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Assessing possible generation portfolios for China's future carbon constrained electricity industry

by

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Abstract

China's extraordinary economic growth and transformation over recent decades has gone hand in hand with the expansion of its electricity industry, which is now the largest in the world. It is also emissions intensive due to its dependence on coal fired The Chinese Government has ambitious plans to curb both greenhouse emissions and local air pollutants over coming decades, including increasing the share of renewable energy through various policy mechanisms.

This modelling study assesses the possible industry costs, risks and emission impacts of different future generation portfolio investment in China out to 2030 given highly uncertain future fuel prices, carbon pricing policy, electricity demand and plant capital costs in 2030. Analysis is undertaken using a probabilistic generation portfolio investment modelling tool, drawing on extensive data collection and analysis. Different combinations of future generation portfolios in 2030 with renewable penetration levels ranging from 20% to 60% are considered. The main technologies considered are coal, combined cycle gas turbine (CCGT), nuclear, integrated gasification combined cycle (IGCC), hydro, wind and solar PV.

In meeting future electricity demand growth while achieving meaningful emissions reduction outcomes, this study suggests that utility-scale wind and solar PV can usefully play a particularly useful role in reducing expected future industry costs and associated cost risks, as well as emissions. For central estimates of future demand, plant costs, and fuel and carbon prices, generation scenarios with a 60% renewable penetration offered the best balance of costs, risks and emissions of. Effective carbon pricing can be a key driver in providing incentives for low-carbon technology investment, particularly wind and PV. The analysis suggests that a relatively modest carbon price could still lead to a significant increase in the share of wind and PV generation from the present 5% up to around 50% in 2030. This represents an additional 1,200 GW of combined wind and PV capacity. CCGT and nuclear generation can complement renewables in future generation portfolios. Investment in new coal-fired generating plants is problematic due to their high capital cost and high emissions. However, the existing coal generation fleet can still play a useful role by operating as intermediate or peaking units. The study also provides some important insights into the impacts of, and interactions between, future fuel and carbon prices in reducing carbon emissions and regional air pollution.

Contents

1. Introduction

China's extraordinary economic growth and transformation over recent decades has been mirrored in the expansion of its electricity industry which is now the largest in the world, representing almost a quarter of total global electricity demand (IEA, 2016b). With its population size, continued growth in electricity demand and rapid development of electricity supply infrastructure, China seems certain to play an increasing influential role in global energy demand for the next decade. In 2015, investment in China on generation and networks totalled some US$214 billion, o ver 30% of global expenditure (IEA, 2016c). At the end of 2015, the total installed generation capacity was over 1,500GW, 10.6% greater than the previous year. China's electricity generation is dominated by fossil-fuels, particularly coal, which represents 73% of total generation, followed by hydro and nuclear at around 20% and 3% respectively. Although the share of grid-connected wind and solar power generation has rapidly increased over the past few years, they still accounted for only 4% of total electricity generation in 2015 (Wang, 2016).

Due to the significant share of coal-fired power plants in the generation mix, China's electricity industry contributes over 30% of global greenhouse emissions from electricity and heat, although it should be noted that China's per capita emissions remain well below those of the OECD (World Bank, 2015; IEA, 2016a). The past 15 years have seen emissions more than double, driven by demand growth, although there was some reduction from fuel switching and generation efficiency improvements (IEA, 2016a). Beyond greenhouse emissions, the rise in regional air pollution in China, particularly NO_x, SO_2 and particulate matter (PM), has caused significant adverse impacts domestically. The electricity sector is the largest contributor to China's greenhouse gas and regional air pollution, and hence has been a particular focus of policy makers.

The last five years have certainly seen growing policy efforts. The Chinese Government announced an action plan in 2012 to curb the rise in both greenhouse emissions and local air pollutants with targets to control coal consumption. This plan also involved promoting hydropower development, gradually increasing the share of nuclear power and accelerating the deployment of renewable technologies, particularly wind, solar and biomass. A number of policy mechanisms have been introduced to achieve this, which include renewable energy targets and the plan to establish a national Carbon Emissions trading Scheme (ETS) by 2017. This plan aims to increase the renewable energy to achieve at least 20% of total power generation, while reducing coal-fired electricity generation's contribution to around 65% in the 12th five year period (The State Council of China, 2012; IEA, 2014). Given those developments China has now become a key global player for combating climate change and the *China-US Joint Announcement on Climate Change* in November 2014 can therefore be viewed as a milestone for achieving the global climate agreement that emerged in Paris in December 2015.[1] China has also become a global powerhouse in renewable energy technology manufacturing and deployment (REN21 2016).

[1] The announcement was issued after the China-US summit talks in Beijing and China committed to peak CO_2 emissions at the latest in 2030 (The United States Government, 2014).

Looking further ahead, China faces a range of globally shared, as well as unique, clean energy challenges given energy's key role in economic development yet present adverse environmental impacts. In the electricity sector, China's policy makers face large and growing uncertainties in areas including future demand growth, the costs of different generation technologies, fossil fuel prices and possible carbon prices and other policy measures to improve energy and climate outcomes.

The study presented in this paper aims to contribute to these policy questions by assessing how different generation investment priorities over the next decade might impact on the overall costs, associated risks and environmental impacts of the future Chinese electricity industry. It is by no means the first or only quantitative modelling effort exploring these questions. However, this work aims to provide a more formal treatment of future uncertainties than such efforts normally deploy, and a better appreciation of the possible trade-offs between different future generation options across cost, cost risk and emissions.

Existing modelling studies on future electricity sector investment in China often focus on determining a least cost generation mix based to meet expected future electricity demand based upon deterministic assumptions on key factors including future costs of different fuels and capital costs of possible generation technology options as well as related energy and climate policies (Chandler et al., 2013; Energy Foundation China, 2015). While making a valuable contribution towards assessing the costs and benefits of different technology options for future China's electricity sector, they have some important limitations, in how they incorporate uncertainty and hence assess risk. This is particularly important of high renewable future since renewable technologies have the potential to hedge against some key future uncertainties, and therefore reduce the associated cost risks (Awerbuch, 2006; Doherty et al., 2006; Vithayasrichareon et al., 2015).

Our study employs a probabilistic generation portfolio investment modelling tool(Vithayasrichareon and MacGill, 2012a) to assess different possible future generation portfolio options in China's electricity industry for 2030 under highly uncertain future fuel prices, carbon pricing policy, electricity demand and generation capital costs. The study adopts a long-term societal perspective focusing on overall industry costs, cost risks and emissions. Different renewable penetration scenarios for 2030 ranging from 20% to 60% are considered in the modelling. The key renewable technologies considered are utility-scale wind, solar PV and hydro. Sensitivity analyses are also conducted to explore further the impact of different possible pathways of future carbon prices, gas prices, coal prices and electricity demand growth.

The paper is structured as follows: Section 2 gives an overview of China's policies and development strategies and the current situation of electricity market operation and investment in China. Modelling methods used in this study for assessing different future generation portfolios are provided in Section 0. Section 4 describes the details of generation investment scenarios considered followed by input data and uncertainty modelling in Section 5. Modelling results and their policy implications are presented and discussed in Section 6 and 7 followed by the conclusions in Section 8.

2. Current climate mitigation and renewable energy legislation and regulations in China

China committed in the Paris agreement inter alia to achieve the peaking of CO_2 emissions around 2030, to reduce their CO_2 emissions per unit of GDP by 60-65% in 2030 compared to 2005 and to increase the share of non-fossil fuels in primary energy consumption by 20% in the same timeframe. These ambitious targets reflect the government's determination to contribute appropriately to a global effort to avoid dangerous global warming. Past developments support the fact that China is likely to achieve those future targets. According to its own assessment in 2015, the country is well on track meeting targets set by the Chinese government in 2009 (e.g. by 2014 they have reached 33.8% of a max 45% target of reducing CO_2 emissions per GDP in 2020 based in 2005 levels and a share of non-fossil fuels in primary energy consumption of 11.2% compared to the 15% target). Those achievements are the results of various plans and policies including strong renewable energy support from a number of different institutions and levels ranging from National Development and Reform Commission (NDRC) to institutions such as the State Electricity Regulatory Commission. For example, in September 2014, the NDRC issued the National Plan for Addressing Climate Change (2014-2020), which aims to gradually establish a national carbon emissions trading market based on learning from international experiences and in line with China's national conditions.

In July 2012, the NDRC issued the Renewable Energy Development 12th Five Year Plan. This plan aims to increase the renewable energy power generation capacity by 160 GW in the 12th five year period (The State Council of China, 2012). Also on the State level the need to increase non-fossil energy generation has been acknowledged. In January 2013, the State Council of China issued the Energy Development 12th Five Year Plan, which also focused on increasing the proportion of non-fossil energy. It includes an energy structure optimisation target by 2015 which states that the proportion of coal in energy consumption structure is to be decreased to 65% and the proportion of non-fossil energy consumption to be increased to 11.4%, and the proportion of non-fossil energy power generation installed capacity should reach 30%. By the end of 2015, the installed capacity of renewable power generation in China had reached 480 GW and corresponding generation also achieved the target in which renewable energy generation were required to account for at least 20% of total power generation (National Energy Administration, 2016b). According to the National Energy Administration, the Energy Development 13th Five Year Plan will specifiy that coal consumption will reach a peak in the 13th five year period with a total control of 4.1 billion tons or less. In terms of total energy consumption, while the proportion of coal will reduce to 58%, the ratio of non-fossil energy will increase to 15% or more(Wu, 2016). Specifically, according to the preliminary outcome from the Renewable Energy Development 13th Five Year Plan, the installed capacity of renewable energy power generation will reach 680 GW with renewable generation accounting for 27% of total power generation by 2020(Du and Wang, 2016). In line with those ambitious targets, and more stringent environmental standards approval for new thermal power plants, particularly coal generation capacity, has become more and more difficult (2015b).

In order to reach the targets various policies have been introduced. To foster renewable energies they range from Research and Development Funds over tax support to financial subsidies such as feed-in tariffs (Zhao et al., 2016). However, due to a lack of coordination between the different institutions, slow grid investments and a lack of proper enforcement of targets the integration of renewables is providing challenging (Hua et al., 2016). In addition, the different views on future oil and gas price developments as well as the broad range of carbon prices in the pilot schemes (ChinaCarbon, 2016) reflect the very high uncertainties involved in policy efforts to transform the china electricity industry.

Given such uncertainties, the modelling undertaken in this study is able to simulate different possible generation mix futures including costs, emissions and trade-offs between these under high level of future energy and climate policy uncertainties. The modelling methodology is described in more detail in the following sections.

