IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 21 September 2022, accepted 18 October 2022, date of publication 28 October 2022, date of current version 4 November 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3218060

RESEARCH ARTICLE

Investment Cost Forecasting for Low Carbon Power System Planning Considering Technical Progress and Scale Effect

WEI SUN[1,2], JINYU XIAO[1,2], (Associate Member, IEEE), JINMING HOU[1,2], CHEN JIN[1,2], AND YUANHONG NIE[3]

[1]Global Energy Interconnection Group Company Ltd., Xicheng, Beijing 100031, China
[2]Global Energy Interconnection Development and Cooperation Organization, Xicheng, Beijing 100031, China
[3]State Grid Anhui Electric Power Company Ltd., Economic Research Institute, Hefei, Anhui 230061, China

Corresponding author: Jinming Hou (jinming-hou@geidco.org)

This work was supported by the Science and Technology Project of State Grid Corporation of China: Model Research and Key Technology Evaluation on Low Carbon Development of Energy and Power in China under the Background of Carbon Peak and Carbon Neutralization under Grant 1300-202155460A-0-0-00.

ABSTRACT Low carbon power system with high penetration of clean energy is an effective way to realize the carbon emission target. Long term power system planning should consider both technical constraints and reasonable investment cost forecasting. For reasonable investment cost forecasting in long term, the effect on investment cost by technical progress and scale effect should be taken into consideration both. Investment cost can affect the planning results of installed capacity, while installed capacity affects the investment cost forecasting result mutually. There is no paper that takes technical effect into investment cost forecasting or analyzes the mutual effect between planned installed capacity and investment cost forecasting. Technical progress can be quantified by TRL (Technical Readiness Level) while scale effect can be quantified by installed capacity. The novelty of this paper is proposing the 3D curve function which qualified the relationship between investment cost and technical progress & installed capacities for the first time to realize investment forecasting in long term. And the 3D curve is combined with the GESTP model by feedback the forecasting investment cost to power system planning which reveals the mutual effect between installed capacity planning and investment cost forecasting for the first time. The study case indicates that accelerating of technical progress will decrease the investment cost and increase the installed capacity of this technology and affect other technologies with interaction in the whole power system.

INDEX TERMS TRL, learning curve, curve fitting, log-log regression, low carbon power system, long term planning, onshore wind power, LCOE, investment cost.

I. NOMENCLATURE

Symbol	Description
a	Learning rate.
b	Saturation value of investment cost in this paper.
c	The ramp rate of the curve.
C_0	Initial investment cost in USD/kW.
C_{gen}^{inv}, C_{line}^{inv}, C_{sto}^{inv}	Investment cost of power source, power grid and power storage respectively.
C_{sys}^{oper}	O&M cost of power system.
d	The location parameter which is the year when the technology has been mature and started to decline.
$F_{l,t}^{L}$	Transmission power.
$F_{l}^{L,Max}$	Maximal transmission capacity.
H_b^B	Continuous charging and discharging time of storage.
G_b^B	Installed capacity of power storage units.

The associate editor coordinating the review of this manuscript and approving it for publication was S. Ali Arefifar.

G_g^G	Installed capacity of thermal power plants.
k	The shape parameter of log-log regression model which is the ramp rate of the curve.
L	Saturation value of log-log regression model which is the up limit of patent numbers in this paper.
$L_{n,t}$, $L_{n,t}^{\mathrm{Cur}}$	The load at node and load shedding rate respectively.
l	The number of transmission line.
$O_{g,t}^G$	The operational capacity of thermal power unit at t time.
p	The annual accumulative patent numbers.
$P_{g,t}^G$	The output of thermal power unit at t time.
$P_{b,t}^{B,cha}$, $P_{b,t}^{B,dis}$	The charging power and discharging power at t time of storage respectively.
$S_{b,t}^B$	The remaining electricity in storage equipment.
$X_{b,t}^{B,cha}$, $X_{b,t}^{B,dis}$	0-1 valuables which represent the charging or discharging states.
$T_g^{G,on}$, $T_g^{G,off}$	The minimal start and stop time respectively.
$U_{g,s,t}^{G,on}$, $U_{g,s,t}^{G,off}$	The operational capacity and stopped capacity at t time respectively.
x	The annual accumulative installed capacity in GW.
y	Annual TRL which should be less than 1.
z	Annual investment cost in USD/kW.
$\alpha_g^{G,Rd}$	Low limit of ramp rate.
$\alpha_g^{G,Ru}$	Up limit of ramp rate.
η_b^B	The charging or discharging efficiency.
$\lambda_g^{G,Min}$	Proportion of thermal unit minimum output.
τ	The location parameter which is the year when patents number start to increase quickly.

II. INTRODUCTION

As more and more serious of carbon emission and global warming, clean energy development become more and more important. The "Paris Agreement" signed in 2016 proposed the global goal of controlling temperature rise no more than 2°C and striving to control below 1.5°C. To realize this target, the global carbon emission in 2050 should be lower than 9.7 billion tons [1].

To realize the "Paris Agreement", many countries in the world have laid out a carbon emission reduction plan. For example, European Union claimed a carbon emission reduction of 60% by 2030, Russian claimed a carbon emission reduction of 30% by 2030 and China claimed a Carbon intensity reduction of 60% [2]. On 22nd September 2020, Chinese President Xi Jinping mentioned in the general debate of the seventy-five UN General Assembly that China should strive to achieve carbon neutralization by 2060, which means that from 2020 to 2060, China's carbon emissions should be reduced from 160 million tons per year to almost no emissions.

Most clean energies need to be converted to electricity before they can be utilized. So the low carbon power system with high penetration of clean energy is an effective way to achieve the "Paris Agreement". It takes a long time to achieve this target and reasonable planning for a low carbon power system would promote its development. The existing power system planning method is to calculate the minimal LCOE (Levelized Cost of Electricity) based on technical constraints or investment forecasting.

Some of the planning methods are only focused on technical constraints such as carbon emission, ramp rate of generation units, transmission limit, power storages charging rate, and balancing between power generation and load. The medium or long term power generation planning methods considering carbon emission ([3] and [4]) or balancing capacity ([5] and [6]) have been proposed. The power generation planning methods considering power generation ramp rate ([7]) or power storage charging rate ([8] and [9]) have been proposed, and the power grid planning methods under transmission limit have been present in [10] and [11].

Some of the planning methods are only focused on investment forecasting. LCOE is an important evaluation indicator for low carbon power system planning. According to [12], LCOE is the sum of investment cost, operation & maintenance cost (O&M cost) and fuel cost (for renewable energy, the fuel costs are low-to-zero), divided by total electricity generation in a lifetime. The investment cost is separated into three categories: equipment cost, construction & installation cost and grid integration cost. To simplify, in this paper, the investment cost is forecasted as a whole. The O&M cost is a fixed proportion of investment cost. So the reasonable investment cost is important to realize reasonable LCOE calculation in the future. The learning curve is a widely used method for investment cost forecasting. The investment costs forecasting for wind power and PV by learning curve are proposed in [13] and [14] respectively.

