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**A multi-period power generation planning model incorporating the non-carbon external costs: A case study of China**

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**Abstract:**

The negative externalities apart from carbon emissions are often neglected in most power generation planning models, which will affect the human health, biodiversity, crop yield and land use greatly. To achieve a sustainable development of China's power industry, this paper develops a deterministic linear programming model with consideration of the non-carbon externalities. This model has been applied for the case study of China for the period from 2015 to 2030, through which some interesting results have been drawn. Firstly, most of the new capacity additions are from the non-fossil fuel power plants in this planning horizon, which account for 84% of the total new capacity additions. Secondly, the power generation priority would better be given to the non-fossil fuel power plants in this horizon under the cost-effectiveness criteria. Thirdly, the minimum total cost of China's power planning is 34.48 trillion yuan, which equals to 2% of China's GDP during the planning horizon. Finally, neglecting of non-carbon externalities does have a significant influence on the power planning results, which will lead to a higher power generation share of technology with bigger negative externalities.

**Keywords:** Power planning; Investing strategy; Operating strategy; Externalities; Linear programming

**Highlights**

- A deterministic linear programming model is established for China's power planning.
- The non-carbon external cost of different power generating technologies is incorporated into the model.

- The construction lead time of different technologies is taken into consideration in this study.
- Operating strategies of different technologies in the planning horizon are analyzed.
- Government policy concerning the power development are included in the optimization model.

**JEL classification:**

Q41
Q42
Q47
Q48
Q51
Q53

## 1 Introduction

Thanks to the rapid growth of China's electricity consumption and its coal-dominated power generating structure,[1] the power industry is the largest contributor of China's carbon emissions, which accounts for 43% of the national carbon emissions in 2013 (Teng et al., 2014). Therefore, the power industry is often blamed for its negative externalities of carbon emissions in the context of coping with climate change issues (Mi et al., 2015; Wei et al.,

[1] The coal-fired power account for 71% of China's total electricity consumption in 2014.

2008; Wei et al., 2015). However, apart from the $CO_2$ emissions, there are also sulfur dioxide ($SO_2$), nitrogen dioxide ($NO_2$) and particulate matters (PM) emitted during the power generating process, which have negative effects on the human health, biodiversity, crop yield and land use (Mi et al., 2014; Wang et al., 2015; Wei et al., 2012; Zhang et al., 2007). To achieve a sustainable and environmentally friendly development of China's power industry, incorporating the external effects into the power planning is a good approach (Hondo, 2005; Rentizelas and Georgakellos, 2014). This is because a newly constructed power plant can usually work for several decades and has a lock-in effect,[2] so it will have long-term impacts on the economic growth and environmental protection. Moreover, internalizing the external cost into the power production will obtain a better choice of the technology deployments and operations.

The power industry's external effects have received great attention of the Chinese government, and a series of policies concerning the power planning have been issued to reduce the carbon emissions and other pollutants. After the 2009 Copenhagen climate conference, Chinese government proposed the target that China's renewable energy consumption must account for 15% the total primary energy consumption in 2020 (Cong and Shen, 2014). In the US-China climate agreement issued in November 2014, Chinese government declared that China aim to peak its greenhouse gas emissions ahead of 2030 and it also planned to increase the share of renewables and nuclear in its primary energy consumption mix to 20% by 2030. Moreover, the National Climate Change Plan (2014-2020) released in 2014 stated that the installed capacities of hydropower, nuclear power, wind power and solar power will strive to reach 350GW, 58GW, 200GW, and 100GW respectively in 2020.

However, a country's power planning is truly a challenging task. Since many power generating and operating technologies are available now, it is difficult to obtain an optimal portfolio of technologies with different parameters, such as the construction lead time, operating life time and cost. Moreover, power planning faces various kinds of uncertainties, such as the electricity price and fuel price fluctuations, technological innovations and new climate policies (Cong and Wei, 2010, 2012). In addition, power planning is also subjected to a lot of constraints, like the economic constraints, technical constraints, environmental constraints and government policy constraints. All these factors pose difficulties and challenges to the China's power planning and investment.

To provide a decision-making support for China's power planning, this paper establishes a linear programming optimization model named Power Planning Optimization Model of China (PPOM-CHINA) with consideration of the non-carbon external costs. This model is applied to the China's power planning for the period from 2015 to 2030, from which the optimal development roadmap of China's power sector are drawn. Moreover, the investing strategies and operating strategies of every technology are summarized based on the optimized results, and the power generation cost are estimated based on the optimized results. Finally, the influence of non-carbon external cost on the power planning is explored.

The remainder of this paper is organized as follows：Section 2 is the literature review. Section 3 presents the methodology and data. Section 4 provides the empirical results of China's power planning, and Section 5 summarizes the primary conclusions and proposes some policy implications.

[2] the lock-in refers to the self-perpetuating inertia created by these power plants that inhibits public and private efforts to introduce alternative energy technologies.

## 2 Literature review

Power planning involves large amounts of money and resources, which has attracted many researchers' interests (Amagai and Leung, 1991; Connolly et al., 2010; Eto, 1990; Hobbs, 1995; Koltsaklis et al., 2014; Koltsaklis and Georgiadis, 2015; Talukdar and Wu, 1981; Turvey and Anderson, 1977). The initial focus of power planning is mainly about how to choose the right type and size of power plants to invest to meet the demand at an acceptable economic cost (Hobbs, 1995). However, the problem has become more complex today with the development of the electric system and carbon market (Cong, 2013; Li et al., 2015; Mirzaesmaeeli et al., 2010; Rentizelas et al., 2012; Zhang et al., 2012a).

To cope with the power planning problems, various optimization methods and simulation tools have been developed and applied, including the linear (Cheng et al., 2015; Wu and Huang, 2014; Zhang et al., 2013a; Zhang et al., 2013b) and non-linear (Cai et al., 2009; Delarue et al., 2011; Huisman et al., 2009; Roques et al., 2008; Vazhayil and Balasubramanian, 2013), deterministic (Choi and Thomas, 2012; Cong, 2013) and stochastic models (Heinrich et al., 2007; Kumbaroğlu et al., 2008; Madlener et al., 2005; Tolis and Rentizelas, 2011; Zhou et al., 2015). All these models have three basic elements, an objective of the desired future power system, a set of decision variables standing for the design and operation of the future power system, and a set of constraints which limit the decision variables to be feasible in the context of a region or a country (Hobbs, 1995). Moreover, there are also some commercial software and tools that can be applied to the power planning problems, such as the long-range energy alternative planning system (LEAP), Wien Automatic System Planning Program (WASP-IV) and MARKet Allocation (MARKAL) (Amorim et al., 2014; Hu and Hobbs, 2010). However, these commercial software are originally designed for the entire energy and economy system rather than for the power planning, and the power plants in these software are considered to be the same elements with standard inputs and outputs. Therefore, the applicability of the commercial software are poor in the power planning (Chen et al., 2010).

Among these power planning researches, few have incorporated the non-carbon external cost into their power planning models, especially for the developing countries like China (Heinrich et al., 2007; Rentizelas and Georgakellos, 2014), which was also the original motivation of this research. Some studies have already been done to estimate the negative effects of power production (Budischak et al., 2013; Georgakellos, 2012; Lee and Kang, 2016), and the commonly accepted method depends on the external cost of the power generation, which is expressed in the monetary value of damages. Frankhauser and Tol (1996) employed the methodology of willingness to pay, or the willingness to accept compensation to appraise the power generation's external cost. NEEDS (2009) adopted the 'impact pathway' approach to calculate the external cost of electricity production on the human health, loss of crop yield, biodiversity and material damage. These external cost estimation can be served as good references for the power planning models.

Several researches have already been done concerning China's power planning and they laid good foundation for our study. Cai et al. (2007) used the LEAP model to simulate the different development paths in China's power sector and did a scenario analysis on the $CO_2$ emissions reduction potential. Zhang et al. (2012b) analyzed the impacts of different carbon mitigation policies on China's power planning basing on a multi-period linear programming model. Cong (2013) developed a renewable energy optimization model to analyze the development of three renewable sources in China combining with the learning curve model and the technology diffusion model. Cheng et al. (2015) employed a multi-region optimization model to minimize the total cost of China's power sector with consideration of the resources availabilities and line transmission capacity. However, some gaps are still worthy to be bridged. Firstly, the existing researches about China's power planning have mainly focused on the external cost of carbon emissions, while ignored non-carbon externalities. Secondly, most studies have fixed the annual operating hours of different technologies in the planning period, but the operating hours should not be predetermined and they will change with the power demand and cost (Choi and Thomas, 2012; Davidson et al., 2016). Thirdly, most researches have ignored the construction lead time of different power generating technologies in the planning models, thus leading to errors to the final results (Cheng et al., 2015; Zhang et al., 2012a). On the one hand, the new capacity additions in the early planning period does not depend on the optimized model results, but are determined by the completion of the previous installing capacity instead. On the other hand, some technologies has a rather long construction time, such as hydropower and nuclear power. Therefore, these technologies cannot be put into operation in just one year after starting construction, which is assumed by most researches. Finally, some China's power planning models have neglected the influence of government policies on the power development (Cheng et al., 2015; Zhang et al., 2012b), which will influence the development path of China's power sector by setting the capacity targets.