3. Modelling methods

The modelling tool employed in this study extends the conventional load duration curve (LDC) optimal generation mix methods by incorporating Monte Carlo Simulation (MCS) to formally accounts for key uncertainties in generation investment and planning decision-making. With MCS techniques, outputs for each of the possible future generation portfolios consist of many thousands simulated overall generation costs, environmental emissions including CO_2, NO_X and SO_2, as well as other key performance criteria such as generator revenue and profits. These outputs can, therefore, be represented by probability distributions, which are typically summarised by statistical parameters such as mean (i.e. expected value) and standard deviation (SD).

Financial portfolio analysis methods are then employed to determine an Efficient Frontier (EF) that formally identifies tradeoffs between different criteria across the different future generation portfolios. Since the outputs (i.e. cost, emissions, revenue, profit) can be represented by probability distributions, different forms of risk-weighted uncertainty measures and criteria can also be used for valuing the risk of generation portfolios such as Value-at-Risk (VaR). A graphical description of the modelling is shown in Figure 1.

In the modelling, a large number of possible generation portfolios are assessed rather than focusing on particular generation mixes (e.g. finding the least cost generation mix). In order to effectively facilitate decision making under uncertainty, it is important to evaluate possible outcomes for each of the decision choices. Therefore, different possible generation mixes should be evaluated and compared on a range of criteria, rather than focusing only on a particular generation mix. In this way, decision-makers can identify the most appropriate choice of generation portfolio that suits a potentially diverse and partially conflicting range of objectives. This approach has advantages over scenario and sensitivity techniques often used to incorporate future uncertainties in more conventional modelling studies in its mapping of potential tradeoffs between objectives. As this study highlights, MC techniques can also be extended to incorporate discrete scenarios.

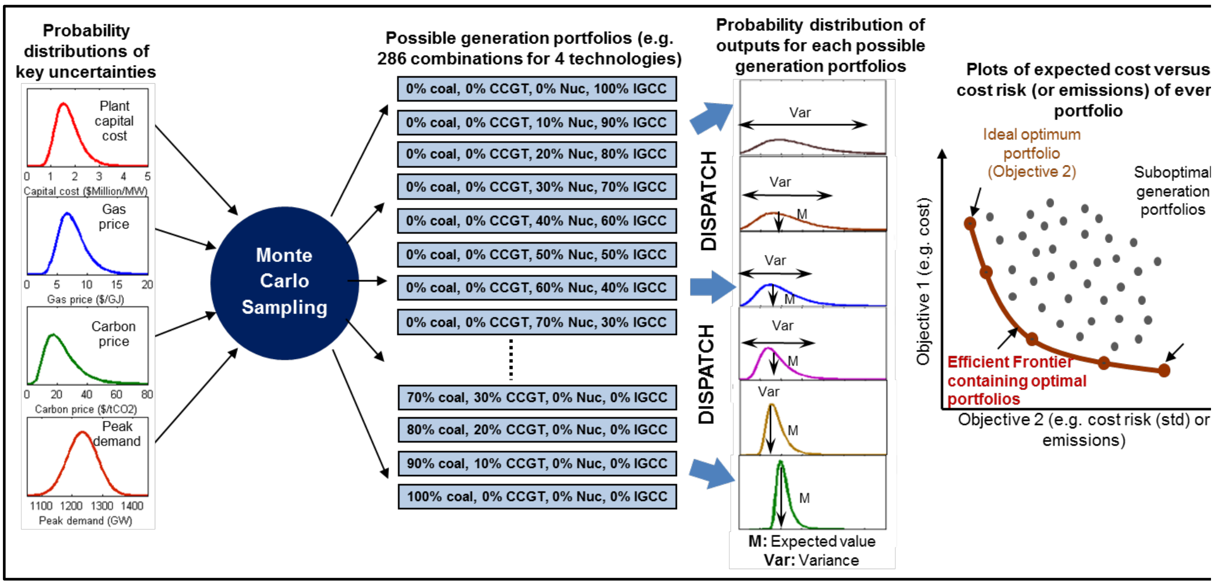


Figure 1. Modelling methodology.

For each possible generation portfolio considered in the modelling, the generation output of each technology in each period across the Load Duration Curve is determined using merit order dispatch, which is based on the short run marginal costs (SRMC) of each thermal technology.

Total annual generation cost of each generation portfolio consists of total annual fixed costs and variable costs. The fixed cost is made up of annualised plant capital cost, fixed operation & maintenance (O&M) as shown in (1).

$$FC_n = (Annualised\ CapCost_n + FOM_n) \times I_n \tag{1}$$

where *Annualised CapCost*$_n$ is the annualised capital cost ($/MW), FOM_n is the annual fixed O&M cost ($/MW) and I_n is the installed capacity (MW) of technology *n* in the portfolio.

Annual variable cost of generation portfolio is calculated based on annual energy (MWh) generated by each technology in the portfolio. The variable cost comprises variable O&M, fuel costs, carbon costs and other environmental externalities as shown in (2).

$$VC_n = (VOM_n + FuelCost_n + CarbonCost_n + EXTERNCost_n) \times E_n \tag{2}$$

where VOM_n is the variable O&M cost ($/MWh), E_n is the annual energy (MWh) generated by each technology n in the portfolio.

PV and wind generation pose particular challenges for LDC techniques given their variability. We use a residual load duration curve approach to capture the dynamic relationship between demand and such variable generation Hourly simulated time-varying PV and wind generation outputs in are subtracted from demand over the same time period. The resulting net demand after accounting for PV and wind is then rearranged in order of magnitude to obtain a residual load duration curve (RLDC), which is to be served by thermal generation technologies in the portfolio.

Hydro generation in China was also treated as exogenous to the dispatch given its unique characteristics of being dispatchable but energy limited, and opportunities for major deployment being very context specific. The modelling assumes an ambitious but realistic deployment of new hydro to 2030 for all future generation scenarios. An aggregate hydro duration curve is subtracted from the RLDC. With this approach, historical hydro generation patterns are re-mapped onto the new residual demand curve, taking into account the real operation constraints of hydro while better accounting for the fact that the future generation mix will likely be very different from the present mix.

This modelling framework (Vithayasrichareon and MacGill, 2012a) has previously been applied to analyse future generation portfolios in the context of the Australian National Electricity Market (NEM) (Riesz et al., 2015; Vithayasrichareon et al., 2015) and Thailand (Vithayasrichareon and MacGill, 2012b). This paper presents its first application to China's electricity industry.

4. Generation investment scenarios for China in 2030

4.1. Generation investment scenarios

Seven possible new generation options for 2030 are assumed in the modelling: coal, combined cycle gas turbine (CCGT), nuclear, Integrated Gasification Combined Cycle (IGCC), wind (onshore), PV (fixed flat plate) and hydro generation. New coal plants are assumed to utilise ultra-supercritical combustion (NDRC, 2014).

The existing generation capacity (as of 2013) and possible plant retirements are incorporated in the modelling as shown in Table 1. Only some of existing coal generation capacity is assumed to be retired in 2030 while all of the existing nuclear, CCGT, hydro, wind and PV capacity is assumed to still be operating in 2030. Hydro generation capacity is projected to reach 400 GW in 2030 (China Census for Water, 2013). In the modelling, the hydro capacity is fixed for every generation portfolio of thermal technologies. Investment costs of the existing capacity for each technology are considered 'sunk' and therefore are not included in the calculation of generation costs.

Table 1. Existing and estimates of retired capacity between 2013 and 2030.

Technology	Capacity in 2013 (GW)	Retired capacity during 2013 – 2030 (GW)	Existing capacity in 2030 (GW)
Coal	754	78.3	676
CCGT	37	0	37
Nuclear	13	0	13
Hydro	250	0	250
Wind	61	0	61
Solar PV	3.4	0	3.4

The study assumes six different scenarios for PV and wind generation for 2030 ranging from 10% to 50% combined PV and wind energy penetration.[2] These scenarios and corresponding total renewable penetrations (including hydro) are summarised in Table 2. Note that as the renewable penetration increases, the growing levels of

[2] The penetration includes both new and existing PV and wind generation.

variable PV and wind generation may result in energy spillage.

Table 2. Different renewable penetration scenarios considered in the modelling.

Renewable penetration scenario (%)	Achieved total renewable penetration (%)	% PV energy	% Wind energy	Spilled PV and wind (%)	Hydro (%)	Others (thermal) (%)
20	22	5	5	0	12	78
25	27	5	10	0	12	73
30	32	10	10	0	12	68
40	42	10	20	0.03	12	58
50	51	20	20	2.2	12	49
60	58	20	30	5.1	12	42

4.2. Installed generation capacity and portfolio determination

For each renewable penetration scenario, the installed capacity of PV and wind are determined based on their targeted energy outputs and a capacity factor of 21% and 30% respectively (Wang et al., 2014).

$$Wind\,(or\,PV)\,IC(MW) = \frac{Annual\ wind(or\ PV)\,energy\,in\,2030}{wind(or\ PV)\,CF \times 8760\,hours} \tag{3}$$

Installed conventional generation capacity is determined using a probabilistic approach by assuming a 99% reliability criterion, which implies that there is sufficient conventional generation capacity to meet the expected residual demand for at least 99% of the time during the Monte Carlo simulation. A cost for energy not served (ENS) of $1,000/MWh is included in the period when demand is greater than total installed capacity.

Table 3 shows the installed capacity for 2030. Residual peak demand refers to the peak demand of the net load duration curve (after wind, PV and hydro generation have been subtracted in each hour).

Table 3. Different renewable penetration scenarios for 2030 and corresponding installed generation capacity and residual peak demand.

Renewable penetration scenario (%)	% PV energy	% Wind energy	Residual peak demand (GW) (exclude PV, wind, hydro)	Installed capacity (GW)			
				PV	Wind	Hydro	All other (coal, gas, nuclear, IGCC)
20%	5%	5%	1,234	299	209	400	1,362
25%	5%	10%	1,227	299	419	400	1,353
30%	10%	10%	1,227	598	419	400	1,353
40%	10%	20%	1,223	598	837	400	1,349
50%	20%	20%	1,223	1,196	837	700	1,349
60%	20%	30%	1,219	1,196	1,256	400	1,345

Figure 2 shows the capacity of each generation technology for each of the PV and wind energy penetrations. Note that installed capacity increases substantially with higher PV and wind penetrations due to additional PV and wind capacity required to compensate for their relatively low capacity factors. For each renewable penetration scenario) shown in Figure 2, different combinations of thermal generation portfolio mixes (coal, CCGT, nuclear and IGCC) are simulated by varying each technology in 10% increments. This results in a maximum of 286 possible thermal generation portfolios for each renewable penetration scenario (subject to the limit of nuclear generation capacity). Hence there are a maximum of 1,716 portfolios in total across the six renewable penetration scenarios.