Some of the planning methods are focused on both technical constraints and investment cost forecasting. But only the scale effect is taken into consideration in these models. The ETP model from IEA (International Energy Agency) is a bottom-up, technology-rich model that depicts primary energy supply and transformation to final energy demand up to 2070. The supply model of ETP integrates the technical and economic characteristics of new technologies that could be added to the energy system in the future. The model can then determine the least-cost technology mix needed to meet the final energy demand calculated in the ETP end-use sector models for agriculture, buildings, industry, and transport [15]. The NEMS model from EIA (U.S. Energy Information

Administration) is an energy-economy modeling system for the United States. NEMS projects the production, imports, conversion, consumption, and prices of energy, subject to assumptions on macroeconomic and financial factors, world energy markets, resource availability and costs, behavioral and technological choice criteria, cost and performance characteristics of energy technologies, and demographics [16]. In ETP, NEMS, and IRENA model [12], a learning curve was used to forecast the investment cost. The learning curve depicts the development of investment cost as a function of increased cumulative installed capacities of technologies. It reflects the impact of scale effect of technologies on investment cost reduction.

For long term investment cost forecasting, the technical progress and scale effect of technologies promote investment cost reduction both. Technological progress can improve energy efficiency and reduce unit investment cost. But in the existing models or methods, technical progress hasn't been taken into consideration, since technical progress is difficult to be quantified. There are many papers that researched the quantitative analysis methods of technical progress, [17] and [18] proposed that patent numbers can be used to quantify TRL (Technology Readiness Level) of ocean energy generation technology and thermal generation technology respectively. Investment cost can affect the planning results of installed capacity, while if installed capacity changes, it means the scale effect changes, and the investment cost forecasting result would change. So there is a mutual effect between planned installed capacity by power system planning and investment cost forecasting.

But there is no paper that takes technical effect into investment cost forecasting and no paper analyzes the mutual effect between power system planning and investment cost forecasting. ETP or NEMS model is long term planning model for the whole energy system including oil, gas, coal, and electricity. The investment costs are forecasted by the learning curve in these models. Learning curve is a widely used, simple, and effective way to forecast investment cost which can be used for many different technologies in power system such as onshore and offshore wind power, PV, solar thermal, power storage, and so on since little historical data such as installed capacity, patent numbers and investment cost are needed for each technology. Compared to artificial intelligence methods such as neural network or PSO, see in [19] and [20], less historical data is needed for the learning curve. There are some papers researched the improved learning curve method in recent years. Reference [21] presented the self-similarity-based learning curve for onshore wind investment forecasting which forecast the cost of multi-level components of onshore wind farms. Reference [22] presented the inter-regional learning curve for investment cost forecasting of li-ion battery which reflects spillover effect on cost reduction and estimates the impact of local-regional learning experience on the overall region. But the technical progress isn't taken into consideration in these papers. The learning curve can reflect the decrease of investment cost caused by increasing of installed capacity, but the technical progress still can affect the investment cost, especially at the early stage of the whole life of technology. But technical progress is not included in the learning curve. And in these models, forecasting result of learning curve is only used for energy planning, it isn't feedback to energy planning, so the mutual effect between investment cost forecasting and energy planning can't be analyzed. Different from ETP and NEMS models, GTSEP (Generation Transmission Storage Expansion Planning, GTSEP) is professional model for electrical power system planning which has a time interval of one hour rather than one year of the ETP or NEMS model. GTSEP has more detailed technical constraints for power system technologies but it doesn't have a function of investment cost forecasting.

According to the above reference papers, technical progress can be quantified by TRL while scale effect can be quantified by installed capacity. In this paper, the 3D relation function between investment cost, installed capacity, and TRL of technologies is derived for the first time. Then the investment cost can be forecasted by the relation function which means the technical progress is taken into consideration for the first time. Then the forecasting investment cost is transmitted to the existing GTSEP model which realizes optimal power system planning under technical constraints. With the forecasted investment cost, the GTSEP will carry on annual hourly calculations and give comprehensive LCOE of whole low carbon power system and installed capacities of different technologies. The LCOE is compared with empirical value, and the comparison results and installed capacity are feedback to the 3D curve. The coefficients of the 3D curve can be adjusted by the feedback of LCOE comparison result. It means that the 3D prediction curve and GTSEP model are combined by feedback.

This paper analyzed the effect on investment cost of technology caused by technical progress at different developing stages. Based on the analysis, this paper proposed an improved investment costs forecasting method of 3D curve which quantified effect caused by technical progress for the first time. Then this paper combined the improved investment costs forecasting with GTSEP model for the first time, analyzed the mutual effect between investment costs forecasting and installed capacity planning of power system. The proposed forecasting method is a worthy complement to GTSEP model. So the novelty of 3D curve method proposed in this paper is that the technical progress can be qualified and involved in power system optimal planning for the first time.

The study case indicates that: 1 at the early stage of the whole life of a specified technology, and the technology is not mature, the decreasing of investment cost is mainly caused by technical progress. At the mature stage when technology has been mature, the decreasing of investment cost is caused mainly by increasing of installed capacity, the effect caused by technical progress becomes less and less weak. 2 If the development of a specified technology accelerates, the investment cost will be future reduced and the installed capacity

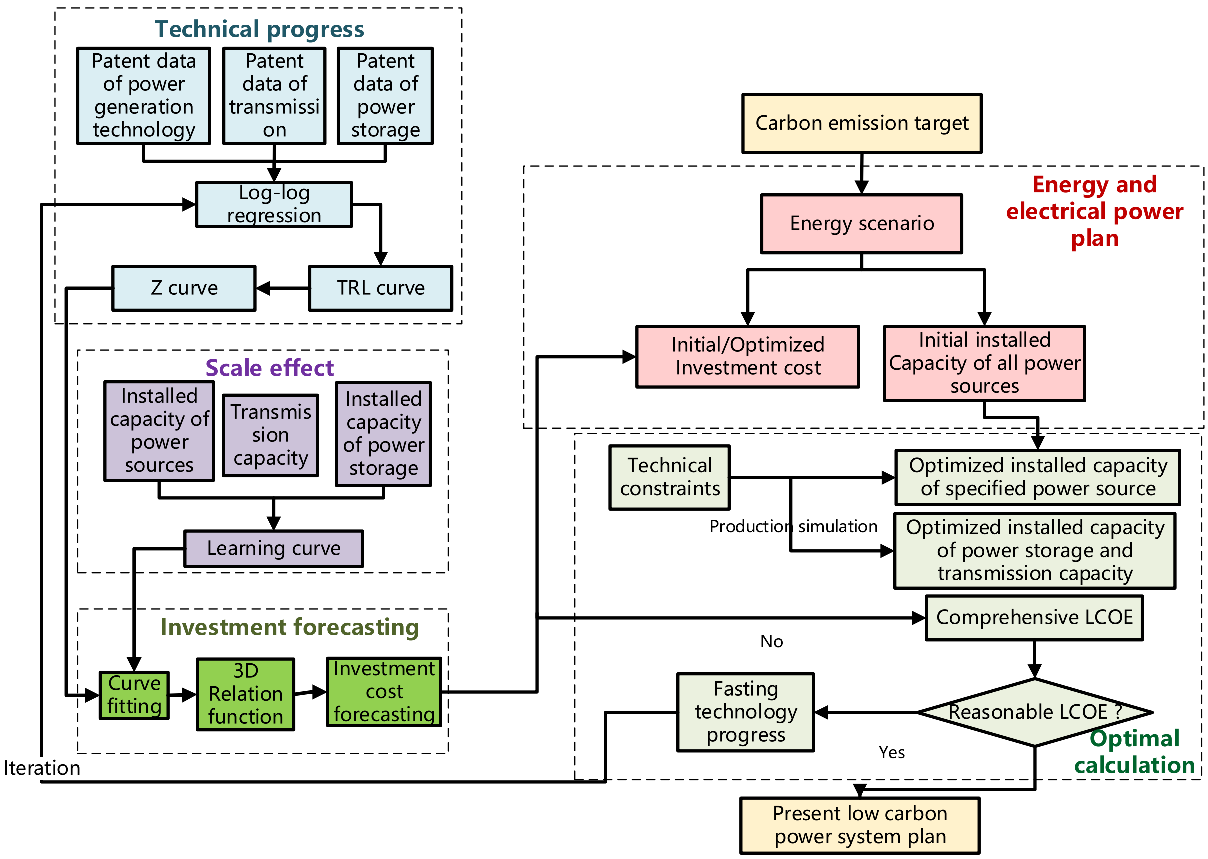

FIGURE 1. Flow chart of low-carbon power system planning.

will be increased, the installed capacity of other technology such as power storage may be reduced.

