Electric Power Systems Research 141 (2016) 363–371

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

A dynamic model for generation expansion planning based on Conditional Value-at-Risk theory under Low-Carbon Economy

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ARTICLE INFO

Article history:
Received 4 May 2015
Received in revised form 8 July 2016
Accepted 5 August 2016

Keywords:
Low-Carbon Economy
Generation expansion planning
Uncertainties
Conditional Value-at-Risk
Investment decisions

ABSTRACT

Realizing low-carbon development of power system is one of the most urgent issues among power industry, especially under the era of Low-Carbon Economy. Generation expansion planning (GEP) plays a key role in reducing carbon emission. In this paper, after revealing the impact of uncertainties on GEP, simulating the uncertainties of fuel price, carbon dioxide (CO_2) emission reduction technology and carbon price, considering high grid integration of micro-grids, a dynamic model for GEP based on Conditional Value-at-Risk theory is proposed. On the basis of traditional GEP, the model analyzes the investment decisions which are made by generation company in different risk scenarios and considers the constraint of the risk of uncertainties. An actual case is studied based on a provincial grid in China by applying the proposed model, and the results prove it to be more adaptable and effective for the sustainable development of future power system.

1. Introduction

As the global temperature rises and world climate anomalies appear, environmental issues gradually draw people's great attention, especially for greenhouse gases produced by human activities. In order to tackle the problem of climate change, governments and relevant organizations have adopted some active measures. In 1997, the United Nations Framework Convention on Climate Change passed the Kyoto Protocol with the goal of limiting greenhouse-gas concentrations in the atmosphere. In 2009, China announced the target that carbon dioxide (CO_2) emission per unit of GDP in 2020 would drop 40–50% than that in 2005 at the Copenhagen World Climate Conference. The statistics from International Energy Agency (IEA) suggested that more than 50% of electricity was generated from fossil-fuel sources [1]. In China, power sector is an important industry of fossil energy consumption, with its CO_2 emission accounting for about 40% of the total emission. So realizing cleanness and high efficiency in power sector is vital to the development of Low-Carbon Economy.

The main purpose of traditional generation expansion planning (GEP) of power system is to seek the most appropriate power investment decision based on the predicted electricity demand and a certain reliability criterion [2]. Unlike traditional GEP that mainly analyses the result from economic benefit, the GEP under Low-Carbon Economy takes CO_2 emission and its relevant factors into account. In [3–5], the CO_2 emission control is treated as an additional constraint in GEP model. On this basis, the carbon capture and storage (CCS) power plant as an effective way to reduce emission is considered in [6]. Ref. [7] provides a comprehensive GEP model considering the impact of feed-in tariffs, quota obligation, emission trade, and carbon tax. Governments have interest in renewable energy sources to make the mix of generation facilities be more reasonable through a long-term GEP. The investment of wind power generation is studied in both [8] and [9].

In previous literature, approaches to investment decision of GEP fall into several categories. (1) Traditional optimization algorithms: the non-dominated sorting genetic algorithm version II (NSGA-II) is adopted to solve two different problem formulations [10]. In [11], a solution algorithm combining Benders decomposition with standard stochastic dual dynamic programming (SDDP) is presented for the optimal GEP problem. (2) System dynamics (SD) theory: Refs. [12,13] describe a GEP model that uses SD to capture the interrelations between the demand and electricity price. (3) Game theory: in [14–17], as there are more than one Generating Company (GENCO) under the electricity markets, to study the influence of the competitive behavior among companies on the GEP problem, the game theory is introduced. (4) Real option theory: because of the irreversibility and multiple uncertainties of the planning, a GEP model based on real option method is established to determine timing the investment, in [18] and [21].

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http://dx.doi.org/10.1016/j.epsr.2016.08.011
0378-7796/

Notation

Sets

T	length of planning horizon ($t = 1, 2, \ldots, T$)
N	set of all involved plants
N^{new}	set of newly added power sources
N^{ext}	set of existing power sources
N^{f}	set of coal and gas fueled power plants
N^{gas}	set of gas-fired power plants

Variables

$E_{j,t}$	energy produced by power plants of technology j in time period t (MWh)
$P^{new}_{j,t}$	capacity of newly added power plants for technology j in time period t (MW)
$P_{j,t}$	capacity of all involved power plants for technology j in time period t (MW)
$x_{j,t}$	proportion of capacity of newly added power source j from the total newly added capacity in time period t
μ_{stg}	technology readiness factor of stages
S_t	total capacity of power plants with CCS in the planning year t
$E(I_{ccs,t})$	expected facility investment cost of CCS power plant for a unit in time period t

Constants

d	discount factor (%)
π^{e}_{t}	electricity price in time period t ($/MWh)
$I_{j,t}$	investment cost for installation of technology j in time period t ($/MW)
H_j	annual generating hour of technology j
$C^{O\&M}_{j}$	operation and maintenance cost for technology j ($/MW)
ε^{f}_{j}	fuel consumption coefficient for technology j corresponding to 1-MWh generation
$\pi^{f}_{j,t}$	fuel price in time period t ($/ton)
$\pi^{CO_2}_{t}$	price of CO_2 emission right in time period t ($/ton)
$\varepsilon^{CO_2}_{j}$	rate of CO_2 emission of technology j
M_t	quota of carbon emission in time period t (ton)
Y_j	service life of j type of power source (year)
D_t	power demand in time period t (MWh)
y_t	maximum consumption of gas in time period t (m^3)
ω	value of risk level ($)
β	confidence level (%)
$\pi^{f}_{j,0}$	initial fuel price for technology j ($)
$E(\pi^{f}_{j,t})$	expected value of fuel price for technology j in time period t ($)
$E(I_{mic,t})$	expected capital cost of micro-grid in time period t
$P_{t,max}$	value of peak load in time period t (MW)
r_{min}, r_{max}	minimum and maximum spare coefficient of power system

It is generally known that many uncertainties do exist in the process of GEP. They are associated with many aspects, for example: inaccuracy of predicted electricity load demand, economic and technical characteristics of new evolving generating technologies, the fossil fuel price, strategies of rival and government policies for environmental protection [22]. More and more researchers attach importance to handling uncertainties. Refs. [23,24] utilize scenario analysis to dispose uncertainties of investment and rival. In [25], the author proposes a model using a two-stage robust optimization methodology to cope with uncertainties in investment costs and load demand. For a long-term GEP issue, as a profitable organization, an evaluation of the risk caused by uncertainties from the quantitative point of view is more critical than that from the perspective of qualitative for whole power system. In contrast, the approaches like Conditional Value-at-Risk (CVaR) theory are introduced to addressing these issues.

