

# Electricity network planning targeting Low-Carbon energy transition

Wei Shen<sup>1</sup>, Jing Qiu<sup>2</sup>, Zhaoyang Dong<sup>1</sup>

1. School of Electrical Engineering and Telecommunications, The University of New South Wales, Sydney, NSW 2052, Australia

2. School of Electrical and Information Engineering, The University of Sydney, Sydney, NSW2006, Australia



Scan for more details

**Abstract:** Electricity sector, as one of the major emission sources of carbon dioxide (CO<sub>2</sub>), is responsible for reducing carbon emissions and is a major player that addresses global climate change. In the efforts to mitigate the impacts of climate change over the coming decades, decarbonizing power systems is critical. To achieve this goal, power generation systems need a transition from a high reliance on coal-fired power stations to a low-carbon energy mix. This paper proposes a transition planning method that includes the retirement of coal-fired generators and the integration of large-scale renewable power plants. Hence, transmission systems need to be upgraded simultaneously with the changing of generation mix to ensure system reliability. This paper also considers carbon emission cost and introduces and compares two models, which include carbon trading and carbon tax. Furthermore, issues related to the ramping of renewable power systems that are caused by the large penetration of renewable power generators are taken into account by adding the cost related to the sudden change of renewable generation (ramping cost) in the objective function. The proposed model is demonstrated on a modified IEEE 24-bus RTS system.

**Keywords:** Carbon tax, Emissions trading, Renewable power systems, Ramping cost, Power plant retirement, Expansion planning.

## 1 Introduction

Greenhouse gas (GHG) emissions are the main cause of climate change, threatening human health and economic development. In 2015, the Paris Agreement was adopted to

combat climate change by controlling the increase of global average temperature to well below 2 °C and pursuing efforts to limit it to 1.5 °C [1]. This climate constraint implies that the total CO<sub>2</sub> emission is finite [2]. To reach these goals, CO<sub>2</sub> emission should be controlled under 1,100 gigatons; moreover, approximately 85%, 50%, and 34% of global coal, natural gas, and oil reserves should remain unburnable before 2050 [3].

The Australian Government ratified the Paris Agreement in 2016 and committed to achieving a 26–28% GHG emissions reduction below 2005 levels by 2030 [4]. In Australia, electricity generation represents the largest share

Received: 3 August 2018/ Accepted: 27 August 2018/ Published: 25 October 2018

✉ Wei Shen  
[wei.shen@student.unsw.edu.au](mailto:wei.shen@student.unsw.edu.au)

Zhaoyang Dong  
[zydong@ieee.org](mailto:zydong@ieee.org)

Jing Qiu  
[Qiujing0322@gmail.com](mailto:Qiujing0322@gmail.com)

of GHG emissions that is nearly 35%, and 77% of GHG emissions are caused by CO<sub>2</sub> [5], [6]. Electricity sector, as an energy industry, is responsible for reducing carbon emissions. Carbon emission reduction in electricity systems will play an important role in achieving the goals of the Paris Agreement [1]. Therefore, planning and achieving reliable, green, sustainable, and low-carbon power systems become crucial.

In 1997, the *Kyoto Protocol* committed the participating countries to adopt three emission reduction mechanisms: emissions trading, joint implementation, and clean development mechanisms; of these, emissions trading is widely adopted [7].

Carbon emissions trading is also known as “cap and trade” and power generation companies are major players in the emissions trading market. Since the establishment of the first carbon emissions trading market by the European Union [8], 21 systems, at different levels of governments, are operating emissions trading systems as of early 2018 [9]. With the development of the cap-and-trade system, the operating cost of the power systems has reduced considerably. To be more specific, the participating generation companies (GENCOs) could buy or sell their emission allowances to optimize their profit and reduce carbon emission correspondingly based on this market mechanism.

Many studies have been performed on the influence of carbon trading on the electricity system planning problems. In [10], a two-stage short-term planning model was proposed to analyze the impacts of the emissions trading mechanism on a GENCO’s operation decisions. The decisions with regard to the electricity market and the fuel market are made in the first stage and those with regard to the carbon market including the trading of emission allowances and emissions constraints are considered in the second stage. An integrated power generation expansion planning (GEP) model was designed to achieve a low-carbon economy in [6] in which the emissions trading cost is considered in the objective function. In [11], a comprehensive GEP model was proposed considering the impact of different policies including feed-in tariffs, emission trade, and carbon tax. In [7], two carbon emissions trading models in the transmission expansion planning (TEP) problem based on a linear dc optimal power flow were considered. The uncertainties of the CO<sub>2</sub> emission price are modeled as a probability density function and the probabilistic approach is applied using Monte Carlo simulation in that model.

In addition to establishing a carbon emissions trading market, generation transition is another essential step to reduce carbon emission. During the generation transition, a

power generation system will change from a high reliance on coal-fired power stations to a low-carbon energy mix. This future transition includes two major parts: 1) retirement of coal-fired generators and 2) installation of new renewable power systems. As many as three-quarters of Australia’s coal-fired power stations are estimated operating beyond their original design life [12]. Therefore, the potential closure of coal-fired stations needs appropriate planning to achieve economic benefits while maintaining system safety and reliability. Moreover, the retirement of existing generators without proper installation of new units could cause an imbalance of power supply and demand. Hence, the retirement and installation decisions require adequate and simultaneous planning. In [13], a stochastic generation expansion and retirement planning model was proposed to minimize the investment cost of new units, operating costs, retirement salvage cost, and the system risk cost. However, this GEP and retirement planning model does not consider the installation of renewable power generators as well as the TEP. A two-stage renewable power generation and TEP model was proposed to achieve renewable power generation targets and maintain system reliability in [14]. However, generation retirements are not involved in that study.

To solve the above issues, this work compares two carbon emission models in the power system transition planning problem from the central planner’s viewpoint, including GEP, TEP, and retirement planning. The framework of this novel model is shown in Fig. 1. The white modules represent normal components of power system planning, while the yellow modules are updated components. This model finds the best planning decisions of renewable power plant sitings, capacities, new transmission lines’ locations, and the best-retired generators to satisfy system safety and reliability requirements with minimum total cost. Apart from the power flow variables, retirement decision variables and carbon emission variables are added in this planning model. The objective function of this model is to minimize the total cost, including not only traditional investment and operating costs, but also the retirement cost, carbon emission cost, and renewable power generation ramping cost. This renewable power generation ramping cost is caused by the sudden increase and decrease in the output of renewable power plants due to the sudden change in weather conditions. Except for traditional power system planning constraints such as power balance constraint, generator capacity constraint, and network constraint, this study introduced power generation ramping constraints and emissions trading constraints. The contributions of this paper are as follows:

- (1) Combining power plant retirement planning with

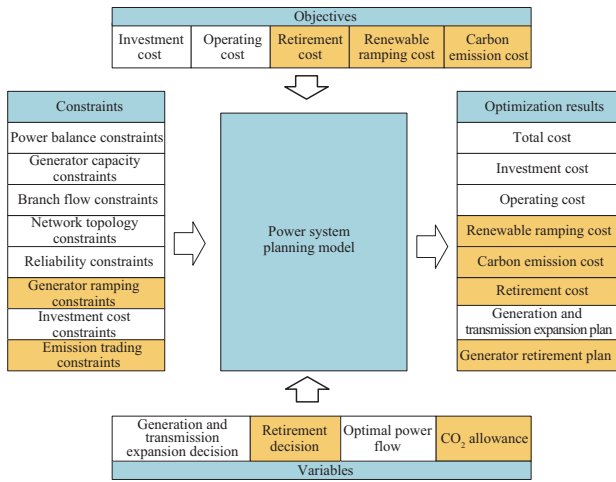
G&TEP in a single planning model.

(2) Comparing two carbon emission models with regard to the planning problem.

(3) Proposing a novel ramping cost formulation to capture the intermittency impact of large-scale renewable power plants on system operations.

(4) Comparing the impacts of carbon trading and carbon tax prices in long-term planning.

The remaining paper is organized as follows. In Section 2, two carbon emission models are presented. The proposed planning model is discussed in Section 3. Section 4 presents the optimization algorithm, followed by a case study tested on the IEEE RTS 24-bus system for both mid-term planning and long-term planning. Section 5 concludes our paper.