III. LONG TERM PLANNING PROCEDURE OF LOW CARBON POWER SYSTEM WITH INVESTMENT COST FORECASTING

The existing GTSEP model can realize optimal planning of low carbon power system under technical constraints. In this paper, investment cost forecasting considering technical progress and scale effort is added to GTSEP model. The whole procedure includes 5 steps, as shown in figure 1:

Step1 energy and electrical power system plan. Based on the carbon emission target and initial forecasting investment costs of all power sources (as shown in appendix table3) in a specified level year (2060 is taken as the level year in this paper), the initial installed capacities of renewable or traditional power sources in future low carbon power system can be given by MESSAGE model, as shown in appendix table3. Similar to ETP or NEMS model, MESSAGE is a global systems engineering optimization model used for long or medium term energy system planning [23]. It is not only for electrical power system planning but for the whole energy system planning including petroleum, gas, coal, etc.

Then the investment cost and installed capacity of a specified generation technology can be optimized by the following steps (There are three main kinds of technologies in power system: power generation technologies, transmission technologies, and power storage technologies, as shown in figure 1. Onshore wind power is taken as an example in this paper).

Step2 scale effect. Based on annual installed capacities, the annual investment costs and initial forecasting investment costs of onshore wind power (as shown in appendix table1), through curve fitting, learning curve (see in (1)) of onshore wind power is derived which describes the relationship between investment costs and installed capacities.

Step3 technical progress. Based on annual patent numbers (as shown in appendix table2), through log-log regression, the TRL curve (see in (2)) of onshore wind power is derived which describes the trend of technical development. Through TRL curve, the future TRL can be calculated (as shown in appendix table1). Then based on the annual TRLs and annual investment costs (as shown in appendix table1), through curve fitting, the Z curve (see in (4)) of onshore wind power is derived which describes the relationship between investment costs and TRLs is derived.

Step4 investment cost forecasting. Based on annual installed capacities, annual TRLs and annual investment costs (as shown in appendix table1), add equations (1) and (4), through curve fitting, the 3D relation function between investment costs, TRLs and installed capacities is derived, see in (5). Based on the future installed capacity planned in Step1 and future TRL calculated in Step2, the future investment cost of onshore wind power can be forecasted using the 3D relation function. The forecasting result can be found in appendix table3, the first forecasting result.

Step5 Optimal planning. With the planned installed capacities of different technologies in Step1, forecasting investment cost of the specified technology in Step4 and forecasting investment costs of other technologies by export experience (as shown in appendix table3), the optimal planning of the 2060 power system by GTSEP model is carried on and the comprehensive LCOE is calculated. Different from MESSAGE model, GTSEP model is a professional model for power system planning, it is in full time scale with time interval of one hour and total of 8760 hours in a year.

If the comprehensive LCOE of future low carbon power system decreases to an unreasonable value according to expert experience, then the coefficients of 3D relation function should be adjusted with a step of 10% of initial value, then second, third and more times forecasting results can be calculated until reasonable LCOE is achieved.

IV. FACTORS AFFECTING INVESTMENT COST

A. SCALE EFFECT

The scale effect means the rise in output of products will lead to a decline in investment costs [13]. Scale effect can be quantified by total quantity of product. For power generation or power storage technologies, total quantity refers to accumulative installed capacities; for power transmission technology, total quantity refers to accumulative transmission capacities. Learning curve also known as experience curve is the relation function that describes the relationship between investment cost and total quantity of products.

With the increasing of accumulative installed capacities of power sources, the investment costs of these technologies will decrease in a certain proportion. So the learning curve of these technologies is:

$$z = C_0^* x^a \tag{1}$$

where, z is annual investment cost in USD/kW, C_0 is initial investment cost in USD/kW, x is the annual accumulative installed capacity in GW, a is learning rate. The larger the learning rate "a" is, the faster the investment cost decreases.

B. TECHNICAL PROGRESS

1) TRL CURVE

The technology readiness level (TRL) evaluation method can be used for quantitative analysis of key technical progress, supporting project decision-making and milestone control [17]. In the 1980s, based on an analysis of a large number of patents, Professor Altshuller found that the accumulative annual number of patents is closely related to the development and evolution of technology, which can be used for TRL analysis and prediction [18]. In the whole life of technology, the growth law of TRL is similar to the pattern of biological evolution which looks like an "S" curve. It means that when a technology develops to a new stage, the number of relevant patents will change. Log-log regression model is a kind of "S" curve. It belongs to the category of multivariate analysis and is a common method of statistical empirical analysis. The mathematical equation of log-log regression model (be called as TRL curve) is:

$$p = \frac{L}{1 + e^{-k(t-\tau)}} \tag{2}$$

where, p is the annual accumulative patent numbers, L is saturation value of log-log regression model which is the up limit of patent numbers in this paper, k is the shape parameter of log-log regression model which is the ramp rate of the curve, τ is the location parameter which is the year when patents number start to increase quickly.

TRL of a specified technology is defined as y:

$$y = \frac{p}{L} \tag{3}$$

The patent numbers can be found in the top five patent offices which are European Patent Office (EPO), China National Intellectual Property Administration (CNIPA), United States Patent and Trademark Office (USPTO), Japan Patent Office (JPO) and Korean Intellectual Property Office (KIPO). All the patent offices have patent literature resources and advanced patent information retrieval systems which provide the database for TRL analysis.

2) RELATION FUNCTION BETWEEN TRL AND INVESTMENT COST

The technical progress can promote investment cost reduction. Based on the quantitative assessment of TRL, by curving fitting, we derive the relation function between TRL and Investment cost can be derived, as (4) which is also called as "Z" curve.

$$z = b - \frac{b}{1 + e^{c(y-d)}} \tag{4}$$

where z is annual investment cost in USD/kW, y is annual TRL which should be less than 1, b is saturation value of investment cost in this paper, c is the ramp rate of the curve, d is the location parameter which is the year when the technology has been mature and started to decline.

V. RELATION FUNCTION OF TRL&INSTALLED CAPACITY AND INVESTMENT COST

According to chapter 2, the investment cost of technology is affected by TRL and installed capacity. The development of a specified technology goes through three stages:

At the early stage, the technology develops slowly and is not mature, while the installed capacity is small, the investment cost is very high.

At the fast developing stage, the TRL of technology increases fast and installed capacity becomes larger and larger, the investment cost has a fast decreasing. Both TRL and installed capacity have a strong influence on the investment cost decreasing during this period.