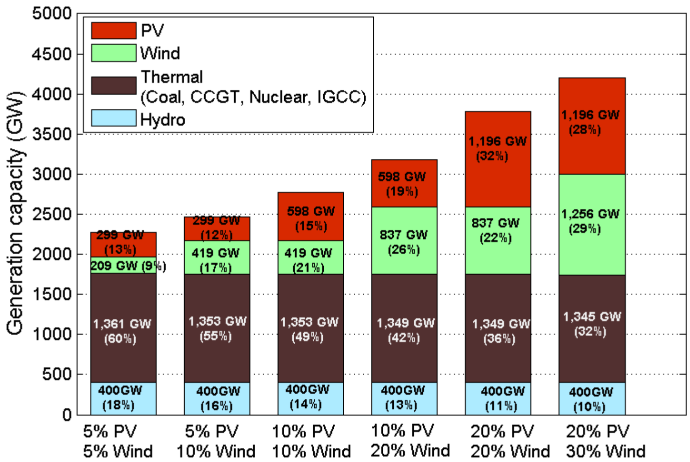


Figure 2. Installed and the share of technology capacity for each renewable penetration scenario for 2030.

The proportion of coal, CCGT and nuclear consists of new and existing capacity. The amount of the remaining existing capacity CCGT and nuclear are fixed for every generation portfolios. The existing coal capacity (676 GW) is allowed to vary in order to consider different retirement plans of existing coal plants. Since there is only13 GW of existing nuclear generation capacity (as of 2013), the study assumes nuclear capacity is capped at 200 GW for 2030.

5. Modelling inputs

Modelling input parameters were estimated based upon a number of consultancy and governmental reports, previous literature in both the Chinese context and internationally, as well as informed and expert opinions. In this modelling, a central estimate of carbon price for 2030 is assumed for the investment scenarios considered in order to reflect climate change policy interventions. However carbon price is not only the policy measure that can be incorporated in the modelling tool. For example shadow prices of emissions that reflect a range of policy measures can be considered. As such, this study also considers the situation where carbon price revenue is used to reduce the overall industry costs. This is further explained in Section 5 and 6.3.

5.1. Generator parameters

Generator parameters for existing and new plants were estimated based on literature wide ranging literature review (Liu, 2007; NDRC, 2007; Zhang et al., 2012; Shi, 2013). For wind, PV and hydro generating plants, the study assumes the same technical and cost parameters for both new and existing plants. For nuclear plants, the fuel costs only considers front-end cost estimated from (MIT, 2009). The back-end fuel cost was included in the variable O&M costs. The back-end cost of nuclear fuel cycle including spent fuel transport, storage, reprocessing and disposal. The emission factors of each technology were estimated based on a number of previous studies

(Liu, 2007; Zhang et al., 2012; Shi, 2013; National Energy Administration, 2014). Table 4 shows the details of generator parameters used in the modelling.

Table 4. Generator Parameters

Generator parameters	New entry plants				Existing plants			Hydro	PV	Wind
	Nuclear	Coal	CCGT	IGCC	Nuclear	Coal	CCGT			
Plant life (years)	40	40	30	20	n/a	n/a	n/a	40	20	20
Overnight capital cost ($Million/MW) – year 2030	3.2	0.51	0.39	1.21	n/a	n/a	n/a	0.98	0.83	0.53
Fixed O&M cost ($/MW/yr)	15,000	21,000	41,000	79,000	154,000	22,000	43,000	49,000	9,600	24,000
Variable O&M cost ($/MWh)	2.2	2.1	1.5	2.95	2.2	2.2	1.5	8.9	7.4	7.4
Average thermal efficiency (%)	37	42	60	46	37	42	56	n/a	n/a	n/a
Heat Rate (GJ/MWh)	9.7	8.6	6	7.8	9.7	8.6	6.4	n/a	n/a	n/a
CO_2 emission factor (tCO_2/MWh)	n/a	0.92	0.38	0.9	n/a	0.98	0.41	n/a	n/a	n/a
NO_x emission factor (g/MWh)	n/a	478	439	182	n/a	478	439	n/a	n/a	n/a
SO_2 emission factor (g/MWh)	n/a	649	49		n/a	649	49	n/a	n/a	n/a
PM 2.5 emission factor (t/MWh)	n/a	53	n/a	22.7	n/a	53	n/a	n/a	n/a	n/a
Expected fuel price ($/GJ)	0.7	4.5	8.9	8.4	0.7	4.5	8.9	n/a	n/a	n/a

** All monetary values are expressed in US$. (exchange rate US$1 = 6.7695 Yuan)

The costs of controlling emissions from coal- and gas-fired generation were also included in the operating costs of generating plants. These costs are associated with the treatment technology which consists of desulfurization, denitration and dedusting. Hence, the NO_X, SO_2 and PM2.5 emission factors used in the modelling, as shown in Table 4 are those after treatment.

Table 5 shows the treatment costs for coal and gas, which were estimated from (Wang, 2013; Fu, 2014; Li et al., 2014; National Energy Administration, 2014).

Table 5. Costs of controlling emissions.

	Coal ($/MWh)	Gas ($/MWh)
Desulfurization	2.216	N/A
Denitration	1.48	1.48
Dedusting	0.3	N/A
Total	4.00	1.48

5.2. Electricity demand and generation

Hourly profiles for electricity demand, wind, PV and hydro generation for 2030 were simulated based upon actual demand and generation data in 2012. The hourly electricity demand profile in 2030 is simulated based on an hourly demand pattern categorised into weekdays and weekends for four different seasons. The actual demand profile in 2012 was then scaled to match the projected electricity consumption in 2030 as shown in Table 6 (Yuan et al., 2012).

Table 6. Actual annual electricity consumption in 2012 and projected consumption in 2030.

Year	Annual Energy (TWh)
2012	4,986
2030	11,000

Hourly wind generation was simulated based on the normalised hourly wind generation data in Hebei province since it provides a reasonable representation of average wind generation across China. The normalised wind generation data is then scaled up to match the actual wind energy in 2012. Hourly PV generation data was simulated for 2012 using System Advisor Model (SAM) across 21 locations in 13 provinces in China and then scaled to match actual annual PV energy of 3.59 TWh in 2012 (China Electricity Council, 2013). Hourly hydro generation for 2030 was simulated based on the actual hydro generation pattern obtained for 2012 (separated into weekdays and weekends for different seasons) and the projected installed hydro capacity and annual hydro generation in 2030 by assuming the same hydro capacity factor as in 2012, which was 45%.

For the merit order dispatch, a 15% synchronous generation constraint is applied in order to provide adequate frequency response of the power system.[3] This constraint represents the minimum amount to which aggregated conventional generators (i.e. coal, CCGT, OCGT, nuclear, IGCC and hydro) can be turned down (to aid frequency control of the power system). Hence PV and wind generation are capped at 85% of demand in every dispatch interval.

Residual load duration curves showing the proportion of PV, wind, hydro and fossil-fuel generation for different PV and wind penetration levels are shown in Figure 3.

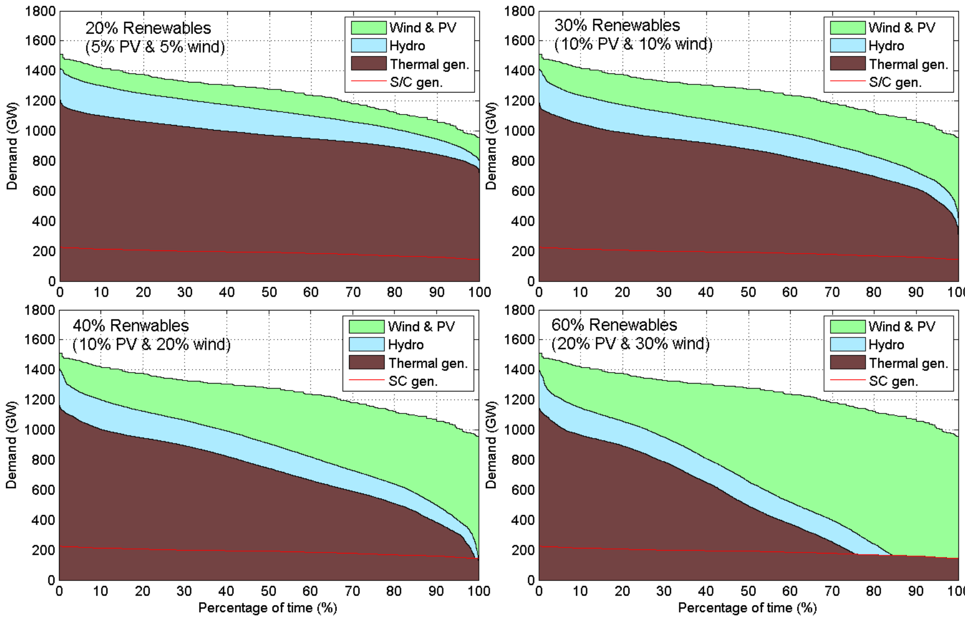


Figure 3. Load duration curve (LDC) for different scenarios of wind and PV penetrations. A minimum of 15% synchronous generation is assumed.

[3] The minimum synchronous generation level of 15% was assumed based upon (AEMO, 2013)

5.3. Modelling uncertainties

Key uncertain parameters considered in the modelling are future fuel prices, carbon prices, electricity demand and plant capital costs. These variables have become increasingly uncertain over recent years (Cobb, 2013) . Lognormal distributions were applied to model future fuel prices, carbon prices and plant capital costs. Electricity demand uncertainty is modelled by assuming a normal distribution of residual demand for each scenario of renewable penetration. Both lognormal and normal distributions can be characterised by their mean (central estimates) and standard deviation.

Due to the very wide ranging uncertainties around future carbon pricing policies, electricity demand growth and natural gas prices in many countries including China, a number of different scenarios of probability distributions for these uncertainty parameters are also considered in Section 6.3 - 0.

Fuel and carbon price uncertainty

The central estimate of carbon price for 2030 used in the modelling is $29/t$CO_2$' A carbon price of this magnitude would likely provide significant incentives to favour low-carbon investments in the electricity sector. In a study applying a dynamic computable general equilibrium (CGE) model a $29/t$CO_2$ carbon price was estimated to achieve a 20% emission reduction (Wu, 2012).

The central projection of fuel costs, shown in Table 4, was applied as the mean while the standard deviation was estimated based upon the spread of historical fuel prices in OECD countries[4] (IEA, 2013). The standard deviation of coal, gas and nuclear fuel costs applied in the modelling is 10%, 30% and 5% of the mean values respectively.
Correlations between fuel and carbon prices were accounted in the modelling given they have exhibited a considerable historical correlation in the EU and UK markets. For example, climate change policies might involve high carbon prices that would increase the consumption of lower emission gas, and hence its cost in relation to coal (Green, 2008). The correlations were estimated based upon quarterly historical coal and gas prices in OECD countries and are shown in Table 7 (IEA, 2013).

