Energy Policy 119 (2018) 377–387

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

On the road to China's 2020 carbon intensity target from the perspective of "double control"

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ARTICLE INFO

Keywords:
Carbon intensity
Quantity & intensity control
Emissions drivers
Pathway Analysis
Markov Chain

ABSTRACT

This paper investigates the path choice of achieving China's 2020 carbon intensity target by using a multiple attribute decision model from the perspective of "double control", i.e. quantity (energy consumption and CO_2 emissions) and intensity (energy intensity and carbon intensity). Firstly, we propose a novel integrated model to predict the quantity and intensity. The cumulative effects of several drivers for CO_2 emissions are examined by Logarithmic Mean Divisia Index method. Secondly, the quantity and intensity are normalized to identify the feasible pathway of "double control" in various scenarios by multiple attribute decision model, and robustness test is carried out by a case study. The results show that per capita GDP has a significantly positive cumulative effect on CO_2 emissions, whereas energy intensity has significantly negative one on it. The targeted carbon intensity by 2020 can be differentially realized in all scenarios. Both slow economic growth speed and substantial energy structure adjustment facilitate "double control". The results suggest that the best pathway of "double control" depends on the policy makers' preferences on the quantity control and intensity control. The policy implications of the findings are discussed.

1. Introduction

Over the past 30 years, the rapid development of China's economy accompanying by considerable amounts of fossil energy consumption has led to increasing emissions of greenhouse gases, especially CO_2. In 2013, the primary energy consumption in China accounted for 21.9% of that in the world. The CO_2 emissions in China also ranked the first in the world (BP, 2014). Therefore, it appears necessary to carry out energy savings and emissions reduction. In December 2009, the Chinese government committed to reducing its carbon intensity – defined as CO_2 emissions per unit of gross domestic product (GDP) – by 40–45% by 2020 compared with that in 2005. As the largest developing country, China is required to sustain an appropriate economic growth to improve people's livelihoods, sustain stability and enhance its international status. However, a series of energy and environmental problems are bound to accompany its rapid economic development. As a result, how to realize the carbon intensity target while sustaining economic growth has become an important topic in the current field of Ecology-Economy- Environment.

Several studies have focused on the achievement of China's carbon intensity target over the past few years. They can be broadly classified into three topics: carbon intensity reduction potential evaluation, carbon intensity decomposition, and reduction costs assessment. The carbon intensity reduction potential evaluation is well documented in the literature. Wang and Feng (2011) and Wang et al. (2013) evaluate the contribution of the energy structure adjustment on meeting this target. Li et al. (2012) assess the contribution of low-carbon energy on the realization of this target under different economic development plans. Wang and Liang (2013) investigate the influences of the energy structure, energy technology, as well as new energy sources on this target. Jiao et al. (2013) resort to the Logarithmic Mean Divisia Index (LMDI) and scenario analysis to explore whether or not China can realize the carbon intensity target while considering the strategies of economy and energy development. Liu et al. (2014) investigate whether or not China can achieve this target by applying an optimal combination model from the perspective of thermal power development. Cansino et al. (2015) evaluate the meeting of China's carbon intensity target by 2020 by using a combined input-output based econometric

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https://doi.org/10.1016/j.enpol.2018.04.025
Received 11 December 2017; Received in revised form 9 April 2018; Accepted 14 April 2018

projection approach and the World Input-Output Database. Yu et al. (2015) propose a Particle Swarm Optimization–Genetic Algorithm (PSO-GA) multivariate environmental learning curve estimation method to estimate the carbon intensity abatement potential in China at the regional level. Zhu et al. (2015) investigate whether or not China can realize the carbon intensity target while ensuring economic growth by employing various methods including cointegration theory, compositional data model, and scenario analysis. They evaluate the contribution of relevant policies to meeting this target.

Some studies shed lights on examining the carbon intensity decomposition. Based on the principle of equity and development, Yi et al. (2011) allocate the carbon intensity target to each province by using the clustering method. Zhou et al. (2014) establish the regional disaggregation model for realizing the carbon intensity target, and they show that energy structure adjustment, technical improvement, and energy substitution are main ways to reduce carbon intensity. Based on the targeted carbon intensity by 2020, Yang et al. (2018) builds a two-stage Shapley information entropy model to allocate CO_2 emission reduction quota among the Chinese provinces based on the equity and efficiency principles.

Additionally, some papers involve cost analysis on carbon intensity decline. Cui et al. (2014) investigate the cost savings effect of the Chinese pilot emissions trading schemes on the realization of the carbon intensity target, and further show that the costs could be reduced by 23.67% with the unified carbon market. Wang et al. (2014) use the HNGP-QAM model to devise optimal strategies for achieving this target at both departmental and provincial levels in China and assess the regional and sectoral costs of achieving the carbon intensity target in two scenarios. Weng et al. (2018) assess the economic impacts of the differentiated CO_2 intensity constraints between Guangxi Province and the rest of China. They show that the highest reduction target of 75% in the P75C65 scenario in Guangxi will lead to a cost of 0.42% in per capita GDP loss, 0.51% of welfare loss.