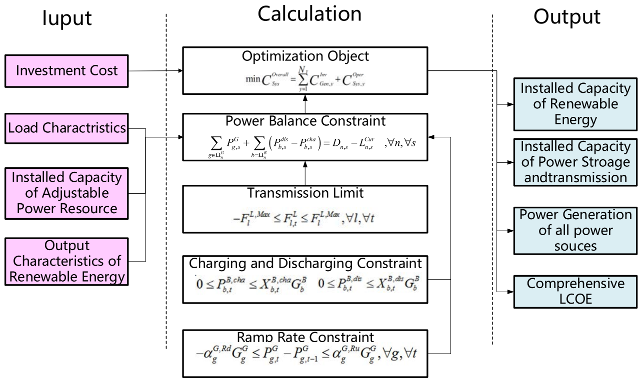

FIGURE 2. Frame work of GTSEP.

At the mature stage, technology has been mature and TRL curve is almost flat which means the influence on investment cost by TRL is weak in this stage. The investment cost decreasing is caused mainly by installed capacity increasing.

To describe the mathematical relationship between TRL& installed capacity and investment cost, we derive the 3D (three-dimensional) relation function by adding learning curve equation and "Z" curve equation, see in (5). MATLAB/Curving fitting tool provides a function to fitting curves or surface to data, we can conduct regression analysis using the library of linear or nonlinear models provided or specify our own custom equations. In this paper, the custom equation is (5). The tool provides optimized solver coefficients to improve the quality of the fits. So by curve fitting, the 5 coefficients of this equation can be calculated, these coefficients are the same as in (1) to (4).

$$z = C_0^* x^a - \frac{b}{1 + e^{-c(y-d)}} + b \tag{5}$$

The independent variables of (5) are installed capacity (x) and TRL (y). Installed capacity is calculated by GTSEP model and TRL is calculated by TRL curve. With the known independent variables, the dependent variable (investment cost) can be calculated according to (5).

VI. OPTIMIZATION PLANNING FOR LOW CARBON POWER SYSTEM

GTSEP (Generation Transmission Storage Expansion Planning) model can realize optimal calculation for power system planning [24], [25], [26]. The model optimizes the installed capacities of power sources, power storages and transmission lines in power system to achieve minimal LCOE. The model carries on annual hourly calculation under technological constraints such as power balancing constraint, charging and discharging constraint, and ramp rate constraint, etc. The time duration is one year which means the hourly data number is 8760. It calls equation server CAPLX to realize optimization calculation. The model has three parts: input, output and optimal calculation.

The inputs of GTSEP are separated into two categories: economical inputs and technical inputs. The economical inputs include the investment costs of the power sources, transmission lines and power storage. The technical inputs include the load characteristics (annual hourly data), the output characteristics of fluctuating power sources (annual hourly data), and installed capacities of power sources that don't need to be optimized (in chapter6, except for onshore wind power and power storage, the installed capacities of other power sources don't need to be optimized).

The outputs of GTSEP are installed capacities of power sources that need to be optimized, power generation of power sources, installed capacity of power storage and transmission, the penetration rate of renewable energy, and the comprehensive LCOE.

The optimal calculation is to minimize the total system cost (or power consumption cost) which is expressed by objective function (6). The total cost of the system divided by the power generation equals the comprehensive LCOE. The calculation should under operation constraints which includes power balancing constraint, transmission limit, charging and discharging constraint of power storage and ramp rate constraint of thermal power unit.

A. OBJECTIVE FUNCTION

The objective function means that the function of gtsep optimal model is realizing the minimal cost of the whole power system composed of investment cost and operation cost.

$$\min C_{sys} = C_{gen}^{inv} + C_{line}^{inv} + C_{sto}^{inv} + C_{sys}^{oper} \tag{6}$$

where, C_{gen}^{inv}, C_{line}^{inv}, C_{sto}^{inv} are investment cost of power source, power grid and power storage respectively, C_{sys}^{oper} is O&M cost of power system.

B. POWER BALANCING CONSTRAINT

Power balancing constraint means power supply should be equal to power consumption. Power supply is power generation plus power storage (discharging power minus charging power) and minus transmission losses. Power consumption is available load which is total load minus shedding load.

$$\sum_{g\in\Omega_n G} P_{g,t}^G + \sum_{b=\Omega_n^B} \left(P_{b,t}^{B,dis} - P_{b,t}^{B,cha}\right) - \sum_{l\in\Omega_n^{LS}} F_{l,t}^L + \sum_{l\in\Omega_n^{LE}} F_{l,t}^L = L_{n,t} - L_{n,t}^{Cur}, \quad \forall n, \quad \forall t$$

where, $P_{g,t}^G$ is the generation output power, $P_{b,t}^{B,dis}$, $P_{b,t}^{B,cha}$ are the charging and discharging power of storage respectively, $F_{l,t}^L$ is transmission power, $L_{n,t}$, $L_{n,t}^{\text{Cur}}$ are the load at node and load shedding rate respectively.

C. TRANSMISSION LIMIT

Transmission limit means the transmission power of a transmission line should be lower than the line's maximal transmission capacity.

$$-F_l^{L,Max} \le F_{l,t}^L \le F_l^{L,Max}, \quad \forall l, \quad \forall t$$

where, $F_l^{L,Max}$ is maximal transmission capacity. L is the number of transmission lines.

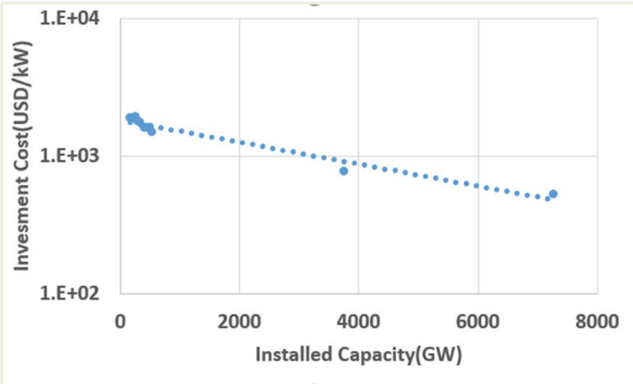

FIGURE 3. Learning curve of onshore wind power.

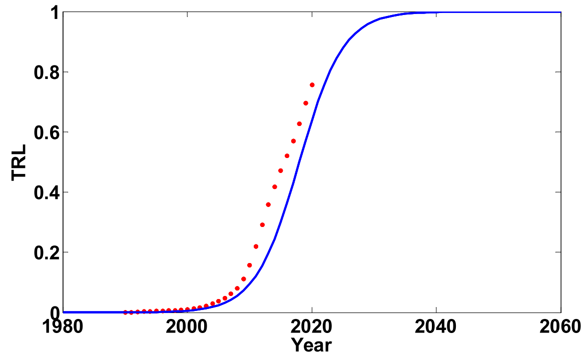

FIGURE 4. TRL curve of onshore wind power.