Table 7. Correlation coefficients between fuel and carbon prices

Correlation Coefficient ($\rho_{i,j}$)	coal price ($\rho_{bl\ oal}$)	Gas price (ρ_{gas})	Nuclear fuel price (ρ_{nuc})	Carbon price (ρ_{carbon})
Coal price ($\rho_{bl\ coal}$)	1	0.6	0	-0.35
Gas price (ρ_{gas})	0.6	1	0	0.45
Nuclear fuel price (ρ_{nuc})	0	0	1	0
Carbon price (ρ_{carbon})	-0.35	0.45	0	1

Correlated samples of coal, gas and carbon prices were generated from their marginal lognormal distributions using a multivariate Monte Carlo Simulation

[4] The historical data from OECD countries were used since historical fuel price data for China were not publicly available.

technique[5]. Histograms showing the distributions of 10,000 simulated coal, gas and carbon prices as well as the scatter plots highlighting their correlations are shown in Figure 4.

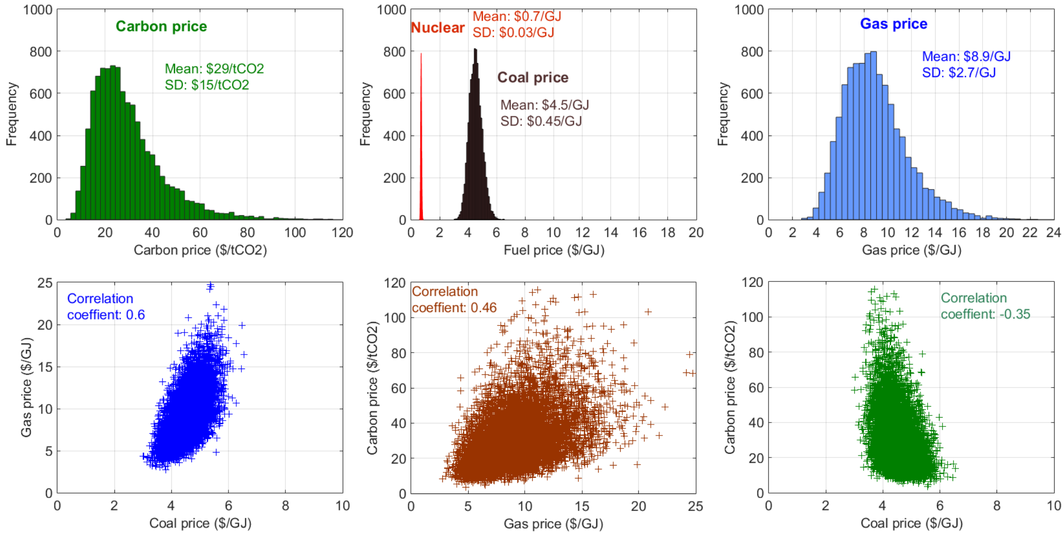


Figure 4. Histograms of 10,000 simulated fuel costs and carbon prices and scatter plots showing their correlations.

There is considerable uncertainty around climate policies in China and hence future carbon prices. the present pilot emissions trading schemes have seen relatively low prices to date. Looking forward to 2030, the modelling already captures a large degree of future carbon price uncertainty. Although a central carbon price of $29/t$CO_2$ was assumed for 2030, carbon prices in the 10,000 simulations considered range from as low as $3/t$CO_2$ to as high as $170/t$CO_2$. However, different expected carbon price sensitivities ranging from zero to as high as $58/tCO2 are also analysed. The high carbon price sensitivity assumes that the carbon price will double the central scenarios in 2030. For a zero carbon price case, the model assumes complete certainty that there will not be any form of carbon price applying to China's electricity sector in 2030. In addition, different gas price and coal price sensitivities are modelled. The sensitivity analysis is shown in Section 6.3.

Electricity demand uncertainty

Electricity demand uncertainty was modelled as uncertainty in the load duration curve (i.e. vertical shifts). A normal distribution was applied to represent residual peak demand with standard deviation of 4% (of residual peak demand), calculated for each renewable penetration.

Plant capital cost uncertainty

The central capital cost estimate for each technology, shown in Table 4 ,was applied as the mean while the standard deviation for the overnight capital costs were estimated from a number of studies as a percentage of the mean values (IEA/NEA,

[5] Multivariate Monte Carlo simulation techniques require the mean, standard deviation and correlations of uncertain parameters to reproduce random variables while preserving their marginal distribution properties and correlation structure.

2010). Table 8 shows the mean and standard deviation of plant capital costs for each of the technologies considered. Histograms showing the distributions of 10,000 simulated capital costs of each generation technology are presented in Figure 5.

Table 8. Mean capital costs and standard deviation.

Technology	Mean ($Million/MW)	Standard deviation (% of mean)
Coal	0.511	20%
CCGT	0.391	10%
Nuclear	1.719	30%
IGCC	1.206	20%
PV	1.462	20%
Wind	0.762	20%
Hydro	0.982	10%

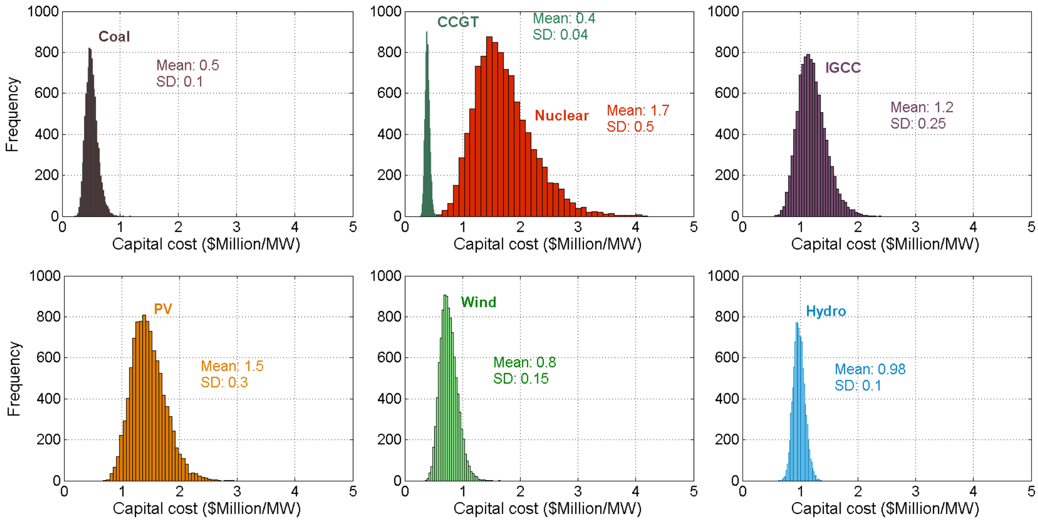


Figure 5. Histograms of 10,000 simulated capital costs.

6. Modelling results

6.1. Efficient generation portfolios for China's electricity sector in 2030

Efficient portfolios in terms of expected costs and cost risks

Figure 6 shows the expected cost and cost risk of every possible generation portfolio in all of the renewable penetration scenarios. Each blue dot represents a single generation portfolio by plotting that portfolio's expected cost against the cost risk (standard deviation of cost), calculated over 10,000 simulations of uncertain parameters. The "*efficient frontier*" containing a set of generation portfolios which represent the most efficient options in terms of cost and cost risk is also shown. This means that generation portfolios that are not on the efficient frontier are considered suboptimal since there are more appropriate options from both cost and cost risk aspects.

There are eight generation portfolios on the efficient frontier, denoted *A – H* in Figure 6. Portfolio H (16% coal, 13% CCGT, 3% nuclear, 0% IGCC, 28% PV, 30% wind, 10% hydro) is the lowest cost portfolio (but with relatively high risk), whereas portfolio A

(19% coal, 0% CCGT, 3% nuclear, 10% IGCC, 28% PV, 30% wind, 10% hydro) is considered as the lowest risk portfolio (but with relatively high expected average industry costs). There is an important tradeoff in terms of expected cost and cost risks among the portfolios that lie on the efficient frontier. The expected costs of the efficient portfolios range from $68/MWh (portfolio A) to $62/MWh (portfolio H). By moving along the efficient frontier the expected industry cost can be reduced but only by increasing the cost risk and vice versa.[6] Regardless of the share of thermal generation capacity, it is notable that all of the efficient generation portfolios contain the same amount of PV and wind capacity, accounting for 28% (1,196 GW) and 30% (1,256 GW) of total installed capacity respectively. Similarly, the efficient portfolios contain the same amount of nuclear capacity (134 GW).

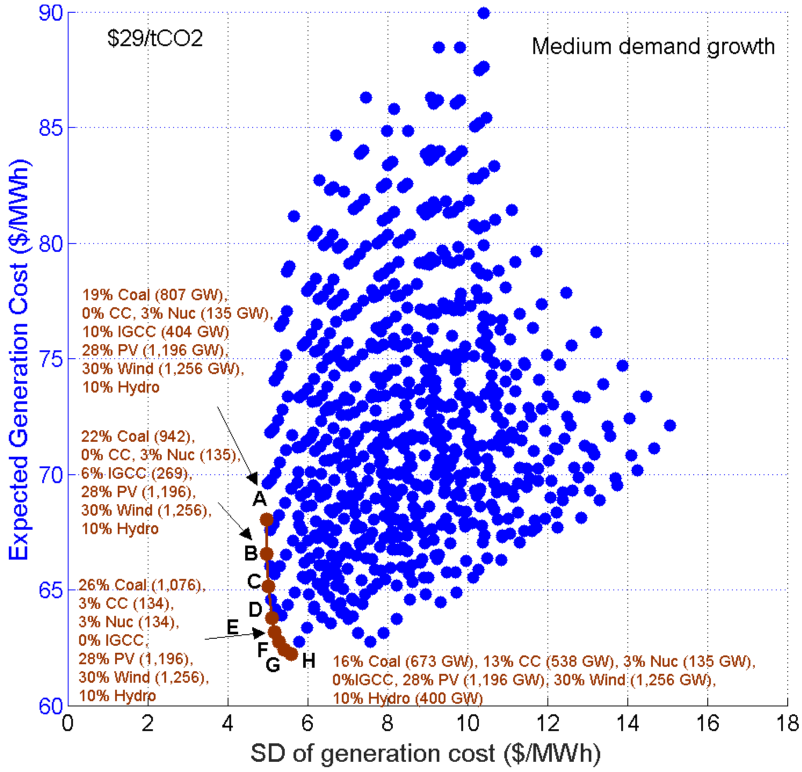


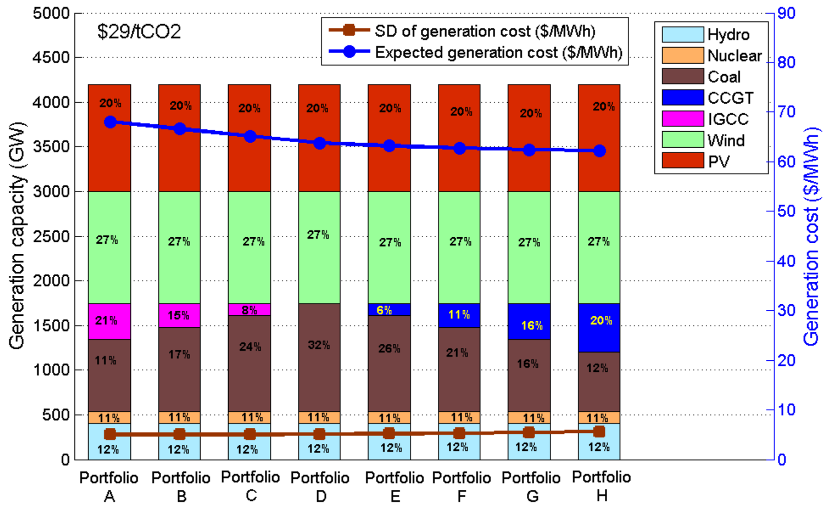
Figure 6. Expected costs and cost risk of every generation portfolio combining every renewable penetration scenario. The overall cost vs cost risk efficient frontier is shown by the solid line. The capacity of each technology is presented (GW, in brackets) as well as the percentage share.

