FLEXIBLE CARBON CAPTURE EXPLOITING DYNAMIC CHANGES IN ELECTRICITY PRICE

A Thesis

by

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ABSTRACT

Global warming is a popular topic and has drawn widespread attention all over the world, because it gradually affects people's normal life. In the long term, carbon capture and storage (CCS) technology is a promising choice to reduce CO_2 emissions efficiently. However, for the fossil fuel power plants, current capture technologies are highly energy intensive and need almost one-third of the electricity generated by the power plant itself. Thus, although showing great potential for environmental benefits, the carbon capture and storage (CCS) technologies have not been applied widely and commercially successful.

Flexible carbon capture technologies, especially with solvent storage, can improve the net power output by reducing the loads of carbon capture systems and capture less CO_2 when the electricity demand and prices are high. Then it will increase the loads of carbon capture systems and capture more CO_2 in order to make the total CO_2 emissions less than the baselines when electricity demand and prices are relatively low. During the scheduling of CO_2 capture power plants (CCPPs), if the operators can consider the uncertainties of electricity prices in different periods, they will improve the scheduling performance based on the nominal values of electricity price.

In this project, a flexible carbon capture operation that changes its production capacity depending on the changes in electricity prices will be performed, incorporating with the bounded and symmetric uncertainty of electricity price by using the robust optimization. Furthermore, a Mixed Integer Nonlinear Programming (MINLP) model will be proposed to maximize the profit in CCPPs, referring the data of the past operation and electricity prices. Finally, the comparison between scheduling with the nominal value of electricity price and with different uncertainty levels will be shown in case study, and the relative optimal output schedules of the power plant under different uncertainty levels of electricity price will be made by Matlab.

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Contributors

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NOMENCLATURE

CO_2	Carbon Dioxide
CH_4	Methane
CCS	Carbon Capture and Storage
CCPP	CO_2 Capture Power Plant
EIA	Energy Information Agency
GAMS	General Algebraic Modeling System
GHG	Greenhouse Gas
IEA	International Energy Agency
IGCC	Integrated Gasification Combined Cycle
IPCC	Intergovernmental Panel on Climate Change
LP	Low Pressure
MEA	Monoethanolamine
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Nonlinear Programming
N_2O	Nitrous Oxide
t	Hours
$\mathrm{Re}v_t$	Revenue ($)
C^{Fuel}	Cost of fuels ($)
$C_t^{O\&M}$	Cost of operation and maintenance ($)
$C_t^{CO_2}$	Cost of CO_2 emission ($)
$C_t^{T/S}$	Cost of CO_2 transport and storage
P_t^e	Nominal electricity Price ($/MWh)
P_t^{e*}	True electricity price ($/MWh)
P^{Fuel}	Fuel price ($/MMBTU)

P^{CO_2}	CO_2 price ($/t CO_2)
$P^{T/S}$	Transport and storage price ($/t CO_2)
OM^b	Marginal operation and maintenance cost ($/MWh)
x_t	Gross power output (MW)
x_t^N	Net power output (MW)
$\overline{x}$	Maximum gross power output (MW)
$\underline{x}$	Minimum gross power output (MW)
Δx_R	Maximum ramp rate for gross power output (MW/h)
E_t^N	Net CO_2 emission (ton)
E_t^s	Amounts of CO_2 stripped
$e_{\max}^{CO_2}$	Baseline CO_2 emission intensity (t CO_2/MWh)
y_t^a	Absorber load (fractional)
y_t^s	Stripper load (fractional)
$\Delta y_{\max}^a$	Maximum ramping rate of absorption load (fractional)
$\Delta y_{\max}^s$	Maximum ramping rate of stripping load ((fractional)
R^b	Base plant CO_2 emission rate (t CO_2/MWh)
F	Design CO_2 removal (fractional)
e^a	Absorption equivalent work (MWh/t CO_2)
e^s	Stripping/compression equivalent work (MWh/t CO_2)
H^b	Base plant heat rate (MMBTU/MWh)
u_t^a	Binary for status of absorber

u_t^s	Binary for status of stripper
$S_{a,t}$	Flowrate of rich solvent (m^3/h)
$S_{s,t}$	Flowrate of lean solvent (m^3/h)
S_{a0}	Flowrates of rich solvent at full load operation (m^3/h)
S_{s0}	Flowrates of lean solvent at full load operation (m^3/h)
$S_{a,t}^T$	Volume of rich solvent in the tank (m^3)
$S_{s,t}^T$	Volume of lean solvent in the tank (m^3)
S_{a0}^T	Initial volume of rich solvent tank (m^3)
S_{s0}^T	Initial volume of lean solvent tank (m^3)
$S_{a,\max}^T$	Maximum capacity of rich solvent tank (m^3)
$S_{s,\max}^T$	Maximum capacity of rich lean tank (m^3)
ξ	Random variable distributed symmetrically in [-1,1]
ϵ	Uncertainty level
δ	Infeasibility tolerance
k	Reliability level
Ω	Related to k [$k = \exp\left(-\Omega^2 / 2\right)$]
$y_{1,t}$	Auxiliary variables
$Z_{1,t}$	Auxiliary variables

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CHAPTER 1
INTRODUCTION

1.1 Background

The issue of global warming has drawn widespread attention at present. In short, global warming is the increase in the average temperature of the earth's atmosphere and oceans, which is caused by the continuous accumulation of the greenhouse effect, resulting in imbalance between the energy absorption and emission of the earth's gas system. Then a large quantity of energy is continuously accumulated in the gas system of earth, so the temperature has been gradually rising in the recent years (Miraglia et al., 2009). Figure 1 shows the temperature anomaly related to the 1981-2000 average temperature in the past few years, and the long-term trend of annual temperature is rising. In this figure, anomalies are deviation from baseline (1981-2010 Average), and the black thin line indicates surface temperature anomaly of each year, and the blue line indicates their 5-year running mean, and the red line indicates the long-term linear trend.

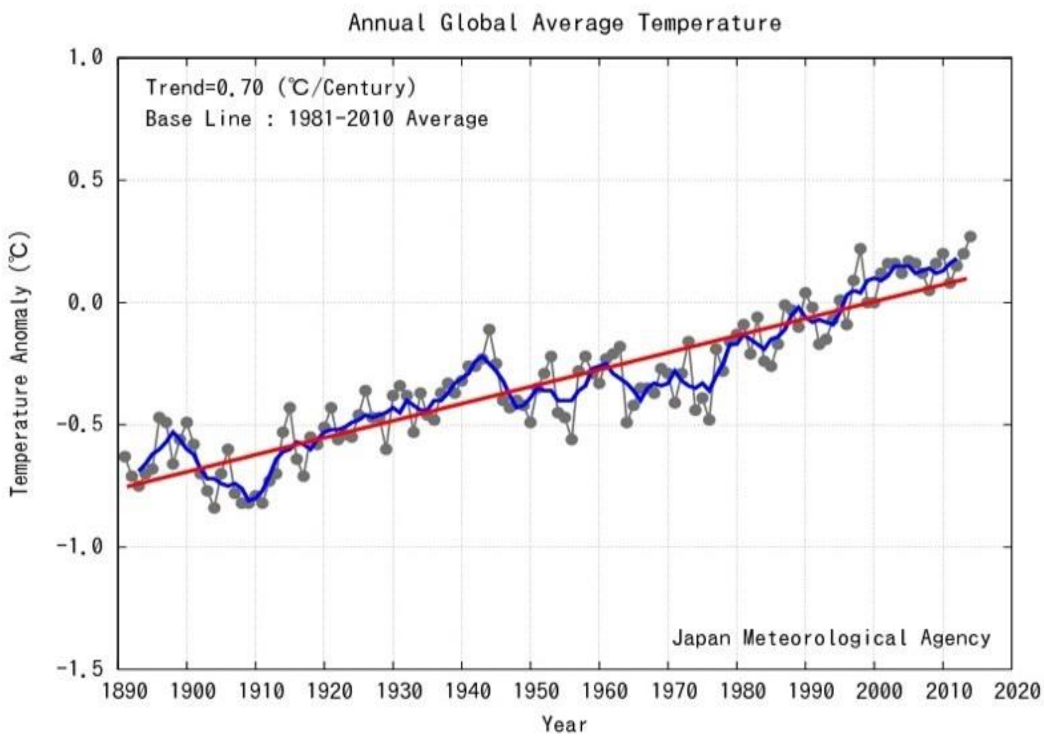

Fig.1. Annual global average temperature curve given by the Japan Meteorological Agency on January 5, 2015 (source: Global Average Surface Temperature Anomalies)

Global warming will cause lots of effects, including changing precipitation, accelerating the melting of glaciers and rising sea levels, expanding deserts in the subtropics, etc., which endanger the balance of natural ecosystems. Furthermore, those probable changes will affect human survival, such as threatening the food security by decreasing crop yields and abandoning densely populated areas as a result of the rise of sea levels. What is the most serious is that because of the "inertia" existing in the climate system and the long-term presence of greenhouse gases in the atmosphere, many of these effects will last for not only decades or centuries, but for tens of thousands of years to come. Greenhouse gas (GHG) emissions, which are now at their highest in history, have led to large increases in the atmospheric concentrations of carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) that are considered the dominant cause that lies behind the global warming (Angel et al., 2017). Then, where the great amount of greenhouse gas come from? The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (2013) concluded that "It is extremely likely that human influence has been the dominant cause of the observed warming since the mid-20th century." The largest human influence has been the emission of greenhouse gases such as carbon dioxide, methane and nitrous oxide. Climate model projections summarized in the report indicated that during the 21st century, the global surface temperature is likely to rise a further 0.3 to 1.7 °C (0.5 to 3.1 °F) in the lowest emissions scenario, and 2.6 to 4.8 °C (4.7 to 8.6 °F) in the highest emissions scenario. These findings have been recognized by the national science academies of the major industrialized nations and are not disputed by any scientific body of national or international standing.

