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A Stochastic Optimization Model for Carbon-Emission Reduction Investment and Sustainable Energy Planning under Cost-Risk Control

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ABSTRACT. Restricted by conventional energy resources and environmental space, the sustainable development of urban power sector faces enormous challenges. Renewable energy generation and carbon capture and storage (CCS) are attractive technologies for reducing conventional energy resource consumption and improving CO_2 emission mitigation. Considering the limitation of expensive investment cost on their wide application, a stochastic optimization model for the optimal design and operation strategy of regional electric power system is proposed to achieve conventional resource-consumption reduction and CO_2 emission mitigation under cost-risk control. The hybrid method integrats interval two-stage stochastic programming with downside risk theory. It can not only effect-tively deal with the complex uncertainties expressed as discrete intervals and probability distribution, but also help decision-makers make cost-risk tradeoff under predetermined budget. The proposed model is applied in the electric power system planning of Zhejiang Province, an economically developed area with limited fossil energy resources. The influences of different resource and environmental policies on the investment portfolio and power system operation are analyzed and discussed under various scenarios. The results indicated that different policies would lead to different generation technology portfolios. The aggressive CO_2 emission reduction policy could stimulate the development of CCS technology, and the electric power system would still heavily rely on coal resource, while the tough coal-consumption control policy could directly promote regional renewable energy development and electric power structure adjustment.

Keywords: CCS, renewable energy, generation expansion programming, policy regulation, risk-aversion

1. Introduction

Along with the intensification of global climate change, greenhouse gas (GHG) emission reduction has been a consensus for developed and developing countries (Guo et al., 2020). For China, as the largest coal consumer and carbon emitter in the world (IEA, 2014), power sector contributes greatly to CO_2 emissions, accounting for approximately 38% of the total CO_2 emissions in 2005 (NDRC, 2012). In addition, extensive coal consumption in electric power and heating sector has led to serious air pollution issues (Hao et al., 2016; Liu et al., 2020). Under the burden of domestic environmental pressures and international responsibility of carbon mitigation, China has committed to achieve its peak CO_2 emissions and increase the share of non-fossil fuels in primary energy consumption to approximately 20% by 2030 (Guo et al., 2016; Liu et al., 2016; Zhai et al., 2020; Zheng et al., 2020). Therefore, faced with tremendous pressures from energy conservation, environmental improvement, and GHG emission reduction, how to develop a low-carbon electric power generation scheme under regional scales has become an increasingly important issue to achieve sustainable socio-economic development in the long-term.

In order to promote electric power system adjustment and GHG emission reduction, many measures have been proposed for increasing green power generation, such as the total coal-consumption cap control, renewable energy generation, and carbon capture and storage (CCS) technologies (Viskovic et al., 2014; Brouwer et al., 2015; Liu et al., 2018a, 2018b; Kozlova and Yeomans, 2019; Yao et al., 2020). However, they will have a profound effect on the conventional power system from many aspects, such as economic feasibility, system stability, and operational efficiency. For example, although considered as a promising option for GHG emission reduction, CCS could

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also cause efficiency losses and penalty load, and increase the total load of coal-fire power generation (Viebahn et al., 2014). Recently, various models have been developed to search the tradeoff between system cost and low-carbon technologies/ measures choice in view of available technologies and locations for capacity expansion. For example, Cristóbal et al. (2012) proposed a novel mixed integer non-linear programming model for seeking optimal schemes on allowances trade and reduction emission amount by investment in CCS technology. Gitizadeh et al. (2013) developed a multi-objective model for power system expansion management, including maximization of the project lifetime economyic return, minimization of CO_2 emission, and minimization of the fuel risk due to non-renewable energy sources utilization. Lee and Hashim (2014) formulated a mixed integer optimization model to determine the optimized economical low-carbon power generation mix among fuel-switching options, renewable energy generation and CCS implementation, Priya et al. (2014) presented a regional low-carbon energy system planning model considering CCS as a major technology option, which indicated that allowing CCS retrofitting of existing power plants could reduce the overall cost requirement significantly.

Moreover, there are many uncertainties existing in power generation processes (Yu et al., 2016; Li et al., 2017; Li et al., 2018), demand-supply relationship, as well as the relative technical and economic parameters (e.g., the intermittent renewable energy generation, the unforeseen accurate load demand, the fluctuated electricity and fuel price, and the uncertain policy environment). These uncertainties could exacerbate the effects of new technologies/measures on regional energy resources supply, electricity load demand, and electric power structure adjustment, and create more disturbances for system robustness and feasibility. In order to reflect those uncertainties, a number of inexact optimization methods have been proposed for obtaining reasonable regional energy system management schemes, including interval-parameter programming, fuzzy mathematical programming, stochastic mathematical programming, and their hybrid optimization methods (Huang et al., 1996, 1997; Weng et al., 2010; Li et al., 2012; Xu et al., 2014; Ji et al., 2015; Carvalho et al., 2017; Jin et al., 2017; Xie et al., 2017, Xie et al., 2018; Yu et al., 2019, Zhang et al., 2019). Among them, stochastic mathematical programming provides more efficient alternate with an expected value, and reflects the uncertainties by generating a sequence of scenarios (Tan et al., 2011; Li and Huang, 2013; Nematin, 2016; Guo et al., 2018). Especially, the inexact two-stage stochastic programming (ITSP) provides great flexibility and efficiency in dealing with uncertainties expressed as intervals following the discrete probability distribution. Besides, ITSP allows the decision-makers to carry out recourse action and refine the pre-schemas, since the decisions are spread over different periods and only implemented if the corresponding scenario occurs (Li et al., 2008). It is efficient for both short-term schedule and long-term macro energy planning. For example, Tajeddini et al. (2014) developed a two-stage stochastic mixed integer programming model for both day-ahead and real-time markets with maximizing the expected profit from the generation company's view. Ji et al. (2014) developed an inexact two-stage stochastic robust programming model for energy management in residential microgrid system under uncertainties. Mohan et al. (2015) proposed a two-stage stochastic model for energy and reserve management in a microgrid system.

Moreover, the tradeoff between system cost and low-carbon choice would also be an important index for electric power system management integrated with new technologies/ measures, and the existing ITSP method might not accomplish to well balance the tradeoffs among multiple conflicting relationships between investment cost and resources-consumption control and GHG mitigation. An attractive technique that can overcome the above weaknesses is downside risk theory, which can avoid imposing a high risk and help seeking for robust solutions through controlling optimality and feasibility robustness. Downside risk theory has been successfully applied in many fields (Tack and Ubilava, 2013; Xie and Huang, 2014; Haneman et al., 2016).