In recent years, the theory of Value-at-Risk (VaR) and CVaR are put forward in financial field to measure the degree of loss [25–27]. VaR is widely applied to quantify the portfolio's risk for a company. It aims to obtain the expected maximum loss with a given confidence level β over a time period, which also means the probability that expected maximum loss exceeding VaR value is $1 - \beta$. Notwithstanding VaR has lots of advantages such as: easy to understand, simple to implement, several limits in VaR impede its application. For instance, one of the main defects is that it ignores the extent of the potential loss that exceeds the VaR. Besides, it is lack of subadditivity and convexity that are important characters of coherent risk measures. Due to these deficiencies, a new method of risk measurement—Conditional Value-at-Risk (CVaR) is proposed. CVaR that is also called tail VaR, means excess loss and it is much easier to deal with the mathematical problems than VaR. CVaR can provide the expected value that exceeds the given VaR and it attaches importance to the expectation of excessive loss.

For further describing and analyzing the risk caused by uncertainties, this article provides a dynamic model for GEP based on CVaR theory considering the high uncertainties in fuel price, the development of emission technologies and carbon price under the background of the Chinese government advocating Low-Carbon Economy.

The remainder of this paper is organized as below: first, in Section 2, three uncertainties are described and the development trends of these uncertainties are simulated. The mathematical formulation of the proposed model is presented in Section 3. In Section 4, the model is employed to study an actual case and the computational result demonstrates the effectiveness of the approach. Conclusions and some possible problems for future research are discussed in Section 5.

2. Analyzing of uncertainties

For the GEP problem, the optimization model mainly considers three important factors: uncertainty surrounding the future fossil fuel price (here through volatile fossil fuel price processes), the uncertainty of investment cost of emission reduction technologies, and the uncertainty in carbon price (here through volatile CO_2 price processes). These three uncertain factors bring greatly investment risk in GEP. So it is necessary to concretely study and simulate these changing processes.

2.1. Dynamic evolution of fossil fuel price

To investigate how uncertainty in fuel prices for the coming decades affects energy technology investment behavior, the fossil fuel price is chosen to be stochastic. Fossil fuel prices are rising along with the rapid decrease of energy reserves for the characteristics of non-renewable. Dynamic evolution of fossil fuel prices can be simulated by a stochastic process, which means fuel price in the future will fluctuate randomly around the basis of existing prices. Change in future fuel prices can follows a geometric Brownian motion (GBM) [29], which can be modeled as (1).

$$\begin{cases} \pi^{f}_{t} = \pi^{f}_{t-1} \exp[(u_f - 0.5\sigma^2_f)dt + \sigma_f dz] \\ E(\pi^{f}_{t}) = \pi^{f}_{0} \exp(u_f dt) \end{cases} \quad (1)$$

In this expression: superscript f is fuel type, which mainly refer to the consumption of coal and gas. u_f and σ_f denote the drift and

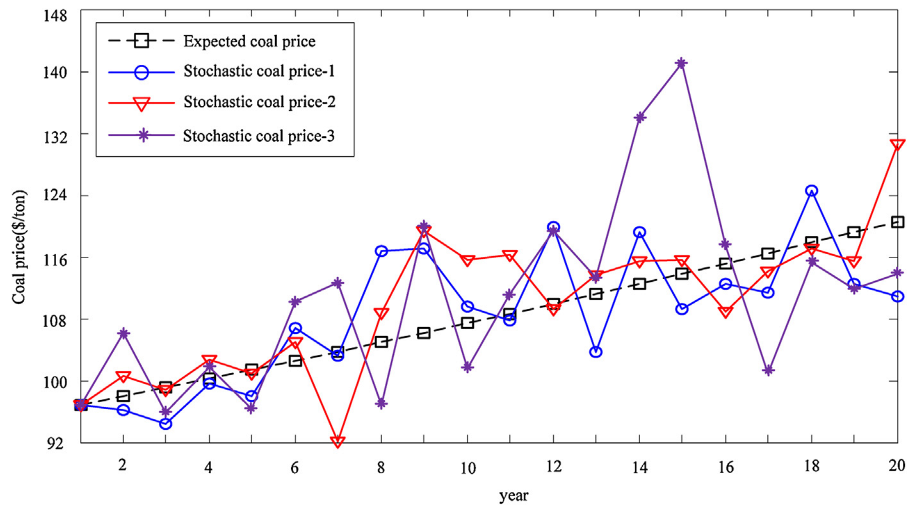

Fig. 1. Simulation of future stochastic coal price and expected coal price.

volatility parameter respectively; dz is the increment of Wiener process, where $dz = \varepsilon\sqrt{dt}$, and ε is a standard normal random variable. Expression (1) shows the uncertainty in the process of price update. To give a more intuitive process of uncertainty in the dynamic evolution of fossil fuel prices, taking the coal price for instance, given parameters $\pi_0^{\mathrm{f}} = 97\,\$/\mathrm{ton}$, $u_{\mathrm{f}} = 1.2\%$, $\sigma_{\mathrm{f}} = 2\%$, Fig. 1 shows three future stochastic coal price trajectory (simulate three times under the same conditions) and the expected coal price.