## 3 Methodology and data

### 3.1 Research framework

The research framework of this study is presented in Fig. 1. Firstly, a multi-period optimization model (PPOM-CHINA) is established to minimize the total cost of the power sector. Secondly, the model is applied to China's power planning for the period from 2015 to 2030, and the optimal installed capacity mix and the power generation mix in the planning horizon are derived from model results. Then, the investing strategies, operating strategies and the power generation cost are analyzed based on the optimal power development path. After that, the impacts of non-carbon externalities on the optimal power planning results are explored, and a sensitivity analysis of some key parameters in the optimization model have been done to test the robustness of the optimized results. Finally, major conclusions are summarized and some policy implications are proposed for the future development of China's power sector.

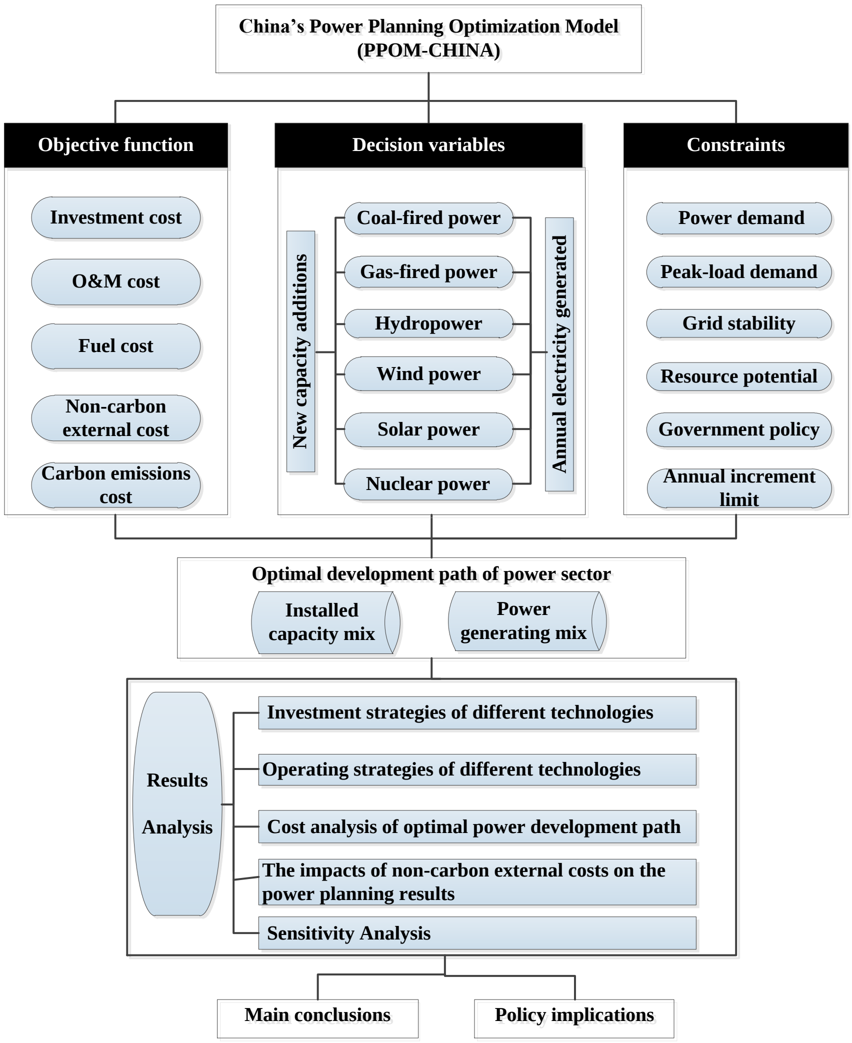



Fig. 1 Research framework

## 3.2 PPOM-CHINA model

In this section, we will describe a deterministic linear programming model established for China's power planning, the definitions and data sources of the indices, parameters and variables used in this model are presented in Table 1.

$EX_i$

Table 1 Indices, parameters and variables in the model

| Indices, parameters and variables | Definitions and specifications | Data sources |
|---|---|---|
| Set and indices | | |
| $t$ | Year in the planning horizon, $t \in [2015, 2030]$ | |
| $i$ | Power generating technologies , $i = 1, 2, ..., 6$ | |
| Parameters | | |
| $I_i(t)$ | Investment cost for technology $i$ in year $t$ (yuan/KW) | Cheng et al. (2015) |
| $OM_i$ | O&M cost for technology $i$ in year $t$ (yuan/KWh) | IEA (2010) |
| $FU_i$ | Fuel cost for technology $i$ in year $t$ (yuan/KWh) | IEA (2010) |
| $EX_i$ | Non-carbon external cost for technology $i$ in year $t$ (yuan/KWh) | NEEDS database[3] |

[3] It can be accesses at http://www.needs-project.org/.

| | | |
|---|---|---|
| $CE_i$ | Carbon emissions of technology $i$ (ton $CO_2$/KWh) | Penman et al. (2006) |
| $CP(t)$ | Carbon prices in year $t$ (yuan/ton $CO_2$) | Jotzo et al. (2014) |
| $CO_i$ | Construction lead time of technology $i$ (year) | IEA (2010) |
| $OP_i$ | Operational lifetime of technology $i$ (year) | IEA (2010) |
| $Len_i$ | Life cycle time of technology $i$ (year) | $Len_i = CO_i + OP_i$ |
| $CF_i$ | Maximum annual capacity factor of technology $i$ | China's Power Statistical Yearbook |
| $D(t)$ | Electricity demand in year $t$ (TWh) | China's Power Statistical Yearbook |
| $P_i(2020)$ | The planned capacity of technology $i$ in 2020(GW) | China's National Plan for Climate Change (2014-2020) |
| $P_i(2030)$ | The planned capacity of technology $i$ in 2030(GW) | China Electricity Council |
| $S_i^{\max}$ | The maximum capacity potential of technology $i$ (GW) | Zhang et al. (2012a) |
| $A_i^{\max}$ | The maximum yearly capacity additions of technology $i$ in a year(GW) | Zhang et al. (2012a) |
| $R_i(t)$ | The retired capacity of technology $i$ in year $t$ (GW) | Calculated based on the lifetime and previous installing capacity of technology $i$ |
| $N_i(2014)$ | The total capacity of technology $i$ in 2014 (GW) | China's Power Statistical Yearbook |
| $LR_i$ | Investment cost reduction rate of technology $i$ | Zhang et al. (2012a) |
| $r$ | Interest rate (5%) | The People's Bank Of China[4] |
| $\mu$ | Grid stability coefficient (0.09) | Cong (2013) |
| $\gamma$ | Peak-load coefficient (0.3) | Estimated from its historical data from 2010 to 2014 |
| $\eta$ | Electricity demand adjustment coefficient (0.9) | Estimated from its historical data from 2010 to 2014 |
| $H$ | Total hours in a year (8760 hours) | 8760=24*365 |
| Decision variables | | |
| $X_{i,t}$ | New capacity additions of technology $i$ in year $t$ | |
| $Z_{i,t}$ | Annual electricity generated from technology $i$ in year $t$ | |

[4] The data of $r$ is based on interest rate of China's long-term bonds.

### 3.2.1 Decision variables

There are two types of decision variables in this model, the first one is the new capacity additions in the planning horizon ( $X_{i,t}$ ), but the capacity additions which come from completion of the previous installing capacity are removed from the set of decision variables (Table 2). The second type of decision variable is the annual electricity generated from technology $i$ in year $t$ ( $Z_{i,t}$ ).

Table 2 The annual installed capacity additions in the planning horizon

| Construction lead time (year) | | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 | … | 2029 | 2030 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Coal-fired power | 4 | | | | | | | | | … | | |
| Gas-fired power | 2 | | | | | | | | | … | | |
| Hydropower | 7 | | | | | | | | | … | | |
| Wind power | 1 | | | | | | | | | … | | |
| Solar power | 1 | | | | | | | | | … | | |
| Nuclear power | 7 | | | | | | | | | … | | |

Notes: indicates that the newly added capacity in this year is determined by the optimized results, whereas indicates that the newly added capacity in this year is determined by the completion of the previous installing capacity, which is calculated based on Zhang et al. (2012a) and the construction lead time of different technologies.

Moreover, the accumulated capacity of technology $i$ in year $t+1$ is calculated as a recursive equation(1), where $N_i(t)$ is the accumulated capacity in year $t$ ; $X_i(t)$ and $R_i(t)$ is the newly added capacity and retired capacity in year $t$ respectively, and $R_i(t)$ is calculated based on the technology $i$ 's construction starting time and its life length ( $Len_i$ ).

$$N_i(t+1) = N_i(t) + X_i(t) - R_i(t) \tag{1}$$

$$Len_i = CO_i + OP_i \tag{2}$$

### 3.2.2 Objective function

The objective function of the linear programming model is to minimize the discounted present value of the accumulated overall cost during the whole planning period, which is presented as follows:

$$min \sum_{t=2015}^{t=2030} \sum_{i=1}^{6} [I_i(t) \times X_{i,t} + (OM_i + FU_i + EX_i + CP(t) \times CE_i) \times Z_{i,t}] \times (1+r)^{-(t-2014)} \tag{3}$$

$$I_i(t) = \sum_{h=t}^{h=min(t+Len_i,2030)} I_i(2014) \times LR_i^{t-2014} \times \frac{r/(1+r)}{(1-(1+r)^{-Len_i})} \times (1+r)^{-(h-t)} \tag{4}$$

The total cost of technology $i$ in year $t$ consists of two major parts, the first one is the investment cost of the new capacity additions ( $I_i(t) \times X_{i,t}$ ), which is the result of multiplying the new installed capacity ( $X_{i,t}$ ) by the unit investment cost ( $I_i(t)$ ). $I_i(t)$ is calculated by equation (4), which not only considers the impacts of technological progress on the investment cost, but also performs reliable calculations for the cases when the operational lifetime of a specific technology is longer than the remaining time period under examination. $LR_i$ is the investment cost reduction rate of technology $i$, and the multiplier $\frac{r/(1+r)}{(1-(1+r)^{-Len_i})}$ is employed to spread the total investment cost over the entire lifetime of technology $i$ equally. Finally, only the annuities belonging to the planning horizon under investigation are discounted to year $t$ and summed（Zhang et al., 2012a).