Therefore, from the above analysis, this paper attempts to find out how to design and operate a low-carbon power system in an economically attractive and environmental-friendly way. As an extension of previous studies, a cost-risk balance programming model based on interval two-stage programming and downside risk theory is proposed for regional low-carbon power system management considering coal-consumption control cap, CCS, and renewable energy development measures. The model could suggest the optimal component sizes for regional electric power system and the GHG capture rates under different constrains on CO_2 emission targets and coal-consumption reduction. The impacts of CO_2 emission reduction policy and coal-consumption cap policy on generation expansion plan and the electricity system operation over a planning horizon are examined via scenario analysis.

There are three primary aims of this paper: (1) to determine the optimal design and operation strategy with risk-aversion; (2) to analyze the effects of different policy regulation on CCS retrofit and renewable energy generation; and (3) to quantify the amount of carbon emission reduction due to CCS investment and renewable energy generation. In this paper, Zhejiang Province, an economic-developed province in the Yangtze River Delta, is taken as an empirical study to explore how different policies influence the regional power system planning under different system risk preferences.

2. Inexact Cost-Risk Balance Programming

2.1. Interval Two-Stage Stochastic Programming

Two-stage stochastic programming (TSP) could provide feasible solutions for programming problems under uncertainties. In the first stage decisions are made before the random events are realized, and in the second stage decisions are scenario-based operation decisions (Li et al., 2010; Xing et al., 2014; Luo, 2016). A general TSP model can be formulated as follows (Huang and Loucks, 2000):

$$\min f = c^T x + \sum_{s=1}^{N} p_s Q(y,\ \omega_s) \tag{1a}$$

subject to:

$$ax \leq b \tag{1b}$$

$$T(\omega_s)x + W(\omega_s)y = h(\omega_s) \tag{1c}$$

$$x \geq 0,\ y(\omega_s) \geq 0 \tag{1d}$$

where x is vector of first-stage decision variables; $c^T x$ is first-stage benefits; ω is random events after the first-stage decisions are made; s is the scenario of the happening of random events; p_s is probability of event ω_s; $T(\omega_s)$, $W(\omega_s)$, and $h(\omega_s)$ are model parameters with reasonable dimensions (random parameters); $Q(y,\ \omega_s)$ is system recourse at the second-stage under the occurrence of event ω_s; $\sum_{s=1}^{N} p_s Q(y, \omega_s)$ is expected value of the second-stage system penalties.

In the above TSP model, the uncertain parameters are expressed as probability distribution functions. It is hard to reflect the independent uncertainties of the model's left-hand sides and cost coefficients. Interval-parameter programming is an alternative for handling uncertainties that cannot be reflected as membership or probability distribution, and can be expressed as interval numbers, i.e., $x^{\pm} = [x^-, x^+] = \{t|x^- < t < x^+\}$. Through introducing interval-parameter programming into the conventional TSP model, the Model 1 could be further modified and named interval two-stage stochastic programming (ITSP) as follows (Maqsood et al., 2015):

$$\text{Min}\ \ f^{\pm} = c^{\pm}x^{\pm} + \sum_{s=1}^{N} p_s Q(y^{\pm},\ \omega_s^{\pm}) \tag{2a}$$

subject to:

$$a^{\pm}x^{\pm} \leq b^{\pm} \tag{2b}$$

$$T(\omega_s^{\pm})x^{\pm} + W(\omega_s^{\pm})y^{\pm} = h(\omega_s^{\pm}) \tag{2c}$$

$$x^{\pm} \geq 0,\ y(\omega_s^{\pm}) \geq 0 \tag{2d}$$

Although the goal of the ITSP model is to minimize the total expected cost or to maximize the total expected profit, it fails to provide appropriate strategies to control the maximum budget or achieve minimum profits under different scenarios. Thus, risk management theory should be integrated to increase the feasibility and reliability of the ITSP model.

2.2. Downside Risk-Aversion

According to previous research on risk management, downside risk theory has been regarded as one of the effective methods for system risk-aversion. It can be used to assist in incorporating risk concern (i.e., the tradeoff between the expected value and variability of the expected value) into many optimization models. To present the concept of downside risk, we define $\delta(x, \Omega)$ as the positive deviation from a cost target Ω for design x, and $Cost(x)$ as system cost during the planning horizon, that is (Bean et al., 1992; Aseeri and Bagajewicz, 2004):

$$\delta(x,\ \Omega) = \begin{cases} Cost(x) - \Omega, & if\ Cost(x) \geq \Omega \\ 0 & if\ Cost(x) < \Omega \end{cases} \tag{3}$$

Downside risk is then defined as the expected value of $\delta(x, \Omega)$:

$$DRisk\ \delta(x,\ \Omega) = E[\delta(x,\ \Omega)] \tag{4}$$

Through introducing the concept of downside risk into the framework of ITSP, the cost-risk balance programming model can be formulated as:

$$\text{Min}\ \ f^{\pm} = c^{\pm}x^{\pm} + \sum_{s=1}^{N} p_s Q(y^{\pm},\ \omega_s^{\pm}) \tag{5a}$$

subject to:

$$a^{\pm}x^{\pm} \leq b^{\pm} \tag{5b}$$

$$T(\omega_s^{\pm})x^{\pm} + W(\omega_s^{\pm})y^{\pm} = h(\omega_s^{\pm}) \tag{5c}$$

$$DRisk\ \delta(x^{\pm},\ \Omega^{\pm}) = \sum_{s=1}^{N} p_s \delta_s(x^{\pm},\ \Omega^{\pm}) \leq \lambda \cdot \psi \tag{5d}$$

$$Cost_s(x^{\pm}) = c^{\pm}x^{\pm} + Q(y^{\pm},\ \omega_s^{\pm}),\ \forall s \tag{5e}$$

$$\delta_s(x^{\pm},\ \Omega^{\pm}) = \begin{cases} Cost_s(x^{\pm}) - \Omega^{\pm}, & if\ Cost_s(x^{\pm}) \geq \Omega^{\pm} \\ 0 & if\ Cost_s(x^{\pm}) < \Omega^{\pm} \end{cases},\ \forall s \tag{5f}$$

$$x^{\pm} \geq 0,\ y(\omega_s^{\pm}) \geq 0 \tag{5g}$$

where $\delta(x, \Omega)$ represents the positive deviation from the cost target Ω for design x and scenario s; $\psi^{\pm}$ is the expected downside risk value which can be calculated through the solution of the ITSP model; and λ is a control factor to acquire a more stringent limitation of risk, $\lambda \in [0, 1]$. By computing the objective function for different values of λ, we can obtain a series of solutions with the consideration of manager's risk tolerance.

In order to solve this cost-risk balance programming model, Model (5) can be transformed into two deterministic submodels that correspond to the lower and upper bounds of the desired objective function value, f^- and f^+. This transformation process is based on an interactive algorithm, which is different from the best/worst case analysis. In minimum problem, the objective function value corresponding to f^- is desired first, then f^+. More detailed solution process can be referred to Huang (1996) and Huang and Loucks (2000).