The effect of different greenhouse gases to the global warming are different. The Fourth Assessment Report of the Intergovernmental Panel on Climate Change (2007) points out that carbon dioxide (CO_2) contributes about 64% of the total warming effect of greenhouse gases and methane (CH_4) contributes about 17%, N_2O contribution about 6%, and other contribution about 13% [4]. Figure 2 shows the main kinds of greenhouse gases and relative emission fraction from human activities. For the predominant greenhouse gas, approximately 70% carbon dioxide (CO_2) come from electricity production due to fossil fuel combustion, such as coal and natural gas (Science Daily, 2007). Table 1 shows the specific data about CO_2 emissions produced by electricity generation in the United States in 2008. Among these data, about 40.3% of anthropogenic CO_2 and 34% of the total anthropogenic GHG emissions come from the electricity generation (EIA, 2010; Bhown et al., 2011).

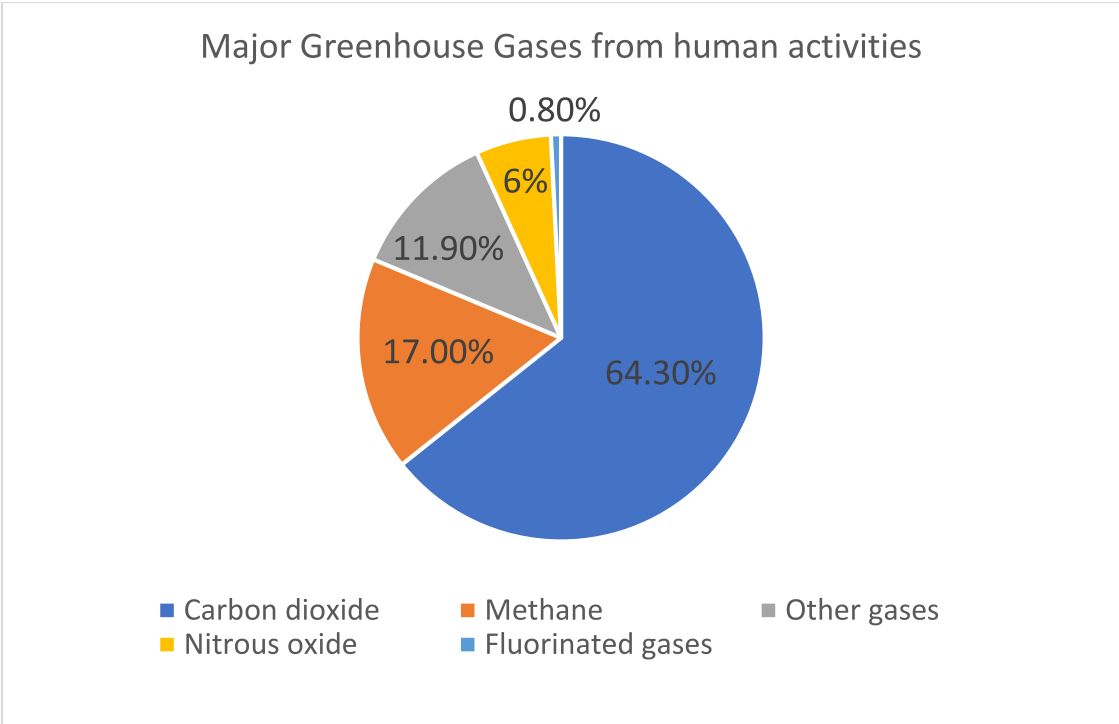

Fig.2. The major greenhouse gases from people's activities (Source: United States Environmental Protection Agency)

Table 1. The quantities of Anthropogenic Greenhouse Gas Emission in United States in 2008 (Source: EIA)

CO_2 emission source	**Gt CO_2**
CO_2 from electricity generation	2.36
CO_2 from non-electricity energy	3.37
CO_2 from other sources	0.11
Total anthropogenic CO_2	5.84
Total anthropogenic non- CO_2 GHG[a]	1.12
Total anthropogenic GHG, CO_2 (equiv.)	6.96

At present, most of power plants use the fossil fuels to generate electricity, such as coal, oil and natural gas, all of which will produce a large quantity of CO_2 during combustion. However, for the foreseeable future, fossil fuels will continue to play an important role in providing the world's energy because of their energy density, plentiful reserves and lower costs. Some kinds of new energy, like solar energy and biofuels, are still in the development stage with lots of difficulties on widespread application, so they will not completely replace the fossil fuels in the short term.

One option for reducing CO_2 emissions is the Carbon Capture and Storage technology (CCS), which provides a promising and effective way to a near-term reduction for the CO_2 emission even if the fossil fuels will be used continuously in the future. The common Carbon Capture and Storage technology consists of three parts, capturing and collecting the carbon dioxide in the vented flue gas with physical or chemical separation, transporting the carbon dioxide, and storing the carbon dioxide underground in depleted gas or oil field, deep oceans and other places where are located several kilometers below the surface of the earth (Haszeldine and Stuart, 2009).

1.2 Challenges and Motivation

Although CCS has great potential for development as a fundamental technical approach to eliminate greenhouse gases, its application will greatly change the traditional way of energy production and affect economic costs. As for the geological structure, marine ecology, human health and the earth cycle, the system has great uncertainty on affecting the living environment of human beings, and it will also change people's existing cognitions, existing laws and regulations and policies, and affect social acceptability potentially (Haszeldine and Stuart, 2009; Murai et al., 2008).

The main challenge which prevents the wide application of CCS technology is also the economic factor—high costs. The International Energy Agency (IEA) showed that the average cost for capture and compression is up to \$58/ton CO_2, which leads to 63% rise for the cost of per kilowatt hour electricity (Finkenrath and Matthias, 2011). Additionally, according to the survey of

American Government Accountability Office in 2010, the current CCS technology will increase the electricity costs by 30% -80% and decrease the electricity production by 15% —32%, even increase the water consumption of power plants, which are the main factors to hinder the application and development of CCS, so if people can solve this economic problem, CCS technology will have better prospects of application and be accepted by more and more owners of power plants.

1.3 Objectives

The main objective of this research is to optimize the flexible operation of power plants with CO_2 capture systems in response to volatile electricity prices with bounded uncertainty. The main aims of this thesis are shown as follows:

1) Develop a model on flexible operation of power plants with carbon capture systems considering volatile electricity prices to maximize the total profits by using mixed-integer nonlinear programming (MINLP) optimization.

2) Build a model in GAMS environment for application in a case study. Then, compare and analyze the results.

CHAPTER 2

LITERATURE REVIEW

2.1 Carbon Capture and Storage Technologies

2.1.1 CO_2 capture technologies

Operating principles for the three main technologies currently proposed for CO_2 capture are shown in Fig.3.

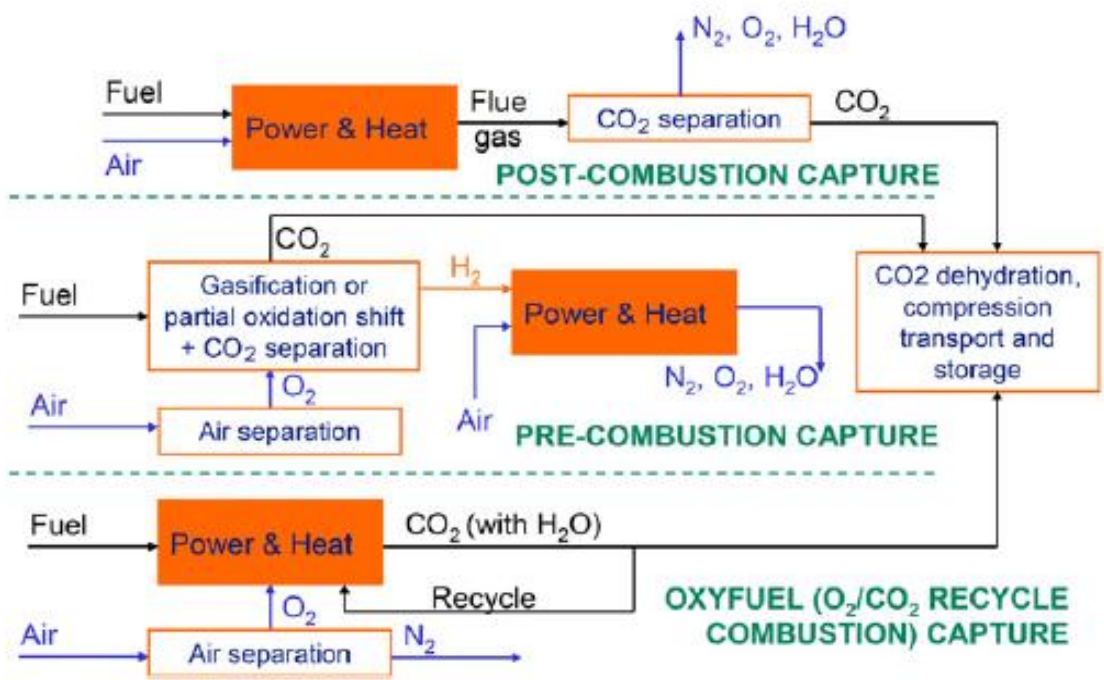

Fig. 3. Principles of three main CO_2 capture options (Jordal et al., 2004)

Pre-combustion capture focuses on taking measures on the burning reaction of fuels. The idea of pre-combustion capture is to convert the fuel into a carbon dioxide-containing syngas that is captured and directly combusted with air, such as the combination of IGCC and CO_2 capture. In addition, natural gas and some other syngas, like coal tar, etc. can be captured by this way. In general, pre-combustion capture also requires air separation units to provide a small amount of oxygen, resulting in an increase in energy consumption. The technologies industrial application of pre-combustion capture is not mature until now, but there is a good improvement prospect.