2.2. Dynamic cost evolution of emission reduction technology

2.2.1. Development of CCS technology

Considering the positive effect on emission reduction, it has great significance to invest in power plants with CCS. Based on the development characteristics of CCS technology, the process of the development can be divided into three stages. In each stage, expected investment cost has different technology readiness factor μ_{stg}, $stg = 1, 2, 3$. The first stage is the demonstration stage from 2016 to 2020 in which the expected cost of power plants with CCS follows a distribution [18];

$$E(I_{\mathrm{ccs},t+1}) = E(I_{\mathrm{ccs},t})\mu_1 = E(I_{\mathrm{ccs},t})\mathrm{e}^{-0.01t} \quad (2)$$

Then, the second stage is the expanding scale stage from 2021 to 2030. The expected cost of power plants with CCS will decrease 20%, if the total capacity of power plants with CCS doubles [19], which can be expressed as (3). S_t is the total capacity of power plants with CCS in the planning year t;

$$E(I_{\mathrm{ccs},t+1}) = E(I_{\mathrm{ccs},t})\mu_2 = E(I_{\mathrm{ccs},t})0.8^{((S_t+S_{t+1})/S_t)-2} \quad (3)$$

Finally, the third stage is the commercialization stage from 2031 to 2035, in which the cost becomes stable and has a ±5% fluctuations.

$$E(I_{\mathrm{ccs},t+1}) = E(I_{\mathrm{ccs},t})\mu_3 = E(I_{\mathrm{ccs},t})(1 \pm 5\%) \quad (4)$$

During the planning period, the investment cost of CCS installation $I_{\mathrm{ccs},t}$ also has stochastic volatility. According to mean–variance Markowitz theory, the securities investment is uncertain, because the investment cost is subjects to a multivariate normal distribution and could not be predicted accurately [20]. For the fluctuations in investment cost in GEP problem, it can be expressed as

$$F(I_{\mathrm{ccs},t}) = \frac{1}{\sqrt{2\pi}\sigma_{\mathrm{ccs},t}} \exp\left\{-\frac{[I_{\mathrm{ccs},t} - E(I_{\mathrm{ccs},t})]^2}{2\sigma_{\mathrm{ccs},t}^2}\right\} \quad (5)$$

where $F(I_{\mathrm{ccs},t})$ is the probability density function; $\sigma_{\mathrm{ccs},t}$ is the standard deviation of the cost, and it is set through the expression $\sigma_{\mathrm{ccs},t} = \sqrt{E(I_{\mathrm{ccs},t})\psi_{\mathrm{ccs}}}$, where ψ_{ccs} denotes the proportion of the variance relative to the expected value.

2.2.2. Development of micro-grid

Micro-grid is composed of a variety of distributed power supply, energy storage devices, inverters and controllers and connected with the distribution network through Point of Common Coupling. It is considered to little carbon emission. Micro-grid is connected to the distribution network thought Point of Common Coupling. As each distributed generator has unique operating characteristic with different investment, operation and maintenance (O&M) costs, it is necessary to consider the micro-grid as an integral factor when it is planned with the major power grid together.

The fluctuation of the expected investment cost of facility in a micro-grid for a unit is expressed by the rate of technological progress, and it is given as follows:

$$E(I_{\mathrm{mic},t}) = (1 - r^{\mathrm{mic}})^t E(I_{\mathrm{mic},0}) \quad (6)$$

where $E(I_{\mathrm{mic},0})$ is the expected facility investment cost of a micro-grid for a unit in the starting year; r^{mic} is the rate of technological progress of the micro-grid. Similarly to technology of CCS, supposing the facility investment cost of a micro-grid for a unit follows the normal distribution, and the probability density function can be written as:

$$F(I_{\mathrm{mic},t}) = \frac{1}{\sqrt{2\pi}\sigma_{\mathrm{mic},t}} \exp\left\{-\frac{[I_{\mathrm{mic},t} - E(I_{\mathrm{mic},t})]^2}{2\sigma_{\mathrm{mic},t}^2}\right\} \quad (7)$$

where $\sigma_{\mathrm{mic},t}$ represents the standard deviation of capital cost of a micro-grid for a unit in period t. $\sigma_{\mathrm{mic},t}$ can also be calculated by $\sigma_{\mathrm{mic},t} = \sqrt{E(I_{\mathrm{mic},t})\psi_{\mathrm{mic}}}$, where ψ_{mic} denotes the proportion of the variance relative to the expected value. Fig. 2(a) shows a downward trend for the future expected cost of micro-grid which is deterministic in each period. Two different fluctuations for the capitalized cost of micro-grid in the first year are shown in Fig. 2(b).

2.3. Dynamic evolution of carbon price

Once the government is committed to the goal of reducing carbon emissions, the carbon price is assumed to increase [18]. The

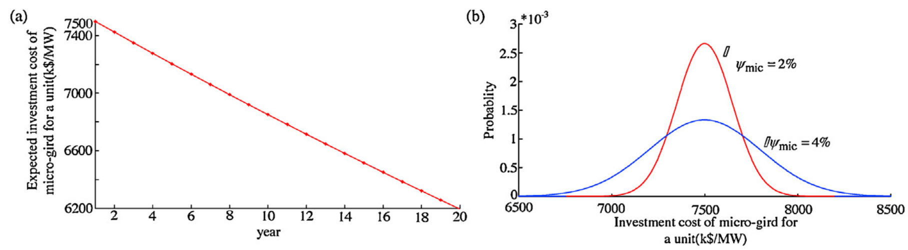

Fig. 2. (a) Decreasing future expected cost of micro-grid. (b) Distribution for cost of micro-grid in first year.

drifting process of the long-term carbon price also uses GBM to describe [31].

$$\begin{cases} \pi_t^{CO_2} = \pi_{t-1}^{CO_2} \exp[(u_{CO_2} - 0.5\sigma_{CO_2}^2)dt + \sigma_{CO_2} dz] \\ E(\pi_t^{CO_2}) = \pi_0^{CO_2} \exp(u_{CO_2} dt) \end{cases} \tag{8}$$

where $E(\pi_t^{CO_2})$ is expected value of carbon price in the year t; $\pi_t^{CO_2}$ is the carbon price of year t; $\pi_0^{CO_2}$ is carbon price of the starting year; u_{CO_2}, σ_{CO_2} are expected value and standard deviation of growth rate of carbon price.