3. Case Study

3.1. Problem Description

Zhejiang Province (27°21′ ~ 31°52′ N, 118° ~ 123° E), located in China's east coast (Figure 1), with an area of approximately 101,800 km^2, is one of the most flourishing economic areas in China. With fast development of light and heavy industries, its gross domestic product (GDP) was ¥ 4,017 billion in 2014. Along with the rapid economic development, electricity demand in Zhejiang Province has experienced a prodigious increase from 72 million MWh in 2000 to 351 million MWh in 2014 (Yu, 2015). The generation expansion could not satisfy such fast growing demand. Extreme demand side management measures such as mandatory outage have been carried out in hot summer to relieve energy supply pressures. In addition, the coal-fired dominated electricity system brings a series of energy resource and environmental issues, which is a great challenge to achieve sustainable development. In 2013, the coal-fired power plants accounted for 78% of total installed capacity, with the total coal consumption of 86.42 million ton. Besides, owing to the limited natural resources, the available renewable energy generation only includes hydropower, wind power, and solar power, with the total power generation capacity of 9,950, 730, and 498 MW, respectively.

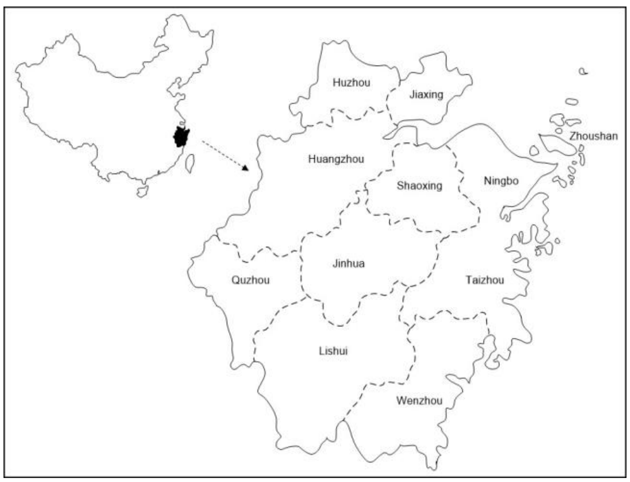

Figure 1. Map of Zhejiang Province.

According to national and regional energy structure adjustment and GHG emission reduction policies, coal consumption and GHG emission control have been proposed and implemented in order to promote the regional harmonious development. From the long- and mid-term development plan for regional GHG mitigation and coal-consumption control, the regional coal-fired power generation will be limited which would aggravate power shortages problem. As power demand increases, the conflicts among power supply safety, coal-consumption control target, and GHG reduction goal would become more prominent. In addition, in order to achieve electric power system's sustainable development, several technologies are considered in the government planning, including CCS retrofitting of existing coal-fired power plants, new coal-fired power plants with CCS, wind power, and solar energy. Thus, under the complexities of the technical-economic condition and resources-environmental pressures, effective and efficient planning of electric power system in Zhejiang Province is vital to deal with the following questions in order to achieve safe, economical, clean and sustainable electricity supply: (1) how to deal with the uncertain information, and avoid the system risk introduced by the tradeoff between system cost and low-carbon development choice; (2) how to determine the optimal design and operation strategy with different risk-aversion levels; (3) how to assess the effects of different policies on CCS retrofit and renewable energy generation investment, and quantify the corresponding carbon reduction amount.

3.2. Data and Assumptions

Since the long-term expansion plans of nuclear and hydropower plants are usually set by the government, we assume the new installed capacity of those units is zero. The planning horizon is from 2015 to 2025, and each planning period covers five years. Due to the long-term economic downturn, the regional power demand in the future is assumed as three possible levels, i.e., low, medium and high, with the probability of 0.3, 0.5 and 0.2, respectively. The annual load peak is 54,630 MW, and a load growth rate at 5 ~ 8% is assumed based on historical data. The main parameters related to various generation technologies (Tables 1 and 2) are expressed as interval values based on the information collected from some existing literatures (Priya et al., 2014; Kocaman et al., 2016). The future budget for the first and second periods is set as $ [62, 77] × 10^9 and $ [45, 65] × 10^9, respectively. In 2010, the coal consumption per local electricity generation was 0.322 ton/MWh, and the CO_2 emission per local electricity generation was 0.849 ton/MWh. In order to realize sustainable development, the coal consumption per local electricity generation will achieve a reduction of 15% in 2020 and 20% in 2050 compared to the year of 2010. The CO_2 emission per local electricity generation will achieve 25% reduction in 2020 and 30% in 2050, respectively.

3.3. Model Formulation

In order to analyze the investment portfolio and operation strategy for different generation technologies and CCS equipment, carbon emission limitation, and coal-consumption control regulation considering the investment and operation cost, an optimization model based on the cost-risk balance programming can be formulated as follows:

$$Min \quad f^{\pm} = CI^{\pm} + OC^{\pm} + FC^{\pm} + IC^{\pm} \tag{6a}$$

where the total system cost $f^{\pm}$ is the sum of capacity investment cost $CI^{\pm}$, operation cost $OC^{\pm}$, fuel cost for power generation $FC^{\pm}$, and the purchase cost of imported electricity $IC^{\pm}$.

(1) Capital cost of new power plants and CCS retrofitting:

$$CI^{\pm} = \sum_{t=1}^{T}\sum_{k=2}^{6} CC_k^{\pm} \cdot NC_{kt}^{\pm} + \sum_{t=1}^{T}\sum_{k=1}^{1} CS_{kt}^{\pm} \cdot NCS_{kt}^{\pm} \tag{6b}$$

where t and k are the indexes of planning period (t = 1, 2) and power conversion technologies (k = 1 for coal-fired power

Table 1. Main Investment and Operational Parameters of Different Generation Technologies

Units	Capital investment (10^6 \$/MW)	CO_2 emission factor (ton/MWh)	Fixed cost (\$/MW)		Variable cost (\$/MWh)	
			$t = 1$	$t = 2$	$t = 1$	$t = 2$
Coal	[0.80, 0.84]	[1.08, 1.09]	[49.29, 50.03]	[47.81, 48.53]	[6.39, 6.52]	[6.20, 6.32]
Coal-CCS	[1.04, 1.09]	[0.10, 0.15]	[51.00, 51.77]	[49.00, 49.74]	[6.50, 6.57]	[6.30, 6.39]
Nuclear	[1.04, 1.09]	[0.02, 0.04]	[88.75, 90.08]	[86.09, 87.38]	[2.04, 2.08]	[1.98, 2.02]
Hydro	[1.30, 1.37]	[0.12, 0.15]	[14.27, 14.48]	[13.84, 14.05]	[2.55, 2.60]	[2.47, 2.52]
Wind	[1.00, 1.05]	[0.07, 0.09]	[28.07, 27.23]	[28.49, 27.64]	0	0
Solar	[4.00, 4.20]	[0.20, 0.22]	[26.04, 26.43]	[25.26, 25.64]	0	0