**Fig. 1 Framework of low-carbon power system transition planning model**

## 2 Carbon emission model

The matter that operating costs of power system changed considerably the carbon emission cost was taken into consideration. This study compares two carbon emission models, namely the cap-and-trade model and the carbon tax model.

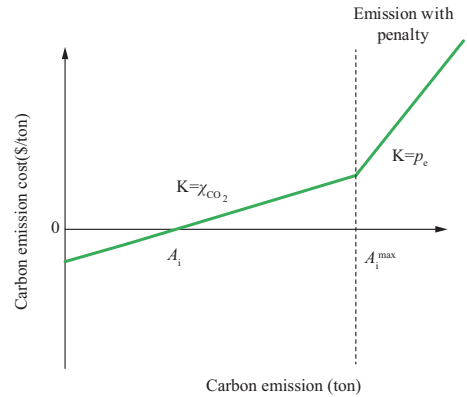
### 2.1 Cap-and-trade model

In the cap-and-trade model, a GENCO could sell remaining allowance or buy additional allowance in the carbon trading market. GENCOs can make profits by selling their allowance, thereby decreasing their operating cost. (1) and (2) are used to calculate the emission cost of generator  $i$ .

$$C_{em,i} = \begin{cases} 0 & E_i = A_i \\ (E_i - A_i) \cdot \chi_{CO_2} & |E_i - A_i| \leq A_i^{\max} \\ A_i^{\max} \cdot \pi_{CO_2} + (E_i - A_i^{\max}) \cdot p_{CO_2} & |E_i - A_i| > A_i^{\max} \end{cases} \quad i \in \Omega_C \quad (1)$$

$$\begin{cases} E_i = \sum_{t=1}^T \zeta_i \cdot P_{i,t}^C \\ A_i = \delta \cdot \sum_{t=1}^T P_{i,t}^{his} \\ Cap = \sum A_i \end{cases} \quad i \in \Omega_C \quad (2)$$

Here,  $C_{em,i}$  refers to the emission cost of conventional generator  $i$ ;  $E_i$ ,  $A_i$ , and  $A_i^{\max}$  are the annual emission, emission allowance, and maximum trading allowance conventional generator  $i$ .  $\chi_{CO_2}$  and  $p_{CO_2}$  denote the trading price in the carbon market and the emission penalty price.  $\Omega_C$  is the set of conventional generators. As shown in Fig. 2, if annual emission equals the allowance, there is no emissions trading, and hence the carbon emission cost equals zero. Once annual emission exceeds the maximum trading allowance, the additional emission should be charged as penalty. For those generators with low emission values, the carbon emission costs are negative, indicating that they could earn money by selling allowance. The slopes in the left and right parts of Fig. 2 represent trading price and penalty price, respectively. The annual emission and allowance are calculated using (2), where  $\zeta_i$  denotes the carbon emission intensity of generator  $i$ ;  $\delta$  is the allocation factor;  $P_{i,t}^C$  and  $P_{i,t}^{his}$  refer to the power output of conventional generator  $i$  at time  $t$  and the historical power output;  $T$  is the total time period, which was set as 8760 hours in this study.  $Cap$  is the emission cap.



**Fig. 2 Emission cost of cap-and-trade model**

### 2.2 Carbon tax model

Another approach to decarbonize a power system is to apply carbon tax for GENCOs. In this model, coal-fired power output should be penalized, as shown in Fig. 3 and (3). Similar to Fig. 2, the slope denotes the carbon tax price  $p_{tax}$ .

$$C_{em,i} = E_i \cdot p_{tax} \quad i \in \Omega_C \quad (3)$$

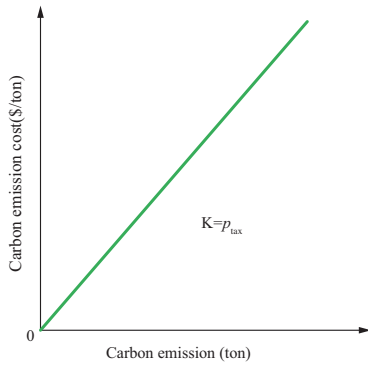


Fig. 3 Emission cost of carbon tax model

### 3 Formulations of transition planning model

#### 3.1 Wind modeling

Large-scale wind farms are potential generation expansion candidates, as wind power generation technology is mature and becoming cheap. Several studies have shown that wind speed follows a Weibull probability distribution [15], [16], [17]. This paper also uses the Weibull distribution to model wind speed. The wind speed distribution function  $f_w(v)$  is shown in (4), where  $m$  and  $n$  are the shape factor and scale factor;  $v$  is the wind speed. Once the wind speed at time  $t$  is determined as  $v_t$ , the wind power output  $P_t^W$  can be calculated using (5), where  $v_{in}$ ,  $v_{rate}$ , and  $v_{out}$  denote the cut-in, rated, and cut-out speeds of wind turbines;  $P_{rate}$  is the rated power of the wind farm.

$$f_w(v) = m/n \cdot (v/n)^{m-1} \exp(-(v/n)^m) \quad (4)$$

$$P_t^W(v_t) = \begin{cases} 0 & 0 \leq v_t < v_{in}, v_t > v_{out} \\ P_{rate} (v_t - v_{in}/v_{rate} - v_{in}) & v_{in} \leq v_t < v_{rate} \\ P_{rate} & v_{rate} \leq v_t < v_{out} \end{cases} \quad (5)$$

$$C_{RR} = \begin{cases} \sum_{t=2}^T \sum_{i \in \Omega_R} (|P_{i,t}^R - P_{i,t-1}^R|)^2 \cdot a_i^R & 0 \leq \sum_{i \in \Omega_R} (P_{i,t}^R - P_{i,t-1}^R) \leq \sum_{i \in \Omega_G} P_{i,t-1}^{G,down}, -\sum_{i \in \Omega_G} P_{i,t-1}^{G,up} \leq \sum_{i \in \Omega_R} (P_{i,t}^R - P_{i,t-1}^R) < 0 \\ \sum_{t=2}^T \sum_{i \in \Omega_G} P_{i,t-1}^{RA,max} \cdot a_i^R + \sum_{t=2}^T \left( \sum_{i \in \Omega_R} (|P_{i,t}^R - P_{i,t-1}^R|) - \sum_{i \in \Omega_G} P_{i,t-1}^{RA,max} \right) \cdot p_{en} & \sum_{i \in \Omega_W} (P_{i,t}^R - P_{i,t-1}^R) > \sum_{i \in \Omega_G} P_{i,t-1}^{G,down}, \sum_{i \in \Omega_R} (P_{i,t}^R - P_{i,t-1}^R) < -\sum_{i \in \Omega_G} P_{i,t-1}^{G,up} \\ 0 & t = 1 \end{cases} \quad (6)$$

#### 3.2 Ramping cost of renewable power generation

Renewable energy, from sources such as wind and solar, is highly dependent on the weather conditions. In other words, the output of renewable energy-based systems fluctuates and is intermittent. Large penetration of variable renewable power systems will give rise to ramping issues. Owing to the sudden change in weather conditions, renewable power output could change dramatically in a

short time, and generation rescheduling is required under such situations. Therefore, renewable power generation involves generation reschedule cost due to this ramping issue. However, power is rescheduled usually by using conventional generators, which have ramping rate limits. Once the ramping of renewable power output exceeds the maximum ramping limits of conventional generators, the power system is at the risk of power supply not matching power demand.

Conventionally, the cost coefficients for renewable power generators are quite low, and even zero as no fuel is used to generate electricity. However, with more large-scale renewable power systems, this renewable power generation ramping cost should be considered. Renewable power generators should be included while determining the ramping and rescheduling costs. The detailed formulation of  $C_{RR}$  is shown in (6), and only wind farms are considered as renewable power generators in the mid-term planning study. Here,  $a_i^R$  is the cost coefficient of the renewable power generator at bus  $i$ ;  $\Omega_R$  is the set of renewable power generators. For the case where renewable power generation ramping is equal to or lower than conventional generators' total ramping limits,  $C_{RR}$  is modeled as a quadratic function.  $P_{en}$  is a penalty coefficient. Once the renewable power generation ramping exceeds conventional generators' total ramping limits, the excess power should be charged as ramping penalty cost.