2.4. Other factors affecting GEP problem

Until now, the terminal sale electricity price is subject to regulation of the National Development and Reform Commission of China [33]. In this paper, electricity prices will be given the fixed value in each planning year. The electricity price trend could be obtained thought the historical data. In addition, governments are making efforts to develop large-scale wind farms, which is considered to have no fuel cost. Grid connection technologies of wind farms become gradually mature and not only improve the utilization of wind power, but also promote the development of global wind power industry. This paper considers that the grid-connected rate of wind farms will increase yearly, and become stable after some stages.

3. Optimal GEP problem formulation

3.1. Objective function

In this paper, the main aim of GEP is to maximize the net profit for the overall power system. Our optimal power expansion planning problem can be formulated as

$$\mathrm{Max}\left\{\sum_{t\in T}(1+d)^{1-t}\left[\sum_{j\in N}E_{j,t}\pi_t^{e} - \sum_{j\in N^{new}}P_{j,t}^{new}I_{j,t}CRF(r,Y_j) - \sum_{j\in N}P_{j,t}C_j^{O\&M} - \sum_{j\in N^{f}}E_{j,t}\varepsilon_j^{f}\pi_{j,t}^{f} - \left(\sum_{j\in N}E_{j,t}\varepsilon_j^{CO_2} - M_t\right)\pi_t^{CO_2}\right]\right\} \tag{9}$$

Objective function (9) is the difference that revenue from selling electricity minus the aggregate of the overall cost. The first item in the bracket is the gross revenue from selling electricity associated to all involved plants; the second part is capital cost of newly added plants; the third part is O&M cost of power system; the fourth part is fuel consumption cost, and the last one is carbon emission cost. The intermediate variable E_{jt} can be written as (10).

$$E_{j,t} = P_{j,t}H_j, \quad j \in N, t \in T \tag{10}$$

When the total planned capacities are much more than that of any single unit, the combination of installed capacities that are of specific discrete values can be taken as a continuous number approximately. In other words, capacity expansion is no longer considered unit-based. Besides, it is unnecessary to consider physical connections among generators in transmission network, because decision variables of power plants are set as "plant-set-based" [6]. After such a treatment, the precision of modeling would be reduced to a lesser extent. Though installed capacities are of specific discrete values, they are also diversified, for example, 0.9, 1.5 and 3 MW for wind turbines.

Taking into account the time value problem of fund, all revenue and cost in the planning period should expressed on the basis of current value. Considering the salvage values among different power sources by the end of planning period, the capital recovery factor for power source type j is written as (11):

$$CRF(d, Y_j) = \frac{d(1+d)^{Y_j}}{(1+d)^{Y_j} - 1} \tag{11}$$

3.2. Constraints

(1) *Equation on power demand and supply:* Generated energy by all plants (existing and new added) should be equal to the power demand annually.

$$\sum_{j\in N^{ex}} E_{j,t}^{ext} + \sum_{j\in N^{new}} E_{j,t}^{new} = D_t, \quad t \in T \tag{12}$$

(2) *Equation on yearly installed capacity:* The total generation capacity for technology j in period t is accumulated by the existing capacity adding the expanded capacity, then subtracting the amount of retired capacity. And the in-service capacity in period $t+1$, $P_{j,(t+1)}^{ext}$ should be equal to $P_{j,t}$, which is the total generation capacity in period t.

$$P_{j,t} = P_{j,t}^{ext} + P_{j,t}^{new} - P_{j,t}^{out} = P_{j,(t+1)}^{ext}, \quad t \in T \tag{13}$$

(3) *Constraints on available reserve capacity:* Available reserve capacities ensure that the power system can avoid unplanned outage and fluctuations of load.

$$(1 + r_{min})P_{t,max} \le P_{j,t} \le (1 + r_{max})P_{t,max}, \quad t \in T \tag{14}$$

(4) *Cap on upper investment:* The investment construction of the wind farm and the micro-grid is affected by the geographical conditions. The annual new added capacity has a certain limit, which can be formulated as

$$0 \le P_{j,t}^{new} \le P_{j,t,max}^{new}, \quad t \in T \tag{15}$$

(5) *Fuel consumption limitation:* China's power generation industry is mainly dominated by coal, and the use of natural gas is limited by the actual supply. Therefore, the use of natural gas within the planning period should be no greater than a given amount y_t, that is

$$\sum_{j\in N^{gas}} E_{j,t}\varepsilon_j^{f} \le y_t, \quad t \in T \tag{16}$$

(6) *Constraints on total investment cost:* A certain investment budget will be made by GENCO before planning programs. And the fixed investment expenditures in planning period will not excess the budget I_{bgt}.

$$\sum_{t\in T}(1+d)^{1-t}\left[\sum_{j\in N^{\text{new}}} I_{j,t}P_{j,t}^{\text{new}}CRF(r,Y_j)\right] \le I_{\text{bgt}} \tag{17}$$

(7) *Variable constraints:* In this problem, the following variables should be non-negative.

$$E_{j,t},\quad P_{j,t}^{\text{new}},\quad P_{j,t} \ge 0 \tag{18}$$

Corresponding to the uncertain parameters described in Section 2, $I_{\text{ccs},t}$, $I_{\text{mic},t}$, π_t^{f}, $\pi_t^{\text{CO}_2}$ are relevant parameters. Note that the uncertain parameters in objective function and constraint conditions (1)–(18) are depicted with the expected values: $E(I_{\text{ccs},t})$, $E(I_{\text{mic},t})$, $E(\pi_t^{\text{f}})$, $E(\pi_t^{\text{CO}_2})$.

