125	5078	8.96	5150	8.85
150	7310	5.93	7389	5.83
200	9064	3.97	9113	3.93

but the options values in scenario 1.3 are higher than that of scenario 1.1 when initial carbon price is low. That is to say, the high volatility increases options value in low initial carbon price cases, and the results of implemented paths and optimal timing also indicate that electric plants have more motivation to invest CCS with high carbon price volatility even when carbon price is low, but the conclusion is opposite when carbon price is high.

Unlike the results of scenario 1.1 and scenario 1.2, gaps between robust ROA and ROA are negative in scenario 1.3. They imply that robust options value is less than ROA options value. The reasons may be that ROA calculates options values without considering uncertainty, and robust ROA gets conservative options values with volatility increases. Table 8 also displays that implemented paths' number of robust ROA is slightly bigger than that of ROA and the optimal investment timing of robust ROA is a little earlier than ROA. It should be noted that although the volatility parameter is double that of scenario 1.1, it just implies uncertainty increases, but carbon prices cannot collapse suddenly. So in a general developing environment of carbon system, robust ROA is more optimistic than ROA to some extent.

5.2. Cost Reductions Scenario. Power plants will engage in CCS R&D if they do not have mature CCS technology, and R&D input would significantly bring the investment cost reduction although it is an expensive undertaking. Operations management cost can also decrease by business process optimization, which will not take lots of input compared with R&D expenditure. Considering technology and management development of power plant, this scenario analyzes the effects of cost reductions for CCS investment. The investment cost and operations management cost are assumed to decrease by exponential processes; we set investment cost reduction to be twice that of total operations management cost saving at initial CCS investment time and be equivalent at the last time. In scenarios 2.1 and 2.2, initial carbon prices are 100 yuan/ton and 125 yuan/ton, respectively, and the exponential process of operations management cost reduction has parameter $\lambda = -0.01$, so that the CCS power plant will have the same operations management cost as conventional power plant in the last period. Taking scenario 2.2 as baseline, the parameter of operations management cost process changes to $\lambda = -0.015$ in scenario 2.3 for comparative analysis; other parameters are the same as scenario 1.1.

5.2.1. Scenario 2.1. Scenario 2.1 considers the impacts of operations management cost reduction and initial investment cost reduction when initial carbon price is 100 yuan/ton. Figure 6 shows options values of robust ROA and ROA under three cases; it illustrates that operations management cost reduction and initial investment cost reduction can increase