The second one is the power generation cost, which is composed of four components, namely the operational and maintenance cost ( $OM_i \times Z_{i,t}$ ), fuel cost ( $FU_i \times Z_{i,t}$ ), non-carbon external cost ( $EX_i \times Z_{i,t}$ ) and carbon emissions cost ( $CE_i \times CP(t) \times Z_{i,t}$ ). $Z_{i,t}$ is the electricity generated from technology $i$ in year $t$, $OM_i$ and $FU_i$ are the operational and maintenance cost and fuel cost per electricity generated respectively, which are drawn from IEA (2010) and transformed to the values in 2014 terms. For simplicity, they are assumed to remain stable in the whole planning horizon, but we have done a sensitivity analysis in section 4.5.3 to explore the impacts of different changing trends of fuel prices on the planning results. The carbon emissions cost is calculated as the result of multiplying the carbon emission factor $CE_i$ by the carbon price $CP(t)$, and the projected carbon prices in the planning period are drawn from Jotzo et al. (2014).

There are few data sources of non-carbon external cost ( $EX_i$ ) of China's power production at a national level, but the non-carbon external cost of European countries is available from the New Energy Externalities Developments for Sustainability (NEEDS) database. The non-carbon external cost in this database consists of five major influences caused by the electricity production, namely the health impacts, biodiversity, crop yield losses, material damage and land damage. Moreover, the database has an external cost data of a case study done in Shandong province of China, from which Zhang et al. (2007) stated that the non-carbon external cost of European countries' power generation is about 5.7 times as much as that of China's. Therefore, we follow his conclusions to derive the data of non-carbon external cost of China's power generating technologies. The non-carbon external cost is also assumed to remain stable in the planning horizon.

### 3.2.3 Model constraints

Power planning must meet the ever-growing demand of electricity consumption as shown in equation (5), where $D(t)$ is the electricity consumption demand in year $t$, which is drawn from the State Grid corporate of China. [5] Due to the data unavailability, some technologies like the biomass power and thermal power are not included in this study, so the demand adjustment coefficient $\eta$ is employed to represent the demand share meet by the six technologies in this research, which are estimated from the historical data from 2010 to 2014. Moreover, the electricity generated from technology $i$ in year $t$ should not exceed the maximum electricity generated when all the power plants operate continuously at full capacity factors in a whole year.

$$\eta \times D(t) \le \sum_{i=1}^{6} Z_i(t) \tag{5}$$

$$Z_i(t) \le N_i(t) \times H \times CF_i \tag{6}$$

Electricity generated from the installed capacity must be able to meet the peak-load demand of electricity consumption as shown in equation (7), where $L(t)$ is the peak-load demand in year $t$, and $\gamma$ is the peak-load reserve margin coefficient.

$$(1+\gamma)L(t) \le \sum_{i=1}^{6} N_i(t) \tag{7}$$

The amount of electricity generated from renewable energies (solar and wind) depends greatly on the weather conditions, which has caused grid stability issues in the power planning. Therefore, the equation (8) refers to constraint for the grid's stable operation, and $\mu$ is the grid stability coefficient which limits the generation share of renewable energies to a certain amount.

$$\sum_{i \in (wind, solar)} Z_i(t) \le \mu \sum_{i=1}^{6} Z_i(t) \tag{8}$$

The available resources and proper climatic conditions are very limited for renewable energy, thus the constraint (9) reflects the maximum potential of technology $i$'s accumulated capacity.

$$N_i(t) \le S_i^{\max} \quad i \in (solar, wind, hydropower) \tag{9}$$

Since the power sector is the key sector of energy conservation and carbon emissions mitigation, Chinese government has put forward a series of policies concerning the renewable energy. Constraints (10) and (11) refer to the policy requirements of installed capacity in 2020 and 2030 respectively.

$$N_i(2020) \ge P_i(2020) \quad i \in (solar, wind, nuclear, hydropower) \tag{10}$$

$$N_i(2030) \ge P_i(2030) \quad i \in (solar, wind, nuclear, hydropower) \tag{11}$$

Due to the constraints of human resource, materials and equipment manufacturing, an

[5] This data can be drawn from http://www.sgcc.com.cn/.

upper limit is set for the annual capacity additions of each technology shown in equation (12), where $A_i^{\max}$ is the maximum capacity additions of technology $i$ .

$$X_i(t) \le A_i^{\max} \quad i \in (coal, gas, solar, wind, nuclear, hydropower) \qquad (12)$$

### 3.3 Data

China's power planning from 2015 to 2030 is employed as a case study for the PPOM-CHINA model, and the major input parameters used in this model are shown in Table 3. All the data sources of these parameters can be found in Table 2.

As can be seen from the Table 3, Each type of technology has its advantages and disadvantages in joining in the power generation system. Among the six power generation technologies, the solar power has the largest investment cost, and the wind power has the highest operational and maintenance cost. Moreover, these two renewable energy have the lowest capacity factors. However, these two types of technology do not consume any fuel or emit any $CO_2$ in their power production process, and their investment cost will decrease sharply due to the technological progress. Although the nuclear power has a relatively high investment cost and a long construction lead period, it has a bigger capacity factor, which will greatly improve its competiveness in the power generation. The hydropower has a long operational lifetime, low O&M cost and zero fuel cost. However, as stated by Cheng et al. (2015), the investment cost of hydropower in China will rise in the near future, this is because the increasing cost of the ecological damage and house relocation of new hydropower plants will outweigh the cost reduction from technological progress. As to the two fossil fuel power generating technologies, they have the lowest investment cost but the highest fuel cost. Therefore, there will be a balance between the strength and weakness of the six technologies in the power planning, which also proves the necessity to employ an optimization model to assist the power planning.

Table 3 Major inputs of the parameters in the optimization model

| Parameters | | Coal-fired power | Gas-fired power | Hydro power | Wind power | Solar power | Nuclear power |
|---|---|---|---|---|---|---|---|
| $N_i(2014)$ | GW | 832.33 | 56.97 | 304.86 | 20.08 | 96.57 | 24.86 |
| $CO_i$ | year | 4 | 2 | 7 | 1 | 1 | 7 |
| $OP_i$ | year | 40 | 30 | 80 | 25 | 25 | 60 |
| $I_i(2014)$ | yuan/KW | 5101.50 | 4290.64 | 7372.39 | 10281.01 | 18048.74 | 15539.61 |
| $OM_i$ | yuan/KWh | 0.0131 | 0.0224 | 0.0203 | 0.1560 | 0.1268 | 0.0567 |
| $FU_i$ | yuan/KWh | 0.1841 | 0.2247 | 0.0000 | 0.0000 | 0.0000 | 0.0745 |
| $CE_i$ | ton/KWh | 0.0013 | 0.0006 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| $EX_i$ | yuan/KWh | 0.0298 | 0.0070 | 0.0131 | 0.0015 | 0.0121 | 0.0018 |
| $A_i^{max}$ | GW | 100 | 30 | 30 | 30 | 30 | 20 |
| $P_i(2020)$ | GW | NA | NA | 350 | 200 | 100 | 58 |
| $P_i(2030)$ | GW | NA | NA | 475 | 350 | 300 | 200 |
| $S_i^{max}$ | GW | NA | NA | 537 | 600 | 600 | NA |
| $LR_i$ | | -1.5% | -1.0% | +1.5% | -4.0% | -5.0% | 0.0% |
| $CF_i$ | | 0.6056 | 0.3637 | 0.4188 | 0.2337 | 0.1624 | 0.8989 |

Notes: 1.NA denotes that no constraint is set for this cell. 2.The assumptions of $LR_i$ are based on Cheng et al. (2015). The reason why the growth rate of hydropower's investment cost is positive is due to fact that the ecological damage cost and house relocation cost caused by new hydropower plants will increase with time.

## 4 Results

### 4.1 The optimal power development path during the planning horizon

The optimal power development path is derived from the PPOM-CHINA model, from which the optimal installed capacity mix and power generation mix are shown in Fig. 2 and Fig. 3 respectively.

As can be seen from the Fig. 2, the total installed capacity of the six technologies will increase from 1336GW in 2015 to 2743GW in 2030, among which the non-fossil fuel power plants contribute to 84% of the newly capacity additions. Although the share of coal-fired power in the installed capacity mix will decrease over the period from 2015 to 2030, it still dominate in the capacity mix in this period, which account for 35.4% of the total capacity in 2030. In addition, the hydropower will constitute 19.58% of the total capacity in 2030, ranking second among the six technologies.