(8) *Constraint on CVaR:* In this paper, CVaR is applied as a constraint to improve the traditional GEP model. It can dispose the trade-off between the expected benefits and the risk caused by kinds of uncertainties in GEP problem. The mathematical expression of CVaR is given as follows.

$$\begin{aligned} CVaR_\beta &= E[f(\mathbf{x},\mathbf{r})\,|f(\mathbf{x},\mathbf{r}) \ge VaR_\beta\,] \\ &= VaR_\beta + E[f(\mathbf{x},\mathbf{r}) - VaR_\beta\,|f(\mathbf{x},\mathbf{r}) \ge VaR_\beta\,] \end{aligned} \tag{19}$$

Here $f(\mathbf{x},\mathbf{r})$ is the negative of the objective function that the loss in GEP. The decision vector $\mathbf{x} = (x_1, x_2, \ldots, x_N)^T$ denotes a portfolio of the investment variables $P_{j,t}^{\text{new}}$; $\mathbf{r} = (r_1, r_3, \ldots, r_N)^T$ represents the random yield vector, which represent the uncertainties in investment.

In most cases, the results of objective function would be non-negative. However, when the market has a high coal prices, high CCS technology investment costs, low carbon tax price, investment on CCS coal-fired power plants may cause business losses. In other words, the results of objective function would be negative. As an endogenous variable, the VaR needs to be obtained before calculating CVaR. The equivalent expressions of CVaR can be formulated as [32].

$$F_\beta(\mathbf{x},\alpha) = \alpha + \frac{1}{(1-\beta)K}\sum_{k=1}^{K}[f(\mathbf{x},\mathbf{r}^k) - VaR_\beta]^+ \tag{20}$$

In this expression, CVaR is replaced by $F_\beta(\mathbf{x},\alpha)$; VaR is the value of α when $F_\beta(\mathbf{x},\alpha)$ attains its minimal value; K is the simulation times of Monte Carlo; $t^+ = \max(0, t)$. In this constraint, it is worth noting that the uncertainties factors adopt the values of stochastic simulation. Through utilizing the stochastic parameters, the yield vector $\mathbf{r}$ in different times of simulation can be acquired. The objective function is a linear expression about investment variables. So the yield vector $\mathbf{r}$ can be obtained by the coefficient of investment variables in the objective function. In order to reduce the risk caused by the uncertainties in investment, GENCO needs to set a certain level of CVaR, rather than simply pursuing revenue. The risk constraint can be written as follows:

$$F_\beta(x,\alpha) \le \omega \tag{21}$$

where ω denotes the given risk level.

As the part of $[f(\mathbf{x},\mathbf{r}^k) - VaR_\beta]^+$ in constraint (20) is nonlinear, auxiliary real variables z_k, $k = 1, 2, \ldots, K$ is presented. Finally, the risk constraint which contain $2K+1$ inequality inequalities are equivalently expressed by the set of constraints

$$\begin{cases} \alpha + \dfrac{1}{(1-\beta)K}\displaystyle\sum_{k=1}^{K} z_k \le \omega \\ z_k \ge f(x, r_k) - \alpha \quad k = 1, 2, \ldots, K \\ z_k \ge 0 \end{cases} \tag{22}$$

Table 1
The data of existing generators in power system.

Existing type	Coal-fired	Gas-fired	Hydro	Nuclear	Wind
Installed capacity (MW)	87,158	8925	3814	7368	6474
Percentage (%)	76.63	7.85	3.35	6.48	5.69

4. Case studies

4.1. Basic data

In this paper, the planning horizon consists of 20 years spanning from 2016 to 2035. The maximum load demand and the annual electricity consumption in 2015 benchmark are 103 GW and 600 TWh. Considering retirement schedule of existing plants and the government's agenda of "closing down small thermal power plants", some coal-fired sources will be out of service in the planning horizon. The data of the existing capacity can be seen in Table 1. Here, the 20-year planning horizon is divided into four five-year plans, and the rate of the annual average load growth in each period is 6.4%, 5.25%, 3.5% and 2.5%. We consider 6 candidate power sources excluding nuclear and hydro invested by the government in general. The specific information of candidate energy sources are shown in Table 2.

Note that most of the data come from a regional power grid in China, and some of them are obtained in the government reports and serial references [6,7,10,18,32]. Several parameters related to the GEP problem need to be set. The discount rate r is set as 6%; coal price, gas price and carbon price of the beginning of the plan period are 97 $/ton, 0.38 $/m^3 and 20 $/ton respectively; the simulation times of Monte Carlo is 1000. In addition, the service life of coal-fired plants, gas-fired plants, coal-fired plants with CCS and gas-fired plants with CCS is 30 years, while the lifespan of wind and micro-grid is 20 years. The fuel and the carbon price growth is 1.2%. And the investment cost of technology of CCS and micro-gird declines at 1%.

The posed dynamic model for GEP based on CVaR is a linear programming problem with inequality constraints, which can be simulated by the linear programming function in MATLAB. Fig. 3

Table 2
Parameters of candidate power sources.

Candidate type	Investment cost (k$/MW)	Fixed O&M cost (%Inv. cost)	CO_2 Intensity (t/MW h)	Fuel consumption (kg/MW h or m^3/MW h)	Utilization hours (h)
Coal-fired	617	3.0	0.769	0.33	5211
Coal-fired with CCS	650	3.3	0.113	0.363	5211
Gas-fired	525	3.0	0.385	200	3500
Gas-fired with CCS	558	3.3	0.056	220	3500
Wind	1500	3.0	–	–	2047
Micro-grid	7500	2.5	–	–	6000

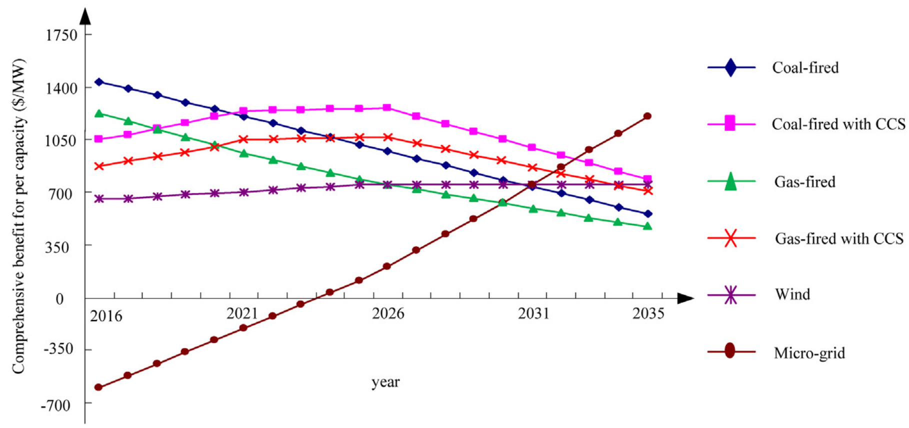

Fig. 3. The trends of comprehensive benefit for per unit of the candidate power sources.

shows the comparison of the trends of comprehensive benefit among different power sources.