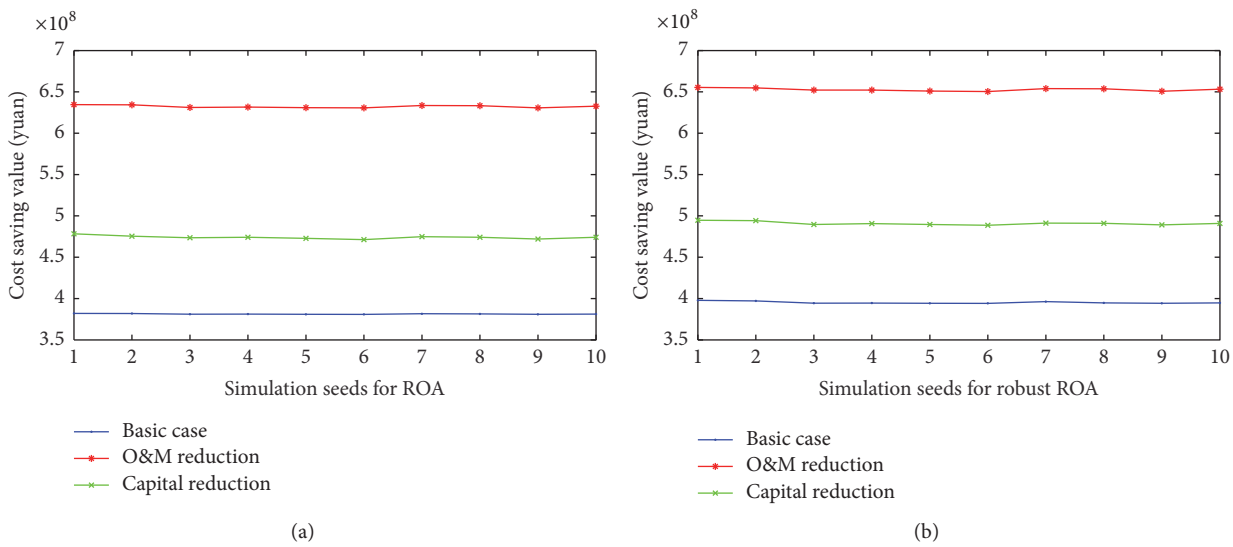

Figure 7: CCS cost saving values of two methods in scenario 2.2.

Table 9: Simulation results in scenario 2.1.

		Basic	O&M	Capital
Implemented paths	Robust ROA	1228	1821	1387
	ROA	1138	1684	1251
Gaps of two methods		$1.6640E+06$	$3.8406E+06$	$2.4573E+06$
Percentage of gaps		4.64%	4.15%	4.49%

Table 10: Simulation results in scenario 2.2.

		Basic	O&M	Capital
Implemented paths	Robust ROA	6109	9719	9490
	ROA	5987	9655	9076
Gaps of two methods		$1.3910E+07$	$2.0412E+07$	$1.6919E+07$
Percentage of gaps		3.66%	3.13%	3.45%

options value significantly, and operations management cost decrease has more significant positive impact on CCS investment than capital cost decrease. By comparing two parts of Figure 6, it can be found that the robust ROA has higher options value than ROA which is consistent with the results of scenario 1. Except the findings shown in Figure 6, Table 9 also shows that although the two cost reductions can increase options value greatly, both of them cannot obviously improve the motivation of electric plant to CCS investment when carbon price is 100 yuan/ton or lower.

5.2.2. Scenario 2.2. Scenario 2.2 considers the impacts of operations management cost reduction and initial investment cost reduction when initial carbon price is 125 yuan/ton; see Figure 7 and Table 10. The results illustrate that cost reduction can increase option value greatly and operations management cost decrease is more effective in accordance with scenario 2.1. The results of Table 10 also show that electric plants have motivation to engage in CCS investment when initial carbon price 125 yuan/ton. Compared with scenario 2.1, it can be found that cost reductions are an effective means for promoting CCS investment unless the initial carbon price is set to a reasonable extent.

5.2.3. Scenario 2.3. Scenario 2.3 sets initial carbon price to be 125 yuan/ton and cost reductions to be more than scenario 2.2; the results can be found in Figure 8 and Table 11. The results also show that both two cost reductions can increase options value greatly and operations management cost decrease is more effective for CCS cost saving. Table 11 displays that the robust ROA has higher options value and makes more positive decision than ROA. Compared with scenario 2.2, although options values increase largely, cost reductions do not have a significant effect on promoting CCS investment. Therefore, the effectiveness of cost reduction is diminishing with reduction increase, and the level of cost reduction should be set in accord with carbon price. All three subscenarios indicate that electric plants are more interesting in operations management cost reduction instead of investment cost reduction in CCS deployment.