Details of the efficient generation portfolios are shown in Figure 7. These include capacity, expected average industry costs, associated cost risks and emissions as well as the annual generation and capacity factor (CF) of each technology within the portfolios. The results indicate that the expected cost and emissions reduce as the share of CCGT capacity in a portfolio increases, replacing coal and IGCC. This is due to the relative low capital costs of CCGT in relation to coal and IGCC. However, the higher proportion of CCGT will lead to higher cost risk since CCGT is exposed to high gas price uncertainty. The total renewable energy penetration of any efficient portfolios is around 60% (47% of which from PV and wind and 12% from hydro), which implies that whether the objective is to minimise overall industry cost or minimise cost

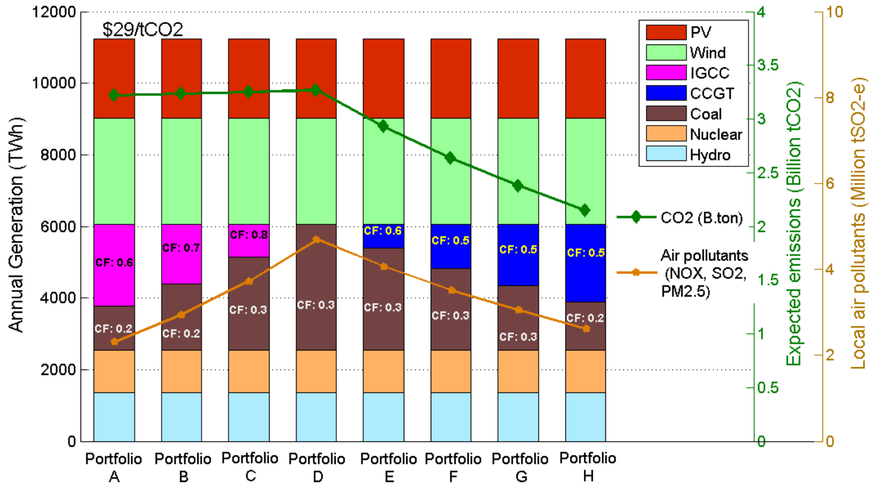
[6] Decision makers will need to determine their preferred trade-off between expected cost and cost risk.

risk, the appropriate renewable penetration level for 2030 should be around 60%.[7]

Among the efficient portfolios, varying the share of coal, CCGT and IGCC capacity will not greatly impact the expected cost or the cost risk (the maximum difference is around 7% for the expected cost and 10% for the cost risk). In all of the efficient portfolios, the capacity factor of coal-fired generation is only around 0.2 – 0.3, which suggests that coal-fired plants will be dispatched as intermediate or peaking capacity at this level of renewable penetration.



(a)



(b)

Figure 7. (a) Installed capacity, expected costs and standard deviation of generation costs (cost risk). Percentages indicate the % of annual generation (TWh) from each technology and (b) annual generation, expected CO_2 and local air pollutants of the efficient generation portfolios (on the cost and cost risk efficient frontier). Capacity factor (CF) is also presented.

Although the differences in cost as well as cost risk among the efficient portfolios are relatively small, the differences in the expected emissions (CO_2, NO_x, SO_2 and $PM_{2.5}$)

[7] Although not shown in the paper, generation portfolios with renewable penetration greater than 60% have also been tested and they are found to lie outside the efficient frontier. This testing is to ensure that the results were not influenced the highest renewable scenarios modelled in the paper.

can be quite significant. For example, significant reductions in CO_2 (1 billion ton) NO_X (4 million ton), SO_2 (14 million ton) and $PM_{2.5}$ (4 million ton) can be achieved if portfolio H (16% coal, 13% CCGT) is chosen over portfolio D (29% coal, 0% CCGT). Since portfolio H is also the least cost portfolio, it could be regarded as an appropriate option, albeit its relatively higher cost risk. In portfolio H, the coal-fired capacity is made up entirely of the existing coal-fired capacity (676 GW), which suggests that the least cost option does not involve investment in new coal-fired generation. Hence, the most economically sound option would seem to be continuing to operate the existing coal fleet out to 2030 in an intermediate or peaking capacity and making substantial investment in PV and wind generation complemented by moderate proportions of CCGT and nuclear.

Efficient portfolios in terms of expected costs and expected emissions

Figure 8 displays the efficient frontier showing tradeoffs between expected costs and CO_2 emissions among generation portfolios. This frontier was constructed using similar techniques as the cost versus cost risk efficient frontier described above. There are six portfolios, denoted I – H, which are considered efficient in terms of expected cost and CO_2 emissions. Interestingly, these portfolios also contain the same amount of renewable generation (i.e. 60% renewable penetration) as the cost vs cost risk efficient portfolios shown in Figure 6 and Figure 7. The portfolios that appear on the cost vs cost risk efficient frontier are also highlighted on the graph.

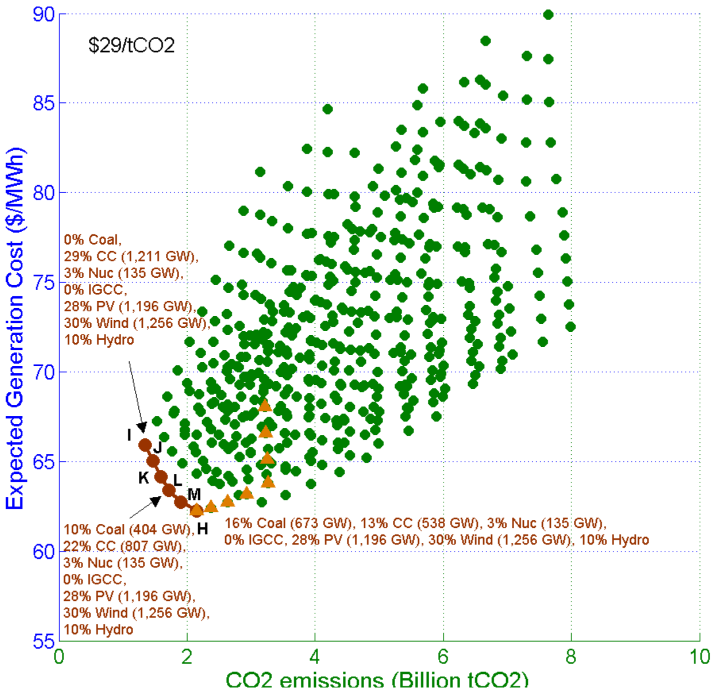


Figure 8. Expected costs and CO2 emissions of every generation portfolio. Triangles indicate generation portfolios in the cost vs cost risk efficient frontier. The capacity of each technology is presented (GW, in brackets) as well as the percentage share.

Details of the cost vs emissions efficient portfolios are shown in Figure 9. Generation portfolio that would result in the least possible CO_2 emissions level is portfolio I (0% coal, 29% CCGT, 3% nuclear, 0% IGCC), which also has the lowest NO_X, SO_2 and $PM_{2.5}$ levels (local air pollutants are correlated with CO_2 emissions). The results in Figure 9 show the influence of gas and coal-fired generation on the expected costs and emissions and their tradeoffs among the efficient generation portfolios. Increasing the share of gas-fired generation instead of coal in the generation portfolios will result in emissions reduction but at the expense of an increase in costs. In the lowest emissions portfolio (portfolio I), the expected average industry cost is \$66/MWh while the CO_2 emissions is 1.3 BtCO_2 compared to \$62/MWh and 2.1 BtCO_2 in the least cost portfolio (portfolio H). Hence, the least emission portfolio arguably represents a more appropriate option, particularly if emissions reduction is the main policy objective, since it has significantly lower emissions in both CO_2 and local air pollutants (up to 80% lower) while the costs will only be around 5% higher in relation to the least cost portfolio.

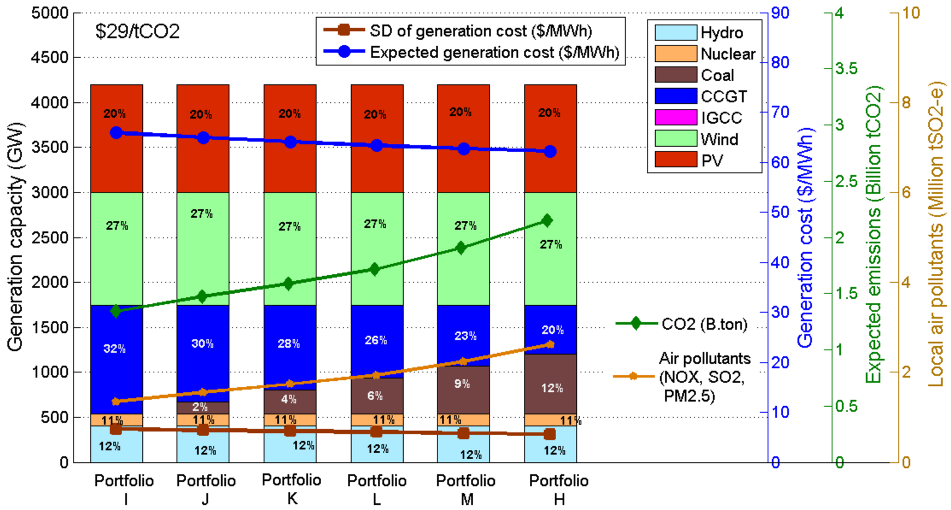


Figure 9. Installed capacity, expected costs, CO_2, and local air pollutants of the Cost VS emissions efficient generation portfolios. Percentages indicate the % of energy (TWh) from each technology.