Here, comprehensive benefit also means the yield vector. As shows in Fig. 3, different power sources have different trends along with the time. Affected by the rising fuel price, comprehensive benefit of coal-fired plants and gas-fired plants will decrease year by year. Meanwhile, the comprehensive benefit of coal-fired plants is much better, because the fuel cost of gas-fired plants is higher than that of coal-fired plants. In the beginning of the planning horizon, comprehensive benefit of coal-fired plants with CCS and gas-fired plants with CCS will increase owing to the progress of carbon mitigation technology. With the rising fuel price and the technology becoming mature, comprehensive benefits of coal-fired plants with CCS and gas-fired plants with CCS also begin to decrease after a few years. The biggest problem for the wind power is the low proportion of grid-connected. It is predicted that the proportion of grid-connected of wind power will reach the maximum by 2026, and then it will remain stable. Considering the advantages of no fuel cost and cleanness, comprehensive benefit of wind power will keep growing at a low rate before 2026 and then keep unchanged. As a new form of energy supply, micro-grid has great supports of government. As shown in Fig. 3, the curve of micro-grid will has a rapid growth and will be the greatest among all energy sources at the end of planning period.

Furthermore, all energy sources except coal-fired plants have the character of low carbon emission. The rising carbon price acts as a brake on the fall of comprehensive benefit and plays a catalytic role in the rise of comprehensive benefit. In the next section, the investment decision is analyzed under three different scenarios considering uncertainties. Additional quantitative assessment is made for the influence of uncertainties through the comparison of investment decisions between different risk levels.

4.2. Scenario 1: uncertainty of fuel price

To study the effect of uncertainty of fuel price, it is assumed that the future fuel price has a high volatility. Based on this, the volatility of fuel price σ_f is set as 4%, which represent its great uncertainty. Meanwhile, $\psi_{ccs} = 0.1\%$, $\psi_{mic} = 0.1\%$, $\sigma_{CO_2} = 0.1\%$, which means that the carbon tax and evolution of emission reduction technology is relatively stable in years. In order to analyze the results more clearly, we adopt a intermediate variable $x_{j,t}$, which represents the proportion of new added power capacity of type j of t year in total new added capacity of the same year, and it can be formulated as

$$x_{j,t} = \frac{P_{j,t}^{\text{new}}}{\sum_{j \in N^{\text{new}}} P_{j,t}^{\text{new}}}, \quad t \in T \tag{23}$$

Table 3 and Fig. 4 show the results of the different risk levels. Project A refers to the higher risk level with ω = 16.5 billion $, while the risk level in project B is 13.0 billion $. A_0, B_0 are situations without taking into account the uncertainty. In both project A and B, the capacity proportion of coal-fired plants and gas-fired plants approximately show decline distributions, whereas the scale of coal-fired plants with CCS, gas-fired plants with CCS and wind power continuously extend yearly. Micro-grid is suitable to be invested in late planning horizon when it is high-yield, rather than the beginning of stage when it is high-cost. However, the results with increasing level of uncertainty deviate from normal investment ratio, which can be seen from the investment in gas-fired plants of last stage. Comparing the two projects, it is found that the capacity proportion of coal-fired plants, gas-fired plants, coal-fired plants with CCS, gas-fired plants with CCS will rise when the risk level is enhanced properly. And it can conclude that the change in the risk level would not affect the changing regularity of portfolio among different sources, which is the typical options effect described by Zhou [18] and verified in applications to energy investments under price uncertainty by e.g. Fleten et al. [31]. The reason is that all these sources are influenced by the fluctuation of the fuel price. For the high benefit, GENCO tends to the programs with high risk which is caused by uncertainty of fuel price. From 2026 to 2030, the condition of low risk level in project B stimulates GENCO to invest micro-grid early.

Table 3
Result of GEP with two different risk levels under scenario 1.

Planning period	2016–2020				2021–2025				2026–2030				2031–2035			
Projects	A	A_0	B	B_0	A	A_0	B	B_0	A	A_0	B	B_0	A	A_0	B	B_0
Coal-fired	0.640	0.618	0.605	0.594	0.585	0.556	0.548	0.525	0.492	0.494	0.485	0.361	0.395	0.404	0.390	0.339
CCS coal-fired	0.155	0.151	0.152	0.142	0.185	0.189	0.148	0.161	0.195	0.188	0.170	0.194	0.199	0.196	0.198	0.212
Gas-fired	0.074	0.076	0.068	0.071	0.054	0.066	0.051	0.047	0.033	0.036	0.030	0.043	0.050	0.034	0.045	0.032
CCS gas-fired	0.031	0.04	0.030	0.038	0.056	0.06	0.053	0.052	0.080	0.077	0.064	0.086	0.084	0.086	0.078	0.088
Wind	0.100	0.115	0.145	0.155	0.120	0.129	0.200	0.215	0.200	0.205	0.230	0.282	0.220	0.216	0.250	0.285
Micro-gird	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.021	0.034	0.060	0.064	0.039	0.044