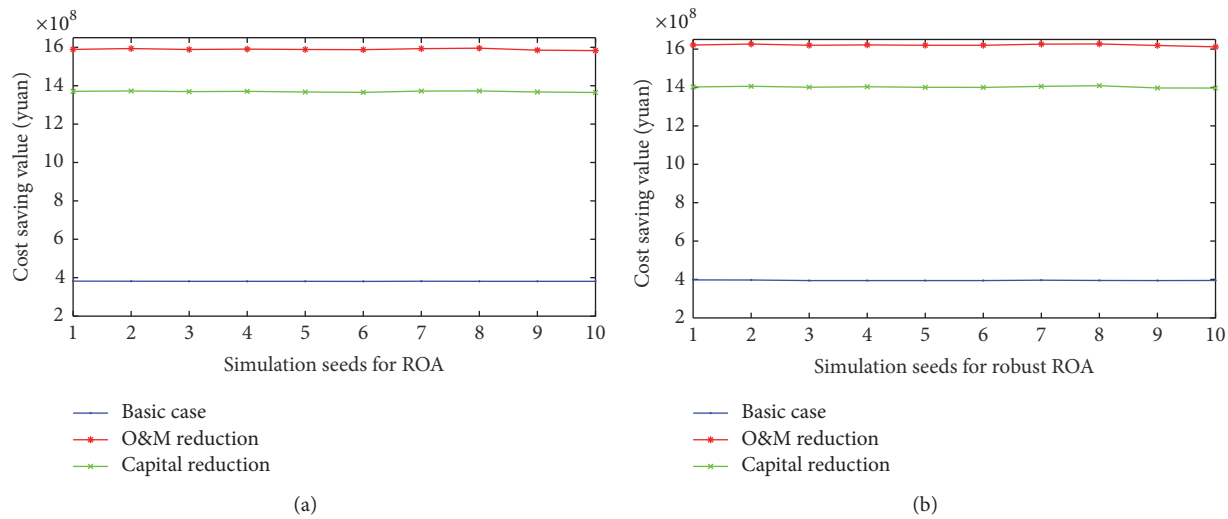

Figure 8: CCS cost saving values of two methods in scenario 2.3.

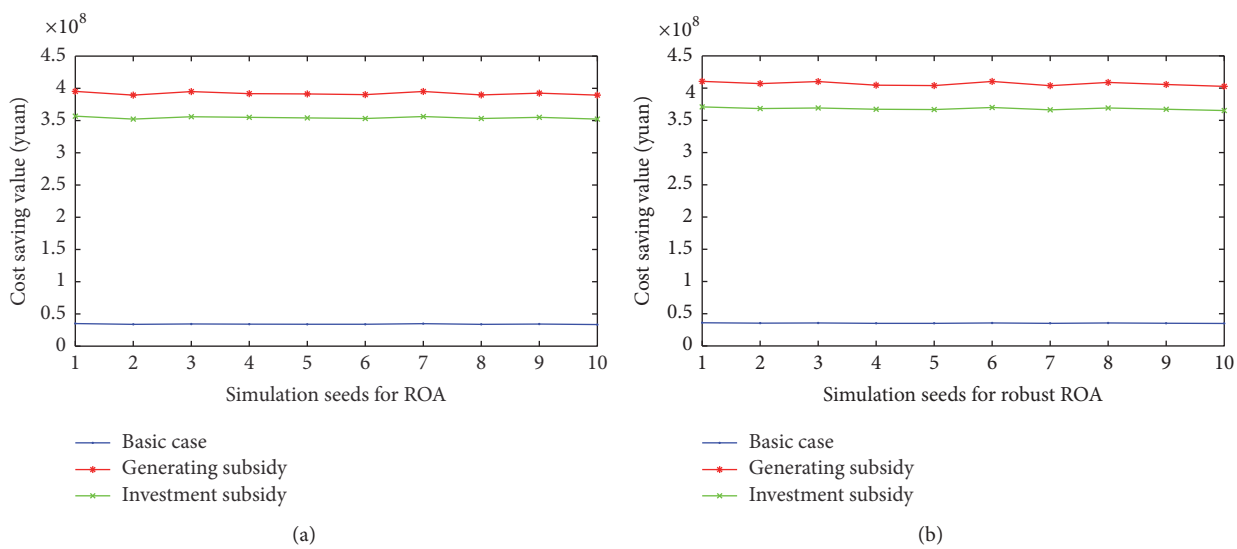

Figure 9: CCS cost saving values of two methods in scenario 3.1.

