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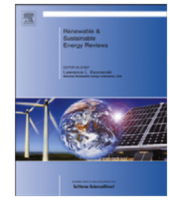

An optimization model for renewable energy generation and its application in China: A perspective of maximum utilization

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A B S T R A C T

In response to climate change, China's power industry is undertaking the task of reducing carbon emissions. Renewable energy generation has become an important option. For the government and state grid companies, it is important to know the maximum possible capacities of renewable energy generation from its different sources in order to plan the construction of the power grid in the future. In this paper, several important factors affecting the development of renewable energy generation are identified through a review of the existing literature (such as cost, technical maturity and so on) and analyzed. Combined with the learning curve model, the technology diffusion model and expectations about future economic development in China, a new model, the Renewable Energy Optimization Model (REOM), is developed to analyze the development of three renewable energy sources (wind power, solar power and biomass power) from 2009 to 2020. Results show that (1) the maximum installed capacities of wind power, solar power and biomass power will reach 233321, 26680 and 35506 MW in 2020; (2) from 2009 to 2020, biomass power will develop rapidly at the early stage while wind power is developed massively at the final stage and solar power has relatively stable growth; (3) due to the added capacity in the early periods, the unit investment cost of solar power shows a large decline, which is good for its following scale development; (4) the investment ratio constraint has a large effect on the development of wind power while the constraint of on-grid proportion of renewable energy generation has a significant effect on the development of wind power and solar power. The results have important policy implications for long-term energy planning in developing countries, such as China and India.

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1. Introduction

An the Copenhagen climate conference, the Chinese government promised that renewable energy consumption would account for 15% of primary energy consumption in China by 2020 [1]. In reality, the development of renewable energy has attracted unprecedented attention not only in China but all over the world [2]. On the one hand, since the oil crisis in the 1970s, people have realized that fossil energy would be exhausted in dozens or hundreds of years according to the exploitation intensity of energy at that time [3]. Development of renewable energy is important for the security of energy supply [4–6]. On the other hand, since 1980s, with global warming and a sharp decline in environmental quality, people have reached a consensus of environmental protection and sustainable development [7]. Compared with fossil fuels, renewable energy is generally characterized by low or zero emission [8]. Development of renewable energy is of great significance for security of energy use [9].

Electricity generation is one of main options to use renewable energy [10]. For the government and state grid companies, it is important to know the maximum possible capacities of renewable energy generation from different sources (mainly wind power, solar power and biomass power[1]) in order to plan construction of the power grid [11]. The perspective of maximum utilization is employed in this paper because the economic use of renewable generation is only a point in the solution space which is vulnerable to a lot of factors. However, the maximum utilization of renewable generation stands for the upper bound of possible solutions, which is relatively credible. The objective of this paper is to analyze the maximum size and structure of renewable energy generation, which is relevant to the planning of state grid companies and reducing the possibility of excess investment or lack of investment. Therefore, it has profound theoretical and practical value.

The main factors affecting renewable energy generation include cost, technology maturity, economic development, grid technology, etc. [12,13]. Some of them can be estimated based on historical data while others can only be determined via planning documents from different sources and expert opinions. Using factors above as inputs, an integrated optimization model (Renewable Energy Optimization Model, REOM) is constructed to analyze the maximum size and structure of renewable energy generation for China in the future (2020).

The paper is structured as shown in Fig. 1. We begin with a literature review and analyze the main affecting factors in Section 2, followed by a description of methodology in Section 3. Section 4 presents the empirical results and relevant sensitive analysis. Finally, some conclusions and possible future work are presented in Section 5.

[1] In the strict sense, renewable energy generation also includes hydro-electricity, geothermal energy, ocean energy, etc. Hydro-electricity has large ecological effects; hence its development is subject to a lot of political and ecological constraints. Therefore, its development is beyond the scope of this article. Other renewable energy generations is omitted because their shares in the total generation are very small.

2. Literature review

The economic literature concerning renewable energy generation mainly includes two aspects: (1) analysis of main affecting factors (cost, technology maturity, etc.); (2) the comprehensive utilization of renewable energy generation based on various affecting factors.

2.1. Cost of renewable energy generation

Different from regular energy generation, cost (especially the unit investment cost) is one of the important factors affecting the scale development of renewable energy generation [14]. The analysis of cost of renewable energy generation focuses on two aspects: (1) using the learning curve to explore the developing characteristic of unit investment cost [15]; (2) combining the learn rates from learning curves with various energy models to study the energy, economic and environmental problems [16].

The learning curve model is used to describe and predict the law of decreasing cost of new technology. Its core idea is that when cumulative production is doubled the cost of new technology will decrease by a certain proportion [17]. Neij used the learning curve model to analyze the prospects of diffusion and application of renewable energy technology, mainly in wind power and photovoltaic systems [18]. His research showed that the cost of renewable energy technology declined with greater probability than conventional energy technology, though a lot of investment and relevant policy support are needed. Furthermore, he analyzed the prospect of cost of wind power using the learn curve model [19]. The result showed that although the decline of the cost of wind turbine was not very significant, there was still large potential for the deceasing cost of wind power due to the continuous improvement of wind turbine performance and decreasing operating costs. Assuming an annual growth rate of 15–20% for the turbine market, in 2020 the average cost of wind power would fall by half. Kuemmel introduced the minimum cost and got a faster declining learning curve when he studied the development of wind power industry in Denmark [20].