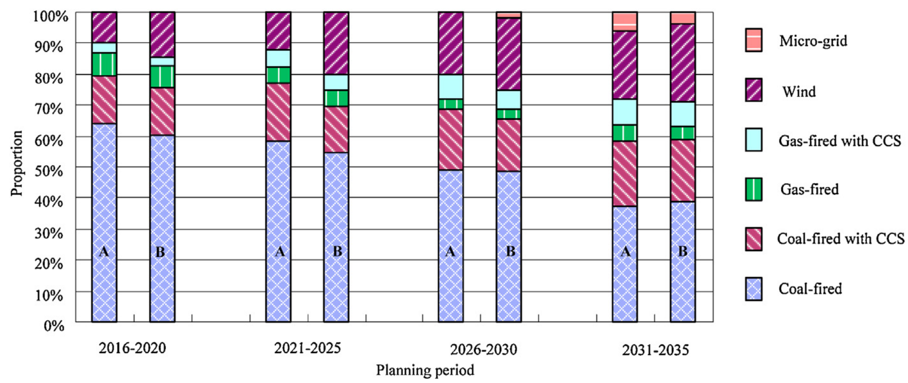

Fig. 4. Capacity proportion for different types of plants in scenario 1.

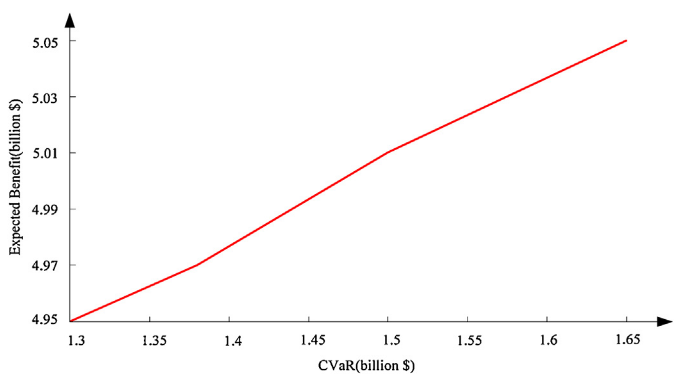

Fig. 5. Expected benefit versus CVaR.

For the variable value of the risk level ω, a curve of CVaR leading edge is shown in Fig. 5. The expected benefit rise with the risk level increasing. Enhancing the risk level can make GENCO be keen to invest the high risk program with the high benefit.

4.3. Scenario 2: uncertainty of investment in emission reduction technology evolution

Under this scenario, the future cost of emission reduction technology evolution has a higher volatility, and the change of the fuel price and the carbon price is relatively stable. The specific parameters are set as follows: $\psi_{\text{ccs}} = 5\%$, $\psi_{\text{mic}} = 5\%$, $\sigma_{\text{f}} = 0.1\%$, $\sigma_{\text{CO}_2} = 0.1\%$.

Table 4 and Fig. 6 show the result of investment decision under the different risk levels. It is clear that the structure of the investment portfolio among different sources is consistent with Scenario 1. When the risk level is enhanced properly, the capacity proportion of coal-fired plants with CCS, gas-fired plants with CCS and micro-grid will rise, because all these sources are influenced by technical progress. But uncertainty in CCS and micro-grid technology make their investment ratio decrease to a certain extent, which can be seen in the last stage in Fig. 6. Some studies, as for example [31], present similar results. Moreover, this research illustrates that the scale of coal-fired plants and gas-fired plants will decrease, whereas it has little effect on wind. And from 2026 to 2030, the capacity proportion of newly added micro-grid in project A and B is 5.7% and 3% respectively. In project A with a high risk level, uncertainty of the cost of micro-grid can promote the development of micro-grid. From 2031 to 2035, with the limitation of geographical conditions, the capacity proportion of micro-grid will decline a little.

4.4. Scenario 3: uncertainty of carbon price

Under this scenario, we assume that the future carbon price has a higher volatility, and the change of the fuel price and cost of emission reduction technology is relatively stable. The specific parameters are set as follows: $\sigma_{\text{CO}_2} = 4\%$, $\sigma_{\text{f}} = 0.1\%$, $\psi_{\text{ccs}} = 0.1\%$, $\psi_{\text{mic}} = 0.1\%$.

When the volatility of carbon price is high, coal-fired plants should pay the higher cost of CO_2 emission since it is not environmentally friendly. Others can bring a certain amount of benefit because of its low emission. It also means that the high volatility can make the benefit of coal-fired plants decrease, but boost the benefit of the other energy sources. For purpose of improving the benefit, GENCO enjoys investing low emission energy sources or clean energy, like the plants with CCS, wind and micro-grid.

Two different risk levels are studied to reveal their impacts on investment decision, which is shown in Table 5 and Fig. 7. When the risk level is enhanced properly, the capacity proportion of the plants with CCS, gas-fired plants, wind and micro-grid will rise, and accordingly the scale of coal-fired plants will decrease. Simultaneously, the uncertainty of carbon price also lead to a lower the investment proportion of coal-fired power plants less than that under the expected carbon price.

4.5. Investment advice

Based on comprehensive analysis of the above three kinds of uncertainty scenarios about power planning, it can provide investment advice for the power generation companies:

Table 4
Result of GEP with two different risk levels under scenario 2.

Planning period	2016–2020				2021–2025				2026–2030				2031–2035			
Projects	A	A_0	B	B_0	A	A_0	B	B_0	A	A_0	B	B_0	A	A_0	B	B_0
Coal-fired	0.635	0.618	0.643	0.594	0.588	0.556	0.622	0.525	0.433	0.494	0.495	0.361	0.416	0.404	0.411	0.339
CCS coal-fired	0.155	0.151	0.149	0.142	0.182	0.189	0.161	0.161	0.200	0.188	0.173	0.194	0.220	0.196	0.200	0.212
Gas-fired	0.074	0.076	0.075	0.071	0.050	0.066	0.050	0.047	0.020	0.036	0.026	0.043	0.030	0.034	0.050	0.032
CCS gas-fired	0.036	0.04	0.033	0.038	0.060	0.06	0.047	0.052	0.090	0.077	0.076	0.086	0.080	0.086	0.060	0.088
Wind	0.100	0.115	0.100	0.155	0.120	0.129	0.120	0.215	0.200	0.205	0.200	0.282	0.250	0.216	0.250	0.285
Micro-gird	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.057	0.060	0.030	0.034	0.004	0.064	0.029	0.044