5.3. Subsidies Scenario. This scenario analyzes government subsidies which include generating subsidy and investment subsidy. Generating subsidy is similar to price subsidy for green manufacturing, such as desulfurization, that directly increase power plants' income in each period while investment subsidy refers to financial aid that help power plants finish CCS project at initial time. Currently, the desulfurization subsidy in China is 15 yuan/MWH, denitrification subsidy is 10 yuan/MWH and dedusting subsidy is 20 yuan/MWH. Considering the high cost of CCS investment, the generating subsidy is set to be 30 yuan/MWH in scenario 3.1 and scenario 3.2. For analyzing the impact of generating subsidy under different carbon system setting, the initial carbon price is 100 yuan/ton in scenario 3.1 and 125 yuan/ton in scenario 3.2. Taking scenario 3.2 as baseline, the CCS generating subsidy is 15 yuan/MWH in scenario 3.3 for comparison. The investment subsidy is calculated by discounting extra profits of generating subsidy in each period; then investment subsidy amount is equal to the total discounted income of generating subsidy. Other parameters are the same as scenario 1.1.

5.3.1. Scenario 3.1. Scenario 3.1 analyzes the effects of government subsidies on CCS cost saving with initial carbon price being 100 yuan/ton. Figure 9 represents that both investment subsidy and generating subsidy can improve CCS cost saving significantly, but the gap between robust ROA and ROA is not significant. Generating subsidy has much larger implemented paths and more positive impact for CCS investment than investment subsidy, which can be derived from Table 12, so generating subsidy is a more effective measure than investment subsidy. Similar to previous findings, the robust ROA has higher options value and more implemented paths than ROA.

Table 11: Simulation results in scenario 2.3.

		Basic	O&M	Capital
Implemented paths	Robust ROA	6109	9838	9780
	ROA	5987	9797	9475
Gaps of two methods		$1.3910E+07$	$3.1654E+07$	$3.3223E+07$
Percentage of gaps		3.66%	1.95%	2.37%

Table 12: Simulation results in scenario 3.1.

		Basic	Generating subsidy	Investment subsidy
Implemented paths	Robust ROA	1228	8638	6500
	ROA	1138	7696	6224
Gaps of two methods		$1.0863E+06$	$1.4776E+07$	$1.4664E+07$
Percentage of gaps		3.09%	3.63%	3.71%

Table 13: Simulation results in scenario 3.2.

		Basic	Generating subsidy	Investment subsidy
Implemented paths	Robust ROA	6109	10000	9890
	ROA	5987	9513	9355
Gaps of two methods		$8.8030E+06$	$3.6299E+07$	$3.4749E+07$
Percentage of gaps		2.26%	2.77%	2.86%