The maximum renewable ramping capacity at bus  $i$  at time  $t-1$   $P_{i,t-1}^{RA,max}$  is shown in (7), where  $P_{i,t-1}^{G,up}$  and  $P_{i,t-1}^{G,down}$  are generators' maximum ramping up and down limit for the power system at bus  $i$ , time  $t-1$ , excluding renewable power generators. When the output of renewable power systems increases from  $t-1$  to  $t$ , it means that conventional generation

ramping is down during this period, or vice versa.  $P_{i,t-1}^R$  and  $P_{i,t}^R$  are the renewable power outputs at time  $t$  and  $t-1$ .

$$P_{i,t-1}^{RA,max} = \begin{cases} P_{i,t-1}^{G,down} & P_{i,t}^R - P_{i,t-1}^R > 0 \\ P_{i,t-1}^{G,up} & P_{i,t}^R - P_{i,t-1}^R \leq 0 \end{cases} \quad (7)$$

#### 3.3 Uncertainties modeling

Many uncertainties need to be considered while addressing the power system planning problem, such

as power demand, system component availability, etc. Two major methods are adopted to solve the uncertainty problems: the robust model and the stochastic model. This work addresses the uncertainty problems using the stochastic model in which scenarios are generated using Monte Carlo (MC) simulation based on the probability density function. Load forecast errors are modeled by the Gaussian distribution. Wind speed and system component forced outage rate (FOR) are modeled by the Weibull and binomial distributions, respectively [18]. To be more specific, a scenario could be, “load increased level = 1.1 times existing load level, wind speed = 12 m/s, system status = conventional generator at bus 16 outage.” The accuracy of the simulation results can be improved by increasing the MC sampling numbers.

### 3.4 Detailed planning model

Power system transition planning including renewable expansion, transmission expansion, and retirement planning is presented in detail below. The objective function is to minimize the total cost  $C_{\text{total}}$  as shown in (8), including the annualized investment cost  $C_{\text{inv}}$ , annual operating cost  $C_{\text{ope}}$ , annual carbon emission cost  $C_e$ , annualized retirement cost  $C_{\text{re}}$ , and annual renewable ramping cost  $C_{\text{RR}}$ .

#### • Objectives

$$\min C_{\text{total}} = C_{\text{inv}} + C_{\text{ope}} + C_e + C_{\text{re}} + C_{\text{RR}} \quad (8)$$

$$C_{\text{inv}} = \sum_{(i,j) \in \Omega_L} C_{ij}^{\text{TL}} \lambda_{ij}^{\text{TL}} + \sum_{i \in \Omega_R} C_i^{\text{R}} \lambda_i^{\text{R}} \quad (9)$$

$$C_{ij}^{\text{TL}} = LC \cdot L_{ij} \quad (i, j) \in \Omega_L \quad (10)$$

$$C_{\text{ope}} = \sum_{t=1}^T \sum_{i \in \Omega_G} \left( a_i (P_{i,t}^{\text{G}})^2 + b_i P_{i,t}^{\text{G}} + c_i \right) \cdot (1 - \lambda_i^{\text{retire}}) \quad (11)$$

$$C_e = \sum_{i \in \Omega_C} C_{\text{em},i} \cdot (1 - \lambda_i^{\text{retire}}) \quad (12)$$

$$C_{\text{re}} = \sum_{i \in \Omega_C} P_i^{\text{C,max}} \left( u_i - s_i - A_i \cdot \chi_{\text{CO}_2} \right) \cdot \lambda_i^{\text{retire}} \quad (13)$$

$$C_{\text{RR}} = \begin{cases} \sum_{t=2}^T \sum_{i \in \Omega_R} \left( P_{i,t}^{\text{R}} - P_{i,t-1}^{\text{R}} \right)^2 \cdot a_i^{\text{R}} & 0 \leq \sum_{i \in \Omega_R} (P_{i,t}^{\text{R}} - P_{i,t-1}^{\text{R}}) \leq \sum_{i \in \Omega_G} P_{i,t-1}^{\text{G,down}} (1 - \lambda_i^{\text{retire}}) - \sum_{i \in \Omega_C} P_{i,t-1}^{\text{G,up}} (1 - \lambda_i^{\text{retire}}) < 0 \\ \sum_{t=2}^T \sum_{i \in \Omega_G} P_{i,t-1}^{\text{RA,max}} (1 - \lambda_i^{\text{retire}}) \cdot a_i^{\text{R}} + \sum_{t=2}^T \left( \sum_{i \in \Omega_R} |P_{i,t}^{\text{R}} - P_{i,t-1}^{\text{R}}| - \sum_{i \in \Omega_C} P_{i,t-1}^{\text{RA,max}} (1 - \lambda_i^{\text{retire}}) \right) \cdot p_{\text{cn}} & \sum_{i \in \Omega_R} (P_{i,t}^{\text{R}} - P_{i,t-1}^{\text{R}}) > \sum_{i \in \Omega_G} P_{i,t-1}^{\text{G,down}} (1 - \lambda_i^{\text{retire}}) + \sum_{i \in \Omega_C} (P_{i,t}^{\text{R}} - P_{i,t-1}^{\text{R}}) < - \sum_{i \in \Omega_G} P_{i,t-1}^{\text{G,up}} (1 - \lambda_i^{\text{retire}}) \\ 0 & t = 1 \end{cases} \quad (14)$$

$$P_{i,t-1}^{\text{RA,max}} = \begin{cases} P_{i,t-1}^{\text{G,down}} \cdot (1 - \lambda_i^{\text{retire}}) & P_{i,t}^{\text{R}} - P_{i,t-1}^{\text{R}} > 0 \\ P_{i,t-1}^{\text{G,up}} \cdot (1 - \lambda_i^{\text{retire}}) & P_{i,t}^{\text{R}} - P_{i,t-1}^{\text{R}} \leq 0 \end{cases} \quad t = 2, 3, \dots, T \quad (15)$$

Here, (9) denotes the investment cost that comprises the transmission line cost and the renewable power system installation cost, where  $C_{ij}^{\text{TL}}$  and  $C_i^{\text{R}}$  are the cost of a new line between bus  $i, j$  and the cost of the renewable power

generator at bus  $i$ ;  $\lambda_{ij}^{\text{TL}}$  and  $\lambda_i^{\text{R}}$  are the decision variables of new lines and renewable power generators, respectively. In (10),  $C_{ij}^{\text{TL}}$  is proportional to the length of the line  $L_{ij}$  and  $LC$  is the per-kilometer cost of the transmission line [18];  $\Omega_L$  represents the set of candidate transmission lines. (11)–(15) show the operating cost, emission cost, and renewable ramping cost with the coal-fired plant retirement decision, where  $a_i$ ,  $b_i$ , and  $c_i$  are the cost coefficients of generator  $i$ ;  $P_{i,t}^{\text{C}}$  denotes the power output of generator  $i$  at time  $t$ ;  $\lambda_i^{\text{retire}}$  refers to the decision variable of the retirement unit at bus  $i$ ;  $P_i^{\text{G,max}}$  is the maximum capacity of the coal-fired generator  $i$ ;  $u_i$  and  $s_i$  are the uninstalation fee and the salvage fee of power plant  $i$ , where the salvage fee could come from selling retired devices and the land of power plant; the retirement cost could be negative when the salvage fee of the coal-fired generator is higher than the uninstalation fee. For the case with carbon trading, the retired units could also make profits by selling their allowances to the carbon market. (14) and (15) are upgraded equations of (6) and (7) with the retirement decisions of coal generators added.  $\lambda_i^{\text{retire}} = 1$  means the generator at bus  $i$  retired, whereas  $\lambda_i^{\text{retire}} = 0$  means the generator still operating.