6.2. The least cost options for achieving long-term emissions targets

This section examines the least cost generation portfolio mix in achieving particular CO_2 emissions targets. The portfolios modelled were arranged into eight groups based on their CO_2 emissions levels. The lowest cost generation portfolios in each emissions level was then selected as shown in Figure 10. The emission ranges were determined in such a way that generation portfolios were not heavily concentrated in certain emissions ranges.

Figure 10 illustrates that the portfolio with the lowest renewable penetration level (i.e. 20%) not only has the highest CO_2 and local air pollutions, but also the highest cost and cost risk. This portfolio consists mainly of coal-fired generation and relatively moderate amount of gas-fired generation. On the other hand, the least cost portfolio in the lowest emissions range (1.5-2.5 BtCO_2) has the lowest industry cost and cost risk.

Present CO_2 emissions from the electricity sector in China are around 4 billion tCO_2 (IEA, 2016a). The lowest cost option in maintaining the current emissions level while meeting the electricity demand growth in 2030 involves generation portfolios with around 40% renewable penetration (i.e. portfolio in the range 3.5 - 4.0 and 4 - 5 BtCO_2). This amount of renewables is similar to the high renewable penetration study recently conducted by China Energy Foundation (Energy Foundation China, 2015). However, a renewable penetration greater than 40% would be required if China is to achieve its ambitious emission reduction targets, which aim to achieve a 40% - 45% reduction in CO_2 intensity (CO_2 per unit of GDP) from 2005 levels by 2020. For example, in order to reduce the CO_2 emissions to be in the 1.5 – 2.5 $BtCO_2$ range in 2030, the lowest cost option is to source around 60% of energy from renewables and only 10% from coal-fired generation. The results also suggest that nuclear and CCGT also play a key role in low-carbon electricity generation portfolios, providing around 10% and 20% of total annual electricity generation respectively.

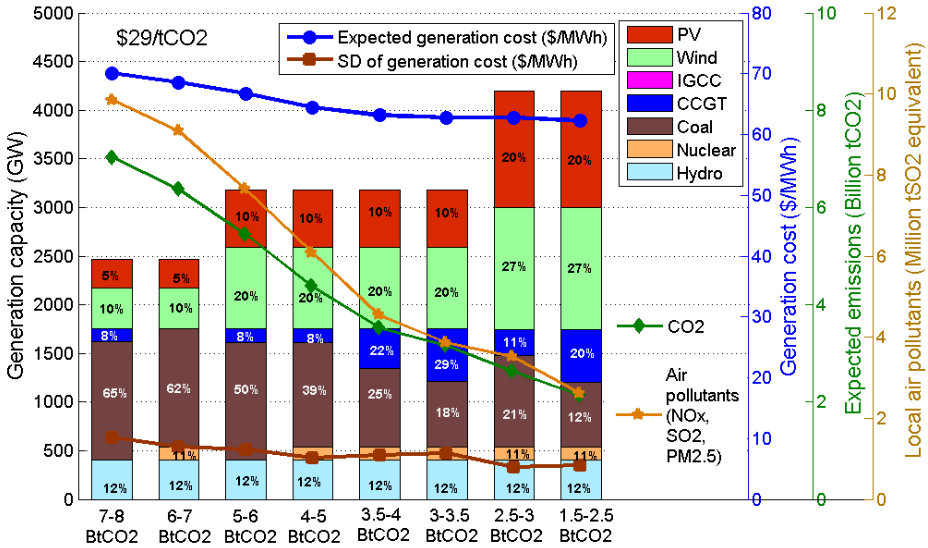


Figure 10. The least cost generation portfolios for each emission range. Percentages indicate the share of energy generated from that technology.

6.3. Sensitivity analysis for different expected carbon prices, gas prices, coal prices and demand growth

Sensitivity analysis for different expected carbon prices, gas prices and demand growth rate has also been modelled given the particularly large uncertainty around these key cost factors.

Different expected carbon price sensitivities

In addition to the medium estimate of carbon price, which is centered around $29/t$CO_2$ in 2030, the model has also been applied to six different expected carbon price sensitivities: $0, $10, $20, $30, $40, $50 and $58/t$CO_2$. For the highest carbon price sensitivity (i.e. $58/tCO2), it was assumed that the expected carbon price is double of that in the medium estimate. For a zero carbon price case, the model assumes complete certainty that there will not be any form of carbon price applying to the electricity sector.

Figure 11 shows the cost vs cost risk efficient frontiers for the zero, medium ($29/t$CO_2$) and high ($58/tCO_2) carbon price sensitivities in 2030. The figure also illustrates the efficient frontiers in the case of carbon revenue recycling, which assumes that the carbon revenue is recycled to reduce the overall industry generation costs.[8] Generally, the carbon price would increase the industry costs and cost risks as illustrated by the efficient frontier for each of the expected carbon prices. This is due to the uncertainty associated with future carbon pricing policies in China. However, if the carbon revenue were used in reducing the generation costs, the differences in the expected cost in the case with and without the carbon price would be quite small.

The impact of coal-fired and renewable generation on costs and cost risks is also evident, particularly in the case without a carbon price. In this case, the lowest cost portfolio has a 22% combined share of PV and wind capacity (and 20% renewable energy penetration) but this portfolio has relatively high cost risk. Increasing the share of PV and wind capacity from 22% to 45% reduces the cost risk (i.e. standard deviation of cost) from \$3 to \$2.5/MWh (a 15% reduction) while only increases the costs from \$50 to \$53/MWh (a 6% increase). This suggests that PV and wind generation can be valuable in hedging against the risk caused by uncertainty in future fuel and carbon prices.

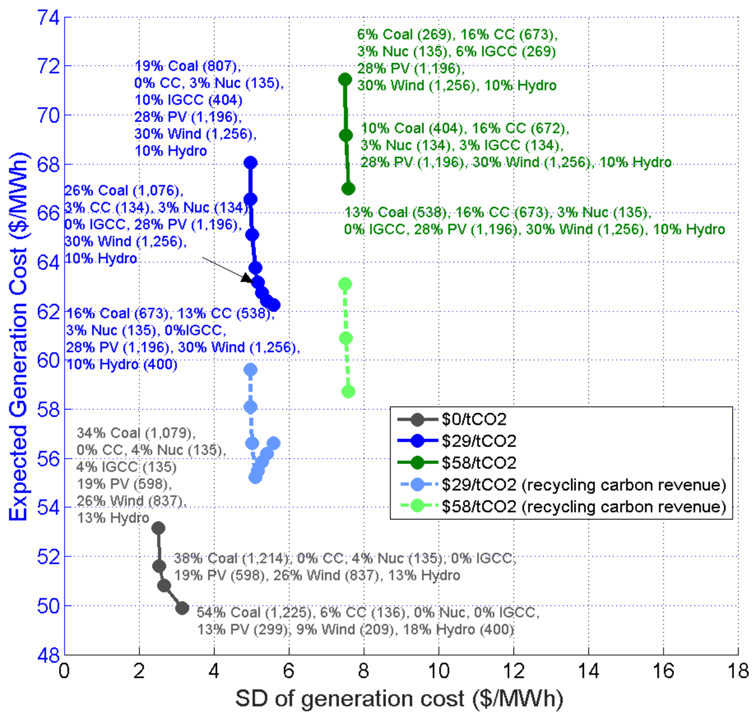


Figure 11. Efficient frontiers containing generation portfolios for different expected carbon price scenarios. Dashed lines indicate efficient frontiers when carbon revenues are used to reduce the generation costs.

The details of the least cost portfolio for the seven different expected carbon price sensitivities are shown in Figure 12. In the case without a carbon price, the least cost generation portfolio comprises a significant share of coal-fired generation and only small amount of gas-fired, PV and wind generation while nuclear and IGCC are deemed too expensive, and hence are not featured in the least cost portfolio.

[8] Carbon revenue can be returned to consumers by using it to offset the added cost due to the carbon price.

Without carbon pricing mechanisms, there is a relatively low incentive to invest in renewable technologies, and hence coal will continue to be the main generation source resulting in high CO_2 emissions and local air pollution. In this scenario, the least cost technology share obtained from the modelling for 2030 is somewhat similar to the current generation mix in China where the share of coal-fired generation is more than 70% of total generation followed by hydro at 17% while the combined share of gas and nuclear generation is only around 3% (IEA, 2015). The modelling also suggests that, in order to achieve the least cost option in 2030, the combined share of wind and solar generation could increase from the present 5% in to 15% in 2030.

With a carbon price, however, the share of coal-fired generation will be replaced by renewable and gas-fired generation in the least cost portfolios, as shown in Figure 12. A carbon price as low as $10/t$CO_2$ could result in a considerable increase in the share of wind and PV generation (from 15% in the case without the carbon price to 30%) as well as gas-fired generation, while reducing the share of coal-fired generation. As a result, both CO_2 emissions and local air pollutions can be reduced by around 40% (from 7 to 4 BtCO_2 and from 10 to 6 Mt$SO_{2\text{-eq}}$), while the cost only increases by around 10% (from $50 to $56/MWh) as the carbon price increases from $0 to $10/t$CO_2$. As the carbon price reaches $29/t$CO_2$, which is the central carbon price estimate in 2030, the share of wind and PV generation in the least cost portfolios increases to 50% (which the maximum wind and PV modelled in this study), resulting in further significant reductions in CO_2 and air pollutions, while the costs only increase very slightly.

Although the scenario without a carbon price has the lowest cost and cost risk, the emissions are extremely high. When carbon revenue recycling is assumed (as shown by the dotted lines), the cost difference in the least cost portfolio between the zero and the medium carbon price is around $7/MWh (or 10%) while the difference in CO_2 emissions can be as high as 6 BtCO_2 (or 80%). Such tradeoffs between expected costs and emissions are arguably worth making. Once the carbon price is greater than $29/t$CO_2$, the emission reductions as a result of higher carbon prices are less apparent (around 10% emission reduction for every $10/t$CO_2$ increase in the carbon price).[9] Based on this modelling, a carbon price of around $29/t$CO_2$ in 2030 appears reasonable since the tradeoffs between the emissions reduction and the cost increase are less apparent when the carbon price is greater than $29/t$CO_2$ (up to $58/t$CO_2$).

Figure 12 also shows that the total installed capacity increases with higher carbon prices. This is due to higher wind and PV penetration, and hence addition amount wind and PV capacity is required given their relative low capacity factors (i.e. higher capacity is required to maintain system adequacy).

[9] At $29/t$CO_2$, the share of wind and PV generation is already at the maximum level modelled in this study. Increasing the carbon price further will only increase the share of gas-fired generation, replacing coal in the least cost portfolios.