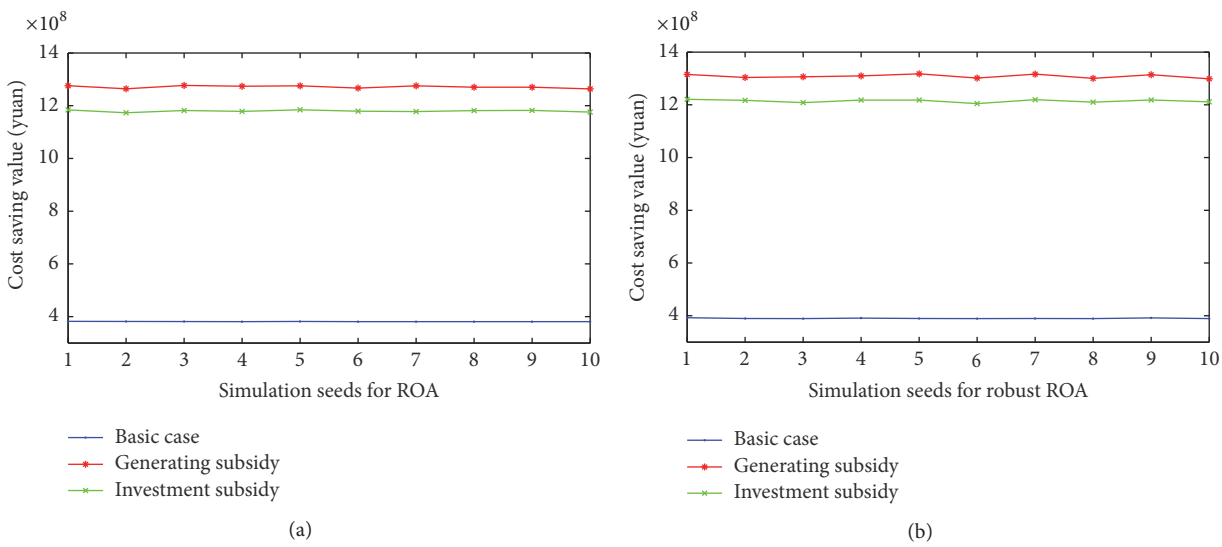

Figure 10: CCS cost saving values of two methods in scenario 3.2.

5.3.2. Scenario 3.2. Scenario 3.2 discusses the effects of government subsidies on CCS cost saving with initial carbon price is 125 yuan/ton; the results are listed in Figure 10 and Table 13. Figure 10 shows that investment subsidy and generating subsidy can increase options values greatly, but the difference between generating subsidy and investment subsidy is not as significant as scenario 3.1. Comparing Table 12 with Table 13, the subsidies have great impacts on promoting CCS investment when initial carbon price is 100 yuan/ton, and the effects become weak with initial carbon price increase. Electric plants get great cost saving value and have interesting in CCS investment in scenario 3.2; therefore, the subsidies make the most effective contribution to CCS investment when initial carbon price lies in a reasonable range. Similar to previous findings, the robust ROA has higher options value and more implemented paths than ROA in scenario 3.2.

5.3.3. Scenario 3.3. Scenario 3.3 presents the effects of government subsidies when generating subsidy is 15 yuan/MWH and initial carbon price is 125 yuan/ton; the results are listed in Figure 11 and Table 14. The results show that the options values of two subsidies are about half of the corresponding options values in scenario 3.2, but implemented paths do not decrease greatly and electric plants also have great interesting