As to the power generation mix in the planning period (Fig. 3), the total electricity generated from the six technologies will experience a significant upward trend in the planning horizon, increasing from 5600 TWh in 2015 to 10510 TWh in 2030. The major source of the generated electricity is from the coal-fired power which will account for 45.85% of the total generated electricity in 2030. However, the share of electricity generated from fossil fuel power plants will reduce sharply from 73.0% in 2015 to 50.6% in 2030, which confirms to China's energy policies aimed at adjusting the energy consumption structure to a less carbon intensive one. The share of renewable energy in the power generation mix will exhibit a rising trend in this period, reaching 31.95% in 2030. Moreover, the hydropower occupies the largest share in the generated electricity from the renewable energy sources, followed by the wind power and solar power.

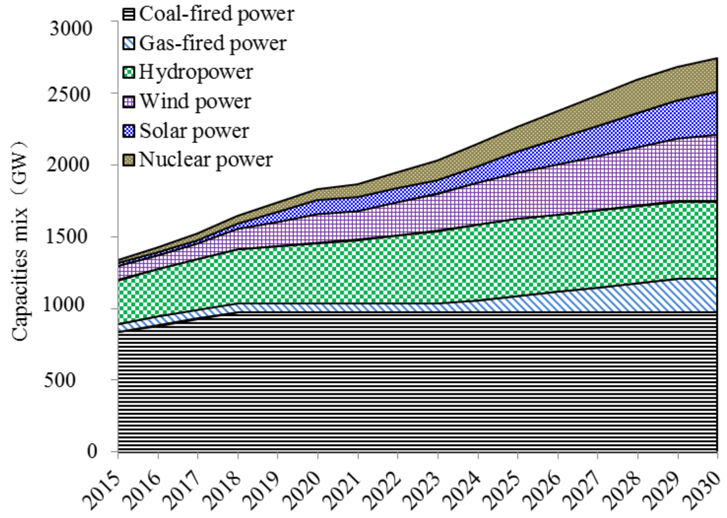



Fig. 2 Capacity mix in the planning horizon

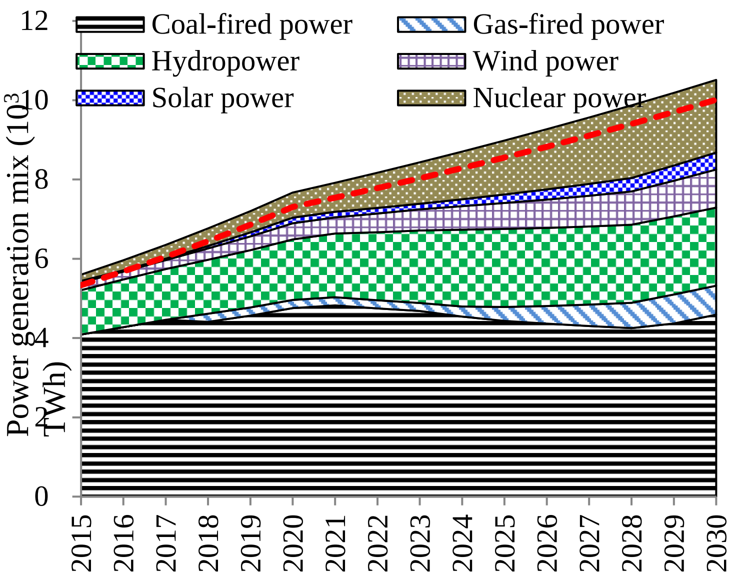



Fig. 3 Power generation mix in the planning horizon

### 4.2 Investing and operating strategies of the optimal future power system

Basing on the new power capacity invested in the planning horizon (Fig. 4), the investing and operating strategies of the power sector can be summarized as below.

From the perspective of the power generating technologies invested, the non-fossil fuel power plants are the focus of investment in this planning horizon, especially the wind power and solar power. Moreover, these two technologies' installed capacity almost expand at the maximum potential of their annual capacity additions. However, no new coal-fired power plants are invested in this period due to their higher power production cost.

From the perspective of the investing time of these technologies, the hydropower is mainly invested at the beginning of the period (2015 to 2018). This is because the hydropower has the lowest generating cost, and a long construction lead time (7 years). Moreover, the investment cost of hydropower will increase with time due to the ecological damage cost and house relocation cost caused by the newly constructed hydropower plants. Similar to the hydropower plants, nuclear power plants are also invested in the early period (2015 to 2021). Although both the wind power and solar power have larger amount of initial investment cost, the advantage of zero fuel cost and zero carbon emissions cost make them competitive when compared with other technologies. Therefore, their investment time nearly spread over the whole planning horizon. However, due to the highest electricity generating cost initially, the gas-fired power plants are only invested in the latter part of the planning horizon. This is because they will not have an advantage in cost over the coal-fired power plants when the carbon prices are not high enough.

From the perspective of the investment cost allocation among the six technologies, we can see from Fig. 5 that 4.2 trillion yuan in total are needed for the investment in the planning horizon, and the majority of the investment cost goes to the solar power (30.70%) and wind power (29.66%), which not only have larger capacity additions in the period, but also have higher unit investment cost. Therefore, the government should not only promote R&D in these technologies to reduce their investment cost, but also introduce some relevant policies to support the development of solar power and wind power, such as subsidies and low-interest loans.

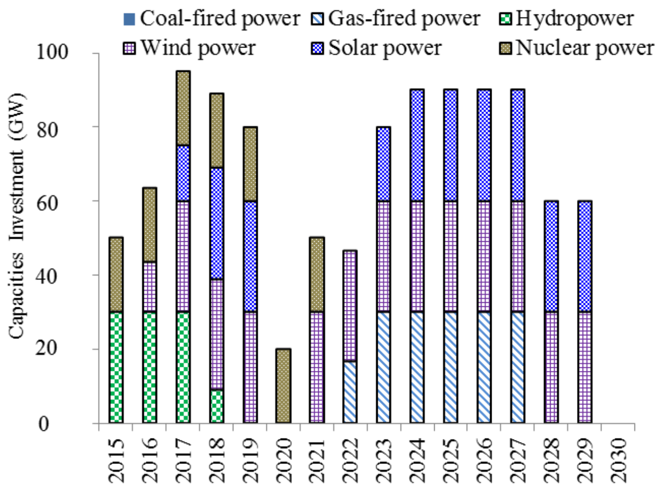



Fig. 4 New power capacity invested in the planning horizon

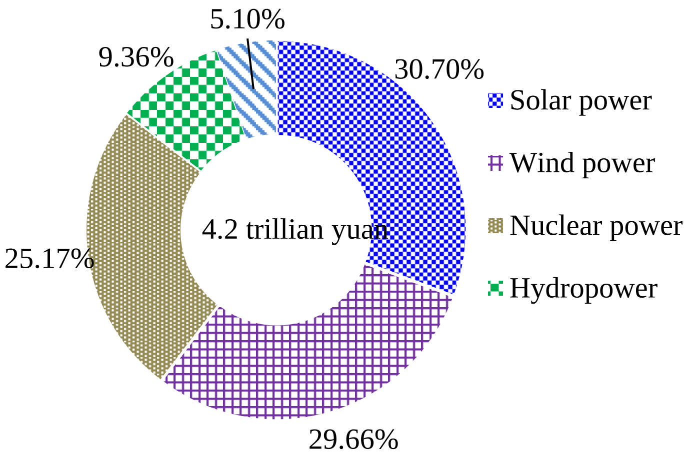



Fig. 5 Investment allocation to different technologies in the planning horizon

As to the operating strategies of the future power system, it can be seen from the Fig. 6 that it is optimal to run the hydropower plants, wind power plants, solar power plants and nuclear power plants at their maximum capacity factors in this planning period. This is because these four technologies have significant power generation cost advantages over the traditional fossil-fuel power plants. By contrast, the average capacity factors of coal-fired power and gas-fired power are only 88.5% and 80.7% of their capacity factor upper-limits respectively, indicating that the priorities of power generation would better be given to the non-fossil fuel power plants in this period.

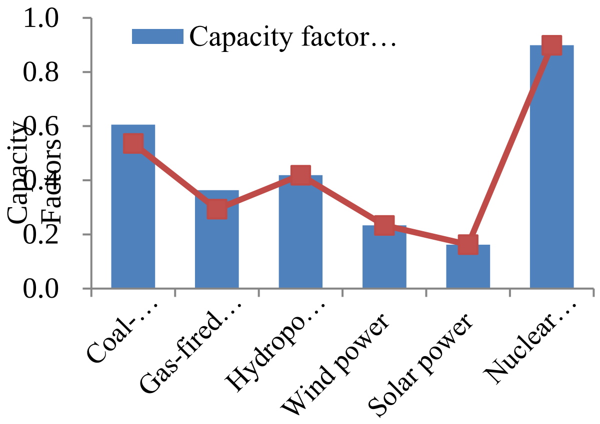



Fig. 6 Average capacity factors in the planning horizon

### 4.3 Cost analysis of optimal power development path

As can be seen from Fig. 7, the total cost of the optimal power system shows a significant upward trend in planning horizon, increasing from 1.32 trillion yuan in 2015 to 2.71 trillion yuan in 2030. The total cost of the optimal power planning is 34.48 trillion yuan, which equals to 2% of China's GDP during the planning horizon (2015-2030).[6] As to the components of the total cost, the fuel cost ranks first and accounts for on average 45.0% of the total cost during the planning horizon, which is mainly due to China's coal-dominated power generating structure and the high fuel prices.[7] However, the share of fuel cost will be squeezed with the integration of renewable energy and implementation of China's national carbon emission trading market. In addition, the share of carbon emissions cost will increase sharply once the carbon emissions trading market being implemented in 2017,[8] reaching as high as 35.6% in 2030. Similar to the share of carbon emissions cost, the O&M cost share will also exhibit an increasing trend in the planning horizon and increases from 9.1% in 2015 to 15.6% in 2030. Finally, the share of non-carbon external cost will make up 7.53% of the total cost in the planning horizon, which deserves the power planners' attention considering the large amount of total cost.