D. CHARGING AND DISCHARGING CONSTRAINT

Charging and discharging constraint means the charging or discharging power should be lower than the nominal power of storage equipment and can't be operated at same time (see in first and second equations). The charging and discharging efficiency at t time should be lower than the efficiency of storage equipment (see in third equation). The charging and discharging electricity should be lower than the storage capacity of storage equipment (see in fourth equation).

$$\begin{cases} 0 \le P_{b,t}^{B,cha} \le X_{b,t}^{B,cha} G_b^B \\ 0 \le P_{b,t}^{B,dis} \le X_{b,t}^{B,dis} G_b^B \end{cases} \quad \forall b, \quad \forall t$$
$$X_{b,t}^{B,cha} + X_{b,t}^{B,dis} = 1, \quad \forall b, \quad \forall t$$
$$S_{b,t}^{B} - S_{b,t-1}^{B} = \eta_b^B P_{b,t}^{B,cha} - P_{b,t}^{B,dis}/\eta_b^B, \quad \forall b, \quad \forall t$$
$$0 \le S_{b,t}^{B} \le H_b^B G_b^B, \quad \forall b, \quad \forall t$$

where, $P_{b,t}^{B,cha}$, $P_{b,t}^{B,dis}$ are the charging power and discharging power at t time of storage respectively, G_b^B is installed capacity of power storage units, $S_{b,t}^B$ is the remaining electricity in storage equipment, η_b^B is the charging or discharging efficiency, H_b^B is continuous charging and discharging time of storage, $X_{b,t}^{B,cha}$, $X_{b,t}^{B,dis}$ are 0-1 valuables which represent the charging or discharging states.

E. RAMP RATE CONSTRAINT

Ramp rate constraint means the output and its ramp of thermal power unit should be lower than technical limit value (see in first and second equations). The output of thermal power unit should be larger than the minimum technology output and lower than the total operational capacity and total operational capacity is equal to the previous operational capacity plus current start capacity (see in third to fifth equations).

$$0 \le P_{g,t}^{G} \le G_g^G, \quad \forall g, \quad \forall t$$
$$-\alpha_g^{G,Rd} G_g^G \le P_{g,t}^{G} - P_{g,t-1}^{G} \le \alpha_g^{G,Ru} G_g^G, \quad \forall g, \quad \forall t$$
$$\lambda_g^{G,Min} O_{g,t}^{G} \le P_{g,t}^{G} \le O_{g,t}^{G}, \quad \forall g, \quad \forall t$$
$$O_{g,t}^{G} = O_{g,t-1}^{G} + G_{g,t}^{G,on} - G_{g,t}^{G,off}, \quad \forall g, \quad \forall t$$
$$\sum_{\tau=1}^{T_g^{G,On}} G_{g,t-\tau}^{G} \le O_{g,t}^{G} \le G_g^G - \sum_{\tau=1}^{T_g^{G,Off}} G_{g,t-\tau}^{G}, \quad \forall g, \quad \forall t$$

where, $P_{g,t}^G$ is the output of thermal power unit at t time, G_g^G is installed capacity of thermal power plants, $\alpha_g^{G,Rd}$ is low limit of ramp rate, $\alpha_g^{G,Ru}$ is the up limit of ramp rate, $O_{g,t}^G$ is the operational capacity of thermal power unit at T time, $\lambda_g^{G,Min}$ is proportion of thermal unit minimum output, $U_{g,s,t}^{G,on}$ and $U_{g,s,t}^{G,off}$ are the operational capacity and stopped capacity at T time respectively, $T_g^{G,on}$ and $t_g^{g,off}$ are the minimal start and stop time respectively.

VII. CASE STUDY

In this chapter, the investment cost forecasting of onshore wind power is carried out considering technical progress and scale effect.

A. STEP1: ELECTRICAL POWER SYSTEM PLANNING

According to the "Paris Agreement", the global goal of controlling temperature rise no more than 2 °C, so the total captured CO_2 minus CO_2 emission in 2060 should be more than 6400 million tons of standard coal. In power system, the power generation of renewable energy should account for more than 95% of total power generation [27]. Based on these constraints and initial forecasting investment costs, the installed capacities of renewable energy and traditional energy were calculated by MESSAGE model. appendix table3 gives installed capacities and initial forecasting investment costs of onshore wind power, offshore wind power, PV, CSP and power storage [28], [29], [31]. Since the investment costs of renewable power generation technologies and power storage will decrease greatly in the future, so these technologies are chosen to list in table 3, and other technologies are not listed in this paper which can be found in [28].

The following step is to optimize the forecasting investment cost and installed capacity of onshore wind power.

B. STEP2: SCALE EFFECT

According to the statistical data from IRENA [33], the historical annual installed capacities and investment costs of

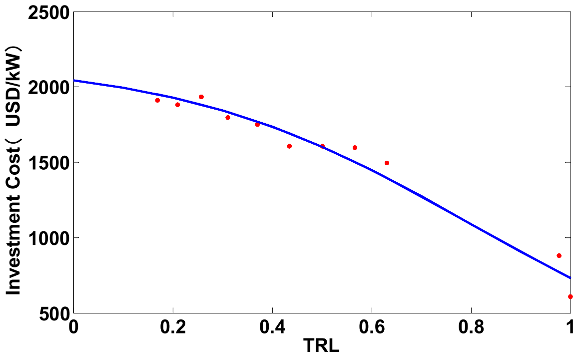

FIGURE 5. Z curve of onshore wind power technology.

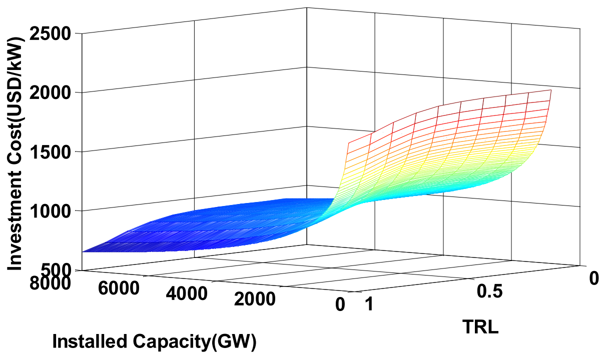

FIGURE 6. 3D relation function map of onshore wind power.

onshore wind from 2010 to 2018 can be found, as shown in appendix table1. Through equation (1), the learning curve of onshore wind power is shown in figure 3 and the equation is:

$$z = 6494 \times x^{-0.228} \tag{7}$$

The learning rate of onshore wind power is 22.6%. In 2021, the installed capacity of onshore wind power is about 830GW, the TRL is 0.71, so the investment cost of onshore wind power is 1459 USD/kW as calculated by (7).

C. STEP3: TECHNICAL PROGRESS

According to database of top five patent offices, the annual patent numbers of onshore wind power from 1990 to 2020 can be found, as shown in appendix table2. The patent numbers had a quick increasing during 2010-2020. By MATLAB/fitting curve tool, the coefficients of (2) are: $\tau = 2016$, $L = 49250$, $k = 0.226$, see in (8). With these coefficients, the R-square of fitting curve is 0.9952 which is approximate to 1. It means that (8) matches the patent numbers well.

$$p = \frac{49250}{1 + e^{-0.226(t-2016)}} \tag{8}$$

TRL of onshore wind technology is defined as y = p/49250, so the TRL curve equation is:

$$y = \frac{1}{1 + e^{-0.226(t-2016)}} \tag{9}$$

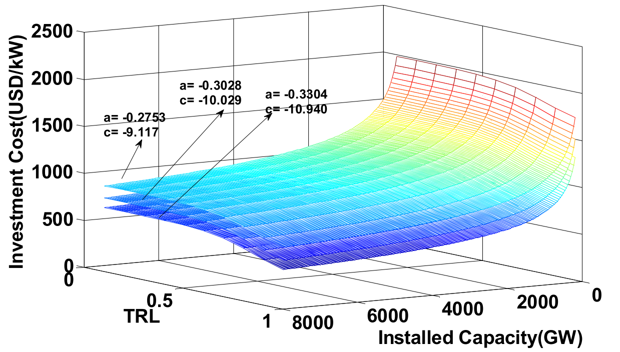

FIGURE 7. Relation function map of onshore wind power with different coefficient.