#### • Constraints

The objective function (8) is subject to the following constraints.

$$\begin{cases} P_{i,t}^{\text{G}} + P_{i,t}^{\text{R}} - (P_{i,t}^{\text{D}} - P_{i,t}^{\text{D,curt}}) = V_{i,t} \sum_{j=1}^N V_{j,t} (G_{ij} \cos \theta_{ij,t} + B_{ij} \sin \theta_{ij,t}) & i \in \Omega_N \\ Q_{i,t}^{\text{G}} - Q_{i,t}^{\text{D}} = V_{i,t} \sum_{j=1}^N V_{j,t} (G_{ij} \sin \theta_{ij,t} - B_{ij} \cos \theta_{ij,t}) & i \in \Omega_N \end{cases} \quad (16)$$

$$\begin{cases} 0 \leq P_{i,t}^{\text{G}} \leq P_i^{\text{G,max}} (1 - \lambda_i^{\text{retire}}) & i \in \Omega_G \\ 0 \leq Q_{i,t}^{\text{G}} \leq Q_i^{\text{G,max}} (1 - \lambda_i^{\text{retire}}) & i \in \Omega_G \end{cases} \quad (17)$$

$$0 \leq P_{i,t}^{\text{R}} \leq P_i^{\text{R,max}} \lambda_i^{\text{R}} \quad i \in \Omega_R \quad (18)$$

$$-S_{ij}^{\text{max}} \leq S_{ij,t} \leq S_{ij}^{\text{max}} \quad (i, j) \in \Omega_L \quad (19)$$

$$V_i^{\text{min}} \leq V_{i,t} \leq V_i^{\text{max}} \quad i \in \Omega_N \quad (20)$$

$$\begin{cases} P_{i,t}^{\text{G}} - P_{i,t-1}^{\text{G}} \leq P_i^{\text{G,up}} (1 - \lambda_i^{\text{retire}}) & (i, j) \in \Omega_G \\ P_{i,t}^{\text{G}} - P_{i,t-1}^{\text{G}} \geq -P_i^{\text{G,down}} (1 - \lambda_i^{\text{retire}}) & (i, j) \in \Omega_G \end{cases} \quad (21)$$

$$\begin{cases} Y_{ii} = y_i + \sum_{(i,j) \in \Omega_N} (y_{ij}^0 + \lambda_{ij}^{\text{TL}} \gamma_{ij}) & i \neq j \\ Y_{ij} = -(y_{ij}^0 + \lambda_{ij}^{\text{TL}} \gamma_{ij}) & i \neq j; (i, j) \in \Omega_N \end{cases} \quad (22)$$

$$EENS = \sum_{i \in \Omega_D} P_{i,t}^{D,curt} \quad (23)$$

$$EENS \leq EENS_{max} \quad (24)$$

$$0 \leq C_{inv} \leq C_{inv}^{max} \quad (25)$$

Here, (16) is the power balance constraint, where  $P_{i,t}^R$ ,  $P_{i,t}^D$ , and  $P_{i,t}^{D,curt}$  are the renewable power generator's active power output, active power demand, and curtailed power at time  $t$ ;  $V_{i,t}$  and  $V_{j,t}$  are the bus voltages at node  $i$  and  $j$ ;  $G_{ij}$ ,  $B_{ij}$ , and  $\theta_{ij,t}$  denote the conductance, susceptance, and voltage angle between branch  $i, j$ ;  $Q_{i,t}^G$  and  $Q_{i,t}^D$  refer to the reactive power output and reactive demand;  $\Omega_N$  is the set of nodes. The generator power output constraints are shown in (17) and (18).  $Q_i^{G,max}$  and  $P_i^{R,max}$  are the maximum reactive power output and the maximum renewable power output;  $\Omega_G$  is the set of all existing generators. The reactive power of renewable power generators is not considered in this paper. (19) and (20) represent the branch flow constraint and the nodal voltage constraint;  $S_{ij,t}$  and  $S_{ij}^{max}$  denote the power flow and maximum rating of branch  $ij$ ;  $V_i^{max}$  and  $V_i^{min}$  are the maximum and minimum voltages at bus  $i$ . The ramping constraint of generators is presented in (21), where  $P_i^{G,up}$  and  $P_i^{G,down}$  are the ramp-up and ramp-down limits of generator  $G$  at bus  $i$ . Once a coal-fired generator retired, there is no power output and the ramping up and down limits are zero. (22) shows the power network topology constraint.  $Y_{ij}$  and  $y_i$  denote the new and old self-admittance matrix elements;  $Y_{ij}$  and  $y_{ij}^0$  are the new and old mutual admittance elements.  $\gamma_{ij}$  is the new circuit admittance. (23) and (24) show the reliability constraint [19].  $\Omega_D$  is the set of load nodes; except energy not served ( $EENS$ ) is limited by the maximum  $EENS$  ( $EENS_{max}$ ), which is set as 0.3% of the total demand in this work, according to [20]. The investment constraint is the last constraint as presented in (25).  $C_{inv}$  and  $C_{inv}^{max}$  are the annual investment cost and the maximum annual investment budget for future planning.

## 4 Solution algorithm

The proposed transition planning model considering carbon emission cost is regarded as a mixed integer nonlinear nonconvex optimization problem, and it is difficult to analyze using conventional mathematical methods. Therefore, in this work, we applied a modified differential evolution (DE) algorithm with fitness sharing to handle the optimization problem; more details about this modified DE algorithm can be found in [21]. The fitness sharing strategy of this algorithm can improve search capability while maintaining search diversity. Fig. 4 shows the detail of the transition planning using the modified DE algorithm.

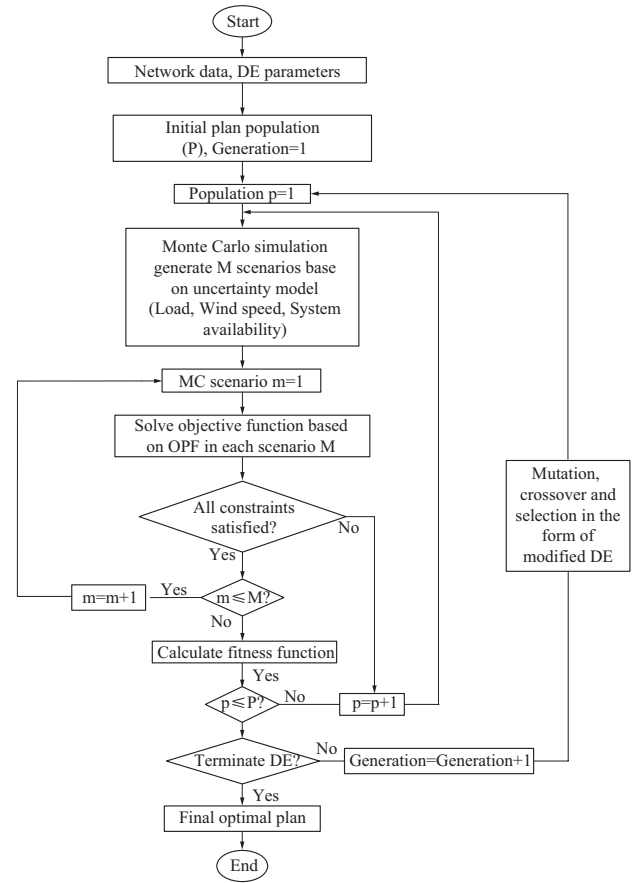


Fig. 4 Flow chart of proposed planning problem with improved differential evolution (DE) algorithm

## 5 Case studies

### 5.1 Experiment setting

The proposed transition planning model was tested on a modified IEEE 24-bus reliability test system (RTS) [22]. The power system is assumed to transit to a low-carbon system in the future when the network would need expansion, and expansion and retirement of the generation system would need to be carried out. The case studies are divided into two parts: mid-term planning and long-term planning. In the mid-term planning case, it is a single stage planning problem, and the model provides the planning results for the year 2025. In the long-term planning case, it becomes a multiyear planning problem, and the model provides the results from 2025 to 2050, at intervals of 5 years. The system includes 24 buses, 32 units, and 38 branches. In Fig. 5, generators shown in yellow color in buses 1, 2, 15, 16, and 23 are coal-fired generator units; blue and green generators represent hydro and nuclear units, respectively. The FORs for the transmission lines are set as 0.01, and for generator units as 0.02. The cut-in, cut-out, and rated wind speeds of wind turbines are

set as 5, 25, and 15 m/s. Potential locations of renewable energy farms are assumed to be at buses 17, 21, 22, and 23. Renewable ramping cost coefficient  $a_i^R$  and  $P_{en}$  are 0.5 and 5, respectively. Only wind farms are considered in mid-term planning, and both wind and solar farms are considered in long-term planning. The carbon trading price and carbon tax are \$15/t and \$25.53/t in mid-term planning. The candidate powerline rating is 500 MVA and the line cost is assumed to be 50 M\$/100 km [20]. The carbon allocation factor is set as 0.65 t/MWh. The carbon emission intensities  $\zeta_i$  and other generator parameters are shown in Table 1. Note that this paper only considers the carbon emission from the generation side, and emissions from the transmission and demand side are ignored. The peak load is 2350 MW with 1% annual load growth rate, and total generation is 3450 MW. The simulation was performed on a PC with an Intel Core i7-6700 CPU @ 3.40 GHz with 16.0 GB RAM.