Table 2. Economic and Technological Parameters of CCS Equipment

Time period	Investment cost (10^3 \$/MW)	Fixed cost (\$/MW)	Variable cost (\$/ton)	Electricity consumed by per unit CO_2 capture (MWh/ton)
$t = 1$	[214, 252]	[0.05, 0.06]	[6.6, 7.0]	[0.16, 0.17]
$t = 2$	[204, 240]	[0.04, 0.05]	[6.4, 6.8]	[0.15, 0.16]

plants, $k = 2$ for coal-fired power plants with CCS, $k = 3$ for nuclear, $k = 4$ for hydro, $k = 5$ for wind, and $k = 6$ for PV). $NC_{kt}^{\pm}$ denotes the new installed capacity of technology k during period t (MW). $NCS_{kt}^{\pm}$ is the new installed capacity of CCS for technology k during period t (MW). $CC_{kt}^{\pm}$ and $CS_{kt}^{\pm}$ are the capital cost of power generation technology k and CCS retrofitting, respectively (\$/MW).

(2) Operation cost of existing and new power plants:

$$\begin{aligned} OC^{\pm} = & \sum_{t=1}^{T}\sum_{k=1}^{6}\sum_{h=1}^{H}\left(F_{kt}^{\pm}\cdot C_{kt}^{\pm} + V_{kt}^{\pm}\cdot E_{kt}^{\pm} + p_h \cdot VP_{kt}^{\pm}\cdot EP_{kth}^{\pm}\right) \\ & + \sum_{t=1}^{T}\sum_{k=1}^{1}\left(FS_{kt}^{\pm}\cdot CCS_{kt}^{\pm} + VS_{kt}^{\pm}\cdot ECS_{kt}^{\pm}\right) \end{aligned} \tag{6c}$$

where h is the index of scenarios; p_h represents the probability of scenario h; $C_{kt}^{\pm}$ and $CCS_{kt}^{\pm}$ are the installed capacity of technology k and the corresponding CCS during period t (MW); $E_{kt}^{\pm}$ is the predetermined power generation target (MWh); $EP_{kth}^{\pm}$ is the extra power generation amount under scenario h (MWh); $F_{kt}^{\pm}$ and $V_{kt}^{\pm}$ denote the fixed cost (\$/MW) and variable cost (\$/MWh) for technology k in period t; $VP_{kt}^{\pm}$ and $FS_{kt}^{\pm}$ are the extra penalty variable costand the fixed cost of CCS, respecttively (\$/MWh); $ECS_{kt}^{\pm}$ represents the amount of CO_2 captured by CCS(ton); and $VS_{kt}^{\pm}$ is the variable cost of CCS (\$/ton).

(3) Fuel cost of coal-fired power plants:

$$FC^{\pm} = \sum_{t=1}^{T}\sum_{k=1}^{6}\sum_{h=1}^{H}\beta_{kt}^{\pm}\cdot\xi_{kt}^{\pm}\cdot p_h\cdot\left(E_{kt}^{\pm} + EP_{kth}^{\pm}\right) \tag{6d}$$

where $\beta_{kt}^{\pm}$ is the fuel price(\$/ton), and $\xi_{kt}^{\pm}$ represents the conversion efficiency of power generation technology i during period t (ton/MWh).

(4) Cost of imported electricity:

$$IC^{\pm} = \sum_{t=1}^{T} IP_t^{\pm}\cdot IE_t^{\pm} \tag{6e}$$

where $IE_t^{\pm}$ is the imported electricity during period t (MWh), and $IP_t^{\pm}$ denotes the price of imported electricity during period t (\$/MWh).

Constraints:

(1) Constraints for energy balance:

$$\sum_{k=1}^{K}\left(E_{kt}^{\pm} + EP_{kth}^{\pm}\right)\cdot(1 - Tr) - \mu_{kt}^{\pm}\cdot ECS_{kt}^{\pm} + IE_t^{\pm} \geq D_{th}^{\pm}, \forall t, h \tag{6f}$$

$$E_{kt}^{\pm} + EP_{kth}^{\pm} \leq ST_{kt}^{\pm}\cdot C_{kt}^{\pm}, \forall k, t, h \tag{6g}$$

$$IE_t^{\pm} \leq 0.25 \times D_{th}^{\pm} \tag{6h}$$

where $D_{th}^{\pm}$ denotes regional electricity demand (MWh), $C_{kt}^{\pm}$ is the capacity of power generation technology k during t (MW), $ST_{kt}^{\pm}$ is the average service time of power conversion technology k in period t (h), Tr is the prespecified loss factor for the transmission system, assumed as 0.1, and $\mu_{kt}^{\pm}$ represents the electricity consumption by per unit CO_2 capture (MWh/ton).

(2) Constraint for the safety capacity margin:

$$\sum_{k=1}^{K} C_{kt}^{\pm} \geq (1 + r) P_{\max t}^{\pm}, \forall t \tag{6i}$$

where $P_{\max t}^{\pm}$ is annual zonal peak demand (MW) and r represents the capacity reserve margin which is set to 20% in this case study.

(3) Constraint for the availability of renewable energy supply:

The supply of RE power plants (wind and solar) depends greatly on regional available sources:

$$\varepsilon_{kt}^{\pm} \cdot \left(E_{kt}^{\pm} + EP_{kth}^{\pm}\right) \le SR_{kt}^{\pm}, k \in \{4,5\}, \forall k,t,h; \tag{6j}$$

where $SR_{kt}^{\pm}$ denotes the annual energy generation potential for energy supply (PJ).

(4) Dynamic constraint for the capacity addition:

$$C_{kt}^{\pm} = C_{k,t-1}^{\pm} + NC_{kt}^{\pm},\ k \in \{2,3,4,5,6\}, \forall t \tag{6k}$$

(5) Constraint for regional coal-consumption cap:

$$\sum_{k=1,2} \xi_{kt}^{\pm} \cdot \left(E_{kt}^{\pm} + EP_{kth}^{\pm}\right) \le CL_t^{\pm}, \forall t \tag{6l}$$

where $CL_t^{\pm}$ is the coal-consumption cap (ton).

(6) Constraint for regional carbon emission cap:

$$CCS_{kt}^{\pm} = \sum_{t=1}^{t} NCS_{kt}^{\pm}, \forall k,t \tag{6m}$$

$$CCS_{kt}^{\pm} \le C_{kt}^{\pm}, \forall k,t \tag{6n}$$

$$ECS_{kt}^{\pm} \le \varpi \cdot COE_k^{\pm} \cdot ST_{kt}^{\pm} \cdot CCS_{kt}^{\pm}, \forall k,t \tag{6o}$$

$$\sum_{k=1}^{K} \left(E_{kt}^{\pm} + EP_{kth}^{\pm}\right) \cdot COE_k^{\pm} - ECS_{kt}^{\pm} \le COL_t^{\pm},\ \forall t,h \tag{6p}$$

where $COL_t^{\pm}$ represents the carbon emission limit (ton), $COE_k^{\pm}$ is the CO_2 emission factor of generated electricity (ton CO_2/MWh), and ϖ is the CO_2 capture rate of fossil energy with CCS, here ϖ = 90%.