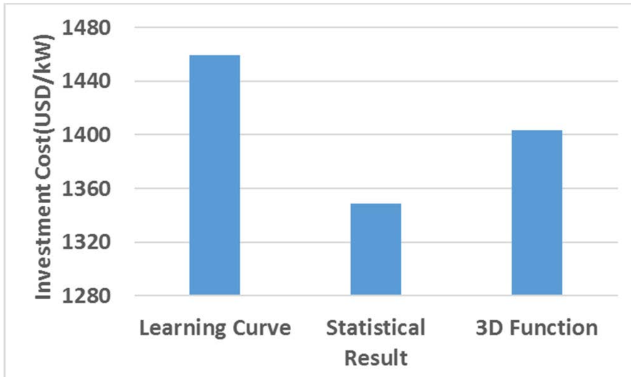

FIGURE 8. Investment costs of onshore wind power forecasted by different methods.

According to (9), the TRL of onshore wind in future years can be calculated, as shown in appendix table1. The TRL curve is shown in figure 4. Before 2000, the onshore wind power technology has not been mature and the accumulative annual patent numbers had a slow increasing. During 2000-2030, the technology develops fast and the annual installed capacities of onshore wind farms increase fast while patent numbers also increase fast. After 2030, the onshore wind technology still keep an increasing trend, but its developing speed will slow down. The patent numbers will tend to be saturated.

According to chapter 2.2, the Z curve (4) can be used to describe the relationship between investment cost and TRL. Based on the TRLs and investment costs of onshore wind power generation technology from 2010 to 2018 in appendix table1, through curve fitting, the coefficients can be derived, see in (10) and Z curve is shown in figure 5. When the technology starts to develop fast while TRL is larger than 0.2, the investment costs start to decrease fast. When the technology have been matured while TRL is approximate 1, the investment costs will have a slow decreasing. The R-square of the fitting curve is 0.967 which means the curve matches the data well.

$$z = 2178 - \frac{2178}{1 + e^{-3.411(y-0.8)}} \tag{10}$$

D. STEP4: INVESTMENT FORECASTING

Based on the annual TRLs, annual installed capacities and initial forecasting investment costs (as shown in appendix table1), through MATLAB 3D curve fitting, the relation function is derived, see (11). With the same method, the 3D curve of offshore wind power, PV, CSP and power storage (Lithium ion battery) are given in Appendix Table5. The S-square of curve fitting is 0.9806 which means (11) matches the data well. The fitting curve is shown in figure 6, this is a 3D surface map. The X axis represents global annual accumulative installed capacities of onshore wind farms in GW, the Y axis represents the annual TRLs of onshore wind power technology and Z axis represents global annual average investment costs of onshore wind power. TRLs have a fast increasing from 0.2 to 0.85, during this period, technical progress affected investment cost strongly, and technical progress promote fast reduction of investment cost. When technology is mature enough while TRL is larger than 0.85, technical progress slows down and TRLs tend to saturation value 1. Effect on investment cost by technical progress becomes weak, investment cost is effected by increasing of installed capacity strongly.

$$z = 7000^{*}x^{-0.2753} - \frac{320}{1+e^{-9.117(y-0.85)}} + 320 \qquad (11)$$

In 2060, the x is 6750 GW and y is 0.99 (see in appendix table 1), so z is calculated to be 688, see in appendix table 4. This is the result of first forecasting.

According to chapter 2, the coefficient a and c affect the shape of 3D curve. In (1), the investment cost (z) will decrease faster as the installed capacity(x) increases by decreasing coefficient a. In (4), the investment cost (z) will decrease faster as the TRL(y) increases by decreasing coefficient c. In (5), coefficients a and c have the same effort, the investment cost will decrease faster by decreasing a and c, as seen in figure 7.

In 2021, the installed capacity (x) of onshore wind power is about 830GW, the TRL (y) is 0.756, so the investment cost of onshore wind power is 1404 USD/kW calculated by (11). According to stpe2 in this chapter, the investment cost of onshore wind power is 1459 USD/kW calculated by learning curve (7). From statistical data of IRENA, the investment cost of onshore wind power is 1349 USD/kW [32]. The forecasting results by 3D function are similar to statistical investment cost, it is less than results by learning curve because technical progress is taken into consideration which causes investment cost reduction. The error between forecasted result by 3D curve and statistical result is about 4%.

E. STEP5: OPTIMAL PLANNING

By first forecasting, the investment cost of onshore wind power is 688 USD/kW in 2060. The investment costs of other power sources in power system except for onshore wind have been given by export experience and the installed capacities of all the power sources have been calculated by MESSAGE in step1. With the input data, the installed capacity of power storage and the comprehensive LCOE are calculated by GTSEP. The results can be found in appendix table4, the comprehensive LCOE of power system is 3.3 cents/kWh under first forecasting scenario. Since power storage is the adjustable power source to balance the electrical power and generation, so it was listed in table 4 with onshore wind power and comprehensive LCOE.

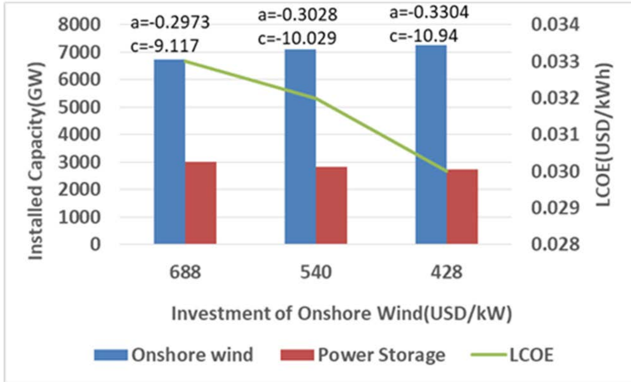

FIGURE 9. Optimized results of power system in 2060.

If 3.3 cents/kWh is higher than expected, then coefficients a and c could be adjusted by iteration step of 10% (as shown in figure 8). When a and c decrease (which means acceleration of technical progress), the forecasting investment cost of onshore wind power will decrease to 540 USD/kW, so the installed capacity of onshore wind power calculated by GTSEP will increase to 7114 GW since onshore wind power becomes cheaper. The installed capacity of power storage will decrease since less power storage is needed with more cheap onshore wind power, as shown in figure 9. This is the second forecasting, under this scenario, the comprehensive LCOE of power system is 3.2 cents/kWh which is cheaper than in first scenario.

If 3.2 cents/kWh isn't lower enough, then the same procedure could be carried on as in second forecasting scenario. For third forecasting, the installed capacity of onshore wind increases to 7269 GW and comprehensive LCOE decreases to 3 cents/kWh.

In this study case, the comprehensive LCOE decreases from 3.3 cents/kWh to 3 cents/kWh as the investment cost of onshore wind power decreases from 688 USD/kW to 428 USD/kW. If the comprehensive LCOE does not decrease to a reasonable value according to export experience, this means the technology development needs to speed up, coefficient a and c can be adjusted to achieve reasonable comprehensive LCOE. According to the expert experience from IRENA report [34], the reasonable investment cost of onshore wind power is between 400 USD/kW to 800 USD/kW. So all the forecasting results in this range are reasonable. The different forecasting results of first forecasting, second forecasting and third forecasting in Table4 mean the low, average and high scenarios in which the technical progress have a low, average and high developing speed.