[6] The forecasting data of China's GDP is from http://cass.cssn.cn/.
[7] The fuel share of the coal-fired power, gas fired power and nuclear power is 85%, 7% and 8% respectively.
[8] In COP21, Chinese government announced that the national carbon emission trading market will be implemented in 2017.

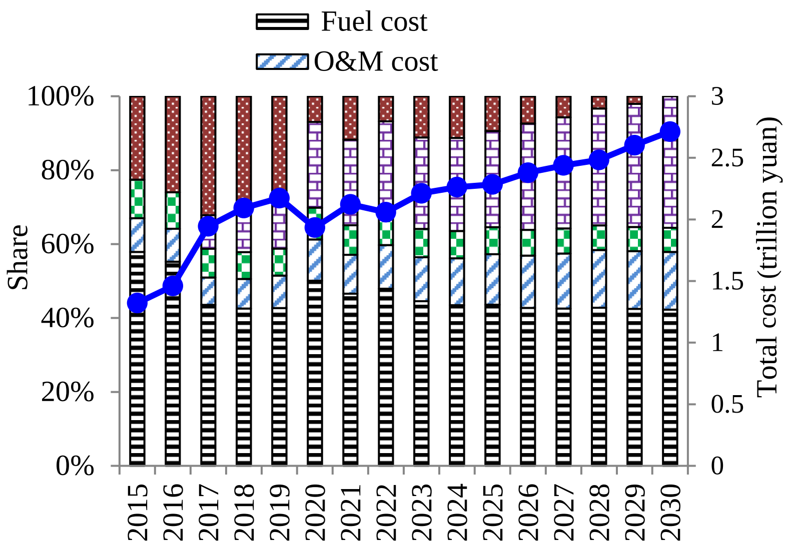
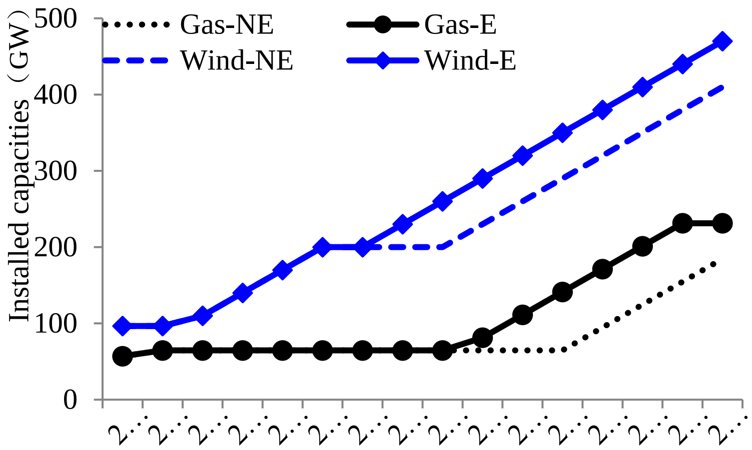



Fig. 7 The power generation cost in the planning horizon

### 4.4 Differences in the results with or without consideration of non-carbon externalities

To analyze the impacts of non-carbon externalities on the optimal power planning results, we have compared the results with or without consideration of non-carbon externalities from two aspects, namely the installed capacities (Fig.8) and the average capacity factors (Table 4).

It is apparent that the results differs a lot between the cases whether the non-carbon externalities are considered or not, proving the necessity to introduce the non-carbon external cost into the power planning models. When the non-carbon external cost are included in the total cost, there will be more installed capacity of gas-fired power (47GW) and wind power (60GW) in the end of the planning horizon. Moreover, the average capacity factors of gas-fired power plants will increase by 30.7%, while the average capacity factors of coal-fired power plants will decrease by 4.3%. Therefore, the neglecting of non-carbon externalities will result in a higher power generation share of technologies with bigger negative externalities, which will no doubt cause more damage to the environment and ecosystem.




Notes: 1.NE indicates the results without consideration of non-carbon externalities, while E indicates the results with consideration of non-carbon externalities.

2. The results are the same for the remaining technologies, and they are not shown in this figure.

Fig. 8 Installed power capacity with or without consideration of non-carbon externalities

Table 4 Average Capacity factors with or without consideration of non-carbon externalities

| Average Capacity factors | Coal | Gas | Hydro | Wind | Solar | Nuclear |
|---|---|---|---|---|---|---|
| Without externalities | 0.5568 | 0.2245 | 0.4188 | 0.2336 | 0.1624 | 0.8989 |
| With externalities | 0.5331 | 0.2933 | 0.4188 | 0.2336 | 0.1624 | 0.8989 |

### 4.5 Sensitivity analysis of some key parameters

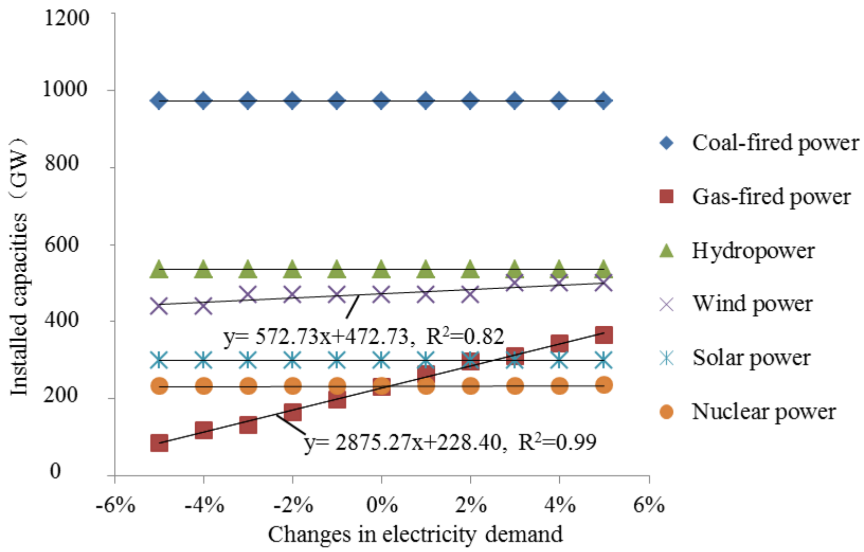
In this section, we will analyze the impacts of electricity demand, carbon prices, fuel cost, investment cost, maximum capacity factors and renewable mandates on the investing strategies and operating strategies of the optimal power system.[9] To present the sensitivity analysis results more clearly, the capacity mix of different technologies in 2030 are employed as a reflection of the investing strategies, while the average capacity factor of a certain technology in the whole planning horizon is utilized as a representation of the operating strategies. Moreover, the parameters used in section 3 are seen as a base case in the sensitivity analysis.

#### 4.5.1 Electricity demand

As can be seen from the Fig.9, the accumulated capacity of gas-fired power in 2030 will increase by 28.75GW when the electricity demand increase by 1%, while the accumulated capacity of wind power in 2030 will increase by 5.73GW. However, the installed capacity of other technologies in 2030 will remain unchanged, indicating that the investing strategies of other technologies drawn from section 4.2 are robust to the power demand changes. Therefore, the priority of adding more capacities should be given to the gas-fired power and wind power when the power demand increases.

As to the responses of operating strategies to the electricity demand changes, we can see from the Fig. 10 that the only significant changes appear in the average capacity factors of coal-fired power and gas-fired power. When the electricity demand increase by 1%, the average capacity factors of coal-fired power and gas-fired power will increase by 0.0057 and 0.0002 respectively. Therefore, we could adjust the capacity factors of fossil fuel power plants in response to the demand changes.

[9] The power generation cost of the optimal power system can be calculated based on the investing strategies and operating strategies, and we do not show the sensitivity analysis results of cost in this paper to save space, but they can be obtained upon request.




Notes: Only the equations of fitted lines who are not parallel to the X axis are added.