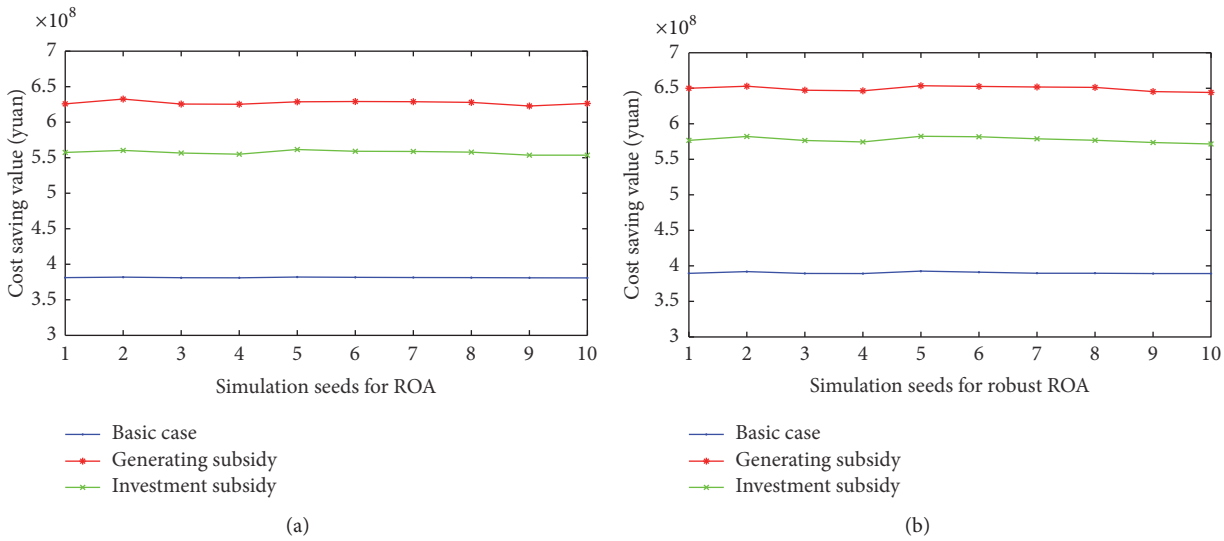

Figure 11: CCS cost saving values of two methods in scenario 3.3.

Table 14: Simulation results in scenario 3.3.

		Basic	Generating subsidy	Investment subsidy
Implemented paths	Robust ROA	6109	9270	8702
	ROA	5987	9100	8532
Gaps of two methods		$8.8030E + 06$	$2.2225E + 07$	$2.0119E + 07$
Percentage of gaps		2.26%	3.42%	3.48%

in CCS investment in scenario 3.3. Therefore, when initial carbon price is not heavily low, current government subsidies for green manufacturing can promote CCS investment effectively. And CCS generating subsidy can reduce CCS investment risk more effectively than investment subsidy with promotive effect on CCS investment.

6. Conclusions

As a high cost and energy consumption technology to mitigate CO_2 emission, CCS has caused much debate on whether it should be invested. For China electric plants, the evaluation of CCS investment is especially important with increasingly environmental protection pressure. In this context, this paper evaluates CCS investment by applying a robust real options approach in an uncertainty environment. The study considers the uncertainties of carbon price, fuel input price, and electricity output price. After determining model parameters by historical data and relevant research, a case study is taken to analyze the CCS investment strategies for China's energy sector.

The simulation results illustrate that robust ROA has higher options value than ROA method when carbon price fluctuates smoothly, and the gap decreases with carbon price, cost reduction, and subsidy increase, respectively. The implemented paths and optimal investment timing also show that robust ROA is a little optimistic for CCS investment compared with ROA when carbon price fluctuates slightly. These findings turn to the opposite when carbon price volatility becomes large, which implies that robust ROA has a pessimistic view of CCS investment compared with ROA when carbon price fluctuates greatly. In reality, electric plants should be positive for CCS investment to avoid opportunity loss when carbon system has a good and stabile development prospect and postpone the investment in the opposite environment to avoid loss. Therefore, robust ROA is more suitable for different carbon development environments and makes a more realistic decision than ROA.

We also analyzed three incentives for CCS investment and found some instructive findings for both electric plants and climate policy maker which can be summarized as follows.

First, carbon price has a significant impact on CCS investment. Both high carbon price and rapid growth of carbon price can increase CCS investment value and reduce CCS investment risk effectively, while volatility of carbon price will put off CCS deployment unless the carbon price is low. Carbon price is the expression of climate policy, low carbon price has little effects on promoting CCS investment, and high carbon price will increase price of electricity for the residential sector, so government should take policy means to keep carbon price in a reasonable range and fluctuate smoothly.

Second, operations management cost reduction and investment cost reduction can boost electric plants' enthusiasm for CCS investment, but the effects are limited if carbon price is too low and become weak with cost reductions increase. Meanwhile, operations management cost reduction

is more effective than investment cost reduction. Therefore, electric plants will make efforts to reduce CCS operations management cost when carbon price is not too low, but they would not improve technique or operations management when the carbon price is high enough.

Third, government subsidies have a great effect on promoting CCS project even with low carbon price; the effect is significant according to current subsidy levels for green manufacturing. With the same subsidy quantity, generating subsidy is not as effective as investment subsidy to trigger CCS investment. So government could provide generating subsidy to help electric plants invest CCS, but the subsidy should not be too high; otherwise it will cause social welfare loss.