If trying to concentrate on the oxidant in the combustion reaction, such as oxygen instead of air combustion, people can get oxygen-rich capture method, oxy-combustion. Oxy-combustion capture uses oxygen instead of air for combustion, so that the flue gases after combustion mainly contain carbon dioxide and water (volume fractions are separately about 70% and 15%, and the rest is nitrogen, oxygen, argon and other gases). After condensing the water directly, the carbon dioxide can be captured by purifying the carbon dioxide by flashing at a low temperature. The advantages of these methods are the elimination of solvent absorption and desorption processes and their potential for improvement in terms of energy consumption, but the current energy consumption is still comparable to that of other capture methods and can only be applied to retrofit of new and existing power plants.

In post-combustion capture, most of CO_2 will be removed from the combustion products before they are vented to atmosphere. Figure 4 shows the generic scheme of CO_2 capture process with chemical absorption. At present, the most common and commercial method is to use aqueous amine solutions, such as monoethanolamine (MEA) and ammonia. During this process, the CO_2-containing flue gas will enter into the bottom of absorption column and be absorbed by the lean chemical solvent from the top of the absorber at relative low temperatures and the rest of flue gas, including nitrogen and a small quantity of carbon dioxide which is not absorbed by the chemical solution, will be vented to atmosphere. Then, the rich solvent with absorbed CO_2 is transferred to the desorber after passing through the heat exchanger. In the latter, CO_2 will be released from the rich solvent in the reboiler which provides a large amount of heat, and the lean solvent will be regenerated for re-use to absorb CO_2 in the absorption column. Finally, the CO_2 removed from the solvent will be dried, compressed and transported to safe geological storage (Gibbins and Chalmers, 2008).

Compared with the other two methods, post-combustion capture technologies on coal have higher thermal efficiencies for conversion to electricity and its total electricity costs appears to be lower. Also, the equipment of post combustion capture can be installed conveniently, which is an important factor to publish this technology widely. Thus, in most fossil-fuel power plants, post-combustion capture technologies are applied to reduce the CO_2 emissions with the good economy.

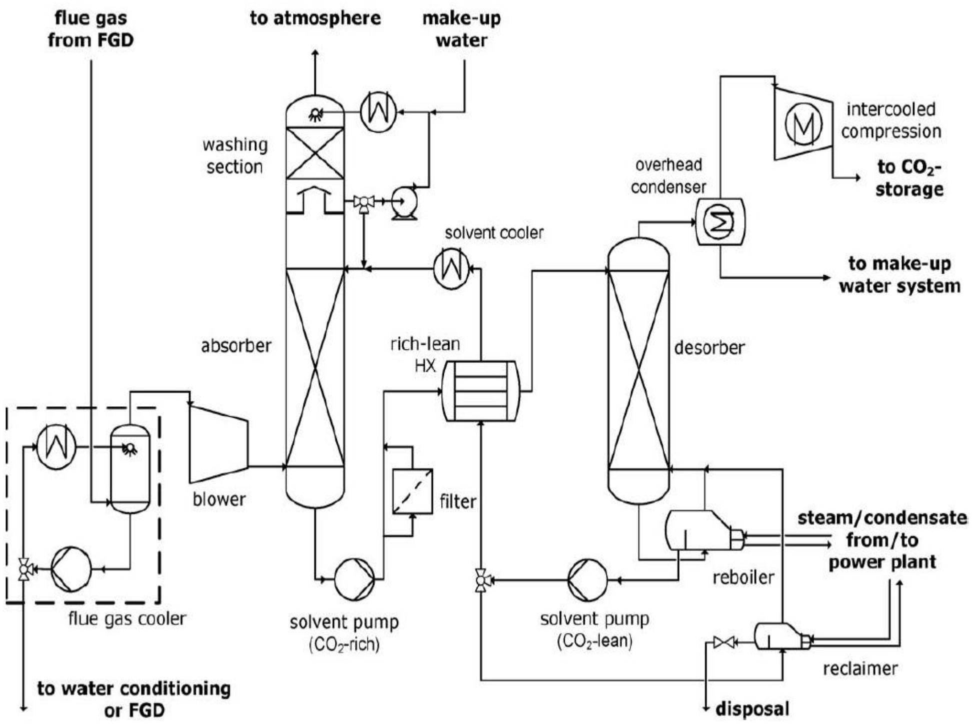

Fig.4. Simplified scheme of CO_2 capture process (Oexmann et al., 2010)

2.1.2 Flexible post-combustion carbon capture

Operating carbon capture system could reduce the CO_2 emission efficiently. However, if the CO_2 capture systems are operated continuously at a full-load operating condition, which is called as inflexible operation, the energy consumption for CO_2 capture and associated electricity production costs will be always high over plant lifetime. For coal-fired power plants which use post-combustion amine absorption/stripping to remove CO_2, CO_2 capture under full-load could reduce net energy output by 11 to 40% compared with those same size plants without CO_2 capture (Davidson and Robert, 2007; Bergerson and Lave, 2007).

Thus, in order to reduce the energy consumption for carbon capture systems and increase the net power output when the electricity is high so that the power plants with CCS technologies could reduce the difference of total profits with those plants without CCS, some people proposed many different methods to operate the carbon capture systems flexibly, which could help most CCPPs improve their profits. For example, bypassing the capture unit when electricity price is high enough is economically preferable to pay the penalty for CO_2 emission instead of operating the capture systems to absorb and strip a large quantity of CO_2 with high electricity consumption (Gibbins and Crane, 2004; Chalmers et al., 2009), which means the method of bypassing could be constrained by some potential regulatory requirements. The configuration of bypassing method is shown in Figure 5. In this way, the CO_2 removal rate decreases by redirecting rich solvent to the absorber. Although it can reduce the energy consumption of capture systems, increased CO_2 emissions and some associated costs will appear, which means the total costs of power plants may increase. Chalmers and Gibbins (2007) show that when only electricity sales are considered and the price is at least two to three times higher than the price of per ton CO_2 emission, it could be economically beneficial to bypass the post-combustion capture systems.

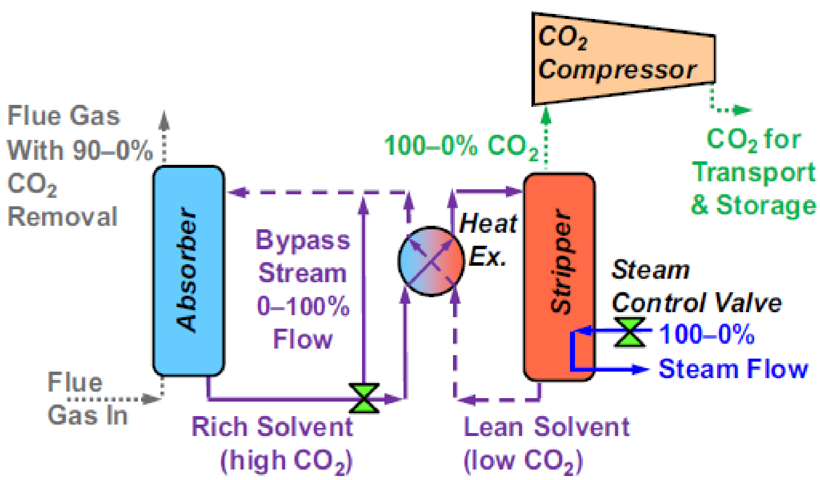

Fig.5. Flexible carbon capture by venting additional CO_2 emissions during reduced capture load (Cohen et al., 2011)

Lucquiaud and Gibbins (2009) have identified and discussed three possible steam cycle configurations, which are separately clutched LP turbine, throttled LP turbine and floating IP/LP crossover pressure, for making coal-fired power plants capture ready for post-combustion capture and have evaluated their respective capability for flexible operation.