Fig.9 Capacity mix of the power system in 2030

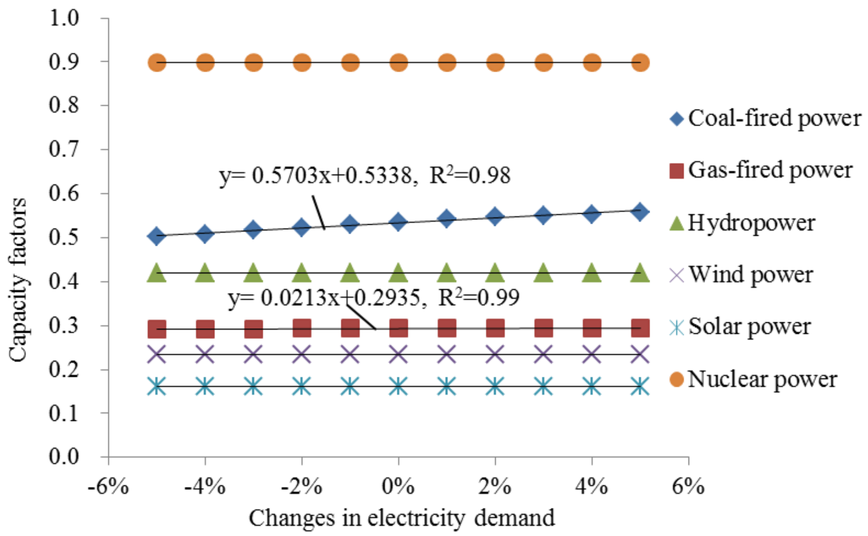



Fig.10 Average capacity factors in the planning horizon

### 4.5.2 Carbon prices

As can be seen from the Fig. 11, the accumulated capacity of wind power in 2030 will increase by 3.92GW when annual carbon prices increase by 1%, while the accumulated capacity of gas-fired power in 2030 will decrease by 2.52GW. This opposite change direction indicates that more wind power capacity will be built to replace the gas-fired power capacity when the carbon prices increase. As to the responses of operating strategies to the carbon price changes, the annual running hours of coal-fired power plants will decrease to make room for a longer running hours of gas-fired power plants (Fig. 12), this is because the gas-fired power has a cost advantage over coal-fired power when the carbon prices are high.

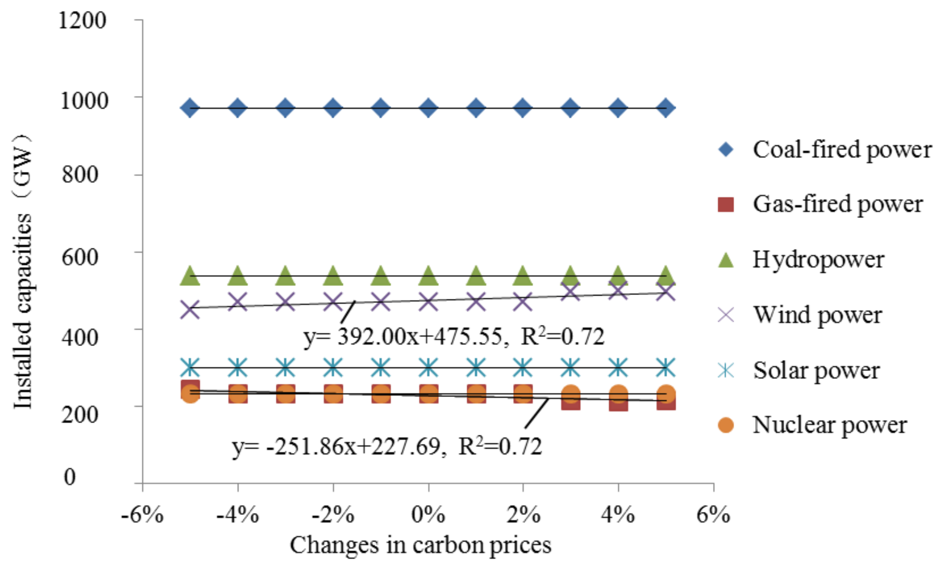



Fig.11 Capacity mix of the power system in 2030

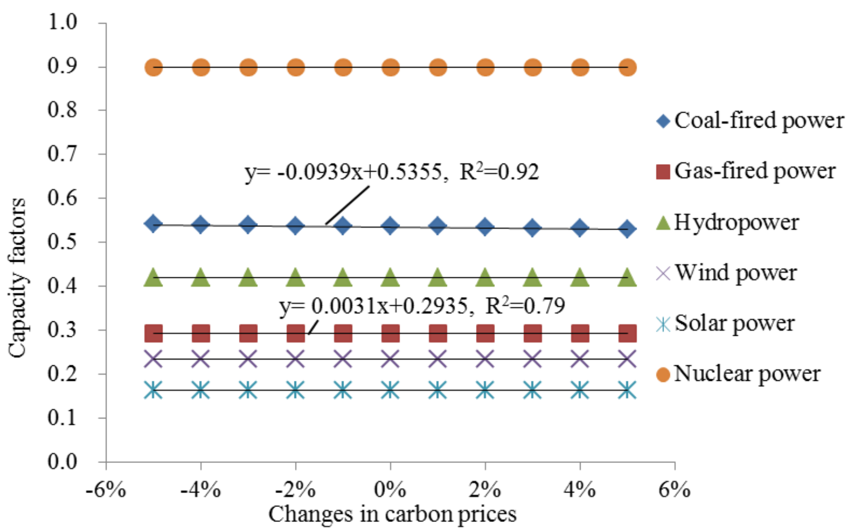



Fig.12 Average capacity factors in the planning horizon

### 4.5.3 Fuel cost

As already been mentioned in the section 4.3, the fuel cost occupies the largest share of the total cost, and the fuel cost of coal-fired power plants are taken as an example to analyze the impacts of fuel cost changes on the optimal power planning. In section 3.2, the PPOM-CHINA model assumes that the fuel cost remain unchanged throughout the planning horizon to simplify the problem, but in this section the coal prices are allowed to show a certain upward trend or a downward trend while keeping other fuel cost unchanged.

When the growth rate of the coal prices increase by 1%, the total installed capacity of coal-fired power in 2030 will decrease by 16GW, while the capacity of gas-fired power and wind power will increase by 50GW and 21GW respectively (Fig. 13), indicating that gas-fired power and wind power are good substitutions for the coal-fired power when the coal prices are high.

As to the responses of operating strategies to the coal price changes, gas-fired power plants, with a lower power generation cost, will work for longer hours and squeeze the operating time of coal-fired power plants (Fig. 14). Therefore, it can offset the impacts of increasing coal prices on the total power generation cost.

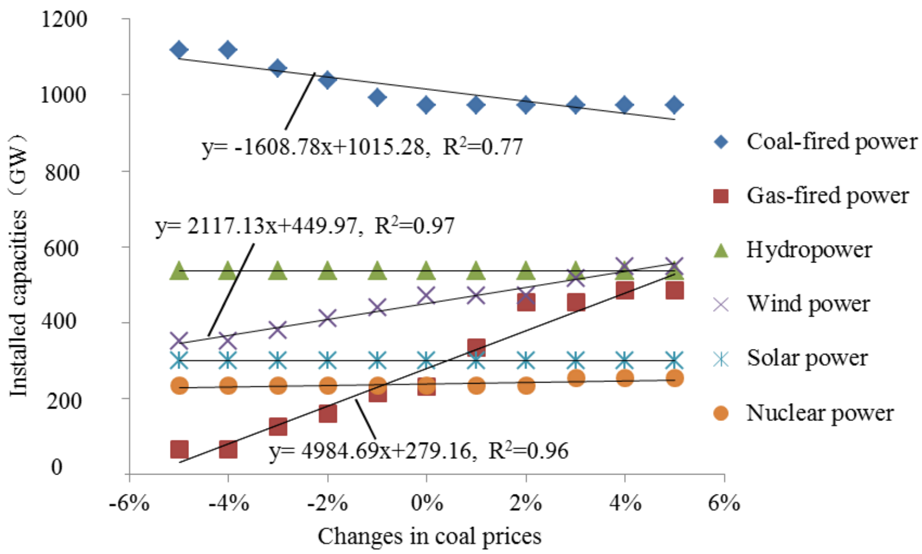



Fig.13 Capacity mix of the power system in 2030

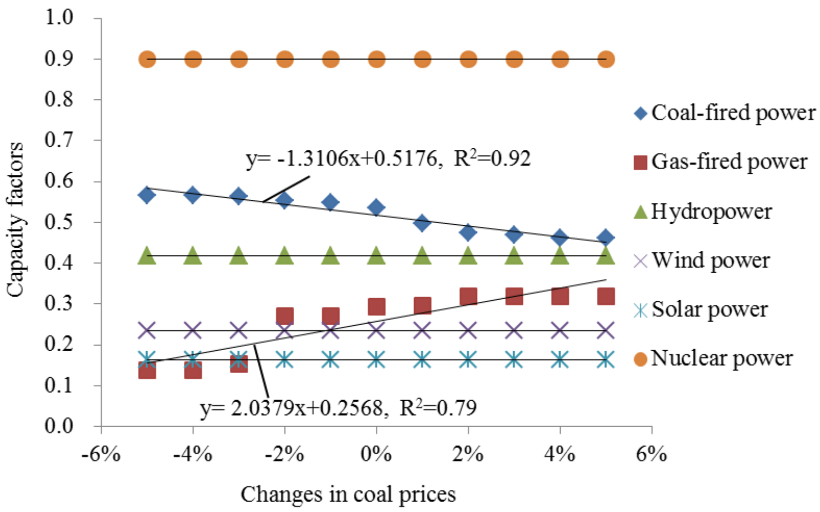



Fig.14 Average capacity factors in the planning horizon

### 4.5.4 Investment cost

Since the solar power capacity additions occupy the largest share of the total investment cost (Fig. 5), the solar power is taken as an example to analyze the influence of investment cost changes on the power planning results.