(7) Constraint for downside risk:

$$\begin{aligned} Cost(t,h) = & \sum_{k=2}^{6} CC_k^{\pm} \cdot NC_{kt}^{\pm} + \sum_{k=1}^{1} CS_{kt}^{\pm} \cdot NCS_{kt}^{\pm} \\ & + \sum_{k=1}^{6} \left(F_{kt}^{\pm} \cdot C_{kt}^{\pm} + V_{kt}^{\pm} \cdot E_{kt}^{\pm} + VP_{kt}^{\pm} \cdot EP_{kth}^{\pm}\right) \\ & + \sum_{k=1}^{1} \left(FS_{kt}^{\pm} \cdot CCS_{kt}^{\pm} + VS_{kt}^{\pm} \cdot ECS_{kt}^{\pm}\right) \\ & + \sum_{k=1}^{6} \beta_{kt}^{\pm} \cdot \xi_{kt}^{\pm} \cdot \left(E_{kt}^{\pm} + EP_{kth}^{\pm}\right) \end{aligned} \tag{6q}$$

$$\delta_{th}\left(\Omega_t^{\pm}\right) = \begin{cases} Cost(t,h) - \Omega_t^{\pm} & Cost(t,h) > \Omega_t^{\pm} \\ 0 & Cost(t,h) \le \Omega_t^{\pm} \end{cases}, \forall t,h \tag{6r}$$

$$DRisk\ \delta\left(\Omega_t^{\pm}\right) = \sum_h p_h \delta_{th}\left(\Omega_t^{\pm}\right) \le \lambda \cdot \psi_t^{\pm}, \forall t \tag{6s}$$

where $\Omega_t^{\pm}$ is the predefined budget, $\Psi_t^{\pm}$ is the expected downside risk value, and λ is the control factor.

4. Result Analysis and Policy Implications

4.1. Risk-Aversion Analysis

In this section, the impact of risk attitude of decision-makers on the optimal solution has been analyzed and compared by varying the adjustment factor λ from 1 to 0, with 0.1 step. Lower λ value means more conservative attitude. Table 3 illustrates the objective value under different risk attitudes. In general, the objective value would increase as λ value decreasing. The reason is that λ acts as a factor controlling the positive deviation of system cost from the target cost, and a lower λ value indicates more conservative attitude of decision maker. Therefore, it is interesting that the decrease in λ results in an increase in the objective values. It should be noticed that when λ is set as 0.3 or even smaller, there would be no feasible solution, which indicates it is impossible to find any feasible solution under the predefined budget when the risk tolerance of decision maker is too little.

Although different risk attitudes influence the total system cost, there is no impact on investment portfolio strategy, as shown in Table 4. In general, conventional coal-fired power plants would still play a dominant role in the future. In periods 1 and 2, the new installed capacity of conventional coal-fired power plants would be [38.55, 39.21] × 10^3 and [43.70, 44.57] × 10^3 MW. During the first period, the new installed capacity of coal-fired power plants with CCS would be [17.89, 19.08]×10^3 MW, and the new installed capacity of wind power would be 12.00×10^3 MW, reaching the maximum available resource. In period 2, where the budget is less than that of the first period, the investment would focus on CCS devices, with [5.34, 8.61]×10^3 MW. There would be no investment on coal-fired power plants with CCS and wind power. Under the predesigned economic and environmental constraints, due to its high capital cost, the investment in solar power would be zero.

The future load demand will mainly depend on the coal-fired power, including the conventional coal-fired power plants and the coal-fired power plants with CCS. Their electricity generation amounts are affected by the risk preference change and load demand fluctuation. Figure 2 illustrates the impact of risk tolerance levels on the first and second decision process when the load demand is low. It can be found that with less risk tolerance, the optimal strategy in the first stage is more conservative, which means more power generation is predetermined before actual uncertain event occurs. As a result, the extra electricity generation supplied in the second stage would be less accordingly. For example, during the first planning horizon, when λ is fixed as 1.0, 0.8, 0.6 and 0.4 without risk consideration, the predetermined electricity generation in the first stage would be 143.85×10^6, 194.80×10^6, 214.29× 10^6, 260.77×10^6, and 287.70×10^6 MWh, respectively. The cor-

Table 3. Total System Cost under Different Risk Attitude (Unit: 10^9\$)

Risk preference	without risk	$\lambda = 0.9$	$\lambda = 0.8$	$\lambda = 0.7$	$\lambda = 0.6$	$\lambda = 0.5$	$\lambda = 0.4$
Total cost	[116.17, 142.84]	[117.09, 143.79]	[117.97, 144.68]	[118.59, 145.31]	[119.21, 145.95]	[119.88, 146.65]	[120.92, 147.69]

responding extra power generation in the second stage would be $[123.09, 131.38]\times10^6$, $[72.14, 80.43]\times10^6$, $[53.00, 61.00]\times10^6$, $[6.17, 14]\times10^6$, and 0 MWh, respectively. In addition, the load demand level influences the decision in the second stage. In general, higher load demand requires more electricity generation. Figure 3 presents the power generation amount of the conventional coal-fired power plants under different load demand levels at the second stage with λ set as 1.0. For example when λ is fixed as 1.0 in period 1, the electricity generation determined in the second stage would be $[72.14, 80.43]\times10^6$, $[92.90, 97.74]\times10^6$, and $[96.70, 103.97]\times10^6$ MWh under the low, medium, and high demand level, respectively.

However, the risk tolerance changes and load demand fluctuation has no effect on the performance of other generators, i.e., 31.18×10^6 MWh for nuclear power, 20.71×10^6 MWh for hydropower, 23.66×10^6 MWh for wind power, and 0.31×10^6 MWh for solar power in each planning period. In addition, the imported electricity would be $[28.34, 40.14]\times10^6$ MWh in period 1 and $[61.60, 91.42]\times10^6$ MWh in period 2, which also immune to the risk attitude of decision-makers.