The enlightenment of climate policy can be obtained by results; to launch a nationwide carbon market for carbon emission reduction, initial carbon price should be low at early stages, government can provide generating subsidy to help electric plants finish CCS investment and then decrease generating subsidy to trigger electric plants' effort on operations management improvement.

In this paper, robust ROA program consumes much more time than ROA program in numerical computation, and some hypotheses are set for modeling and case study. In the further work, we will focus on designing efficient algorithm for robust Least Squares Monte Carlo method and introducing more uncertain variables in CCS evaluation model.

Competing Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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References

[1] IPCC, *Climate Change 2014: Mitigation of Climate Change*, Cambridge University Press, Cambridge, UK, 2014.

[2] K. Wang, X. Zhang, Y.-M. Wei, and S. Yu, "Regional allocation of CO_2 emissions allowance over provinces in China by 2020," *Energy Policy*, vol. 54, pp. 214–229, 2013.

[3] National Bureau of Statistics of China, *China Energy Statistical Yearbook*, China Statistics Press, Beijing, China, 2013.

[4] J. Gibbins and H. Chalmers, "Carbon capture and storage," *Energy Policy*, vol. 36, no. 12, pp. 4317–4322, 2008.

[5] D. Charles, "Stimulus gives DOE billions for carbon-capture projects," *Science*, vol. 323, no. 5918, p. 1158, 2009.

[6] IPCC, *IPCC Special Report on Carbon Dioxide Capture and Storage*, Cambridge University Press, Cambridge, UK, 2005.

[7] R. C. Sekar, J. E. Parsons, H. J. Herzog, and H. D. Jacoby, "Future carbon regulations and current investments in alternative coal-fired power plant technologies," *Energy Policy*, vol. 35, no. 2, pp. 1064–1074, 2007.

[8] M. C. Bohm, H. J. Herzog, J. E. Parsons, and R. C. Sekar, "Capture-ready coal plants—options, technologies and economics," *International Journal of Greenhouse Gas Control*, vol. 1, no. 1, pp. 113–120, 2007.

[9] W. Zhou, B. Zhu, S. Fuss, J. Szolgayová, M. Obersteiner, and W. Fei, "Uncertainty modeling of CCS investment strategy in China's power sector," *Applied Energy*, vol. 87, no. 7, pp. 2392–2400, 2010.

[10] V. Kaminski, "The challenge of pricing and risk managing electricity derivatives," in *The U.S. Power Market*, vol. 10, chapter 10, Risk Publications, London, UK, 1997.

[11] M. Hsu, "Spark spread options are hot!," *The Electricity Journal*, vol. 11, no. 2, pp. 28–39, 1998.

[12] C.-L. Tseng and G. Barz, "Short-term generation asset valuation: a real options approach," *Operations Research*, vol. 50, no. 2, pp. 297–310, 2002.

[13] T. Park, C. Kim, and H. Kim, "A real option-based model to valuate CDM projects under uncertain energy policies for emission trading," *Applied Energy*, vol. 131, pp. 288–296, 2014.

[14] L. M. Abadie and J. M. Chamorro, "European CO_2 prices and carbon capture investments," *Energy Economics*, vol. 30, no. 6, pp. 2992–3015, 2008.

[15] S. Fuss, J. Szolgayová, M. Obersteiner, and M. Gusti, "Investment under market and climate policy uncertainty," *Applied Energy*, vol. 85, no. 8, pp. 708–721, 2008.

[16] X. Zhang, X. Wang, J. Chen, X. Xie, K. Wang, and Y. Wei, "A novel modeling based real option approach for CCS investment evaluation under multiple uncertainties," *Applied Energy*, vol. 113, pp. 1059–1067, 2014.