It can be seen from the Fig. 15 and Fig. 16 that only the accumulated capacity and average capacity factors of gas-fired power will change in response to the investment cost changes. When the annual reduction rate of solar investment cost increase by 1%, the accumulated solar power capacity in 2030 will increase by 0.55GW while the accumulated gas-fired power capacity in 2030 will decrease by 0.24GW. Moreover, the average capacity factor of gas-fired power will also decrease very slightly ($3*10^{-6}$). Actually, the accumulated installed capacity and average capacity factors of gas-fired power do not begin to change until the annual reduction rate of solar investment cost reach 10%, indicating that the investing strategies and operating strategies are robust to the investment cost changes of solar power to some extent. Moreover, since the solar power has the highest unit investment cost and occupies the largest share of the total investment cost in the planning horizon, it is easy to deduce that the investment cost changes of other technologies will not have a significant impact on the investing and operating strategies drawn in section 4.2.

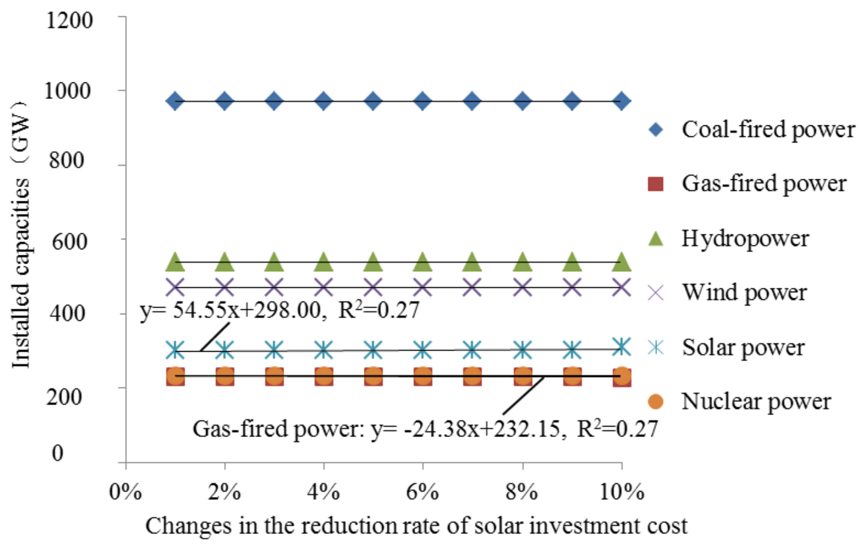



Fig.15 Capacity mix of the power system in 2030

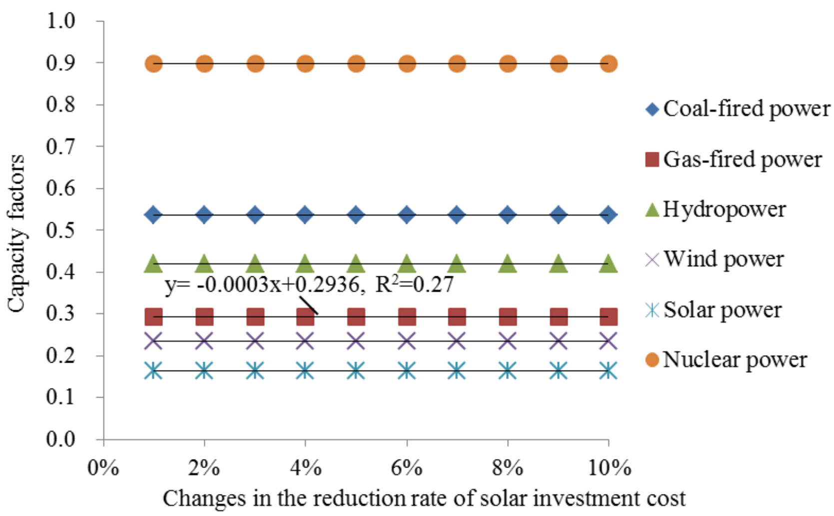



Fig.16 Average capacity factors in the planning horizon

### 4.5.5 Capacity factors limits

As can be seen in section 4.1, all the non-fossil power plants will operate at their maximum capacity factors, and the wind power is taken as an example to show the impacts of capacity factor limits on the optimal power planning.

When the capacity factor limits of wind power increase by 1%, the accumulated capacity of wind power in 2030 will increase by 7.09GW, while the accumulated capacity of gas-fired power will decrease by 7.58GW (Fig.17). As to the impacts on the operating strategies, the average capacity factor of wind power will increase, while the average capacity factor of coal-fired power and gas-fired power will decrease (Fig.18). This is because the wind power has a lower power generation cost, and the increasing of its capacity factor limits allow it to run for a longer time, thus squeezing the running time of the fossil fuel power plants.

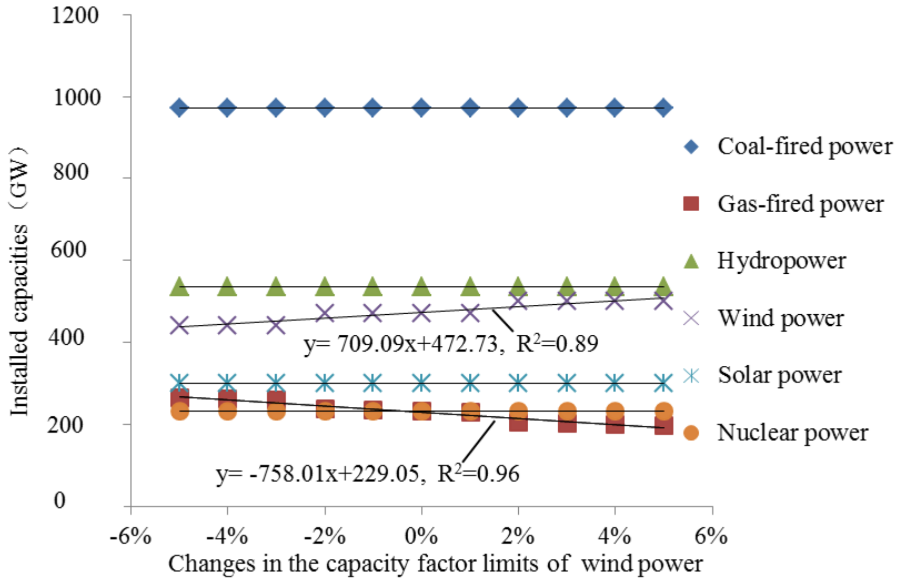



Fig.17 Capacity mix of the power system in 2030

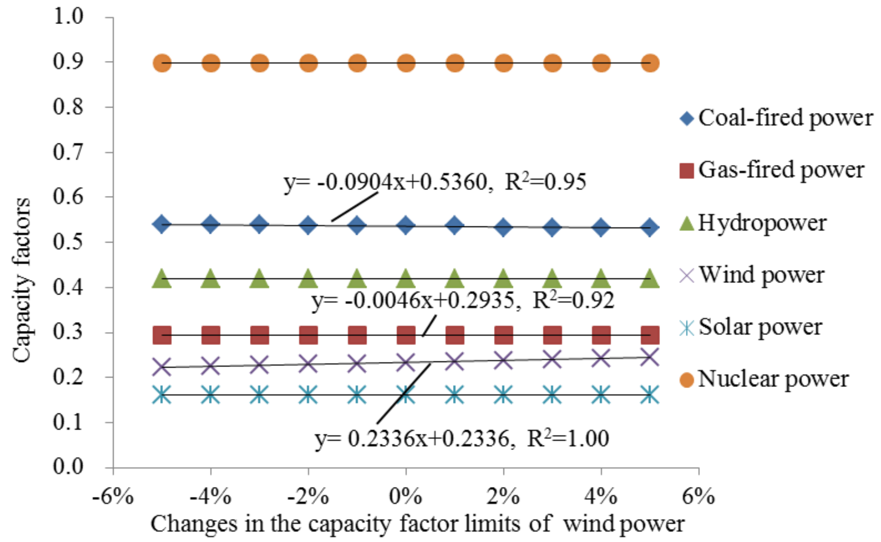



Fig.18 Average capacity factors in the planning horizon

#### 4.5.6 Renewable mandates

In this section, the impacts of renewable energy mandates on the optimal power planning are analyzed by taking the solar power as an example. It can be seen from the Fig.19 that when the solar mandates increase, the total installed capacity of solar power in 2030 will always reach the quantity required by the government policy, which will result in the decreasing of the gas-fired power's installed capacity. Moreover, the average capacity factors of coal-fired power and gas-fired power will also be squeezed by the capacity expansion of solar power (Fig. 20).

