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

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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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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)
$P^{\mathrm{new}}_{j,t}$	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
$E(I_{\mathrm{ccs},t})$	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
$C^{\mathrm{O\&M}}_j$	operation and maintenance cost for technology j ($/MW)
$\varepsilon^{\mathrm{f}}_j$	fuel consumption coefficient for technology j corresponding to 1-MWh generation
$\pi^{\mathrm{f}}_{j,t}$	fuel price in time period t ($/ton)
$\pi^{\mathrm{CO_2}}_t$	price of CO_2 emission right in time period t ($/ton)
$\varepsilon^{\mathrm{CO_2}}_j$	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 (%)
$\pi^{\mathrm{f}}_{j,0}$	initial fuel price for technology j ($)
$E(\pi^{\mathrm{f}}_{j,t})$	expected value of fuel price for technology j in time period t ($)
$E(I_{\mathrm{mic},t})$	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).

$$\begin{cases} \pi^{\mathrm{f}}_t = \pi^{\mathrm{f}}_{t-1}\exp[(u_{\mathrm{f}} - 0.5\sigma^2_{\mathrm{f}})\mathrm{d}t + \sigma_{\mathrm{f}}\mathrm{d}z] \\ E(\pi^{\mathrm{f}}_t) = \pi^{\mathrm{f}}_0\exp(u_{\mathrm{f}}\mathrm{d}t) \end{cases} \tag{1}$$

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