In summary, the learning curve has become a mainstream method for forecasting the cost of renewable energy and has been studied continuously.

2.2. The technology maturity of renewable energy generation

Scale development of renewable energy cannot be separated from relevant technical support. The commonly used Theory of Invention Problem Solving (TIPS) states that any products are the technical systems supported by their core technology. The evolution of a technology system includes four stages: infancy, growth, maturity and recession, which constitutes the life cycle of a product's technology [21]. The stage of renewable energy generation technology in its evolutionary process is technological maturity.

There are a lot of methods for forecasting the maturity of the technology, such as patent analysis, bibliometrics, S-curve or a combination of them. In this paper, we would like to examine the

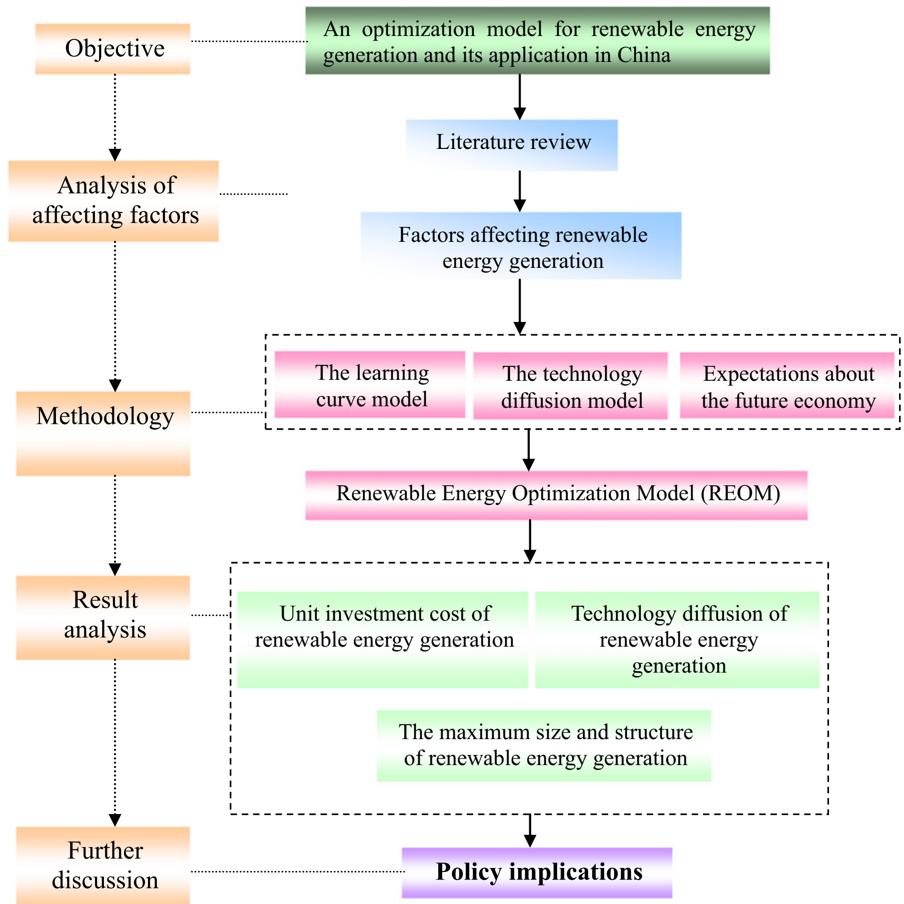

Fig. 1. Structure of this paper.

effect of renewable energy technology maturity on its installed capacity, which is commonly referred to as the renewable energy technology diffusion model [22]. Collantes analyzed the potential for vehicle fuel technology using the logistic model [23]. Usha Rao and Kishore studied the growth of wind power in different states in India using the mixed influence model proposed by Bass [24]. Lund analyzed the potential for large-scale development and utilization of new energy technology using the experience curve and found that public policy and subsidies had important effects on the market penetration of new technology [25]. Purohit and Kandpal used the Bass model, logistic model, Pearl model and Gompertz model to study the potential of four pumping energy technologies in India and also estimated relevant investment costs [26].

The technology diffusion models can be classified in three categories: (1) external influence models; (2) internal influence models; (3) mixed effects models [27]. In general, technology diffusion model is a relatively mature method for research on renewable energy development. Despite the development of renewable energy technology being a complex process that does not follow a fixed pattern, technology diffusion model can still be used to estimate the potential of renewable energy from the perspective of historical data.

2.3. The comprehensive utilization of renewable energy generation

The development of renewable energy generation is subject to economic, environmental, technical and other constraints.

Since the 1980s scholars have begun to study the comprehensive utilization of renewable energy. Jain believed that Integrated Renewable Energy System (IRES) for solar, wind and biomass was feasible from the perspectives of energy production and use [28]. Ramakumar extended the concept of renewable energy to include hydro and solar thermal energy [29]. Ramakumar further used linear programming to develop the IRES model for minimizing the annual cost under the constraints of energy and power [30]. Ashenayi and Ramakumar designed the IRES model based on technical and economic scenarios and included the loss of power supply as an important system variable [31]. Iniyan et al. developed an Optimal Renewable Energy Model (OREM) which minimized the ratio of cost and efficiency under the constraints of social acceptance, resource constraints, demand and reliability. The model took about 38 different types of renewable energy options into account [32]. As more and more attention was paid to climate change, environmental constraints were also integrated into the comprehensive utilization of renewable energy generation. Iniyan used Modified Econometric Mathematical (MEM) model, Mathematical Programming Energy-Economy-Environment (MPEEE) model, and Optimal Renewable Energy Mathematical (OREM) model to study the optimal utilization of Renewable Energy in India. In the model they took account of factors, such as cost, efficiency, social acceptance, reliability, potential and demand [33].