TABLE 1. Data for curve fitting of onshore wind technology.

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2030	2060
Investment cost(USD/kW)	1913	1883	1936	1798	1751	1609	1609	1599	1497	770 （Initial value）	630 （Initial value）
Installed Capacity(GW)	177.8	216.2	261.6	292.7	340.8	404.6	452.5	495.6	540.2	3750	6750
TRL	0.17	0.21	0.26	0.31	0.37	0.43	0.50	0.57	0.63	0.85	0.99

TABLE 2. Annual patents number from 1990 to 2020.

Year	Patents number	Year	Patents number
1990	27	2006	448
1991	43	2007	726
1992	48	2008	872
1993	47	2009	1444
1994	27	2010	2257
1995	46	2011	2925
1996	43	2012	3486
1997	43	2013	3197
1998	41	2014	2810
1999	70	2015	2562
2000	87	2016	2345
2001	143	2017	2404
2002	154	2018	2682
2003	268	2019	3318
2004	345	2020	2925
2005	420		

The study case indicates that the accelerating of technical progress of onshore wind would decrease its investment cost and increase the installed capacity in future. The increase of installed capacity will cause the decreasing of investment cost future and the decreasing of regulatory power supply such as power storage.

VIII. CONCLUSION

The low carbon power system is an effective way to realize the carbon emission target. For power system planning, the technical constraints and reasonable investment cost forecasting should be included. The existing GTSEP model has included technical constraints, the improved investment cost forecasting model is combined with GTSEP in this paper. Since it is long term planning which means, technical progress and scale effect will both affect the investment cost of technologies. This paper used TRL to quantify technical progress and installed capacity to quantify scale effect, then the 3D relation function between investment cost, TRL and installed capacity was established by MATLAB/curve fitting tool. Then the 3D curve was combined with GTSEP model with feedback. Based on the improved GTSEP model, the planning of low carbon power system in 2060 was given and the investment cost of onshore wind power in 2060 was forecasted. The main conclusions are:

- For long term planning of power system, the effect on investment cost by technical progress and scale effect should be taken into consideration;
- Investment cost would decrease faster either by speeding up technical progress or by increasing installed capacity;
- At the early stage, the technology is not mature and installed capacity is little, the investment cost is very high. At the developing stage, the TRL increases fast and installed capacity becomes larger and larger, the investment cost has a sharp decreasing. At the mature stage when technology has been mature and start to decline, the decreasing of investment cost is caused mainly by increasing installed capacity and the effect caused by TRL becomes less and less weak.
- There is a mutual effect between technical progress and power system planning. If the development of a specified technology accelerates, the investment cost will be future reduced and the installed capacity will be increased, the installed capacity of other technologies such as power storage may be reduced.

The presented 3D curve is a simple and effective way to forecast investment cost in the future, only historical investment, installed capacity and patent numbers are needed. So it can be used for all the technologies in power system such as onshore and offshore wind power generation technologies, PV technology, CSP technology and so on. Compared to IRENA model, the limitation of this method is that detailed cost can't be forecasted, such as equipment cost, construction cost, grid integration cost and O & M cost, etc. Since these detailed costs need very detailed project level data. Compared to learning curve, 3D curve needs more historical patent numbers to qualify technical progress. Compared to complicated artificial intelligence methods such as neural network or PSO, the 3D curve is simple and effective, since the former methods need lots of historical data to train the model.

The novelty of 3D curve method proposed in this paper is that the technical progress can be qualified and involved in power system optimal planning for the first time. It takes technical progress into investment cost forecasting in long time, and it combined investment cost forecasting and power system planning by feedback which can be used to analyze the mutual effect between technical progress and power system planning. The proposed method is an improved method based on learning curve, so it can be used in the existing models such as ETP (IEA) or NEMS (EIA) which adopt learning curve to realize investment forecasting now. So it is a worthy complement to the existing models. It has been used in GEIDCO model, see in [27], [28], [29], [30], and [31].

TABLE 3. Investment cost and installed capacity of difference technology in 2060.

Technology	Onshore Wind	Offshore Wind	PV	CSP	Power Storage
Investment cost (USD/kW)	688 (first forecasting)	890	175	2000	65
Installed Capacity (GW)	6750 (first forecasting)	4993	20402	1064	3008

TABLE 4. Forecasted installed capacity of major power sources in china 2060.

	Coefficient	Investment Cost of Onshore Wind Power (USD/kW)	Comprehensive LCOE (USD/kWh)	Onshore Wind Power Installed Capacity (GW)	Power Storage Installed Capacity (GW)
First Forecasting	a= -0.2753 c= -9.117	688	0.033	6750	3008
Second Forecasting	a= -0.3028 c= -10.029	540	0.032	7114	2826
Third Forecasting	a= -0.3304 c= -10.940	428	0.03	7269	2749

TABLE 5. 3D curve function of renewable energy power generations.

Technology	3D Curve Function
Onshore wind	$z=7000*x^{-0.2753}-\frac{320}{1+e^{-9.117(y-0.85)}}+320$
Offshore wind	$z=8000*x^{-0.0801}-\frac{268.3}{1+e^{-1797(y-0.6)}}+268.3$
PV	$z=20000*x^{-0.2732}-\frac{5195}{1+e^{-0.04335(y-0.4)}}+5195$
CSP	$z=10000*x^{-0.1451}-\frac{5711}{1+e^{-42.41(y-0.8)}}+5711$
Power Storage	$z=100*x^{-0.3667}-\frac{1816}{1+e^{-5.546(y-0.35)}}+1816$

APPENDIX

See Tables 1–5.

REFERENCES

[1] *Global Energy Transformation: A Roadmap to 2050*, IRENA, Abu Dhabi, United Arab Emirates, Apr. 2018.

[2] (Oct. 11, 2020). *CAT: Climate Tracker*. [Online]. Available: https://climateactiontracker.org/

[3] A. A. Muthahhari, L. M. Putranto, Sarjiya, Tumiran, F. S. Anugerah, A. Priyanto, S. Isnandar, and I. Savitri, ‘‘Environmental considerations in long-term generation expansion planning with emission limitations: An analysis of the sulawesi power system in Indonesia,’’ Presented at the FORTEI-Int. Conf. Electr. Eng. (FORTEI-ICEE), Bandung, Indonesia, Sep. 2020.

[4] J. Fan, X. Wang, Q. Huang, C. Zhu, and Z. Wang, ‘‘Medium and long-term power system development planning considering carbon dioxide mitigation,’’ Presented at the IEEE Int. Conf. Environ. Electr. Eng. IEEE Ind. Commercial Power Syst. Eur. (EEEIC/ICPS Europe), Weihai, China, Jun. 2019.

[5] M. D. P. B. Villada, C. E. G. Bujanda, E. S. Baeza, and A. M. Matus, ‘‘Optimal expansion and reliable renewable energy integration in long-term planning using FESOP,’’ Presented at the IEEE Kansas Power Energy Conf. (KPEC), Manhattan, KS, USA, Apr. 2022.

[6] S. Mukhopadhyay, P. Gupta, B. K. Arya, A. K. Rajput, V. Menghani, P. Batra, and S. Sharma, ‘‘Long term planning for Indian power sector with integration of renewable energy sources,’’ Presented at the IEEE 9th Power India Int. Conf. (PIICON), Sonepat, India, Feb./Mar. 2020.