[17] J. Szolgayová, S. Fuss, and M. Obersteiner, "Assessing the effects of CO_2 price caps on electricity investments—a real options analysis," *Energy Policy*, vol. 36, no. 10, pp. 3974–3981, 2008.

[18] S. Heydari, N. Ovenden, and A. Siddiqui, "Real options analysis of investment in carbon capture and sequestration technology," *Computational Management Science*, vol. 9, no. 1, pp. 109–138, 2012.

[19] A. L. Soyster, "Technical note—convex programming with set-inclusive constraints and applications to inexact linear programming," *Operations Research*, vol. 21, no. 5, pp. 1154–1157, 1973.

[20] A. Ben-Tal, L. El Ghaoui, and A. Nemirovski, *Robust Optimization*, Princeton University Press, Princeton, NJ, USA, 2009.

[21] D. Bertsimas, D. B. Brown, and C. Caramanis, "Theory and applications of robust optimization," *SIAM Review*, vol. 53, no. 3, pp. 464–501, 2011.

[22] L. El Ghaoui and H. Lebret, "Robust solutions to least-squares problems with uncertain data," *SIAM Journal on Matrix Analysis and Applications*, vol. 18, no. 4, pp. 1035–1064, 1997.

[23] S. Chandrasekaran, M. Gu, A. H. Sayed, and K. E. Schubert, "The degenerate bounded errors-in-variables model," *SIAM Journal on Matrix Analysis and Applications*, vol. 23, no. 1, pp. 138–166, 2001.

[24] H. Geman, *Commodities and Commodity Derivatives: Modeling and Pricing for Agriculturals, Metals and Energy*, John Wiley & Sons, Chichester, UK, 2005.

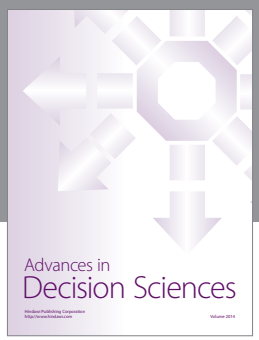
[25] R. S. Pindyck, "The long-run evolution of energy prices," *The Energy Journal*, vol. 20, no. 2, pp. 1–27, 1999.

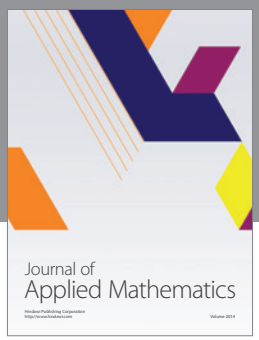
[26] G. H. Golub and C. F. Van Loan, "An analysis of the total least squares problem," *SIAM Journal on Numerical Analysis*, vol. 17, no. 6, pp. 883–893, 1980.

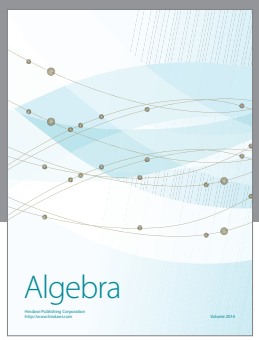
[27] China Electric Power Publishing Committee, *China Electric Power Yearbook*, China Electric Power, Beijing, China, 2014.

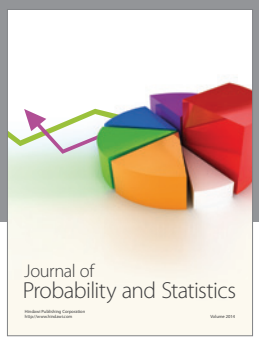
[28] P.-L. Lam, "Pricing of electricity in China," *Energy*, vol. 29, no. 2, pp. 287–300, 2004.

[29] D. Zhang, P. Liu, L. Ma, Z. Li, and W. Ni, "A multi-period modelling and optimization approach to the planning of China's power sector with consideration of carbon dioxide mitigation," *Computers & Chemical Engineering*, vol. 37, pp. 227–247, 2012.









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