In summary, the idea of mathematical optimization in the integrated planning of renewable energy has proven to be feasible. The contribution of this paper is to extend existing models to take account of the learning effects of costs, the technology diffusion effects, etc. and dynamically optimize the development path of renewable energy generation.

3. Methodology

In this section, two sub-models (the learning curve model and the technology diffusion model) and the optimization model are introduced. The outputs of two sub-models are the inputs of the optimization model.

3.1. The learning curve model

The cost of renewable energy generation is one of the important factors affecting the scale development of renewable energy generation. The learning curve model is employed to describe the relationship between cumulative installed capacity and unit investment cost. The classical learning model [34,35] is

$$C(t) = C_0 \times N(t)^{\phi} \times e^{\mu(t)} \quad (1)$$

where $C(t)$ is the unit investment cost for the renewable generation in the year t; C_0 is the unit investment cost for the renewable generation in the base year; $N(t)$ is the cumulative installed capacity of the renewable generation in the year t; ϕ is the cumulative installed capacity elasticity coefficient of unit investment cost for the renewable generation; $\mu(t)$ is the random factor in the year t.

The learning curve model is used to describe the downward trend of unit investment cost due to accumulated experience. Because there should be a minimum level for the unit investment cost [36], the learning curve model can be improved to consider this effect, as follows.

$$C(t) - C_{\min} = C_0 \times N(t)^{\phi} \times e^{\mu(t)} \quad (2)$$

where $C_{\min}$ is the minimum unit investment cost for renewable energy generation.

The technology Progress Rate (PR) can be defined as

$$PR = 2^{\phi} \quad (3)$$

For PR=0.8, it means if cumulative installed capacity is doubled, the unit investment cost will decrease by 20% (1–0.8).

Learning Rate (LR) can be defined as

$$LR = 1 - 2^{\phi} \quad (4)$$

In order to facilitate the calculation, Eq. (2) can be transformed to Eq. (5).

$$\ln(C(t) - C_{\min}) = \ln C_0 + \phi \ln(N(t)) + \mu(t) \quad (5)$$

Using the least square method, the cumulative installed capacity elasticity coefficient of unit investment cost (ϕ) can be estimated. Furthermore, Progress Rate (PR) and Learning Rate (LR) can be calculated according to Eqs. (3) and (4).

3.2. The technology diffusion model

The diffusion law of renewable energy generation reflects the time needed for people to adopt it [37], which represents its potential to some extent. Technology diffusion theory believes that the development of renewable energy technology generally experiences three stages: (1) a long period of slow growth; (2) a fast take-off period; (3) finally saturation. Therefore, the development of renewable energy technology generally follows the sigmoid curve.

The basic diffusion model can be expressed as

$$dM(t)/dt = f(t)[m - M(t)] \quad (6)$$

where $M(t)$ is the maximum possible cumulative installed capacity (potential) in period t: m is the theoretical maximum possible installed capacity; $f(t)$ is a function dependent on time which determines the type of technology diffusion model.

This paper adopts the mixed effects model presented by Collantes [23], which is

$$\ln\left(\frac{M(t)}{m - M(t)}\right) = \alpha + \beta t \quad (7)$$

where α and β are parameters. The model considers the impact of time and resource endowment on the diffusion of renewable energy technology.

3.3. Renewable Energy Optimization Model (REOM)

In this section, we want to forecast the maximum size and structure of renewable generation. Inspired by the IRES and OREM models, a dynamic optimization model is employed in this section. The objective function is to maximize total generation from three renewable sources in 2020. There are four types of constraints: (1) installed capacity of a renewable energy type is less than its potential (given by the diffusion model) in each year; (2) total investment for renewable generation is affordable in each year; (3) total on-grid renewable generation is less than a certain proportion (the technology constraint of the power grid) in each year; (4) installed capacities of renewable generation must meet the state's plans. The specific

Table 1
Definitions of variables.

Variable	Definition	Variable	Definition
$M_w(t)$	Potential of wind power in year t (MW)	$M_s(t)$	Potential of solar power in year t (MW)
$M_b(t)$	Potential of biomass power in year t (MW)	$A_w(t)$	Newly added capacity of wind power in year t (MW)
$A_s(t)$	Newly added capacity of solar power in year t (MW)	$A_b(t)$	Newly added capacity of biomass power in year t (MW)
$C_w(t)$	Unit investment cost for wind power in year t (10^4Yuan/KW)	$C_s(t)$	Unit investment cost for solar power in year t (Yuan/MW)
$C_b(t)$	Unit investment cost for biomass power in year t (10^4Yuan/KW)	γ	The maximum proportion of GDP which can be used for investment of renewable generation
$G(t)$	GDP in year t	μ	The maximum on-grid proportion of renewable generation
I_t	Total installed capacity in year t (MW) (given by IEA's forecasting)	$P_w(t)$	The planned capacity of wind power in year t (MW)
$P_s(t)$	The planned capacity of solar power in year t (MW)	$P_b(t)$	The planned capacity of biomass power in year t (MW)
$C_{w,\min}$	The minimum unit investment cost of wind power (10^4Yuan/KW)	$C_{s,\min}$	The minimum unit investment cost of solar power (10^4Yuan/KW)
$C_{b,\min}$	The minimum unit investment cost of biomass power (10^4Yuan/KW)	$N_w(t)$	The cumulative installed capacity of wind power in the year t
$N_s(t)$	The cumulative installed capacity of solar power in year t	$N_b(t)$	The cumulative installed capacity of biomass power in the year t