Table 4. New Installed Capacity of Various Technologies (Unit: 10^3 MWh)

Technology	$t = 1$	$t = 2$
CCS	-	[5.34, 8.61]
Coal	[38.55, 39.21]	[43.70, 44.57]
Coal-CCS	[17.89, 19.08]	-
Nuclear	-	-
Hydro	-	-
Wind	12	-
Solar	-	-

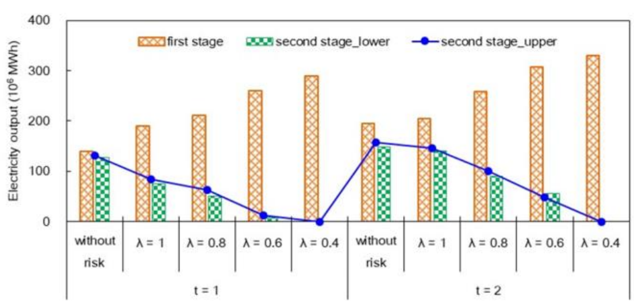

Figure 2. Electricity output of conventional coal-fired power plants under different risk preferences with low load demand.

4.2. Sensitivity and Scenario Analysis

In this part, the specific effects that different environmenttal policies (i.e., coal-consumption control and CO_2 emission cap) on the optimal strategies of the hybrid system are discussed, respectively. The coal-consumption reduction and CO_2 emission reduction target set in Sector 3.2 is named as the base scenario, then different policy reduction targets will be designed respectively. It should be noticed that since it is improper to adopt the uniform budget when environmental policy changes, we remove the downside risk constraint, i.e., Equations (6q) ~ (6s) in modelling.

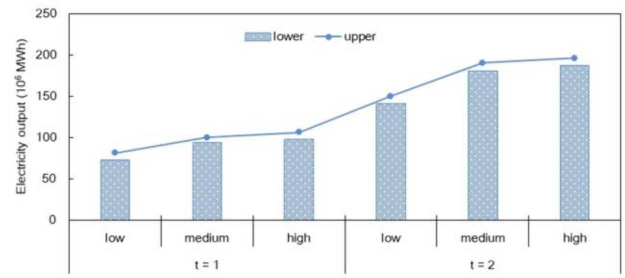

Figure 3. Electricity output of conventional coal-fired power plants under different load demand levels at the second stage with λ set as 1.

4.2.1. Changes in the Carbon Emission Target

In this part, 10 and 20% carbon emission reduction targets compared with base scenario are analyzed. In general, with more aggressive carbon emission target, the total system cost would increase. Under the base, 10 and 20% reduction scenarios, the total system cost would be \$ $[116.17, 142.84]\times10^9$, \$ $[123.78, 151.31]\times10^9$, and \$ $[131.39, 159.78]\times10^9$, respectively.

Table 5 illustrates the capacity investment portfolios under different CO_2 emission reduction targets. The aggressive CO_2 emission reduction target stimulates the development of CCS and the coal-fired power plants with CCS. During the first period, the aggressive CO_2 emission reduction is mainly achieved by the extra coal-fired power plants with CCS. Under the base, 10 and 20% reduction scenarios, the newly installed capacity of coal-fired power plants with CCS would be $[17.89, 19.08]\times10^3$, $[23.21, 24.84]\times10^3$, and $[28.53, 30.60]\times10^3$ MW, respecttively. In period 2, more CCS devices would be required to meet the aggressive CO_2 emission reduction target. The newly installed capacity of CCS devices would be $[5.34, 8.61]\times10^3$, $[6.50, 9.48]\times10^3$, and $[7.67, 10.36]\times10^3$ MW under the base, 10 and 20% reduction scenarios, respectively. Meanwhile, the aggressive CO_2 reduction target would lead to the decrease in the capacity investment of the conventional coal-fired power plants in period 1.

In general, there is no change in the capacity investment of nuclear, hydro, wind and solar power, and their power generation would be always the same, i.e., 31.18×10^6 MWh for nuclear power, 20.71×10^6 MWh for hydropower, 23.66×10^6 MWh for wind power, and 0.31×10^6 MWh for solar power. Whereas

Table 5. Capacity Investment Portfolios under Different CO_2 Emission Target (Unit: 10^3 MW)

Technology	Base		10% Reduction		20% Reduction	
	t = 1	*t* = 2	*t* = 1	*t* = 2	*t* = 1	*t* = 2
CCS	-	[5.34, 8.61]	-	[6.50, 9.48]	-	[7.67, 10.36]
Coal	[38.55, 39.21]	[43.70, 44.57]	[33.22, 33.46]	[43.70, 44.75]	[27.70, 27.93]	[43.70, 44.57]
Coal-CCS	[17.89, 19.08]	-	[23.21, 24.84]	-	[28.53, 30.60]	-
Nuclear	-	-	-	-	-	-
Hydro	-	-	-	-	-	-
Wind	12	-	12	-	12	-
Solar	-	-	-	-	-	-

Table 6. Capacity Investment Portfolios under Different Coal-Consumption Reduction Targets (10^3 MW)

Technology	Base		10% reduction		20% reduction	
	t = 1	*t* = 2	*t* = 1	*t* = 2	*t* = 1	*t* = 2
CCS	-	[5.34, 8.61]	-	[3.73, 6.87]	-	-
Coal	[38.55, 39.21]	[43.70, 44.57]	[45.57, 46.77]	[41.59, 43.70]	[43.69, 50.67]	[22.81, 28.53]
Coal-CCS	[17.89, 19.08]	-	[10.86, 11.53]	-	[3.92, 4.60]	[2.91, 5.17]
Nuclear	-	-	-	-	-	-
Hydro	-	-	-	-	-	-
Wind	12	-	12	[0, 2.99]	12	10
Solar	-	-	-	-	[1.00, 1.84]	[0, 8.85]

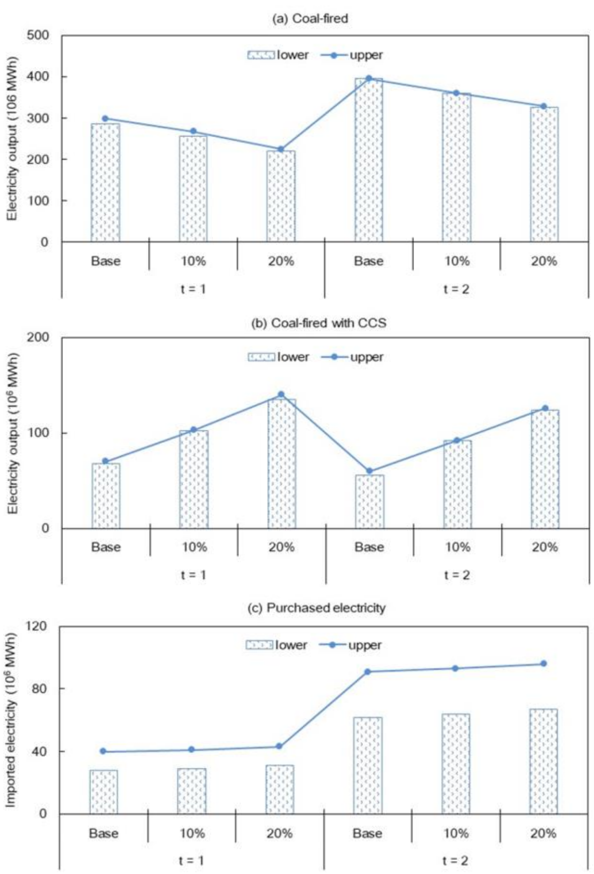

Figure 4. Electricity supply arrangements under different CO_2 emission targets for the medium load demand.