**Table 1** Generator parameters of IEEE 24-bus RTS system

Bus	Capacity (MW)	Type	$\zeta_i$ (t/MWh)
1;2	152;152	Coal	1.005
15;16;23	155;155;310	Coal	0.950
23	350	Coal	0.846
22	300	Hydro	0
18;21	400;400	Nuclear	0
1;2;7;13;15	40;40;300;591;60	Gas	0.37

## 5.2 Mid-term planning

Mid-term planning is performed for a single year, which is 2025, in this work. Case 1 and Case 2 are compared in Table 2 without considering coal-fired generators' retirements.

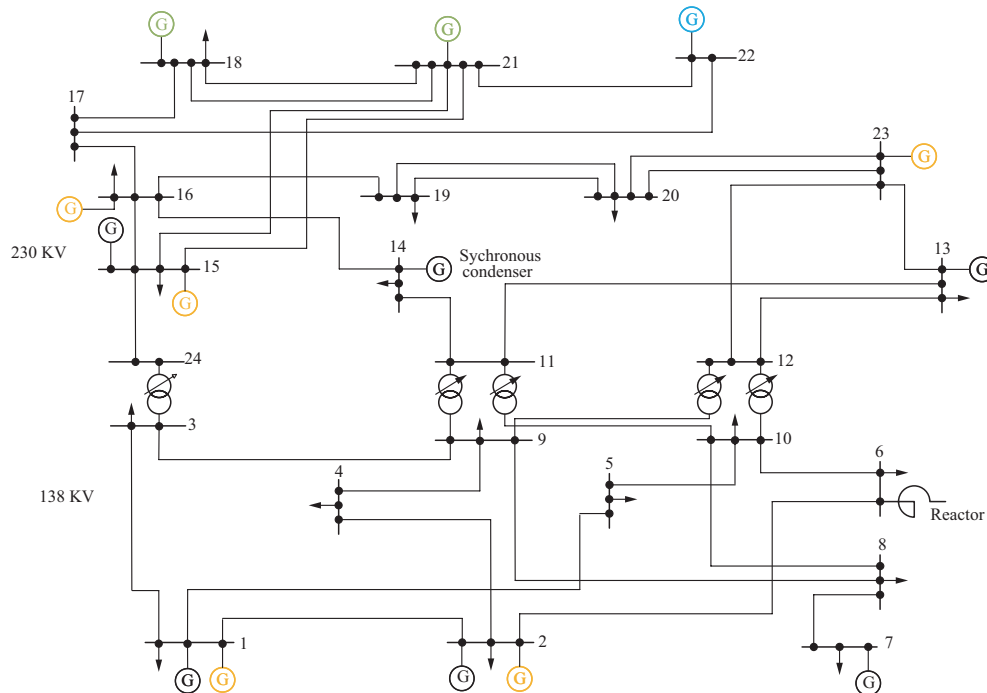
Case 1: Transition planning model with carbon trading.

Case 2: Transition planning model with carbon tax.

**Table 2** Results comparison for case 1 and 2

	Case 1	Case 2
Transmission line	Bus 18–21	Bus 20–23
Wind farms	Bus 21; 200 MW	Bus 21; 200 MW
Total cost (M\$)	1076.41	1204.75
New line cost (M\$)	41.20	40.0
Wind power investment (M\$)	11.81	11.81
Operation cost (M\$)	860.94	882.32
Carbon cost (M\$)	123.75	231.81
Renewable ramping cost (M\$)	38.81	38.81
EENS (%)	0.11	0.20
Carbon emission (Mt)	8.20	9.08

As shown in Table 2, in both cases one transmission coordinator is installed. The case considering carbon trading has lower total cost and operating cost. Renewable power ramping costs are almost at the same level, as in both of the cases 200 MW wind farms are installed at bus 21. In case 1, the new line connects bus 18 and 21 that could better



**Fig. 5** Modified IEEE 24-bus RTS

transmit power from the new wind farm to other buses. Case 1 has a lower carbon emission value, as GENCOs need to satisfy carbon allowance. The total carbon emission in base year (2018) is 9.54 tons. In conclusion, both carbon trading and carbon tax could decrease carbon emission, but carbon trading decreases more. Moreover, the total cost for the carbon trading case is lower as carbon trading has a lower emission cost.

Table 3 provides a comparison of Case 3 and Case 4, considering coal-fired units' retirement decisions.

Case 3: Transition planning model with carbon trading and unit retirement.

Case 4: Transition planning model with carbon tax and unit retirement.

**Table 3 Results comparison for case 3 and 4**

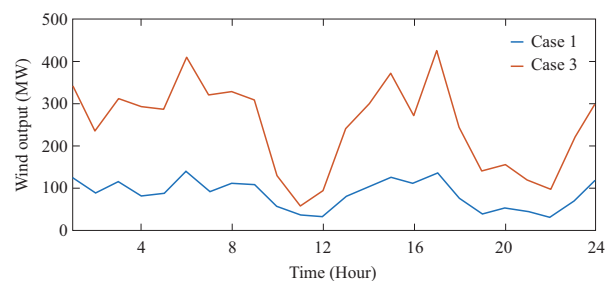
	Case 3	Case 4
Transmission line	Bus 13–23 Bus 18–21 Bus 12–23	Bus 20–23 Bus 13–23 Bus 14–16 Bus 18–21
Wind farms	Bus 21; 600 MW	Bus 23; 500 MW
Retired generators	Bus 1 (152 MW) Bus 2 (152 MW)	Bus 1 (152 MW) Bus 2 (152 MW)
Total cost (M\$)	1061.77	1177.20
New line cost (M\$)	121.80	140.90
Wind power investment (M\$)	35.45	29.54
Operation cost (M\$)	691.39	699.84
Carbon cost (M\$)	121.80	210.29
Renewable ramping cost (M\$)	116.43	97.03
Retirement cost (M\$)	-25.1	-0.4
EENS (%)	0.27	0.20
Carbon emission (Mt)	8.12	8.24

Similar to the previous two cases, results for case 3 and case 4 are compared to show the impact of carbon trading and carbon tax on the power system. In case 3, three new lines are planned to be built, whereas in case 4, four new lines are required. Case 3 has lower total and system operation costs compared to case 4. In both cases, two generators are retired, at bus 1 and bus 2. After the retirement of conventional generators, more wind power plants are integrated into the system; 600 MW and 500 MW wind farms are planned to be built for case 3 and case 4, respectively. The carbon emission levels are almost the same for both cases, whereas carbon trading spends less money on emission. The retirement costs are -25.1 M\$ and

-0.4 M\$ for cases 3 and 4, indicating that the retirement of coal-fired units could benefit from the salvage cost, and for the carbon trading case, the retirement decision also benefits from selling the allowance to the carbon market. Overall, carbon trading is more competitive compared to carbon tax.