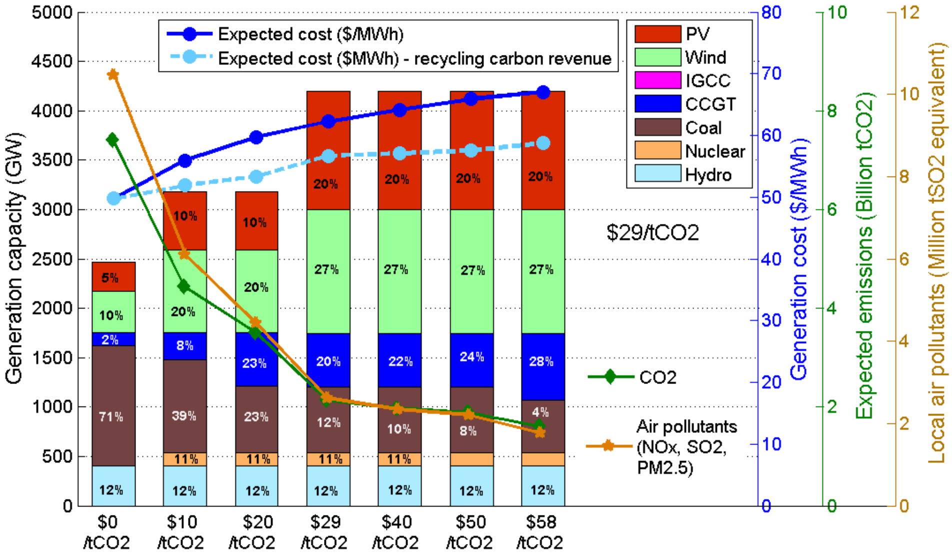


Figure 12. Installed capacity, expected costs, cost risk and emissions of the least cost portfolio for different expected carbon prices. Percentages indicate the share of energy generated from that technology.

Different gas price sensitivities

With the recent developments in global gas markets (e.g. shell gas, LNG), there is considerable uncertainty around future gas prices in many countries including China. Due to substantial increase in domestic gas consumption, the share of China's gas import has rapidly increased over the past decade, rising from 2% in 2006 to 32% in 2013 (Chen, 2014). Over the next decades, China will be relying on pipeline and Liquefied Natural Gas (LNG) from countries including Russia, Turkmenistan, Myanmar and Australia (Sheehan et al., 2014). International gas markets are highly uncertain looking forward and the dynamics of global gas markets are likely to impact domestic gas prices in China. In order to address this concern, a sensitivity analysis with high and low expected gas prices of $12/GJ and $6/GJ respectively were modelled.

Figure 13 compares the least cost generation portfolio for different expected gas prices (with central estimates of carbon price and demand growth). The different expected gas prices will have an impact on the total installed capacity required, technology mix in the least cost portfolio and subsequently the overall industry costs and emissions. The figure indicates that lower gas prices result in higher share of CCGT capacity as well as annual generation, replacing coal and to a lesser extent wind and PV in the least cost portfolio. In the low gas price scenario, there is only around 400 GW of coal capacity in the least cost portfolio, which means that almost 300 GW of the existing coal plants will be retired. Furthermore, the remaining coal plants are likely to be dispatched as peaking capacity as shown by its low annual capacity factor. CCGT, on the other hand, accounts for 30% of total capacity and 56% of total annual electricity generation.

The total installed capacity required under the low gas price scenario is considerably less than those in the medium and high gas price scenarios, resulting in much lower costs (around 15% lower). With the considerable share of CCGT in the low gas price scenario, the amount of wind and PV generation required is not as much as those in the higher gas price scenarios.

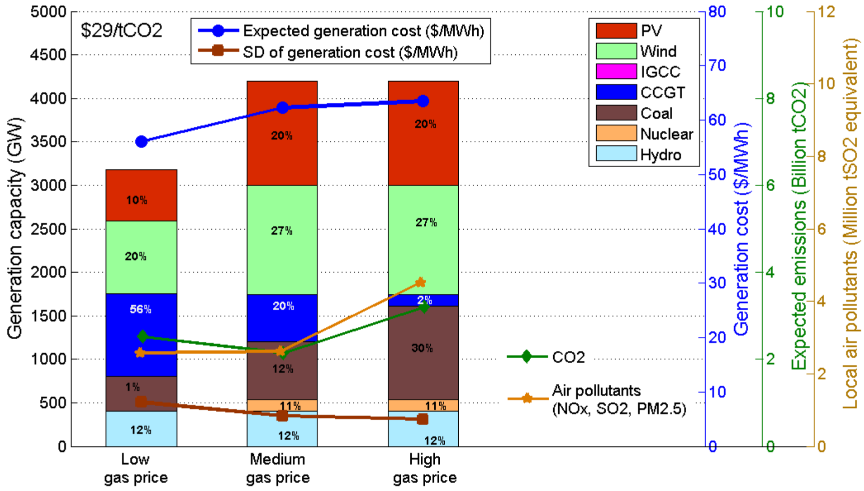


Figure 13. Installed capacity, expected costs, cost risk and emissions of the least cost portfolio for different expected gas prices. Percentages indicate the share of energy generated from that technology.

Wind and PV generation still play an important role regardless of the gas price, accounting for 30% of total generation in the low gas price scenario and around 50% in the medium and high gas price scenarios. The modelling results suggest that it is less costly to invest in new CCGT compared to operating the existing coal-fired generation plants in the case of low gas price. In the medium and high gas scenarios, the investment is shifted from CCGT more towards wind and PV up until the combined wind and PV penetration reaches 50% (which is the maximum modelled in this study). Figure 13 also shows that higher gas prices are likely to increase the overall industry costs and emissions due to the higher share of coal generation (and less CCGT) in the least cost generation.

Low coal price scenario

The future coal price is one of the main factors that can influence generation investment decisions since it also has a direct impact on electricity prices and the merit of coal versus other generation options. To examine the impact of coal price, this modelling considers a low coal price scenario by assuming a coal price of $2/GJ in 2030, which is half of the central coal price estimate.

The impact of coal price on the technology mix, costs, and emissions of the least cost generation portfolios are shown in Figure 14 by comparing the least cost portfolios between the low and medium coal price scenarios. The low coal price would lead to increased investment in coal-fired capacity as well as total generation output from coal-fired generating plants (i.e. higher capacity factor). There will be a considerable amount of coal-fired generation in the least cost portfolio instead of wind, PV, gas and nuclear, even with a carbon price of $29/tCO$_2$. In terms of the overall industry costs, the low coal price would reduce the overall costs by $7/MWh (or around 10%) compared to the medium coal price scenario. The lower cost is a result of less installed wind and PV capacity being required and higher generation outputs from low-cost but emission intensive coal-fired generators. Despite the low electricity costs, the overall industry CO_2 emissions and local air pollutions are at least three times higher than those in the medium coal price scenario.

The results suggest that coal-fired generators would greatly benefit from low coal prices, which could result in increasingly adverse impacts on the environment. If future coal prices are low, a higher carbon price is likely to be required if the electricity industry is to achieve any emission reductions.

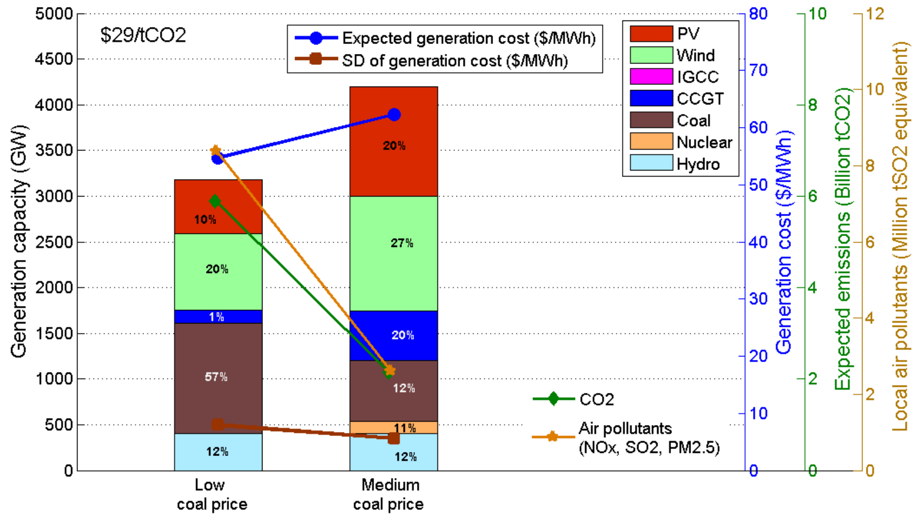


Figure 14. Details of the least cost portfolios for low and medium coal prices. Percentages indicate the share of energy generated from that technology

Low demand growth scenario

Due to mixed economic growth since the Global Financial Crisis of 2008 and increased penetrations of distributed generation and energy efficiency programs, many electricity industries around the world have experienced lower than expected electricity demand growth, or even reductions in demand, over recent years. This also represents a possible future for China's electricity industry therefore a sensitivity analysis with a low demand growth rate is also considered. The central projection of electricity demand in 2030 is 11,000 TWh (shown in Section 0), which is equivalent to an average growth rate of approximately 5% per year. For the low demand growth scenario, this study assumes the demand growth rate to be only half of the central demand growth rate projection, which is 2.5% per year. In the low demand growth rate, the electricity consumption in 2030 is projected at 7,800 TWh.

The efficient frontier containing efficient generation portfolios for the low demand growth scenario is displayed in Figure 15. The figure also shows a comparison of the efficient frontier with the scenario with medium demand growth. Details of the least cost portfolio for different demand growth scenarios are illustrated in Figure 16. With the low demand growth, the expected overall industry costs are around $5/MWh lower, which is approximately 5% lower compared with the medium growth. This is because significantly less investment in generation capacity is required, as well as lower total variable operating expenses.