different CO_2 emission reduction targets would have great impact on the performance of coal-fired power and imported electricity, as shown in Figure 4. With more aggressive CO_2 emission goal, the power generation amount of the conventional coal-fired power plants would decrease during the whole planning horizon. However, due to the great investment in coal-fired power plants with CCS under more aggressive CO_2 emission goal, its electricity generation increases significantly. For example, in period 1 under base, 10 and 20% reduction scenarios, the electricity output of conventional coal-fired power plants would be $[287.70, 298.77] \times 10^6$, $[254.53, 262.59] \times 10^6$ and $[221.37, 226.41] \times 10^6$ MWh, respectively. Meanwhile, the electricity output of coal-fired power plants with CCS would be $[69.19, 70.11] \times 10^6$, $[102.05, 103.73] \times 10^6$, and $[133.98, 138.27] \times 10^6$ MWh, respectively. In addition, the amount of imported electricity would also increase slightly to satisfy CO_2 emission reduction policy.

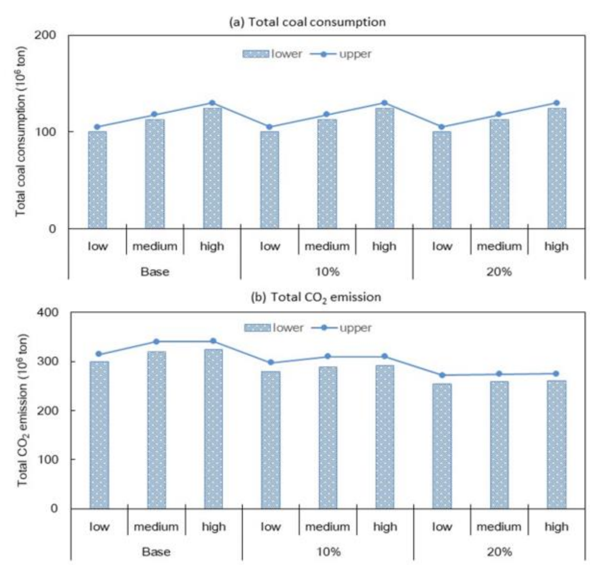

Figure 5. Total coal consumption (a) and CO2 emission (b) under different CO_2 emission caps during the first period.

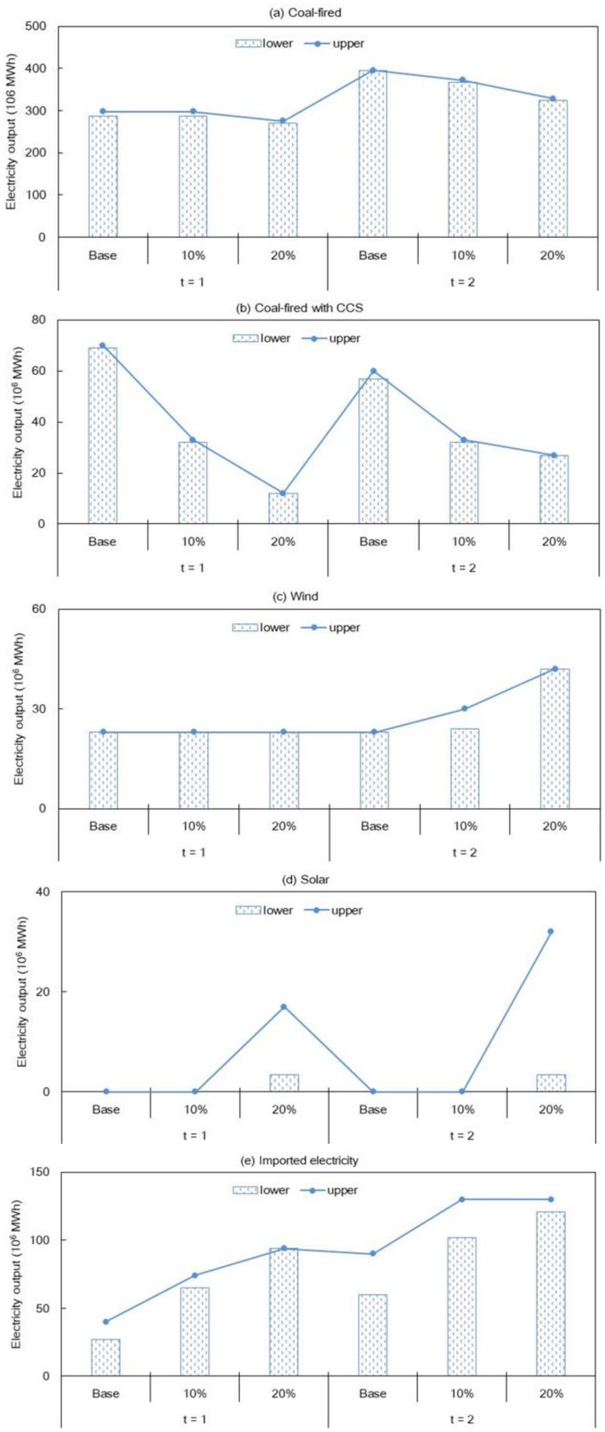

Figure 6. Electricity supply arrangements under different coal-consumption reduction targets for the medium load demand.

Figure 5 shows the total coal-consumption and CO_2 emission under different CO_2 emission reduction targets. In general, higher load demand requires more coal consumption, and leads to a greater CO_2 emission. While under the same load demand level, aggressive CO_2 emission cap control leads to significant CO_2 emission reduction decrease. In addition, under aggressive CO_2 emission cap, although the investment on CCS technology would increase, the total electricity output of coal-fired power plants, including both conventional coal-fired power plants and coal-fired power plants with CCS, would decrease, and the unsatisfied electricity would rely more on imported electricity. As a result, the total local coal consumption would decrease accordingly. However, in general, the effect on coal-consumption would be light. For example, in the base, 10 and 20% reduction scenarios under the low load demand level, the total coal consumption would be $[100.03, 104.41] \times 10^6$, $[99.84, 104.13] \times 10^6$, and $[99.78, 103.96] \times 10^6$ ton, respectively. However, the corresponding CO_2 emission would be $[298.49, 314.60] \times 10^6$, $[281.51, 297.80] \times 10^6$, and $[253.58, 274.07] \times 10^6$ ton, respectively.