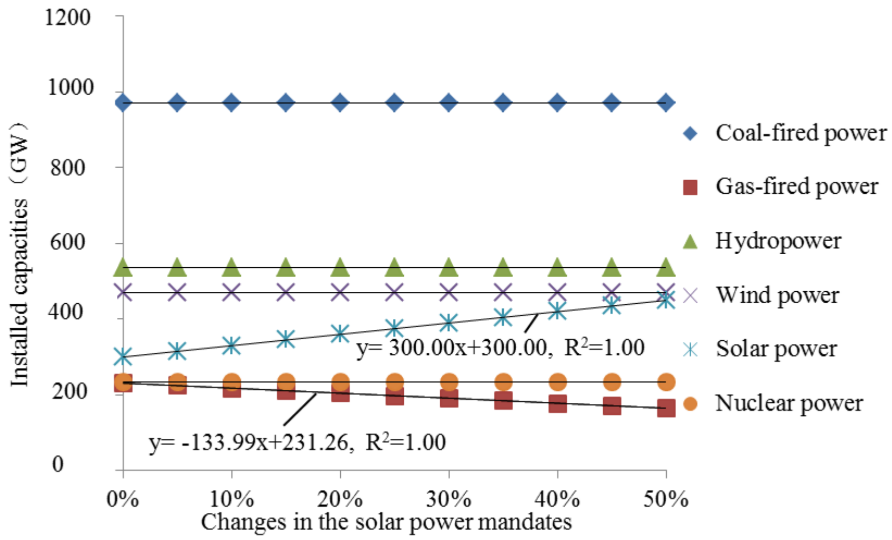



Fig.19 Capacity mix of the power system in 2030

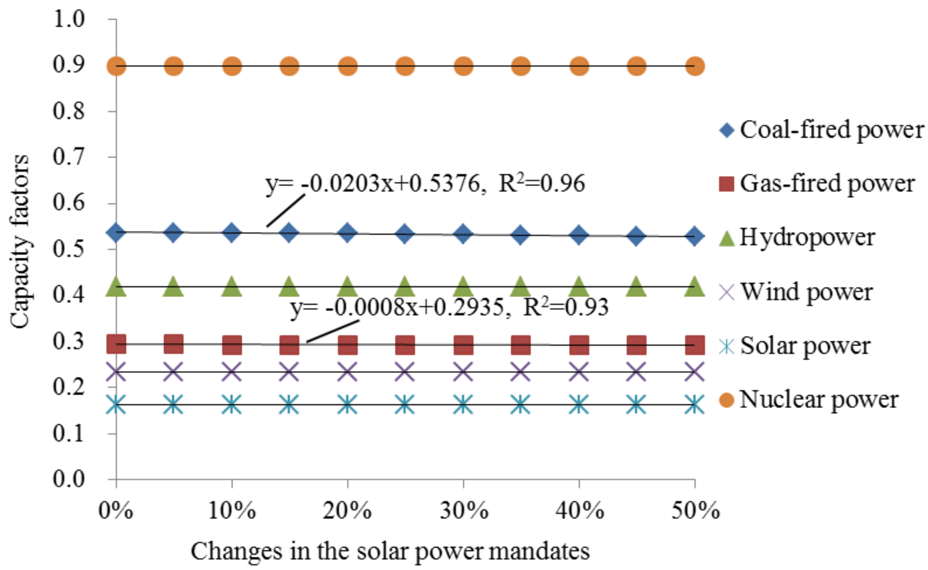



Fig.20 Average capacity factors in the planning horizon

### 4.5.7 Sensitivity analysis summary

As can be seen from the sensitivity analysis of the six key parameters in the PPOM-CHINA model, the wind power and gas-fired power are the most frequently influenced by the changes of these parameters in terms of the accumulated installed capacity, while the two fossil fuel power are the most frequently affected by the changes of these parameters in terms of capacity factors. Installed capacity and capacity factors of other technologies generally remain the same in comparison with that in the base case, proving the robustness of the investing strategies and operating strategies drawn in section 4.2. Moreover, the coal prices are the most significant factor which affect the optimal installed capacity and average capacity factors, while the reduction rates of different technologies' investment cost have the least significant influence on the optimal power planning.

## 5 Conclusions and policy implications

### 5.1 Conclusions

Power planning is of great significance to China’s economic growth and sustainable development, and it also plays an important role in China’s carbon emissions mitigation. To assist the investment and operation planning of China’s power sector, a multi-period optimization model has been established incorporating the non-carbon external cost. Then, this model has been applied to the China's power planning for the period from 2015 to 2030, from which the optimal development roadmap of China’s power sector have been drawn. Moreover, the investing strategies and operating strategies of every technology have been summarized, and the power generation cost have been estimated based on the optimized results. Finally, the impacts of non-carbon external cost on the power planning have been explored. This research has got some interesting results, which can be summarized as follows:

(1) Most of the new capacity additions are from the non-fossil fuel power plants in this planning horizon, which account for 84% of the total newly added capacity. Among these six power generating technologies, the wind power and solar power occupy the largest share (60.36% in total) of total investment cost. Due to the lowest power generation cost and a longer construction lead time, the hydropower would better be invested as early as possible. Moreover, it is also optimal to invest into the nuclear power in the early period due to its longer running hours and cheap power generation cost. However, the gas-fired power would not be invested until the carbon price is high enough, and investing into new coal-fired power plants may not be a wise choice in this planning horizon.

(2) Among the six power generating technologies, the power generation priority would better be given to the non-fossil fuel power plants, it is more cost-effective for these non-fossil fuel power plants to achieve the maximum potential of their capacity factors. However, the electricity generated from coal-fired power and gas-fired power is more flexible and can be used as a supplement to these non-fossil fuel power plants.

(3) The minimum total cost of China’s power planning from 2015 to 2030 is 34.48 trillion yuan, which is equivalent to 2% of China’s GDP during this period. Among the five components of total power generation cost, the fuel cost ranks first and accounts for 45.0% of the total cost in the planning horizon. The share of carbon emissions cost will increase sharply when the carbon emissions trading market implements in 2017, reaching as high as 35.6% of the total cost in 2030. The share of the O&M cost exhibits an upward trend in the planning horizon and increases from 9.1% in 2015 to 15.6% in 2030. In addition, the non-carbon external cost, which is often neglected by the power planners, makes up 7.53% of the total cost in the period.

(4) Neglecting of non-carbon externalities does have a significant influence on the power planning results. It will not only result in smaller amount of capacity addition from wind power and gas-fired power, but also lead to a higher power generation share of technology (coal-fired power) with bigger negative externalities.

(5) From the sensitivity analysis of six key parameters in the PPOM-CHINA model, we can see that the majority of investing strategies and operating strategies are robust to the changes of these parameters. In addition, the optimal power planning results are most significantly affected by the coal prices, while they are least significantly affected by the reduction rates of

different technologies' investment cost.

### 5.2 Policy implications

Based on the conclusions above, several relevant policy implications are proposed to foster a better development of China's power sector.

(1) Power policies can provide good signals for the investors to choose specific technologies and schedule the best time to invest. However, the existing power supporting policies in China are mostly designed for the development of a single technology, but lacking comprehensive consideration of other technologies in power sector. However, the optimal investment for a technology will be affected by other technologies when the target is the optimal development of a whole country' power sector. Therefore, it would be better for the power supporting policies of different technologies to be well coordinated. Moreover, a supporting focus of power policies should be identified in different period according to the cost change patterns of different technologies. For example, the focus of China's power supporting policies in the early period (2015-2018) would better be the hydropower and nuclear power.

(2) The operating strategies obtained under the minimum cost criteria have important implications for China's power dispatch mechanism. The present dispatching model in China is mainly based on a production quota system, which ensures a minimum number of operating hours for the power plants in a year (Lu et al., 2016). This equal-share dispatch mechanism will result in a predetermined amount of electricity output, and provide limited incentive for the power companies to accommodate the renewable energy or adjust their own output. However, it is not energy-saving and cost-effective because some low-cost technologies do not achieve their greatest potential. Even though some obstacles still exist, such as the insufficient transmission lines and financial interest re-distribution problems, the great benefits brought by a cost-effective and more flexible dispatching model could not be ignored. A higher generation share of non-fossil power plants will not only save energy and reduce emissions, but also facilitate the transmission of the electricity sector to a lower carbon one. Therefore, more efforts need be made to introduce a higher-efficiency power dispatching model. In addition, the deployment of the new power plants and transmission investment could be coordinated so that the dispatching model could be better implemented.

(3) Since fuel cost occupies the largest share (45%) in the total power generation cost in the planning horizon, among which 85% of the fuel cost is from coal consumption. Moreover, considering the fact that the coal-power plants will still play a major role in the future, increasing the fuel efficiency of the coal-fired power plants is an important opportunity to reduce the power generation cost of the whole power industry. On the one hand, the fuel consumption standard of coal-fired power plants could be constantly updated to the latest level, which will motivate the power generation companies to improve their fuel efficiency. Moreover, the low-efficiency power plants will be replaced by higher ones. On the other hand, the government could promote the application of energy conservation technologies in the coal-fired power plants, such as the Integrated Gasification Combined Cycle (IGCC) technology and the Circulating Fluidized Bed Combustion (CFBC).

(4) As already been proved by our results, ignoring non-carbon externalities does have a significant influence on the optimal power planning results, which might cause more damage on the human health, environment, biodiversity and crops. To ensure the sustainable

development of China's power sector and increase the social welfare, internalization of external costs into the full power generation cost is an efficient policy instrument. However, a necessary step before effectively employing this instrument is to develop a comprehensive mechanism for the estimation of different technologies' external cost, such as the installation of monitoring device and the establishment of relevant database. Therefore, the government officials, power companies and researchers could coordinate and cooperate, so as to promote a sound assessment of power generation's external cost.

Although we have settled several critical problems about China's power planning, there are still some things left to be done in our future work, such as taking more power generating technologies into consideration when the new data is available, like the biomass power, tidal power and geothermal power. Moreover, the risk indicators of different technologies could be considered in the PPOM-CHINA model, which might provide more support for a long-term power planning and investment analysis.

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