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Low-carbon technology diffusion in the decarbonization of the power sector: Policy implications

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ABSTRACT

The Chinese power sector faces a significant challenge in attempting to mitigate its CO_2 emissions while meeting its fast-growing demand for electricity. To address this challenge, an analytical framework is proposed that incorporates technological learning curves in a technology optimization model. The framework is employed to evaluate the technology trajectories, resource utilization and economic impacts in the power sector of Tianjin in 2005–2050. Using multi-scenario analysis, this study reveals that CO_2 emissions could be significantly reduced if relevant mitigation policies are introduced. The main technologies adopted are ultra-super-critical combustion, integrated gasification combined cycle, wind power, hydropower, biomass power, solar photovoltaic power and solar thermal power. Despite uncertainties, nuclear power and CO_2 capture and storage technology could be cost competitive in the future. The CO_2 emissions cap policy has the advantage of realizing an explicit goal in the target year, while the renewable energy policy contributes to more cumulative CO_2 emissions reduction and coal savings. A carbon tax of 320 CNY/ton CO_2 would contribute to early renewable energy development and more CO_2 reduction in the short run. A sensitivity analysis is conducted to examine the impacts on the power system of learning rates, technology cost reductions and energy fuel price trajectories.

1. Introduction

Due to its coal-dominant energy mix, China is the world's leading emitter of carbon dioxide (CO_2), accounting for 26% of global emissions in 2012 (IEA, 2014). China is striving to peak its CO_2 emissions around 2030, a goal defined in the U.S.-China Joint Announcement on Climate Change in 2014 (Ottmar, 2015). Similarly, a reduction of carbon intensity by 60–65% from the 2005 level by 2030 was proposed in China's national contribution scheme prior to the Paris 2015 Climate Summit. The electricity and heating sector accounted for approximately 50% of the total emissions in 2012 (IEA, 2014); thus, the Chinese power sector must play a crucial role in achieving the 2030 CO_2 emissions reduction target. For the power sector, the main CO_2 emissions reduction technologies are renewable energy, nuclear energy and fossil power plants with CO_2 capture and storage (CCS) technology (IEA, 2008; Shaikh et al., 2015). However, significant uncertainties are associated with these technologies, such as policy interventions, resource limits, security concerns, technology development, and economic impacts (Sovacool, 2009). It is imperative to examine the dynamic relationship between policies and technologies to address these uncertainties.

The policy-technology nexus has many dimensions. For instance, policy interventions could be designed to promote a low-carbon transformation of the power sector using CO_2 mitigation targets, energy conversion measures, renewable energy development policy, carbon taxes or greenhouse gas fees (Brown et al., 2013; Calderón et al., 2016; Chappin and Dijkema, 2009; Kumbaroğlu et al., 2008; Mallah and Bansal, 2010a, 2010b; Mathur et al., 2003; Mondal et al., 2010, 2011; Roehrl and Riahi, 2000). Technology interventions can emphasize a range of alternative technologies, such as wind, solar, biomass, and CCS. However, the effects of technology uncertainties may dominate the design of a low-carbon approach, emphasizing the lifetime of power plants, technology availability, technology restriction/promotion, and fuel prices (Eom et al., 2015; Ko et al., 2010; Paul et al., 2013; Simoes et al., 2015; Yang et al., 2015). In addition, a faster or slower decline in the cost of electricity generation technologies may affect the technological development strategy. Thus, technological learning has been

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employed to forecast technology's cost patterns, suggesting that global learning can have positive effects on the performance of low-carbon technologies as well as the costs of the energy system (Barreto and Kypreos, 2004; Martinsen, 2010, 2011a; Rout et al., 2009). In investigating the policy-technology nexus in the Chinese power sector, Chen (2005) and Chen et al. (2007) examined the technology mix and marginal abatement cost in the energy system, including the electricity sector, under carbon emissions reduction strategies. Zhang et al. (2012a), (2012b), (2013a), (2013b) proposed the optimal technology pathway for the power sector considering different carbon tax policies. From a multi-regional perspective, Cheng et al. (2015) identified the generation mix in different regions and the power transmission pathway.

On one hand, there has been little discussion of the endogenous incorporation of technological learning under various low-carbon policies in China's power sector, possibly resulting that the low-carbon technology cost as well as the technology development could not be well predicted. Therefore, building on the existing studies, this study focuses on the technological learning effects of alternative technologies in China. On the other hand, the existing studies focus on optimizing the Chinese power sector as a whole, whereas regional differences have been overlooked in areas such as resource supply endowment and electricity demand.