model is shown as follows:

$$\max\ 2000N_w(2020)+1300N_s(2020)+2380N_b(2020) \quad (8)$$

$$subject\ \ to: \begin{cases} N_w(t)\le M_w(t) & (9)\\ N_s(t)\le M_s(t) & (10)\\ N_b(t)\le M_b(t) & (11)\\ C_w(t)A_w(t)+C_s(t)A_s(t)+C_b(t)A_b(t)\le \gamma G(t) & (12)\\ N_w(t)+N_s(t)+N_b(t)\le \mu I(t) & (13)\\ N_w(2010)\ge P_w(2010) & (14)\\ N_s(2010)\ge P_s(2010) & (15)\\ N_b(2010)\ge P_b(2010) & (16)\\ N_w(2020)\ge P_w(2020) & (17)\\ N_s(2020)\ge P_s(2020) & (18)\\ N_b(2020)\ge P_b(2020) & (19)\\ N_w(t)=N_w(t-1)+A_w(t) & (20)\\ N_s(t)=N_s(t-1)+A_s(t) & (21)\\ N_b(t)=N_b(t-1)+A_b(t) & (22)\\ C_w(t)=C_{w,\min}+C_w(t_0)N_w(t-t_0)^{\phi_w} & (23)\\ C_s(t)=C_{s,\min}+C_s(t_0)N_s(t-t_0)^{\phi_s} & (24)\\ C_b(t)=C_{b,\min}+C_b(t_0)N_b(t-t_0)^{\phi_b} & (25)\\ A_w(t)\ge 0 & (26)\\ A_s(t)\ge 0 & (27)\\ A_b(t)\ge 0 & (28)\\ t=2009,\ldots,2020 \end{cases}$$

The meanings of the variables in Eqs. (8)–(28) are listed in Table 1.

The objective function, Eq. (8), is to maximize total renewable generation in 2020 where 2000, 1300 and 2380 are the annual utilizable hours per unit capacity of wind power, solar power and biomass power respectively. Constraints (9)–(11) are potential limitations, which mean that the installed capacities of renewable generation cannot exceed their potential in each year. Constraint (12) is the economic limitation, which means that the total cost of added capacity cannot exceed a certain proportion of GDP. Constraint (13) is the power grid technology limitation, which means that the total installed capacity of renewable generation cannot exceed a certain proportion of total installed capacity. Constraints (14)–(19) are planning limitations, which mean that installed capacity of renewable generation must achieve targets in 2010 and 2020. Constraints (20)–(22) are state transition functions, which indicate the dynamic relations between added and cumulative capacities in each years. Here we do not consider the retirement of generators because currently most renewable generators are quite new and will not be retired before 2020. Constraints (23)–(25) are dynamic cost functions of renewable generation considering the learning effects. Constraints (26)–(28) are non-negative constraints, which mean that added capacities cannot be negative in each year. The initial values of the main parameters are listed in Table 2.

Table 2
Initial values of main parameters in the optimization model.

Parameter	Initial value	Parameter	Initial value
$N_w(2008)$	12153	$N_s(2008)$	145
$N_b(2008)$	3150	γ	0.00005
μ	0.3	$P_w(2010)$	5000
$P_w(2020)$	100000	$P_s(2010)$	1000
$P_s(2020)$	20000	$P_b(2010)$	5500
$P_b(2020)$	30000	$C_{w,\min}$	0.2
$C_{s,\min}$	0.3	$C_{b,\min}$	0.55

4. Model results and sensitivity analysis

4.1. Cost of renewable energy generation

4.1.1. Wind power

The data relating to installed wind power capacity in China is from the Chinese Wind Energy Association and World Wind Energy Council and shown in Fig. 2. The data of unit investment cost of wind power is from Zhang [38].

The results for wind power from Eqs. (3)–(5) are shown in Table 3.

It can be seen from Table 3 that as the minimum unit investment cost of wind power ($C_{\min}$) increases, the value of ϕ decreases and the learning rate (LR) increases, which means that the decline rate of unit investment cost increases when the cumulative installed capacity is doubled. For example, when $C_{\min}$ is zero, the technological progress rate is 0.886; while $C_{\min}$ is 0.4×10^4 Yuan/KW, the technological progress rate becomes 0.821. If the cumulative installed capacity of wind power is doubled, the decline rate of its unit investment cost increases from 11.4% (1-0.886) to 17.9% (1-0.821).

4.1.2. Solar power

The data of unit investment cost and cumulative installed capacity of solar power is mainly from Zheng and Liu [39]. The remaining data is collected by the author, as shown in Fig. 3.

The results for solar power from Eqs. (3)–(5) are shown in Table 4.

It can be seen from Table 4, solar power shows similar learning effects to wind power. As the minimum unit investment cost of solar power ($C_{\min}$) increases, the value of ϕ decreases which lowers the technological progress rate and increases the learning rate. It means that unit investment cost declines faster when the cumulative capacity is doubled. For example, when $C_{\min}$ is zero the technological progress rate is 0.873, while $C_{\min}$ is 12 Yuan/Wp the technological progress rate becomes 0.826. Thus when the minimum unit investment cost increases from 0 to 12 Yuan/Wp, the decline rate of unit investment cost changes from 12.7% (1-0.873) to 17.4% (1-0.826) when the cumulative installed capacity is doubled.

4.1.3. Biomass power

Current utilization of biomass in China mainly focuses on biomass power, biogas and biomass liquid fuel, etc. In respect to biomass power, there are agricultural and forestry waste generation, waste generation and biogas generation.

Because various types of biomass power have not yet entered the phase of scale development, there are neither commercial examples nor enough historical data to estimate coefficients. According to Pu [40], the learning curve can instead be approximated as Eq. (29).

$$C=5500+8500\times(N(t)/720)^{-0.48} \quad (29)$$

Table 3
PR and LR of wind power for different $C_{\min}$.

$C_{\min}$ (ten thousands Yuan/KW)	ϕ	PR	LR
0	−0.174	0.886	0.114
0.1	−0.193	0.875	0.125
0.2	−0.216	0.861	0.139
0.3	−0.245	0.844	0.156
0.4	−0.284	0.821	0.179

Note: The results in Table 3 are all statistically significant at the 99% confidence level.

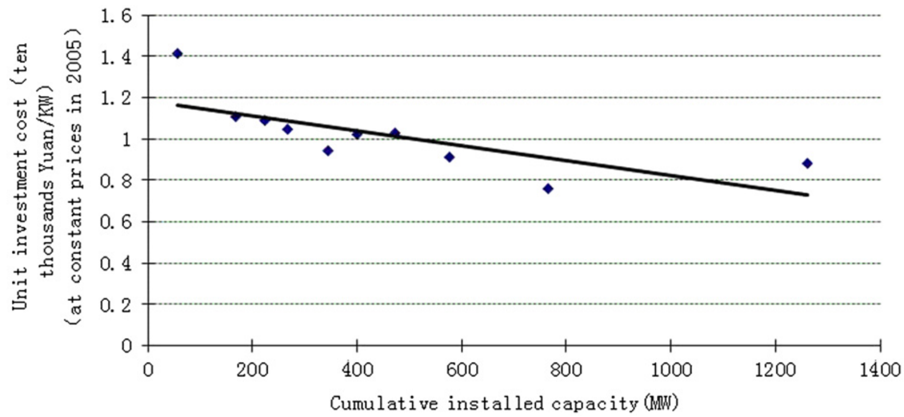

Fig. 2. The relationship between cumulative installed capacity and unit investment cost of wind power in China.

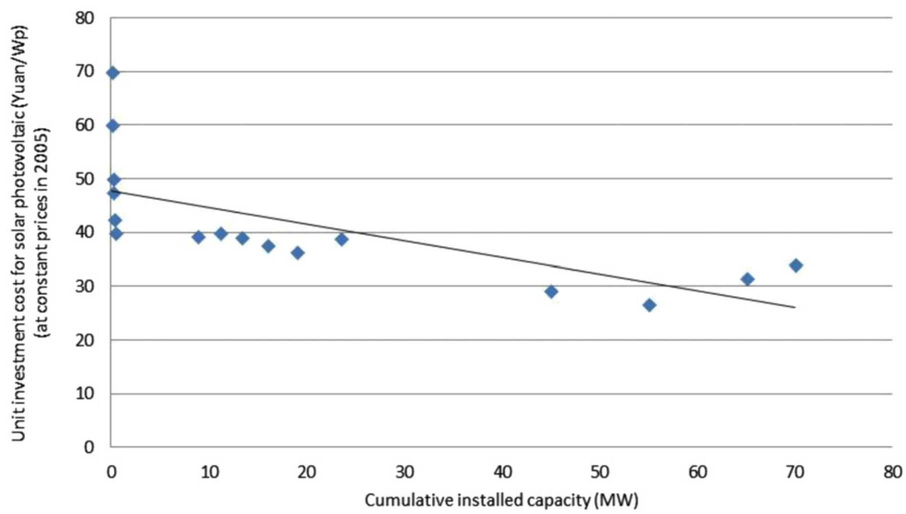

Fig. 3. The relationship between cumulative installed capacity and unit investment cost of solar power in China.

Table 4
PR and LR of solar photovoltaic for different C_{min}.

C_{min} (Yuan/Wp)	ϕ	PR	LR
0	−0.196	0.873	0.127
3	−0.211	0.864	0.136
6	−0.229	0.853	0.147
9	−0.25	0.841	0.159
12	−0.276	0.826	0.174

Note: The results in Table 4 are statistically significant at the 99% confidence level.

4.2. *The potential of renewable energy generation*

4.2.1. *Wind power*

The results for wind power from Eq. (7) are listed in Tables 5 and 6.

It can be seen from Tables 5 and 6 that the diffusion model fits the historical data well. Based on the model above, the potential of wind power from 2011 to 2020 can be calculated and is shown in Fig. 4.

It can be seen from Fig. 4 that potential of wind power in China can reach 194 GW in 2015 and 433 GW in 2020.

4.2.2. *Solar power*

The same method is employed for solar power. Some results are listed in Tables 7 and 8.

Table 5
Coefficient estimation of technology diffusion model for wind power.

Model	Unstandardized coefficients		t	Sig
	B	Std. error		
α	−8.982	0.228	−38.243	0.000
β	0.367	0.032	11.354	0.000

Table 6
Model summary of the diffusion model for wind power.

R	R square	Adjusted R Square
0.96	0.928	0.922

It can be seen from Fig. 5 that potential of solar power in China can reach 4.8 GW in 2015 and 26 GW in 2020.

4.2.3. *Biomass power*

Because the development of biomass power is relatively late, relevant data is limited. The diffusion of biomass power is judged mainly according to the construct plan of biomass power plant. The potential of biomass power is estimated to be 15 GW in 2015 and 30 GW in 2020.

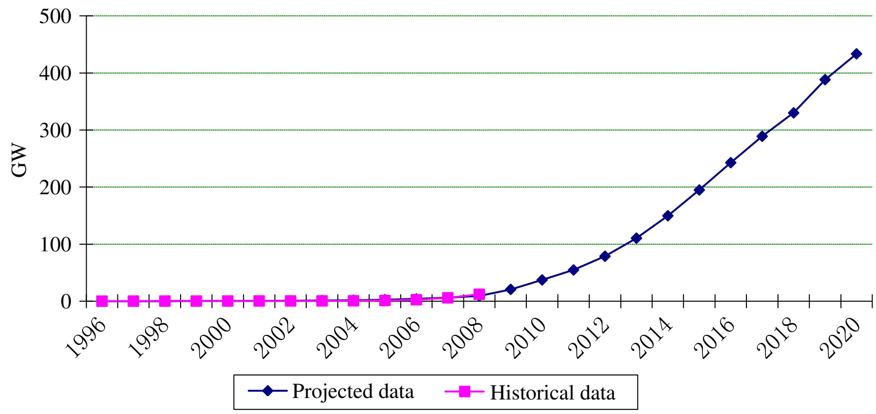

Fig. 4. Projected and historical data of potential of wind power in China.

Table 7
Coefficient estimation of technology diffusion model for solar power.

Model	Unstandardized coefficients		t	Sig
	B	Std. error		
α	−18.746	0.149	−125.744	0.000
β	0.267	0.012	21.477	0.000

Table 8
Model summary of the diffusion model for solar power.

R	R square	Adjusted R Square
0.981	0.962	0.96

4.3. Model results

It can be seen from Fig. 6 that from the perspective of maximum utilization installed capacities of wind power, solar power and biomass power will reach 65999, 8000 and 12210 MW in 2015, and reach 233321, 26680 and 35506 MW in 2020, respectively. According to the draft of the new energy promotion plan and the long-term development planning of renewable energy, the expected install capacities of wind power, solar power and biomass power will reach 150000, 20000 and 30000 MW. Therefore, the total installed capacities of three renewable sources from the perspective of maximum utilization will be 47.75% higher than planned. The installed capacities of wind power, solar power and biomass power will be 55.5%, 33.4% and 18.4% higher than planned. Compared with biomass power, wind power and solar power have larger development potential.

It can be seen from Fig. 7 that from the perspective of maximum utilization and considering the downward trends of unit investment costs, biomass power will develop fast in the initial stage, and newly added capacity will reach 7189 MW in 2012. Wind power will increase rapidly in the final stage: newly added wind power will reach 75619 MW from 2019 to 2020. Solar power will maintain relatively stable growth with average annual installed capacity reaching 2211 MW from 2009 to 2020.

It can be seen from Fig. 8 that there are downward trends for the unit investment costs of renewable energy generation. Wind power has the lowest unit investment cost and solar power the largest. There is a sharp decline in the unit investment cost for solar power because of the large investment in solar power in the early stage, which underlies its subsequent scale development. According to the model, the unit investment costs of wind, solar and biomass power will fall to 4900 13300 Yuan/KW and 5800 in 2015, and to 4400 11000 Yuan/KW and 5700 Yuan/KW in 2020.

4.4. Sensitivity analysis of main uncertainties

The maximum size of renewable energy generation is primarily affected by the unit investment cost technology maturation, macro investment ratio and acceptable capacity of power grid for renewable generation. However, there are large uncertainties in these factors. We focus on the macro investment ratio and the acceptable capacity of power grid, and test how different values for these two factors influence the results.

It can be seen from Fig. 9 that when the investment ratio increases from 2‰ to 5‰, the maximum sizes of renewable energy generation approaches to the saturation. When the investment ratio is less than 1‰, the model cannot find a feasible solution which implies a too strict financial constraint. With the increase of investment ratio, wind power can have a considerable development. When γ is 2‰, the installed capacity of wind power will reach 139049 MW in 2020. If γ is changed to 4‰, the installed capacity of wind power will reach 233321 MW (increase by 67.7%). When γ is increased from 2‰ to 4‰ the installed capacities of solar power and biomass power in 2020 increase by 33.4% and 18.35% compared with them when γ is 2‰.

It can be seen from Fig. 10 that with the increase of μ the maximum installed capacities of renewable energy approaches to the saturation. The increase of on-grid proportion of renewable energy has mainly a strong effect on the installed capacities of wind power and solar power in 2020. When μ is 0.15, the installed capacities of wind power and solar power in 2020 are 163494 and 20000 MW. When μ is larger than 0.25, the installed capacities of wind power and solar power will reach 233321 and 26680 MW respectively.

5. Main conclusions and future work

The presented model maximizes the future generation of renewable energy (wind power, solar power and biomass power) by optimal planning of investment in capacity, subject to a number of constraints: economic, technological, etc. The main conclusions are:

(1) The installed capacities of wind power, solar power and biomass power will reach 65999, 8000 and 12210 MW in 2015, and

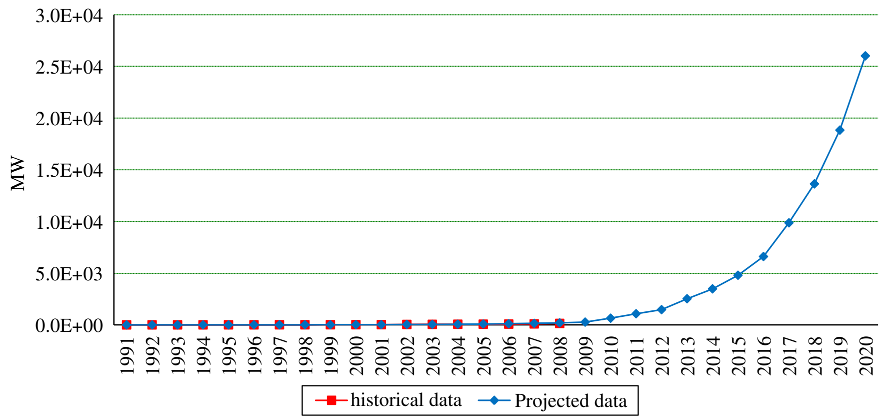

Fig. 5. Projected and historical data of potential of solar power in China.

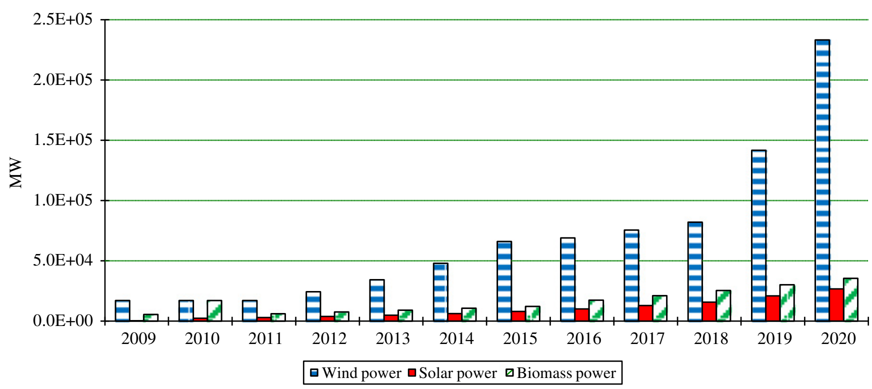

Fig. 6. Installed capacities of three types of renewable generation from the perspective of maximum utilization.

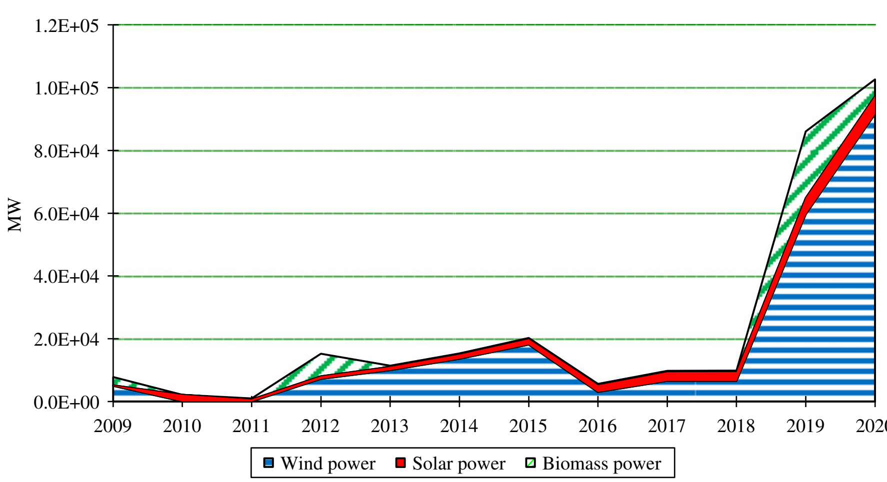

Fig. 7. Newly added capacities of three types of renewable generation from the perspective of maximum utilization.

233321, 26680 and 35506 MW in 2020 respectively. Compared with relevant plans, it is found that wind power and solar power have larger development potential than biomass power.

(2) When considering expected declines in the unit investment cost and a constraint on technology diffusion, the added capacities of the three types of renewable energy generation show different developments. Biomass power grows rapidly in the early periods, while wind power grows rapidly in the final periods. Solar power maintains relatively stable growth.

(3) Unit investment cost declines with increasing installed renewable energy capacity. The unit investment cost of wind power is the least and solar power is the largest. Due to the added capacities of solar power in the early stage, its unit investment cost shows a large decline, which is good for its following scale development. The unit investment costs of wind power, solar power and biomass power will reach 4900 13300 and 5800 Yuan/KW in 2015, and 4400, 11000 and 5700 Yuan/KW in 2020.

(4) The investment ratio constraint has a large effect on installed capacity of wind power in 2020. The increase of on-grid proportion of renewable energy generation has a significant effect on installed capacities of wind power and solar power in 2020.

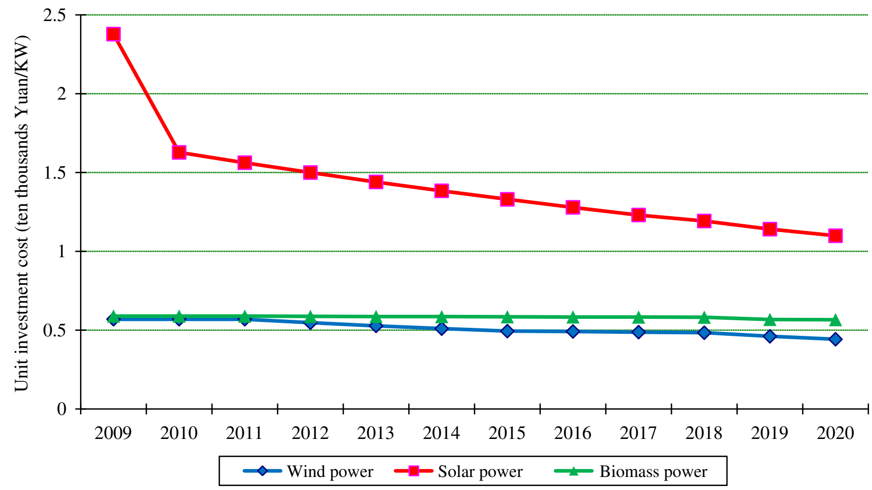

Fig. 8. The unit investment costs of three renewable energy sources from the perspective of maximum utilization.

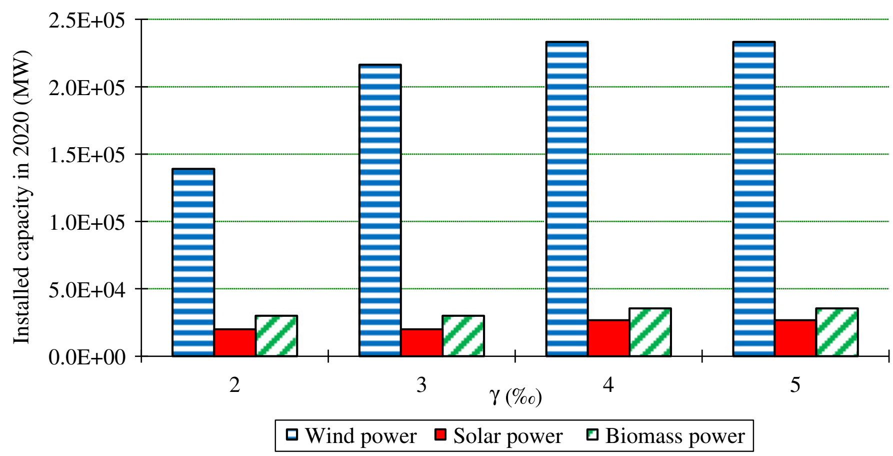

Fig. 9. Effect of the investment ration (γ) on the maximum sizes of renewable generation in 2020.

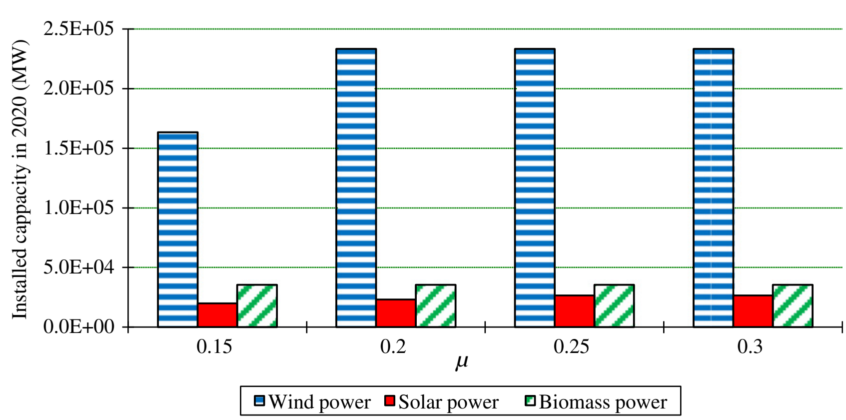

Fig. 10. The effects of acceptable capacity of power grid (μ) on the maximum installed capacities of three renewable sources in 2020.

Forecasting the development of renewable energy generation is difficult but an important challenge. This paper provides an integrated framework for analyzing the development path of renewable energy generation dynamically while considering the learning effect of unit investment cost and the effect of technology diffusion. Other potential constraints on development of renewable energy, such as environmental constraint, can be added in the future. And the forecasting can be renewed once new data is available.

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