After comparing Table 2 and Table 3, we found that after the retirement of coal-fired units, more transmission lines are needed, as the system becomes less reliable. Although the investment costs in cases 3 and 4 are higher than in cases 1 and 2, the total costs of generation retirement cases are lower, because they have lower operating costs. Because the emission cap is the same, generation retirement has little impact on carbon emissions in the emissions trading cases. The renewable power ramping cost increases dramatically for cases 3 and 4, not only because of the larger capacity of wind farms, but also the retirement of conventional units which decreases the system ramping limits that could cause potential ramping issues. With the retirement of coal-fired units, the carbon emissions decrease considerably at the same time. Those retired energies are compensated by the wind farms and the retirement of coal-fired units brings more wind energy into the power system, causing more renewable ramping cost. However, retirement could accelerate the transition to a low-carbon, renewable energy-oriented power system.

Fig. 6 compares the daily average wind power output between case 1 and case 3. As shown in Fig. 6, the average daily wind power output for case 3 is higher than that for case 1, as the wind farm expansion plan for case 3 is 600 MW, whereas for case 1 it is only 200 MW. It is clear that the output fluctuations in case 3 are larger than in case 1, especially between 17 pm to 19 pm. Hence, the renewable ramping cost for case 3 is far higher than for case 1, owing to the larger fluctuation value.



**Fig. 6 Daily average wind power output**

Fig. 7 shows the selected 24-h power outputs of different generation types in the four cases. After the retirement of power plants, the output of coal-fired power plants decreases, whereas wind power increases. As shown in Fig. 7, from 17 pm to 19 pm, wind power reduces considerably,



whereas power demand increases remarkably, reaching a peak level at 19 pm. The reduced wind power output is mostly compensated by the gas power, as the ramping rate is

relatively large. During that period, the slopes in cases 3 and 4 for gas power are larger, as more gas power is required to satisfy system reliability.

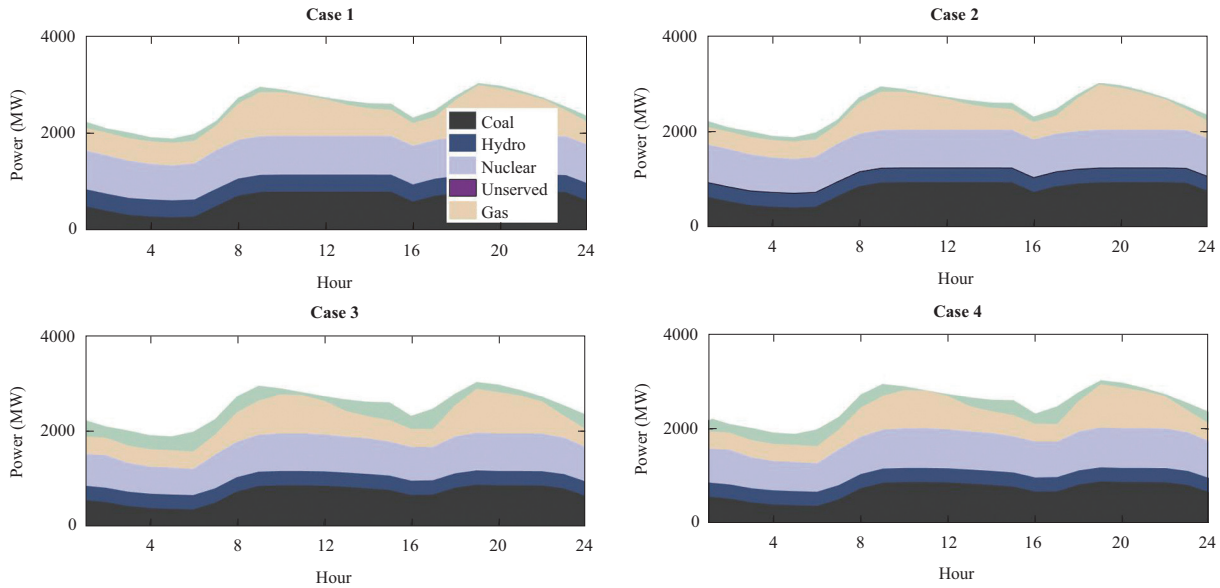


Fig. 7 Daily power output from different generator types for four cases

In Fig. 8, one coal-fired generator at bus 23 is chosen to compare the annual energy between different cases. For the case in 2018, the energy is the highest, whereas case 1 has the lowest energy. Although cases 1 and 3 have the same carbon allowance, annual energy only decreases slightly in case 3. Once this unit reaches its allowance, additional allowance is brought from the retired units. As for the carbon tax cases, annual energy in case 4 is lower. The reason is that case 4 has more wind power plants integrated, because of which wind power could not only compensate the power used to be generated by the retired units but also partly replace the power generated by coal-fired units, as there is no carbon emission cost for wind energy. Overall, both carbon trading and carbon tax could reduce the annual energy of this selected coal-fired unit and correspondingly reduce carbon emission.



Fig. 8 Annual generated energy for coal-fired generator at bus 23

The decision of retiring power plants could increase the integration of renewable power plants, correspondingly accelerating the low-carbon energy transition process.

### 5.3 Long-term planning

In long-term planning, the time span is expanded from 2025 to 2050, at 5-year intervals. The planning decisions including transmission investment, renewable power plants sitings, and coal-fired units' retirements are made every 5 years and power system topologies are updated correspondingly. Large-scale solar systems are assumed as expansion candidates from 2030 and the solar power generation model can be found in [23].

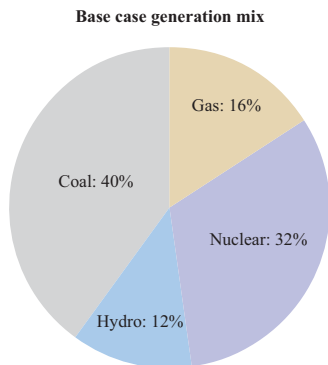
#### 5.3.1 Carbon trading

In long-term planning, the emission cap decreases every 5 years and the decreasing levels are shown in Table 4. The emission allowance for the next five years is calculated based on the generators' previous annual generation results and we assume the emission of 2018 as the base emission cap. The trading price is set as \$15 in 2025 and assumed to increase 2% every 5 years.

Table 4 Decreasing levels of emission caps in different years

Year	2025	2030	2035	2040	2045	2050
Cap	0.85	0.65	0.50	0.40	0.30	0.15

Fig. 9 shows the power generation mix in 2018 without any emission policies. Conventional coal-fired generation has the largest proportion, which is 40%, followed by nuclear and gas power plants, and hydro power plant has the lowest share of energy generation.



**Fig. 9 Power generation mix in 2018**

Fig. 10 and Fig. 11 present the generation mix in different years and the energy generation from different resources. Due to the reduction of the emission caps, the annual generation from coal-fired power plants decreases during the planning period and finally disappears in 2050. The coal-fired units' retirements lead to the decreasing share in proportion. This lost energy from retired coal units are mostly compensated by the output of power systems based on renewable energy, including wind and solar. The wind and solar power generation increases dramatically, contributing the largest part of the power generation mix

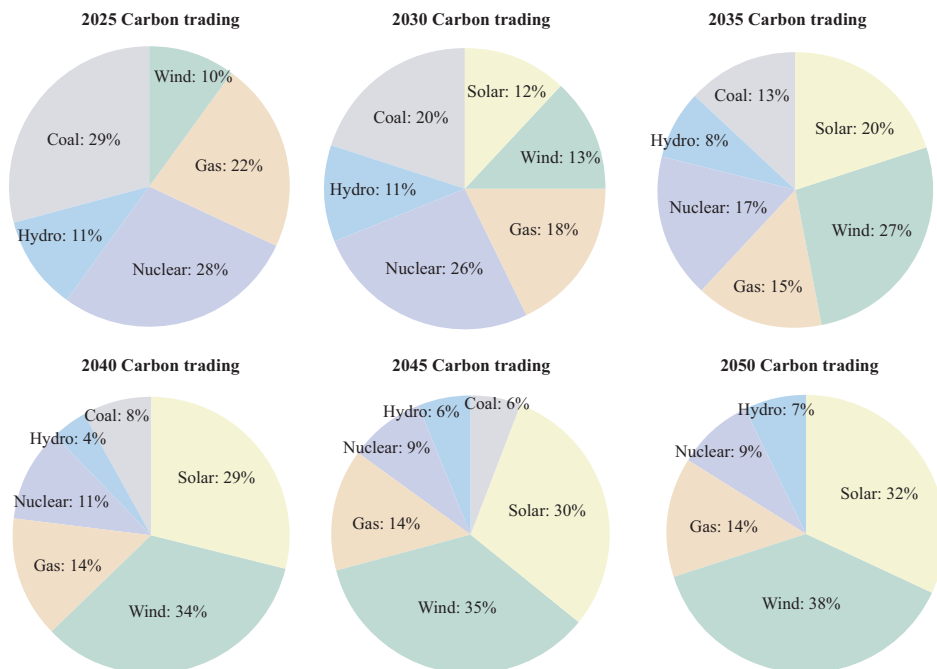
in 2030 and finally reaches 60% of total generation in 2050. Compared to Fig. 9 and Fig. 10, the power system is transited from the existing coal-based power system to the future-ready renewable energy-based system. In 2050's electricity system, nuclear, hydro and gas power generators could assist in large-scale renewable power generation to solve the ramping issues and satisfy the reliability criteria.