An alternative option for flexible operation is solvent storage, which would allow the majority of power output available to the electricity gird by storing the solvents in tanks and reducing the stripping load for limited periods, but without high CO_2 emissions (Chalmers et al., 2009). For this method, two tanks are set in the capture systems. One of them is for rich solvent and the other one is for lean solvent. When carbon capture systems operate, the rich solvents leave the absorber column and can be stored in the rich solvent tank temporarily during times of high electricity price, which will make the stripping load decrease and reduce the energy consumption of capture systems. In the short term, the majority of the energy penalty associated for the CO_2 capture process can be avoided. Later, when electricity price is lower, the stored rich solvent will enter into the stripping column with new rich solvent to be heated and regenerated for re-use, so the profits will increase compared with the inflexible operation under same conditions (Dowell et al., 2014). The schematic of the CO_2 capture systems with solvent storage is shown in Fig.6. Although this configuration could increase the net power output without larger CO_2 emissions and improve the total profits, the capital cost of equipment, including storage tanks, solvent consumption and stripping/compression equipment, should be considered, which may counteract some operating profits. Even so, flexible carbon capture with solvent storage is still a good approach for power plants to reduce the CO_2 emissions with great economy in the perspective of long-term operation.

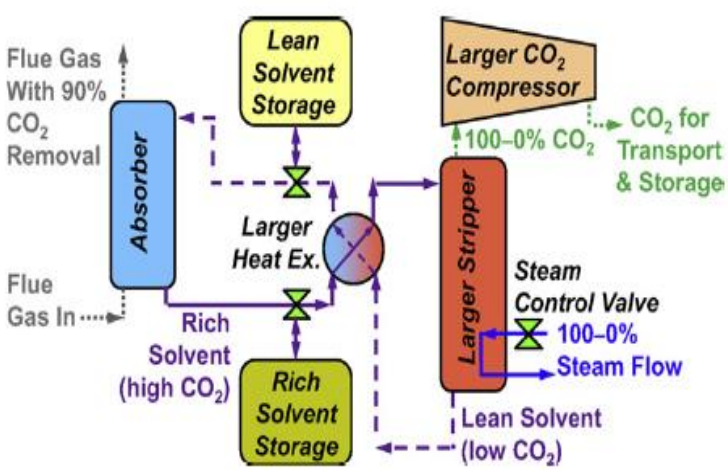

Fig.6. CO_2 capture system with solvent storage (Cohen et al., 2011)

2.2 Scheduling under uncertainty

2.2.1 Background introduction

Within the chemical industry, several uncertainties such as demand fluctuation, and processing time uncertainty frequently happen during the realistic operations. In the presence of these uncertainties, the nominal schedule may often be suboptimal or even become infeasible, so if these uncertainties can be considered and introduced to the industry scheduling, the actual performance of the plants will be more stable and it is economically beneficial for the plants (Ye et al., 2014).

In general, there are two approaches to address those uncertainties: reactive scheduling and preventive scheduling. Reactive scheduling is to change the generated schedule which was made in advance when the unforeseen events occur during the actual execution of the schedule, such as order modification, machine breakdowns, electricity congestion and so on (Tang et al., 2008). At present, there are some various methods for reactive scheduling. Vin et al. (2000) and Rodrigues et al. (1996) provided a new approach for reactive scheduling applied to the multiproduct batch plants. Additionally, Janak et al. (2006) developed a reactive scheduling framework which systematically takes into account the machine shutdown and the modification of orders and used a mixed-integer linear programming (MILP) framework to improve the performance of the current production schedule considering these two unforeseeable events.

The other approach is preventative scheduling, which is to accommodate future uncertainty. The uncertainty can be explicitly taken into account through preventive approaches such as two-stage stochastic programming, parametric programming, fuzzy programming, chance constraint programming, robust optimization techniques (Verderame et al., 2010). For two-stage stochastic programming, all input parameters should be assumed to be known without uncertainty in the first stage. Then, in the second stage, a recourse decision will be made to reduce negative effects of the work in the first stage when a random event occurs, so collecting recourse decisions for all possible and random results is significant (Janak et al., 2007). Bassett et al. (1997) applied stochastic approaches to improve the scheduling performance for chemical industries with uncertainty parameters, including processing time, product demands and equipment conditions, which used

Monte Carlo sampling to generate some stochastic instances with uncertainty and make a schedule for those instances. Taking into account the problem of scheduling under demand uncertainty, Balasubramanian and Grossmann (2004) used a multistage stochastic mixed-integer linear programming model to introduce the uncertainty parameters on scheduling, where some decisions are made upon realization of the uncertainty and an approximation strategy was proposed to solve a two-stage problem with a shrinking-horizon.

For fuzzy programming, the uncertainty parameters are regarded as fuzzy numbers and the relative constraints are also considered as fuzzy sets, which is the fuzzy set theory utilized when distribution information is unknown. Petrovic and Duenas (2006) proposed a new fuzzy logic decision support system for scheduling or rescheduling considering the uncertain disruption of machine systems. Moreover, other scholars, like Balasubramanian et al. (2003) and Wang (2004), utilized fuzzy programming to the scheduling with uncertainty parameters.

Chance constraint programming is also a common method toward the problems with uncertainty. You and Grossmann (2008) applied chance constraint programming on the supply chains with demand uncertainty. Additionally, Mitra et al. (2008) also utilized chance constraint programming to solve the problems of midterm supply chain planning under uncertainty. However, the chance constraints programming cannot guarantee that the solution for all uncertain parameters is feasible, which can only assure the feasibility for a specified probability distribution. On the contrary, another technique is robust optimization could ensure the obtained solution is feasible under the nominal conditions, which will be introduced in the next section.

2.2.2 Bounded uncertainty with robust optimization

Robust optimization techniques have been developed where probabilistic constraints are converted into deterministic robust counterpart problem by introducing some auxiliary variables under the given magnitude of uncertainty level, an infeasibility tolerance and a reliability level, which guarantees that the obtained solution is feasible for the nominal set of system conditions and is robust to the multiple uncertainties present in the system under study (Chen et al., 2012).

The robust optimization framework firstly needs to express the actual parameter values through the declaration of random variables, then the formulation of probabilistic constraints, and finally converting these probabilistic constraints into their deterministic counterparts, which are added to the existing model (Verderame et al., 2010).

In this work, the theorems of a novel robust optimization methodology proposed by Lin et al. (2004) will be applied to a MINLP model, aiming at maximizing the operating profits of CCPPs under the uncertainty of electricity prices. The main theorems in the aforementioned paper are shown as follows:

1) Considering the following generic MILP problem:

$$\begin{aligned} & \underset{x,y}{Min\,/\,Max} \quad c^T x + d^T y \\ & s.t.\;\; Ex + Fy = e \\ & Ax + By \le p \\ & \underline{x} \le x \le \overline{x} \\ & y = 0,1 \end{aligned} \tag{1}$$

Assume that the bounded and symmetric uncertainty arises from both the coefficients and the right-hand-side parameters of the inequality constraints, which is denoted as follow:

$$\sum_m a_{lm}^* x_m + \sum_k b_{lk}^* y_k \le p_l^* \tag{2}$$

$$\begin{aligned} a_{lm}^* &= (1+\epsilon \xi_{lm}) a_{lm} \\ b_{lk}^* &= (1+\epsilon \xi_{lk}) b_{lk} \\ p_l^* &= (1+\epsilon \xi_l)\, p_l \end{aligned} \tag{3}$$

where a_{lm}, b_{lk} and p_l are the nominal values of the uncertain parameter, and a_{lm}^*, b_{lk}^* and p_l^* are the "true" values of the uncertain parameters, and ϵ >0 is a given uncertainty level. ξ_{lm}, ξ_{lk} and ξ_l are independent random variables, which are distributed symmetrically in the interval [-1,1].

2) The two requirements of a solution (x, y) robust:

(i) (x, y) is feasible for the nominal problem.

(ii) For every inequality l, the probability of violation of the uncertain inequality is at most *k*:

$$\Pr\left\{\sum_m a_{lm}{}^* x_m + \sum_k b_{lk}{}^* y_k > p_l{}^* + \delta \max[1, |p_l|]\right\} \le k \tag{4}$$

where δ is infeasibility tolerance and *k* is reliability level.

3) Theorem 2 in the previous paper is based on the aforementioned two requirements to generate robust solutions under an infeasibility tolerance (δ) and a reliability level (k). Then, the following robust counterpart of the original uncertainty MILP problem in equation (1) can be derived:

$$\begin{gathered}
\underset{x,y,u,z}{Min / Max} \quad c^T x + d^T y \\
s.t. \ \ Ex + Fy = e \\
Ax + By \le p \\
\sum_m a_{lm} x_m + \sum_k b_{lk} y_k + \epsilon[\sum_{m \in M_l} |a_{lm}| u_{lm} \\
+\Omega \sqrt{\sum_{m \in M_l} a_{lm}^2 z_{lm}^2 + \sum_{k \in K_l} b_{lk}^2 y_k + p_l^2} \,] \\
\le p_l + \delta \max[1, \ |p_l|], \quad \forall l \\
-u_{lm} \le x_m - z_{lm} \le u_{lm}, \quad \forall l, m \\
\underline{x} \le x \le \overline{x} \\
y_k = 0,1, \quad \forall k
\end{gathered} \tag{5}$$

Where Ω is a positive parameter with $\kappa = \exp\{-\Omega^2/2\}$.