4.2.2. Changes in Coal Consumption Reduction Target

Similarly, the influence of coal-consumption cap policy on the design and operation of the power system in Zhejiang Province is analyzed in this part. The coal-consumption reduction targets are set as 10 and 20% compared with the base scenario. With tough coal-consumption control goal, the total system cost would increase. Under the base, 10 and 20% reduction scenarios, the total system cost would be $ $[116.17, 142.84] \times 10^9$, $ $[142.23, 172.17] \times 10^9$, and $ $[182.06, 248.58] \times 10^9$, respectively.

Table 6 illustrates the capacity investment portfolios under different coal-consumption targets. The investment on coal-fired power plants, including the conventional and CCS equipped coal-fired power plants, would greatly decrease under tough coal-consumption control policy. In addition, the CCS investment in retrofitted coal-fired power plants would also decrease. Under the base, 10 and 20% reduction scenarios, the capacity investment on CCS retrofit would be $[5.34, 8.61] \times 10^3$, $[3.73, 6.87] \times 10^3$, and 0 MW, respectively. On the other hand, tough coal-consumption policy could promote the expansion of renewable energy generation. For example, under the base scenario, the investment on wind power is only in the first period, reaching its maximum available capacity; when the coal-consumption reduction target is 10%, the wind power expansion would occur in the second period, with $[0, 2.99] \times 10^3$ MW; and under the 20% reduction scenario, the capacity of wind power would reach its maximum. At the same time, only under such aggressive reduction control, solar power gains the opportunity to expand, $[1.00, 1.84] \times 10^3$ MW in period 1 and $[0.00, 8.85] \times 10^3$ MW in period 2.

The coal-consumption cap control policy would also influence the operation strategy of the hybrid power system. Figure 6 presents the optimized electricity supply strategies with different coal-consumption reduction targets under the medium demand level. With tough coal-consumption control, there would have a slightly decreasing trend in power generation of conventional coal-fired power plants; however, the coal-fired power generation amount would decrease greatly. Since the performance of CCS requires extra electricity, the coal consumption per unit final output of coal-fired power plants with CCS is higher than that of the conventional coal-fired power plants. Thus, the tough coal-consumption cap limits the promotion of coal-fired power plants with CCS. However, tough coal-consumption cap control policy would stimulate more investment in renewable energy generation. During the second period, under the base, 10 and 20% reduction scenarios, the wind power generation would be 23.66×10^6, $[23.66, 29.33] \times 10^6$, and 42.66×10^6 MWh, respectively. For solar power, its corresponding amount would be 0.31×10^6, 0.31×10^6, and $[3.43, 32.36] \times 10^6$ MWh, respectively. In addition, the tough coal-consumption limitation would require more imported power to satisfy regional load demand. Under the base, 10 and 20% reduction scenarios in period 2, the imported electricity would be $[61.60, 91.42] \times 10^6$, $[103.34, 128.55] \times 10^6$, and $[122.43, 128.55] \times 10^6$ MWh, respectively.

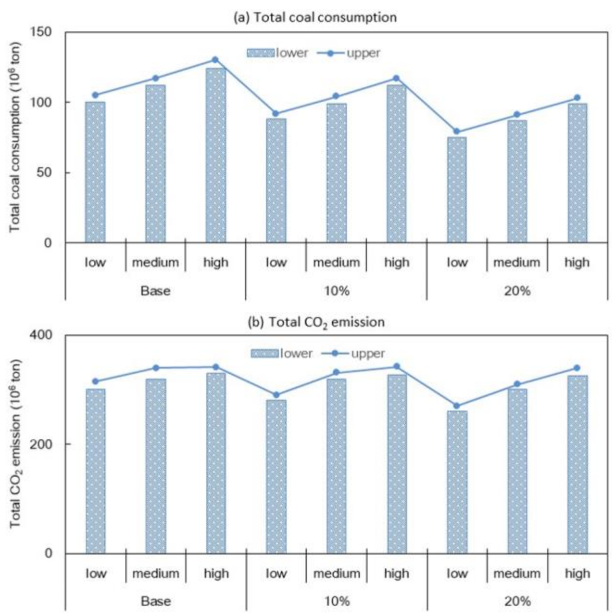

Figure 7. Total coal consumption (a) and CO_2 emission (b) under different coal-consumption caps during the first period.

Figure 7 illustrates the total coal consumption and CO_2 emission under different coal-consumption caps. Tough coal-consumption cap control policy could lead to resources utilization reduction directly; as a result, the CO_2 emission decrease accordingly. For example, for medium load demand in period 1, under the base, 10 and 20% reduction scenarios, the total coal consumption would be $[111.76, 116.95] \times 10^6$, $[99.45, 104.08] \times 10^6$, and $[87.32, 91.40] \times 10^6$ ton, respectively. The corresponding CO_2 emission amount would be $[322.55, 342.59] \times 10^6$, $[318.00, 334.41] \times 10^6$, and $[297.63, 314.89] \times 10^6$ ton, respectively.

4.3. Policy Implications

Due to the high capital cost and natural condition limitation of renewable energy, the coal-fired power plants will still play the dominate role in Zhejiang Province in the future. Implementing environmental policies, i.e., CO_2 emission cap and coal-consumption cap policy, could healp to realize the total coal-consumption and CO_2 emission reduction directly, which mitigates the conflicts among load demand increase, environmental quality improvement, and resource limitation.

However, the resources and environmental policies would lead to different capacity investment portfolios. CO_2 emission cap policy provides the priority for CCS devices. Under aggressive CO_2 emission reduction target, more conventional coal-fired power plants would be retrofitted with CCS device, and new coal-fired power plants with CCS would become popular. However, threre is no impact on the renewable energy generation. This is mainly because CCS with less capital cost is more favorable than renewable energy generation in achieving the CO_2 emission reduction target, while tough coal-consumption cap policy could directly improve renewable energy utilization, and wind power would gain the priority to develop than solar power. In addition, the aggressive CO_2 emission reduction or toug coal-consumption control would require more imported power to satisfy regional load demand in Zhejiang Province.

5. Conclusions

In this paper, a cost-risk balance programming, integrating interval two-stage stochastic optimization model with downside risk theory, is developed for sustainable electric power system planning under different resource and environment pressures. It provides suitable risk-aversion against uncertainties on load demand, fuel price, investment/operation cost, and other economic and technological factors. The method is a feasible and flexible way for decision-makers making better tradeoff between system cost and risk. The empirical study of Zhejiang Province in China verifies the efficiency of the optimization framework. Different resources and environmental policies have great impact on the future investment and operation performance of power system in Zhejiang Province. Although the aggressive CO_2 emission cap policy would impel CO_2 emission reduction target by large investment on CCS retrofit and new coal-power plants with CCS, without achieving local coal-consumption reduction; while the tough coal-consumption control policy could directly reduce CO_2 emission and coal consumption by stimulating renewable energy utilization, which can improve energy system structure adjustment in Zhejiang Province. Therefore, according to the above different policy effects, mandatory coal-consumption control policy would be more effective to release energy and resource pressure in Zhejiang Province.

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