5.3.2 Carbon tax

During long-term planning, the carbon tax price is assumed to increase. Four tax scenarios are selected in this study as shown in Fig. 12. The increasing rates of tax (per 5 years) are 1% and 5% for scenarios 1 and 2, and scenarios 3 and 4, respectively.

In Fig. 13, the energy generation mix for the four scenarios is compared. In scenario 1, tax price and increasing rate are both relatively low, indicating that the tax prices are not enough to penalize coal units. Therefore, energy generation is not influenced by the carbon tax. Due to the increase of power demand, the output of renewable energy-based systems increases slightly. The nuclear, hydro, and gas energies are not influenced by the tax as well. Similar to scenario 1, although scenario 2 has a slightly higher carbon tax, the impact on coal energy is still small, decreasing coal-based energy slightly since 2030. The expansion of renewable energy-based systems is higher than in scenario 1.

The carbon tax increasing rates for scenarios 3 and 4 are large and have a great impact power system transition. In scenario 3, although the increasing rate is considerably high,



**Fig. 10 Generation mix for carbon trading in different years**

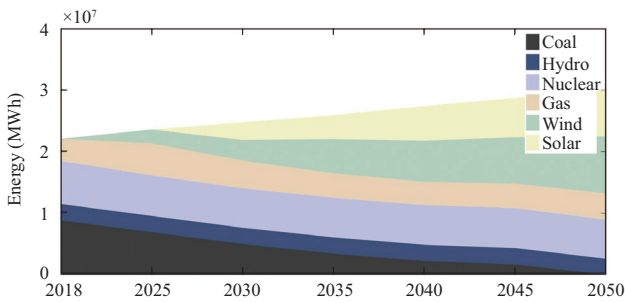


Fig. 11 Energy generation from different resources

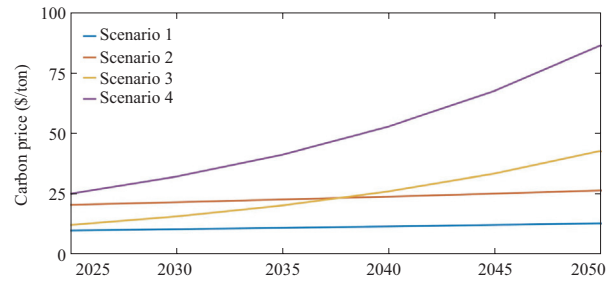


Fig. 12 Carbon tax price scenarios

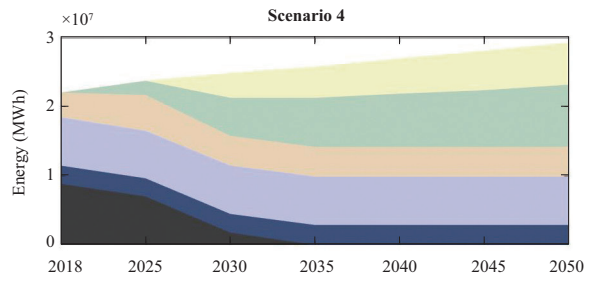
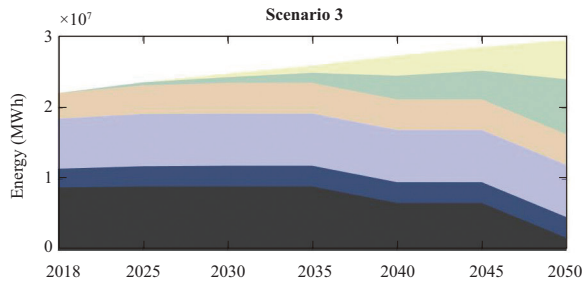
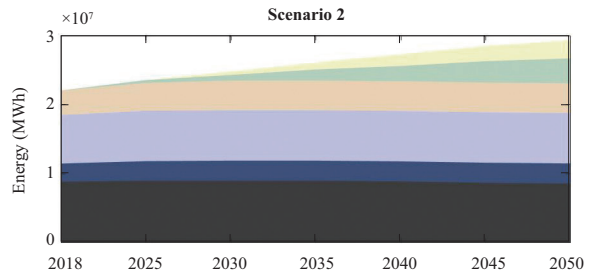
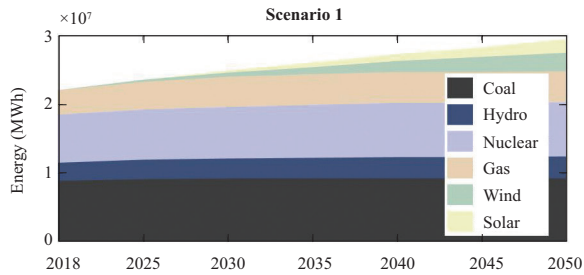


Fig. 13 Energy generation from different resources in different cases

the starting tax level is low; therefore, the carbon tax has little impact on coal energy before 2035. In 2040 and 2050, the tax pushes the retirements of 2 and 4 coal-fired units, respectively. Both carbon tax and the tax increasing rate are the highest in scenario 4. This high tax has large impacts on system transition. To be more specific, two coal units retire in 2025, followed by four other coal units in 2030, and all coal units in the system are retired in 2035. Renewable power generation increases dramatically when coal units retire. After all the units retire, renewable energy-based generation increases steadily with power demand. Although a higher tax rate means a higher operating cost, the gas units cannot quit the power system as they have to operate during the ramping period of renewable energy-based generation to satisfy system reliability requirements. Energy generation by hydro and nuclear power plants are almost at the same level during the planning period. Overall, a large carbon tax could influence the future energy generation mix and coal-fired units' retirement decisions.

5.3.3 Carbon tax vs. carbon trading

Fig. 14 compares carbon trading and carbon emission

for four carbon tax scenarios. The carbon emissions for different carbon tax scenarios are considerably different. The carbon tax for scenario 1 is relatively low, and the emission is almost unchanged during the planning period. The emission in scenario 2 decreases slightly with the increase in carbon tax. In scenario 3, the carbon emission decreases dramatically since 2040 and finally reach approximately 30% of the 2018 emission level; once the tax reaches \$30, coal units start to retire. The emission reduces significantly from 2025 to 2035 and then remains at almost a certain level for scenario 4. The reason for this is the higher carbon tax and tax increasing rate that bring the closure of coal units; once all coal units retire, although tax is still increasing, gas units have to pay higher operating costs to satisfy system reliability requirements. Therefore, the remaining emissions are emitted from the gas generators. As for the carbon trading case, to meet the decreasing annual emission cap, GENCOs need to satisfy their annual carbon allowance. Therefore, the carbon emission decreases gradually and finally reaches 15% of the 2018 emission level.

The emission reduction level for carbon trading is

relatively stable due to the emission cap, whereas the reduction levels depend on the carbon tax prices. The sudden increase in carbon tax leads to the retirement of many coal-fired units, leading to increased investment cost because of renewable energy-based system installation and transmission expansion.

Combining the testing results for mid-term and long-term planning, it is clear that both carbon trading and high carbon tax could decrease carbon emission. Carbon trading inspires coal-fired units' retirements, as the retired units could not only benefit from selling their equipment, but also make profits by selling their carbon emission allowance. On the other hand, carbon tax punishes the carbon emission units, once the tax price is high enough; GENCOs could not benefit from selling their electricity and hence close their units.