4) In addition, Lin, et al [24] apply the above-mentioned theorem to address the problem of scheduling under uncertainty of the market prices. The general objective function is to maximize

the total profit, which is the difference between the revenue of product sales and the cost of raw materials:

$$Maximize\ \ \text{Profit} = \sum_{s\epsilon S_p} P_s \cdot STF(s) - \sum_{s\epsilon S_r} p_s \cdot STI(s) \tag{6}$$

where S_p and S_r are the sets of final products and raw materials, respectively; STI(s) and STF(s) are continuous variables representing the initial amount of state (s) at the beginning and the final amount of state (s) at the end, respectively. This objective function can be expressed in an equivalent way as follows:

$$Maximize\ \ \text{Profit}$$

$$\text{s.t. Profit} \le \sum_{s\epsilon S_p} P_s \cdot STF(s) - \sum_{s\epsilon S_r} p_s \cdot STI(s) \tag{7}$$

Then, if the uncertainty of market prices is bound and symmetric:

$$p_s^{\ *} = (1+\epsilon\xi_l)\, p_s \tag{8}$$

Based on the theorem 2, the prices uncertainty ϵ can be introduced in the model, so the deterministic robust counterpart problem could be created:

$$\begin{gathered}
-\sum_{s\epsilon S_p} P_s \cdot STF(s) + \sum_{s\epsilon S_r} P_s \cdot STI(s) + \text{Profit}(1-\delta) \\
+\epsilon\left[\sum_{s\epsilon S_r} P_s y(s) + \sum_{s\epsilon S_p} P_s y(s) + \Omega\sqrt{\sum_{s\epsilon S_r} p_s^2 z(s)^2 + \sum_{s\epsilon S_p} p_s^2 z(s)^2}\,\right] \le 0 \\
-y(s) \le STI(s) - z(s) \le y(s), \quad \forall s \in S_r \\
-y(s) \le STF(s) - z(s) \le y(s), \quad \forall s \in S_p
\end{gathered} \tag{9}$$

where $\kappa = \exp\{-\Omega^2/2\}$.

CHAPTER 3

MODEL FORMULATIONS FOR FLEXIBLE CARBON CAPTURE

3.1 Base Scenario

In the field of optimal flexible operation of CO_2 capture, Cohen et al. proposed a price-based profit maximization model considering the short-term price volatility and intertemporal plant operating constraints to study generator operation in competitive electricity markets [25]. They used the day-ahead forecasting with pseudo-forecasted prices to produce the input electricity prices considering historical prices (Cohen et al., 2011). In addition, Chen Qixing et al. (2012) also proposed a profit maximization model for flexible carbon capture, which is based on a day-ahead electricity market and a cap-and-trade carbon emission market, and operators of the CCPPs could make reasonable decisions with the model on their power output, CO_2 capture schedules and bidding strategies in day-ahead markets in response to volatile electricity prices and carbon prices.

In this work, a mixed-integer nonlinear program (MINLP) is created based on the aforementioned papers and simulated in the General Algebraic Modeling System (GAMS). The bounded and symmetric uncertainty in the real-time electricity market price is introduced to this model, which will help operators of the CCPPs schedule their next-day work reasonably to reduce risks and maximize their profit.

3.2 Objective Function

This objective function is to maximize the total profits of one-day operation in the CCPPs. This profit is the sum of the revenues ($\mathrm{Re}v_t$) from the real-time electricity market during 24 hours subtracts the total costs including sum of the fuel cost (C^{Fuel}), base plant operation and maintenance cost ($C_t^{O\&M}$), CO_2 emissions cost ($C_t^{CO_2}$) and CO_2 transport and storage cost ($C_t^{T/S}$):

$$Max\ \text{Profit} = \sum_{t=1}^{T} (\mathrm{Re}\, v_t - C_t^{Fuel} - C_t^{O\&M} - C_t^{co_2} - C_t^{T/S}) \tag{10}$$

1) The revenue at time t, $\mathrm{Re}\, v_t$, is product of the hourly electricity price and the hourly net power output, which could be expressed as follow:

$$\mathrm{Re}\, v_t = P_t^e x_t^N \tag{11}$$

where P_t^e represents the electricity price at hour t, and x_t^N is the net power output at hour t.

2) Net power output is the difference between gross output and the energy requirements of absorption and stripping/compression systems (Eq. 12).

$$x_t^N = x_t - e^a R^b F \bar{x} y_t^a - e^s R^b F \bar{x} y_t^s \tag{12}$$

where e^a and e^s separately represent the absorption equivalent work and stripping/compression equivalent work. y_t^a and y_t^s separately represent the absorber load and stripper load. R^b is base plant CO_2 emissions rate. F is design CO_2 removal fraction. x_t is gross power output, and $\bar{x}$ is maximum gross power output. Thus, $R^b F \bar{x} y_t^a$ is the quantity of CO_2 absorbed, and $R^b F \bar{x} y_t^s$ is the quantity of CO_2 stripped.

3) The fuel cost at hour t, C_t^{Fuel}, is product of the fuel price, the gross power output and the base plant heat rate, which is as Eq. (13) shows:

$$C_t^{Fuel} = P^{Fuel} H^b x_t \tag{13}$$

where P^{Fuel} is the fuel price, which is constant, and H^b is the base plant heat rate, and x_t is the gross power output at hour t.

4) Operation and maintenance costs for the base plant are the product of marginal operation and maintenance costs (OM^b) and gross power output (x_t):

$$C_t^{O\&M} = OM^b x_t \tag{14}$$

5) CO_2 emission costs are the product of the assumed CO_2 price (P^{CO_2}) and the net CO_2 emission, E_t^N , which is the difference between the quantity of CO_2 produced by the base plant during the power generation ($R^b x_t$) and the amounts of CO_2 absorbed ($R^b F \bar{x} y_t^a$):

$$C_t^{CO_2} = P^{CO_2} E_t^N = P^{CO_2}(R^b x_t - R^b F \bar{x} y_t^a) \tag{15}$$

6) CO_2 transport and storage costs are the product of the transport and storage price ($P^{T/S}$) and the amounts of CO_2 stripped ($E_t^s = R^b F \bar{x} y_t^s$):

$$C_t^{T/S} = P^{T/S} R^b F \bar{x} y_t^s \tag{16}$$

3.3 Constraints

1）Capacity Constraints for Generation System: The gross power output of the plants has the lower and upper bound:

$$\underline{x} \le x_t \le \bar{x} \tag{17}$$

where $\underline{x}$ is minimum gross power output and $\bar{x}$ is maximum gross power output.

2) Constraints for absorption load and stripping load:

$$\begin{cases} u_t^a y_{\min}^a \le y_t^a \le u_t^a y_{\max}^a \\ u_t^s y_{\min}^s \le y_t^s \le u_t^s y_{\max}^s \end{cases} \tag{18}$$

where u_t^a and u_t^s are binary variables, which separately control startup and shutdown of the absorber and stripper and prevent operation between zero and the minimum load.

3) Ramping Constraints for the Generation System:

$$-\Delta x_R \le x_{t+1} - x_t \le \Delta x_R \tag{19}$$

where Δx_R is the maximum ramp rate for the gross power output.

4) Ramping Constraints for the Capture System:

$$\begin{cases} -\Delta y_{\max}^a \le y_{t+1}^a - y_t^a \le \Delta y_{\max}^a \\ -\Delta y_{\max}^s \le y_{t+1}^s - y_t^s \le \Delta y_{\max}^s \end{cases} \tag{20}$$

where $\Delta y_{\max}^a$ and $\Delta y_{\max}^s$ denote the maximum ramping rates for the absorption load and stripping load.

5) Constraints on the Solvent tanks: These constraints are created to ensure that the quantity of solvent stored in the rich solvent tank and the lean solvent tank cannot exceed their capacities.

$$\begin{cases} S_{a,t} = S_{a0} y_t^a \\ S_{s,t} = S_{s0} y_t^s \end{cases} \tag{21}$$

where $S_{a,t}$ and $S_{s,t}$, respectively, denote the flowrates at which the rich solvent is pumped into the tank from the absorber and the lean solvent is pumped into the tank from the stripper at time t, and they are both the product of the flowrates at full load operation, S_{a0} & S_{s0} , and the relative load, y_t^a & y_t^s.

Then the volume of solvent in the tanks at time t, $S_{a,t}^T$ and $S_{s,t}^T$, are shown as follow:

$$\begin{cases} S_{a,t}^T = S_{a0}^T + \sum_{i=1}^{t}(S_{a,i} - S_{s,i}) \\ S_{s,t}^T = S_{s0}^T + \sum_{i=1}^{t}(S_{s,i} - S_{a,i}) \end{cases} \tag{22}$$

where S_{a0}^T and S_{s0}^T are the initial volumes of solvent in the two tanks. It is obvious that the volume of solvent in the tanks should be non-negative and could not exceed the maximum capacities, $S_{a,\max}^T$ and $S_{s,\max}^T$:

$$\begin{cases} 0 \le S_{a,t}^T \le S_{a,\max}^T \\ 0 \le S_{s,t}^T \le S_{s,\max}^T \end{cases} \tag{23}$$

6) CO_2 Emission Intensity Constraints:

$$\sum_{t=1}^{T} E_t^N \le e_{\max}^{CO_2} \sum_{t=1}^{T} x_t^N \tag{24}$$

where E_t^N is the net CO_2 emission and $e_{\max}^{CO_2}$ is the baseline CO_2 emission intensity, then x_t^N is the net power output.