The existing studies have explored the realization of China's carbon intensity target from different perspectives. They represent an important reference and scientific basis for devising policies about energy savings and emissions reduction. However, existing studies also present two limits: (i) they mainly investigate how to achieve the carbon intensity target at the departmental or provincial levels rather than at the national level; (ii) they mostly focus on the carbon intensity control, and rarely deal with the optimal path choice of achieving the target from a strategic height of “double control” – i.e. quantity control & intensity control simultaneously.

In order to fill this gap, this study identifies the path choice of achieving China's 2020 carbon intensity target at the national level whilst sustaining economic growth. The main contributions are twofold. (i) We forecast the energy consumption by 2020 under various economic growth scenarios with an extended Cobb-Douglas production function, the energy consumption structure by 2020 using the Markov chain model and scenario analysis, measure the CO_2 emissions under different scenarios of economic growth, and explore the drivers of CO_2 emissions by using the LMDI method. (ii) We assess the completion degree of the carbon intensity target under different scenarios of economic growth. We examine the path choice of achieving the target in different decision preferences by resorting to the multiple attribute decision model from the perspective of “double control” – quantity control & intensity control.

This article is structured as follows: after this introduction, Section 2 details the methodology and Section 3 presents the data. Section 4 contains the results and discussions, while the conclusions and policy implications are provided in Section 5.

2. Methodology

As a relative index, carbon intensity is obtained by the comparison of CO_2 emissions and GDP, namely carbon intensity = CO_2 emissions/GDP. Thus, it is needed to forecast these two factors respectively. Inspired by the reference method for estimating CO_2 emissions of the International Panel on Climate Change (IPCC), which is widely used (Wang et al., 2013; Wang, 2011; Wang et al., 2011), we predict the energy consumption and energy structure respectively, and then calculate the CO_2 emissions. First, we establish three economic growth scenarios to predict GDP. Second, we employ an extended Cobb-Douglas production function to predict the energy consumption under different economic growth scenarios. Third, we predict the energy structure with the Markov chain model and scenario analysis. On this basis, we calculate the CO_2 emissions and the carbon intensity under various economic growth scenarios. Furthermore, we explore the main drivers of CO_2 emissions. We evaluate the completion degree of the carbon intensity target and examine a pathway analysis with the multiple attribute decision model for achieving it.

2.1. Energy consumption prediction with an extended Cobb-Douglas production function

With adequate predictive and explanatory capabilities, the Cobb-Douglas production function can effectively capture the quantitative relationship between energy consumption and economic growth. In this study, we introduce an extended Cobb-Douglas production function to predict the energy consumption by 2020 under different economic growth scenarios.

Energy, as a productive factor, is introduced into the extended Cobb-Douglas production function:

$$Y(t) = A_0 e^{vt} K(t)^{\alpha} E(t)^{\beta} L(t)^{\gamma}$$

with, Y the GDP; K the material capital stock; E the energy consumption; L the human capital stock; A_0 the total factor productivity (*TFP*) of the initial year ; v the annual growth rate of *TFP*, which reflects the improvement of production efficiency caused by technological advancement. t denotes a given year.

Taking a natural logarithm on both sides of this function, a linear regression equation for parameter estimation is obtained as:

$$\ln Y = c + vt + \alpha \ln K + \beta \ln E + \gamma \ln L$$

where c refers to lnA0. Once parameters are estimated with the ordinary least squares (OLS), partial least squares (PLS) or ridge regression method, the linear regression equation between energy consumption and economic growth can be obtained. Moreover, by setting the economic growth scenarios and corresponding variables by 2020, using an inverse transformation, the energy consumption by 2020 can be predicted while sustaining the economic growth.

2.2. Energy structure prediction with the Markov chain

The energy structure presents a special evolution law under the influences of drivers such as the level of economic development, resource endowment, the industrial structure, or energy technology. This historical evolution law can provide a basis for the prediction of the energy structure in the future (Zhu et al., 2015). The national energy structure is only related to its recent state but is independent of its past state, which shows the “*No after-effect*” character of the Markov chain. That is to say, the change of the energy structure exhibits the Markovian characteristic. Thus, the evolution of the energy structure can be approximated by a Markov chain (Wang and Niu, 2004). In this study, we use the Markov chain model to predict the energy structure by 2020.

The state vector of the primary energy structure at a year n is defined as $S(n)$: $S(n) = \{s_a(n), s_b(n), s_c(n), s_d(n)\}$, where, $s_a(n)$, $s_b(n)$, $s_c(n)$, $s_d(n)$ are the respective proportions of coal, petroleum, natural gas, and non-fossil energy in primary energy.

The one-step transition probability matrix of the primary energy structure from n to $n + 1$ is defined as: