Quantitative Evaluation of the Effects of Different Cost Experience Curve on Total Energy Investment Cost: Endogenous VS Exogenous

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Abstract. Endogenous learning curve (endogenous method) and set value exogenously (exogenous method) are two widely used methods for non-fossil energy cost experience curve in energy transition research based on quantitative model. The difference between endogenous method and exogenous method on total energy investment cost are compared, and the effect of key factors such as the learning rate of endogenous curve, cumulative installation capacity of the electricity supply technology, growth pathway of the electricity supply technology are analyzed. Recommendation for pay more attention to the effects of different cost experience curves on results of quantitative models are made for better decision-making support.

Keywords: Non-fossil energy; Energy transition pathway; Learning curve; Quantitative analysis.

1. Introduction

Low-carbon transition have become a global consensus of energy development [1]. There have been more than 180 countries formulated their own targets on clean energy development by 2019 [2]. China has become the leader of non-fossil energy development, with the largest hydropower, wind power, and photovoltaic installation capacity in the world. In Energy Production and Consumption Revolution Strategy (2016-2030) issued in 2016, China made a more ambitious of non-fossil energy development plan to increase the proportion of non-fossil energy to 15%, 20% and 50% by 2020, 2030 and 2050, respectively [3]. During the general debate of the 75th session of the United Nations General Assembly in September, China announced it would see carbon dioxide emissions peak before 2030 and achieve carbon neutrality before 2060.

Quantitative energy model, such as TIMES/MARKAL, MESSAGE, and NEMS have played important roles in supporting energy transition strategy [4-6]. The optimization objective of energy transition is cost minimization or revenue maximization. Non-fossil energy cost is the most important model input parameter. Due to insufficient cognition and information, the cost of non-fossil energy in the future is uncertain [5-6]. At present, two mainstream non-fossil energy cost parameter curves are exogenously given cost curve (hereinafter referred to as exogenous method) and endogenous cost learning curve (hereinafter referred to as endogenous method). For exogenous method, the experience curve of non-fossil energy cost is directly exogenously given by input parameter, its value is not affected by other variables in the model. For endogenous method, the non-fossil energy cost or power generation cost is indirectly given by establishing learning curve function and learning rate for the variables of non-fossil power generation installed capacity, etc. [7-11].
After reviewing a lot of relevant studies, Literature [12] pointed out that the differences of the above two cost parameter given methods will greatly affect the optimized results of energy and power transition. For example, the optimized results of the model applying endogenous method tend to invest wind power and PV installed capacity at the early stage to lower the cost; while exogenous method tends to postpone the investment of corresponding installed power-generating capacity, until the exogenously given cost is low enough to be competitive.

However, there is no quantitative analysis for the differences of the economic cost appraisal value of exogenous method and endogenous method. Hence, this paper firstly evaluates the differences and effects of key parameters in a quantitative method when endogenous method and exogenous method are used to calculate the total investment cost, aiming to provide reference to appropriate cost parameter given method when conducting power and energy transition optimization based on quantitative model. The remainder of the paper is structured as follows: Section 1 briefly introduces widely used non-fossil energy cost experience curves; Section 2 describes the methodology for analysis; Section 3 is the comparative analysis of the cases; Section 4 and 5 are discussion and conclusion, respectively.

2. Common Non-fossil Energy Cost Experience Curve

2.1. Exogenous Method

Generally, exogenous method explicitly set the values of cost experience curve, its function forms include equal difference, equal ratio, index and segmented equal ratio, etc. There are also some studies set the cost of follow-up years in the cost curve by annual change rate related to special base year [13-14]. Exogenous cost curve can be inferred in accordance with historical statistical data.

2.2. Endogenous Method

Endogenous learning curve is also called as experience curve. It means the cost of unit product will lower with a certain proportion with the increase of product production experience. There are many factors can affect the increase of production experience, therefore, there are many learning curves. The most used learning curve model is "one factor learning curve". It is expressed as logarithmic and linear relation between unit cost of technologies and cumulative production or installed capacity, as shown in Formula (1):

\[ C = C_0 \times i^b \]  

Wherein, \( C \) is unit cost for power generation technologies, \( C_0 \) is initial unit cost, \( i \) is generally represented as cumulative installed capacity, \( b \) is learning index [15]. The percentage of unit cost reduction associated with a doubling of cumulative installed capacity growth is called as learning rate, as shown in Formula (2):

\[ LR = 1 - 2^b \]  

The unit cost of learning curve is related to cumulative installed capacity, therefore, if the pathway of installed power capacity is different, the cost experience curve with endogenous method will also be different.

In addition, more complex learning curves, such as "two-factor learning curve" of cumulative expenditure of research and development (R&D) and cumulative installed capacity or production [16] are used in some research, as shown in Formula (3):

\[ C = C_0 \times i^{b_{bd}} \times R^{b_{br}} \]  

Wherein, \( b_{bd} \) is the learning index of learning by doing, \( b_{br} \) is the learning index of learning by research, and \( R \) is the cumulative R&D expenditure or knowledge stock.
3. Methodology

3.1. Evaluation Indicator

The purpose of this study is to compare the relative differences of total investment cost with endogenous method and exogenous method. The relative difference of total investment cost between exogenous method and endogenous method are used as the evaluation indicator, refer to Formula (4):

\[ \delta = \frac{W_{ex} - W_{en}}{W_{ex}} \]  

Wherein, \( \delta \) is the relative difference, \( W_{ex} \) and \( W_{en} \) are the total investment cost with exogenous method and endogenous method, respectively.

The total investment cost is described as Formula (5) and (6):

\[ W = \sum_{t=t_0}^{t_f} C_t \times \Delta Q_t \]  
\[ \Delta Q_t = Q_t - Q_{t-1} \]  

Wherein, \( W \) is total investment cost, \( t \) represents one year, \( t_0 \) is initial year, \( t_f \) is end year, \( C_t \) is unit cost of power generation technology in year \( t \), \( \Delta Q_t \) is newly increased installed capacity of generation technology in year \( t \), \( Q_t \) is cumulative installed capacity by year \( t \), which can be described as Formula (7):

\[ Q(t) = Q_0 + (Q_f - Q_0) \times \left( \frac{t - t_0}{t_f - t_0} \right)^{PP} \]  

Wherein, \( Q(t) \) is the cumulative installed capacity trajectory (hereinafter referred to as pathway) of a given power generation technology, \( Q_0 \) is the cumulative installed capacity of the initial year, \( Q_f \) is the cumulative installed capacity of the end year (\( Q_f \geq Q_0 \)), \( PP \) is power function parameter that determines the shape of the pathway.

As for parameter \( PP \), When \( PP = 1 \), it represents the uniform growth of the power generation capacity process, and the total amount of increased installation during the whole time period will be evenly distributed (hereinafter referred to as uniform pathway); When \( 0 < PP < 1 \), it indicates the pathway is pre-accelerated (hereinafter referred to as pre-accelerated pathway), the task of installation growth is distributed to the early stage, the smaller the value of \( n \) is, the heavier the task in the early stage is; conversely, when \( nPP1 \), it indicates that the pathway is post accelerated (hereinafter referred to as post-accelerated pathway).

3.2. Cost Experience Curves

As for endogenous method, the one factor learning curve model is used in this study for simplicity, \( C_t \) can be expressed as Formula (8)

\[ C_t = C_0 \times \left( \frac{Q_t}{Q_0} \right)^b \]  

As for exogenous method, three most commonly used functions are selected: 1) equal difference change curve, which means the changes rate of unit cost is equal each year; 2) equal ratio change curve, which means the absolute value of the unit cost changes in an equal difference; 3) piecewise equal ratio change curve, which divides the whole time period into three time periods, and the change rate in each time period is different.

To ensure comparability, the unit cost of the start point (\( C_0 \)) and end point (\( C_f \)) of exogenous curves are the same as endogenous learning curve, as shown in Figure 1.

3.3. Parameters Setting

According to the evaluation indicator and cost experience curves described above, The key parameters in this study include cumulative growth multiple of capacity by the end year relative to the initial year (\( GM = Q_f / Q_0 \)), pathway parameter (\( PP \)) and learning rate (\( LR \)).

However, the conclusions for cumulative growth multiple of installed capacity and cost tend of non-
fossil power generation technologies (including wind power, PV, hydropower and nuclear power) in the future from different researches varied in a quite wide range. Research results from different institutions/teams for China’s wind power, PV, hydropower and nuclear power installed capacity in 2050 are shown in Table 1.

Table 1. China’s Installed Capacity of Non-fossil Power in 2050 derived from different research.

| Power generation technology | Capacity in 2050 (Billion kW) | Ratio of value in 2050 and the actual value in 2018 | Issuing years of research |
|-----------------------------|-------------------------------|---------------------------------------------------|---------------------------|
| Wind power                  | 1.0–2.32                      | 5.4–12.6                                          | 2016–2019                 |
| PV                          | 1.3–2.8                       | 7.4–16.0                                          | 2016–2019                 |
| Hydropower                  | 0.52–0.64                     | 1.5–1.8                                           | 2016–2018                 |
| Nuclear power               | 0.12–0.5                      | 2.7–11.2                                          | 2011–2018                 |

The cumulative growth multiple of wind power and PV is commonly large, which is [5.4–12.6] and [7.4–16.0] respectively; the value for hydropower is the smallest (1.5–1.8); and the difference between the minimum value and maximum value of that for nuclear power is the largest [2.7–11.2].

Literature [13] reviewed the learning rate of different power generation technologies from different research, as shown in Table 2.

Table 2. One-factor Learning Rate Range of Non-fossil Power.

| Power generation technology | One-factor learning rate range | The years covered by researches |
|-----------------------------|--------------------------------|--------------------------------|
| Wind power                  | 8–32%                          | 1979–2010                      |
| PV                          | 10–47%                         | 1959–2011                      |
| Hydropower                  | 1.4%                           | 1980–2001                      |
| Nuclear power               | -38%–6%                        | 1972–2004                      |

The learning rates for wind power and PV are relatively high, which is [8–32%] and [10–47%] respectively; the value for hydropower is a very small positive value (1.4%), which means the cost is quite stable; the value for nuclear power learning rate is [-38%–6%], the negative value means the cost of nuclear power increases with the growth of installed capacity, the causes may include improvement of safety standards [21–22].

Refer to the statistical data in Table 1 and Table 2, the values of key parameters in this study are shown in Table 3. The value range of LR and GM is set as [-20%~20%] and [1 ~10],While the value of n is set as 2/3, 1 and 3/2, indicating three typical pathways of pre-acceleration, uniform and post-acceleration respectively.

Table 3. Parameter Setting.

| GM          | LR          | PP          |
|-------------|-------------|-------------|
| [a~10a]     | [-20%~20%]  | 2/3, 1, 3/2 |

Figure 1 is the unit cost curve of endogenous method and three exogenous methods when LR=20%, GM = 10 and PP = 1. There are significant differences among the curves, wherein, the unit cost given by endogenous method is significantly lower than other three unit costs given by exogenous method. Obviously, the differences of unit cost will lead to the differences of the cumulative amount invested.
4. Result Analysis

4.1. Effects of One-parameter
Firstly, the effects of the value of three parameters on relative difference $\delta$ are analyzed when $\mathcal{G}, \mathcal{L}, \mathcal{P}$ are independently changed while all the other parameters are fixed.

4.1.1. Effect of cumulative growth multiple ($\mathcal{G}$). When $\mathcal{L}$ and $\mathcal{P}$ are fixed, the larger the value of $\mathcal{G}$ is, the larger the variations of unit cost is. As shown in the Figure 2: $\mathcal{L}=20\%$, $\mathcal{P}=1$, when $m=\mathcal{G}$, the unit cost of the end year decreases to 80% of the initial year, however, when $\mathcal{G}=10$, the unit cost of the end year is only 48% of the initial year.

If the difference of unit cost of the end year increases the difference of the unit cost in each year described by the experience curves of endogenous method and exogenous method will enlarged, as well as the relative difference $\delta$ of total investment cost. Figure 3 shows the change of the relative difference $\delta$ between endogenous method and three exogenous methods when $\mathcal{G}$ is enlarged from 2 to 10 ($\mathcal{L}=20\%$, $\mathcal{P}=1$). The cumulative growth multiple of capacity by the end year relative to the initial year increase, the value of total investment cost calculated with endogenous method will be much lower. Among three exogenous methods, $\delta$ will be slightly different, but the overall trend is the same. Compared with endogenous method, $\delta$ will increases from 1.7% to 19.9%, from 1.3% to 14.6%, from 0.2% to 10.5% for equal difference, equal ratio, and piecewise equal ratio. In general, for exogenous method with equal difference change curve, the relative difference $\delta$ is the largest.

![Figure 1](image1.png)

**Figure 1.** Unit Cost Curves Given by Endogenous Method and Three Exogenous Methods.

![Figure 2](image2.png)

**Figure 2.** Change of Unit Cost of End Year along with $\mathcal{G}$s.
4.1.2. Effects of Learning Rate ($LR$). When $GM$ and $PP$ are fixed, the value of $LR$, also greatly affects unit cost experience curves, as shown in Figure 4. When $LR$ is positive, the larger $LR$ is, the larger the decrement of unit cost is; When $LR$ is negative, the larger the absolute value of $LR$ is, the larger the increment of unit cost is. Similar with the effects of $GM$, the different values of $LR$ will affect the value of $\delta$, as shown Figure 5. If $LR$ increases from $10\%$ to $20\%$, $\delta$ will double. And $LR$ and $\delta$ are not with linear relation. Taking change of exogenous equal difference as an example, when $LR$ is $20\%$ and $-20\%$, the differences of the absolute value of $\delta$ are large.
4.1.3. Effects of Pathway Parameter (PP). When $GM$ is fixed, the task of installation growth is distributed to the early stage, the smaller the value of $PP$ is, the newly added installed capacity in each year is larger. Therefore, when the costs of each curve in the initial year and end year is are fixed, the smaller $PP$ is, the faster the unit cost with endogenous method decrease to the value of end year. Figure 6 shows the unit costs endogenous experience curve when $PP$ equals to $3/2, 1, 2/3$, respectively ($LR = 20\%, \ GM = 2$ ), as well as exogenous experience curve of equal difference. Figure 7 shows the differences of $\delta$ between endogenous method and exogenous method with different $PP$ ($LR = 20\%, \ GM = 2$ , take equal difference change curve as example). For pre-acceleration pathway, the total investment cost with exogenous method is larger than the value of endogenous method; conversely, for post-acceleration pathway, the total investment cost with exogenous method is lower than endogenous one.

![Figure 6. Unit Cost Curve of Different Path Coefficient.](image)

![Figure 7. Relative Differences of Total Investment Cost for Different.](image)

5. Discussion

The expected installation capacity targets, pathways, and cost experience curve of different kind of non-fossil power generation technologies are greatly different. In accordance with the analysis of this paper, the total investment cost evaluated with endogenous method and exogenous methods are difference, which are affected by a lot of parameters including the cumulative capacity growth, capacity growth pathway, and cost learning rate.
The difference value of total investment cost by using endogenous and exogenous methods for a specific power generation technology, such as hydropower, could be very close with slight expected installation capacity growth and low learning rate. Taking the hydropower development in China as the example, if the installed capacity reaches 520 million kilowatts by 2050 (which means almost all the hydropower resources are developed), and the unit cost learning rate stabilizes at 1.4%, the difference of total investment cost with the two methods would only be about CNY 300 million, the relative difference would be 0.052%. Therefore, the cost experience curve used will have little effect on the outcome of the assessment under this condition.

Conversely, the difference value could be large with large amount of expected installation capacity targets and high learning rate. It is quite a consensus that the installation capacities of wind power and PV will keep in a strong growth during China’s energy low-carbon transition, and the cost will decrease continually in the foreseeable future. While the nuclear power would see a substantial growth in China, and the cost change in the future remain highly uncertain, which is possible to increase significantly as has happened in the past few decades. Take PV as an example, If China’s PV installed capacity reaches 2 billion kilowatts by 2050, and the unit cost learning rate maintains at 20%, the differences of the total investment cost with the two methods will be as high as CNY 1.7 trillion, equivalent to the GDP of Shanxi Province in 2019. Therefore, it is necessary to detailed examine the effects of endogenous method and exogenous method on quantitative analysis results to provide more comprehensive support to relevant decision-making.

6. Conclusion
How the costs of energy technologies change over time is of key importance for energy transition strategic. Endogenous and exogenous cost experience curves are two kinds of methods widely used in quantitative modes supporting decision-making. This paper quantitatively evaluates the differences of investment cost for a specific power generation technology with endogenous method and exogenous method for the first time. The results indicate that, when expected installation capacity growth and learning rate are relatively high (no matter positive or negative), the differences of the evaluation results of these two methods are large.

It is strongly recommended that researches, model developer, policy and decision makers should pay more attention to the effects of different cost experience curve on results of quantitative models for better decision-making support, especially when wind power, PV, and nuclear power are involved in relevant research.

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