7) Constraints for the deterministic robust counterpart problem considering the bounded and symmetric uncertainty of electricity price: According to the theorems in the work of Lin, Xiaoxia et al. (2004), which are shown in the Chapter 2, if the electricity price is bounded and symmetric:

$$P_t^{e*} = (1+\epsilon\xi)P_t^e \tag{25}$$

where ξ is the random variable, which is distributed symmetrically in [-1.1], and ϵ denotes the uncertainty level. Then, P_t^{e*} is the actual electricity price, whereas P_t^e is the nominal or predicted electricity price. The deterministic robust counterpart could be obtained by introducing the following constraint:

$$-\sum_{t=1}^{T} P_t^e x_t^N + \sum_{t=1}^{T} (P^{Fuel} H^b + OM^b) x_t + \sum_{t=1}^{T} P^{CO_2} E_t^N + \sum_{t=1}^{T} P^{T/S} E_t^s + \text{Profit}(1-\delta)$$

$$+\epsilon[\sum_{t=1}^{T} P_t^e y_{1,t} + \Omega\sqrt{\sum_{t=1}^{T} (P_t^e)^2 Z_{1,t}^2}\,] \le 0 \tag{26}$$

$$-y_{1,t} \le x_t^N - Z_{1,t} \le y_{1,t} \tag{27}$$

where $y_{1,t}$ and $Z_{1,t}$ are the auxiliary variables, and δ is infeasibility tolerance, and k is reliability level, which is expressed by $k = \exp\left(-\Omega^2 / 2\right)$.

CHAPTER 4
CASE STUDY

4.1 Model input parameters

The data used in this work comes from the literature (Cohen et al., 2012; Chen, Qixin et al., 2012). Specifically, a 500-MW coal-fired power plant is chosen as a representative size. The minimum power output is 150MW and base plant heat rate is 10.8MMBTU/MWh. Additionally, the CO_2 emission rate is 0.43t/MWh. The maximum ramp rate of power generation is assumed to be 360MW/h.

For the capture system, a typical 90% CO_2 removal is used. Then, 11% of the total energy assumption for CO_2 capture system is supplied to absorption system, and 89% is attributed to stripping and compression systems. Moreover, the minimum values of absorption load and stripping load are both 0.3. Besides, the maximum values of absorption load are 1, but the upper bound of stripping load is 1.25, which is larger than 1, because some rich solvent was stored in the past leading to the mass flow to the stripper exceeding the mass flow at 100% load. In addition, the flow rates of rich solvent and lean solvent are both set at 7300m3/h, and the capacities of two tanks are 14600m3, which allows 2 hours of solvent storage under full-load operation. Also, the baseline CO_2 emission intensity is set at 0.3t/MWh. Then, all the key input parameters are shown in Table 2 and the nominal electricity prices with bounds are shown in Fig.7.

Table 2. The key data is used in the profit maximization model.

Parameter	Value
Maximum output (MW)	500
Minimum output (MW)	150
Heat rate (MMBTU/MWh)	10.8
CO_2 emission rate (t CO_2/MWh)	0.43
Baseline CO_2 emission intensity (tons/MWh)	0.3
Maximum ramp rate of power generation (MW/h)	360
Design CO_2 removal (fractional)	0.9
Absorber equivalent work (MWh/t CO_2)	0.0296
Stripper/compression equivalent work (MWh/t CO_2)	0.2394
Minimum absorber/stripper load (fractional)	0.3
Maximum absorber load (fractional)	1.0
Maximum stripper load (fractional)	1.25
Maximum ramp rate of absorption and stripping load	1
the initial volume of solvent in the tanks (m3)	7300
Base case solvent flowrate (m^3/h)	7300
Maximum of tank capacity (m^3)	14600
Fuel price ($/MMBTU)	1.54
Marginal operation and maintenance cost ($/MWh)	15
CO_2 price ($/t)	50
CO_2 transport and storage cost ($/t)	7
Infeasibility tolerance (fractional)	0.1
Reliability level (fractional)	0.1

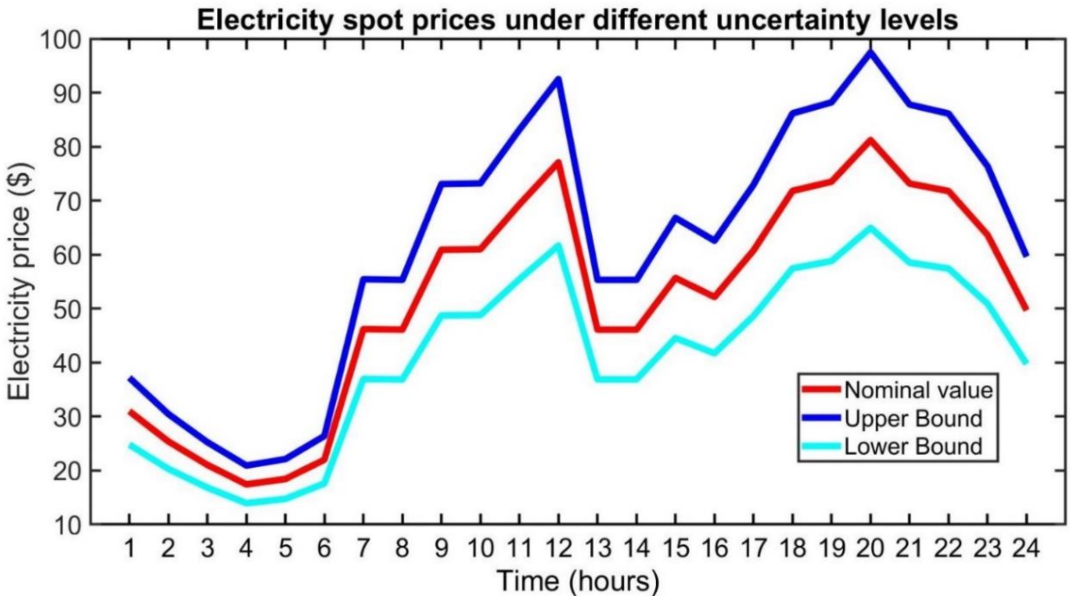

Fig.7. Daily profile of forecast electricity prices with 20% uncertainty.

4.2 Results comparison

Table 3 shows the maximum operating profits of the power plant under different uncertainty of electricity prices, and the trend of profits with uncertainty is shown in Fig.8. It is obvious that the higher the uncertainty level of electricity prices is, the lower the operating profit becomes. One of the explanations is that the feasible range of the model will reduce with the increasing uncertainty levels.

Table 3. The total profits of the power plant under different uncertainty of electricity prices

Uncertainty Level	Profit ($)
0% (Nominal Solution)	152443.276
5%	144481.919
10%	139418.170
15%	137528.969
20%	135204.624

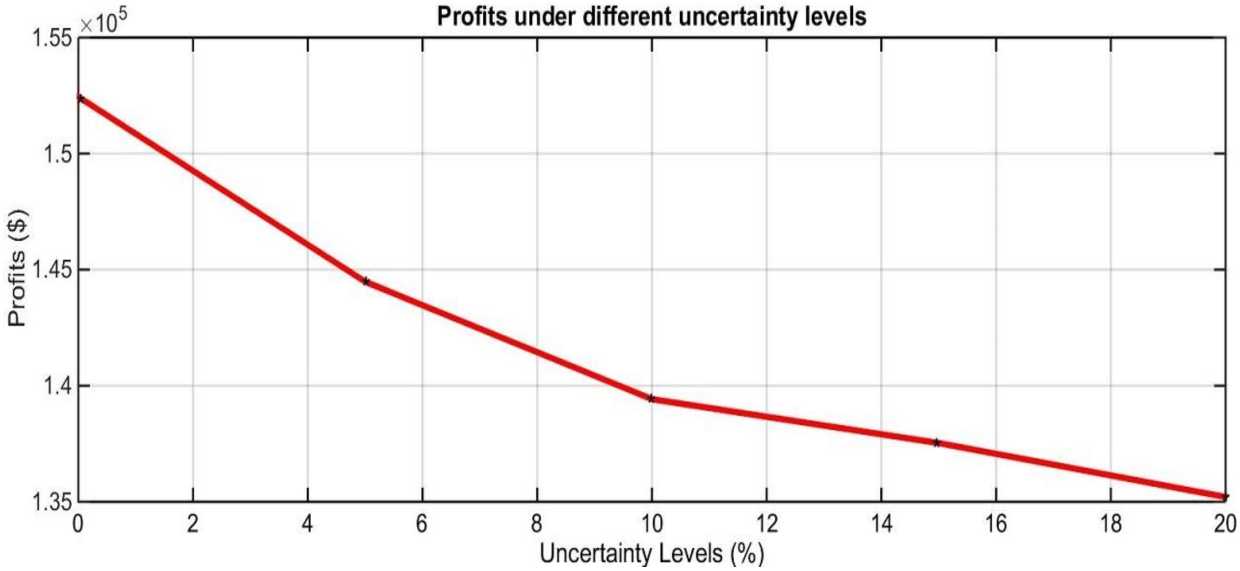

Fig.8. The trend of total profits with different uncertainty.