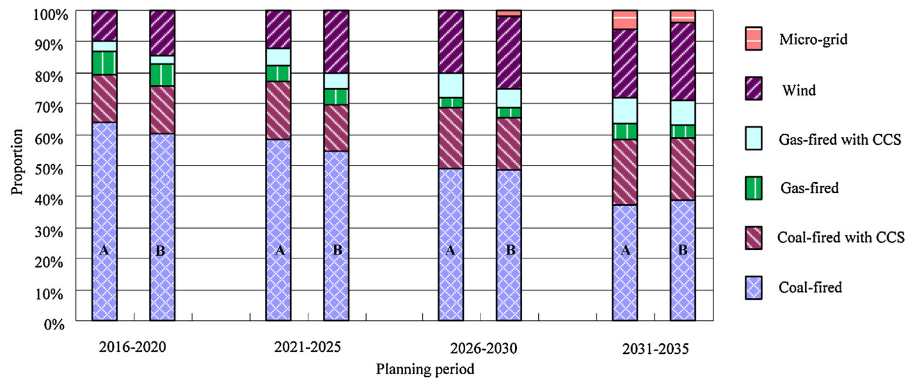

Fig. 6. Capacity proportion for different types of plants in scenario 2.

Table 5
Result of GEP with two different risk levels under scenario 3.

Planning period	2016–2020				2021–2025				2026–2030				2031–2035			
Projects	A	A_0	B	B_0	A	A_0	B	B_0	A	A_0	B	B_0	A	A_0	B	B_0
Coal-fired	0.628	0.618	0.607	0.594	0.553	0.556	0.592	0.525	0.492	0.494	0.529	0.361	0.356	0.404	0.451	0.339
CCS coal-fired	0.160	0.151	0.166	0.142	0.174	0.189	0.170	0.161	0.180	0.188	0.174	0.194	0.200	0.196	0.180	0.212
Gas-fired	0.074	0.076	0.077	0.071	0.078	0.066	0.075	0.047	0.080	0.036	0.080	0.043	0.082	0.034	0.079	0.032
CCS gas-fired	0.038	0.04	0.040	0.038	0.045	0.06	0.043	0.052	0.048	0.077	0.048	0.086	0.060	0.086	0.058	0.088
Wind	0.100	0.115	0.110	0.155	0.150	0.129	0.120	0.215	0.200	0.205	0.150	0.282	0.250	0.216	0.200	0.285
Micro-gird	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.019	0.034	0.020	0.064	0.041	0.044

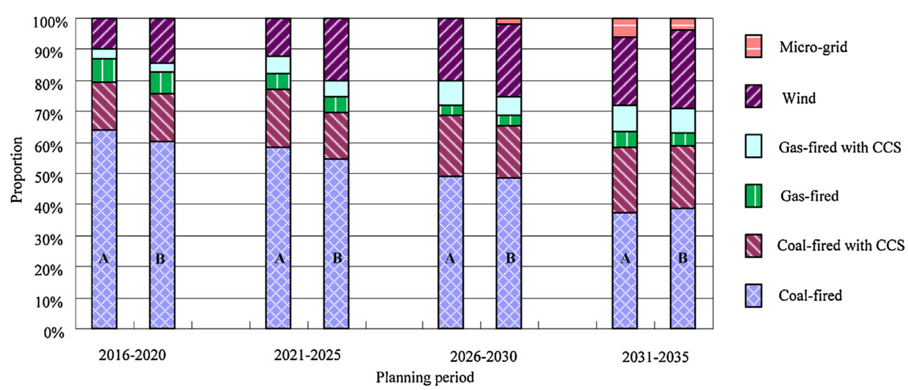

Fig. 7. Capacity proportion for different types of plants in scenario 3.

In current energy investment market, the conventional coal-fired power plants still have high efficiency. Large-scale investment in the CCS power plant and micro-grid investment which are high-cost is not suitable in the beginning of planning horizon.

GENCO needs to consider a variety of uncertain factors in the market. GENCO can increase investment in the clean energy and low-carbon technology when the carbon tax prices are higher and costs of emission reduction technology fall earlier than expected.

Government and related departments can provide assistance from the following two aspects. First, the government could moderate the regulation of carbon tax appropriately to reduce uncertainty. Then, due to the high cost of new emission reduction technology in early stage, government could give a certain amount of subsidies to encourage generation companies to investment, and promote the progress of the emission reduction projects.

5. Conclusion

In this paper, a dynamic GEP model based on CVaR theory is proposed, which quantitatively analyzes the influence of uncertainties (produced in fuel price, carbon price, and the development of emission reduction technology) on investment decision. The concept of low carbon economy and the theory of conditional value at risk are introduced into the traditional power supply rules. The optimal decision can be obtained under certain risk level. Besides, micro-grid, as a new form of energy supply, is combined with multiple power sources to be planned in the presented collaborative planning model, and it has advantages in flexible operation, reliable power supply and environmental protection. Finally, multi scenario analysis is carried out to simulate the power system planning in a certain area. And validity the practicability of the proposed model are illustrated with the example. At the end of the paper, it gives some reasonable suggestions on the investment portfolio to the generation companies and the government. That is, (1) the uncertainty in the investment environment means the risk to the investors, and the change of the risk level will affect the planning strategy of the investors. (2) As a new type of energy supply at present, micro-grid has a high cost of electricity generation and is not suitable for investment. With the gradually mature technology, it has certain advantage in the late planning horizon.

In addition, the influence of load forecasting, wind power and photovoltaic prediction on GEP problem is not considered detailedly in this paper, and it will become the next research work of the author.

Acknowledgements

The authors would like to thank the editor and reviewers for their sincere suggestions on improving the quality of this paper. Project 61374098 supported by National Natural Science Foundation of China.

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