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An optimization model for China's emission reduction resulting from the shift to wind power

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Abstract

Energy conservation and emissions reduction has become a major environmental concern for all both in China and beyond. The Chinese government has announced ambitious domestic indicative autonomous mitigation targets for 2030. The objective function of this paper is to maximize the total emission reduction resulting from the shift to wind power generation from 2016 to 2030. Combined with several important factors affecting the development of wind power, the study explores the development path and emission reduction potential of wind energy in China based on Sensitivity analysis and scenario analysis.

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Keywords: Emission reduction; Wind power; Dynamic programming; Learning curve; Technology diffusion model

1. Introduction

At recent United Nation's climate change conference held in Paris in November 2015, China further affirmed her commitment to the ambitious domestic indicative autonomous mitigation targets for 2030: increasing the ratio of non-fossil energy to 20% and reducing carbon dioxide emissions per unit of GDP by 60–65% from 2005 levels. Because wind energy is clean-burning and ultra-low carbon energy source [1], it is one of the renewable energy sources most likely to be developed commercially on a large scale. With the advancement of technology [2], wind energy will become an important primary energy source and, as an alternative to fossil fuels, will play a crucial role in helping reduce carbon emissions. Therefore, it is of profound theoretical and practical value to set reasonable and effective wind power development goals and paths for achieving autonomous mitigation targets, optimizing the energy structure, and realizing harmonious and sustainable development of energy, economy and environment.

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2. Methodology

2.1. The optimization model for carbon dioxide emission reduction resulting from the shift to wind power

In this paper, we want to forecast the development of wind power in China until 2030 and examine the role of wind power in achieving the mitigation targets set by China. A dynamic optimization model is employed and the objective function is to maximize total emission reduction resulting from the shift to wind power from 2016 to 2030. The reduction of emissions by using wind energy generation should be equal to the reduction of emission from wind energy instead of coal and other fossil energy power generation minus the emission during the life-cycle of wind power generation. Thus, we can get the final dynamic optimization model of emission reduction:

$$\max \sum_{t=2016}^{2030} f(t) = \max \sum_{t=2016}^{2030} [n(t)\times\lambda(t)\times(1-\xi(t))\times(1-\beta(t))\times T(t)\times\eta(t) - n(t)\times T(t)\times\gamma(t)] \qquad (1)$$

where $n(t)$ (KW) is the cumulative installed capacity of China's wind power in year t ; $\lambda(t)$ is the integration proportion of wind power in year t ; $\xi(t)$ is the utilization rate of wind farm in year t ; $T(t)$ (h) is the annual average operational hours of a wind farm in year t ; $\beta(t)$ is the curtailment rate of a wind farm in year t ; $\eta(t)$ (kg/KWh) is carbon dioxide emission factor of coal in year t ; $\gamma(t)$ (kg/KWh)is life cycle carbon dioxide emission intensity of a wind farm in year t . We express the state transition equation of the dynamic optimization model as follows:

$$n(t) = n(t-1) + x(t) \qquad (2)$$

where $x(t)$ (KW) is the new installed capacity of China's wind power in year t .

2.2. The learning curve model

$$C_{IN}(t) = C_0 \times (n(t)/n_0)^{\alpha} \qquad (3)$$

where $C_{IN}(t)$ (Yuan/KW) is the unit investment cost of a wind farm in year t ; C_0 (Yuan/KW) is the unit investment cost of a wind farm in the base year; n_0 (KW) is the cumulative installed capacity of wind power in the base year; α is the cumulative installed capacity elasticity coefficient of the unit investment cost of a wind farm. Based on, the learning-by-doing rate (LR) is defined as:

$$LR = 1 - 2^{\alpha} \qquad (4)$$

2.3 The technology diffusion model

This paper adopts the Bass diffusion model presented by Bass FM [3], which is

$$\frac{dN(t)}{dt} = p(m - N(t)) + \frac{q}{m} N(t)(m - N(t)) \qquad (5)$$

the Bass model is a mixed influence model with three parameters p , q and m , where $N(t)$ is the possible maximum cumulative installed capacity of wind power in year t , m is the theoretical maximum cumulative installed capacity of wind power, p represents the coefficient of innovation , q is the coefficient of imitation.

2.4. Constraints and parameter setting

Referring to the characteristics of China's economic growth as reported by International Bank for Reconstruction and Development, many signs point to a growth slow down in China [4]. We therefore take 6.5 percent in 2016–2020, 6 percent in 2021–2025, and 5.5 percent in 2026–2030 as the economic