Fig.9 shows the optimal power production schedule of the CCPP under the nominal electricity price. Fig.10, Fig.11, Fig.12 and Fig.13 show the optimal power production schedule of the carbon capture power plant respectively under different uncertainty of electricity prices. In these plots, the blue bars represent the net power outputs in each hour and the red bars represent the energy supply to the carbon capture system, and the sum of the two kinds of bars is described as the gross power outputs of the CCPP. Besides, the curve shows the forecast electricity prices by the CCPP, which are also the nominal electricity prices. During the high electricity price periods, the power plant will increase its net power output by increasing the gross output and simultaneously reducing the power output for the capture system. On the contrary, during the lower price periods, the power plant will reduce the gross output in order to decrease the net power output, but it will increase the energy supply to the capture system so that it could capture more CO_2, which may be stored in the solvent in the past few hours. However, due to the flowrate of solvent and the size of storage tanks, the maximum storage time under full-load operation is two hours, so sometimes the power plant has to provide extra energy for capture systems during the high electricity price periods, which is as the following figures present. Moreover, if the electricity prices are uncertain and fluctuate between the upper and lower bounds, then the preventive schedules of power production schedule will be different under different uncertainty levels.

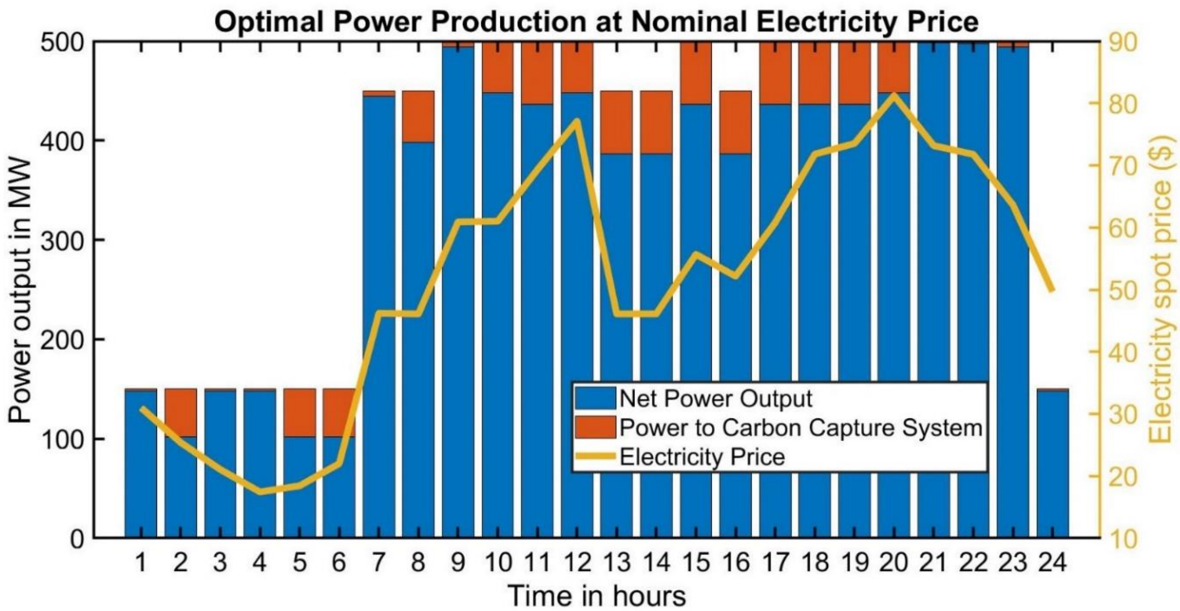

Fig.9. Optimal power production schedule under the nominal value of electricity price.

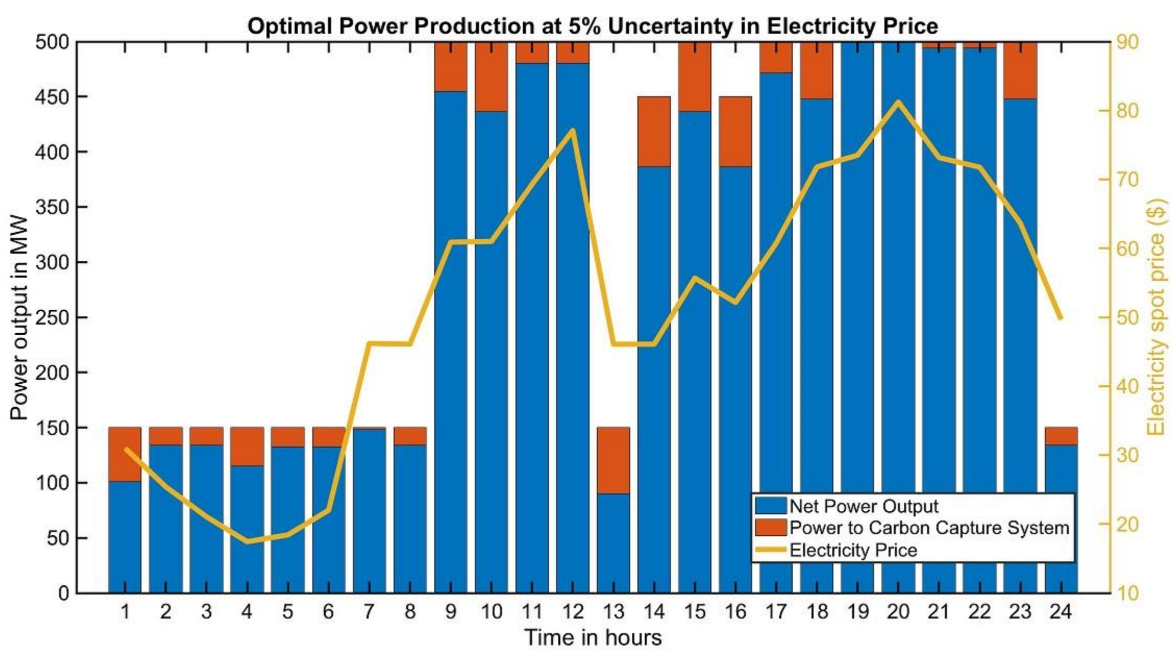

Fig.10. Optimal power production schedule with 5% uncertainty of electricity price

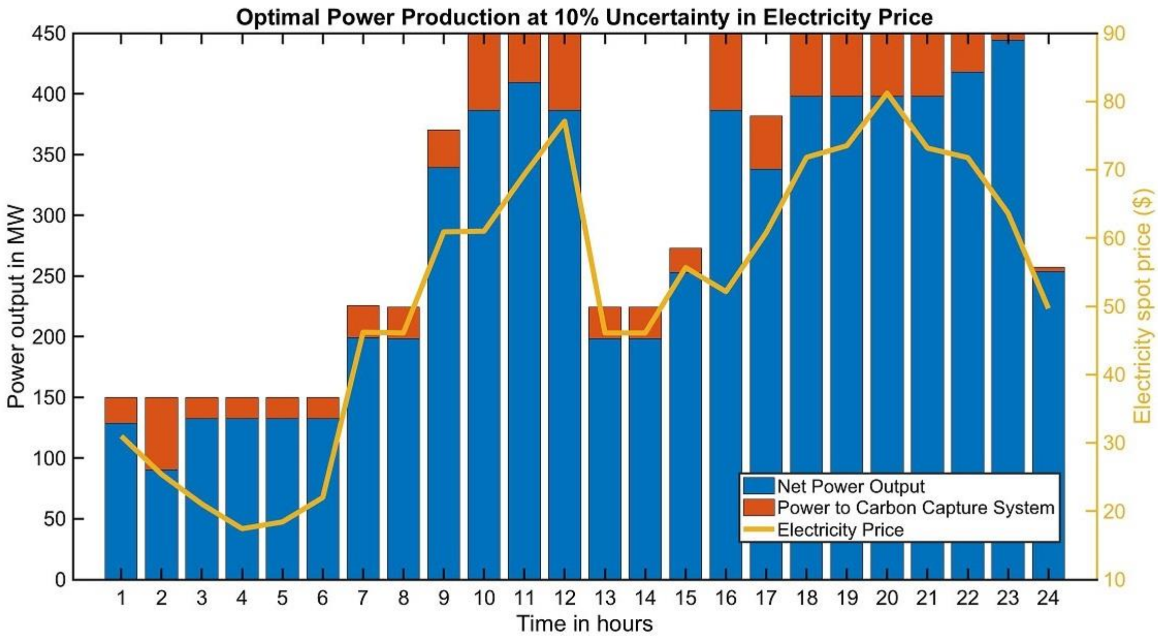

Fig.11. Optimal power production schedule with 10% uncertainty of electricity price.