## 6 Conclusions

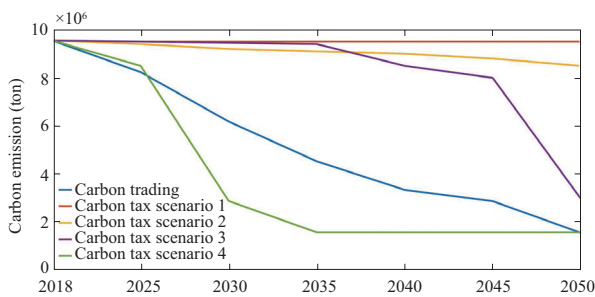


Fig. 14 Comparison of annual carbon emission

This paper proposed a transition planning framework from a central planner's perspective, including coal-fired units' retirements and large-scale renewable energy-based system integration. Except for the planning of generation side, the transmission system was expanded simultaneously to ensure system reliability. In mid-term planning, two carbon emission models, namely carbon trading and carbon tax were proposed and compared. Meanwhile, issues related to the ramping of renewable energy-based systems arising due to the large penetration of renewable power generators were taken into account by adding the ramping cost of renewable energy-based generation in the objective function. The impact of different carbon price scenarios and carbon trading were analyzed with regard to long-term planning. The numerical results in the case study showed that

(1) both carbon trading and carbon tax could decrease power system emission and the carbon trading model is more competitive than the carbon tax model.

(2) For carbon tax scenarios, the reduction values, coal-fired units' retirement decision, and low-carbon power

system transition processes highly depended on the carbon tax level.

(3) In this study, the retirements of coal-fired generators were mostly compensated by the new installations of renewable power generators, leading to the transition from coal-based power systems to renewable energy-based low-carbon power systems.

## Acknowledgements

The work in this paper is supported by by Hong Kong RGC Theme Based Research Scheme Grants No. T23-407/13N and T23-701/14N and the Shenzhen Municipal Science and Technology Innovation Committee International R&D project (GJHZ20160301165723718 and JCYJ20170410172224515). This work is also partly supported by the FEIT Early Career Researcher and Newly Appointed Staff Development Scheme, The University of Sydney.

## References

- [1] UNFCCC. (2015) Adoption of the Paris Agreement. Report No. FCCC/CP/2015/L.9/Rev.1, <http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf>
- [2] Solomon S., Qin D., Manning M., et al (2007). Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change, 2007
- [3] McGlade C., Ekins, P. (2015). The geographical distribution of fossil fuels unused when limiting global warming to 2 C. *Nature*, 517(7533), 187
- [4] Campey T., Bruce S., Yankos T. et al (2017) Low Emissions Technology Roadmap. CSIRO, Australia. Report No. EP167885
- [5] Australia's emissions projections 2017, Commonwealth of Australia 2017
- [6] Chen Q., Kang C., Xia Q., et al (2010). Power generation expansion planning model towards low-carbon economy and its application in China. *IEEE Transactions on Power Systems*, 25(2), 1117-1125
- [7] GFC, CBEEEX (2016) A study on China's carbon Finance Market.
- [8] Kazerooni A. K., Mutale J. (2010). Transmission network planning under security and environmental constraints. *IEEE Transactions on Power Systems*, 25(2), 1169-1178
- [9] ICAP. (2018). Emissions Trading Worldwide: Status Report 2018. Berlin: ICAP
- [10] Li X. R., Yu C. W., Xu Z., et al (2013). A multimarket decision-making framework for GENCO considering emission trading scheme. *IEEE Transactions on Power Systems*, 28(4), 4099-4108
- [11] Careri F., Genesi C., Marannino P., et al (2011). Generation expansion planning in the age of green economy. *IEEE Transactions on Power Systems*, 26(4), 2214-2223
- [12] Stewart, M. (2016). The retirement of coal fired power

- stations. Engineers Australia
- [13] Tohidi Y., Aminifar F., Fotuhi-Firuzabad, M. (2013). Generation expansion and retirement planning based on the stochastic programming. *Electric power systems research*, 104, 138-145
- [14] Moreira A., Pozo D., Street A., Sauma E. (2017). Reliable renewable generation and transmission expansion planning: Co-optimizing system's resources for meeting renewable targets. *IEEE Transactions on Power Systems*, 32(4), 3246-3257
- [15] Yao F., Dong Z. Y., Meng K., et al (2012). Quantum-inspired particle swarm optimization for power system operations considering wind power uncertainty and carbon tax in Australia. *IEEE Transactions on Industrial Informatics*, 8(4), 880-888
- [16] Carta J. A., Ramirez P., Velazquez S. (2009). A review of wind speed probability distributions used in wind energy analysis: Case studies in the Canary Islands. *Renewable and Sustainable Energy Reviews*, 13(5), 933-955
- [17] Shen W., Dong Z. Y., Meng K., et al (2017). Transmission expansion planning with wind generation considering TCSC. In *Energy Internet and Energy System Integration (EI2)*, 2017 *IEEE Conference on* (pp. 1-6). IEEE
- [18] Qiu J., Yang H., Dong Z. Y., et al (2016). A probabilistic transmission planning framework for reducing network vulnerability to extreme events. *IEEE Transactions on Power Systems*, 31(5), 3829-3839
- [19] Billinton R., Wang P. (1999). Teaching distribution system reliability evaluation using Monte Carlo simulation. *IEEE Transactions on Power Systems*, 14(2), 397-403
- [20] Qiu J., Dong Z. Y., Zhao J. H., et al (2015). Multi-stage flexible expansion co-planning under uncertainties in a combined electricity and gas market. *IEEE Transactions on Power Systems*, 30(4), 2119-2129
- [21] Yang G. Y., Dong Z. Y., Wong K. P. (2008). A modified differential evolution algorithm with fitness sharing for power system planning. *IEEE Transactions on Power Systems*, 23(2), 514-522
- [22] Chairman P. F., Bhavaraju M. P., Biggerstaff B. E. (1979). IEEE reliability test system: a report prepared by the Reliability Test System Task Force of the Application of Probability Methods Subcommittee. *IEEE Trans. Power Appar. Syst*, 98, 2047-2054
- [23] Luo F., Zhao J., Qiu J., et al (2014). Assessing the transmission expansion cost with distributed generation: An Australian case study. *IEEE Transactions on Smart Grid*, 5(4), 1892-1904

## Biographies



**Wei Shen** received his bachelor degree in electrical engineering from the University of Sydney, Australia in 2016. He is working towards the Ph.D. degree in electrical engineering at the University of New South Wales, Australia. His research interests include power system planning, carbon emission reduction, renewable energy, and generator retirement.



**Jing Qiu** (M'14) obtained his bachelor degree in control engineering from Shandong University, China; master degree in environmental policy and management, majoring in carbon financing in the power sector, from the University of Manchester, U.K.; and Ph.D. degree in electrical engineering from the University of Newcastle, Australia, in 2008, 2010, and 2014 respectively. He is currently a lecturer in electrical engineering at the University of Sydney, Australia. His areas of interest include power system operation and planning, power economics, electricity market modeling, and risk management.



**Zhaoyang Dong** (F'17) received the Ph.D. degree from the University of Sydney, Australia, in 1999. He is now with the University of New South Wales, Australia. His immediate role is Professor and Head of the School of Electrical and Information Engineering at the University of Sydney. He was previously Ausgrid Chair and Director of the Ausgrid Centre for Intelligent Electricity Networks (CIEN), University of Newcastle, Australia. He also held academic and industrial positions with the Hong Kong Polytechnic University and Transend Networks (now TASNetworks), Tasmania, Australia. His research interests includes smart grid, power system planning, power system security, load modeling, renewable energy systems, electricity market, and computational intelligence and its application in power engineering. Prof. Dong is an editor of the *IEEE Transactions On Smart Grid*, *IEEE Power Engineering Letters*, and *IET Renewable Power Generation*. Prof. Dong is a fellow of IEEE.

(Editor Zhou Zhou)