A TIMES model, which is an evolved version of the Market Allocation of Technologies (MARKAL) model and the Energy Flow Optimization Model (EFOM) with new functions and flexibilities, is adopted in this study by incorporating learning curves. This bottom-up model is one of the most common methods used in previous studies. Compared with top-down models (e.g. computable general equilibrium model, CGE model), the TIMES model has the advantage of investigating the technology option details as well as the interactions between technologies and policies (Dai et al., 2011), rather than identifying the economic impacts of the climate policies (Krook-Riekkola et al., 2017). Alternative bottom-up models include the Long-range Energy Alternatives Planning System (LEAP) model (Özer et al., 2013) and the Model for Energy Supply Strategy Alternatives and their General Environmental Impacts (MESSAGE) (Hainoun et al., 2014). Compared with these models, the MARKAL/TIMES model is a well-developed optimization method from the cost effectiveness perspective (Amorim et al., 2014; Chiodi et al., 2013; Jegarl et al., 2009; Mallah and Bansal, 2011; Mondal et al., 2011; van den Broek et al., 2008). Such model has the advantage of integrating technological learning effects into its technology cost simulation module (Martinsen, 2011b).

This study aims to identify the least-cost technology pathway and energy supply profile for the power sector in Chinese mega-cities under different scenarios until 2050. Via multiple scenario analysis, the TIMES modeling, which considers the technological learning effects, was conducted. As one of four municipalities in China, Tianjin has a high-carbon energy structure in its power sector, with 99% of its total electricity coming from fossil fuels (Tianjin Municipal Bureau of Statistics, 2006–2014). Thus, Tianjin was selected for this research.

2. The power sector in Tianjin

2.1. Overview of Tianjin's power sector

Due to fast-paced economic development and urbanization, Tianjin's electricity demand has grown rapidly in recent years. As shown in Fig. 1, from 2005 to 2013, the total electricity demand grew to 63.8 billion kWh, with an annual growth rate of 6.8%. Thermal power generation accounts for 99.1% of the total electricity use in 2013. The installed capacity increased to 11.4 GW in 2013, with the thermal power capacity accounting for 97.8% (Tianjin Municipal Bureau of Statistics, 2006–2014). Meanwhile, Tianjin imports electricity from other regions to meet its total electricity demand, and the amount imported increased from 2.0 billion kWh in 2005–18.6 billion kWh in 2013.

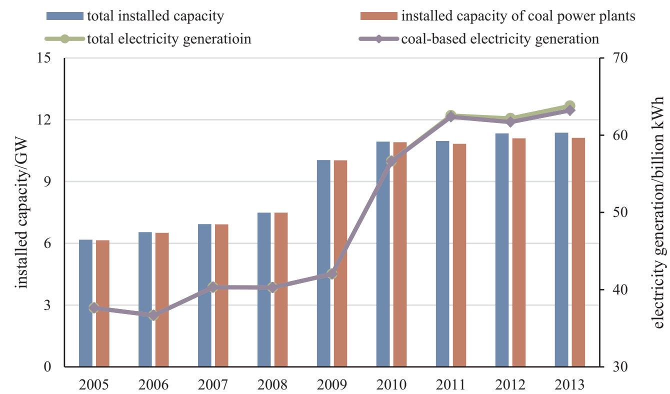

Fig. 1. The annual electricity generation and installed capacity of coal power plants. *Data source*: Tianjin Municipal Bureau of Statistics (2006–2014). Tianjin Statistical Yearbook 2006–2014. Beijing: Beijing INFD Press.

For Tianjin, there are three main approaches to decarbonize the power sector, i.e., developing clean and efficient coal power generation technologies, using more renewable energy sources, and increasing the electricity import from other regions. Renewable energy has gained market share since 2010, with wind power, hydropower and solar power accounting for 0.56, 0.02 and 0.002 billion kWh in 2013, respectively.

Tianjin's total electricity demand increased constantly from 39.6 billion kWh in 2005–82.3 billion kWh in 2013. The main electricity consumers in Tianjin include agriculture, industry, construction, transport, the wholesale and retail trade, and household consumption.[1] Among these sectors, the industry sector has always dominated the electricity demand, accounting for more than 70% in 2005–2013.

2.2. The reference energy system of Tianjin's power sector

A reference energy system (RES) shows various activities, energy flows, and technologies within an energy system (Mondal et al., 2011). Building an RES is usually the first step towards energy system modeling, as in our TIMES modeling for Tianjin's power system. As shown in Fig. 2, the energy fuels used in Tianjin's power sector include coal, hydro, solar, wind, biomass, geothermal and uranium. The electricity generation technologies include coal power plants, CCS technology, nuclear power, renewable energy technologies such as wind power, solar power, geothermal power, hydropower, etc. These technologies would compete to fulfill the exogenously defined end-use demand under different constraints.

3. The modeling methodology

3.1. TIMES model with endogenous learning curve

The TIMES model is a dynamic partial equilibrium model of energy markets that aims to illustrate an energy system in detail via linear programming. Incorporating complicated data spanning 40–50 years, it simulates the evolution of specific energy systems at the national, regional, provincial or community level. Theoretically, the TIMES model is a multi-stage linear optimization model, including three vital components, i.e., the decision variables, the objective function and the constraints. As outputs of the model, the *decision variables* include new technology capacity, technology activity level, etc. These variables are

[1] The agriculture sector includes farming, forestry, animal husbandry, fishery and water conservancy; the transport sector includes transportation, storage and postal services; and the wholesale and retail trade sector includes the wholesale and retail trade, accommodations and catering services.