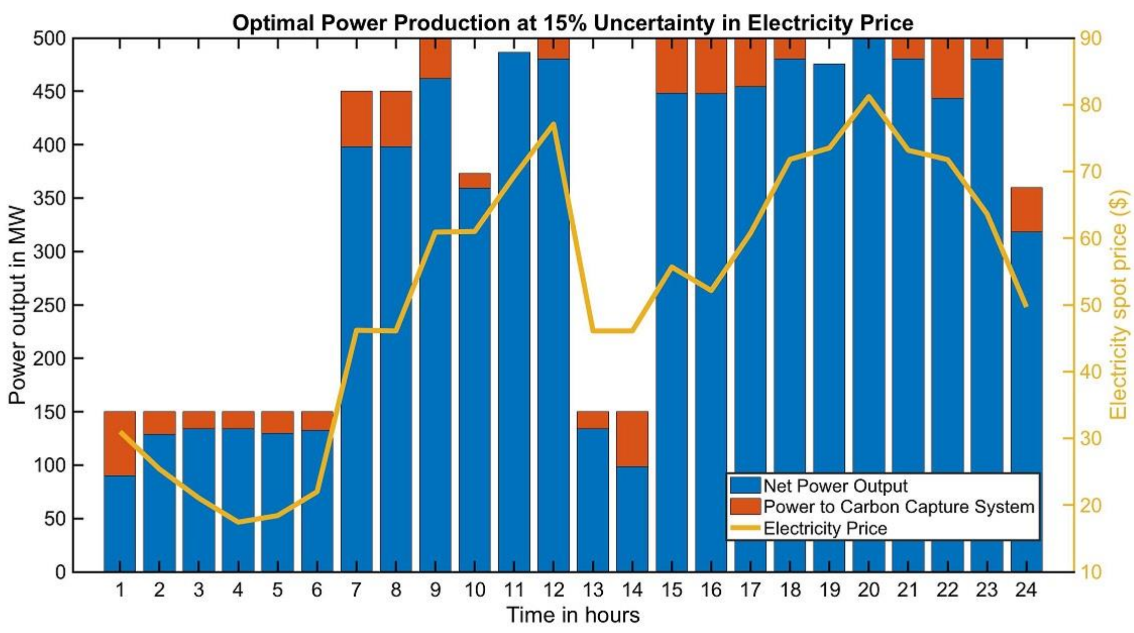

Fig.12. Optimal power production schedule with 15% uncertainty of electricity price.

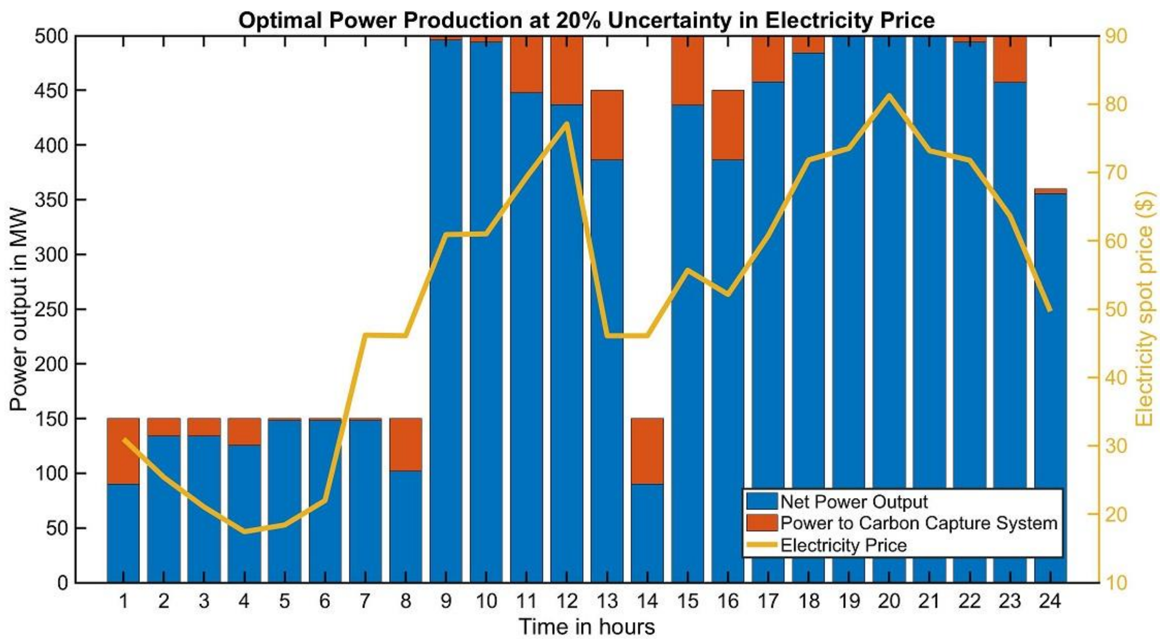

Fig.13. Optimal power production schedule with 20% uncertainty of electricity price.

In fig.14, the red points show the optimal operating profits considering different uncertainty levels of electricity prices, which is also shown in figure 8. The blue points represent the maximum profits without uncertainty, which use upper bound electricity prices as input parameters. The yellow points denote the minimum profits without uncertainty, which use lower bound electricity prices as input parameters. The specific data is shown in Table 4. It is obvious that the range is increasing when the uncertainty level rises up. If the power plant can consider the uncertainty of electricity prices, they will assure that the profits are relatively stable under the changeable electricity prices, so it is beneficial for the power plant to make the next-day production schedule.

Table 4. The profits with and without uncertainty

Uncertainty Level	Lower Bound without uncertainty ($)	with uncertainty ($)	Upper Bound without uncertainty ($)
0% (Nominal Solution)	152443.276	152443.276	152443.276
5%	128550.356	144481.919	177296.920
10%	103189.7	139418.170	202562.285
15%	89130.602	137528.969	226600.326
20%	66847	135204.624	252771.918

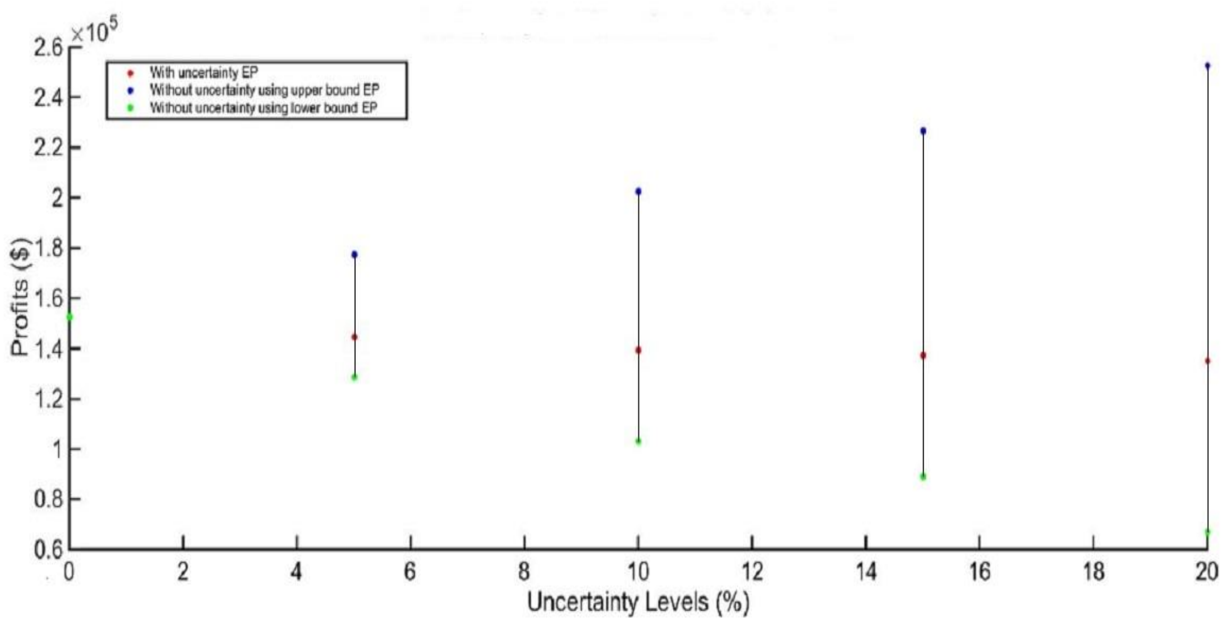

Fig.14 Comparison of obtained profits with and without uncertainty

CHAPTER 5
CONCLUSIONS

The main objective of this thesis is to introduce the bounded and symmetric uncertainty of electricity market prices by robust optimization based on the previously cited study to scheduling for flexible operation of power plants with CO_2 capture systems. Then, a MINLP model is proposed, which uses maximizing the total profits as objective function and considers constraints, like gross output capacity, the ramp rate of generation systems and capture systems, solvent tanks capacity and the constraint with electricity uncertain using robust optimization. Additionally, a typical coal-fired power plant with carbon capture systems has been chosen as the target and the data of input parameters are all based on the previous work. Then, the results of simulation by GAMS are obtained, including operating profits, gross output and net output in each hour under different uncertainty levels of electricity prices. Also, the optimal output scheduling of power plants under different uncertainty levels of electricity prices have been shown by stack column charts in Chapter IV. Finally, the total operating profits under different uncertainty levels of electricity prices have been compared, which denote that the higher the uncertainty level of electricity prices is, the lower the operating profit becomes.

Future directions are listed below:

1) Studying other technologies of preventive scheduling addressing uncertainty, such as stochastic programming, parametric programming and fuzzy programming.

2) Applying those technologies to the model under the uncertainty of electricity prices and comparing the final profits obtained by each technology.

3) Studying the other approach addressing market price uncertainty, which is reactive scheduling, and use it to treat the unforeseeable events during the production of power plants.

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