[7] M. Mehrzadi, C.-L. Su, Y. Terriche, and C. Juan Vasquez, ‘‘Operation planning of standalone maritime power systems using particle swarm optimization,’’ Presented at the 1st Int. Conf. Electr., Control Instrum. Eng. (ICECIE), Kuala Lumpur, Malaysia, Nov. 2019.

[8] J. Choi and K. Y. Lee, ‘‘Reliability evaluation for power system planning with wind generators and multi-energy storage systems,’’ in *Probabilistic Power System Expansion Planning With Renewable Energy Resources and Energy Storage Systems*. Hoboken, NJ, USA: Wiley, 2020, pp. 141–176.

[9] M. Yang, H. Liu, and L. Zhao, ‘‘Optimal configuration method of hybrid storage system tracking the wind power plan,’’ Presented at the IEEE 3rd Student Conf. Electr. Mach. Syst. (SCEMS), Jinan, China, Dec. 2020.

[10] S. Yin and J. Wang, ‘‘Generation and transmission expansion planning towards a 100% renewable future,’’ *IEEE Trans. Power Syst.*, vol. 37, no. 4, pp. 3274–3285, Jul. 2022.

[11] W. Shen, J. Qiu, K. Meng, X. Chen, and Z. Y. Dong, ‘‘Low-carbon electricity network transition considering retirement of aging coal generators,’’ *IEEE Trans. Power Syst.*, vol. 35, no. 6, pp. 4193–4205, Nov. 2020.

[12] *The Power to Change: Solar and Wind Cost Reduction Potential to 2025*, Int. Renew. Energy Agency, Abu Dhabi, United Arab Emirates, Jun. 2016.

[13] W. Qia, L. Qiang, and L. Ping, "Effect on LCOE of Chinese wind power by installed capacity-based on learning curve empirical research," *Energy China*, vol. 51, no. 6, pp. 37–42, 2019.
[14] L. Pengyan and S. Shuo, "Analysis of COST of the photovoltaic industry in northwest China based on learning curve," *Energy Conservation Technol.*, vol. 35, no. 5, pp. 87–92, 2017.
[15] *Energy Technology Perspectives 2020*, Int. Energy Agency, Paris, France, Sep. 2020.
[16] *The National Energy Modeling System: An Overview 2018*, U.S. Energy Inf. Admin. (EIA), Washington, DC, USA, Apr. 2019.
[17] W. Ji, L. Yuxin, C. Libo, and T. Jiuting, "Using the technology readiness levels to support technology management in the special funds for marine renewable energy," Presented at the OCEANS, Shanghai, Shanghai, China, Apr. 2016.
[18] L. Zhigang, Y. Ting, J. Ting, and S. Yangzhou, "Maturity prediction and key fields analysis of ocean thermal energy conversion technology based on patent information," *China Offshore Oil Gas*, vol. 32, no. 6, pp. 185–190, 2020.
[19] D. Chen, D. Ding, X. Zhai, X. Zhou, H. Liu, and L. Wu, "Intelligent prediction of power grid project cost based on PSO-BP model," Presented at the 7th Int. Conf. Syst. Informat. (ICSAI), Chongqing, China, Nov. 2021.
[20] H. Wang, "Forecast and analysis of substation project investment based on multi-factor matching," Presented at the 5th Adv. Inf. Technol., Electron. Autom. Control Conf. (IAEAC), Chongqing, China, Mar. 2021.
[21] Y. Dai and Y. Zeng, "A self-similarity-based approach of learning curve for renewable technology," Presented at the 6th Asia Conf. Power Electr. Eng. (ACPEE), Chongqing, China, Apr. 2021.
[22] Y. Dai and Y. Zeng, "Inter-regional learning curve model of renewables in the context of technology spillover," Presented at the 3rd Asia Energy Electr. Eng. Symp. (AEEES), Chengdu, China, Mar. 2021.
[23] O. Fricko et al., "The marker quantification of the shared socioeconomic pathway 2: A middle-of-the-road scenario for the 21st century," *Global Environ. Change*, vol. 42, pp. 251–267, Jan. 2017.
[24] H. Jiang, E. Du, and C. Jin, "Optimal planning of multi-time scale energy storage capacity of cross-national interconnected power system with high proportion of clean energy," *Proc. CSEE*, vol. 12, no. 1, pp. 40–45, 2020.
[25] J. Xiao, J. Hou, E. Du, C. Jin, Y. Zhou, and C. Kang, "Quantitative analysis model and case study of energy storage requirement supporting clean transformation of electric energy system," *Automat. Electr. Power Syst.*, vol. 45, no. 18, pp. 9–17, 2021.
[26] C. Jin, D. Ren, J. Xiao, J. Hou, E. Du, and Y. Zhou, "Optimization planning on power system supply-grid-storage flexibility resource for supporting the 'carbon neutrality' target of China," *Electr. Power*, vol. 54, no. 8, pp. 164–174, 2021.
[27] *The Road to Global Carbon Neutrality*, Global Energy Interconnection Develop. Cooperation Org., China Electr. Power Press, Beijing, China, Nov. 2021.
[28] *The Development and Outlook of Clean Energy Power Generation Technology*, Global Energy Interconnection Develop. Cooperation Org., China Electr. Power Press, Beijing, China, Nov. 2020.
[29] *The Development Roadmap of Large-Scale Energy Storage Technology*, Global Energy Interconnection Develop. Cooperation Org., China Electr. Power Press, Beijing, China, Nov. 2020.
[30] *The Development Roadmap of High Voltage Large Capacity DC Submarine Cable Technology*, Global Energy Interconnection Develop. Cooperation Org., China Electr. Power Press, Beijing, China, Nov. 2020.
[31] *Research and Outlook on Global Energy Interconnection*, Global Energy Interconnection Develop. Cooperation Org., China Electr. Power Press, Beijing, China, Nov. 2020.
[32] *Renewable Technology Innovation Indicators: Mapping Progress in Costs, Patents and Standards*, Int. Renew. Energy Agency, Abu Dhabi, United Arab Emirates, Mar. 2022.
[33] *Renewable Power Generation Costs in 2020*, Int. Renew. Energy Agency, Abu Dhabi, United Arab Emirates, Mar. 2021.
[34] *Future of Wind-Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects*, Int. Renew. Energy Agency, Abu Dhabi, United Arab Emirates, Oct. 2019.

WEI SUN was born in Shandong, China, in 1982. She received the Ph.D. degree from the China University of Mining and Technology, in 2010. Her research interests include wind turbine and wind farm modeling, power system analysis and DC grid operation and protection, and LCOE calculation for renewable energy.

JINYU XIAO (Associate Member, IEEE) received the Ph.D. degree in electrical engineering from Tsinghua University, in 2005. He is currently working at GEIDCO, Beijing. His research interests include electrical system planning and new clean energy technologies.

JINMING HOU received the bachelor's and master's degrees in electrical engineering from North China Electric Power University, in 2002 and 2006, respectively. His research interests include power systems and automation.

CHEN JIN received the M.Sc. degree in photovoltaic solar energy from the Instituto de Energía Solar (IES), Universidad Politécnicade Madrid, Spain, in 2014, and the Ph.D. degree in electronic engineering from the Universitat Politècnica de Catalunya, Barcelona, Spain, in 2018.

YUANHONG NIE received the master's degree in software engineering from the University of Science and Technology of China, in 2012. He is currently working at State Grid Anhui Electric Power Company Ltd., Economic Research Institute, Hefei, Anhui. His research interests include the application of digital technologies and image recognition.