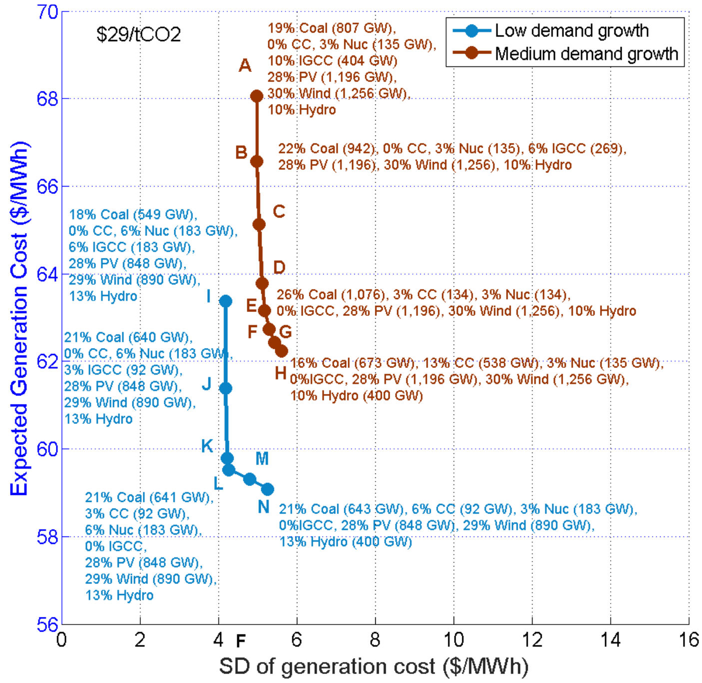


Figure 15. Efficient frontiers containing efficient portfolios for different scenarios of electricity demand growth

Figure 16 shows that the installed generation capacity required in the low demand growth scenario is significantly less than that in the medium growth scenario (2,400 GW compared to 4,200 GW in the medium demand growth scenario), hence lower overall industry costs. However the emissions level in both demand growth scenarios are relatively the same, suggesting that it is possible for the electricity sector to accommodate higher demand growth without increasing emissions. This can be achieved by investing in new wind and PV as well as CCGT capacity.

Similar to the central demand growth scenario, the modelling suggests that there would be no new investment in coal-fired generation. As shown in Figure 16, the coal-fired generation capacity in the least cost portfolio consists only of the existing coal capacity, which is 676 GW. The amount of nuclear capacity installed is also the same for both of the demand growth scenarios. However, both coal and nuclear plants in the low demand scenario are dispatched at a higher capacity factor. Coal and nuclear generation account for approximately 50% of total generation in the low demand growth scenario compared to 25% in the medium demand growth scenario.

In the low demand growth scenario, significantly less investment in large-scale wind and PV generation capacity are required. The combined wind and PV generation capacity in the least cost portfolio reduces from around 2,400 GW in the high demand scenario to around 1,000 GW in the low demand scenario. However, the total renewable penetration level is still significant in the low demand scenario, accounting for almost 50%, out of which wind and PV account for 30% of annual electricity generation compared to 60% in the medium demand growth scenario.

The results from the different demand growth scenarios appear to suggest that regardless of the demand growth rate, PV and wind generation and, to a lesser extent CCGT, represent a more viable generation option than coal. In addition to their shorter construction time and hence less investment risk, both wind and solar PV plants can be commissioned in sequence without having to wait for every wind turbine or solar panel to be installed.

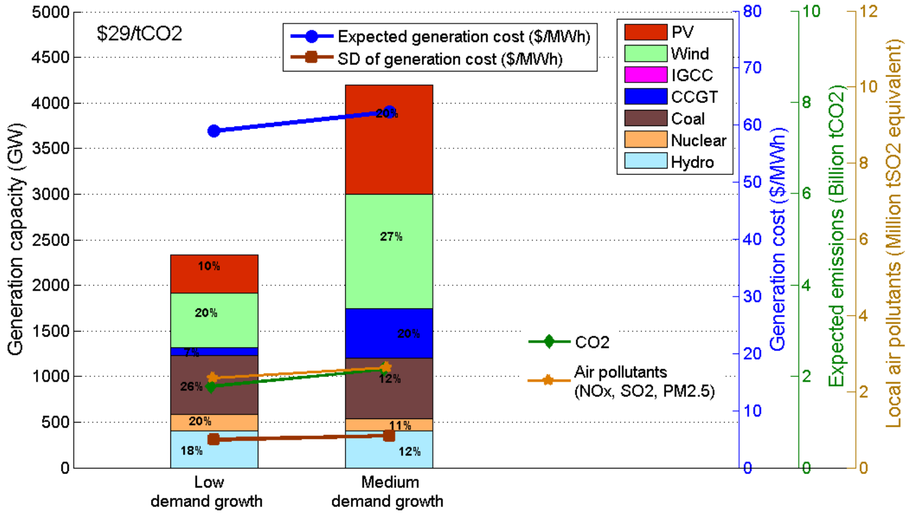


Figure 16. Installed capacity, expected costs, cost risk and emissions of the least cost portfolio for different demand growth scenarios. Percentages indicate the share of energy generated from that technology.

7. Discussion

Under the central estimates of future costs and demand growth, the modelling findings suggest that a renewable penetration of around 60% in 2030 would perform well in terms of overall industry generation costs, cost risks and emissions for a wide range of possible future generating plant, fuel and carbon costs. This share of renewables consists of 20% PV, 30% wind and 10% hydro. Unless the future coal price is low and there is neither a meaningful carbon price nor restrictions on local air pollutants, there appears to be little incentives to invest in new coal-fired generation due to its high capital. Wind, PV and, to a lesser extent CCGT, represent a more viable option in terms of costs, cost risk and emissions. However, the existing coal-fired plants can still play a role in the future least cost portfolio by operating as intermediate and peaking capacity. In this scenario, considerable investment in PV and wind generation are required by 2030 complemented by moderate proportions of CCGT and very small proportion of nuclear. Although the share of nuclear generation capacity in the future least cost portfolio is only around 3% (135 GW), they complement renewables by providing baseload capacity.

If China's electricity sector is to avoid any increase in greenhouse emissions from the current levels (around 4 $BtCO_2$ in 2013) while meeting electricity demand in 2030 in a cost effective manner, the modelling suggests that at least 40% of electricity generation in China would need to come from renewable sources. For emissions reductions in 2030 compared to present levels, renewable penetration greater than 40% are likely to be required. The modelling results suggest that the generation portfolio with a 60% share of renewable generation and a 10% share of coal would be cost-effective in achieving such emissions reductions objectives.

A future carbon price has been shown to significantly impact the cost, cost risk and emissions of generation portfolios. The modelling suggests that if there is no carbon price or the carbon price is low, the least cost technology share in 2030 would roughly reflect China's present generation mix. Coal-fired generation would continue to play a dominant role resulting in significant CO_2 emissions and local air pollutions.

With a carbon price of \$29/tCO_2, the emissions from the electricity sector in 2030 would be four times less than those in the scenario without a carbon price, while the increase in the overall industry costs due to the carbon price is moderate at around 30%. With carbon revenue recycling schemes in place, however, the impact of carbon pricing on the overall cost is modest at around 10%. Higher carbon prices result in further emissions reductions, but the emissions savings diminish.

Future gas prices, coal prices and electricity demand growth can also influence the share of generation technology in the least cost portfolio, and subsequently overall costs and emissions. In the case of low demand growth, significantly less investment in new generation capacity is required, resulting in much lower overall industry costs. This suggests that demand side management measures could be valuable as a means for minimizing future industry costs as a result of delaying investment in generation capacity. The direction of future gas and coal prices is likely to affect the level of CCGT and coal plant investment and retirements of existing coal plants as well as the way in which generating plants are dispatched. Unless the gas price is high or coal price is extremely low, there are no incentives in investing in new coal-fired capacity given its relatively high capital costs and significant emissions in both CO_2 and local air pollutions. Regardless of future carbon price, gas price, coal price and demand growth, wind and PV generation appear to be the most viable generation options and would play a significant role in future generation portfolios in minimizing overall industry costs and cost risk as well as achieving emission reduction targets.

The findings are consistent with the high renewable penetration study recently conducted by China Energy Foundation (EF) (Energy Foundation China, 2015). The China EF study also recognizes that renewables are the essential sources for replacing fossil-fuel technology in future generation portfolios. The renewable penetration recommended in the China EF study for 2030 is around 40% and the combined wind and PV installed capacity is around 2,000 GW.

The modelling results provide key energy and climate policy implications for China's electricity sector, particularly with regard to the future role of conventional and renewable generation, future carbon prices. The renewable penetrations of 40% – 60% by 2030 require suitable policy and mechanisms to drive investment and support growth in large scale renewable generation. To avoid any delay in renewable investment, strong renewable energy and emission targets represent a suitable policy response. A sufficiently high carbon price or equivalent policy efforts can play an important role in achieving the targets required. Carbon price revenue can also be invested to provide further support for zero carbon investment. In addition, there may be benefits to implement policy and regulatory initiatives to encourage demand side participation in order in minimising overall industry costs.

Note that this modelling doesn't consider electricity market and institutional arrangements although these have adversely impacted progress in some regards. For example, generation dispatch is still often based on allocating predetermined shares of generation to individual plants, rather than dispatching them according to their generation costs. Such dispatch model has proved to hinder the efficient dispatch of low-operating cost renewable generation, which was evidenced by the wind generation curtailment of 16.2 TWh in 2013 at an estimated loss of 8.3 billion yuan to wind farm developers under the lowest Feed-in-Tariff (FiT) of 0.51 yuan/kWh (Wu and Yang, 2014; Li, 2015). This dispatch model is a relic of the planned economy and does not conform with a liberalised market model which is generation cost-based and has been tested in pilot-regions in China since 2007 (Teng et al., 2014). The regulation on electricity prices does also hinder the pass-through on CO_2 prices, which makes it difficult for the electricity industry to recover their costs (Teng et al., 2014). These market and institutional arrangements will also require attention in order to meet China's electricity industry objectives.

8. Conclusions

This modelling study provides an analysis of future generation portfolio investment in China's electricity industry under highly uncertain fossil-fuel prices, carbon pricing policies, electricity demand growth and plant capital costs. In particular, it focuses on the potential impact of carbon pricing on future electricity sector investment in China. The modelling provides important insights into issues that are related to energy and climate policy decision making in China's electricity industry, particularly relating with the future role of each generation technology, the impact of renewable generation on overall industry cost, cost risk and emissions.

The modelling results highlight some of the key synergies and tradeoffs between multiple electricity industry objectives involving costs, energy security and environment emissions, as well as the role of different generation technologies in contributing to such objectives. Utility-scale renewable generation options, particularly wind and PV, have been shown to likely play a key role in future generation portfolios. The modelling suggests that renewable penetration in China's power generation of around 40%-60% at 2030 would be efficient to minimize future generation costs, cost risk and emissions. Utility-scale wind and PV generation will play a key role in future generation portfolios in meeting such objectives, complemented by gas-fired and nuclear generation.

The results also highlight the extent to which fuel and carbon price and their interactions might affect generation technologies and future generation portfolios. The modelling suggests that a moderate carbon price could achieve emission reductions outcomes in a cost-effective manner through increased investment in large-scale renewables. A sufficient carbon price that results in desired emission reduction outcomes also depends on the level of future fuel prices, particularly coal prices.

As with any other modelling studies, the findings are highly dependent on input assumptions. In addition, the modelling tool employed in the study has some limitations. Short-term power system operational implications associated with high renewable penetrations have not been considered in detail beyond the application of a 15% minimum synchronous constraint in each dispatch period. The transmission costs that may arise due to the connections with new generating plants and possible need for energy storage under high renewables penetrations are not included in the simulations. Addressing these limitations represents an area for future work.

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